The conflict between systemic risk and idiosyncratic risk.

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Abstract

We highlight the role revenue portfolio diversification plays in determining idiosyncratic and systemic risk in a global sample of large banks. We find that increased bank revenue diversification reduces idiosyncratic risk but increases systemic risk, while also demonstrating that increased bank equity will not necessarily reduce idiosyncratic risk. Bank size and market concentration have a role in the relationship between bank revenue portfolio composition and systemic risk. We argue that the current stance of the global regulatory architecture may not necessarily be effective in reducing bank systemic risk in the future.

Keywords: Systemic risk, Idiosyncratic risk, G-SIBs, Non-interest income.

JEL Codes: G21, G18

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1. Introduction

Bank failure contagion imperiling financial system stability (systemic risk), resulting in a loss of economic welfare, is a well-known problem (Allen and Gale, 2000; Brunnermeier and Sannikov, 2014; Diamond and Dybvig, 1983). This concern can be likened to the problem of the first domino/bank falling, resulting in the subsequent collapse of all the related dominos, represented by the financial system. The financial crisis of 2007–2008 brought concerns about systemic interdependence back to policy prominence, as policy makers became increasingly worried about the global nature of banking interdependence. Consequently, a set of large and globally active banks, known as Global Systemically Important Banks (G-SIBs), was identified, requiring them to hold higher levels of capital on their balance sheets than their peers along with increased regulatory surveillance.

This aspect of increased prudential regulation stresses the potential negative externalities caused by systemic interconnectedness in times of bank failure. This paradigm shift in regulatory methodology reflects a two-pronged approach. Regulators are primarily concerned with preventing the first domino from falling, especially when this domino is a large bank. Simultaneously, they are also concerned with the proximity of each domino to its peers in a globalized financial market. Therefore, the trade-off between idiosyncratic versus systemic risk adds a layer of complexity for regulators as they juggle between the too big to fail vs. the too systemic to fail phenomena.

Against this policy backdrop, bank revenue has also been evolving (Abedifar, *et al.*, 2018; Nguyen, 2012). Increasingly, bank revenues have emphasized non-interest income from the provision of financial services not associated with traditional intermediation products. This change is particularly apparent for larger banks (Allen and Santomero, 2001), where the current regulatory focus is concerned with both size and systemic connectedness. In our study, we consider the implications of both G-SIB status and non-interest income for bank risk. Prudential regulators are concerned with both stopping the initial fall of the domino, particularly if that domino is a large bank.[2] Furthermore, they also evaluate the systemic impact of subsequent dominos falling, i.e., systemic contagion within the relevant financial systems. Therefore, overall, we consider bank risk from the perspectives of both idiosyncratic and systemic risk.

This observed change in bank revenue mix has resulted in a stream of research, especially in regards to the impact on bank risk (Stiroh, 2004; Williams, 2016). Studies such as those of DeYoung and Rice (2004) and Laeven and Levine (2007) have documented that increased bank non-interest income is associated with higher income volatility and the worsening of risk-return trade-offs. Conversely,

[2] See, for example, Paroush (1988).

DeYoung and Torna (2013) have found that non-interest income has the beneficial effect of reducing the risk of bank failure during periods of financial crisis. Abedifar, *et al.* (2018) found that US bank non-interest activity has no impact on bank credit risk. It is the interaction between the two issues of changing bank revenue and global systemic risk that motivates the research paper's agenda. We therefore consider (i) if interest income increases large bank systemic and idiosyncratic risk, and (ii) if the marginal impact on bank systemic and idiosyncratic risk of increased non-interest differs for G-SIBs as compared to other large global banks. Within this context, the effectiveness of large bank capital holdings in ameliorating bank risk is also explored.

Our study makes several contributions to the current evidence regarding the impact of non-interest income on bank risk. We study a global sample of large banks, employing measures of both idiosyncratic and systemic risk. By employing estimates of marginal expected shortfall (MES) and variance drawn from VLab (as detailed by Acharya, *et al.*, 2012)[3] we are able to utilize a relatively recent measure of systemic risk that would be readily available to prudential regulators when monitoring the health of their banks. By considering a global sample of large banks, which we view as too big to fail in their relevant national jurisdictions, we are able to increase our focus upon the issues associated with idiosyncratic and systemic risk.

Our global sample adds a second policy-relevant element to this study, as the issue of global contagion is again at the forefront of policy consideration after the Global Financial Crisis of 2007–2008, as evidenced by the development of a list of G-SIBs. Further, a global approach allows this paper to consider global idiosyncratic risk issues rather than idiosyncratic risk from the perspective of a single nation. The inclusion of idiosyncratic risk within this paper adds a valuable dimension to the study. Many financial crises commence with the failure of a single (usually large) bank, triggering a contagious effect across the financial system. We argue that this systemic risk is analogous to the domino effect of a series of interconnected failures started by the fall of a single domino. In this context, the first domino falling is often a reflection of idiosyncratic risk, while the collapse of subsequent dominos reflects systemic risk. From a regulator's perspective, the challenge is to mitigate both scenarios, preventing the fall of the first domino as well as keeping the other dominos spaced far enough apart so idiosyncratic risk has limited repercussive effects. It is debatable whether regulators may address both concerns simultaneously, as generally reducing one type of risk comes at the expense of increasing the other.

We find that increased levels of non-interest income are associated with increased systemic risk and reduced global idiosyncratic risk. We confirm G-SIBs have higher systemic risk than the rest of our sample of large global banks, but are no different in terms of idiosyncratic risk. Consistent with Engle,

[3] See also Benoit, *et al.* (2017)

et al. (2014), the concentration of the relevant bank market impacts on this relationship, with increased market concentration reducing the systemic risk impact of non-interest income. Since the first capital adequacy accord was issued in 1988, capital levels held by banks have been a focus of the global prudential architecture. Subsequent iterations of the capital accord have been consistent with the prudential regulatory view that more is better in terms of bank capital. This is consistent with Merton's (1977) seminal work. Our results indicate that this perspective may need to be moderated, or that a more nuanced approach to bank regulation considered. We find that idiosyncratic risk has a U-shaped relationship with respect to bank capital holding. Thus continuous increases in bank capital requirements will result in bank idiosyncratic risk increasing[4]. We further find that increased bank capital is associated with increased systemic risk.

In total, these results pose something of a conundrum for the Basle Committee on Banking Supervision and for national financial system regulators. When considering the risk impact of non-interest income, whether regulations focusing primarily upon equity holdings are an effective response to global systemic risk remains an open question. This paper indicates that a one-size-fits-all global regulatory stance is likely to be less effective in reducing global systemic risk in the future. We argue that any attempt to minimize one aspect of bank risk will have the potential to result in the increase of another dimension. Thus, policies aimed at reducing idiosyncratic risk, i.e., reducing the chance of the first domino falling, are likely to have the effect of placing the global dominoes closer together, the overall impact being an increase in the severity and depth of any contagious event. Alternatively, reducing global systemic risk is likely to increase bank idiosyncratic risk, the implication being that the failure of a large bank triggers more contagious risk. The severity and depth of the global contagion is less likely if the dominos are now placed further apart. We further argue that these results imply a risk transfer from bank management to the tax payers underwriting bank bailout programs, which is not necessarily in the interests of bank shareholders who are not bank management.

The rest of this paper is organized as follows. The next section reviews the literature and develops the testable hypotheses. Section 3 describes the data and methodology employed. Section 4 reports the results, with the final section concluding the study and identifying some further policy implications of these results.

2. Literature review and hypotheses development

The relative importance of the traditional banking business of accepting deposits and making loans has declined as banks have become increasingly active in the provision of non-traditional services such as

[4] Williams (2014) finds a similar result for Asian banks.

insurance products, funds management and securitization (Allen and Santomero, 2001). As a result of both regulatory and environmental changes, banks have developed a proactive strategy to remain competitive, resulting in an increasing share of non-interest income in revenue (Lepetit, *et al.* 2008).

