How does the capital ratio affect the systemic risk of financial and non-financial institutions?

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1 Introduction

The nature of commercial banking is inherently unstable. This is because banks fund most of their long-term lending with either short-term debt in the form of insured deposits or by borrowing from other banks or investors by issuing bank bonds. This results in banks being highly leveraged and means that, in the case of an adverse shock, the confidence in the financial system falls. Even banks unexposed to catastrophic losses are vulnerable to the panic-selling of assets to meet worried depositors' and creditors' sudden demand in their surge for liquidity. If the ECB were to increase capital requirements, banks would be able to absorb a larger portion of the demand for liquidity. Thereby, the risk that they will be forced to sell off their assets at fire-sale prices and trigger systemic risk contagion is reduced.

Systemic risk is caused by two types of systemic failures. Firstly, there is contagion. The existence of contagion risk is a topic of controversy in the literature on banking regulation. Schoenmaker (1996) defines contagion risk as the risk that financial difficulties at one or more bank(s) spill over to a large number of other banks or the financial system as a whole. He finds that, after controlling for macro-economic influences, bank failures are interdependent. Consequently, without intervention by the authorities, an initial failure could generate further failures.

Secondly, multiple banks might be hit simultaneously by macro factors such as extreme movements in exchange or interest rates. Macroeconomic shocks have an important impact on bank risk and on other bank-level variables. Average bank lending increases following expansionary shocks, consistent with an increased demand for loans to finance investment and working capital during boom periods. Meanwhile, average bank risk declines after expansionary macroeconomic shocks, with the exception of supply shocks. Buch et al (2010) find that shocks to banking factors matter for the economy, especially in the medium-term, with which they explain more than 20 percent of macroeconomic volatility. Their explanatory power is largest for shocks in the monetary policy interest rate and for house prices.

The relevance of systemic risk is best illustrated by the 2007-2008 crisis, which had its origins in systemic risk exposure and had a profound impact on the world economy. In the wake of the global financial crisis, there has been increasing awareness of the necessity in addressing systemic risk as opposed to focusing on individual banks (Haldane, 2009). Borio (2003) argues that systemic risk is mainly driven by the banking system's exposure to macro factors. This was the case in 2008, where numerous banks were holding similar financial products that ended up being worth significantly less than expected. In the midst of the Corona crisis banks are once again facing severe adverse macroeconomic shocks. These concerns are shared by central banks, which have increased capital requirements for large banks (DNB, 2018; N Martynova. 2015; B Cohen, 2013; ECB, 2017). By increasing capital requirements, large banks are required to build up a safety buffer, which reduces the size of any future bailout.

However, given that higher capital requirements stall economic growth, is increasing the capital requirements worth it? From a theoretical perspective yes, higher capital ratios should lead to a lower probability of default. However, it is not clear how changes in capital regulation affect the likelihood of a new crisis, the dynamics of the banking industry, or business cycle fluctuations in credit. Larger banks will, to an extent, be better able to increase their capital. As such, higher minimums will reduce competition and consequently lead to a reduction of efficient intermediation due to higher borrowing costs. The main issue with understanding whether capital requirements will be effective lies in the challenge of measuring the cost of a crisis. The size of the contraction generally depends on the size of the expansion that led to the crisis. To adequately measure how capital requirements affect the banking system and economy as a whole, one would have to observe how the economy would have behaved with and without capital requirements during both the boom and bust cycle, not merely the decline. However, this is an ideal scenario which is impossible in the real world and as such we are unable to observe this.

The effect of capital requirements in terms of a regulatory measure to reduce systemic risk remains unresolved. In theory higher capital requirements seem to be a suitable measure to reduce risk as banks should have more capital and, as a consequence of higher capital requirements, can absorb a larger adverse shock. Regulatory reforms, such as an increased capital buffer, are designed to enhance the safety and robustness of the financial system. Reint et al. (2018) find that banks primarily shrank their total assets by reducing the supply of credit, rather than reducing risk. Moreover, an important policy implication of Reint et al. (2018) is that capital requirements which target the regulatory capital ratio have potentially adverse effects on the real economy. Additionally, Dautovic (2019) finds that there are unintended consequences of bank regulation, most interestingly a more pronounced risk-taking behaviour. This indicates that there is indeed a risk-capital trade-off: if banks consider that higher capital requirements can hinder further their profitability prospects, they will invest in potentially more profitable but riskier assets. As such, the literature is divided and the question remains, what is the effect of the capital ratio on the systemic risk exposure of financial institutions? Moreover, as the systemic risk level between financial and non-financial institutions is vastly different, and as the former has far lower capital ratios than does the latter, it would be interesting to see whether the effect of increasing capital requirements have similar effects.

Lastly, higher capital requirements reduce the incentives for a bank to increase asset risk. A value-maximizing bank prefers to meet higher required capital ratios by raising additional capital, rather than merely by selling assets and retiring deposits. In this way, the bank maximizes its volume of assets and thereby the value of the deposit insurance subsidy. Regulatory efforts to raise the capital ratio thus lead to a value-maximizing bank to hold a less risky asset portfolio and hence a reduction in systemic risk. It should thus be optimal to have more stringent capital regulation as it will reduce the risk exposure of the deposit insurance system. However, is this really the case? We are left with the central question we will address in this paper:

"How does the capital ratio affect the systemic risk exposure of financial and non-financial institutions?"

This paper is structured as follows. Section 1.1 defines risk, section 2 exhibits the literature, section 3 illustrates the data and includes basic summary statistics, section 4 shows the methodology of the study, which consists of standard β analysis followed by robustness tests with an alternative risk measure, MES_i. Next, section 5 presents the results, with the main findings discussed in section 5. We end this paper with the main conclusion in section 6.

1.1 Defining risk

The capital asset pricing model (Sharpe, 1963) suggests there are two types of risks associated with financial assets: systemic and idiosyncratic risk. Systemic risk is related to the market whilst idiosyncratic risk is linked to an individual firm (Rowe and Kim, 2010). In general terms, systemic risk is the risk related to the general market, whilst idiosyncratic risk is stock-specific risk. When portfolios are diversified, idiosyncratic risk is reduced.

Nonetheless, there remains a great deal of confusion about what types of risk are truly considered "systemic"—relating to a system, especially as opposed to a particular part[1]—and what types of risk should be regulated (Schwarcz, 2008). Summing up the confusion, Alan Greenspan (1995) noted that "it is generally agreed that systemic risk represents a prosperity for some sort of financial system disruption (...) one might use the term 'market failure' to describe what another would deem to have been a market outcome that was natural and healthy, even if harsh" (Kaufman, 1996). The definition of systemic risk is unsettled. Kaufman (1996), defines systemic risk as "the probability that cumulative losses from an event that ignites a series of successive losses along a chain of financial institutions or markets comprising a system". Likewise, the Bank for International Settlements (BIS) defines systemic risk as "the risk that the failure of a participant to meet its contractual obligations may in turn cause other participants to default, with a chain reaction leading to broader financial difficulties" (BIS 1994, 177).

Systematic risks are understood to occur when a trigger event, such as an economic shock or institutional failure, causes a chain of bad economic consequences—sometimes referred to as a domino effect. These consequences could include a chain of market failures or institutional collapse. Consequences might include a cascade of significant losses to financial institutions or substantial financial-market price volatility (Schwarcz, 2008). Systemic risk on the the other hand, is defined as the probability that cumulative losses will occur from an event that ignites a series of successive losses along a chain of institutions or markets comprising a system (Kaufman 1995b).

Following Gai and Kapadia (2010), we present a simplified example of how systemic risk works. Consider a bank's activities which are partitioned into four categories. There are two assets, interbank loans (l_i) and external assets (e_i), and two liabilities, interbank borrowing (b_i) and deposits (d_i). In this example, we take i to be a given bank ($i = 1, 2, \ldots, N$ for N banks). In order for the bank to be solvent, the difference between its assets and liabilities must be positive. Let γ_i be the capital reserve so that $\gamma_i = (e_i + l_i) - (d_i + b_i) \geq 0$, and we denote θ the loan-asset ratios.

[1]System, (n.d.). In *Oxford Dictionary.* Retrieved from `https://www.lexico.com/en/definition/system`

Note that we assume that the banks have the same size. Moreover, we take banks to be linked to z other banks, and consider all loans (w), capital reserves (γ), and loan-asset ratios (θ) to have fixed magnitudes. Now assume a shock which initially only affects a single bank, wiping out a fraction (f) of its external assets. If the magnitude of this shock then exceeds the capital reserve, so that $f(1-\theta) > \gamma$, the bank fails. If a different bank is linked with this bank via z, and if that loss also exceeds γ, that bank will also fail. As there are multiple banks that connect to each other, the losses are diluted with each failure so that the persistence of the shock will die out over time. Thus, we can clearly see that given an increase in the connectivity between banks (z), shocks will involve more banks and increase systemic risk provided that the initial shock is sufficiently large.

The foundation of the current international administrative agenda is the setting of higher requirements for banks' capital and liquid assets (Haldane, 2011). The motivation behind this is that higher capital requirements are expected to reduce idiosyncratic risks. An alternative explanation is that they also contribute in strengthening the financial system by limiting spillover effects. Over the years, capital ratios have been declining relative to banks' total assets (BoE, 2009). Consequentially, banks' capacity to absorb adverse shocks has been declining with it. This trend could be reversed by setting higher capital requirements. While we assumed that all banks have the same size, this is not necessarily the case in reality. Anderson and May (1991) establish a theoretical case on preventive action against 'super-spreaders' to limit system-wide spread. The same logic can be applied to significantly large banks, such as those considered 'too big to fail'. An example of this is the collapse of the Lehman Brothers in the 2008 crisis. The sheer size and leverage of the bank resulted in immense collateral damage, both to the financial and real economy. Preventing such failures is thus in our best interest, and one way to do this is with higher capital buffers.

2 Literature Review

Existing literature has tried to capture the effects of contagion risk with studies of the consequences of bank failures on the stock prices of other banks, mainly using data for the United States (Aharony, 1983; Swary, 1986; Peavy, 1988). The outcome of these effects is often mixed, depending mostly on the type of bank considered (Docking et al. 1997; Sloving et al. 1999). Competitive effects may arise, in which banks in the same region benefit from the complications of others. However, others argue that adverse stock market reactions are related to similar exposures across banks rather than the contagion effect, meaning it can be difficult to distinguish contagion from adverse shocks (Smirlock, 1987; Musumeci, 1990; Kho, 2000; Karafiath et al., 1990).

In contagion risk simulations, researchers assume one or multiple banks will fail and derive how many other banks would fail as a consequence. The results suggest significant contagion risk (Van Lelyveld, 2006). Typically, however, the results are dependent on assumptions about the amount of money recovered from the assets of failing banks. In a number of cases, evidence suggests that cross-border contagion risks in Europe are indeed increasing. However, since these simulations ignore internal emerging risks and feedback mechanisms, they may exhibit biases (Upper, 2004).

The financial crisis of 2007-2008 made it clear that the widespread failure of financial institutions inflicts significant negative externalities to the real economy. When the economy is in a downturn, bankruptcy can no longer be absorbed by stronger competitors as would normally be the case. When the system is undercapitalized, it cannot supply credit for typical, commonplace business and the economy will deteriorate. Hence, capital shortfalls are risky for the firm and its bondholders, but, most importantly, are also perilous for the entire economy if it occurs while the financial sector is undercapitalized.

Post-crisis, concerns for systemic risk have been expressed by the U.S. Federal Reserve, the European Central Bank, and other monetary agencies worldwide. Governments have been raising concerns about the potential for systemic failure originating from hedge-fund collapses, unease originating in the near-failure of Long-Term Capital Management in 1998, which was saved from collapse only by Fed intervention.

