Nijmegen School of Management
Department of Economics and Business Economics
Master's Thesis Economics (MAN-MTHEC)

The Financial Structure and Systemic Risk

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Nijmegen, August 15th 2022

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Specialisation: Financial Economics
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Abstract

Financial structures matter not only for economic development, but also for systemic risk. This study is among the first to operationalize three new risk measures, two of which are skewness parameters and one of which is a tail index parameter to proxy for systemic risk. Unlike earlier studies, a much larger sample is used including 303 publicly traded financial firms across 30 countries. Quantile regression is used as main methodological approach which allows for non-linearity testing and differences in size effects across quantiles. The main findings are: (1) bank-based financial systems on average entail more systemic risk than market-based systems; (2) the relationship between the financial structure and systemic risk is non-linear; (3) a newly proposed skewness parameter (*alpha2*), that proxies contagion by measuring the volatility impact on a time-series of returns for an institution conditional upon arrival of market information, seems most promising in measuring systemic risk; (4) developing bank-financing increases systemic risk across all quantiles, developing stock market and debt market financing decreases it, with stock market financing being more effective in bank-based systems and debt market financing being more effective in market-based systems.

Contents

1 Introduction

Literature has extensively examined the relationship between financial development and economic growth, finding a significant positive effect of a country's financial depth on its economic growth (Khan & Senhadji, 2000). Greater financial depth increases economic growth, but the size of this effect may differ across countries (De Gregorio & Guidotti, 1995). In these strands of literature, countries are categorized as having either 'bank-based' or 'market-based' financial systems, which indicates whether channelling funds mainly happens through institutional services (i.e. banks) or capital markets. These types of studies have tried to answer the century old debate on whether bank-based or market-based systems are better in providing long-term economic growth. Whereas earlier studies found a significant effect of the type of financial system on economic growth, later studies suggest that financial development as a whole determines long-term economic growth, rather than the type of financial system (Levine, 2002).

Apart from implications for economic growth, the type of financial system may also have an effect on systemic risk. Systemic risk is especially relevant for policymakers, since understanding this concept and limiting its severeness can help prevent widespread economic crises and contagion (Schwarcz, 2008). Especially after the Great Financial Crisis (GFC), financial regulators sought to address macro-level risk indicators for the whole economy, rather than solely investigating individual, micro-level indicators which overlook interconnectedness and possible contagion. These developments led to the implementation of macroprudential policy, which aims to safeguard a country's financial system as a whole (Kahou & Lehar, 2017).

The type of financial system has important implications for both the level of economic growth and the level of systemic risk in an economy. Moreover, the initial development of a country's financial system into either bank- or market-based yields significant institutional developments specific to that system, preventing it from quickly changing its nature due to high switching costs. Hence, the path-dependent outcome of a country's financial system has important implications for an economy (Bianco, Gerali & Massaro, 1997).

The literature on bank- versus market-based financial systems has focused on systemic risk implications rather than economic growth after the GFC. Policymakers often struggle with the trade-offs between adopting one system over another. One particular problem in a heavily bank-based system, is the possible emergence of excessively powerful banks, leading to moral hazard issues and Too-Big-To-Fail (TBTF) concerns (Stern & Feldman, 2004). The TBTF phenomenon became especially visible during the GFC, in which many excessively large banks were bailed out by governments at the cost of the taxpayer out of fear of widespread contagion and negative externalities to the real economy.

A recent study concludes that bank-based financial systems are associated with higher systemic risk than market-based systems (Bats & Houben, 2020). These results suggest that a market-based financial system may be more resilient to financial crises during times of economic downturn. This study, and many others, use risk measures that indicate a nominal value of expected loss over a specified range for specific institutions, rather than trying to connect each institution's contribution to systemic risk with each other. Also, limited samples, often including just one country, are used to investigate the effect of the financial structure on systemic risk. At last, while the directional relationship between the financial system and systemic risk has been investigated, its effect strengths have not yet been tested thoroughly across different domains of the financial system (i.e. testing whether the relationship takes on another form than linear).

This study investigates whether the type of financial system significantly influences and predicts systemic risk, using a relatively newer risk-measure that has not received much attention in the literature yet. A dynamic CoVar forecasting method developed by Nolde & Zhang (2020) combines features such as asymmetry in returns and heavy tails with simulations to proxy systemic risk, relying on extreme value theory (EVT). Their approach produces several tail dependence coefficients which can be used to proxy financial contagion. This study adds to existing research in three ways. First, a relatively new method is used to proxy systemic risk by using two skewness parameters and a tail dependence coefficient. This is the first study known to operationalize this method in a cross-border setting to measure systemic risk. Secondly, a much larger sample is used than in previous studies, including 303 publicly traded financial institutions across 30 countries. Thirdly, quantile regression is used as main methodological approach to test for non-linearity and disentangle effect strengths across different domains for the financial system categorization.

The study is organized as follows: section 2 describes the theoretical concept of systemic risk and describes various methods that have been proposed in the literature to measure it. Section 3 operationalizes four testable hypotheses in retrospect of the theoretical background. Section 4 describes the methodological approach used. Section 5 describes the data sample and variables distributions. Section 6 presents results and section 7 adds additional information by robustness tests. Section 8 shows possible shortcomings and gives directional advice for future research, while section 9 concludes the study.

2 Literature Review

2.1 Bank-based versus market-based financial systems

Bank-based and market-based financial systems each have comparative advantages over one another. Bank-based financial systems are often praised for providing strong foundations for developing countries, especially with a weak institutional environment. Moreover, a bank-based financial system is argued to be better at mobilizing savings and identifying good investments due to trust-based relationships and long-term partnerships. A market-based financial system on the other hand is argued to provide better capital allocation and risk-sharing abilities (Levine, 2002).

Due to financial deregulation in the 1980s, the banking sector worldwide has grown tremendously and banks have also moved away from the traditional lending model, engaging in more risky activities as well. An increase in the banking sector leads to both more individual and systemic risk (Laeven, Ratnovski & Tong, 2014). Moreover, the growth of shadow banking, in which financial intermediaries outside of the traditional banking regulation start to engage in activities of the 'traditional' banking sector by providing financing services, increased systemic risk as well (Pozsar et al., 2010). These shadow banks are not subject to tight regulation to which the traditional banking sector must obey, but are also not eligible to opt for lender-of-last-resort (LOLR) safeguards. Moreover, these shadow banks are highly interconnected with financial markets, being able to significantly increase their leverage by circumventing capital restrictions in the traditional banking environment (Adrian & Shin, 2009). Hence, an increase in the banking sector (both in its 'traditional' form and its 'newer' form) is likely to increase systemic risk.

2.2 Defining systemic risk

Before the GFC, there was little attention to the concept of systemic risk. It was simply thought to be the sum of all individual risk components. However, interconnectedness of the financial system (and thus that of individual risks) showed the underestimation and lack of understanding of the concept of systemic risk after the GFC (Smaga, 2014). This is partly due to difficulty in assessing systemic risk. Individual risks (e.g. credit risk, liquidity risk, market risk) can all be measured directly for a given institution. The overarching concept of systemic risk cannot. The aggregation from individual components to a systemic measure overlooks the correlations across individual risk components, and hence underestimates the systemic risk component. Specifically, the interaction between financial institutions and markets shape systemic risk (Allen & Carletti, 2013).

There is no consensus on the exact definition of systemic risk. This is partly due to the fact that central banks seldom explicitly state their definition of systemic risk, even though they do have explicit definitions for financial stability (Smaga, 2013). However, a number of studies conclude that most systemic risk definitions share some common characteristics (Smaga, 2014 – Hendricks, 2009 – Allen & Carletti, 2013):

- Systemic risk concerns a large part of the financial system or many financial institutions;
- An systemic event disrupts a large part of the aforementioned financial system;
- An systemic event triggers a significant loss of confidence in the system;

- The aforementioned characteristics have significant negative influences on the real economy.

This broad characterization can be made even more specific, as done by Allen & Carletti (2013), who divide systemic risk into four areas: (1) panics, (2) banking crises, (3) contagion and (4) foreign exchange mismatches. Especially the second and third point of their study are relevant in measuring financial distress in the economy. Bank runs, imploding speculative bubbles and liquidity shortages may also lead to systemic risk concerns.

2.3 Measuring systemic risk

Broadly speaking, systemic risk indicators can be divided into two-categories: either a (low frequency) balance sheet or macro-level data approach or a (high-frequency) market data approach (Rodríguez-Moreno & Peña, 2013). Measures often compute the minimal capital requirements by aggregating individual risks, quantifying the costs of expected bailouts. Apart from *ex-post* bailout costs, *ex-ante* capital requirements to prevent systemic crises need to be considered as well, since these limit bank's ability to invest freely (Feinstein, Rudloff & Weber, 2017). However, as stated before, these measures often overlook the possible contagion and spill-over effects of default in real terms.

Newer risk measures compute expected losses in the loss-tail of return distributions in the financial sector. One method is to compute the systemic expected shortfall (SES), which measures the likelihood of an individual institution to be undercapitalized when the system as a whole is (Acharya et al., 2017). This risk-measure is an increasing function of leverage and its marginal expected shortfall (MES). The latter measures the expected losses an institution can expect when being in the tail of the loss distribution. Other studies incorporate other risk-related factors to the SES-measure. For example, the SRISK measure (i.e. expected capital shortfall, conditional on severe market declines) uses long-term marginal expected shortfall (LRMES) in combination with size and leverage to compute a measure which indicates which financial institutions contribute most to undercapitalization of the financial system as a whole during times of economic downturn

(Brownlees & Engle, 2017). The sum of this measure across all institutions/firms in an economy then indicates the overall systemic risk in an economy. These types of risk measures have two important advantages. First, data to compute either the MES or SRISK is readily available from financial market data. Secondly, these methods have been proven to have significant explanatory power and ability to predict financial crises. Thus, (at least) three main variables are important in measuring systemic risk: size, leverage and expected capital shortfall (either MES or LRMES). The MES/LRMES are obviously related to the size factor as well: the larger an institution is in capitalization, the larger the expected losses will be in the tail distribution.

2.4 Systemic risk measures

In this section, we briefly discuss different risk measures that have been proposed in the literature to measure systemic risk. We start by discussing the three most-used idiosyncratic measures (Z-score, VaR and ES) and then look at three systemic measures (CoVar, SRISK and SES). Lastly, we take an in-depth look at the dynamic CoVar forecasting approach by Nolde & Zhang (2020).

2.4.1 Z-scores

One of the first and most easy-in-use methods of measuring systemic risk is by computing a country's Z-score. The Z-score measures the probability of default of a country's banking sector by aggregating all individual institution's Z-scores (Boyd & Runkle, 1993). This measure connects the capital buffer of banks to its volatility risk and is calculated as follows:

$$(1)\ Z = \frac{k+\mu}{\sigma}$$

In which *k* is the percentage of a bank's equity as percentage of assets, μ the percentage return on those assets, and σ the standard deviation of the bank's return on assets. Heavily indebted banks entail more solvency risk, hence the *k* factor is lower, leading to a lower Z-score. Therefore the Z-score is lower for bank's with higher risk of default, and higher for bank's with lower risk of default. Z-scores are widely available and easily computable, hence it is often used as 'simple' proxy for probability of banking default. Chiaramonte, Croci, & Poli (2015) conclude that Z-scores are at least as good as other methods in predicting bank defaults, but with the major advantage of being less demanding with regards to data input.

2.4.2 Value at Risk (VaR)

Many financial institutions compute their Value at Risk (VaR), which is a standard risk measure which relies on a certain timeframe *t* and a confidence interval *p*. This measure tries to capture the maximum loss that an institution may incur given a chosen confidence interval. The actual VaR is then the possible loss in value over that timeframe given the confidence interval *(*Duffie & Pan, 1997). For example, an *x*-time VaR of *p*% of value *z* implies that an institution does not expect to incur losses exceeding value *z* during time *x*, given the chosen confidence interval *p*. Or put differently: the probability for an loss exceeding *z* during time *x* is *1 – p*. The VaR-measure is typically used to estimate the amount of capital needed to cover possible losses. The VaR-methodology has been in use since the 1980s and remains very popular in communicating market-risk characteristics (Linsmeier & Pearson, 2000). One important shortcoming of VaR is that it specifies a certain amount of loss given 'normal' market conditions; it does not consider the expected loss given that the confidence-interval is exceeded in the left-part of the distribution (i.e. fat tails). Tail VaR (otherwise known as Expected Shortfall) corrects for this by incorporating the expected losses beyond the specified confidence level (Yamai & Yoshiba, 2005).

2.4.3 Expected Shortfall (ES)

VaR is mainly used due to its simplicity and applicability. However, VaR violates the risk measure axiom of subadditivity and only considers the loss distribution given normal return distributions (Acerbi & Tasche, 2002). Due to the presence of kurtosis in stock return distributions (Kon, 1984), standard VaR may not be an adequate measure of risk. VaR does not compute the expected loss beyond the specified confidence interval, and hence may underestimate the total amount of risk (thus also the risk present in the tail of the loss distribution). Expected Shortall (ES) quantifies the expected amount of loss given that the worst state proceeds (i.e. the VaR threshold is surpassed). The ES measure can be computed by incorporating the conditional expectation on being below the chosen confidence interval into the VaR calculation. Its downside with comparison to VaR is that it requires a larger sample size to obtain the same reliability (Yamai & Yoshiba, 2005). Often a threshold of a 40% stock market decline is used to be considered a systemic worst-case scenario (Bats & Houben, 2020).

2.4.4 Conditional Value at Risk (CoVar)

The conditional value at risk (CoVar) is an extension of the VaR model, in which CoVar equals the VaR of the financial system conditional on institutions being distressed (Adrian & Brunnermeier, 2011). The marginal contribution of an institution to systemic risk is then defined as the difference between the CoVar in distressed times and that in 'normal' times:

$$(2)\ \Delta CoVar = CoVar_{distressed} - CoVar_{median}$$

The extension from VaR to CoVar allows for generalization from an individual institution's risk to a measure proxying for the system as a whole. The definition of 'being distressed' in the original CoVar study is that of the institution being exactly at the VaR level. This has been modified later to being close, but at most equal to the VaR level (Girardi & Ergün, 2013). This extension of the original CoVar using a GARCH-model allows for investigating probabilities that lie further in the tail of the loss distribution (i.e. the most severe events).

2.4.5 SRISK

Thus far, the systemic risk measures we discussed did not provide any information on which institutions contribute most to the systemic risk component. The SRISK measure, which is defined as the expected capital shortfall in a prolonged market decline, allows for ranking of financial institutions on basis of which institutions contribute most to systemic risk (Brownlees & Engle, 2017). The SRISK measure takes the following form:

$$(3)\ SRISK_{i,t} = Median_t(Capital\ Shortfall_{i,t} \mid Crisis_{i,t})$$

Which can then be altered to:

$$(4)\ SRISK_{i,t} = Median_t(k(debt_{t+n} - equity_{t+n}) - equity_{t+n} \mid Crisis_{i,t})$$

In which it is assumed there is a desired level of capital, which equals factor *k* times the total number of assets (i.e. debt + equity). *K* is set to 8% as indication of a 'well-managed' firm. The numerical outcome of the SRISK formula is the median value of capital shortfall, conditional on a systemic crisis. The sum of all SRISK values for each institution is then used to proxy the systemic risk component. The SRISK measure is a weighted average on the long-run marginal expected shortfall (LRMES), size and leverage. The LRMES is often computed via simulations.

2.4.6 Systemic Expected Shortfall (SES)

The difficulty in computing an systemic risk measurement is the justification of both a theoretically sound foundation and practically useful application. Hence, regulators still often rely on individual risk measures such as VaR in assessing institution's risk. In their widely-cited study, Acharya et al. (2017) provide both a theoretical justification and practical applicability by computing a new risk measure called Systemic Expected Shortfall (SES). The SES measures the expected undercapitalization of an institution, given that the system as a whole is undercapitalized. Thus, SES measures the individual contribution of each institution to the systemic risk component. SES bridges the gap from individual risk measures (e.g. VaR and ES) into a systemic component.

The intuition behind SES is that each financial institutions keeps a minimal required amount of capital to meet obligations in distressed times. If this buffer is insufficient to cover potential losses, the institutions adds to systemic risk, as measured by the SES function:

$$(5)\ SES_{i,t} = E\left[za_{i,t} - w_{i,t} \,\middle|\, W_{i,t} < zA\right]$$

Which states that the expected SES equals the amount of equity value (*w*) that drops below the required level of equity (fraction *z* times assets *a*), conditional upon that aggregate banking assets (*W*) is less than the possible amount of value that needs to be covered (fraction *z* times aggregate banking assets *A*). SES is an increasing function of an institution's Marginal Expected Shortfall (MES) and leverage, which comes as no surprise. In section 2.3, we already touched upon the effect of size and leverage on systemic risk.

2.5 Dynamic CoVar and tail coefficients: A new way to measure systemic risk

Tail dependence in stock returns is a widely observed phenomenon in financial economics. Extreme co-movements in asset prices have been observed in the latest financial crisis, pointing at significant contagion among financial institutions (Balla, Ergen & Migueis, 2014). However, fat-tailed behaviour of returns prohibits simpler approaches of correlation testing, since normal distribution is not persistent in stock returns. This relates to Extreme Value Theory (EVT) in which extreme deviations from a set of parameters is accounted for (De Haan, Ferreira & Ferreira, 2006). Drawing upon principles and tools derived from EVT, normal distribution analysis can be extended to allow for non-normal distributions such as those present in stock returns.

The dynamic CoVar forecasting method developed by Nolde & Zhang (2020) has its foundations in a slightly modified definition of CoVar developed by Girardi & Ergün (2013), which defines distress as losses in excess of VaR instead of at the VaR-level. This alteration allows for more extreme events to be captured and has later been shown to be able to capture the fact that a stronger dependence on the financial system as a whole leads to an increase in systemic risk estimations. This improves the CoVar approach of Adrian & Brunnermeier (2011), which does not account for dependence on the financial system. Hence, the proposed approach by Nolde & Zhang (2020) accounts for tail dependencies better than earlier measures. Their approach is semi-parametric: observed financial data such as asymmetry in stock returns and heavy tailed-behaviour is used as input together with simulations for extreme values. Hence, they relax the assumption of purely elliptical distributions whilst still retaining connection to real-world phenomena by using features of observed data. They produce several tail dependence coefficients which can be used to measure contagion in the financial system. Specifically, estimates of *alpha1* and *alpha2* are used as skewness parameters and estimates of *nu* used as a tail index parameter. *Alpha1* measures volatility-impact on a time-series of returns conditional upon firm-specific information arriving, while *alpha2* measures this impact conditional upon market information arriving while correcting for the effect of *alpha1*. Higher values of *alpha1*/*alpha2* indicate that returns of an institution are more reactive to arrival of either institution-specific or market-specific information, and hence are more contagious to economic downturns. *Nu* values indicate deviations in returns from elliptical symmetry. Hence, the higher *nu*, the 'heavier' the tail in the loss distribution. Their back-testing results indicate that a semi-parametric, EVT-based approach dominates a fully parametric approach, since the 99%-confidence fully parametric approach is insufficient to measure CoVar, while the EVT method does satisfy this criteria and performs better in terms of calibration. Even though this relatively new risk measure has received little attention in the literature, it might pose as fruitful approach when returns of certain institutions are heavily dependent on the system as a whole. The study by Nolde & Zhang (2020) has been published in the Journal of Business & Economic Statistics, yet has not been applied in a practical setting to proxy for systemic risk.