The resulting change in income mix has been documented as leading to increased earnings volatility (DeYoung and Roland 2001). Furthermore, DeYoung and Rice (2004) argue that increased non-interest income is associated with worsening a bank's risk-return trade-off, with higher profitability but also disproportionately higher profit volatility. Brunnermeier, *et al.* (2012) found that banks with higher levels of non-interest income make a greater contribution to the systemic risk of the financial system compared to those engaged in traditional banking (i.e., deposit taking and lending). In contrast, Engle, *et al.* (2014) use the local market index to benchmark systemic risk estimates (marginal expected shortfall) and find that the impact of non-interest income on systemic risk is conditional on bank market concentration. It was found that in less concentrated banking systems, such as those of Japan and the United States, increased non-interest income is associated with higher returns but also increased systemic risk, consistent with DeYoung and Rice (2004). In more concentrated banking systems, increased non-interest income reduces profit volatility and systemic risk.

Furthermore, several reasons have been advanced to explain why non-interest income is more volatile than margin income (DeYoung and Roland, 2001). Firstly, the revenue from a bank's lending activities are more stable, owing to relationship banking and the high information costs faced by the borrowers. In contrast, fee-based income sources lack this strong relationship component and are often faced with high competitive rivalry. Secondly, fee-based income sources require banks to hire highly qualified staff, increasing fixed input costs and the operating leverage of the bank. This is in contrast to margin income relying mainly on variable interest expenses as an input. The increase in operating leverage eventuates from a high fixed-to-variable cost ratio so increasing earnings volatility. Finally, fee income has high financial leverage due to lower levels of required equity implying increased financial risk and higher revenue volatility.

The traditional theory supporting banks increasing the diversity of their revenues stems from the mean-variance efficiency model of portfolio theory (Markowitz 1991). Diamond (1984) developed a theory of financial intermediation, and suggested that diversification within the financial intermediary results in a reduction of information asymmetry between the depositors and borrowers, as the intermediary is delegated the role of monitoring the financial health of the borrowers. Models of intermediation such as those proposed by Diamond (1984) and Ramakrishnan and Thakor (1984) have argued that bank diversification acts to increase the credibility of a bank in its role of reducing information asymmetry. On the other hand, Jensen (1986) applied agency theory to this issue and suggested that internally financing projects, or diversifying income sources, reduces managerial incentives to grow their firms beyond optimal size, reducing potential moral hazard problems. Further, Boot and Ratnovski (2016) have found that increased market-based activities by banks reduces the relationship component of banking.

Diversification benefits do exist in banks as a result of increased reliance upon fees as a revenue source. However, these gains have been found to be offset by the negative impact of the relatively high volatility of non-interest income (Stiroh and Rumble 2006). These results could reflect a failure in portfolio optimisation, in that banks are over-exposed to volatile revenue sources. This increases returns and risk, but also reduces bank risk at a lower level of exposure. Stiroh (2006) indicated that the banks most reliant on non-interest income do not earn higher average equity returns, and are much more risky in terms of return volatility (total and idiosyncratic) and market betas. Furthermore, Stiroh (2004) also found that the cross-sectional correlation between net interest income growth and non-interest income growth across banks increased over time, suggesting that risk reduction may not occur due to increased non-interest income. Thus, greater emphasis on non-interest income may diversify income sources but is more likely to be risk-increasing than mitigating.

A US market study by Laeven and Levine (2007) found that the market values of banks engaging in multiple activities were much lower than those banks segmented into specialized financial intermediaries. They concluded that diversification intensifies adverse selection problems in financial conglomerates and reduces market valuation. This reduction in valuation due to diversification outweighs the benefits accruing from economies of scope. Using data from Chinese banks, Nguyen (2012) supported Laeven and Levine (2007) and suggested that increasing reliance on non-traditional activities is negatively correlated with risk-adjusted profitability measures and that there were no diversification benefits from increased non-interest income.

With respect to agency costs and income diversification, Stiroh and Rumble (2006) argue that bank management is more concerned with absolute levels of returns rather than managing risk-return trade-offs. This reveals an agency conflict between regulators, who are concerned with financial system stability, and bank management, who are focused on the absolute level of profits. It is argued that the too-big-too-fail phenomenon has encouraged big banks to focus on absolute levels of profits, as the regulators bear any costs of bank failure due to increased risk (Stiroh and Rumble 2006).

A European bank study by Lepetit, *et al.* (2008b) found that expansion into fee-based services affects a bank's net interest margins and loan pricing. They concluded that income from non-traditional activities reduces net interest margins through cross-subsidization effects. Banks use lower rates of interest on loans to attract customers with the intent of extracting increased fee income from customers by virtue of establishing a long term relationship. It was argued that this cross-selling results in lower lending rates, and that borrower default risk may be underpriced in the lending rates charged by the banks with higher non-interest income (Lepetit, *et al.* 2008b). Laeven and Levine (2007) have suggested a similar outcome, in that a greater focus on non-interest income results in a systematic diversification discount for financial conglomerates (a reference to the tendency of the stock market to undervalue the stocks of conglomerate businesses (Villalonga, 2004)). In relation to such diversification measures, various concerns have been raised, such as agency problems and information opacity associated with lower loan portfolio quality and increased loan mispricing, hence augmenting the risk exposure in banks (Lepetit, *et al.* 2008a). However, Abedifar, *et al.* (2018) found that non-interest activity has no impact on US bank loan quality.

While diversification benefits are important for individual banks, there are negative externalities arising from bank failure associated with diversification of income sources. Ibragimov, *et al.* (2011) have shown that diversification initiatives by individual banks may prove to be suboptimal for society, especially when intermediaries have return distributions with heavy tails and high correlation. It has been suggested that as more banks diversify their portfolios, they become exposed to the same risks due to similarities in their investment strategies, and a fall in the value of these portfolios may lead to joint failures in the system (Wagner, 2010). This joint risk or systemic risk (Acharya, *et al.* 2016) is a key concern for financial system regulators. The contagion effect from one institution to another can arise from the prevalence of a complex network of financial contracts. These contracts are composed of three main types of operations, namely: (i) the payments system; (ii) the interbank market; and (iii) the market for derivatives, and are regarded as essential attributes for financial intermediaries to provide liquidity and to service clients (Freixas, *et al.* 2000). Recent studies, such as those of DeYoung and Torna (2013) and Engle, *et al.* (2014) suggest that such revenue diversification contributes significantly to increased levels of systemic risk in the financial system.

Our measure of systemic risk has been well-developed by Acharya, *et al.* (2017). Marginal expected shortfall (MES) is a measure of financial institutions' contribution to systemic risk (Benoit, *et al.*, 2017). Furthermore, Systemic Expected Shortfall (SES) extends MES to measure the propensity of a financial institution to be undercapitalized when the system as a whole is undercapitalized. If a regulator imposes a tax related to the expected default losses contributing to systemic crisis (measured by the SES), then banks are obliged to inject additional capital to address the externalities arising from systemic risk, ensuring creditor protection. Acharya, *et al.* (2017) suggested that the systemic risk component measured by SES was equal to the expected amount by which banks were undercapitalized in the 2007–2008 Global Financial Crisis. As further discussed by Acharya, *et al.* (2017), the advantage of MES over other methods, such as historical Value at Risk (VaR), stems from it being a market-based measure of risk which allows for extreme events and for provision of a reliable estimate for the worst performing banks.