Containing systemic risk has become a crucial objective for policymakers around the world. Berger et al. (2018) focused on understanding the impact of policy interventions on various measures of systemic risk. This study focussed at the American bailout system, the Troubled Asset Relief Program (TARP), to assess success in reducing systemic risk. An alternative to TARP is to increase capital requirements for banks, resulting in an increase in the capital ratio. Bostandzic et al. (2018) find that, in the midst of a sovereign debt crisis, shoring up confidence in the European banking sector can be done by increasing Tier 1 capital requirements to 9% for European Banking Association (EBA) banks. Moreover, they uses SRISK[2], a measure first proposed by Acharya et al. (2012) which captures an institution's estimated capital shortfall conditional on a market downturn. SRISK measures the amount of capital required to reestablish the capital ratio of a financial institution following a deterioration in the financial markets. Brownlees & Engle (2011) find that, following Acharya et al. (2010), capital shortfall in a crisis can be seen as a measurement of systemic risk. They argue that an institution in distress, conditionally to the economy being in distress, provides the government with the problem of deciding whether to 'bail out' the bank with taxpayer's money.

Firstly proposed by Acharya et al. (2010) under a general equilibrium model, an important factor in constructing systemic risk is the contribution of a financial institution to a systemic risk crisis. This is more accurately measured by the Marginal Expected Shortfall (MES). The MES of a financial institution is defined as the expected loss on its equity return conditional on the occurrence of an extreme loss in the aggregated return of the financial sector (Cai et al. 2012). Governments have found the MES to provide a useful tool for monitoring and assessing systemic risk in the early stages of a financial crisis. It offers a simple and intuitive way to measure a bank's contribution to systemic risk. Bostandzic et al. (2018) find that capital requirements primarily lead to a decline in the expected returns of EBA bank stocks and an increase in their covariance with market returns. Consequentially, this leads to a rise in systemic risk and a reduction in the Value at Risk (VaR).

The MES measures two things: firstly, the MES measures the contribution of an institution, be it financial or non-financial, to the overall risk of its financial system.

[2]SRISK measures the capital shortfall of a firm conditional on a severe market decline, and is a function of its size, leverage, and risk (Brownlees & Engle, 2011)

In this case, let i be an individual institution, the MES_i for institution i can then be measured by estimating how group i's risk exposure adds to the bank's overall risk (Acharya, 2016). In other words, MES_i can be measured by estimating individual firm $i's$ losses when the group as a whole is doing poorly. Since a fall in a bank's stock return dents its equity basis, the MES hints at future probabilities of default and can be used to gauge expected losses for banks' non-financial creditors (Drehman & Tarashev, 2011).

Secondly, the MES measures how market failures impact on individual institutions. Individual MES is a reliable predictor, at least in relative terms, of the losses banks would face in case of a true systemic event. However, whether the MES is estimated over normal times, i.e. in non-crisis periods, it can be a useful proxy of expected losses conditional to a true crisis remains an open empirical issue (Idier et al. 2013). The MES will be explained further in section 3.2.

For commercial banks, the Basel Committee on Banking Supervision (BCBS) stipulated a capital requirement of three times the 99% ten-day Value at Risk (VaR) for market risk. However, the Basel Committee (2019) has since adjusted such regulations under the sensitivities-based method. This method is calculated by aggregating delta, vega, and curvature capital requirements. Delta is a measure of the marginal change in an option's price resulting from a change in the underlying security. It measures actual price changes whereas vega is focused on changes in expectations for future volatility. Vega measures the changes in implied volatility or the forward-looking expected volatility of the underlying asset price. Moreover, the Basel Committee (2019) has decided to move away from VaR towards the Expected Shortfall (ES) measure of risk under stress.

It is known that portfolio optimisation under a VaR constraint can induce undesired behaviour (Dert & Oldenkamp (2015). Dert & Oldenkamp (2015) show in a discrete time setting that when the expected return is maximised under a VaR constraint, the optimal portfolio includes the 'casino effect'. This implies it is optimal for an investor to use an investment strategy with firstly a small probability, small enough to be out of the scope of the VaR constraint, on a very large loss and a small probability on a large profit. The investor is thus incentivised to take extra risks which results in an extremely skewed probability distribution, whereas the VaR was introduced to achieve the opposite. Thus, under casino portfolio, the VaR does not accurately capture the risk of such a portfolio. To prevent the use of casino portfolios, the use of ES will help ensure a more prudent capture of 'tail risk' and capital adequacy during periods of significant stress in financial markets.

The necessity for an economic baseline as a systemic risk measure is more than just an academic concern, with regulators around the world considering approaches to reduce the risks and costs of systemic crises.[3] It is indeed a complex task, if not outright impossible, to find a practically relevant systemic risk measure which could also be rationalized by a general equilibrium model. Allen and Saunders (2002) find that the gap between theoretical models and practical requirements of regulators is so severe that measures such as the VaR, which are designed to address idiosyncratic risk, have persisted in regulation assessing risks of the monetary system. Acharya et al. (2016) attempt to bridge this gap by developing a theoretical model that is based on various general equilibrium models, and which is simple enough to provide clear recommendations, and relies on well-known statistical measures. Most importantly, they find that the leverage ratio had the most pernicious effect on systemic risk during the 2007-08 crisis. In contrast, even though deposits can in principle be demanded instantly and consequentially require short-term liquidity at the bank, the presence of deposit insurance meant that commercial banks with access to insured deposits were in fact relatively stable during the crisis.

Fang et al. (2018) use the Kolmogorov-Smirnov statistic to test for the significance of the systematic risk beta on tail risk. They find that commercial banks take on more risk during tranquil periods because of their huge size and impact on the financial system. They predict that the risk contribution will rise when the book-to-market ratio is lower. Hill & Stone (1980) show that the systematic risk beta is affected by the financial structure and operating risk of a firm. Fabozzi & Francis (1979) show beta to be significantly influenced by the size, financial leverage, and the dividend record of the firm. Hong & Sarkar (2007) show that, while beta is virtually independent of bankruptcy costs, it is generally an increasing function of the leverage ratio, volatility, market price of risk, correlation with the market, and growth opportunities, and a decreasing function of the tax rate, earnings level, and earnings growth rate.

[3] Global Financial Stability Report, IMF, April 2010

Moreover, it is also increasing with the risk-free interest rate at high leverage ratios. This seems counter-intuitive considering other empirical papers, which argue that beta is in fact a decreasing function of the leverage ratio (Bostandzic et al. (2018); Brownlees & Engle (2011); Subrahmanyam & Thomadakis (1980)).

3 Data

In this section, we first describe the main method of measuring systemic risk. We then describe the robustness test, and how we apply extreme value theory and extrapolation. The dataset is constructed from daily data of the 30 largest banks in Europe, 25 largest oil companies in Europe, and both the Stoxx600 and SP500 indices from 2002Q1 to 2019Q4. This compromises 4,697 daily observations per institution. The series is drawn from Datastream with the exception of the T-bill rate, which is drawn from the U.S. Department of the Treasury.

Variable	Obs		Mean		Std. Dev		Min.		Max.	
	Fin.	Non-Fin.	Fin.	Non-Fin.	Fin.	Non-Fin.	Fin.	Non-Fin.	Fin.	Non-Fin.
β_i	78	57	1.417	.524	.311	.147	.708	.205	2.206	.980
Capitalratio	78	57	.047	.511	.016	.109	.024	.372	.077	.703
Tax rate	78	57	23.440 %	25.195 %	4.699	3.955	15.83	19.667	31.68	33.667

Table 1: Summary Statistics

Table 1 summarizes crucial variables in the dataset. Following Benink & Benston (2005), the capital ratio is constructed as total capital over total assets;

$$CR_i = \frac{\text{total capital}_i}{\text{total assets}_i}$$

For example, the capital ratio for ING is calculated to be $2.96\%, 3.89\%$, and 5.94% for $02-07, \ldots, 14-19$ respectively, this is in accordance with results from Benink & Benston (2005). Alternatively, we calculate the leverage ratio, which is defined as debt over the sum of debt and capital, for ING to be $97.03\%, 96.11\%$, and 94.06% for $02-07, \ldots, 14-19$ respectively. For a too high leverage ratio (a too low capital ratio), banks will have an incentive to adjust the weights to ensure they do not hold any more capital than needed. This is a cost minimization exercise for banks that will see regulators effectively setting maximum rather than minimum capital ratios. This process will most likely be distortionary pushing banks towards lower-weighted assets and shifting promises outside the banking system - with the risks of creating new bubbles and/or unintended shadow banking developments via the regulatory arbitrage process (Blundell-Wignall Atkinson, 2010). Hence, it is optimal to set higher capital requirements (lower leverage ratio) such that these effects will be washed out and systemic risk should hypothetically be reduced.

The mean beta for financial institutions, 1.417, is considerably higher than that of non-financial institutions, .524. This gives a first indication that systemic risk of financial institutions is far greater than that of non-financial institutions. Moreover, both the min. and max. values for $\beta_{\text{financial}}$ are far greater than that of non-financial institutions. The average capital ratio of sample banks is 4.7%, whereas for non-financial institutions this is 51.1%. The standard deviation is around 1.6% and 10.9% respectively. We observe that for non-financial institutions the capital ratio is significantly higher than that of financial institutions.

An important explanatory variable is the tax rate, as a higher tax-shield incentivices institutions to increase their debt. Thus, for the tax rate we use the statutory corporate tax rate, which averages around 0.25. This may seem low relative to higher rates in, for example, Germany, where the statutory corporate tax rate is around 0.35.[4] However, it is in line with most countries, e.g. Netherlands (0.25), Spain (0.25), Poland (0.20). As there the banks in the dataset are dispersed across different countries the higher variance in tax rates does not present an issue.

Macroeconomic drivers, such as volatility, both equity and market volatility, and credit spread, are calculated using a mix of data from Datastream and IMF Financial Statistics.

[4] Deloitte Corporate Tax Rates 2020

Driver	*Subdivision*	*Definition*
M^{i}_{t-1} : lagged macroeconomic state variables	VIX^{i}_{t-1} : volatility	The average of daily return square over the weekly frequency
	LS^{i}_{t-1} : liquidity spread	Difference between three-month collateral repo rate and three-month treasury bill rate
	ST^{i}_{t-1} : spread term	Difference between ten-year treasury bill rate and three-month treasury bill rate
	CS^{i}_{t-1} : credit spread	Change in ten-year BAA rated bond and treasury bill rate
Z^{i}_{t-1} : lagged firm-specific characteristics	LEV^{i}_{t-1} : leverage	The value of total assets over total equity
	BM^{i}_{t-1} : market-to-book value	Market value/book value
	Size^{i}_{t-1} : market capitalization	The logarithm of market valued total assets
	VOL^{i}_{t-1} : equity return volatility	the volatility of the equity return from daily equity return data
R^{i}_{t-1} : the lagged return		The firm-specific lagged return

Table 2: Macroeconomic Drivers

Table 2 gives a brief description of the drivers included, the subdivision of the drivers, and the definition of said subdivision variables. In the following, I will shortly discuss the drivers in more detail and the importance of the given sub-driver.

Volatility, in this case of the market, is calculated as the square root of annualized volatility

$$VIX_i = \sqrt{\Big[\sum_{t=1}^{N} \sigma_i^2\Big] * 252} \tag{1}$$

where σ_i^2 is the variance of the market for a given cohort, e.g. σ_{02-07}^2. It is a good indicator for the macroeconomic state as an increase in volatility leads to a more risky market environment and thus worse economic health since risk has increased compared to the case where there is no increase in market volatility.