2.6 Overview of risk measures

In the table below, we provide a brief overview of the aforementioned risk measures:

Table 1: Overview of several measures that have been used in literature to proxy systemic risk.

Risk measure	Proposed by	Scope	Data input	Aim
Z-score	*Boyd & Runkle, 1993*	Idiosyncratic	Bank-level data	Defines probability of default of a country's banking system
Value at risk (VaR	*Duffie & Pan, 1997*	Idiosyncratic	Market data	Defines expected losses within a certain level of confidence
Expected shortfall (ES)	*Acerbi & Tasche, 2002*	Idiosyncratic	Market data	Defines expected losses beyond the VaR threshold (i.e. in the tail of the loss distribution)
Conditional value at risk (CoVar)	*Adrian & Brunnermeier, 2011*	Systemic	Market data	Defines marginal contribution of institution to systemic risk component
SRISK	*Brownlees & Engle, 2017*	Systemic	Market data & simulations for LRMES	Investigates prolonged market declines and incorporates size and leverage factors
Systematic expected shortfall (SES)	*Acharya et al., 2017*	Systemic	Market data	Defines marginal contribution of institution to systemic risk component conditional on undercapitalization of the system as a whole
Dynamic CoVar forecasting	*Nolde & Zhang, 2020*	Systemic	Market data & simulations	Defines two skewness and one tail-dependence coefficients which proxy for financial contagion and deviations from elliptical symmetry in returns

As seen in table 1, all risk measurements apart from the Z-score use market data to compute the systemic risk component. Using market data has several advantages. Firstly, market data is readily available, also for non-OECD countries. Secondly, using market data rather than solely bank-level data, we get an better overview of the system as a whole rather than focussing on the centralized banking institutions. Thirdly, market data allows for useful comparisons around periods of crises (i.e. investigate how certain risk measures might have predicted severe market declines). The dynamic forecasting of CoVar distinguishes itself by computing several coefficients which proxy for contagion and heaviness of tails, rather than producing a nominal value which is at risk given certain parameters.

3 Hypotheses

Both bank-based and market-based financial systems share the risk of a severe decline of asset values in times of economic downturns. A bank's risk profile can be divided into three categories: financial, operational and environmental risk (Greuning & Bratanovic, 2009). The first category is especially relevant since banks face major liquidity risk due their asset-liability mismatch (Choudhry, 2011). The maturity transformation of turning short-term, liquid deposits into long-term illiquid investments creates additional liquidity risk for banking operations, of which markets do not suffer. Moreover, increasing bank size can lead to TBTF concerns, which is a classic example of moral hazard: banks take excessive risk because they do not bear the negative externality of default, which causes major losses to the real economy (Stern & Feldman, 2004). Further, excessive leverage of banking institutions may lead to solvability issues (Adrian & Shin, 2010). Thus, banking institutions face additional risks in comparison to financial markets due to their leveraged position and asset-liability mismatch.

The asset-liability mismatch, size and leverage of banking institutions suggest that a heavily bank-based system entails more risk to an economy than a well-functioning market system. This suggestion is supported by the findings of Bats & Houben (2020), who also find a non-linear relationship between the two. However, their study focusses primarily on developed OECD-countries and does not consider data before 2000 or after 2014. Using a larger sample, spanning from 2003 to 2019 (pre-Covid), this study investigates whether these results are still hold using three newly proposed systemic risk measures by Nolde & Zhang (2020) together with quantile regression as main methodological approach. The propositions which will be tested are presented below.

Since banks suffer from an asset-liability mismatch, have a leveraged position and interconnected relationship, from which markets do not suffer, we expect bank-based financial system to entail more systemic risk than a market-based financial system:

H1a: Bank-based financial systems entail more systemic risk than market-based systems.

Using the newly proposed method by Nolde & Zhang (2020) using two skewness parameters measuring contagion and one tail index coefficient indicating tail 'heaviness', which all show significant explanatory power in their study, we do not expect outcomes to differ between the three different risk proxies:

H1b: Proposition H1a holds regardless of what systemic risk proxy is used.

As proposed by Bats & Houben (2020), the relationship between the financial structure and systemic risk is non-linear. Both bank- and market-financing are desirable to some level due to their comparative advantages of another (see section 2.1), but especially bank-based financial systems may pose an extra threat when banks grow excessively and raise TBTF concerns:

H2: The relationship between the financial structure and systemic risk is non-linear.

4 Methodology

4.1 Financial system categorization

Earlier studies adopt different approaches with respect to categorizing financial systems as either bank-or market based. For instance, some simply categorize the economy in Japan and Germany as bank-based and that of the US and the UK as market-based (Lee, 2012). However, this approach prohibits us to 'rank' countries by the relative weight of each sector. A more fruitful approach is to define a country's financial structure by its degree of source of financing, which can be done by simply adopting the ratio of bank to market financing (Bats & Houben, 2020*)*:

$$(6)\ F_{i,t} = \frac{B_{i,t}}{DM_{i,t} + SM_{i,t}}$$

Where $F_{i,t}$ is the financial structure ratio, $B_{i,t}$ is the degree of bank financing, $DM_{i,t}$ is the degree of debt market financing and $SM_{i,t}$ is the degree of stock market financing. In essence, the financial structure indicator is the ratio of bank-financing to market-financing. Hence, higher values of *F* indicate that a country's economy is relatively more bank-based. A similar ratio is used by Gambacorta, Yang & Tsatsaronis (2014), who compute a financing ratio by dividing the total bank loans (i.e. the bank financing proxy) by the total liabilities of an economy (i.e. the market financing proxy). These approaches allow us to rank countries in terms of their degree of source of financing. This study uses the financing ratio as adopted by Bats & Houben (2020) since this ratio differentiates between debt market and stock market financing. This distinguishment proves significant in section 6.5 in which the individual component effects of the financing ratio are investigated.

4.2 Control variables

Apart from the financial structure in an economy, a number of other factors influence systemic risk. Firstly, banking concentration may play an important role. The more bank financing takes place in a select number of banks, the greater the potential losses to society when one of these major banks defaults. This also again relates to the earlier-mentioned TBTF concept. To account for banking concentration in an economy, the *Herfindahl-Herschman Index (HHI)* is widely used in literature:

$$(7)\ HHI_{i,t} = \sum_{i=1}^{N} s_{i,t}^2$$

In which $S_{i,t}$ is the market share of institution *i* in the market which consists of *N* firms (Rhoades, 1993*)*. The HHI ranges from 1/N to 1, in which full concentration is obtained when the HHI approximates 1. However, simplicity and data-limitations make a *k-bank concentration ratio* perhaps more suitable (Bikker & Haaf, 2002):

$$(8)\ CR_k = \sum_{i=1}^{k} S_{i,t}$$

In which S_i is the cumulative market share of the k largest banks. The chosen value of k is an arbitrary decision and all banks outside the range of this k are neglected. We use the percentage of bank assets held by the three largest banks in each economy, measured as percentage of GDP, to proxy for banking sector concentration.

Secondly, excessive leverage of banking institutions has been accepted as one of the main underlying problems of many financial crises (Hildebrand, 2008). Moreover, excessive leverage can have an amplifying effect on systemic risk, since leveraged institutions may face additional difficulties in repaying debts when their asset value falls significantly. Hence, we expect leverage to have an positive effect on systemic risk.

Thirdly, on the market side of an economy, market risk may also possess possible spill-over effects. High volatility and liquidity shortages can lead to system-wide distress. Earlier studies suggest that markets may absorb these risks if they are 'deep' and liquid enough (Aglietta, 1996). The concept of 'market depth' can be measured by taking the private credit to GDP or by taking the total bank assets to GDP. The latter measure seems to be more suitable than the former since it also includes credit to government as well as other banking assets.[1] Hence, we use the percentage of total banking assets to GDP to proxy for financial market depth.

4.3 Quantile regression

This study uses quantile regression as main methodological approach. This holds several advantages. Firstly, instead of pooling the entire dataset, subdividing into quantiles allows for investigating inter-quantile differences. Secondly, observing possible inter-quantile differences can detect non-linear relationships (e.g. quadratic or cubic relationships). Thirdly, the effect of outliers is mitigated and hence no observations need to dropped from the dataset. Details on the

[1] https://www.worldbank.org/en/publication/gfdr/gfdr-2016/background/financial-depth

construction of quantiles are presented in section 5.3. The quantile regression takes the following form:

$$(9)\ S_{Q1,Q2,Q3,Q4,Q5} = \beta_0 + \beta_1 F_i + \beta_2 BSC_i + \beta_3 BSL_i + \beta_4 MD_i + \epsilon_i$$

In which *S* denotes the systemic risk proxy, *F* denotes the financial structure, *BSC* the banking sector concentration, *BSL* the banking sector leverage and *MD* the financial market depth of an economy. Subscripts Q_i denote the quantiles.

5 Data

5.1 Variable measurement

Table 2 presents an overview of the variables and corresponding proxies to measure them:

Table 2: Overview of dependent, independent and control variables, proxies, data sources and frequency of observations.

Variable	Proxy	Source	Observation frequency
Dependent variable (systemic risk)			
Alpha1	Volatility impact generated by institution-specific information (skewness parameter 1)	EIKON	Daily
Alpha2	Volatility impact generated by market information, whilst correcting for *alpha1* (skewness parameter 2)	EIKON	Daily
Nu	Tail index parameter (deviation from elliptical symmetry)	EIKON	Daily
Independent variable (financing ratio)			
Bank financing, *B*	Bank credit given (% of GDP)	World Bank / FRED St. Louis	Yearly
Debt market financing, *D*	Total debt to the non-financial sector (% of GDP)	World Bank / CEIC	Yearly
Stock market financing, *S*	Total stock market capitalization (% of GDP)	Bank for International Settlements (BIS)	Yearly
Control variables			
Banking sector concentration	% assets held by 3 largest banks	Theglobaleconomy.com	Yearly
Financial market depth	% bank assets to GDP	Theglobaleconomy.com	Yearly
Banking sector leverage	% total debt to equity	OECD	Yearly

One important assumption in computing the systemic risk proxies (*alpha1*, *alpha2* and *nu*) is that returns are measured in its continuously compounded form:

$$(10)\ R_{i,t} = \ln\left(\frac{P_{t+1}}{P_t}\right)$$

5.2 Sample

Earlier studies such as that by Bats & Houben (2020) mainly focus on developed OECD countries. In their study, their sample contains the following 22 OECD countries: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Luxembourg, Netherlands, Norway, Poland, Portugal, Spain, Sweden, Turkey the UK and the US. Their sample is predominantly EU-based, hence we try to add more countries outside the Eurozone. This study adds Chile, Colombia, Czech Republic, Hungary, Israel, Korea (South), Mexico and New Zealand to broaden the scope of this study instead of being predominantly Eurozone focused. These 30 countries will be divided into 5 quantiles of 6 countries each on basis of their financial structure ratio *F*. These quantiles are ranked from heavily bank-based to heavily-market based to perform quantile regression. The data will constitute from 2003 until 2019 (pre-covid) using daily returns for each institutions. Data on the financing ratio and its components will span even a bit longer (starting from 2000 until 2019).

For each country, the leading stock index is used to proxy the financial system as a whole in computing CoVar estimations and risk proxies. Details on stock indices used as proxy for the country's financial system can be found in Appendix A. Returns are all computed in logarithmic form and stock values are measured in USD. The full panel consists of 303 publicly available financial institutions that consist of 185 banking & investment services (B&I), 77 insurance companies (I), 24 collective investments (C) and 17 investment holding companies (H). this panel is considerably larger than the 99 institution panel considered by Achayra et. al (2017) and Bats & Houben (2020). Details on the full panel can be found in Appendix B. To be included, the financial institutions must have a market capitalization in excess of 1 billion USD, with the only exception being New Zealand which does not have financial institutions which exceed this threshold. The maximum number of firms per category equals 10. (i.e. for large economies such as the UK or US, only the 10 largest institutions are included per category).

5.3 Finance ratio and quantile construction

From the total 30 sample countries, 5 quantiles are constructed of equal size based on the finance ratio *F* discussed in section 4.1. Descriptive statistics on bank credit (*BC*), stock market capitalization (*MC*) and non-financial depth (*NFD*), which together provide the finance ratio *F*, are provided below in table 3:

Table 3: descriptive statistics components financing ratio *F*: bank credit (*BC*), market capitalization (*MC*) and non-financial debt (*NFD*).

	N	Mean	Std.Dev.	Median	min	max
BC	586	90.573	42.442	89.816	11.612	216.6
MC	566	66.864	40.012	59.742	10.287	322.344
NFD	599	217.827	80.661	215.9	42.3	438.6
F	600	.321	.109	.309	.104	.626

BC, *MC* and *NFD* are all measured as percentage of GDP of the respective country, hence permitting inter-country comparisons. Missing values on each variable are computed by calculating the median of either *BC*, *MC* or *NFD* for each country. Median values are used instead of mean due to non-normal distribution of each. Details on variable distribution can be found in appendix C. This leads to 600 observations for the financing ratio *F* (20 yearly observations for all 30 countries).

This leads to the following construction of quantiles (median values for the finance ratio *F* are below each country/quantile):

Table 4: Quantile construction based on the financing ratio *F*. Values presented are median values of each country across the whole time-series of observations

Q1: predominantly bank-based 0.472	Q2: bank-based 0.368	Q3: neutral 0.308	Q4: market-based 0.281	Q5: predominantly market-based 0.210
New Zealand 0.570	Spain 0.393	Greece 0.313	Finland 0.295	Colombia 0.241
Denmark 0.487	Australia 0.392	Ireland 0.311	Poland 0.293	Hungary 0.239
Korea 0.468	Belgium 0.363	Czech Republic 0.309	Italy 0.286	Japan 0.237
Canada 0.463	Austria 0.363	Sweden 0.308	Netherlands 0.279	Mexico 0.207
Portugal 0.431	Germany 0.349	Chile 0.305	Israel 0.266	Luxembourg 0.187
UK 0.413	Norway 0.348	Turkey 0.302	France 0.265	US 0.145

Note that in each country, more financing is done in absolute terms by markets rather than banks. However, relative differences across countries are large. For example, in the UK the financing of banks is almost three times as large as that of the US. The median values of quantile 1 to 5 show significant differences in the financing ratio between quantiles, with the financing ratio in the top quantile being more than twice as large as that in the bottom quantile.

5.4 Control variables distribution

Descriptive statistics on the control variables banking sector concentration (*BSC*), banking sector leverage (*BSL*), financial market depth (*MD*) and the logarithmic version of banking sector leverage (*logBSL*) are provided in table 5 below. We use a logarithmic version of banking sector leverage since this control variable is extremely skewed (see Appendix C).

Table 5: Descriptive statistics control variables: banking sector concentration (*BSC*), banking sector leverage (*BSL*), financial market depth (*MD*) and a logarithmic version of banking sector leverage (*logBSL*).

	N	Mean	Std.Dev.	Median	min	max
BSC	538	20.029	21.973	13.62	3.938	170.502
BSL	563	68.99	19.144	70.57	21.45	100
MD	575	102.133	40.743	100.85	24.67	225.33
logBSL	538	2.703	.686	2.612	1.371	5.139

For New Zealand, no data on banking sector leverage is available. Hence the relatively smaller number of observations in comparison to the other control variables. Again, non-normal distributions of all control variables (see Appendix C) leads us to use median values across the timeframe.

6 Results

6.1 Descriptive statistics

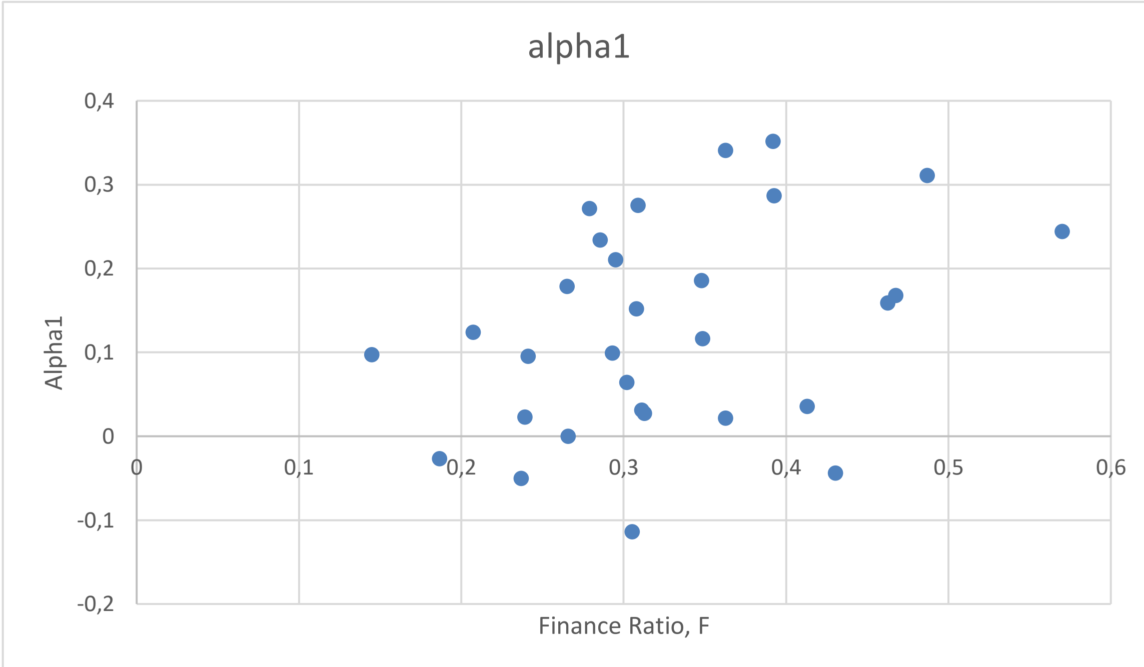
Descriptive statistics on *alpha1*, *alpha2* and *nu* are presented in Table 6 below, which shows considerable variation across risk-measures and significant differences between percentiles, indicating a wide enough sample:

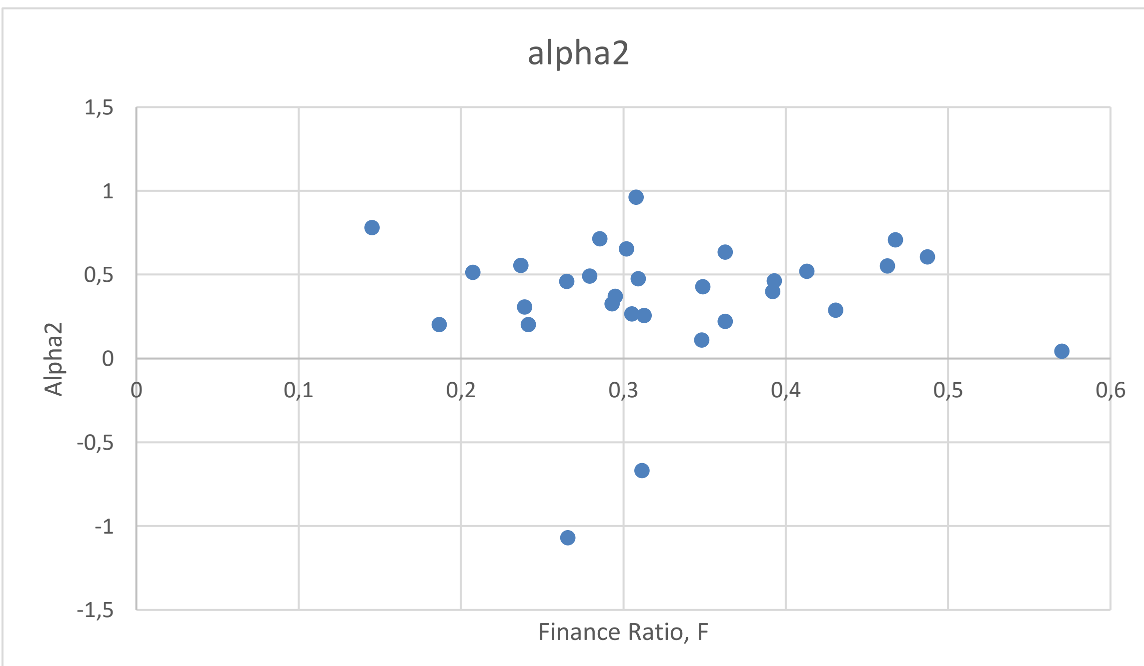
Table 6: Descriptive statistics systemic risk proxies

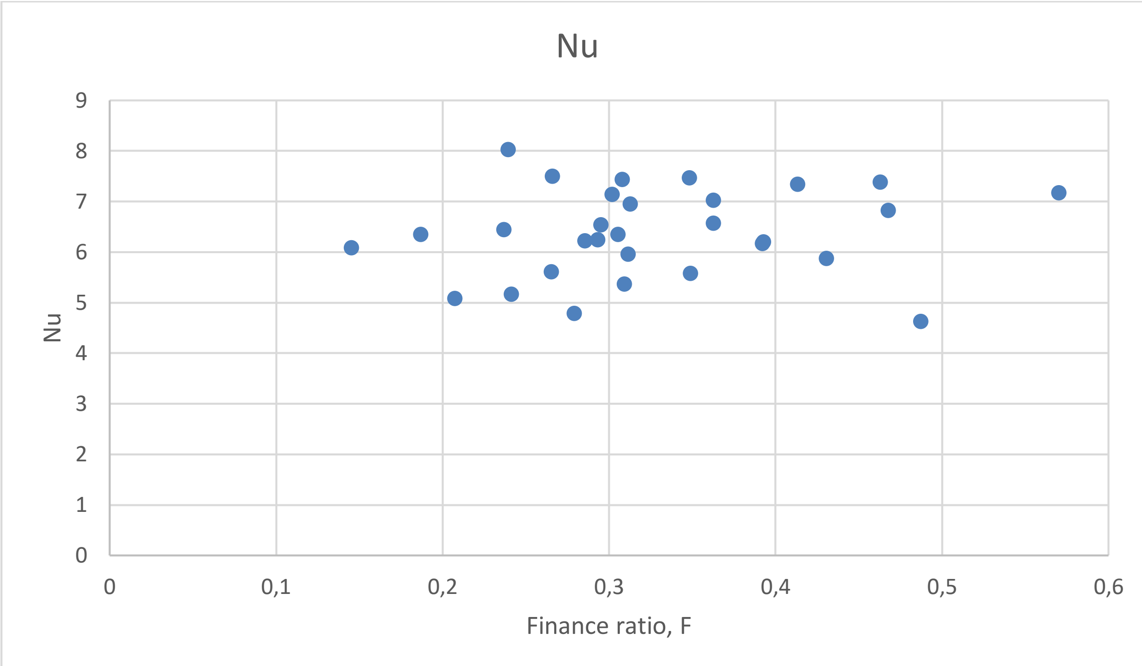
	N	Mean	Std.Dev.	p5	p25	Median	p75	p95	min	max
alpha1	304	.128	.181	-.165	.019	.122	.239	.443	-.39	.695
alpha2	304	.435	.384	-.012	.315	.484	.645	.844	-1.242	1.178
nu	304	6.18	1.307	4.123	5.469	6.287	7.13	7.9	1.009	9.646

We start the analysis by plotting each individual country's finance ratio *F* against the median estimates of *alpha1*, *alpha2* and *nu* for each country to see whether relatively more bank-based financial systems entail more systemic risk:

Figure 1: ***alpha1, alpha2*** **and** ***nu*** **estimates for country median values.**

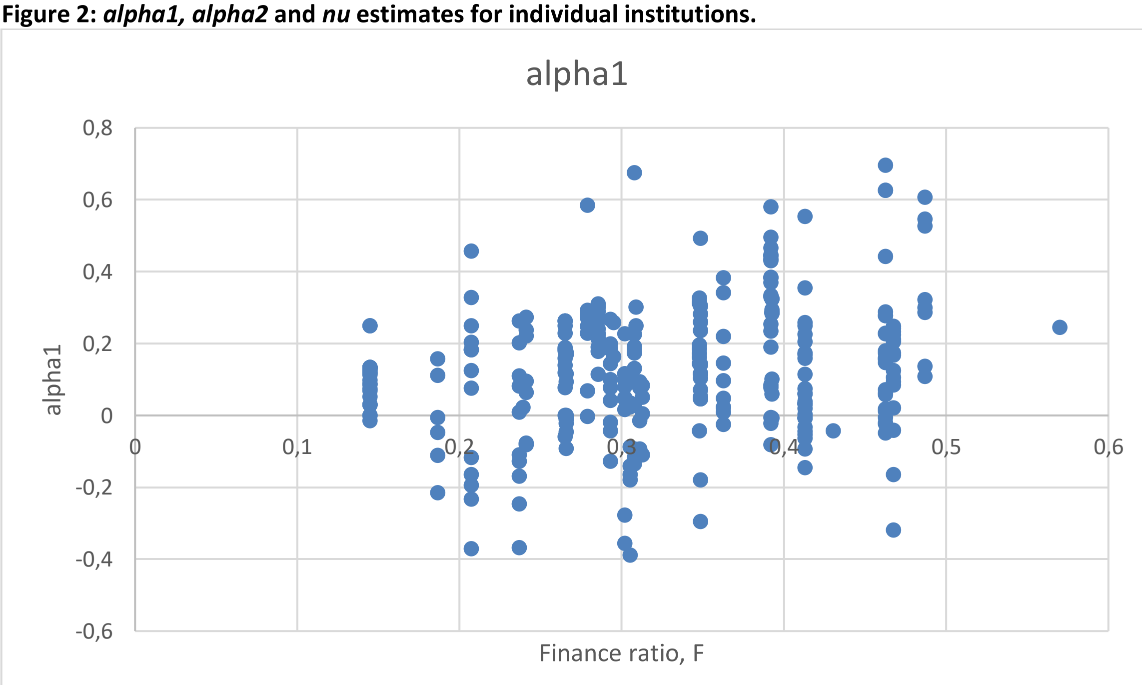


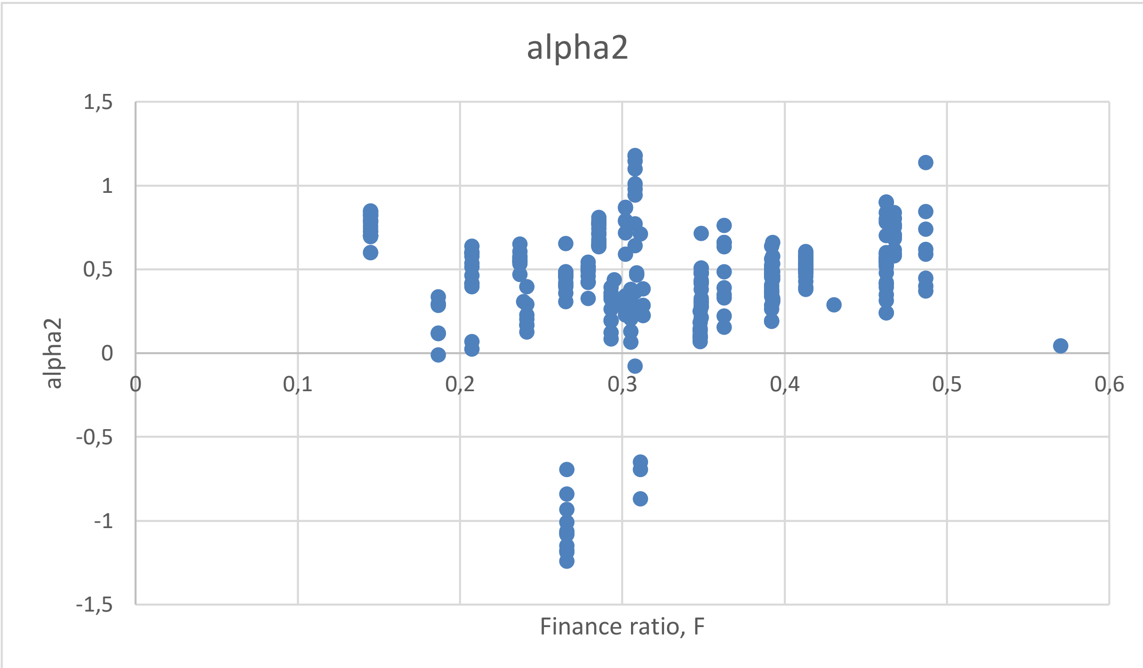




At first glance, it seems that *alpha1* estimates are somewhat higher for countries with higher financing ratios. *Alpha2* and *Nu* estimates show little to no relationship to the financing ratio for individual country observations. Next, we repeat the same process but now include all individual institution's observation instead of computing the median values for each country:

Figure 2: *alpha1, alpha2* and *nu* estimates for individual institutions.





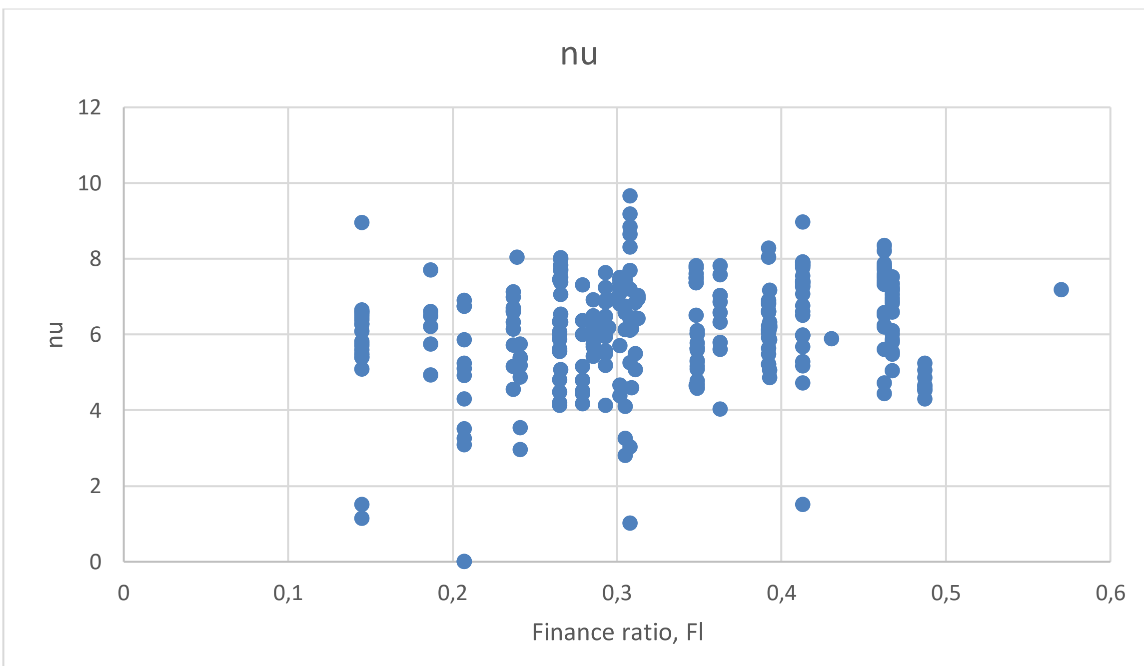


Figure 2: *alpha1*, *alpha2* and *nu* estimates individual observations

Again, it seems that *alpha1* estimates are somewhat related to the finance ratio, whilst *alpha2* and *nu* estimates show little to now relationship at all. However, the Pearson's correlation matrix (*Benesty et. al, 2009*) below shows *alpha1*, *alpha2* and *nu* are all positively correlated to the finance ratio *F*, with *alpha1* and *nu* being significant even at the 99% confidence interval.

Table 7: Pairwise correlations between variables.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) F	1.000						
(2) alpha1	0.229*	1.000					
	(0.000)						
(3) alpha2	0.094	0.020	1.000				
	(0.103)	(0.733)					
(4) nu	0.195*	0.106	-0.041	1.000			
	(0.001)	(0.065)	(0.476)				
(5) BSC	0.408*	0.257*	-0.240*	0.069	1.000		
	(0.000)	(0.000)	(0.000)	(0.231)			
(6) logBSL	-0.002	-0.151*	-0.036	-0.041	-0.140	1.000	
	(0.973)	(0.008)	(0.534)	(0.473)	(0.015)		
(7) MD	0.624*	0.231*	0.120	0.152*	0.354*	0.065	1.000
	(0.000)	(0.000)	(0.036)	(0.008)	(0.000)	(0.259)	

**** p<0.01, ** p<0.05, * p<0.1*

These results provide our first general indication that the financing ratio is positively related to systemic risk.

6.2 OLS regression estimations

We run a simple OLS regression for each independent systemic risk proxy in the following form:

$$(11)\ \alpha_{1,i} = \beta_0 + \beta_1 F_i + \beta_2 BSC_i + \beta_3 \ln(BSL)_i + \beta_4 MD_i + \epsilon_i$$

$$(12)\ \alpha_{2,i} = \beta_0 + \beta_1 F_i + \beta_2 BSC_i + \beta_3 \ln(BSL)_i + \beta_4 MD_i + \epsilon_i$$

$$(13)\ \nu_i = \beta_0 + \beta_1 F_i + \beta_2 BSC_i + \beta_3 \ln(BSL)_i + \beta_4 MD_i + \epsilon_i$$

Results are presented in table 8 below:

Table 8: OLS regressions results for *alpha1*, *alpha2* and *nu* values. Variance Inflation Factors (VIF) are reported at the bottom to test for multicollinearity.

	(1) alpha1	(2) alpha2	(3) nu
F	.151	.591**	2.284**
	(.137)	(.289)	(1.031)
BSC	.002**	-.009***	-.002
	(.001)	(.001)	(.005)
logBSL	-.033**	-.049*	-.084
	(.013)	(.028)	(.099)
MD	.001*	.002**	.002
	(0)	(.001)	(.003)
_cons	-.02	.733***	5.562***
	(.06)	(.127)	(.453)
Observations	303	303	303
R-squared	.109	.127	.041
Mean VIF	1.43	1.43	1.43
Highest VIF	1.74	1.74	1.74

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Contrary to expectations based on scatter plots, the finance ratio *F* only has significant influence at the 95% confidence interval for *alpha2* and *nu* values. Table 8 reports the strongest influence of the finance ratio on *nu* estimates, even though model strength is the lowest for *nu* values. The above results indicate that higher financing ratios lead to higher systemic risk. This indicates that bank-based financial systems entail more systemic risk than their market-based counterparts. Hence, we accept H1a:

H1a: The more bank-based an economy is, the higher systemic risk the respective economy entails.

Multicollinearity is of no issue since the highest VIF value is 1.74. Simple rules of thumb such as the VIF remaining below 10 have been questioned. However, literature concludes that high VIF values do not necessarily imply problems with regards to interpretation of regression results. Rather, high VIF values may still produce reliable results if the data fulfils certain criteria (O'brien, 2007). The VIF values as presented in table 8 are low enough to conclude that multicollinearity is of no concern when it comes to the OLS regression results.

6.3 Quantile regression estimations

Next, we perform identical analysis as in section 6.2, but now we divide the finance ratio *F*, variable into 5 quantiles as described in section 5.3 (Table 4) to see whether there are significant differences between quantiles based on the degree of either bank- or market financing. Descriptive statistics for each quantile are provided below in table 9. It seems that mean values of the systemic risk proxies increase slightly as higher quantiles are reached for *alpha2* and *nu* values, with no clear direction for *alpha1* values:

Table 9: Descriptive statistics on systemic risk proxies based on financing ratio quantiles.

Variable	Quantile	*N*	Mean	Std.	Min	Max
alpha1	Q1	79	0.151	0.192	-0.319	0.695
	Q2	65	0.198	0.175	-0.296	0.581
	Q3	40	0.035	0.189	-0.390	0.6754
	Q4	60	0.159	0.128	-0.128	0.584
	Q5	60	0.053	0.165	-0.371	0.456
alpha2	Q1	79	0.575	0.173	0.041	1.135
	Q2	65	0.384	0.166	0.068	0.761
	Q3	40	0.442	0.479	-0.872	1.178
	Q4	60	0.204	0.621	-1.242	0.807
	Q5	60	0.531	0.242	-0.12	0.847
nu	Q1	79	6.573	1.265	1.499	8.959
	Q2	65	6.178	0.962	4.019	8.276
	Q3	40	6.297	1.797	1.009	9.646
	Q4	60	6.090	1.040	4.122	8.017
	Q5	60	5.680	1.398	1.135	8.952

Next, we run regressions similar to the OLS estimations in section 6.2 for each quantile based on the financing ratio:

Table 10.1: OLS regression estimates for *alpha1* based on categorical quantiles of financing ratio *F* .