The financial crisis of 2007–2008 re-emphasised the risks associated with large banks operating in a complex, interconnected global financial system. The issues associated with some banks being too big to fail were also highlighted (Kaufman 2014). The outcome (in part) was the development of a list of Global Systemically Important Banks (G-SIBs) (Financial Stability Board, 2015). The G-SIBs are a group of large banks with high levels of global systemic interconnectedness to the financial system (Bongini, *et al.* 2014), which are subject to an increased regulatory burden (especially required capital holdings), to offset the potential risk and costs of their failure. As previously discussed, bank revenue diversification involving increased non-interest income results in a worsening of bank risk-return trade-off. Against the backdrop of global systemic risk, interconnectedness and the too-big-to-fail status of large banks, this increase in bank risk has significant policy implications.

Therefore, this research will test a number of hypotheses investigating the relationship between increased bank non-interest income and systemic/idiosyncratic risk. We focus on the largest banks in the world, ranked by volume of assets. This sample is representative of the too-big-to-fail institutions, as these banks are the most influential financial conglomerates in the world. These banks are expected to significantly contribute to the global systemic risk of the banking system via increased non-interest income. Thus, our first hypothesis argues that banks with higher non-interest income have increased systemic and idiosyncratic risk.

H1: Increased non-interest income leads to higher systemic and idiosyncratic risk.

G-SIBs have incentives to engage in higher risk-seeking activities owing to their too-big-to-fail status. In line with Allen and Santomero (2001), the largest US banks have increasingly emphasized non-interest activities, especially after the repeal of the Glass-Steagall Act. While such a change in income mix results in increased absolute levels of returns, DeYoung and Roland (2001) demonstrated that banks exhibit higher earnings volatility as a consequence of this increase and are exposed to a worsening risk-return trade-off. The characteristics of the G-SIBs include the risk-seeking incentives of the too-big-to-fail institutions and too-systemically-relevant to fail.

As previously established, these large banks have an increased focus on non-interest activities and consequently an increased exposure to both systemic and idiosyncratic risk. Therefore, G-SIBs would be expected to have adopted similar strategies to many other large banks, primarily to maintain their global competitiveness. Thus, we would expect G-SIBs to have increased their focus on non-interest activities, subsequently facing increased levels of systemic risk. Brunnermeier, *et al.* (2012) found that banks with higher levels of non-interest income, comprising of non-core activities such as investment banking, venture capital and trading activities, have a higher contribution to systemic risk than those with a focus on the traditional banking activities of deposit taking and lending. Hence, G-SIBs potentially have high levels of increased systemic risk and make a greater contribution to the overall systemic risk in the banking system. The second hypothesis is therefore set to test this possibility and proposes that the marginal impact of non-interest income on systemic risk (and idiosyncratic risk) is greater for G-SIBs compared to a control sample drawn from the largest banks in the world (by assets).

H2: The marginal impact of non-interest income on systemic risk and idiosyncratic risk is greater for G-SIBs than for other large banks.

3. Data and methodology

3.1 Sample selection

Our initial sample is drawn from the largest 500 banks in the world in BankScope, based on asset size (in USD) as at the end of each year. The sample period covers 2000 to 2016 and the specializations of commercial banks, savings banks, cooperative banks, real estate and mortgage banks, bank holding and bank holding companies are included. Banks in the initial sample that are subsidiaries of a larger parent were removed to ensure there were no double-counting affects. Those banks lacking sufficient detail in BankScope to allow bank-specific control variables to be implemented were removed from the sample, as were unlisted banks. VLab provided systemic and idiosyncratic risk data for a total of 119 banks. The estimation procedure for the data provided by VLab is detailed by Acharya, *et al.* (2012), and will be discussed below.[5] The sample includes banks drawn from 35 countries, with all listed G-SIBs in the final sample. Table 1 reports a country-by-country breakdown and banks per country.

TABLE 1 ABOUT HERE.

3.2 Dependent variable

The focus of our study is to investigate the impact of non-interest income upon systemic risk. Systemic risk is typically defined as the degree of contagion between financial institutions in the event of the failure of a single financial institution. The concern is not with the failure of a single institution *per se*, but rather with the impact that such a failure has on the ongoing viability of the overall financial system. The Marginal Expected Shortfall (MES) measure developed by Acharya, *et al.* (2017) has been shown to be a good predictor of bank capital shortfalls during the financial crisis of 2007–2008. Furthermore, unlike CoVaR (Adrian and Brunnermeier, 2016), MES does not require data that is not readily available for a global study (Engle, *et al.* 2014). As our focus is upon global systemic bank risk, we employ the

[5] We are grateful for the assistance provided by Michael Robles, Rob Capellini and Brian Reis from VLab.

Morgan Stanley Capital International (MSCI) World Index for Commercial Banks as our benchmark. This is in contrast to previous studies which have used bank-specific measures of risk such as beta or volatility (DeYoung and Rice 2005; Stiroh and Rumble 2006) or used a local market index to measure systemic risk (Engle, *et al.* 2014; Williams 2016). We argue that this index reflects the global interconnectedness of internationally active banks, and as such provides an effective measure of systemic risk directly relevant to G-SIBs. As developed by Acharya, *et al.* (2012), MES is estimated whereby the 5% worst days for the market returns *(R)* in any given year is considered and then the average return on any given bank (R^b) is computed for those 5% of worst days : $MES_{5\%}^b = \frac{1}{\# \, days} \sum_{t: system \, is \, in \, its \, 5\% \, tail} R_t^b$. We employ the version of MES as developed by Brownlees and Engle (2017) and calculated by VLab, employing the dynamic conditional beta of Engle (2016) as follows: $LRMES = 1 - \exp(\log(1-d) * beta$. Where LRMES is the Long Run MES, or the fraction of the firm loss when the market index declines forty percent (d) over a six month window and beta is the dynamic conditional beta (Benoit, *et al.*, 2017; Engle, 2016). To measure the idiosyncratic component of a bank's risk, we use the observed share market variance of the relevant listed bank. In each case, the daily observations of LRMES and provided by VLab are transformed into annual averages and matched to annual balance sheet data sourced from BankScope.[6]

The daily variance estimates are calculated using a Glosten-Jagannathan-Runkle GARCH (*p,q)*[7] model, (GJR-GARCH, hereafter) using all data available back to 1990.[8] VLab uses $p = 1$ and $q = 1$ as this is usually the option that best fits financial time series (Glosten, *et al.*, 1993; Zakoian, 1994).[9] The GJR-GARCH model assumes a specific parametric form for this conditional heteroskedasticity, more specifically $\varepsilon_t \sim$ GJR-GARCH, with $\varepsilon_t = \sigma_t z_t$ where z_t is standard Gaussian and:

$$\sigma_t^2 = \omega + (\alpha + \gamma I_{t-1})\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$$

where

$$\mathrm{I}_{t-1} := \begin{cases} 0 & \text{if} \quad r_{t-1} \geq \mu \\ 1 & \text{if} \quad r_{t-1} < \mu \end{cases}$$

VLab estimates all the parameters $(\mu, \omega, \propto, \gamma, \beta)$ concurrently, by maximizing the log likelihood. The GJR-GARCH model, like the GARCH model, captures other stylized facts in financial time series, like volatility clustering. The volatility is more likely to be high at time *t* if it was also high at time *t*-1. Another way of seeing this is noting that a shock at time *t*-1 also impacts the variance at time *t*. However,

[6] This data was downloaded from BankScope just prior to the database becoming Orbis Bank Focus.
[7] Lag lengths were chosen by reference to the Bayesian Information Criterion (BIC), also known as Schwarz Information Centre (SIC), with the (1,1) process providing the best overall fit.
[8] See also https://vlab.stern.nyu.edu/doc/3?topic=mdls (accessed 5 February 2018).
[9] Figlewski (2016) provides an example of using VLab GJR-GARCH estimates to identify risk-neutral densities.

if $\alpha + \frac{\gamma}{2} + \beta < 1$, the volatility itself is mean reverting, and it fluctuates around σ, the sqaure root of the unconditional variance

$$\sigma^2 := \mathrm{Var}(r_t) = \frac{\omega}{1 - \alpha - \frac{\gamma}{2} - \beta}$$

where the $\frac{1}{2}$ multiplying γ comes from the normality assumption of z_t. More intuitively, it comes from the assumption that the conditional distribution of the returns is symmetric around μ. Usual restrictions on the parameters are $\omega, \propto, \gamma, \beta > 0$. The GARCH model is in fact a restricted version of the GJR-GARCH with $\gamma = 0$.