The liquidity spread represents the premium that flows to a party willing to provide liquidity to another party that requires and demands it. As the liquidity ratio increases, banks would be less likely to increase their loan rates to discourage demand for credit since offering more credit imply less liquidity for the bank. Kara and Ozsoy (2014) show that banks react to the introduction of capital requirements (i.e. under the regulatory framework in the pre-Basel III period) by decreasing their liquidity ratios (i.e. increasing their liquidity risk).

Interest rate spread, or, spread term, measures the difference in the ten-year T-bill rate and the three-month T-bill rate. In addition, it is also known as the slope for the bond yield curve. The higher the value of the spread, the steeper the yield curve, since the more attractive, in yield terms - not risk, are long-term bonds. If the spread is negative, the yield curve is inverted. An inverted yield curve occurs often during a crisis and signals the high liquidity risks during a crisis.

The credit spread reflects the difference in yield between a Treasury bond and, in this case, the BAA rated bond. Credit spreads are a good indicator of economic health as when faced with uncertain to worsening economic conditions investors tend to flee to the safety of U.S. Treasuries. This often comes at the expense of corporate bonds, which leads to a price increase in the Treasury bonds and a falling yield T-bond, whilst with corporate bond the opposite happens, prices fall and yields rise. This widens the credit spread, which reflects a worsening of the economy.

The leverage ratio is an important financial measurement to indicate how much capital is supplied in the form of debt and indicates the ability of a company to meet its financial obligations. It is important as companies rely on a mixture of equity and debt to finance their operations. The leverage ratio we use is

$$LEV_{i,t} = \frac{\text{Debt}_{i,t}}{\text{Assets}_{i,t}} \tag{2}$$

The market-to-book value is typically used by investors to show the market's perception of a particular stock's value. A low ratio could indicate that the stock is undervalued, i.e. bad investment, and a high ratio could mean the stock is overvalued, i.e. it has performed well. A low ratio is a cause for concern for the company. Moreover, the ratio helps a company to determine whether or not its book value is comparable to the historical market price of its stock. Thus it is a solid indicator for company performance.

The market capitalization captures the size of the institution, it is calculated as the logarithm of market value of total assets. The larger the institutions, the larger should be the impact on systemic risk. Varotto & Zhao (2018) observe that systemic risk indicators are primarily driven by firm size which implies an overriding concern for "too-big-to-fail" institutions. It is also the criterion used by the Supervisory Review Process (SRP) to designate a bank as a systematically important bank. However, this does not exempt smaller banks as they may still pose considerable systemic threats.

Volatility refers to the amount of uncertainty or risk related to the size of changes in a security's value. In finance, volatility is often used to refer to standard deviation, σ, computed from a set of observations on the returns R

$$\hat{\sigma}_i^2 = \frac{1}{n-1}\sum_{t=1}^{N}(R_t - \bar{R})^2, \tag{3}$$

where $\bar{R}$ is the mean return. The sample standard deviation statistic $\hat{\sigma}$ is a distribution free parameter representing the second moment characteristic of the sample. Volatility is then the square root of equation (3).

4 Measuring systemic risk

There are multiple measures for systemic risk, below we will discuss a measure for systematic and systemic risk. Firstly, we look at the systematic risk beta (β). To see whether results we obtain from this measure make sense, we look at an additional risk measure, the MES_i which we split up into the MES_A following Acharya et al. (2010), and MES_B following Brownlees & Engle (2011). A similar comparison was carried out in Acharya et al. (2016). We do this to ensure the MES_i values that are obtained are plausible. It seems to be the case that systemic risk for financial institutions is greater than that of non-financial institutions. In section 4.3 we take a deeper look into this difference and show graphically how the returns look different. An extension of this is section 4.4 which delves deeper into asymptotic dependence, which is crucial to understand the systemic risk between the two (non)-financial institutions. Lastly, to use equation (22) from section 4.5, we need the Hill-Estimator following Hill (1975), which is discussed in section 4.5.

4.1 Systematic risk beta β

The systematic risk beta is one of the main risk measures used in this paper. In the following, we will show how it is measured using the CAPM model and how we plan to use it in a regression format whilst controlling for macroeconomic state and firm-specific variables.

The systematic risk beta which shows the quantity of the risk. It is the change in the return of a stock due to a shift in the market, or, more comprehensively, it is the covariance of stock returns with capital markets (Gu and Kim, 2002). Beta measures the slope of the regression line between the market return and expected return on a security (Lee and Jang, 2002). Mathematically this can be shown as:

$$E(R_i) = R_F + [E(R_M) - R_F]\beta_i + \varepsilon_i \tag{4}$$

where R_i indicates the return on security i, R_F risk-free return, R_M the return on the market portfolio, and most importantly $[E(R_M) - R_F]$ the expected market risk premium such that β_i is the quantification of the systematic risk. We can rewrite this to obtain the systematic risk of security i:

$$\beta_i = \frac{Cov(R_i, R_m)}{Var(R_m)} \tag{5}$$

The most notable drawback of using beta is its inability to incorporate new information that might shock the future and its reliance exclusively on past returns.

By using equation (4.5), we can calculate the β_i for financial and non-financial institution i. We can calculate the capital ratio and then regress the β_i^{stoxx} and $\beta_i^{S\&P}$ upon the capital ratio, where β_i^{stoxx} is the stoxx600 β_i for financial institution i and $\beta_i^{S\&P}$ is the $S\&P500$ β_i for non-financial institution i. We include all explanatory variables from table 2; the macroeconomic state variables capture the one period lagged state of the macro economy to avoid reverse causality. As, in theory, the macro economy worsens, the risk increases. The firm-specific characteristics include proxies for the risk profile of an institution and the overall size as an increase in either should lead to an increase in risk. The main explanatory variables being the capital ratio for institution i, CR_i, and the tax rate for institution i in country c, $TR_{i,c}$, we then get

$$\beta_i^m = \alpha + \beta \cdot log(CR_i) + \gamma \cdot log(TR_{i,c}) + \delta \cdot M'_{i,t-1} + \lambda \cdot Z'_{i,t-1} + \mu \cdot R'_{i,t-1} + \varepsilon_i$$

where β_i^m is the β for bank i, and $m \in \{stoxx, S\&P\}$. Here CR_i is the capital ratio, which expresses total shareholders equity over total assets for bank i, TR_c^i the corporate tax rate bank i paid in country c, M_{t-1}^i represents a proxy for the lagged macroeconomic state (e.g. market volatility, VOL_{t-1}^M, spread term, ST_{t-1}^i, credit spread, CS_{t-1}^i), Z_{t-1}^i, represents a proxy for the lagged institution-specific characteristic (e.g. market-to-book value, BM_{t-1}^i, market capitalization, $Size_{t-1}^i$, and volatility of return, Vol_{t-1}^i). Lastly, R_{t-1}^i is the lagged firm-specific return. The BAA yields are taken from the St. Louis Fed, the T-Bill rate from the U.S. Department of Treasury, and all other data is taken from Datastream. Similarly, for non-financial institutions:

$$\beta_i = \alpha + \beta \cdot log(CR_i) + \gamma \cdot log(TR_{i,c}) + \delta \cdot M_{i,t-1}^{'} + \lambda \cdot Z_{i,t-1}^{'} + \mu \cdot R_{i,t-1}^{'}$$

where β_i is the $S\&P500$ beta of firm i, as the companies included do not show up in the $STOXX600$.

4.2 Marginal Expected Shortfall

Let us first consider the standard risk measures used for financial institutions, i.e. Value-at-Risk (VaR) and Expected-Shortfall (ES or CVaR). These measures show the potential loss incurred by an institution given an extreme shock. Essentially, VaR is the most a bank loses with a confidence $1 - \alpha$, where α is typically 1% or 5%. Let R be the single period random return on a market portfolio held by a bank. Suppose that the distribution of R is continuous. Then the single period VaR_p (q) at probability p is implicitly defined as:

$$Pr\{R \leq -q\} = p$$

Note that the q is a positive number as it is a loss return. If $F(R)$ is the distribution of the returns and R and $f(r)$ its density, the VaR can also be expressed implicitly as:

$$
\begin{aligned}
p &= \int_{-\infty}^{-q} f(R)dR = F(R)|_{-\infty}^{-q} \\
&= F(-q) - F(-\infty) \\
&= F(-q)
\end{aligned}
$$

The dependent variable is a bank's systemic risk exposure. This can be measured using the Marginal Expected Shortfall (MES), as proposed by De Jonghe et al. (2014). Mathematically, the MES of bank i at time t can be shown as:

$$MES_{i,t} = E[R_{i,t}|R_{m,t} < -q] \tag{6}$$

where R_m is an index for the return of the stock market at time t, R_i the stock return of bank i at time t, and q the Value at Risk. The systemic risk is then the probability R_m is negative. The MES is thus the expected loss of bank i, given that R_m is entering the lower tail area below $-q$. The Expected Shortfall of the market portfolio is given by

$$ES_p = -E[R_m|R_m \leq -q] = E[R_{m,t}|R_{m,t} < q_{m,t}] = \sum_{i=1}^{N} w_{i,t}E[R_{i,t}|R_{m,t} < q_{m,t}] \tag{7}$$

In words, the expected shortfall is the average return on days where the portfolio exceeds the VaR limit and is hence equal to the weighted sum of the MES of all banks in the system. If we then take the first derivative of the Expected Shortfall with respect to $w_{i,t}$ we have that

$$\frac{\partial ES}{\partial w_{i,t}} = -E[R_i|R_m \leq -q] \equiv MES_i \tag{8}$$

The expected shortfall is then the expected loss conditional on an extreme shock, i.e. the loss conditional on the return being less than the VaR at probability p, $VaR_p = q$:

$$ES_p = -E[R_m|R_m \leq -q] \tag{9}$$

Let there be n periods and suppose that the index is k ($k \leq n$) times below q over these n periods. The MES can then be calculated as the conditional average:

$$MES_i^q = \frac{1}{k}\sum_{t=1}^{n} R_{it}|R_{mt} \leq -q$$

Using the aforementioned equations, and defining R_i as

$$R_i = \beta_i * R_m + X_i \tag{10}$$

where X_i is idiosyncratic risk, $E[X_i] = 0$, which is uncorrelated with R_m. From equation (6) we know that the MES is given by

$$MES = E[R_i|R_m < -q]$$

If we then substitute in (8) into (7), we get

$$MES = E[\beta_i * R_m + X_i|R_m < -q_i] \tag{11}$$

we then simplify to get

$$E[\beta_i * R_m|R_m < -q] + E[X_i|R_m < -q] \tag{12}$$

as $E[X_i|R_m < -q] = E[X_i] = 0$ (R_m and X_i independent), and since β_i is a parameter, we can take it out of the equation and thus

$$MES_i = \beta_i * E[R_m|R_m < -q] = \beta_i * ES(R_m) \tag{13}$$

which was also shown by Brownlees & Engle (2011).

We now have two ways to construct the MES_i: Firstly, it is the MES_i proposed by Acharya et al. (2010) which shall be referred to as MES_A. Secondly, we have the MES_i of Brownlees & Engle (2011) of equation (13) which shall be referred to as MES_B. We estimate MES using the $CAPM$ derived method (15) and the MES-measure of Acharya et al. (2016), More on this method later.