	(1) Q1alpha1	(2) Q2alpha1	(3) Q3alpha1	(4) Q4alpha1	(5) Q5alpha1
F	4.345*	7.941**	103.133	4.472**	.117
	(2.284)	(3.891)	(149.005)	(1.7)	(1.534)
BSC	-.006	.009**	.021**	0	0
	(.005)	(.003)	(.01)	(.001)	(.006)
logBSL	.018	.087	-1.2	-.014	-.023
	(.048)	(.115)	(1.917)	(.09)	(.023)
MD	.003***	-.003	-.015	.004***	-.001
	(.001)	(.002)	(.012)	(.001)	(.001)
_cons	-1.923**	-3.277*	-29.08	-1.433**	.197
	(.959)	(1.653)	(40.957)	(.585)	(.129)
Observations	78	65	40	60	60
R-squared	.204	.218	.244	.363	.097
Mean VIF	5.14	7.14	203.41	3.49	6.23
Highest VIF	9.76	15.91	379.37	6.37	9.20

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 10.2: OLS regression estimates for *alpha2* based on categorical quantiles of financing ratio *F.*

	(1) Q1alpha2	(2) Q2alpha2	(3) Q3alpha2	(4) Q4alpha2	(5) Q5alpha2
F	5.987***	-3.237	511.724	21.168***	-3.953**
	(1.833)	(2.987)	(353.563)	(2.845)	(1.752)
BSC	-.005	-.016***	.04*	-.02***	-.002
	(.004)	(.003)	(.023)	(.002)	(.007)
logBSL	.117***	-.08	-7.591	-1.208***	.011
	(.038)	(.089)	(4.548)	(.151)	(.026)
MD	-.001	.001	-.042	.041***	.001
	(.001)	(.002)	(.029)	(.002)	(.001)
_cons	-2.036***	2.943**	-138.72	-5.116***	1.278***
	(.77)	(1.269)	(97.183)	(.979)	(.147)
Observations	78	65	40	60	60
R-squared	.28’	.484	.335	.924	.452
Mean VIF	5.14	7.14	203.41	3.49	6.23
Highest VIF	9.76	15.91	379.37	6.37	9.20

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 10.3: OLS regression estimates for *nu* based on categorical quantiles of financing ratio *F.*

	(1) Q1nu	(2) Q2nu	(3) Q3nu	(4) Q4nu	(5) Q5nu
F	-12.878	18.056	-1488.726	18.44	-27.403**
	(14.418)	(21.341)	(1574.964)	(13.838)	(12.535)
BSC	-.046	.062***	-.069	.004	.093*
	(.034)	(.018)	(.102)	(.01)	(.051)
logBSL	-.714**	-.123	18.427	3.019***	.016
	(.301)	(.633)	(20.261)	(.735)	(.185)
MD	-.013*	-.008	.124	-.061***	.028***
	(.007)	(.013)	(.128)	(.011)	(.01)
_cons	18.959***	-4.008	415.664	-1.424	4.8***
	(6.052)	(9.066)	(432.907)	(4.76)	(1.055)
Observations	78	65	40	60	60
R-squared	.272	.219	.063	.361	.161
Mean VIF	5.14	7.14	203.41	3.49	6.23
Highest VIF	9.76	15.91	379.37	6.37	9.20

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Contrary to what initial scatterplots and the correlation matrix showed, there seems to be no relationship between *alpha1* and the financing ratio. Interestingly enough, there is a significant relationship between the finance ratio and *alpha2* for both the highest and the lowest quantile, but the positive relation for the highest quantile switches direction when the lowest quantile is reached. The same holds for *nu* estimates in which the lowest quantile shows a negative relation to the financing ratio. These findings suggest the following: (1) on average, bank-based systems entail more systemic risk than market-based systems, (2) the relationship between the finance ratio and systemic risk is non-linear. The latter suggests that, increasing bank financing even further in an already predominantly bank-based financial system increases systemic risk, whilst increasing bank financing in a predominantly market-based financial systems decreases systemic risk. However, these results do not hold for *alpha1* values. For *alpha2* values, both the highest and lowest quantile show the expected signs. For *nu* values, only the lowest quantile shows the expected sign. Since the effect is different between risk proxies, we reject h1b:

H1b: Proposition H1a holds regardless of what systemic risk proxy is used.

In the third quantiles for each systemic risk proxy, severe multicollinearity is present as can be seen by the heavily inflated VIF values. In the other quantiles, multicollinearity seems to be much less of an issue, which does not bias the abovementioned results for the highest and lowest quantiles. Results with regards to the middle quantiles should be interpreted with caution.

6.4 Non-linear estimations

The aforementioned findings suggest that it is not solely the type, but also the degree of either bank- or market financing has an profound effect on systemic risk. These results are in line with those of Bats & Houben (2020) who also find a non-linear relationship between the financing ratio and systemic risk and who claim that diversity of the financial system is an important safeguard. To test for non-linearity, we again run the regressions with both a squared term for the finance ratio *F* (sq) and a cubic term (cb). Results are presented in Table 11 below. In the squared model, *alpha2* reaches significance at the 99% confidence interval and coefficients for *alpha2* and *nu* are stronger than in the original model. The R^2 values also increase, with only a slight decrease for the *nu* model with squared term for the finance ratio. The cubic model holds the most explanatory power, but only *alpha2* estimates are significant.

Table 11: Non-linear relationship between the financial structure *F* and systemic risk. Output shows models with linear terms (alpha1, alpha2 and nu), squared terms (alpha1sq, alpha2sq and nusq) and cubic terms (alpha1cb, alpha2cb and nucb).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	alpha1	alpha2	nu	alpha1sq	alpha2sq	nusq	alpha1cb	alpha2cb	nucb
F	.151	.591**	2.284**						
	(.137)	(.289)	(1.031)						
BSC	.002**	-.009***	-.002	.002***	-.009***	-.001	.002***	-.008***	0
	(.001)	(.001)	(.005)	(.001)	(.001)	(.005)	(.001)	(.001)	(.005)
log BSL	-.033**	-.049*	-.084	-.032**	-.047*	-.079	-.032**	-.046*	-.078
	(.013)	(.028)	(.099)	(.013)	(.028)	(.099)	(.013)	(.027)	(.099)
MD	.001*	.002**	.002	.001*	.002**	.003	.001	.002**	.003
	(0)	(.001)	(.003)	(0)	(.001)	(.003)	(0)	(.001)	(.003)
F2				.31	1.112***	3.026**			
				(.202)	(.424)	(1.521)			
F3							.674*	2.287***	4.836*
							(.37)	(.774)	(2.793)
_cons	-.02	.733***	5.562***	-.003	.801***	5.81***	.003	.819***	5.838***
	(.06)	(.127)	(.453)	(.059)	(.124)	(.445)	(.059)	(.124)	(.447)
Observations	303	303	303	303	303	303	303	303	303
R-squared	.109	.127	.041	.113	.135	.038	.116	.14	.035
Relation	linear	linear	linear	quadratic	quadratic	quadratic	cubic	cubic	cubic

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

This cubic relationship again supports the idea that increasing bank-financing in already predominantly bank-based financial systems increases systemic risk, while it can decrease systemic risk in market-based financial systems. Conversely, increasing market financing in predominantly bank-based financial systems can decrease systemic risk, while it is likely to increase when market financing increases in predominantly market-based systems. These findings highlight the importance of diversity in the financial system. The non-linear relationship is also supported by Tables 10.2 and 10.3, which show that the sign effect of the relationship between the finance ratio and systemic risk proxy changes from positive to negative when moving from the top quantile (i.e. bank-based) to the bottom quantile (i.e. market-based). Hence, we accept proposition H2a:

H2a: The relationship between the financial structure and systemic risk is non-linear.

6.5 Individual component analysis

From a policy perspective, regulators ought to minimize systemic risk. We have established in sections 6.2 and 6.3 that a higher financing ratio leads to more systemic risk. This ratio consists of three individual components: bank financing (proxied by bank credit), stock market financing (proxied by stock market capitalization) and debt market financing (proxied by non-financial sector debt). The latter two compose total market financing together. This leads to the question which three of the individual components has the strongest effect on systemic risk and whether debt-market of stock-market financing is preferred when developing market financing in an economy. We again start by looking at the Pearson's correlation matrix between variables, now with the decomposed version of the financing ratio:

Table 12: Pairwise correlations including individual components financing ratio

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) BC	1.000								
(2) MC	0.476*	1.000							
	(0.000)								
(3) NFD	0.584*	0.506*	1.000						
	(0.000)	(0.000)							
(4) alpha1	0.249*	0.047	0.107	1.000					
	(0.000)	(0.410)	(0.062)						
(5) alpha2	0.180*	0.250*	0.106	0.020	1.000				
	(0.002)	(0.000)	(0.065)	(0.733)					
(6) nu	0.213*	0.120	0.125	0.106	-0.041	1.000			
	(0.000)	(0.036)	(0.029)	(0.065)	(0.476)				
(7) BSC	0.303*	-0.243*	0.049	0.257*	-0.240*	0.069	1.000		
	(0.000)	(0.000)	(0.396)	(0.000)	(0.000)	(0.231)			
(8) logBSL	-0.054	-0.179*	0.000	-0.151*	-0.036	-0.041	-0.140	1.000	
	(0.346)	(0.002)	(0.993)	(0.008)	(0.534)	(0.473)	(0.015)		
(9) MD	0.850*	0.289*	0.706*	0.231*	0.120	0.152*	0.354*	0.065	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.036)	(0.008)	(0.000)	(0.259)	

**** p<0.01, ** p<0.05, * p<0.1*

At the 95% confidence interval, bank credit (*BC*) is significantly positively correlated to all risk measures. Market capitalization (*MC*) is only significant for *alpha2* values, which makes sense since this variable measures the volatility impact generated by market information on the time-series of returns. Financial market depth (*MD*) is also severely correlated with debt to the non-financial sector (*NFD*), which will be accounted for in the upcoming regression estimates.

To test which of the three individual components that make up the financing ratio has the most profound effect of systemic risk, we decompose the variable *F* into its three parts: *BC*, *MC* and *NFD*. This produces the following regressions:

$$(14)\ \alpha_{1,i} = \beta_0 + \beta_1 BC_i + \beta_2 MC_i + \beta_3 \mathrm{NFD}_i + \beta_4 BSC_i + \beta_5 \ln(BSL)_i + \beta_6 MD_i + \epsilon_i$$

$$(15)\ \alpha_{2,i} = \beta_0 + \beta_1 BC_i + \beta_2 MC_i + \beta_3 \mathrm{NFD}_i + \beta_4 BSC_i + \beta_5 \ln(BSL)_i + \beta_6 MD_i + \epsilon_i$$

$$(16)\ v_i = \beta_0 + \beta_1 BC_i + \beta_2 MC_i + \beta_3 \mathrm{NFD}_i + \beta_4 BSC_i + \beta_5 \ln(BSL)_i + \beta_6 MD_i + \epsilon_i$$

This produces the following results:

Table 13: Regression results including individual components financing ratio

	(1) alpha1	(2) alpha2	(3) nu
BC	.001	.001	.009**
	(.001)	(.001)	(.004)
MC	0	.001	0
	(0)	(.001)	(.003)
NFD	0	-.001*	.001
	(0)	(0)	(.002)
BSC	.002**	-.008***	.002
	(.001)	(.002)	(.006)
logBSL	-.03**	-.034	-.019
	(.014)	(.029)	(.104)
MD	.001	.002	-.006
	(.001)	(.002)	(.006)
_cons	.011	.759***	5.577***
	(.075)	(.157)	(.562)
Observations	303	303	303
R-squared	.112	.143	.05
Mean VIF	3.26	3.26	3.26
Highest VIF	6.60	6.60	6.60

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Results report significance only for bank credit at 95% level of confidence for nu values. R-squared values are also relatively low. The highest VIF-value of 6.60 for financial market depth (MD) implies some multicollinearity issues. Excluding financial market depth strengthens results significantly whilst also solving the multicollinearity problem

Table 14: Regression results excluding financial market depth (*MD*) as control variable

	(1) alpha1	(2) alpha2	(3) nu
BC	.001***	.003***	.006**
	(0)	(.001)	(.003)
MC	0	.001	.001
	(0)	(.001)	(.003)
NFD	0	0	0
	(0)	(0)	(.001)
BSC	.002**	-.007***	.001
	(.001)	(.002)	(.006)
logBSL	-.029**	-.026	-.04
	(.014)	(.028)	(.102)
_cons	.013	.765***	5.56***
	(.075)	(.157)	(.562)
Observations	303	303	303
R-squared	.111	.137	.046
Mean VIF	1.66	1.66	1.66
Highest VIF	2.08	2.08	2.08

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

It becomes evident that bank credit (*BC*) has the strongest, most profound effect on systemic risk. The positive relation is significant for all three risk measures, with the highest significance obtained for *alpha2* values. This again strengthens our earlier findings that bank-based systems entail more systemic risk than their market-based counterpart. Market capitalization (*MC*) and non-financial sector depth (*NFD*) seem to have nil effect, indicating insignificance for the whole sample.

Next, we again subdivide the sample into the five quantiles mentioned before. However, only the logarithmic version of banking sector leverage (log*BSL*) is included since banking sector concentration (*BSC*) and financial market depth (*MD*) show significant correlation amongst each other (see Appendix D.1 for details). Hence, only *logBSL* is included as control variable. However, caution is needed with interpretation of results since the third up until fifth quantile still show inflated VIF values. This produces the following results:

Table 15.1: Regression results individual components for *alpha1*.

	(1)	(2)	(3)	(4)	(5)
	Q1alpha1	Q2alpha1	Q3alpha1	Q4alpha1	Q5alpha1
BC	.011***	-.001	.014***	.014*	.001
	(.004)	(.001)	(.005)	(.008)	(.005)
MC	-.004***	.004***	-.005**	-.005***	.001
	(.001)	(.002)	(.002)	(.001)	(.002)
NFD	-.002	.001	-.003**	-.003	-.001
	(.001)	(.001)	(.001)	(.003)	(.002)
BSL	.208**	.032	-.286	.051	-.021
	(.102)	(.077)	(.201)	(.107)	(.028)
_cons	-1.362**	-.208	.468	-.187	.152
	(.59)	(.299)	(.404)	(.196)	(.16)
Observations	78	65	40	60	60
R-squared	.204	.242	.224	.361	.105
Mean VIF	9.64	3.03	13.80	84.61	40.25
Highest VIF	19.41	4.62	30.31	169.39	88.48

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 15.2: Regression results individual components for *alpha2*.

	(1)	(2)	(3)	(4)	(5)
	Q1alpha2	Q2alpha2	Q3alpha2	Q4alpha2	Q5alpha2
BC	.009***	.001	.043***	.127***	.017***
	(.003)	(.001)	(.009)	(.019)	(.006)
MC	-.003***	-.004**	-.015***	-.039***	.011***
	(.001)	(.002)	(.004)	(.003)	(.002)
NFD	-.005***	-.001	-.01***	-.028***	-.006***
	(.001)	(.001)	(.002)	(.007)	(.002)
BSL	.18**	-.188**	-1.87***	-.182	.076**
	(.082)	(.076)	(.4)	(.253)	(.03)
_cons	.186	1.262***	3.98***	-.855*	-.24
	(.473)	(.295)	(.806)	(.463)	(.174)
Observations	78	65	40	60	60
R-squared	.28	.176	.519	.848	.506
Mean VIF	9.64	3.03	13.80	84.61	40.25
Highest VIF	19.41	4.62	30.31	169.39	88.48

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 15.3: Regression results individual components for *nu*.

	(1) Q1nu	(2) Q2nu	(3) Q3nu	(4) Q4nu	(5) Q5nu
BC	-.06**	.002	.059	-.01	-.071
	(.026)	(.009)	(.047)	(.069)	(.044)
MC	.046***	-.009	-.03	.006	-.025
	(.009)	(.009)	(.02)	(.012)	(.016)
NFD	.003	.012***	-.007	-.015	.028*
	(.009)	(.004)	(.011)	(.025)	(.015)
BSL	-1.593**	-.933**	-3.165	1.947**	-.027
	(.641)	(.44)	(2.067)	(.898)	(.233)
_cons	14.871***	6.112***	12.002***	4.55***	5.918***
	(3.724)	(1.713)	(4.159)	(1.643)	(1.329)
Observations	78	65	40	60	60
R-squared	.272	.175	.088	.32	.139
Mean VIF	9.64	3.03	13.80	84.61	40.25
Highest VIF	19.41	4.62	30.31	169.39	88.48

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 15.1 shows that, using *alpha1* as systemic risk proxy, bank credit (*BC*) has a significant positive effect on systemic risk. However, this positive effect is also found in 2 other quantiles. Market capitalization (*MC*) has a significant negative effect across 4 quantiles, indicating that a more developed stock market has a dampening effect on systemic risk. Interestingly enough, it loses significance in the lowest quantile (i.e. the predominantly market-based financial systems), indicating that further developing stock markets in already market-based systems does not have a further dampening effect on systemic risk. Debt market development proxied by non-financial debt (*NFD*) only reaches significance in the middle quantile. These results indicate that, when proxying for systemic risk using *alpha1*, developing the stock market further has a stronger effect on decreasing systemic risk than developing the debt market.

Table 15.2 shows that, using *alpha2* as systemic risk proxy, bank credit has a positive effect on systemic risk, reaching significance across 4 quantiles. Market capitalization and non-financial debt show a significant negative effect on systemic risk, with the former reaching significance in four quantiles and the latter reaching significance in all five. In the lowest quantile, the sign effect for market capitalization turns positive, indicating that further developing the stock market in an already predominantly market-based financial system increases systemic risk. These results indicate that, when proxying for systemic risk using *alpha2*, developing the debt market has a stronger effect on decreasing systemic risk than developing the stock market overall. However, developing stock market financing is more effective in predominantly bank-based systems whilst debt market financing holds the edge in market-based systems. Higher significance across the three components of the financing ratio (*F*) is likely due to the fact that *alpha2* measures the volatility impact on time-series of returns generated by arrival of market information rather than an individual institution's impact as measured by *alpha1*.

Table 15.3 shows that, using *nu* as systemic risk proxy, bank credit only has a small significant decreasing effect in the top quantile (i.e. predominantly bank-based financial systems). The same holds for market capitalization, but with an opposing sign. These results are contrary to what is expected and conflict results in table 15.1 and 15.2. This is likely due to the fact that *nu* values indicate 'heaviness' of tails, rather than being a skewness parameter as *alpha1* and *alpha2*. Non-financial debt only reaches significance in the second and fifth quantile, both showing positive effects (again, contrary to results using *alpha1* and *alhpa2*).

Comparing the three systemic risk proxies, *alpha2* by far holds the most explanatory power and shows results which are most in line with economic theory compared to *alpha1* and *nu*. This is likely due to the fact that *alpha2* is a skewness parameter as measured by the volatility generated impact of new information by the market as a whole. This measure thus proxies for contagion in the financial system as a whole rather than firm-specific contagion. *Nu* regression perform the worst, possibly due to the fact that tail 'heaviness' is not an adequate measure for systemic risk.