VLab re-estimates the parameters on a weekly basis and applies these values to the return series for the following week to obtain daily variance forecasts for same six-month forward window as the LRMES forecasts. Table 2 provides details of the calculated MES and market-based variance.

TABLE 2 ABOUT HERE.

3.3 Independent variables

Following previous studies such as those of Engle, *et al.* (2014) and Williams (2016), we use non-interest income as a percent of total revenue as our main variable of interest. We employ a dummy variable to represent G-SIB status, with a value of 1 if the bank is a G-SIB (Financial Stability Board, 2015). An interaction term (non-interest income as a per cent of revenue * G-SIB dummy) has been added to capture the marginal impact of non-interest on the systemic risk of G-SIBs.

3.4 Control variables

We employ two sets of control variables to reflect the mix of bank-specific and country- related characteristics of the sample.

3.4.1 Bank-specific control variables

The first set of control variables will encompass a variety of bank characteristics that have an impact on bank risk. Banks which are risk-seeking tend to have lower levels of capital and often report higher levels of bad debts as a result of lower-quality loan portfolios (Merton 1977). Hence, we include capital adequacy ratios (both Tier 1 ratio and total regulatory capital ratio) as well as the equity to total assets ratio to measure the capitalization of each bank. Following Williams (2014), we also include a control for a nonlinear relationship between bank risk and bank capital, equity squared. Lending is still considered the most important line of business for banks, and it is necessary to take into account loan quality indicators, as credit quality is a key source of bank risk. Furthermore, as found by Lepetit, *et al.*

(2008a), banks may be willing to sacrifice loan portfolio quality to attract increased non-interest income. Thus, to control for asset quality, the Loan Impairment Charge (LIC) scaled by total assets is included in our model.

To control for size effects and the possibly associated risk-seeking effects due to too-big-to-fail status, we include the log of total assets and net loans scaled by total assets (Engle, *et al.* 2014). Since the Global Financial Crisis, it has become increasingly important to consider the relationship between bank size and bank risk, since the too-big-to-fail phenomenon in banks has evidently escalated the impact of the financial meltdown experienced in 2008. Furthermore, net loans to assets provides a control for the differences in lending intensiveness. Banks with lower capitalization are more likely to have higher levels of loan growth (Kwan and Eisenbeis 1997). Thereby, the growth rate of gross loans has been included in our model.

An important element determining the degree of a bank's systemic risk is its degree of risk- seeking. Following Boyd and Nicolo (2005), we will use bank-level profit measures to determine if increased profits are associated with bank risk-seeking. We will also employ alternative profit measures of Return on Average Assets, Return on Average Equity and Net Interest Margins to reflect the different possible dimensions of bank risk impacting on systemic risk. Further, our model will include a cost to income measure to represent differences in bank-level managerial ability.

The imposition of required capital ratio on banks by prudential regulators imposes non-trivial costs on bank shareholders. It is possible that bank management may use increased non-interest income to increase bank revenue and so increase bank risk in a manner not fully compensated for by increased capital holdings. Thus, we will include an interaction variable, (non-interest income * equity) to represent this possibility. In a similar vein, while G-SIB status is accompanied by a further increase in regulatory obligations (higher capital requirements) and regulatory surveillance, it is also an acknowledgement that such banks are too systematic to fail, as well as too big to fail. Thus, risk-seeking is again possible. To control for this possibility, an interaction variable (G-SIB * equity) will measure if increased equity holding by G-SIBs is accompanied by reduced bank risk.

3.4.2 Country-specific control variables

As the study is also heterogeneous as concerns bank nationality, we incorporate a number of measures in our model to represent differences in systemic risk due to economic conditions and financial circumstances. These include GDP per capita to represent financial sophistication (Williams, 2014) as well as the growth rate of GDP per capita. As suggested by Fama (1990), the term structure of interest rates contains information about the stages of the economic cycle. Thus, we use a national yield curve measure in our model (long-term interest rate minus the short-term interest rate), sourced from the IMF International Financial Statistics, to control for these economic cycle differences. As discussed by Levine (2002), amongst others, a considerable literature has been produced debating the merits of bank- and market-based financial systems and their impact upon financial development and economic growth. As this difference may well impact upon the degree of national globalisation and therefore bank-level global system risk, we include a structure activity ratio in our model. We specify this measure as the ratio of stock market turnover to domestic credit provided per annum, again sourced from the IMF International Financial Statistics. As shown by Williams (2014), national governance impacts both the risk of the national banking system and the risk-reducing effects of capital holdings. Accordingly, we include a measure of national governance (regulatory quality) drawn from the world governance index (Kaufmann, *et al.*, 2010). As found by Engle, *et al.* (2014), home nation market concentration has a role in explaining the impact of bank diversification upon bank risk. Our model thus includes a measure of the home market concentration, the Herfindahl-Hirschman Index (HHI), calculated using BankScope data. As Engle, *et al.* (2014) found evidence of a nuanced relationship between market concentration, bank risk and non-interest income, we include in our model a further interaction variable (HII * non-interest income). Details of the independent variables and control variables included in this study are detailed in Table 3, with Table 4 reporting descriptive statistics at country level. Table 5 reports a correlation matrix across the variables employed within the estimation model.

TABLES 3, 4 and 5 ABOUT HERE.

3.5 Estimation model

Following our discussion above, the model we will estimate is as follows:

Systemic or Idiosyncratic Risk = α + $\beta 1$(Non-interest Income as a per cent of total revenue) + $\beta 2$(G-SIB dummy) + $\beta 3$ (G-SIB Dummy*Non-interest Income as a per cent of total revenue) + Σ Bank Characteristics Controls + Σ Country Specific Controls ....(1)

We estimate unbalanced panel regressions for equation (2). All models are estimated using a generalized least squares estimator controlling for both heteroscedasticity and autocorrelation.

4. Results

TABLE 6 ABOUT HERE.

Tables 6 (MES) and 7 (variance) report the results of our regressions. Panel A of each table records the results for the whole sample and the sample broken into three size based sub-samples: (i) the top 25%

of the sample by size, the smallest 25% of the sample and the middle 50% of the sample by size. In Panel B of each table, the study sample is broken into three sub-periods: pre-GFC (2000 to 2006), during the GFC period (2007 and 2008) and the post-GFC period (2009 to 2016). The results from Panel B of each table will enable the identification of any structural breaks in factors associated with bank risk, and so identification of the relevant policy implications of any such changes.

Comparing the results in Table 6 with those in Table 7, it is immediately apparent that policy implications for our independent variables of primary interest are quite different for systemic versus idiosyncratic risk. Considering the results for non-interest income, it is apparent that banks with higher levels of non-interest income have higher systemic risk and lower idiosyncratic risk. G-SIBs have higher systemic risk, justifying their inclusion on a list of systematically riskier banks, but are no different in terms of idiosyncratic risk. This does not mean that all global systemically risky banks are on the G-SIB list, which is an issue separate to this paper. From a policy perspective, these results raise a conundrum, in that policy makers should encourage higher non-interest income if they wish to stop the first domino from falling, but discourage non-interest income if they wish to reduce the likelihood of global bank failure contagion. Given that single market studies, such as those of Stiroh and Rumble (2006) and Williams (2016), find that non-interest income increases bank risk, the policy perspective becomes a key issue. From a global perspective, non-interest income reduces idiosyncratic risk and increases systemic risk, but from a national perspective, non-interest income increases bank risk. Thus the prudential regulator must first decide which type of risk to reduce prior to deciding which policy to adopt with respect to non-interest income. It must be acknowledged that whichever policy stance is adopted, it is likely to result in an increase in one other dimension of bank risk.