As a robustness test we can use alternative measures, such as VaR and MES. We focus on the latter and check if we obtain the same results. We roughly estimate the same type of regression for the MES as we did before with the β, again with main explanatory variables $log(CR_i)$ and $log(TR_{i,c})$ control variables for the macroeconomic state, M^i_{t-1}, and firm-specific drivers, Z^i_{t-1}, from table 2:

$$log(MES_i) = \alpha + \beta \cdot log(CR_i) + \gamma \cdot log(TR_{i,c}) + \delta \cdot M^{'}_{i,t-1} + \lambda \cdot Z^{'}_{i,t-1} + \mu \cdot R^{'}_{i,t-1} + \varepsilon_i$$

4.3 The difference in systemic risk between financial and non-financial institutions

In this section, we investigate whether there is a difference in systemic risk between financial and non-financial institutions. By doing so, we can use the results to aid in our understanding of the difference between the two as a whole and to check that we obtain similar results later on of, for example, regressions. In a bivariate setting there is a simple way to visualize the probability of joint failures. One plots the outcomes of the daily logarithmic returns of one (non-)financial against that of a broad market index e.g. (S&P)Stoxx. If it appears that the bad outcomes are projected along the diagonal in the South West corner, one knows that there is significant dependence (e.g. figures 3 and 4).

We establish a crossplot which contains the daily logarithmic stock return of two (non-)financial institutions over the period 2002-2019. Firstly, consider the following crossplot for two European banks ING and Barclays (from January 2002 to December 2019). These banks hold considerable stakes in each other, apart from having similar exposures in their loan portfolios and through the interbank market. The two banks have a correlation of $\rho = .676$ with the corresponding crossplot

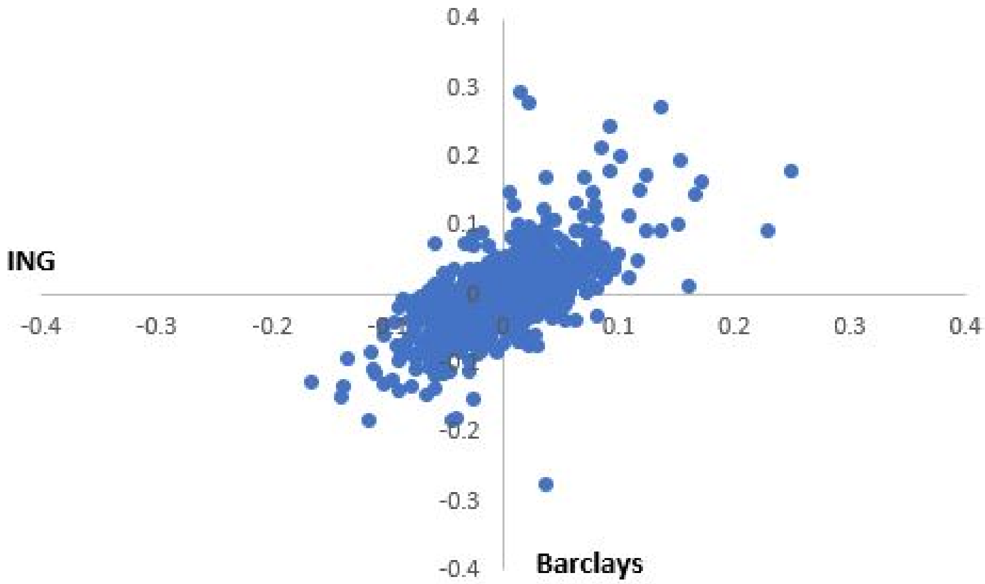

Figure 1: ING against Barclays

Secondly, we consider two European oil companies Shell and Exxon (using the same time period). As these companies hold significantly less stakes in each other, as well has having less systemic risk exposure, the correlation is substantially lower at $\rho = .447$ with the corresponding crossplot

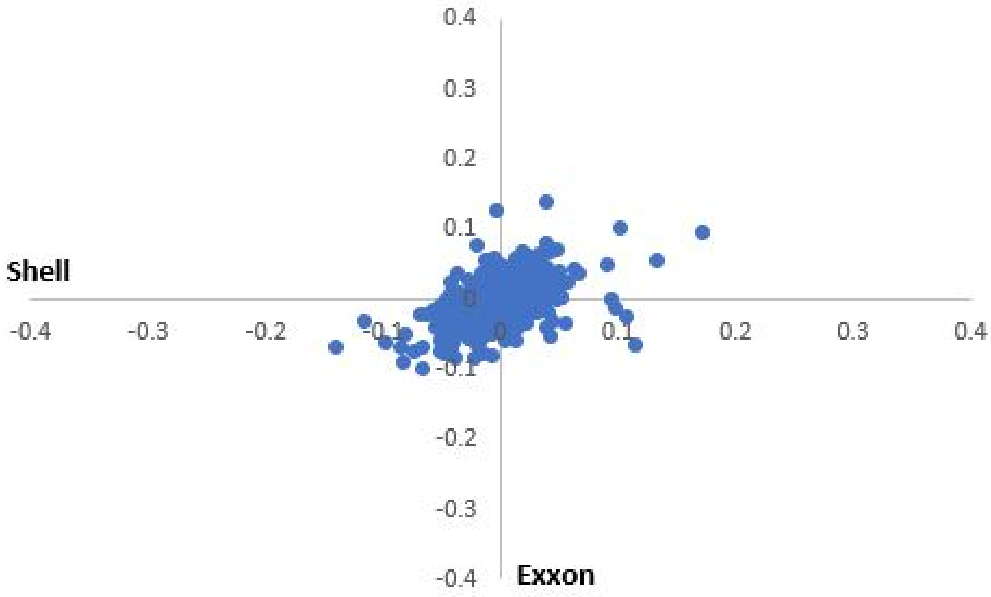

Figure 2: Shell against Exxon

The two bank returns have a significantly higher correlation ($\rho = .676$) than those of non-banks ($\rho = .447$). Graphically one can observe that the returns of non-financial institutions are more clustered (Fig. 2), like a cloud, whereas the returns of banks are more spread out and cigar-shaped (Fig. 1). Moreover, figure 1 shows many more outliers than figure 2 especially in the South West corner which is an indication of a higher dependence. Additionally, the outliers are located along the diagonal, and thus mostly occur jointly which is a clear sign of systemic risk.

To calculate the MES_i we need to know at what point we set the cut-off for the market. In the following we will argue where we set the cut-off and show why the proposed cut-off is a reasonable estimate.

It can be shown that, using a similar crossplot where we plot the bank (non-financial) against the stoxx (S&P) instead of another bank (non-financial). Historically, the largest daily losses realized each year vary depending on the severity of the crisis. For example, a 'regular' year such as 2005 has a largest daily loss of only 1.67%. On the other hand, 2018 has a largest daily loss of 4.0%. The cohorts presented earlier have largest daily losses of 2.71%, 4.97%, and 3.12% for periods $02-07$, $\ldots$, $14-19$ respectively. Crises years such as $2002, 2008$, and 2020 have respective largest daily losses of 4.15%, 9.03%, and 11.98%. In addition, the annual percentage changes were −23.37%, −38.49%, and +2.09% respectively. However, we are interested in periods during which systemic risk enters the market. In these cases[5] the systemic risk is already present and only amplifies the daily market loss. Thus, we want to be between a too high cut-off where we have too little observations, and a too low cut-off where there is no systemic risk. As we are trying to isolate the area in which we are specifically talking about systemic risk, the South-West corner, and based on the aforementioned numbers of largest daily losses and the largest losses in crisis years we set the cut-off at exactly 4%, or −0.04.

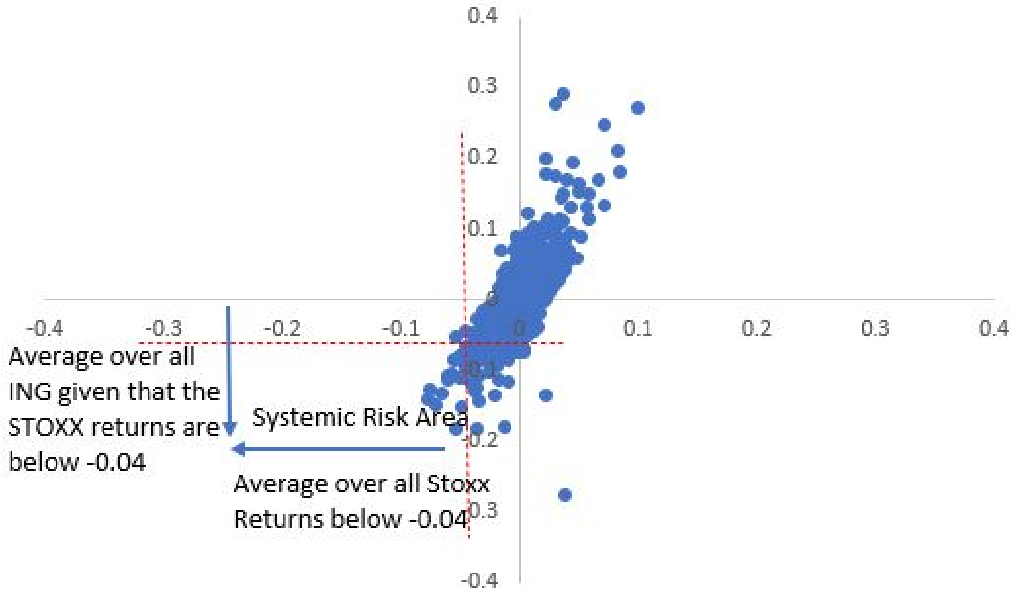

Figure 3: ING against the STOXXX600

As can be observed in the figure, for ING, systemic risk enters the STOXX at 4%. The same is done for other banks and similar results are found.

For non-financial institutions, we instead deal with the $S\&P500$, whilst holding the cut-off at 4% such that we graph Shell against the S&P500:

[5]that of largest daily losses of 2002, 2008 and 2020

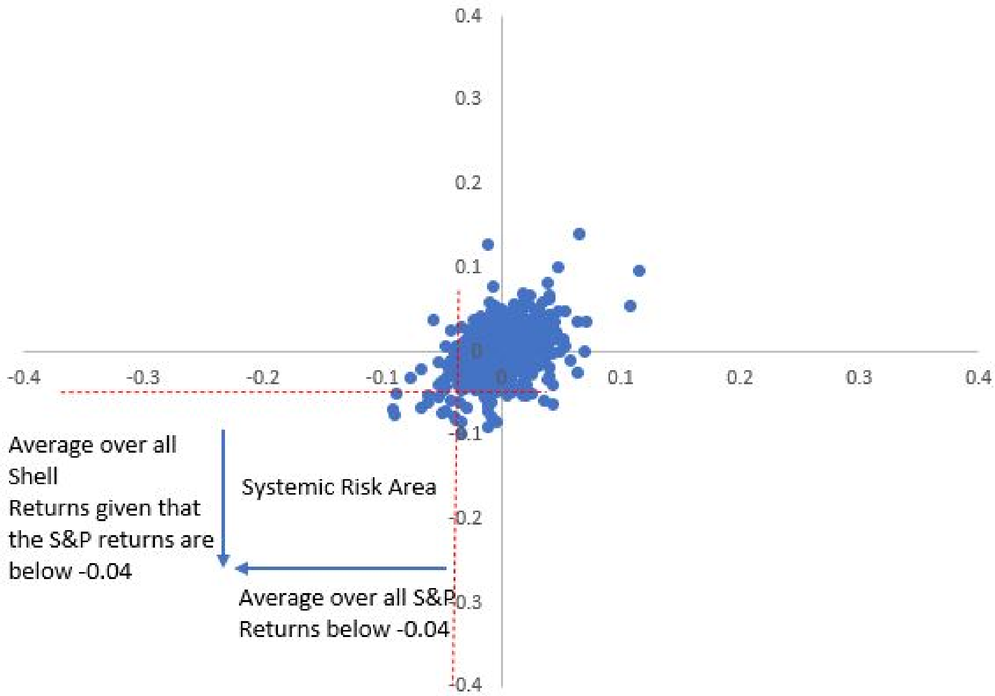

Figure 4: Shell against S&P500

By comparing the two figures (fig 3 and 4) we see that for non-financial institutions like Shell there are fewer observations inside the systemic risk area. Moreover, the shape of the financial institution is more dispersed and is closer to the shape of a cigar, whereas the non-financial institution is more similar to a cloud. An explanation for this could be that banks are long in the economy which exposes banks to macro interest rate risk[6].