Results in table 16 show that *alpha2* is the most promising risk proxy out of the three, followed by the *alpha1* values and *nu* at last. Moreover, the above findings indicate that increasing bank credit across all quantiles increases systemic risk, while developing market financing, especially in bank-based systems, decreases it. More market financing may also decrease systemic risk in market-based systems, however the effect seems to weaken when reaching lower quantiles (i.e. predominantly market-based). Developing stock market financing is preferred among higher quantiles, while debt market financing is preferred among lower quantiles for decreasing systemic risk. Summary of these results together with expected movement of variables and predictive power of each risk proxy are summarized in table 18 below:

Table 16: Expected effects of decomposed finance ratio on systemic risk proxies, together with performance measure

Variable	Quantile	Expected effect *BC*	Expected effect *MC*	Expected effect *NFD*	Significance passed	Effect sign correct	R^2
alpha1	Q1	++	--	--	2/3	3/3	0.204
	Q2	+	-	-	1/3	0/3	0.242
	Q3	~	~	~	3/3	N/A	0.224
	Q4	-	+	+	1/3	0/3	0.361
	Q5	--	++	++	0/3	1/3	0.105
alpha2	Q1	++	--	--	3/3	3/3	0.28
	Q2	+	-	-	1/3	3/3	0.176
	Q3	~	~	~	3/3	N/A	0.519
	Q4	-	+	+	3/3	0/3	0.848
	Q5	--	++	++	3/3	1/3	0.506
nu	Q1	++	--	--	0/3	2/3	0.272
	Q2	+	-	-	2/3	2/3	0.175
	Q3	~	~	~	0/3	N/A	0.088
	Q4	-	+	+	0/3	2/3	0.32
	Q5	--	++	++	1/3	2/3	0.139

6.6 Graphical Illustration

The aforementioned results can be summarized by sketching a simple graph based on the cubic relation between the financing ratio and systemic risk (only in the positive domain of the horizontal axis) since the financing ratio cannot fall below 0). The horizontal axis shows values of the financing ratio whilst the vertical axis shows values of the systemic risk proxy (values are arbitrarily chosen due to the differences in *alpha1/alpha2/nu* values and do not hold any other meaning than showing different levels of systemic risk):

Figure 3: Graphical illustration proposed relation between the financing ratio and systemic risk proxy. The horizontal axis indicates the financing ratio with higher values indicating a financial structure leaning more towards bank-financing, whilst lower values indicate more market-financing in an economy. The vertical axis indicates the level of systemic risk (values are arbitrarily chosen and do not resemble any other meaning than showing different levels of systemic risk.

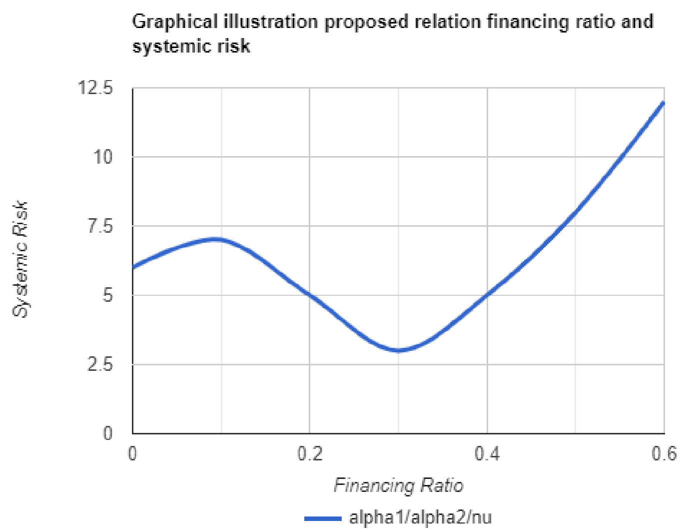


Figure 3 above summarizes all previous findings: (1) on average, bank-based systems entail more systemic risk than market-based systems; (2) the relationship between the financing ratio and systemic risk is non-linear; (3) the relation proposed is a cubic one (only in the positive domain of the horizontal axis) and shows that increasing bank financing further in already predominantly bank-based financial systems increases systemic risk, whilst developing market-financing can decrease it. Increasing bank-financing in predominantly market-based systems has little to no effect (significance is only obtained for *alpha2* values), but these systems can profit by developing bank-financing. Hence diversity in the financial system is important.

7 Robustness tests

As additional robustness check, the two highest and two lowest quantiles are added together, omitting the third (middle) quantile since it shows severe multicollinearity and inflated coefficients. The appendix shows only a significant relationship for *alpha2* values in the highest two quantiles. Explanatory power increases across all models compared to analysis based on 5 quantiles. Details on regression output can be found in Appendix D.2.

Next identical analyses are run with Z-scores, an EVT-based CoVar and fully parametric CoVar as systemic risk proxies (Appendix D.3). Z-scores show a significant negative effect of the financing ratio on systemic risk, both when pooling the whole sample and when dividing into quantiles. This strengthens our earlier results that bank-based systems entail more systemic risk than their market-based counterparts (lower Z-scores imply higher probability of banking sector default, see section 2.4.1 on details). Even though Z-scores have been contested in literature as viable option to measure systemic risk due to its (over-)simplicity, narrow vision on solely the banking sector and assumption of normally distributed asset returns (Lapteacru, 2016), the usage of Z-scores points in the same direction as using *alpha1*, *alpha2* and *nu* estimates.

Both the EVT-based and fully parametric CoVar show identical results. Across the whole sample, the effect of the financing ratio on systemic risk seems negative. However, when subdividing the sample into quantiles, the effect sign turn positive in all but the middle quantile (the latter also shows heavily inflated coefficients, t-values and VIF-values which biases the complete sample into a negative relationship). These results confirm that, on average, bank-based systems entail more systemic risk than market-based systems. However, neither the EVT-based or fully parametric CoVar does not capture the non-linear relationship as proposed in section 6.4.

For individual component analysis, market capitalization seems to be the only factor significantly decreasing systemic risk across the whole sample for fully parametric CoVar values. When subdividing into quantiles, it becomes evident again that developing stock market financing is more effective in reducing systemic risk than developing debt market financing. However, the claim that debt market financing is more effective in bank-based systems and that stock market financing is more effective in market-based systems cannot be made. To summarize robustness tests: (1) proxying for systemic risk using Z-scores corroborates earlier results even though using Z-scores as systemic risk proxy may fall methodologically short; (2) EVT-based and fully parametric CoVar values show a negative effect of the financing ratio across the whole sample, but a positive effect when dividing into quantiles (omitting the third quantile) but fail to capture non-linearity; (3) developing stock market financing seems to be most effective in reducing systemic risk, even though developing debt market financing also holds some significance using the EVT-based CoVar approach.

8 Discussion & further research

The main shortcoming of the proposed method by Nolde & Zhang is the fact that a whole time-series of returns is compressed into one single parameter for each risk proxy. This prohibits time-series or panel analysis on the dataset. This also means that this method is heavily reliant on significant data input (i.e. daily returns of 303 institutions and 30 national indices across a timeframe of 17 years). Moreover, the mathematically complex approach may have less theoretical connection to systemic risk than other proposed methods such as SRISK or SES. As mentioned in the literature section, a 'good' systemic risk proxy should both be justified econometrically and theoretically.

The decision criteria of including public financial institutions with a market capitalization in excess of 1 billion USD also has its shortcomings. Some countries (e.g. Australia, the U.K. and the U.S.) have much more financial institutions present in the sample than relatively smaller economies (e.g. Portugal and New Zealand). Hence, results may be partly biased towards countries with more institutions included in the sample. However, the quantile regression approach partly solves this problem due to each quantile having a similar number of financial institutions.

Further research on the topic of systemic risk should keep trying to develop newer risk measures that are both justified theoretically and have useful practical applications. The study by Nolde & Zhang (2020) took a big step towards laying down complex mathematical foundations to measure contagion in the financial system. However, further research should try to corroborate this by providing more theoretical justification and understanding to this complex approach. The inherent difficulty in measuring an ultra-complex concept such as systemic risk has been attacked in multiple ways, with this study being one of the first to apply a thorough mathematical way to measure systemic risk in a practical setting across a sample much greater than used before.

The study by Nolde & Zhang (2020) is one of the first to develop a systemic risk measure on complex mathematical foundations. They took a big step towards laying down complex mathematical foundations to measure contagion in the financial system. However, further research should try to corroborate this by providing more theoretical justification and understanding to this complex approach. My study is the first (known) one to apply a thoroughly mathematically approach to measure systemic risk in a practical setting across a sample much greater than used before. Current systemic risk measures use a top-down approach in which either country-level stock indices or leading public firms serve as proxy for severeness of economic downturns and/or contagion. Another interesting idea would be to model systemic risk bottom-up by for example aggregating individual household's debts or losses in e.g. housing value or financial assets. At last, systemic risk is an inherently difficult concept to measure, both from an theoretical and empirical perspective. Hence, simplicity might beat complicity in terms of practical applications. For more on this topic, please refer to Rodríguez-Moreno & Peña (2013).

9 Conclusion

Financial structures matter. Literature has extensively investigated its effect on economic growth and is now turning more towards its implications towards systemic risk. This study tries to complement the latter research field by (1) using newly proposed systemic risk measures by Nolde & Zhang (2020), (2) use a wider sample than earlies studies including 303 financial institutions across 30 countries and (3) using quantile regression as main methodological instrument.

Operationalization of systemic risk measurements has seen tremendous progress over the last decades. In the 1990s, it started with Z-scores which tried to measure the probability of default of a country's banking system. Next, Value at Risk (VaR) and Expected Shortfall (ES) were developed, which are idiosyncratic measures of expected losses of a firm conditional on some return distribution given a specified confidence interval. These measures fall short when it comes to measuring systemic risk as indicated by the Great Financial Crisis of 2008, which clearly showed that the systemic element of risk is more than just the sum of its components. This led to the foundation of Conditional Value at Risk (CoVar), SRISK and Systemic Expected Shortfall (SES) as measures to proxy systemic risk. These three measures rely on market data and try to incorporate systemic loss contributions of each financial institution, conditional on some event (i.e. losses in the index as a whole or an institutions being undercapitalized).

The approach of Nolde & Zhang (2020) distinguishes itself by measuring systemic risk and contagion via skewness and tail index parameters, instead of computing a nominal value for each firm's marginal contribution to systemic risk. Their mathematically complicated method to measure financial contagion is promising nevertheless. This study is the first (known) one to use these measures to proxy systemic risk. Main findings are summarized below.

Firstly, bank-based financial systems entail more systemic risk than market-based financial systems. The financing ratio has a significant positive effect for *alpha2* and *nu* values across the whole sample and for about half of the quantiles. These findings are supported across literature so far. Bank-based systems may entail more systemic risk due to their asset-liability mismatch, leveraged position and interconnectedness. The latter becomes especially evident since *alpha2* tries to measure financial contagion, which is likely more present in bank-based financial systems due to interconnectedness and greater size of banks.

Secondly, the choice of either of the three risk proxies proposed by Nolde & Zhang (2020) is important. The *alpha2* measure appears to be most fruitful in measuring systemic risk, followed by *alpha1* and *nu* at last. Since *alpha2* measures the volatility increase of returns across the time-series, conditional on new information arriving on the system as a whole, this should come as no surprise. Contagion among the market as a whole shows far more significance than institution-specific values. *Nu* values measure deviations from elliptical symmetry in returns and thus try to capture the 'heaviness' of the loss tail in return distributions. The latter does not seem to adequately capture the systemic risk element.

Thirdly, the relationship between the financial structure and systemic risk is non-linear. When dividing the sample into quantiles, signs of coefficients change direction when moving from the top to bottom quantile. Also, the cubic model holds most explanatory power compared to the squared and linear estimations. These results also suggest that diversity in the financial system is important. The cubic relationship implies that increasing bank-financing in an already bank-based financial system increases systemic risk, while increasing it in a market-based financial system may decrease it. Vice versa, bank-based financial systems may benefit in terms of risk reduction by increasing market financing, even though this may increase riskiness in market-based financial systems. Increasing the form of financing which already predominantly persists in a financial system increases systemic risk. This hints at the fact that diversity in the financial system is important.

Fourthly, it seems that bank financing increases systemic risk across all quantiles, but lowest quantiles (i.e. predominantly market-based financial systems) seem to be relatively unharmed by increasing bank financing further. Developing market financing seems to decrease systemic risk across most quantiles, with the development of debt market financing being slightly more effective than that of developing stock market financing in terms of reducing systemic risk. This points should come as no surprise since debt instruments are less risky than stocks. For more bank-based systems, the effect of stock market financing is stronger in reducing systemic risk. Conversely, in market-based systems the effect of debt market financing holds the edge.

10 Acknowledgements

Special thanks goes out to dr. I. Sifat (Assistant Professor of International Financial Markets and Monetary Policy) at Radboud University Nijmegen (the Netherlands) in help with coding of individual risk proxies and further supervision of thesis.

11 Bibliography

Acerbi, C., & Tasche, D. (2002). Expected shortfall: a natural coherent alternative to value at risk. Economic notes, 31(2), 379-388.

Acharya, V. V., Pedersen, L. H., Philippon, T., & Richardson, M. (2017). Measuring systemic risk. The review of financial studies, 30(1), 2-47.

Adrian, T., & Brunnermeier, M. K. (2011). CoVaR (No. w17454). National Bureau of Economic Research.

Adrian, T., & Shin, H. S. (2009). The shadow banking system: implications for financial regulation. FRB of New York Staff Report, (382).

Adrian, T., & Shin, H. S. (2010). Liquidity and leverage. Journal of financial intermediation, 19(3), 418-437.

Aglietta, M. (1996). Financial market failures and systemic risk (pp. 41-67). Paris: CEPII.

Allen, F., & Carletti, E. (2013). What is systemic risk?. Journal of Money, Credit and Banking, 45(s1), 121-127.

Balla, E., Ergen, I., & Migueis, M. (2014). Tail dependence and indicators of systemic risk for large US depositories. Journal of financial Stability, 15, 195-209.

Bats, J. V., & Houben, A. C. (2020). Bank-based versus market-based financing: implications for systemic risk. Journal of Banking & Finance, 114, 105776.

Benesty, J., Chen, J., Huang, Y., & Cohen, I. (2009). Pearson correlation coefficient. In Noise reduction in speech processing (pp. 1-4). Springer, Berlin, Heidelberg.

Bianco, M., Gerali, A., & Massaro, R. (1997). Financial systems across “developed economies”: convergence or path dependence?. Research in Economics, 51(3), 303-331.

Bikker, J. A., & Haaf, K. (2002). Measures of competition and concentration in the banking industry: a review of the literature. Economic & Financial Modelling, 9(2), 53-98.

Boyd, J. H., & Runkle, D. E. (1993). Size and performance of banking firms: Testing the predictions of theory. Journal of monetary economics, 31(1), 47-67.

Brownlees, C., & Engle, R. F. (2017). SRISK: A conditional capital shortfall measure of systemic risk. The Review of Financial Studies, 30(1), 48-79.

Chiaramonte, L., Croci, E., & Poli, F. (2015). Should we trust the Z-score? Evidence from the European Banking Industry. Global Finance Journal, 28, 111-131.

Choudhry, M. (2011). An introduction to banking: liquidity risk and asset-liability management. John Wiley & Sons.

De Gregorio, J., & Guidotti, P. E. (1995). Financial development and economic growth. World development, 23(3), 433-448.

De Haan, L., Ferreira, A., & Ferreira, A. (2006). Extreme value theory: an introduction (Vol. 21). New York: Springer.

Duffie, D., & Pan, J. (1997). An overview of value at risk. Journal of derivatives, 4(3), 7-49.

Feinstein, Z., Rudloff, B., & Weber, S. (2017). Measures of systemic risk. SIAM Journal on Financial Mathematics, 8(1), 672-708.

Gambacorta, L., Yang, J., & Tsatsaronis, K. (2014). Financial structure and growth. BIS Quarterly Review March.

Girardi, G., & Ergün, A. T. (2013). Systemic risk measurement: Multivariate GARCH estimation of CoVaR. Journal of Banking & Finance, 37(8), 3169-3180.

Girardi, G., & Ergün, A. T. (2013). Systemic risk measurement: Multivariate GARCH estimation of CoVaR. Journal of Banking & Finance, 37(8), 3169-3180.

Greuning, H. V., & Bratanovic, S. B. (2009). Analyzing banking risk.

Hendricks, D. (2009). Defining systemic risk.

Hildebrand, P. M. (2008). Is Basel II enough?: The benefits of a leverage ratio. SNB.

Kahou, M. E., & Lehar, A. (2017). Macroprudential policy: A review. Journal of financial stability, 29, 92-105.

Khan, M. S., & Senhadji, A. (2000). Financial development and economic growth: An overview.

Kon, S. J. (1984). Models of stock returns—a comparison. The Journal of Finance, 39(1), 147-165.

Laeven, M. L., Ratnovski, M. L., & Tong, M. H. (2014). Bank size and systemic risk. International Monetary Fund.

Lapteacru, I. (2016). On the consistency of the Z-score to measure the bank risk. Available at SSRN 2787567.

Linsmeier, T. J., & Pearson, N. D. (2000). Value at risk. Financial Analysts Journal, 56(2), 47-67.

Lee, B. S. (2012). Bank-based and market-based financial systems: Time-series evidence. Pacific-Basin Finance Journal, 20(2), 173-197.

Levine, R. (2002). Bank-based or market-based financial systems: which is better?. Journal of financial intermediation, 11(4), 398-428.

Mainik, G., & Schaanning, E. (2014). On dependence consistency of CoVaRand some other systemic risk measures. Statistics & Risk Modeling, 31(1), 49-77.

Nolde, N., & Zhang, J. (2020). Conditional extremes in asymmetric financial markets. Journal of Business & Economic Statistics, 38(1), 201-213.

O'brien, R. M. (2007). A caution regarding rules of thumb for variance inflation factors. Quality & quantity, 41(5), 673-690.

Pozsar, Z., Adrian, T., Ashcraft, A., & Boesky, H. (2010). Shadow banking. New York, 458(458), 3-9.

Rhoades, S. A. (1993). The herfindahl-hirschman index. Fed. Res. Bull., 79, 188.

Rodríguez-Moreno, M., & Peña, J. I. (2013). Systemic risk measures: The simpler the better?. Journal of Banking & Finance, 37(6), 1817-1831.

Schwarcz, S. L. (2008). Systemic risk. Geo. Lj, 97, 193.

Smaga, P. (2013). Assessing involvement of central banks in financial stability. Center for financial stability Policy paper.

Smaga, P. (2014). The concept of systemic risk. Systemic Risk Centre Special Paper, (5).

Stern, G. H., & Feldman, R. J. (2004). Too big to fail: The hazards of bank bailouts. Brookings Institution Press.

Yamai, Y., & Yoshiba, T. (2005). Value-at-risk versus expected shortfall: A practical perspective. Journal of Banking & Finance, 29(4), 997-1015.