A similar conundrum is also apparent when examining the results for bank equity holdings. A significant non-linear process was found, with the policy implications differing between systemic and idiosyncratic risk. In the case of systemic risk (MES), Panel A in Table 6 shows increased capital holdings will at first be associated with higher systemic risk, but as equity holding increases, systemic risk reduction will occur, as shown by equity holdings squared. The opposite is found for idiosyncratic risk (stock market variance) (Table 7, Panel A). Initially, increases in bank equity holding will be associated with lower bank risk, but as equity holding increases, so does bank idiosyncratic risk, as shown by equity holding squared. This indicates that increases in required capital holding will not provide a one-size-fits-all solution to bank risk. Again, policy makers must accept trade-offs across different dimensions of bank risk when introducing prudential regulations.

Our next point of concern is the role non-interest income plays in risk reduction (increases) for the G-SIBs. We find that overall, non-interest income reduces G-SIB systemic risk at the margins but G-SIB non-interest income has no impact on bank idiosyncratic risk. It is possible that increased holding of bank equity offset increased systemic risk due to increased non-interest income. To examine this possibility, we included in our model an interaction variable, *non-interest income* * *equity*. We find that for the mid-sized banks in our sample there is some reduction of systemic risk attributable to non-interest income as a result of increased equity holdings. However, for the largest and smallest banks in our sample, equity holdings are not offsetting increased risk due to non-interest income. In the case of idiosyncratic risk, the size effect is more apparent. For larger banks, the reduction in idiosyncratic risk due to non-interest income is being offset by reductions in equity holding, resulting in some marginal increases in bank risk. The magnitudes of the coefficients are such that bank idiosyncratic risk is lower due to non-interest income across all the banks in the sample. However, the results indicate that increases in non-interest income is being accompanied by a marginal reduction in equity capital, with an accompanying marginal increase in bank idiosyncratic risk, for the larger banks in the sample. The opposite effect is found for the smaller banks in the sample, in that the idiosyncratic risk-reducing impact of non-interest income is being reinforced by equity holdings. This indicates that the appropriate prudential regulatory response to increased bank non-interest income is predicated upon the size of the relevant bank.

As we have observed, G-SIB status is associated with higher idiosyncratic risk. It is important to determine if the current regulatory requirement of increased capital holdings for G-SIBs is effective in reducing systemic risk. To this end, we included in our model an interaction variable, *GSIB* * *equity*. We find that in all cases this policy direction is effective in reducing G-SIB systemic risk. As shown in Table 7, this interaction variable has no relationship with bank idiosyncratic risk.

As discussed above, Engle, *et al.* (2014) found that bank market concentration plays a role in determining the impact of non-interest income on systemic risk. We examine this issue by considering the interaction variable *HHI* * *non-interest income*. We find that the previous results of Engle, *et al.* (2014) are confirmed in this study, in that banks from more concentrated markets are more likely to experience systemic risk reductions due to non-interest income. We extend the previous results of Engle, *et al.* (2014) by demonstrating that this result is most likely due to risk reduction effects for those banks closest to the median in size.

Panel B in both Tables 6 and 7 re-consider our model from the perspective of three distinct sub-periods: (i) before the GFC, (ii) during the GFC; and (iii) after the GFC. Thus, we may observe if the GFC has acted as a structural break in the relationship between systemic or idiosyncratic risk and our variables of interest. This is an important issue, as capital holding has been the centerpiece of global regulatory architecture since 1988. It is possible that the combined effects of the GFC, post-GFC regulatory changes and bank activity to mitigate the costs of prudential regulation have together changed the impact of equity holdings on bank risk. Two main systemic risk results are notable. Firstly, after the GFC, the nonlinear relationship between bank equity and systemic risk is no longer apparent, with the implication that increasing bank regulatory capital holdings are likely to be associated with increased bank systemic risk. Second, the marginal systemic risk reduction for G-SIBs due to non-interest income is no longer significant. In terms of idiosyncratic risk, the risk reduction impact of non-interest income is no longer apparent post-GFC. Any idiosyncratic risk reductions post-GFC due to non-interest income are isolated to nations with more concentrated banking systems. However, this conclusion should be accompanied by the caveat that nations with more concentrated banking systems display higher levels of idiosyncratic risk and this first order effect dominates the second order risk reduction impact of non-interest income. Thus, any increase in bank market concentration will increase national bank idiosyncratic risk on average, despite any idiosyncratic risk reduction due to non-interest income. Furthermore, the idiosyncratic risk-reducing impact of increased capital for G-SIBs is no longer apparent post-GFC, reducing the arguments in favour of this policy direction.

5. Conclusion.

This paper has found that increased non-interest income is associated with higher levels of systemic risk and lower levels of idiosyncratic risk. This conclusion should be tempered by the observance that this study employed a sample of large banks drawn from a global population. Focused single-nation studies such as Stiroh (2006) and Williams (2016) have concluded that increased non-interest income will increase bank idiosyncratic risk. Further, it is found that the idiosyncratic risk-mitigating properties are less apparent after the GFC. We also find that the risk-reducing properties of bank equity differ between systemic risk and idiosyncratic risk. Thus, policies aimed at employing bank capital to reduce bank risk must address the question of which aspect of bank risk these regulations will minimize.

Our initial reference to the domino effect is again germane. By reducing bank idiosyncratic risk, the probability of the first domino failing is reduced. Given that our sample is drawn from the world’s largest banks by assets, the failure of a large bank is likely to stimulate a systemic crisis in the relevant national banking system. However, from the perspective of global systemic risk, such policies will place the global dominos of the banking system closer together, thus increasing the severity of any repercussive crisis globally. Given the non-linearity we have identified, any attempt to simultaneously reduce both idiosyncratic risk and systemic risk is likely to induce an interior solution that is sub-optimal across both risk metrics. Given that prudential regulators have a national focus and operate within the frameworks dictated by national regulations, a focus on the idiosyncratic risk of large national banks as a pathway to reducing national systemic risk is understandable. The results of this paper may simply indicate that any attempt to attain an optimal regulatory solution mitigating all aspects of bank risk is the enemy of a sub-optimal, but nonetheless potentially effective, regulatory structure.

Our results also have some valuable implications for the various stakeholders in the banking system. Merton (1977) established that the put option component of deposit insurance results in increased bank shareholder wealth when bank idiosyncratic risk increases, and this effect is reduced by increased bank capital. The trend of banks increasing noninterest income has been well documented (Allen and Santomero, 2001; Stiroh, 2004), Our results suggest that this change in revenue reduces this put option value for bank shareholders, consistent with Merton (1977). While bank regulators would appreciate the reduction of bank idiosyncratic risk due to increased non-interest income, they would not favour the resulting increased systemic risk (or the associated risk increasing impact of increased capital holdings). However, bank management hold a poorly diversified wealth portfolio (which includes shares in the bank they manage). Thus, increasing non-interest income, with its associated reduction in idiosyncratic risk reduces their risk of wealth losses due to individual bank failure. While this reduced idiosyncratic risk comes at the cost of higher systemic risk, we argue that the large banks that make up our sample are those that are most likely to be rescued during a systemic crisis. We argue that this trade-off is rational in the presence of these asymmetric risk exposures. This trade-off, however, is not necessarily value enhancing economy wide, but instead represents a risk transfer from bank management to the tax payers underwriting bank rescue programs, without necessarily increasing the wealth of diversified bank shareholders.