[6]Being long means the bank owns shares on account. Because of the long-term maturity of loans and the uncertainty over transaction arrivals, the bank will face an interest-rate risk whenever it holds an unmatched portfolio of loans and the short-term rate of interest changes. That is, suppose a deposit is made at the bank at some long-term rate. If this deposit arrives at a different instant in time from a new loan demand, the bank will have to temporarily invest the funds in the money market at the short-term risk-free rate. In doing so the bank faces a reinvestment risk (Thomas, 1981)

4.4 Asymptotic Dependence

De Vries (2010) shows that the mutual and cross institution exposures to fat tail distributed risks determine the potential impact of a financial crisis on banks and insurers. Moreover, he examines the systemic interdependencies within and across European banking and insurance sectors by means of extreme value analysis. In this section we provide a similar approach, but instead we focus on the European banking and oil sectors during times of stress. We look purely at the scenario in which there are two firms.

De Vries (2010) uses the systemic risk indicator of Huang (1992)

$$E[\kappa|\kappa \geq 1]$$

to show that with two firms, the conditional expected number of failures is

$$E[\kappa|\kappa \geq 1] = \frac{P(X > t) + P(Y > t)}{1 - P(X \leq t, Y \leq t)} \tag{14}$$

where κ is the number of firms that crash and X and Y the stochastic loss returns of two financials (or non-financials) at the common high loss level t, where t is the loss level that triggers a failure. The basis for estimation of the systemic risk measure (15) is a simple non-parametric count measure. From probability theory we have that

$$P(X \leq t, Y \leq t) = 1 - P(max[X, Y] > t)$$

and by using

$$P(X > t) + P(Y > t) - P(X > t, Y > t)$$

we have that

$$P(max[X, Y] > t) + P(min[X, Y] > t)$$

We can therefore rewrite (15) as follows

$$E[\kappa|\kappa \geq 1] = 1 + \frac{P(min[X, Y] > t)}{P(max[X, Y] > t)}$$

The estimation of (15) can thus be reduced to the estimation of two univariate probabilities. The probabilities in the numerator and denominator can be easily estimated by counting the number of minima and maxima that exceed the threshold t. The count estimator thus reads

$$\widehat{SR(\kappa)} = 1 + \frac{\#(min[X,Y] > t)}{\#(max[X,Y] > t)} \tag{15}$$

as a measure of downside dependence.

Consider the systemic risk measure (15) from De Vries (2010), we implement this empirically by taking $\widehat{SR(\kappa)} - 1$, such that we can plot it on the y-axis, and counting

$$\frac{\#min(X,Y) > t}{\#max(X,Y) > t}$$

where # is the number of times that the condition applies in the data. That is, we count how many times both items from the pairs (X, Y) exceed t, and divide this by how many times at least one of the two items from the pairs exceeds t.

4.5 Hill estimator α

To use equation (22) we need to calculate the α, in the following we show how this is done. The tail estimation is that of Danielsson and de Vries (1997). Let x be the return on a risky financial asset where the distribution of x is heavy tailed. Suppose the distribution function $F(x)$ varies regularly at infinity with tail index α:

$$lim_{t\to\infty} \frac{1 - F(tx)}{1 - F(t)} = x^{-\alpha}, \quad \alpha > 0, \quad x > 0 \tag{16}$$

From this property it directly follows that such distributions (e.g. Student-t) have bounded moments only up to α, where α is the tail index. In contrast, distributions with exponentially decaying tails or with finite endpoints have all moments bounded. This implies that the unconditional distribution of the returns is heavy tailed and that unconditional moments larger than α are unbounded. This assumption is the only one necessary for a tail analysis of x returns. Regular variation at infinity is a necessary and sufficient condition for the distribution of the maximum or minimum to be in the domain of attraction of the limit law for heavy tailed distributed random variables.

Suppose that, based on some theoretical model, one predicts a distribution density $f(x)$ which can be loosely defined as follows:

$$f(x) \approx g(x)x^{-\alpha} \quad \text{when} \quad x \to \infty \tag{17}$$

where f and x are real and the critical exponent μ is a positive real parameter. When $x \to \infty$, the function $g(x)$ is supposed to be a smooth function, which is often assumed, for large x, to be a constant λ:

$$f(x) \approx \lambda x^{-\alpha} \quad \text{when} \quad x \to \infty \tag{18}$$

The tail index can be estimated by the Hill estimator (Hill, 1975), where M is the random number of exceedances over a high threshold observation X_{M+1}:

$$\frac{1}{\alpha} = \frac{1}{M}\sum_{i=1}^{M} log\frac{X_i}{X_{M+1}} \tag{19}$$

A parametric form for the tail shape of $F(x)$ can be obtained by taking a second order expansion of $F(x)$ as $x \to \infty$. The only non-trivial possibility under mild assumptions is:

$$F(x) = 1 - ax^{-\alpha}[1 + bx^{-\beta} + o(x^{-\beta})], \quad \beta > 0 \quad \text{as} \quad x \to 0 \tag{20}$$

It is possible to use (4.16) and (4.17) to obtain estimates for out of sample quantile and probability combinations. To derive the out of sample estimator, consider two excess probabilities p and t with $p < 1/n < t$, where n is the sample size. Corresponding to p and t are the large quantiles, x_p and x_t. We now have $1 - F(x_i) = i, i = t, p$. Using the expansion of $F(x)$ in (4.16) with $\beta > 0$ we can show that by ignoring the higher order terms in the expansion and replacing t by M/n and x_t by the $(M+1)$-th descending order statistic, one obtains the estimator:

$$\hat{x}_p = X_{(M+1)}\Big(\frac{m}{np}\Big)^{\frac{1}{\alpha}} \tag{21}$$

Danielsson and de Vries (1997) note that only one limit law governs the tail behavior of data drawn from all fat tailed distribution. Equation 4.15 supplies the condition for which distribution $F(x)$ is in the domain of attraction of the limit law. Since financial returns are heavy tailed, this implies that to obtain the tail behavior we have to deal only with this limit distribution. As mentioned earlier, Hill (1975) proposed a moments based estimator of the tail index which is estimated conditional on a threshold index M where all values $x_i > X_{M+1}$ are used in the estimation. In this estimator, X_i is once again the decreasing order statistic. Danielsson and de Vries (1997) discuss the following estimator for the tail probabilities, given estimates of α and the threshold:

$$\hat{F}(x) = p = \frac{M}{n}\Big(\frac{X_{M+1}}{x}\Big)^{\alpha} \quad x > X_{M+1} \tag{22}$$

n is the number of observations and p is the probability. An important aspect of the estimator (15) is that it can extend the empirical distribution function outside the domain of the sample by means of its asymptotic Pareto tail (10). The estimator is conditional upon the tail index α which comes from combining (18) and $\alpha = 1/H_k$.

To estimate the $MES(k/n)$, we use the method described by Cai et al. (2012). I first denote the loss of the equity return of a financial firm i and that of the entire market as X and Y respectively[7]. The MES is then defined as $E(X|Y > t)$, where t is a high threshold such that $p = P(Y > t)$ is extremely small. In other words, the threshold t is the $(1 - p)$-th quantile of the distribution of Y defined by $P(Y > Q_Y(1 - p)) = p$. Thus, the MES at probability level p is defined as:

$$MES(p) = E(X|Y > Q_Y(1 - p)) \tag{23}$$

in applications the probability p can be even lower than $1/n$, where n is the sample size

[7]Note that Y in the case of financial institutions is simply β^i_{stoxx}

of historical data that are used for estimating the MES.[8] Cai et al. (2012) tackel the extreme value problem by a two-stage approach. Firstly, they consider the estimation of the $MES(p)$ at an intermediate probability level. This is done by just averaging over the $R_{i,t}$ that realize in the case that $R_M < -q_i$. More specifically, they consider an intermediate sequence $k = k(n)$ such that $k/n \to 0, k \to \infty$, as $n \to \infty$, and estimate $MES(k/n)$. At such an intermediate level, there are many observations (X/Y) such that $Y > Q_Y(1 - k/n)$. Thus the $MES(k/n)$ can be estimated non-parametrically by taking the average over the X components of those selected observations.

Secondly, they follow the above extrapolation method in extreme value statistics to obtain an estimator for $MES(p)$ for the intended low probability level p. Assuming that X follows a heavy-tailed distribution with finite mean, and the dependence structure of (X, Y) follows the bivariate EVT framework, they show that the MES can be extrapolated similarly to those for for high quantiles of the distribution of X. More specifically, they estimate $MES(p)$ (23) by multiplying the estimator of $MES(k/n)$ with the same extrapolation factor (22) used to extrapolate the $(1-k/n)$-th quantile to the $(1-p)$-th quantile of the distribution of X.

5 Results

In the following subsections we will calculate the β_i^m and two types of MES. We start with ranking financial and non-financial institutions based on the quantity of systemic risk β to which a firm is exposed. The respective MES for the institution is added and we then compare the two types of MES; MES_A and MES_B as defined in section 4. We start with financial institutions and the same is then repeated for non-financial institutions. Next, the regression results of the β regression are presented in section 5.2. We then check for periods where extrapolation is necessary, and whether the extrapolated MES comes close to the regular MES which is shown in table 8. Then, we perform a robustness check using the MES regression from section 4.2, results are presented in tables 9 and 10 (where table 9 shows the MES_A and table 10 the MES_B). Finally, as a test for a viable explanation as for the phenomenon observed in table 7, which will be discussed further, figures 7 and 8 show the evolution

[8]For example, an extreme even that happens once a decade will give us $n = 2513$ and thus $1/2513$

and trend of the capital ratio. Lastly, as a final check for the phenomenon table 11 presents the new two-cohort regression results, which will be discussed in section 5.3.

5.1 Asymptotic Dependence

If we incorporate the count measure from De Vries (2010) discussed in section 4.4, we can graphically show that the asymptotic dependence between the two banks is considerably higher than for the two oil companies.

If we compare the banks' returns to that of the oil companies, we have a correlation of $\rho = .715$ and $\rho = .447$ respectively for ING & Barclays and Shell & Exxon. However, other than the simple fact that one value is higher than the other, how can we compare and interpret these values? The amount of asymptotic dependence provides a scale along which one can judge financial fragility or the amount of systemic risk. Such a scale may be useful to determine the level of supervision and regulation that one wants to impose on the banking sector (C.G. De Vries, 2005).

In Figures 5-8 we plot the ratio of the number $min[X, Y] > t$ to $max[X, Y] > t$ by varying the threshold t. The tresholds are the order statistics from the two series; the x-axis gives the indices from the descending order statistics. The y-axis gives $\widehat{SR(\kappa)} - 1$ (16), plotted against the increasing rank order of the descending ordered statistics. As the rank along the x-axis increases, we move into the center of the sample and obtain more pairs with maxima and minima that exceed the threshold order statistic. For any finite sample from whatever distribution, eventually $\widehat{SR(\kappa)} - 1$ equals 1 at the lowest threshold t, when t equals the smallest order statistic. But this is not the relevant area, since $SR(\kappa) = lim_{t\to\infty} E[\kappa|\kappa \geq 1]$ should be judged from using a low number of order statistics only. Hence, the plots are based only on the first 300-400 (50-80) descending order statistics from the combined series (for zoom). The figures show the dependence between the two banks (non-financial institutions). For example, in figure 5 we observe that the asymptotic dependence for the two banks is about 0.35, meaning that in about one in every three times that one of the banks is in trouble, the other bank suffers as well. For non-financial institutions this ranges between 0.2-0.25, which translates to one in four to five cases.