12 Appendices

Appendix A: Financial Indices

Country	Index	*N*	Average (log)return	Standard deviation	Min.	Max.	Data availability
Australia	S&P/ASX200	4,301	0.0002351	0.0139693	-0.1475426	0.1362753	02-Jan-2003 - 31-Dec-2019
Austria	Austrian Traded Index - ATX	4,216	0.0002581	0.016593	-0.1149571	0.1334685	02-Jan-2003 - 30-Dec-2019
Belgium	Bel20	4,301	0.0002351	0.0139693	-0.1475426	0.1362753	02-Jan-2003 - 31-Dec-2019
Canada	Toronto Stock Exchange - TSX	4,264	0.0002694	0.135376	-0.129338	0.103555	02-Jan-2003 - 31-Dec-2019
Chile	S&P IPSA CLP Index	4,237	0.000353	0.0132345	-0.0929131	0.148825	02-Jan-2003 - 30-Dec-2019
Colombia	MSCI COLCAP Index	2,913	0.0001889	0.010163	-0.0892394	0.0973145	16-Jan-2008 - 30-Dec-2019
Czech Republic	PX Prague SE Index	4,264	0.0002726	0.0161591	-0.1770291	0.1997328	02-Jan-2003 - 30-Dec-2019
Denmark	OMXC 25 CAP Index	755	0.0003912	0.0087372	-0.034971	0.0276754	19-Dec-2016 - 30-Dec-2019
Finland	OMX Helsinki 25 Index	4,301	0.0002351	0.0139693	-0.1475426	0.1362753	02-Jan-2003 - 30-Dec-2019
France	CAC 40 Index	4,351	0.0001621	0.0150286	-0.1153338	0.1223828	02-Jan-2003 - 31-Dec-2019
Germany	Deutsche Boerse DAX	4,315	0.0003542	0.0149743	-0.0946778	0.126464	02-Jan-2003 - 30-Dec-2019
Greece	Athex Composite Share Price Index	4,210	-0.0001385	0.0201714	-0.196576	0.1350795	02-Jan-2003 - 31-Dec-2019
Hungary	Budapest SE Index	4,242	0.0003535	0.0193924	-0.2055958	0.1654594	02-Jan-2003 - 30-Dec-2019
Ireland	ISEQ Overall Price Index	4,311	0.0001504	0.0151111	-0.1532064	0.1061583	02-Jan-2003 - 31-Dec-2019
Israel	Tel Aviv 35 Index	4,162	0.0004663	0.0128525	-0.0769828	0.1067159	01-Jan-2003 - 31-Dec-2019
Italy	FTSE MIB Index	4,314	0.00000888	0.0166319	-0.1573195	0.1220006	02-Jan-2003 - 30-Dec-2019

Japan	Nikkei 225 Index	4,165	0.0002615	0.0144991	-0.141092	0.1171597	06-Jan-2003 - 30-Dec-2019
Korea (South)	Korea SE Kospi Index	4,204	0.0003014	0.0165267	-0.2004916	0.227658	02-Jan-2003 - 30-Dec-2019
Luxembourg	Luxembourg SE LUXX Index	4,299	0.0001575	0.0148218	-0.1251566	0.0998704	02-Jan-2003 - 31-Dec-2019
Mexico	S&P/Bmv Ipc	4,281	0.0003139	0.0162632	-0.1192809	0.1697587	02-Jan-2003 - 31-Dec-2019
Netherlands	Amsterdam Exchanges Index	4,354	0.0001594	0.0144555	-0.1165218	0.124118	01-Jan-2003 - 31-Dec-2019
New Zealand	S&P/NZX 50 Index	4,273	0.0004714	0.0105906	-0.0784856	0.0626826	03-Jan-2003 - 31-Dec-2019
Norway	Oslo Stock Exchange Equity Index	4,266	0.0004616	0.0186576	-0.1396807	0.1427028	02-Jan-2003 - 30-Dec-2019
Poland	Warsaw SE WIG Poland Index	4,255	0.0003292	0.0167012	-0.1164304	0.1146452	02-Jan-2003 - 30-Dec-2019
Portugal	Euronext Lisbon PSI Index	4,388	-0.0000101	0.013605	-0.1244102	0.1103537	01-Jan-2003 - 31-Dec-2019
Spain	IBEX 35 Index	4,328	0.0001149	0.0157786	-0.1558578	0.1365603	02-Jan-2003 - 31-Dec-2019
Sweden	OMX Stockholm 30 Index	4,266	0.0002722	0.0166975	-0.1361168	0.1511024	02-Jan-2003 - 30-Dec-2019
Turkey	BIST 30 Index	4,265	0.002539	0.0238796	-0.1734479	0.1594515	02-Jan-2003 - 31-Dec-2019
UK	FTSE 100 Index	4,297	0.0001042	0.0129536	-0.1160661	0.1114789	2-Jan-2003 - 31-Dec-2019
US	S&P 500 Index	4,278	0.0002964	0.011323	-0.0946951	0.109572	02-Jan-2003 - 31-Dec-2019

Appendix B: Financial Institutions

- B&I = banking & investment services
- I = insurances
- C = collective investments
- H = investment holding companies

Country	**Financial institution name**	**Type**	**Market cap (billion USD)**	**Data availability**
Australia	Commonwealth Bank of Australia	B&I	130.40	02-Jan-2003 - 31-Dec-2019
	National Australia Bank Ltd	B&I	72.93	02-Jan-2003 - 31-Dec-2019
	Westpac Banking Corp	B&I	61.04	02-Jan-2003 - 31-Dec-2019
	Macquarie Group Ltd	B&I	51.29	02-Jan-2003 - 31-Dec-2019
	Australia and New Zealand Banking Group Ltd	B&I	50.78	02-Jan-2003 - 31-Dec-2019
	ASX Ltd	B&I	11.42	02-Jan-2003 - 31-Dec-2019
	Australian Foundation Investment Company Ltd	B&I	7.28	02-Jan-2003 - 31-Dec-2019
	Argo Investments Ltd	B&I	5.13	02-Jan-2003 - 31-Dec-2019
	Bendigo and Adelaide Bank Ltd	B&I	4.38	02-Jan-2003 - 31-Dec-2019
	Bank of Queensland Ltd	B&I	3.56	02-Jan-2003 - 31-Dec-2019
	QBE Insurance Group Ltd	I	12.96	02-Jan-2003 - 31-Dec-2019
	Suncorp Group Ltd	I	10.17	02-Jan-2003 - 31-Dec-2019
	Insurance Australia Group Ltd	I	7.63	02-Jan-2003 - 31-Dec-2019
	Medibank Private Ltd	I	6.38	25-Nov-2014 - 31-Dec-2019
	Steadfast Group Ltd	I	3.72	02-Aug-2013 - 31-Dec-2019
	Challenger Ltd	I	3.50	02-Jan-2003 - 31-Dec-2019
	NIB Holdings Ltd	I	2.45	05-Nov-2007 - 31-Dec-2019
	AUB Group Ltd	I	1.21	16-Nov-2005 - 31-Dec-2019
	PSC Insurance Group Ltd	I	1.13	15-Dec-2015 - 31-Dec-2019
	Metrics Master Income Trust	C	1.15	09-Oct-2017 - 31-Dec-2019
Austria	Erste Group Bank AG	B&I	13.59	02-Jan-2003 - 30-Dec-2019
	Raiffeisen Bank International AG	B&I	4.36	25-Apr-2005 - 30-Dec-2019
	Oberbank AG	B&I	3.73	02-Jan-2003 - 30-Dec-2019
	Bank fuer Tirol und Vorarlberg AG	B&I	1.23	25-Feb-2003 - 30-Dec-2019
	Vienna Insurance Group AG Wiener Versicherung Gruppe	I	3.13	02-Jan-2003 - 30-Dec-2019
	Uniqa Insurance Group AG	I	2.40	02-Jan-2003 - 30-Dec-2019
Belgium	Kbc Groep NV	B&I	26.07	02-Jan-2003 - 31-Dec-2019
	Ageas SA	I	8.72	02-Jan-2003 - 31-Dec-2019
	Groep Brussel Lambert NV	H	14.22	02-Jan-2003 - 31-Dec-2019
	Sofina SA	H	8.04	02-Jan-2003 - 31-Dec-2019

Canada	Royal Bank of Canada	B&I	149.85	02-Jan-2003 - 31-Dec-2019
	Toronto-Dominion Bank	B&I	140.09	02-Jan-2003 - 31-Dec-2019
	Brookfield Asset Management Inc	B&I	84.32	02-Jan-2003 - 31-Dec-2019
	Bank of Nova Scotia	B&I	82.44	02-Jan-2003 - 31-Dec-2019
	Bank of Montreal	B&I	73.90	02-Jan-2003 - 31-Dec-2019
	Canadian Imperial Bank of Commerce	B&I	51.00	02-Jan-2003 - 31-Dec-2019
	National Bank of Canada	B&I	26.19	02-Jan-2003 - 31-Dec-2019
	IGM Financial Inc	B&I	7.41	02-Jan-2003 - 31-Dec-2019
	TMX Group Ltd	B&I	6.21	02-Jan-2003 - 31-Dec-2019
	iA Financial Corporation Inc	B&I	5.70	02-Jan-2003 - 31-Dec-2019
	Manulife Financial Corp	I	36.04	02-Jan-2003 - 31-Dec-2019
	Sun Life Financial Inc	I	29.19	02-Jan-2003 - 31-Dec-2019
	Intact Financial Cor	I	25.86	10-Dec-2004 - 31-Dec-2019
	Great-West Lifeco Inc	I	25.07	02-Jan-2003 - 31-Dec-2019
	Power Corporation of Canada	I	18.02	02-Jan-2003 - 31-Dec-2019
	Fairfax Financial Holdings Ltd	I	13.83	02-Jan-2003 - 31-Dec-2019
	E-L Financial Corp Ltd	I	2.50	02-Jan-2003 - 31-Dec-2019
	Trisura Group Ltd	I	1.18	30-May-2017 - 31-Dec-2019
	Sprott Physical Gold Trust	C	5.79	26-Feb-2010 - 31-Dec-2019
	Sprott Physical Gold Trust and Silver Trust USD	C	3.90	02-Jan-2003 - 31-Dec-2019
	Sprott Physical Silver Trust USD	C	3.46	29-Oct-2010 - 31-Dec-2019
	Sprott Physical Uranium Trust	C	2.77	10-May-2005 - 31-Dec-2019
	Canoe EIT Income Fund	C	1.69	02-Jan-2003 - 31-Dec-2019
	Fairfax India Holdings Corp	H	1.27	30-Jan-2015 - 31-Dec-2019
Chile	Banco de Chile	B&I	10.65	02-Jan-2003 - 30-Dec-2019
	Banco Santander-Chile	B&I	9.56	02-Jan-2003 - 30-Dec-2019
	Banco de Credito e Inversiones	B&I	5.89	02-Jan-2003 - 30-Dec-2019
	Sociedad de Inversiones Pampa Calichera SA	B&I	2.53	06-Jan-2003 - 30-Dec-2019
	Itau Corpbanca	B&I	2.52	02-Jan-2003 - 30-Dec-2019
	Bicecorp SA	B&I	1.41	24-Jan-2003 - 30-Dec-2019
	Sociedad de Inversiones Oro Blanco SA	H	2.15	06-Jan-2003 - 30-Dec-2019
	Norte Grande SA	H	1.89	03-Jan-2003 - 30-Dec-2019
Colombia	Bancolombia SA	B&I	11.04	02-Jan-2003 - 30-Dec-2019

	Grupo Aval Acciones y Valores SA	B&I	5.69	02-Jan-2003 - 30-Dec-2019
	Banco de Bogota SA	B&I	5.23	02-Jan-2003 - 30-Dec-2019
	Corporacion Financiera Colombiana SA	B&I	2.47	26-Feb-2003 - 30-Dec-2019
	Grupo Bolivar SA	B&I	1.79	19-Feb-2003 - 30-Dec-2019
	Banco Bilbao Vizcaya Argentaria Colombia SA	B&I	1.39	15-Jan-2003 - 30-Dec-2019
	Grupo de Inversiones Suramericana SA	I	6.32	02-Jan-2003 - 30-Dec-2019
Czech Republic	Komercni Banka as	B&I	5.98	01-Jan-2003 - 30-Dec-2019
	Moneta Money Bank as	B&I	1.69	06-May-2016 - 30-Dec-2019
Denmark	Danske Bank A/S	B&I	13.97	02-Jan-2003 - 30-Dec-2019
	Jyske Bank A/S	B&I	3.94	02-Jan-2003 - 30-Dec-2019
	Ringkjoebing Landbobank	B&i	3.34	02-Jan-2003 - 30-Dec-2019
	Sydbank A/S	B&i	2.04	02-Jan-2003 - 30-Dec-2019
	Spar Nord Bank A/S	B&i	1.39	02-Jan-2003 - 30-Dec-2019
	Tryg A/S	I	15.07	14-Oct-2005 - 30-Dec-2019
	Topdanmark A/S	I	4.71	02-Jan-2003 - 30-Dec-2019
	ALM. Brand A/S	I	2.55	02-Jan-2003 - 30-Dec-2019
Finland	Nordea Bank Abp	B&I	37.73	02-Jan-2003 - 30-Dec-2019
	Sampo plc	I	23.62	02-Jan-2003 - 30-Dec-2019
France	BNP Paribas SA	B&I	69.90	02-Jan-2003 - 31-Dec-2019
	Credit Agricole SA	B&I	32.89	02-Jan-2003 - 31-Dec-2019
	Societe Generale SA	B&I	22.25	02-Jan-2003 - 31-Dec-2019
	Amundi SA	B&I	11.72	12-Nov-2015 - 31-Dec-2019
	Eurazeo SE	B&I	6.16	02-Jan-2003 - 31-Dec-2019
	Tikehau Capital SCA	B&I	4.02	07-Mar-2017 - 31-Dec-2019
	Rothschild & Co SCA	B&I	3.06	02-Jan-2003 - 31-Dec-2019
	Peugeot Invest SA	B&I	2.84	02-Jan-2003 - 31-Dec-2019
	AXA SA	I	58.40	02-Jan-2003 - 31-Dec-2019
	CNP Assurances SA	I	15.42	02-Jan-2003 - 31-Dec-2019
	Scor SE	I	4.60	02-Jan-2003 - 31-Dec-2019
	Coface SA	I	1.76	27-Jun-2014 - 31-Dec-2019
	Wendel SE	H	4.55	02-Jan-2003 - 31-Dec-2019
Germany	Deutsche Boerse AG	B&I	31.45	02-Jan-2003 - 30-Dec-2019
	Deutsche Bank AG	B&I	22.47	02-Jan-2003 - 30-Dec-2019
	Commerzbank AG	B&I	10.80	02-Jan-2003 - 30-Dec-2019

	DWS Group GmbH & Co KgaA	B&I	6.73	23-Mar-2018 - 30-Dec-2019
	Tradegate AG Wertpapierhandelsbank	B&I	2.95	12-Oct-2006 - 30-Dec-2019
	Aareal Bank AG	B&I	2.07	02-Jan-2003 - 30-Dec-2019
	flatexDEGIRO AG	B&I	1.57	30-Jun-2009 - 30-Dec-2019
	Deutsche Pfandbriefbank AG	B&I	1.46	16-Jul-2015 - 30-Dec-2019
	Grenke AG	B&I	1.31	02-Jan-2003 - 30-Dec-2019
	Berliner Effektengesellschaft AG	B&I	1.17	02-Jan-2003 - 30-Dec-2019
	Allianz SE	I	84.68	02-Jan-2003 - 30-Dec-2019
	Muenchener Rueckversicherungs Gesellschaft in Muenchen AG	I	33.32	02-Jan-2003 - 30-Dec-2019
	Hannover Rueck SE	I	17.92	02-Jan-2003 - 30-Dec-2019
	Talanx AG	I	10.35	02-Oct-2012 - 30-Dec-2019
	Wuestenrot & Wuerttembergische AG	I	1.70	02-Jan-2003 - 30-Dec-2019
	Rocket Internet SE	H	3.09	02-Oct-2014 - 30-Dec-2019
Greece	Eurobank Ergasias Services and Holdings SA	B&I	4.02	02-Jan-2003 - 31-Dec-2019
	National Bank of Greece SA	B&I	3.53	02-Jan-2003 - 31-Dec-2019
	Alpha Services and Holdings SA	B&I	2.40	02-Jan-2003 - 31-Dec-2019
	Piraeus Financial Holdings SA	B&I	1.57	02-Jan-2003 - 31-Dec-2019
Hungary	OTP Bank Nyrt	B&I	6.92	02-Jan-2003 - 30-Dec-2019
Ireland	Ishares Physical Gold ETC	B&I	16.39	11-Apr-2011 - 31-Dec-2019
	Bank of Ireland Group PLC	B&I	7.08	02-Jan-2003 - 31-Dec-2019
	Aib Group PLC	B&I	7.05	02-Jan-2003 - 31-Dec-2019
	Aon PLC	I	59.18	02-Jan-2003 - 31-Dec-2019
Israel	Bank Leumi Le Israel BM	B&I	14.26	01-Jan-2003 - 31-Dec-2019
	Bank Hapoalim BM	B&I	12.33	01-Jan-2003 - 31-Dec-2019
	Mizrahi Tefahot Bank Ltd	B&I	8.95	01-Jan-2003 - 31-Dec-2019
	Israel Discount Bank Ltd	B&I	7.03	01-Jan-2003 - 31-Dec-2019
	First International Bank of Israel Ltd	B&I	3.85	01-Jan-2003 - 31-Dec-2019
	FIBI Holdings Ltd	B&I	1.52	01-Jan-2003 - 31-Dec-2019
	Phoenix Holdings Ltd	I	2.64	01-Jan-2003 - 31-Dec-2019
	Harel Insurance Investments and Financial Services Ltd	I	2.31	01-Jan-2003 - 31-Dec-2019
	Migdal Insurance and Financial Holdings Ltd	I	1.65	01-Jan-2003 - 31-Dec-2019
	Clal Insurance Enterprises Holdings Ltd	I	1.48	01-Jan-2003 - 31-Dec-2019
	Menora Mivtachim Holdings Ltd	I	1.44	01-Jan-2003 - 31-Dec-2019