Overall, these results also pose something of a puzzle for both future developments of global benchmark prudential regulations as well as for individual national regulators. The current regulatory stance is aimed at reducing bank risk by increasing the levels of required bank capital and the use of global benchmarks for prudential regulations. Such an approach is based upon the "more is better" view of capital, in which level playing fields and global consistency are key considerations. Our results suggest a more nuanced approach to reduce the multidimensional aspects of bank risk globally, at the cost of reduced cross-border comparability. Furthermore, such a policy approach, allowing for differences in national bank market concentration, differences in bank size, as well as different national non-interest income is a fundamental divergence from the previous policy agenda. As such, a considerable body of supporting research will be needed before the implications of this study (and other similar work) flows into mainstream regulatory policy.

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Table 1. Sample Details

Country	Number of Banks	Number of Observations
Australia	7	95
Austria	1	7
Argentina	2	30
Belgium	3	29
Brazil	3	42
Canada	6	54
China	13	93
Colombia	1	10
Denmark	2	18
Finland	1	10
France	6	73
Germany	5	63
Greece	5	64
Hungary	1	6
Hong Kong	3	43
Israel	4	60
Italy	11	142
India	5	58
Indonesia	4	50
Japan	29	294
Jordan	1	8
Korea	4	26
Kuwait	1	9
Luxembourg	1	4
Netherlands	3	27
Norway	1	7
Portugal	2	30
Russia	2	14
South Africa	6	79
Spain	7	81
Sweden	1	13
Switzerland	6	68
Thailand	6	90
Turkey	7	88
United Kingdom	5	65
United States	34	487

Sample based on the top 500 banks by size (assets in USD) in BankScope (2000 to 2016), which are the global ultimate owning banks, which are also listed on the relevant stock exchange for which Marginal Expected Shortfall and GJR-GARCH variance forecasts were available from VLab.

Table 2. Descriptive Statistics for the calculation of Marginal Expected shortfall.

Variable	Observations	No. of Banks	Mean	Std. Dev.	Min	Max
Long Run Marginal Expected Shortfall year average	2,337	199	0.364546	0.131738	-0.3058	0.742768
Market Variance Year average (GJR-GARCH forecast)	2,337	199	0.000836	0.001549	2.58E-05	0.0402

Source: VLab.[10] MES calculated according to Acharya, *et al.* (2012). Daily data transformed into annual averages by calendar year. MES calculated as $LRMES = 1 - \exp(\log(1-d) * beta$. Where LRMES is the Long Run MES and employing the dynamic conditional beta of Engle (2016). LRMES the fraction of the firm loss when the market index declines forty percent (d) over a six month window. The daily variance estimates are calculated using a Glosten-Jagannathan-Runkle GARCH (1,1) model (Glosten, *et al.*, 1993; Zakoian, 1994), using all data available back to 1990, estimated using quasi-maximum likelihood estimation. All data available from 1990 forward are used to generate volatility forecasts, with exponentially declining weights used to apply greater importance to recent observations.

[10] See https://vlab.stern.nyu.edu/doc/3?topic=mdls (accessed 5 February 2018)

Table 3. Descriptive Statistics: Independent variables.

Variable	Observations	No. of Banks	Mean	Std. Dev.	Min	Max
Equity to total assets	1,897	189	7.806666	5.01347	-3.931	86.552
Equity to total assets Squared	1,897	189	86.06567	334.723	0.006084	7491.249
Return on Average Assets	1,891	189	0.793553	1.189141	-12.367	8.69
Log Total Assets	1,897	189	18.62838	1.376846	14.68966	22.06034
Cost to income ratio %	1,879	188	59.73921	22.61211	12.936	426.485
Net loans to total assets	1,884	186	54.4045	18.63767	0	89.309
Liquid assets tot deposits and ST funds	1,888	188	31.48638	52.30139	0.531	966.547
Growth of Gross loans %	1,795	186	9.620674	24.84074	-100	704.69
GSIB 2015 list	2,337	199	0.138211	0.345196	0	1
Non-interest income as a percent of revenue	1,889	190	26.64418	21.51377	-132.075	491.4366
GSIB 2015 list * non-interest income	1,889	190	4.951916	14.19222	-6.87409	85.45703
Loan impairment change to average gross loans	1,756	182	0.945279	1.451953	-8.8	16.36

All bank level variables drawn from the BankScope database for each bank, with the exception of the G-SIB dummy (sourced from Financial Stability Board, 2015). All variables are measured as per cent with the exception of total assets which is the log of USD in thousands.

Table 4. Descriptive Statistics: Country level data.

National bank market HHI index	2,337	199	1190.773	1245.474	129.3523	9797.724
Regulatory quality	2,337	199	1.026823	0.658054	-1.07904	2.076643
National Long term interest rate less ST interest rate	2,304	199	2.510452	5.049723	-3.56951	45.11264
Structure ratio	2,310	199	24.75483	108.781	0.024571	1977.8
GDP per capita	2,337	199	34158.93	18412.38	835.3779	103923.9
Growth of GDP per capita	2,337	199	2.433155	3.187866	-10.8945	14.19496

National HHI Index (Herfindahl-Hirschman Index) calculated from BankScope, regulatory quality drawn from the world governance index (Kaufmann, *et al.*, 2010). Interest rate data from the IMF International Financial Statistics. Structure ratio measures the ratio of stock market turnover per annum divided by domestic credit provided per annum and is sourced from the IMF International Financial Statistics. GDP per capita and growth in GDP per capital are also sourced from the IMF International Financial Statistics.

Table 5. Correlation Matrix.

	Long Run MES	Variance	Equity to Total assets	Equity to Total Assets squared	Return on average assets	Log Total Assets	Cost to income ratio %	Net loans to total assets
Long Run MES	1							
Variance	0.2464	1						
Equity to Total assets	-0.0374	-0.0365	1					
Equity to Total Assets squared	-0.0147	0.0057	0.9613	1				
Return on average assets	-0.1062	-0.3024	0.4398	0.3576	1			
Log Total Assets	0.3803	0.0252	-0.3214	-0.2796	-0.1383	1		
Cost to income ratio %	0.1122	0.1732	-0.1793	-0.1431	-0.4302	0.0148	1	
Net loans to total assets	-0.2312	-0.0629	0.1768	0.1273	0.0092	-0.388	-0.186	1
Liquid assets to deposits and ST funds	0.2136	-0.0043	-0.1357	-0.1037	-0.0123	0.2017	0.1512	-0.4953
Growth of gross loans %	-0.0137	-0.0544	0.0584	0.038	0.2325	-0.0197	-0.1735	-0.0056
GSIB 2015 list	0.2433	0.016	-0.169	-0.1552	-0.064	0.6501	0.1095	-0.457
Non-interest income as % of revenue	0.2072	-0.0439	0.2764	0.2629	0.1755	0.0782	0.1371	-0.3266
GSIB 2015 * non-interest income	0.2101	0.0033	-0.0907	-0.0897	-0.041	0.5169	0.0984	-0.482
Loan impairment change to average gross loans	0.2406	0.3494	0.1229	0.1448	-0.1331	0.0106	0.0131	-0.0818
National Bank market HHI index	-0.094	-0.0017	-0.1869	-0.1488	-0.0414	-0.0691	-0.0889	0.0405
Regulatory Quality	0.1349	-0.0546	-0.1289	-0.1159	-0.1919	0.257	0.2464	-0.0315
National LT rate – ST rate	0.0711	0.1514	0.0335	0.0546	-0.1037	-0.1067	-0.0301	-0.0422
Structure Ratio	0.1049	0.0837	0.0172	0.0346	-0.0019	0.1223	0.0892	-0.0882
GDP per capita	0.103	-0.0463	-0.0686	-0.0484	-0.2154	0.2552	0.2881	-0.0573
Growth of GDP per capita	-0.3205	-0.3014	0.0775	0.0397	0.3798	-0.1327	-0.2069	-0.0443