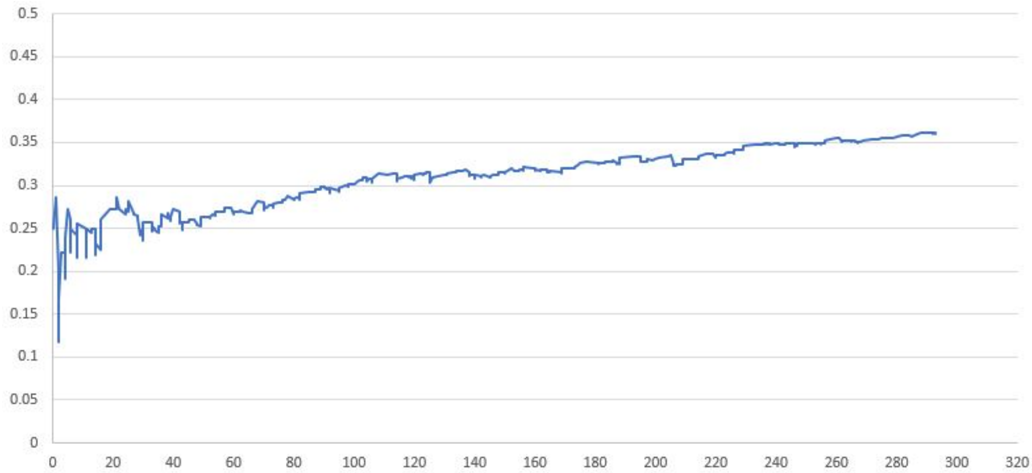

Figure 5: Asymptotic Dependence ING & Barclays - with bias

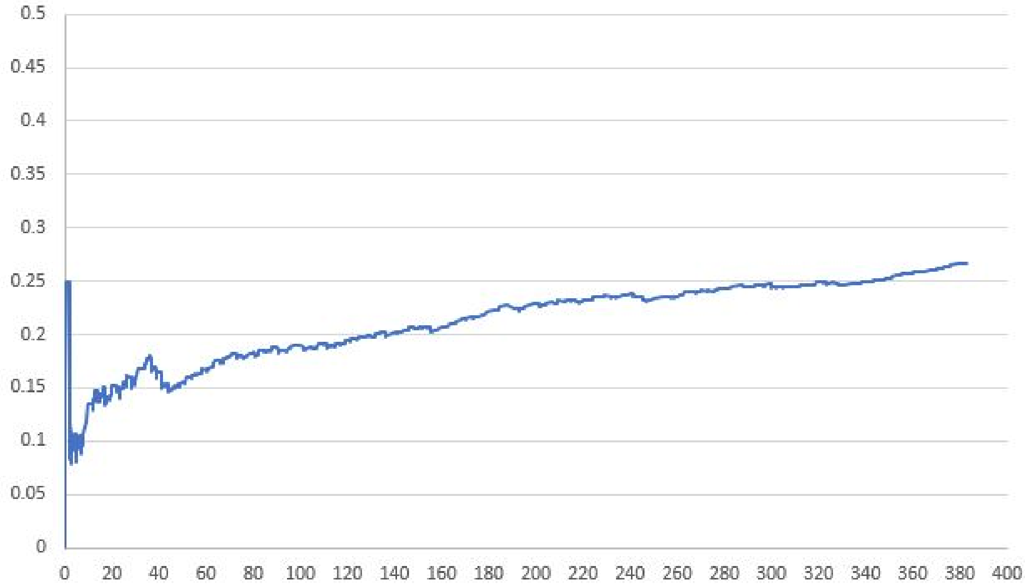

Figure 6: Asymptotic Dependence Shell & Exxon - with bias

The issue at hand here is however, that the figures we are observing above contain a bias. To get a clearer image, we should sail between two cliffs so to speak. That is, we should not be at a point where we have too little observations, as the fluctuations will be too large, additionally, we should also not have too many observations as this contains bias, the case of the figures above, since as $n \to \infty$ we move towards 1.0. We can thus, for the same financial and non-financial institutions, zoom in to obtain a better picture of the asymptotic dependence since we attempt to exclude the bias.

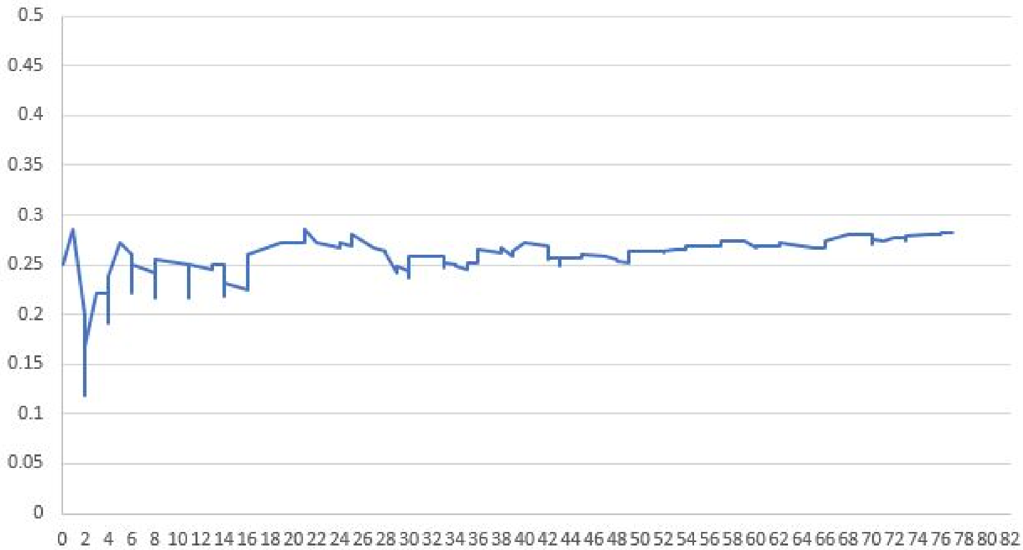

Figure 7: Asymptotic Dependence ING & Barclays

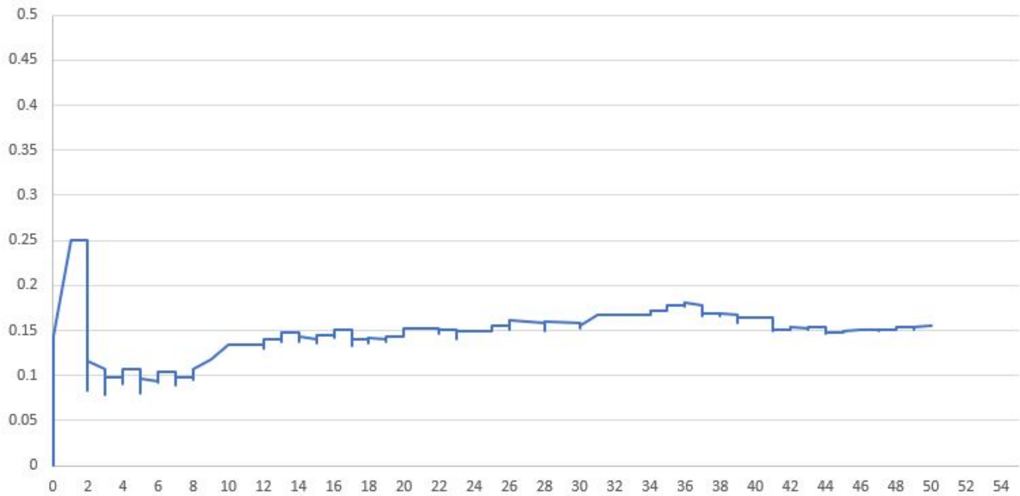

Figure 8: Asymptotic Dependence Shell & Exxon

With the same interpretation as before, in the case of no bias, we have that the asymptotic dependence for the two banks is about 0.25, meaning that in about one in every four times that one of the banks is in trouble, the other bank suffers as well. For non-financial institutions this is around 0.15, which translates to one in seven to eight cases.

What we can conclude from this is that the systemic risk for financial institutions is significantly higher than that of non-financial institutions.

5.2 General results

In the following we discuss the general results of the paper starting with tabulating the systemic risk β_i and MES_A as a comparison. Next, we compare the two types of MES_i, Acharya et al. (2010) and Brownlees & Engle (2011).

Given β_{stoxx}, we can determine the banks that face the most risk in Europe for 2002-2007, 2008-2013, and 2014-2019. We consider multiple time periods so we can observe what happens when the period incorporates either a financial crisis, such as the period 2008-2013, or the long-lasting aftermath, such as the period 2014-2019 in terms of their exposure to systemic risk. We arrive at following risk-orderings for β_{stoxx} with the MES of Acharya at al. (2010), MES_A, as a comparison:

2002-2007			*2008-2013*			*2014-2019*		
Bank	β_{stoxx}	MES_A	***Bank***	β_{stoxx}	MES_A	***Bank***	β_{stoxx}	MES_A
ING	1.726	0.076	***ING***	2.196	0.106	***Banco BPM***	1.738	0.117
Credit Suisse	1.497	0.065	***KBC***	1.992	0.085	***Unicredit***	1.702	0.127
Societe Generale	1.466	0.074	***Barclays***	1.898	0.086	***Intesa Saopaolo***	1.513	0.133
BNP Paribas	1.390	0.063	***Royal Bank of Scotland***	1.802	0.083	***Societe Generale***	1.493	0.118
Commerzbank	1.362	0.061	***Credit Agricole***	1.785	0.075	***Banco Santander***	1.456	0.098
Banco Santander	1.303	0.050	***Societe Generale***	1.773	0.080	***Deutsche Bank***	1.450	0.083
BBV	1.301	0.054	***Erste Group***	1.711	0.078	***ING***	1.363	0.093
Deutsche Bank	1.254	0.052	***Unicredit***	1.706	0.078	***BNP Paribas***	1.345	0.095
Average (N=30)	1.028	0.042	Average (N=30)	1.527	0.071	Average (N=30)	1.184	0.085

Table 3: β_i and MES for financial institutions

Firstly, for table 3 during the period $2002-2007$ we can observe that banks higher in the ranking have 125% to 173% more volatile returns than the market (β_{stoxx} of 1.254 and 1.726 for Deutsche Bank and ING respectively). Moreover, the MES_A indicates that, in the higher rankings, banks experience a 5 to 7% loss in their share value when the Stoxx600 experiences a loss of about 4%. Note that this assumes that the loss of capital is translated into a loss of share value as mentioned earlier. For the period of $2008-2013$ we observe an increase of both the β_{stoxx} and the MES_A. This seems logical as this period includes the financial crisis of 2008. Here we see that banks higher up in the ranking have between 170% to 220% more volatile returns than the market and experience a 7.8 to 10% loss in their share value. Additionally, the average for both risk measures has increased substantially to 48.54& and 40.85% for β_{stoxx} and MES_A respectively. What is surprising is that, for the period of $2014 - 2019$, β_{stoxx} shows that systemic risk has decreased by 22.46%, whereas the MES_A has increased by 19.72%. By extrapolating with (20) and setting $p = \frac{1}{2513}$, we obtain similar rankings. The MES_A is then multiplied by extrapolating factor 4.69, 4.52, and 4.18 for periods 2002-2007, 2008-2013, and 2014-2019 respectively.

Next, we order by $MES_{acharya}$, in table MES_A, and compare to the $MES_{Brownlees}$, in table MES_B, from equation (13).