Italy	Intesa Sanpaolo SpA	B&I	41.37	02-Jan-2003 - 30-Dec-2019
	UniCredit SpA	B&I	24.84	02-Jan-2003 - 30-Dec-2019
	Mediobanca Banca di Credito Finanziario SpA	B&I	8.86	02-Jan-2003 - 30-Dec-2019
	FinecoBank Banca Fineco SpA	B&I	6.55	02-Jul-2014 - 30-Dec-2019
	Banca Mediolanum SpA	B&I	5.80	02-Jan-2003 - 30-Dec-2019
	Banco BPM SpA	B&I	5.21	02-Jan-2003 - 30-Dec-2019
	Banca Generali SpA	B&I	4.04	15-Nov-2006 - 30-Dec-2019
	Azimut Holding SpA	B&I	3.07	07-Jul-2004 - 30-Dec-2019
	Bper Banca SpA	B&I	2.93	02-Jan-2003 - 30-Dec-2019
	Credito Emiliano SpA	B&I	2.22	02-Jan-2003 - 30-Dec-2019
	Assicurazioni Generali SpA	I	28.44	02-Jan-2003 - 30-Dec-2019
	UnipolSai Assicurazioni SpA	I	7.64	02-Jan-2003 - 30-Dec-2019
	Societa Cattolica di Assicurazione SpA	I	1.66	02-Jan-2003 - 30-Dec-2019
	Italmobiliare SpA	H	1.27	02-Jan-2003 - 30-Dec-2019
Japan	Mitsubishi UFJ Financial Group Inc	B&I	75.67	06-Jan-2003 - 30-Dec-2019
	Sumitomo Mitsui Financial Group Inc	B&I	42.32	06-Jan-2003 - 30-Dec-2019
	Mizuho Financial Group Inc	B&I	29.98	14-Feb-2003 - 30-Dec-2019
	Japan Post Bank Co Ltd	B&I	28.48	04-Nov-2015 - 30-Dec-2019
	Orix Corp	B&I	23.79	06-Jan-2003 - 30-Dec-2019
	Nomura Holdings Inc	B&I	12.64	06-Jan-2003 - 30-Dec-2019
	Sumitomo Mitsui Trust Holdings Inc	B&I	11.6	06-Jan-2003 - 30-Dec-2019
	Resona Holdings Inc	B&I	9.20	06-Jan-2003 - 30-Dec-2019
	Japan Exchange Group Inc	B&I	8.45	04-Jan-2013 - 30-Dec-2019
	Daiwa Securities Group Inc	B&I	7.56	06-Jan-2003 - 30-Dec-2019
Korea (South)	KB Financial Group Inc	B&I	19.35	10-Oct-2008 - 30-Dec-2019
	Shinhan Financial Group Co Ltd	B&I	17.56	02-Jan-2003 - 30-Dec-2019
	Hana Financial Group Inc	B&I	11.36	12-Dec-2005 - 30-Dec-2019
	Woori Financial Group In	B&I	8.57	19-Nov-2014 - 30-Dec-2019
	Industrial Bank of Korea	B&I	6.69	02-Jan-2003 - 30-Dec-2019
	Mirae Asset Securities Co Ltd	B&I	4.44	02-Jan-2003 - 30-Dec-2019
	Korea Investment Holdings Co Ltd	B&I	3.50	21-Jul-2003 - 30-Dec-2019
	Meritz Securities Co Ltd	B&I	3.19	02-Jan-2003 - 30-Dec-2019
	Samsung Life Insurance Co Ltd	I	10.71	12-May-2010 - 30-Dec-2019

	Samsung Fire & Marine Insurance Co Ltd	I	7.94	02-Jan-2003 - 30-Dec-2019
	Meritz Fire & Marine Insurance Co Ltd	I	3.72	02-Jan-2003 - 30-Dec-2019
	DB Insurance Co Ltd	I	3.70	02-Jan-2003 - 30-Dec-2019
	Hyundai Marine & Fire Insurance Co Ltd	I	2.30	02-Jan-2003 - 30-Dec-2019
	Hanwha Corp	I	2.08	02-Jan-2003 - 30-Dec-2019
	Hanwha Life Insurance Co Ltd	I	1.81	17-Mar-2010 - 30-Dec-2019
	Macquarie Korea Infrastructure Fund	C	4.63	15-Mar-2006 - 30-Dec-2019
	Meritz Financial Group Inc	H	3.36	13-May-2011 - 30-Dec-2019
Luxembourg	Reinet Investments SCA	B&I	4.13	21-Oct-2008 - 31-Dec-2019
	Universal Securitisation Solutions SA	B&I	3.36	20-Jun-2014 - 30-Dec-2019
	Brederode SA	B&I	2.93	21-Jul-2014 - 31-Dec-2019
	Luxempart SA	B&I	1.62	02-Jan-2003 - 31-Dec-2019
	BBGI Global Infrastructure SA	C	12.63	21-Dec-2011 - 31-Dec-2019
	Robeco Global Total Return Bond Fund SICAV	C	1.54	02-Jan-2003 - 31-Dec-2019
Mexico	Grupo Financiero Banorte SAB de CV	B&I	18.39	02-Jan-2003 - 31-Dec-2019
	Grupo Elektra SAB de CV	B&I	13.87	02-Jan-2003 - 31-Dec-2019
	Grupo Financiero Inbursa SAB de CV	B&I	11.85	02-Jan-2003 - 31-Dec-2019
	Banco Santander Mexico SA Institucion de Banca Multiple Grupo Financiero Santand	B&I	7.52	02-Jan-2003 - 31-Dec-2019
	Banco del Bajio SA Institucion de Banca Multiple	B&I	2.90	08-Jun-2017 - 31-Dec-2019
	Regional SAB de CV	B&I	1.96	15-Jul-2011 - 31-Dec-2019
	Grupo Bursatil Mexicano SA de CV Casa de Bolsa	B&I	1.35	02-Jan-2003 - 31-Dec-2019
	Gentera SAB de CV	B&I	1.30	24-Dec-2010 - 31-Dec-2019
	Bolsa Mexicana de Valores SAB de CV	B&I	1.10	13-Jun-2008 - 31-Dec-2019
	CFECapital S de RL de CV	B&I	1.10	08-Feb-2018 - 31-Dec-2019
	Qualitas Controladora SAB de CV	I	2.07	17-Jul-2012 - 31-Dec-2019
	Grupo Nacional Provincial SAB	I	1.46	02-Jan-2003 - 31-Dec-2019
	Grupo Profuturo SAB de CV	C	1.20	02-Jan-2003 - 31-Dec-2019
Netherlands	ING Groep NV	B&I	43.39	02-Jan-2003 - 31-Dec-2019
	Euronext NV	B&I	9.03	20-Jun-2014 - 31-Dec-2019
	ABN Amro Bank NV	B&I	5.41	20-Nov-2015 - 31-Dec-2019
	Flow Traders NV	B&I	1.47	10-Jul-2015 - 31-Dec-2019

	Van Lanschot Kempen NV	B&I	1.09	02-Jan-2003 - 31-Dec-2019
	NN Group NV	I	15.11	02-Jul-2014 - 31-Dec-2019
	Aegon NV	I	10.79	02-Jan-2003 - 31-Dec-2019
	ASR Nederland NV	I	6.30	10-Jun-2016 - 31-Dec-2019
	Rolinco NV	C	3.05	02-Jan-2003 - 31-Dec-2019
New Zealand	Heartland Group Holdings Ltd	B&I	0.81	01-Feb-2011 - 31-Dec-2019
Norway	DNB Bank ASA	B&I	31.14	02-Jan-2003 - 30-Dec-2019
	Storebrand ASA	B&I	4.21	02-Jan-2003 - 30-Dec-2019
	Sparebank 1 SR Bank ASA	B&I	3.21	02-Jan-2003 - 30-Dec-2019
	Sparebank 1 SMN	B&I	1.75	02-Jan-2003 - 30-Dec-2019
	Sparebank 1 Ostlandet	B&I	1.63	13-Jun-2017 - 30-Dec-2019
	Sparebanken Vest	B&I	1.13	02-Jan-2003 - 30-Dec-2019
	Sparebank 1 Nord-Norge	B&I	1.00	02-Jan-2003 - 30-Dec-2019
	Gjensidige Forsikring ASA	I	10.66	10-Dec-2010 - 30-Dec-2019
	Aker ASA	H	7.07	08-Sep-2004 - 30-Dec-2019
Poland	Powszechna Kasa Oszczednosci Bank Polski SA	B&I	9.13	10-Nov-2004 - 30-Dec-2019
	Santander Bank Polska SA	B&I	6.03	02-Jan-2003 - 30-Dec-2019
	ING Bank Slaski SA	B&I	5.80	02-Jan-2003 - 30-Dec-2019
	Bank Polska Kasa Opieki SA	B&I	5.77	02-Jan-2003 - 30-Dec-2019
	mBank SA	B&I	2.74	02-Jan-2003 - 30-Dec-2019
	BNP Paribas Bank Polska SA	B&I	2.10	27-May-2011 - 30-Dec-2019
	Bank Handlowy w Warszawie SA	B&I	1.85	02-Jan-2003 - 30-Dec-2019
	Bank Millennium SA	B&I	1.34	02-Jan-2003 - 30-Dec-2019
	Kruk SA	B&I	1.17	10-May-2011 - 30-Dec-2019
	Alior Bank SA	B&I	1.05	14-Dec-2012 - 30-Dec-2019
	Powszechny Zaklad Ubezpieczen SA	I	6.36	11-May-2010 - 30-Dec-2019
Portugal	Banco Comercial Portugues SA	B&I	3.13	02-Jan-2003 - 31-Dec-2019
Spain	Banco Santander SA	B&I	54.18	02-Jan-2003 - 31-Dec-2019
	Banco Bilbao Vizcaya Argentaria SA	B&I	35.74	02-Jan-2003 - 31-Dec-2019
	Caixabank SA	B&I	29.15	10-Oct-2007 - 31-Dec-2019
	Bankinter SA	B&I	5.66	02-Jan-2003 - 31-Dec-2019
	Banco de Sabadell SA	B&I	4.97	02-Jan-2003 - 31-Dec-2019
	Corporacion Financiera Alba SA	B&I	3.50	02-Jan-2003 - 31-Dec-2019

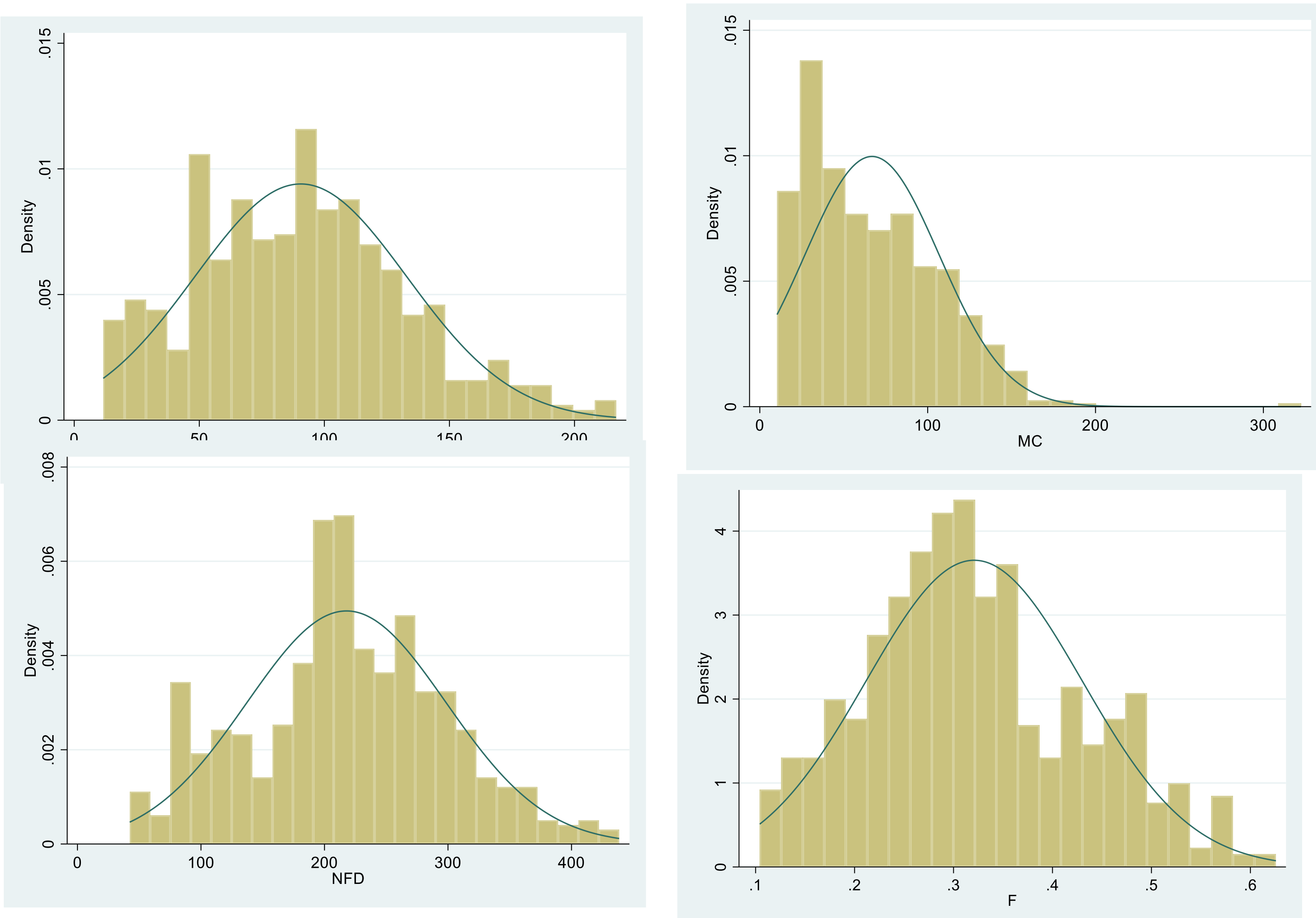
	Unicaja Banco SA	B&I	2.60	30-Jun-2017 - 31-Dec-2019
	Mapfre SA	I	5.68	02-Jan-2003 - 31-Dec-2019
	Grupo Catalana Occidente SA	I	3.69	02-Jan-2003 - 31-Dec-2019
Sweden	EQT AB	B&I	28.81	24-Sep-2019 - 30-Dec-2019
	Skandinaviska Enskilda Banken AB	B&I	24.76	02-Jan-2003 - 30-Dec-2019
	Svenska Handelsbanken AB	B&I	19.59	02-Jan-2003 - 30-Dec-2019
	Swedbank AB	B&I	17.42	02-Jan-2003 - 30-Dec-2019
	Avanza Bank Holding AB	B&I	3.58	02-Jan-2003 - 30-Dec-2019
	Intrum AB	B&I	2.80	02-Jan-2003 - 30-Dec-2019
	Ratos AB	B&I	1.82	02-Jan-2003 - 30-Dec-2019
	Investor AB	H	60.80	02-Jan-2003 - 30-Dec-2019
	Industrivarden AB	H	11.30	02-Jan-2003 - 30-Dec-2019
	Lifco AB (publ)	H	8.59	21-Nov-2014 - 30-Dec-2019
	Kinnevik AB	H	5.66	02-Jan-2003 - 30-Dec-2019
	Bure Equity AB	H	1.91	02-Jan-2003 - 30-Dec-2019
Turkey	QNB Finansbank AS	B&I	7.28	02-Jan-2003 - 31-Dec-2019
	Turkiye Garanti Bankasi AS	B&I	3.86	02-Jan-2003 - 31-Dec-2019
	Turkiye Is Bankasi AS	B&I	3.06	02-Jan-2003 - 31-Dec-2019
	Akbank TAS	B&I	2.80	02-Jan-2003 - 31-Dec-2019
	Yapi ve Kredi Bankasi AS	B&I	2.50	02-Jan-2003 - 31-Dec-2019
	Turkiye Vakiflar Bankasi TAO	B&I	1.89	18-Nov-2005 - 31-Dec-2019
	Turkiye Halk Bankasi AS	B&I	1.78	10-May-2007 - 31-Dec-2019
	Turkiye Kalkinma ve Yatirim Bankasi AS	B&I	1.59	02-Jan-2003 - 31-Dec-2019
	Koc Holding AS	H	6.42	02-Jan-2003 - 31-Dec-2019
	Haci Omer Sabanci Holding AS	H	2.61	02-Jan-2003 - 31-Dec-2019
UK	HSBC Holdings PLC	B&I	133.86	02-Jan-2003 - 31-Dec-2019
	London Stock Exchange Group PLC	B&I	50.15	02-Jan-2003 - 31-Dec-2019
	Lloyds Banking Group PLC	B&I	39.20	02-Jan-2003 - 31-Dec-2019
	Barclays PLC	B&I	35.29	02-Jan-2003 - 31-Dec-2019
	Natwest Group PLC	B&I	29.88	02-Jan-2003 - 31-Dec-2019
	Standard Chartered PLC	B&I	23.62	02-Jan-2003 - 31-Dec-2019
	Legal & General Group PLC	B&I	19.19	02-Jan-2003 - 31-Dec-2019
	3i Group PLC	B&I	15.16	02-Jan-2003 - 31-Dec-2019
	Schroders PLC	B&I	9.96	02-Jan-2003 - 31-Dec-2019

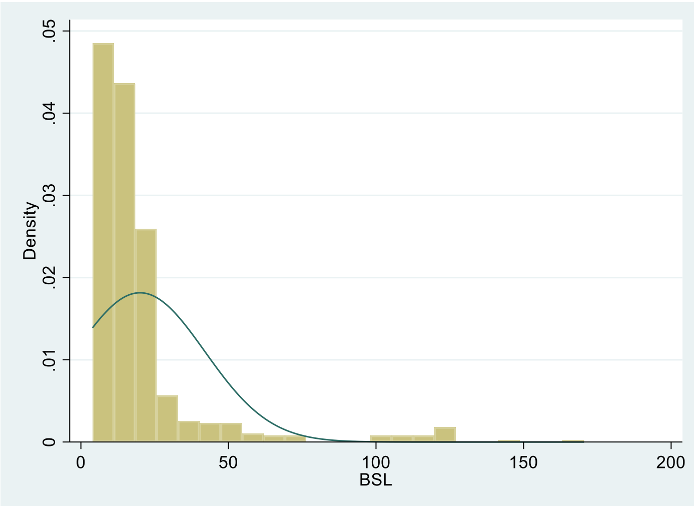
	St James's Place PLC	B&I	8.52	02-Jan-2003 - 31-Dec-2019
	Prudential PLC	I	35.20	02-Jan-2003 - 31-Dec-2019
	Willis Towers Watson PLC	I	23.82	02-Jan-2003 - 31-Dec-2019
	Aviva PLC	I	15.11	02-Jan-2003 - 31-Dec-2019
	Admiral Group PLC	I	8.30	23-Sep-2004 - 31-Dec-2019
	Phoenix Group Holdings PLC	I	7.96	17-Nov-2009 - 31-Dec-2019
	Direct Line Insurance Group PLC	I	4.22	11-Oct-2012 - 31-Dec-2019
	Beazley PLC	I	3.68	02-Jan-2003 - 31-Dec-2019
	Just Group PLC	I	1.05	12-Nov-2013 - 31-Dec-2019
	Scottish Mortgage Investment Trust PLC	C	14.43	02-Jan-2003 - 31-Dec-2019
	F&C Investment Trust PLC	C	5.45	02-Jan-2003 - 31-Dec-2019
	RIT Capital Partners PLC	C	4.76	02-Jan-2003 - 31-Dec-2019
	Greencoat UK Wind PLC	C	4.36	27-Mar-2013 - 31-Dec-2019
	HICL Infrastructure PLC	C	4.28	29-Mar-2006 - 31-Dec-2019
	Alliance Trust PLC	C	3.62	02-Jan-2003 - 31-Dec-2019
	Polar Capital Technology Trust PLC	C	3.22	02-Jan-2003 - 31-Dec-2019
	Smithson Investment Trust PLC	C	2.95	19-Oct-2018 - 31-Dec-2019
	Monks Investment Trust PLC	C	2.77	02-Jan-2003 - 31-Dec-2019
	Caledonia Investments PLC	C	2.61	02-Jan-2003 - 31-Dec-2019
US	JPMorgan Chase & Co	B&I	387.69	02-Jan-2003 - 31-Dec-2019
	Bank of America Corp	B&I	295.69	02-Jan-2003 - 31-Dec-2019
	Wells Fargo & Co	B&I	171.82	02-Jan-2003 - 31-Dec-2019
	Morgan Stanley	B&I	149.04	02-Jan-2003 - 31-Dec-2019
	Blackstone Inc	B&I	147.52	22-Jun-2007 - 31-Dec-2019
	Charles Schwab Corp	B&I	135.91	02-Jan-2003 - 31-Dec-2019
	American Express Co	B&I	127.37	02-Jan-2003 - 31-Dec-2019
	Goldman Sachs Group Inc	B&I	111.36	02-Jan-2003 - 31-Dec-2019
	BlackRock Inc	B&I	104.81	02-Jan-2003 - 31-Dec-2019
	Citigroup Inc	B&I	101.81	02-Jan-2003 - 31-Dec-2019
	Marsh & McLennan Companies Inc	I	80.35	02-Jan-2003 - 31-Dec-2019
	Progressive Corp	I	69.83	02-Jan-2003 - 31-Dec-2019
	MetLife Inc	I	54.51	02-Jan-2003 - 31-Dec-2019
	American International Group Inc	I	46.08	02-Jan-2003 - 31-Dec-2019
	Travelers Companies Inc	I	42.73	02-Jan-2003 - 31-Dec-2019