	Liquid assets to deposits and ST funds	Growth of gross loans %	GSIB 2015 list	Non-interest income as % of revenue	GSIB 2015 * non-interest income	Loan impairment change to average gross loans	National Bank market HHI index	Regulatory Quality
Liquid assets to deposits and ST funds	1							
Growth of gross loans %	-0.0232	1						
GSIB 2015 list	0.1871	0.0231	1					
Non-interest income as % of revenue	0.1145	-0.0097	0.2168	1				
GSIB 2015 * non-interest income	0.1618	0.0256	0.8878	0.3602	1			
Loan impairment change to average gross loans	-0.0318	-0.0183	0.0105	0.1814	0.001	1		
National Bank market HHI index	0.1247	0.0254	-0.1346	-0.2929	-0.1783	-0.1003	1	
Regulatory Quality	0.0907	-0.1349	0.176	0.2355	0.1944	-0.0983	-0.1148	1
National LT rate – ST rate	-0.0034	-0.042	-0.0751	-0.0414	-0.0635	0.2428	0.1704	-0.3133
Structure Ratio	0.0391	0.0177	0.0775	0.1113	0.0881	0.0464	-0.0968	0.3237
GDP per capita	0.1292	-0.1493	0.2043	0.2725	0.2294	-0.101	-0.1576	0.8675
Growth of GDP per capita	-0.0208	0.2162	-0.0576	-0.0756	-0.0623	-0.1975	0.1047	-0.3693

	National LT rate – ST rate	Structure Ratio	GDP per capita	Growth of GDP per capita
National LT rate – ST rate	1			
Structure Ratio	-0.1677	1		
GDP per capita	-0.3249	0.2759	1	
Growth of GDP per capita	-0.0612	-0.0418	-0.397	1

All bank level variables drawn from the BankScope database for each bank, with the exception of the G-SIB dummy (sourced from Financial Stability Board, 2015). All variables are measured as per cent with the exception of total assets which is the log of USD in thousands. National HHI Index (Herfindahl-Hirschman Index) calculated from BankScope, regulatory quality drawn from the world governance index (Kaufmann, *et al.*, 2010). Interest rate data from the IMF International Financial Statistics. Structure ratio measures the ratio of stock market turnover per annum divided by domestic credit provided per annum and is sourced from the IMF International Financial Statistics. GDP per capita and growth in GDP per capital are also sourced from the IMF International Financial Statistics. MES and variance sourced from VLab.[11] MES calculated according to Acharya, *et al.* (2012). Daily data transformed into annual averages by calendar year. MES calculated as $LRMES = 1 - \exp(\log(1-d) * beta$. Where LRMES is the Long Run MES and employing the dynamic conditional beta of Engle (2016). LRMES the fraction of the firm loss when the market index declines forty percent (d) over a six month window. The daily variance estimates are calculated using a Glosten-Jagannathan-Runkle GARCH (1,1) model (Glosten, *et al.*, 1993; Zakoian, 1994), using all data available back to 1990, estimated using quasi-maximum likelihood estimation.

[11] See https://vlab.stern.nyu.edu/doc/3?topic=mdls (accessed 5 February 2018)

All data available from 1990 forward are used to generate volatility forecasts, with exponentially declining weights used to apply greater importance to recent observations.

Table 6.

Panel A

Dependent Variable: Long Run Marginal Expected Shortfall.

VARIABLES	Entire Sample	Top 25% by size	Bottom 25% by size	Middle 50% by size
Equity to Total assets	0.00759***	0.0258***	0.0150***	0.00702**
Equity to Total Assets squared	-0.000293**	-0.000465	-0.000981***	0.000477***
Return on average assets	0.00336**	-0.0312***	-0.00232	0.00327
Log Total Assets	0.0447***	0.0140*	0.0311***	0.0108
Cost to income ratio %	0.000237***	0.000800***	-4.77e-05	0.000502***
Net loans to total assets	0.000129	-8.75e-05	0.000562*	0.000450
Liquid assets to deposits and ST funds	0.000307***	0.000694**	0.00156***	0.000269***
Growth of gross loans %	7.18e-05*	6.97e-05	4.97e-05	0.000157**
GSIB 2015 list	0.0628***	0.0941***		0.273***
Non-interest income as % of revenue	0.000772*	0.00206*	0.00179*	0.00394***
Non-interest income * equity	4.25e-05	-0.000162	7.03e-05	-0.000263***
GSIB 2015 * non-interest income	0.000799*	0.000492		-0.00248***
Loan impairment change to average gross loans	0.0119***	0.0136***	0.0138***	0.0160***
National Bank market HHI index	-1.70e-07	3.13e-05*	-3.99e-05***	6.61e-05***
Regulatory Quality	0.0190***	0.122***	0.00353	-0.0148
National LT rate – ST rate	0.00235***	0.00232*	-0.00391**	0.00673***
Structure Ratio	7.14e-05	-7.86e-05	0.000280**	0.000605***
GDP per capita	-1.29e-06***	-3.53e-06***	-7.90e-07*	-7.96e-07**
Growth of GDP per capita	-0.00269***	-0.00927***	-0.00185**	-0.00315***
GSIB 2015 * equity	-0.0168***	-0.0197***		-0.00762**
HHI * Non-interest income	-3.40e-07*	6.41e-07	-7.64e-07*	-9.83e-07***
Constant	-0.545***	-0.115	-0.326**	-0.0540
Observations	1,688	419	328	662
Number of Banks	178	59	47	86
Wald chi2	947.8	1604	2319	840

*** p<0.01, ** p<0.05, * p<0.1
Model estimated using Feasible GLS with panel specific corrections for heteroskedasticity and AR1. Structure ratio measures the ratio of stock market turnover per annum divided by domestic credit provided per annum. calculated according to Acharya, *et al.* (2012). Daily data transformed into annual averages by calendar year. MES calculated as $LRMES = 1 - \exp(\log(1-d) * beta$. Where LRMES is the Long Run MES and employing the dynamic conditional beta of Engle (2016). LRMES is the fraction of the firm loss when the market index declines forty percent (d) over a six

month window. All bank level variables drawn from the BankScope database for each bank, with the exception of the G-SIB dummy (sourced from Financial Stability Board, 2015). All variables are measured as per cent with the exception of total assets which is the log of USD in thousands. National HHI Index (Herfindahl-Hirschman Index) calculated from BankScope, regulatory quality drawn from the world governance index (Kaufmann, *et al.*, 2010). Interest rate data from the IMF International Financial Statistics. Structure ratio measures the ratio of stock market turnover per annum divided by domestic credit provided per annum and is sourced from the IMF International Financial Statistics. GDP per capita and growth in GDP per capital are also sourced from the IMF International Financial Statistics.

Panel B

Dependent Variable: Long Run Marginal Expected Shortfall.