2002-2007			2008-2013			2014-2019		
Bank	MES_A	MES_B	***Bank***	MES_A	MES_B	***Bank***	MES_A	MES_B
ING	0.076	0.076	***ING***	0.106	0.116	***Intesa Saopaolo***	0.133	0.072
Societe Generale	0.074	0.068	***Barclays***	0.086	0.101	***Barclays***	0.132	0.059
Credit Suisse	0.065	0.066	***KBC***	0.085	0.105	***Unicredit***	0.127	0.081
BNP Paribas	0.063	0.061	***Credit Suisse***	0.084	0.085	***Royal Bank of Scotland***	0.126	0.056
Commerzbank	0.061	0.060	***DNB***	0.084	0.074	***Societe Generale***	0.119	0.071
Barclays	0.054	0.053	***UBS***	0.082	0.087	***Banco BPM***	0.117	0.082
BBV	0.054	0.057	***Royal Bank of Scotland***	0.082	0.095	***Lloyd's Banking Group***	0.115	0.048
Royal Bank of Scotland	0.054	0.048	***Commerzbank***	0.082	0.084	***KBC***	0.099	0.055
Average (N=30)	0.042	0.045	Average (N=30)	0.071	0.081	Average (N=30)	0.085	0.056

Table 4: β_i and MES for financial institutions

By comparing the MES_A and MES_B, we run into the same phenomenon observed in table 3; MES_A is increasing from 2008-2013 to 2014-2019 whereas the MES_B is decreasing. A reason for this could be that the 2014-2019 period average is too dispersed and does not show a MES being 'unified' as for periods 2002-2007 and 2008-2013. Thus, it is difficult to say which MES would be considered an outlier, as for 02-07 to 08-13 they move in tandem, that is, both increase and the $MES_A \approx MES_B$ are roughly in range of each other. As observed in table 3, the β_{stoxx} has decreased in period 2014-2019, it follows naturally from equation (13) that then also the MES_B will decrease substantially in the same period. Looking deeper into the data, we obtain Expected Shortfall (ES) measures of .043, .052, and .041 respectively for cohort 02-07, ..., 14-19. As they are relatively close together, we are essentially still comparing β_i with MES_A, however, we now compare β_i in terms of MES_B. Additionally, the increase in ES for the period 08-13 explains why the MES_B is higher than MES_A for that period. This essentially tells us that, by looking at the averages in table 4, in period 02-07 and 08-13 the systemic risk measures are similar and estimates seem reasonable. Unfortunately, it does not provide us with an explanation as to which MES could be the outlier.

Next we repeat the same method for non-financial institutions:

2002-2007			2008-2013			2014-2019		
Company	$\beta_{S\&P}$	MES_A	***Company***	$\beta_{S\&P}$	MES_A	***Company***	$\beta_{S\&P}$	MES_A
Schlumberger	1.444	0.032	***Valero Energy***	1.444	0.091	***Valero Energy***	1.158	0.044
Exxon	0.955	0.027	***Schlumberger***	1.339	0.080	***Schlumberger***	1.052	0.033
Valero Energy	0.836	0.023	***Exxon***	0.936	0.053	***Exxon***	0.924	0.027
Repsol	0.559	0.013	***Surgutneftegas***	0.711	0.026	***Repsol***	0.830	0.023
Shell	0.542	0.022	***Repsol***	0.685	0.041	***ENI***	0.778	0.021
ENI	0.494	0.011	***ENI***	0.611	0.033	***OMV***	0.653	0.019
BP	0.484	0.013	***Gazprom***	0.595	0.030	***Shell***	0.649	0.019
Surgutneftegas	0.423	0.006	***Equinor***	0.549	0.037	***BP***	0.635	0.012
Average (N=25)	0.416	0.011	Average (N=25)	0.586	0.033	Average (N=25)	0.599	0.020

Table 5: β_i and MES for non-financial institutions

For the period $2002-2007$ we observe that companies higher in the ranking have 42% to 144% more volatile returns than the market. Furthermore, the MES_A indicates that companies in higher rankings only experience a 0.6% to 3.2% loss in their share value given the 4% loss in the $S\&P500$. The percentage increase from the $2002-2007$ period to the $2008-2013$ period is significantly lower for β_{stoxx} than for MES_A, 40.86% and 200% respectively. Moreover, the $\beta_{S\&P}$ increased slightly by 2.22% following the $2008-2013$ period whereas the MES_A has decreased by 39.39%.

again, we order by $MES_{acharya}$, in table MES_A, and compare to the $MES_{Brownlees}$, in table MES_B, from equation (13).

2002-2007			2008-2013			2014-2019		
Company	MES_A	MES_B	***Company***	MES_A	MES_B	***Company***	MES_A	MES_B
Schlumberger	0.032	0.034	***Valero Energy***	0.091	0.066	***Valero Energy***	0.044	0.042
Exxon	0.027	0.033	***Schlumberger***	0.080	0.061	***Schlumberger***	0.033	0.037
Valero Energy	0.023	0.027	***Exxon***	0.053	0.043	***Exxon***	0.027	0.032
Shell	0.022	0.018	***OMV***	0.042	0.025	***Sinopec***	0.023	0.006
BP	0.012	0.016	***Repsol***	0.041	0.031	***Repsol***	0.023	0.029
Repsol	0.013	0.019	***Equinor***	0.037	0.025	***ENI***	0.021	0.027
ENI	0.011	0.16	***Shell***	0.034	0.023	***OMV***	0.020	0.020
Centrica	0.009	0.012	***ENI***	0.033	0.017	***Hellenic***	0.020	0.015
Average (N=25)	0.011	0.011	Average (N=25)	0.033	0.014	Average (N=25)	0.020	0.021

Table 6: β_i and MES for non-financial institutions

However, if we compare MES_A and MES_B in period 14-19, we see that MES_A has decreased, whereas MES_B has increased. An exact opposite of what we have seen for financial institutions. Looking at the behaviour of $\beta_{s\&p}$ in table 5 we observe that, for the same period, the $\beta_{s\&p}$ has increased which then translates into the increase in MES_B.

An explanation for this can be that for non-financial institutions, the 2008-2013 period MES_A and MES_B are quite dispersed whereas the 2002-2007 and 2014-2019 periods have approximately the same average. Also here it is difficult to say which measure of the MES, be it Acharya (2010) or Brownlees & Engle (2011), is the outlier. The main crux here is that, for table 5, the $\beta_{s\&p}$ increases, so naturally the MES_B increases. Moreover, it seems to be the case that MES_B is undervalued as it has only increased by 27.27% for periods 02-07 to 08-13, however it remains difficult to say.

What is clear from tables 3 and 5 is that the β_i is considerably lower for non-financial institutions than for financial institutions, indicating that financial institutions are significantly more risky. Surprisingly, the $\beta_{s\&p}$ and MES_A behave opposite to the β_{stoxx} and MES_A for financials: the β increased following the $08-13$ period, albeit only by 2.2%, whereas the MES_A fell by 39%. Also here, for the same period, we have for table 5 that $\beta_{S\&P}$ increases whereas the MES_A decreases.

Our conclusions from tables 3-6 further cements the fact that financial institutions have far greater systemic risk, a finding confirmed by both systemic risk measures. Additionally, during the crisis period from 2008−2013, the two risk measures increased for both financial and non-financial institutions, showing that, naturally, systemic risk increases during a crisis.

5.3 Regression Results

To find the effect of the capital ratio on the systemic risk β_i^m, whilst controlling for the macroeconomic state and firm-specific drivers, we run the following regression of section 4.1:

$$\beta_i^m = \alpha + \beta \cdot log(CR_i) + \gamma \cdot log(TR_{i,c}) + \delta \cdot M'_{i,t-1} + \lambda \cdot Z'_{i,t-1} + \mu \cdot R'_{i,t-1} + \varepsilon$$

where β_i^m is either β_i^{stoxx} or $\beta_i^{s\&p}$ depending on whether we looking at financial or non-financial institutions. By excluding insignificant independent variables from the output, we are left with:

	Financial Institution	Non-Financial Institution
	log(β_{stpxx})	log($\beta_{s\&p}$)
$log(CR_i)$	-.896*** (.125)	-1.168*** (.162)
$log(TR_{i,c})$	1.337*** (.354)	.057** (.020)
taxsq	-.012*** (.004)	-.035*** (.007)
size	1.802*** (.373)	1.607** (.546)
volatility equity	3.653*** (.533)	1.545*** (.237)
mtbv	-.521*** (.076)	-.203** (.070)
lag size	2.241*** (.361)	1.863*** (.537)
N	78	78
F-stat	157.48 (0.000)	63.95 (0.059)
R^2	.959	.922

Table 7: Regression Results

Where taxsq is simply tax-squared to identify the long run effect. The lagged return, R_{t-1}^i is insignificant, and from $M'_{i,t-1}$ and $Z'_{i,t-1}$ we take out the significant variables, which can be observed in table 7, e.g. Size and Volatility which are defined as per table 2. As insignificant variables are excluded, we observe is that, for both financial and non-financial institutions, a one-percentage point increase in the capital ratio will decrease β_{stoxx} and $\beta_{S\&P}$ by .896% and 1.168% respectively. Meanwhile, a one percentage point increase in the tax rate increases the β_i by 1.337% and 0.57% respectively. However, the tax^2 term has the opposite sign so that we have an inverted U-shape. A one-percentage point increase in the tax-squared will in fact lead to a respective decrease in β_i of .012% and .035% suggesting that the effect wears off and eventually an increase in the tax rate will lead to a decrease in β_i. As a net-effect, we have a positive 1.325% and .022% change respectively for β_{stoxx} and $\beta_{s\&p}$. Moreover, as the size of the institution increases by one percentage point, systemic risk β_i increases by 1.802% and 1.607% respectively. Additionally, a one-percentage point increase in the volatility of an institutions' equity increases β_i by 3.653% and 1.545% respectively. A one percentage point increase in the market to book value decreases β_i by .521% and .203% respectively, which is in line with Fan et al. (2018).

The R^2 is exceptionally high when compared to purely MES focused papers (Keen De Mooij (2012); Jansen & de Vries (2020); Idier et al. (2013)), as well as compared to the regressions we run later using MES. This is also the case for literature that uses β_i (Gencay & Selcuk, 2004; Hong & Sarkar, 2007)[9].

An explanation could be that we are over-fitting the model where the model is describing the random error in the data rather than the relationships between the variables. Moreover, variables that appear to be significant might only be correlated by chance. Another explanation could be, looking at how beta is calculated (5), β_i is dependent on R_i and R_m, however, so are the macroeconomic drivers. Moreover, the regression we run is similar to that of Hong & Sarkar (2007), yet they obtain an R^2 of only 21.67%. Furthermore, a high significance level in a statistical sense means that it is very probably true, however, not necessarily highly important in explaining the behaviour of the dependent variable. Kruskal & Majors (1989) argue that plenty of articles in the academic literature inappropriately employ statistical significance to measure the relative importance of explanatory variables on the dependent variable. However, theoretically the explanatory variables are all justified and should not be exempt from the equation. Thus, we are left with a questionable explanation as to why the R^2 is so much higher than earlier literature.

[9] Variables have been eliminated one by one to find which is responsible for the high R^2, unfortunately, even in many iterations, none was found to be mainly responsible.

5.4 MES regression & Extrapolation

In the case where we would ideally like to have more observations to calculate an accurate MES_i, extrapolation is possible to go deeper into the tail. If we use the method as described in 4.4 we can extrapolate using equation (20). The reason for this is so that we may obtain a more accurate representation of the MES where significant outliers will be washed out somewhat. However, it might be the case that extrapolation gives us an adverse value for the MES_i, to see whether this is the case, we test whether extrapolating gives similar results to periods where extrapolation is unnecessary. Consequentially we can then compare the MES_i if it were computed regularly, since we did not need to extrapolate in the first place, versus the scenario in which extrapolation would be necessary.