	Prudential Financial Inc	I	39.66	02-Jan-2003 - 31-Dec-2019
	Aflac Inc	I	38.45	02-Jan-2003 - 31-Dec-2019
	Allstate Corp	I	36.89	02-Jan-2003 - 31-Dec-2019
	Arthur J. Gallagher & Co.	I	34.53	02-Jan-2003 - 31-Dec-2019
	Hartford Financial Services Group Inc	I	23.66	02-Jan-2003 - 31-Dec-2019
	Ares Capital Corp	C	9.78	05-Oct-2004 - 31-Dec-2019
	FS KKR Capital Corp	C	6.15	16-Apr-2014 - 31-Dec-2019
	Prospect Capital Corp	C	3.04	27-Jul-2004 - 31-Dec-2019

Appendix C : Variables Distribution

Figure 3: Dependent/control variable distribution; bank credit (*BC*), market capitalization (*MC*), non-financial debt (*NFD*), financing ratio (*F*), banking sector leverage (*BSL*), financial market depth (*MD*), banking sector concentration (*BSC*) and the logarithmic version of banking sector leverage (*logBSL*).

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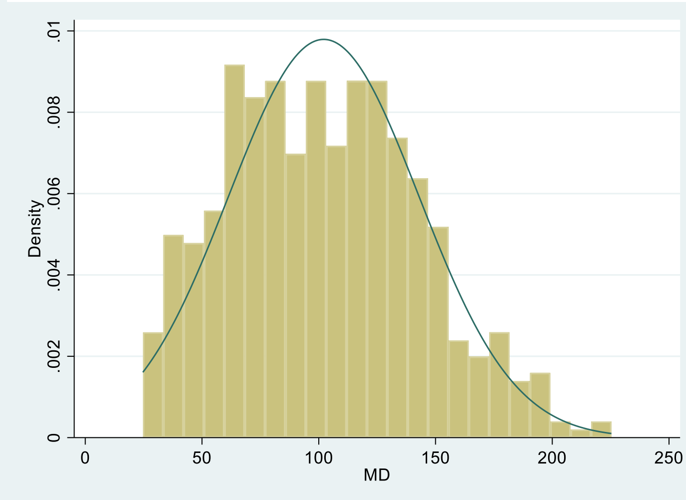
.02
.03
.04
.05
0
50
100
150
200
BSL


Density
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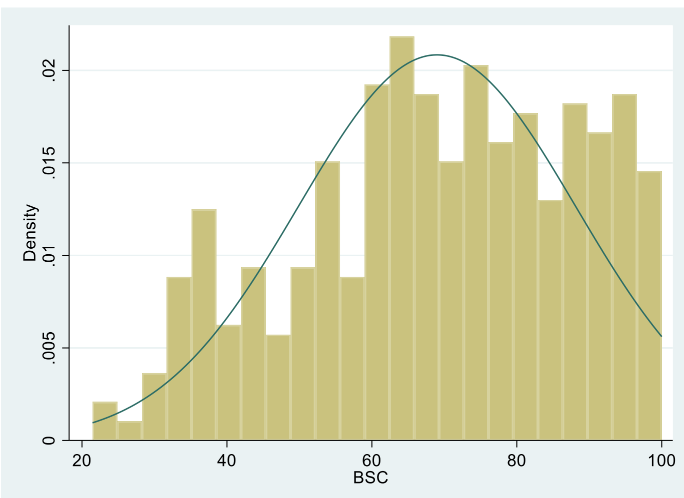
.006
.008
.01
0
50
100
150
200
250
MD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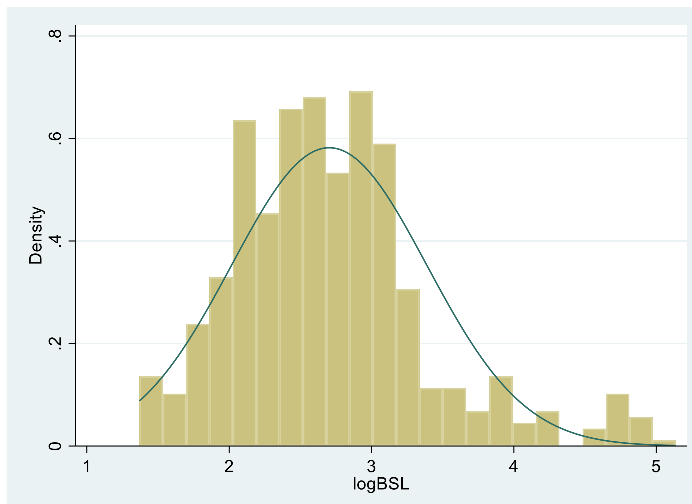
.015
.02
20
40
60
80
100
BSC


Density
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.4
.6
.8
1
2
3
4
5
logBSL

Appendix D: Robustness Tests

Table D.1: Pairwise correlations between control/independent variables. Results show significant correlation among especially *BSC* and *MD*.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) BC	1.000					
(2) MC	0.476*	1.000				
	(0.000)					
(3) NFD	0.584*	0.506*	1.000			
	(0.000)	(0.000)				
(4) logBSL	-0.054	-0.179*	0.000	1.000		
	(0.346)	(0.002)	(0.993)			
(5) BSC	0.303*	-0.243*	0.049	-0.140	1.000	
	(0.000)	(0.000)	(0.396)	(0.015)		
(6) MD	0.850*	0.289*	0.706*	0.065	0.354*	1.000
	(0.000)	(0.000)	(0.000)	(0.259)	(0.000)	

**** p<0.01, ** p<0.05, * p<0.1*

Table D.2.1: Regression results based on two highest quantiles (Q12) and two lowest quantiles (Q34). Only *alpha2* regression estimates show a significant positive effect of the financing ratio on systemic risk. R-squared values across models increase significantly compared to estimates based on 5 quantiles.

	(1)	(2)	(3)	(4)	(5)	(6)
	Q12alpha1	Q12alpha1	Q12alpha2	Q34alpha2	Q12nu	Q34nu
F	.375	.143	2.27***	-.303	-.066	1.032
	(.372)	(.412)	(.321)	(1.196)	(2.412)	(3.42)
BSC	.003**	.003**	-.003**	-.015***	-.029***	.001
	(.002)	(.001)	(.001)	(.003)	(.01)	(.01)
BSL	-.062***	-.033**	.015	.002	-.189	-.113
	(.023)	(.016)	(.02)	(.047)	(.151)	(.133)
MD	.002**	0	-.001**	.002	-.01**	.005
	(.001)	(0)	(.001)	(.001)	(.005)	(.004)
_cons	-.232	.021	-.08	1.069***	10.131***	5.448***
	(.258)	(.074)	(.223)	(.215)	(1.674)	(.615)
Observations	143	120	143	120	143	120
R-squared	.165	.116	.412	.262	.088	.037

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table D.3.1: Summary statistics Z-scores (*Z*), EVT-based CoVar (*evt99*) and fully parametric CoVar (*fp99*).

	N	Mean	Std. Dev.	Median	min	max
Z	304	14.837	7.719	14.416	4.324	32.29
evt99	300	4.626	2.557	4.433	1.006	9.933
fp99	300	4.687	2.606	4.34	.562	10

Table D.3.2: Pairwise correlations between variables. All three robustness proxies are negatively correlated with the financing ratio. Because lower Z-scores imply a higher probability of banking sector default, this corroborates our results. Results using the EVT-based and fully parametric CoVar imply that bank-based systems actually entail less systemic risk than market-based systems. This contradicts results based on *alpha1*, *alpha2* and *nu* values. Only the Z-score is significant as systemic risk proxy at the 90% confidence interval.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) F	1.000						
(2) Z	-0.520*	1.000					
	(0.000)						
(3) evt99	-0.089	-0.137	1.000				
	(0.123)	(0.018)					
(4) fp99	-0.086	-0.101	0.707*	1.000			
	(0.139)	(0.080)	(0.000)				
(5) BSC	0.408*	-0.348*	-0.086	-0.055	1.000		
	(0.000)	(0.000)	(0.136)	(0.338)			
(6) logBSL	-0.002	-0.116	0.049	0.070	-0.140	1.000	
	(0.973)	(0.043)	(0.395)	(0.226)	(0.015)		
(7) MD	0.624*	-0.196*	0.027	0.019	0.354*	0.065	1.000
	(0.000)	(0.001)	(0.643)	(0.745)	(0.000)	(0.259)	

**** p<0.01, ** p<0.05, * p<0.1*

Table D.3.3: OLS regression estimates for all three robustness proxies. All proxies show a significant negative effect of the financing ratio on systemic risk. Results using Z-scores corroborates earlier results, while EVT-based and fully parametric CoVar results contradict earlier results using *alpha1*, *alpha2* and *nu* values. Especially the model using Z-scores holds high explanatory power.

	(1) Z	(2) evt99	(3) fp99
F	-49.451***	-3.962*	-3.9*
	(4.945)	(2.055)	(2.098)
BSC	-.108***	-.012	-.005
	(.025)	(.01)	(.011)
logBSL	-1.678***	.087	.19
	(.474)	(.197)	(.201)
MD	.061***	.01*	.009
	(.014)	(.006)	(.006)
_cons	36.043***	5.332***	4.847***
	(2.174)	(.938)	(.958)
Observations	303	299	299
R-squared	.368	.024	.019
Mean VIF	1.43	1.40	1.40
Highest VIF	1.68	1.68	1.68

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table D.3.4: Quantile regression results using Z-scores. Results show a significant negative effect of the financing ratio on Z-scores across all quantiles, implying that bank-based systems entail more systemic risk than market-based systems. Results concerning the third quantile should be interpreted with caution due to heavily inflated coefficients, t-values and VIF-values. Financial market depth (*MD*) is omitted as control variable due to multicollinearity.

	(1)	(2)	(3)	(4)	(5)
	Q1 Z	Q2Z	Q3Z	Q4Z	Q5 Z
F	-173.64***	-78.038***	-939.517**	-471.236***	-232.618***
	(31.896)	(18.179)	(367.831)	(64.615)	(4.65)
BSC	.335***	-.579***	.162***	-.017	-.221***
	(.073)	(.024)	(.033)	(.049)	(.017)
BSL	-7.265***	.275	7.742	.032	2.444***
	(.759)	(.642)	(5.242)	(2.047)	(.14)
_cons	90.345***	88.071***	267.77**	147.802***	69.296***
	(12.916)	(9.116)	(99.469)	(21.729)	(.669)
Observations	78	65	40	60	60
R-squared	.625	.915	.591	.609	.99
Mean VIF	4.29	3.91	18.05	1.63	1.77
Highest VIF	6.47	5.61	28.13	1.92	2.00

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table D.3.5: Quantile regression results using EVT-based CoVar. Results show a significant positive effect of the financing ratio on the EVT-based CoVar, in all but the third quantile. These regression estimates confirm that a higher financing ratio leads to more systemic risk (i.e. bank-based financial systems entail more systemic risk than market-based systems), but it fails to capture the non-linear relationship. Results concerning the third quantile should be interpreted with caution due to heavily inflated coefficients, t-values and VIF-values. Financial market depth (*MD*) is omitted as control variable due to multicollinearity.

	(1)	(2)	(3)	(4)	(5)
	Q1evt99	Q2evt99	Q3evt99	Q4evt99	Q5evt99
F	41.223*	100.646***	118.995	125.276***	40.133***
	(23.477)	(31.777)	(459.994)	(43.18)	(6.828)
BSC	.061	.048	-.016	-.022	-.102***
	(.054)	(.042)	(.041)	(.033)	(.025)
BSL	2.878***	1.121	.463	.861	.095
	(.559)	(1.123)	(6.556)	(1.368)	(.203)
_cons	-26.966***	-38.922**	-31.611	-31.17**	1.745*
	(9.507)	(15.936)	(124.392)	(14.521)	(1.03)
Observations	78	65	40	60	56
R-squared	.321	.297	.058	.183	.445
Mean VIF	4.29	3.91	18.05	1.63	1.77
Highest VIF	6.47	5.61	28.13	1.92	2.00

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table D.3.6: Quantile regression results using fully parametric CoVar. Results show a significant positive effect of the financing ratio on the EVT-based CoVar, in all but the third quantile These regression estimates confirm that a higher financing ratio leads to more systemic risk (i.e. bank-based financial systems entail more systemic risk than market-based systems), but it fails to capture the non-linear relationshipResults concerning the third quantile should be interpreted with caution due to heavily inflated coefficients, t-values and VIF-values. Financial market depth (*MD*) is omitted as control variable due to multicollinearity.

	(1)	(2)	(3)	(4)	(5)
	Q1fp99	Q2fp99	Q3fp99	Q4fp99	Q5fp99
F	52.587**	98.273***	-634.783	102.358**	46.691***
	(22.301)	(32.235)	(442.121)	(41.93)	(8.208)
BSC	.071	.043	.035	-.063*	-.071**
	(.051)	(.042)	(.039)	(.032)	(.03)
BSL	3.077***	.804	9.41	2.894**	-.029
	(.531)	(1.139)	(6.301)	(1.328)	(.244)
_cons	-33.316***	-36.681**	175.599	-26.944*	-.584
	(9.031)	(16.166)	(119.559)	(14.1)	(1.238)
Observations	78	65	40	60	56
R-squared	.386	.321	.072	.155	.429
Mean VIF	4.29	3.91	18.05	1.63	1.77
Highest VIF	6.47	5.61	28.13	1.92	2.00

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table D.3.7: Individual component analysis. Results show that bank credit (*BC*) has a significant negative effect on Z-scores, which comes as no surprise as greater capital for banks reduce their Z-scores (i.e. larger banks pose a greater threat to systemic risk). For the two CoVar methods, only market capitalization (*MC*) has a significant effect for the fully parametric CoVar approach, implying that developing market financing is more effective in reducing systemic risk than developing debt financing.

	(1)	(2)	(3)
	Z	evt99	fp99
BC	-.118***	-.007	-.007
	(.011)	(.005)	(.005)
MC	.084***	-.006	-.013**
	(.012)	(.005)	(.005)
NFD	.038***	.003	.004
	(.007)	(.003)	(.003)
BSL	-.823*	.091	.114
	(.487)	(.197)	(.198)
_cons	13.533***	4.805***	5.071***
	(1.865)	(.753)	(.758)
Observations	303	299	299
R-squared	.338	.02	.044

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table D.3.8: Individual component analysis using quantile regression based on EVT-based CoVar values. Results show that bank credit (*BC*) has a significant positive effect on systemic risk in the second and fourth quantile, whilst market capitalization (*MC*) has a significant negative effect in the first and fourth quantile. These results imply that bank financing increases systemic risk, whilst developing stock market financing can decrease it and is more effective than developing debt market financing.

	(1)	(2)	(3)	(4)	(5)
	evt99	evt99	evt99	evt99	evt99
BC	.048	.062***	.069	.374*	.07
	(.051)	(.021)	(.049)	(.223)	(.047)
MC	-.068***	-.005	-.022	-.107***	-.016
	(.018)	(.022)	(.021)	(.039)	(.018)
NFD	-.021	.008	-.022*	-.102	-.007
	(.017)	(.01)	(.012)	(.082)	(.016)
BSL	2.48*	-.963	1.63	-.237	-.009
	(1.276)	(1.068)	(2.172)	(2.925)	(.249)
_cons	1.473	-1.024	1.111	4.237	4.546***
	(7.407)	(4.154)	(4.372)	(5.355)	(1.422)
Observations	78	65	40	60	56
R-squared	.338	.317	.145	.211	.467

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table D.3.9: Individual component analysis using quantile regression based on fully parametric CoVar values. Results show that bank credit (*BC*) only has a significant positive effect on systemic risk in the fifth quantile, whilst market capitalization has a significant negative effect on systemic risk in the first and fourth quantile. Non-financial debt (*NFD*) has a significant negative effect on systemic risk in the top quantile, but again stock market financing (*MC*) its effect in decreasing systemic risk is greater than that of debt market financing (*NFD*).

	(1)	(2)	(3)	(4)	(5)
	fp99	fp99	fp99	fp99	fp99
BC	.081	.03	.011	-.039	.113*
	(.049)	(.021)	(.049)	(.216)	(.058)
MC	-.086***	.001	.001	-.071*	-.016
	(.017)	(.022)	(.021)	(.037)	(.022)
NFD	-.03*	.022**	-.011	.046	-.022
	(.017)	(.01)	(.012)	(.079)	(.019)
BSL	3.089**	-1.979*	1.825	-1.921	-.204
	(1.214)	(1.103)	(2.172)	(2.83)	(.305)
_cons	-1.245	1.593	1.162	7.312	5.762***
	(7.05)	(4.292)	(4.371)	(5.181)	(1.74)
Observations	78	65	40	60	56
R-squared	.399	.315	.088	.19	.432

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*