	Regular MES	Extrapolated MES
Financial Institution	.076	.080
Non-Financial Institution	.054	.056

Table 8: MES Extrapolated MES

As observed in table 8, the regular MES for ING and Shell during the period $2002-2007$ was .076 and .054 respectively. We obtain approximately the same MES through extrapolation. Thus, it is safe to assume we can extrapolate deeper into the tail in periods where necessary. Now that we have a MES, either regular or extrapolated, for each financial- or non-financial institution at a given time period, we continue the robustness test by estimating an identical regression but with MES as the dependent variable. Once again, we will use both MES_i measurements where i = Acharya or Eq (13) where again $MES_{acharya} = MES_A$ and $MES_{Brownlees} = MES_B$. Once we remove insignificant variables, which surprisingly seem to be all variables except the $Log(CR_i)$, for MES_A we obtain:

	$\log(\text{MES}_{financial})$	$\log(\text{MES}_{non-financial})$
$log(CR_i)$	.501***	-.472***
	(.176)	(.541)
N	77	55
F-stat	8.12	6.19
	(0.006)	(0.042)
R^2	.097	.089

Table 9: MES

looking at table 9, where we use the MES_A by Acharya (2016), a one-percentage point increase in the capital ratio for financial institutions results in a .501% increase in the MES. This result directly contradicts that of β_{stoxx} as seen in table 7. Conversely, a one-percentage point increase in the capital ratio for non-financial institutions leads to a .472% decrease in the MES_A. This is in line with what we find for $\beta_{s\&p}$ in table 7.

We can then repeat the same regression, however, as a main explanatory variable we instead use $MES_{brownlees}$ so as to see whether we obtain similar results as under $MES_{acharya}$. We exclude all insignificant variables so that we are left with:

	$\log(\text{MES}_{financial})$	$\log(\text{MES}_{non-financial})$
$log(CR_i)$	.493***	-1.125***
	(.196)	(.482)
N	77	55
F-stat	6.32	5.46
	(0.014)	(0.023)
R^2	.077	.090

Table 10: MES

looking at table 10, where we use the MES_B by Brownlees & Engle (2011), a one-percentage point increase in the capital ratio for financial institutions leads to a .493% increase in the MES_B. Conversely, a one-percentage point increase in the capital ratio for non-financial institutions leads to a 1.125% decrease in the MES_B. Just as the MES_A, the MES_B directly contradicts that of β_{stoxx} and $\beta_{S\&P}$.

Additionally, the R-squared observed in tables 9 and 10 seems to be more in line with the literature (Keen De Mooij (2012); Idier et al. (2013); Jansen & De Vries

(2020)) as opposed to the r-squared found in table 7. This may be due to the fact that the explanatory variable has now changed to the MES_i, however, $MES_{brownlees}$ uses β_i in its calculation, so it indirectly represents β_i also. Another explanation for the R-squared being more in line with previous literature is that, all control variables are insignificant which leads to the model being less complex than that of table 7. However, both the model in table 7 and the model used in tables 9 and 10 is based on previous literature such that the high R-squared of table 7 remains a mystery.

Counter intuitively, a rise in the capital ratio leads to an increase in the MES_i. A higher expected return implies higher risk exposure, the reverse is not necessarily true. A higher capital ratio implies lower leverage which in turn implies a lower return on equity. Dautovic (2019) finds that there are unintended consequences of bank regulation, most interestingly a more pronounced risk-taking behaviour. This result indicates that there is indeed a risk-capital trade-off: if banks consider that higher capital requirements can hinder further their profitability prospects, they will invest in potentially more profitable but riskier assets.

Another explanation might be the introduction of Basel III where higher capital requirements have been set. It might have been the case that prior to Basel III it was the case that higher capital requirements would have in fact decreased systemic risk as capital ratios would not have been as high as compared to post-Basel III. To see how Basel III comes into play, we change the structure of the groups, namely pre-Basel III and post-Basel III, that is, 2002-2010 and 2011-2019. If we find a difference between the two time periods, it might provide a realistic explanation for the phenomenon. Whilst the Basel III regulation was set in 2009, we are using datastream data of stocks which is lagged in itself, that is, the data needs time to react to information (e.g. Basel III). To see if this is a valid choice, we look at the evolution of the capital ratio for financial institutions[10].

[10]Note that not all banks show up here as the figure would be clogged, they have however been included in the trendline.

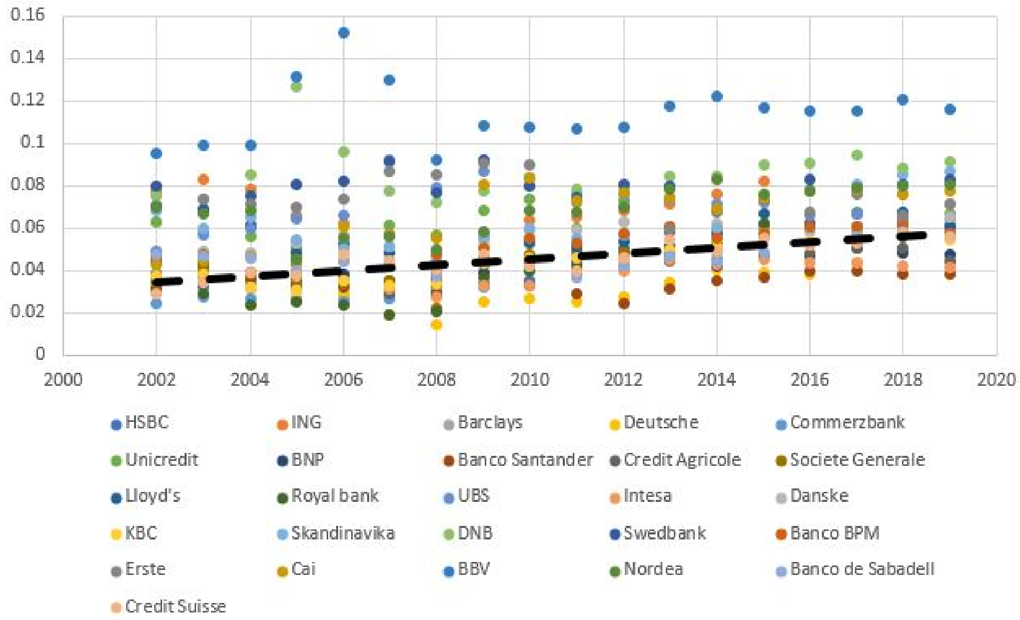

Figure 9: Evolution of the capital ratio for financial institutions

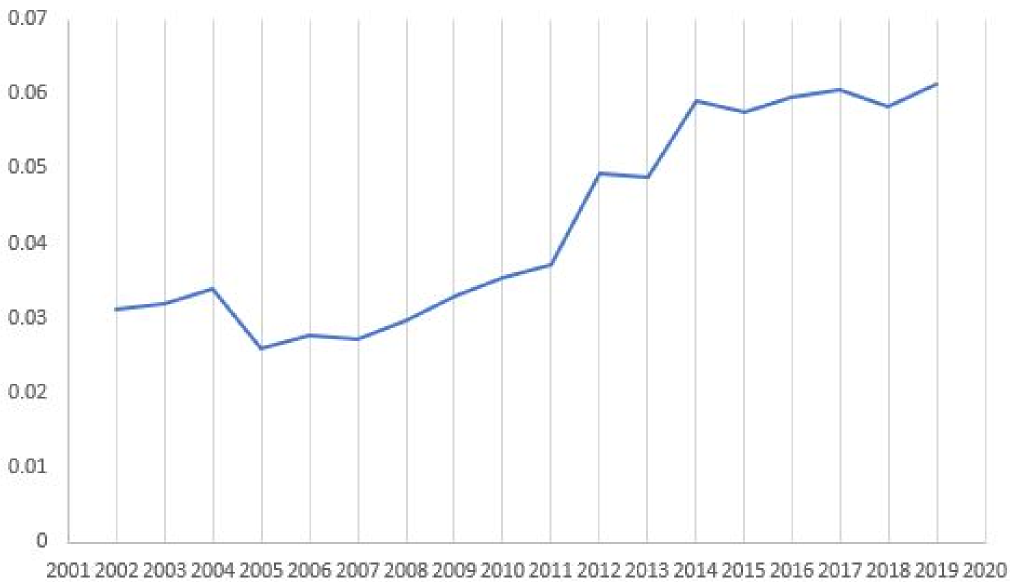

Figure 10: Evolution of the capital ratio for HSBC

As observed in fig 9 we see that over time the capital ratio has been increasing. Take HSBC, in figure 10 most notably we see the steepest jump at 2011-2012. This is most likely because of the realization of Basel-III, thus it seems like a reasonable explanation. If we take a look at the regression for the two new time periods, pre-Basel III and post-Basel III, again mimicking the regression in 3.2 for MES and using both MES_A and MES_B, for pre-Basel III we obtain the following outcome

	$log(MES_A)$	$log(MES_B)$
$log(CR_i)$	-.931***	-.976***
	(.206)	(.222)
N	30	30
F-stat	20.42	19.38
	(0.001)	(0.002)
R^2	.247	.259

Table 11: MES

surprisingly, for post-Basel III no variable is significant, including the capital ratio. As we observe from table 11, a one-percentage point increase in the capital ratio will decrease the MES for financial institutions by .931% and .976% for MES_A and MES_B respectively. What is interesting is that the R-squared is now significantly higher than those in tables 9 and 10. It seems that in pre-Basel III the capital ratio has played a larger role in determining the MES relative to the three cohorts measured before. As the capital ratio post-Basel III is insignificant, it seems to be a plausible explanation as to explain the phenomenon that is occurring in tables 9 and 10, namely, the counter intuitive increase in MES as a result of an increase in the capital ratio.

6 Conclusion

This paper has analysed the effect of a change in the capital ratio on the systemic risk of financial and non-financial institutions. Firstly, we showed that there are clear-cut differences in systemic risk between the two. More specifically, financial institutions have significantly higher systemic risk as they are more correlated, and the asymptotic dependence between banks is greater than that of non-financial institutions. Additionally, the two risk measures of β_i and MES_i behave similarly comparing period

(2002 − 2007) and (2008 − 2013) for financial and (2002 − 2007) and (2014 − 2019) for non-financial institutions. It remains unclear which MES measure is the outlier.

Furthermore, we used the β_i estimator to show that the capital ratio is inversely related to the systemic risk of either a financial or non-financial institution. The MES for non-financial institutions confirms this result, as supported by Fabozzig & Francis (1979) and Hong & Sarkar (2007). However, the MES for financial institutions contradicts this entirely, a finding shared by Brownlees & Engle (2011) and Bostandzic et al. (2018). Once we adjusted for pre- and post-Basel III, we did in fact find results that were in line with those of the β_i estimator for both measures of MES, Acharya (2010) and Brownlees & Engle (2011). In this case, the performance of the β_i and MES seem to be similar and it is unclear which measure should be preferred. The mystery of the high R^2 remains questionable as possible explanations have been presented, yet, remain unconvincing as the regressions stem from earlier literature.

What is clear is that the capital ratio is a critical explanatory variable for the level of systemic risk. It would be beneficial to impose regulations on the amount of debt issued by banks to finance themselves. For example, the Netherlands has imposed an 'earnings-stripping' rule which appears to be a step in this direction. The timing of the corona-crisis is critical, with the results showing that both financial and non-financial institutions' systemic risk has not declined substantially following the 2008 market crash. Once the coronavirus' shock on the market has settled down, a lower tax shield would push banks to finance their operations with equity instead of debt.

Lastly, we find an insignificant capital ratio for the post-Basel III period. Whilst the explanations presented make sense from a theoretical perspective, the capital ratio should in reality not be insignificant as institutions will still alter their behaviour even given that the capital ratio has been increasing over time. It would therefore be interesting to carry out a deeper analysis into pre- and post-Basel III to properly analyse the effect of the capital ratio on systemic risk for this specific time period.

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