VARIABLES	Pre GFC	During GFC	Post GFC
Equity to Total assets	0.00597*	0.0150***	0.00684***
Equity to Total Assets squared	-0.000341*	-0.00124***	0.000143
Return on average assets	-0.00883***	0.0189***	0.000803
Log Total Assets	0.0252***	0.0247***	0.0284***
Cost to income ratio %	-0.000410***	0.000811***	0.000777***
Net loans to total assets	0.000217*	-0.00174***	0.00130***
Liquid assets to deposits and ST funds	0.000732***	0.000165***	0.000272***
Growth of gross loans %c	8.57e-05***	0.000261***	3.68e-05
GSIB 2015 list	0.183***	0.0744***	0.150***
Non-interest income as % of revenue	0.00101*	-0.00413***	0.00375***
Non-interest income * equity	3.96e-06	0.000462***	-0.000177***
GSIB 2015 * non-interest income	0.000955	0.00126***	0.000550
Loan impairment change to average gross loans	0.000334	0.0119***	0.0243***
National Bank market HHI index	-3.92e-05***	-3.06e-05***	7.49e-05***
Regulatory Quality	0.00192	0.0415***	0.0213**
National LT rate – ST rate	-0.00208**	-0.0223***	0.00352***
Structure Ratio	8.91e-06	0.000206***	0.000156
GDP per capita	-8.06e-07***	-3.54e-06***	-1.19e-06***
Growth of GDP per capita	-0.000105	-0.00783***	-0.00401***
GSIB 2015 * equity	-0.0322***	-0.0208***	-0.0185***
HHI * Non-interest income	-2.49e-07	1.02e-06***	-1.29e-06***
Constant	-0.120**	0	-0.454***
Observations	464	260	929
Number of Banks	103	130	176
Wald chi2	1233	3.720e+07	2247

*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Model estimated using Feasible GLS with panel specific corrections for heteroskedasticity and AR1. Structure ratio measures the ratio of stock market turnover per annum divided by domestic credit provided per annum. Source: VLab.[12] MES calculated according to Acharya, *et al.* (2012). Daily data transformed into annual averages by calendar year. MES calculated as $LRMES = 1 - \exp(\log(1-d) * beta$. Where LRMES is the Long Run MES and employing the dynamic conditional beta of Engle (2016). LRMES is the fraction of the firm loss when the market index declines forty percent (d) over a six month window. All bank level variables drawn from the BankScope database for each bank, with the exception of the G-SIB dummy (sourced from Financial Stability Board, 2015). All variables are measured as per cent with the exception of total assets which is the log of USD in thousands. National HHI Index (Herfindahl-Hirschman Index) calculated from BankScope, regulatory quality drawn from the world governance index (Kaufmann, *et al.*, 2010). Interest rate data from the IMF International Financial Statistics. Structure ratio measures the ratio of stock market turnover per annum divided by domestic credit provided per annum and is sourced from the IMF International Financial Statistics. GDP per capita and growth in GDP per capital are also sourced from the IMF International Financial Statistics.

[12] See https://vlab.stern.nyu.edu/doc/3?topic=mdls (accessed 5 February 2018)

Table 7.
Panel A
Dependent Variable: Variance

VARIABLES	Entire Sample	Top 25% by size	Bottom 25% by size	Middle 50% by size
Equity to Total assets	-5.17e-05***	-0.000276***	7.13e-05	-6.87e-05***
Equity to Total Assets squared	2.26e-06*	4.47e-06	-3.45e-06	8.10e-06***
Return on average assets	-9.51e-05***	-6.95e-05	0.000216***	-0.000116***
Log Total Assets	-2.56e-05*	-1.77e-06	0.000176**	-4.01e-05
Cost to income ratio %	3.34e-06***	6.51e-06***	2.17e-05***	3.56e-06***
Net loans to total assets	-4.90e-06***	1.68e-06	-3.09e-06	-8.13e-07
Liquid assets to deposits and ST funds	-4.06e-07	-3.37e-06*	2.94e-06	-1.90e-07
Growth of gross loans %c	9.85e-07**	9.56e-07**	-6.40e-07	6.75e-07
GSIB 2015 list	0.000172	-1.00e-04		0.00167
Non-interest income as % of revenue	-4.24e-06	-2.24e-05**	-1.07e-05	4.61e-06
Non-interest income * equity	2.35e-07	3.74e-06***	1.05e-07	-1.26e-06***
GSIB 2015 * non-interest income	-4.42e-07	-6.34e-06		-2.72e-05
Loan impairment change to average gross loans	0.000260***	0.000516***	0.000408***	0.000197***
National Bank market HHI index	6.85e-08*	1.03e-07	6.13e-08	1.67e-07***
Regulatory Quality	-8.08e-05**	-3.44e-05	-4.68e-05	-0.000153**
National LT rate – ST rate	-1.57e-05**	-5.66e-05***	-4.35e-05**	9.25e-06
Structure Ratio	4.56e-06***	1.59e-06**	3.15e-06	1.18e-05***
GDP per capita	-5.80e-09***	-1.61e-08**	-3.11e-09	-3.96e-09*
Growth of GDP per capita	-5.45e-05***	-0.000101***	-3.37e-05***	-5.24e-05***
GSIB 2015 * equity	-2.18e-05	5.04e-05		0.000100
HHI * Non-interest income	-1.79e-09	7.67e-09	8.16e-10	-7.33e-10
Constant	0.00178***	0.00227	-0.00396**	0.00140**
Observations	1,688	419	328	662
Number of Banks	178	59	47	86
Wald chi2	1160	464.7	5118	551

*** p<0.01, ** p<0.05, * p<0.1
Model estimated using Feasible GLS with panel specific corrections for heteroskedasticity and AR1. The daily variance estimates are calculated using a Glosten-Jagannathan-Runkle GARCH (1,1) model (Glosten, *et al.*, 1993; Zakoian, 1994), using all data available back to 1990, estimated using quasi-maximum likelihood estimation. All data available from 1990 forward are used to generate volatility forecasts, with exponentially declining weights used to apply greater importance to recent observations. All bank level variables drawn from the BankScope database for each bank, with the exception of the G-SIB dummy (sourced from Financial Stability Board, 2015). All variables are measured as per cent with the exception of total assets which is the log of USD in thousands. National HHI Index (Herfindahl-Hirschman Index) calculated from BankScope, regulatory quality drawn from the world governance index (Kaufmann, *et al.*, 2010). Interest rate data from

the IMF International Financial Statistics. Structure ratio measures the ratio of stock market turnover per annum divided by domestic credit provided per annum and is sourced from the IMF International Financial Statistics. GDP per capita and growth in GDP per capital are also sourced from the IMF International Financial Statistics.

Panel B.

Dependent Variable: Variance

VARIABLES	Pre GFC	During GFC	Post GFC
Equity to Total assets	1.96e-05	0	-0.000116***
Equity to Total Assets squared	-4.27e-07	2.74e-06***	4.88e-06***
Return on average assets	-0.000152***	-0.000616***	-3.94e-05*
Log Total Assets	-7.87e-05***	0	-0.000103***
Cost to income ratio %	-1.81e-07	-1.52e-06***	5.93e-06***
Net loans to total assets	-2.76e-06***	1.01e-05***	-6.81e-06***
Liquid assets to deposits and ST funds	9.92e-08	1.25e-05***	-1.04e-06*
Growth of gross loans %c	7.59e-08	-1.60e-06***	4.32e-07
GSIB 2015 list	0.000631***	0.000135***	7.61e-05
Non-interest income as % of revenue	-2.98e-08	5.69e-06***	5.33e-06
Non-interest income * equity	1.97e-07	2.66e-06***	-8.90e-07**
GSIB 2015 * non-interest income	-4.90e-06	1.79e-05***	3.71e-06
Loan impairment change to average gross loans	7.71e-05***	0.000548***	0.000310***
National Bank market HHI index	-1.07e-07***	9.38e-07***	1.60e-07***
Regulatory Quality	-0.000236***	0.000242***	6.41e-05
National LT rate – ST rate	-8.21e-06	-7.06e-05***	2.38e-05***
Structure Ratio	-1.48e-06**	-1.13e-07***	1.11e-05***
GDP per capita	-9.16e-10	-1.85e-08***	-7.53e-09***
Growth of GDP per capita	-1.65e-05***	-5.84e-05***	-4.82e-05***
GSIB 2015 * equity	-4.38e-05**	-6.63e-05***	-3.97e-06
HHI * Non-interest income	1.72e-09*	-3.40e-08***	-4.94e-09***
Constant	0.00241***	0	0.00312***
Observations	464	260	929
Number of Banks	103	130	176
Wald chi2	381.3	8.380e+07	1441

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

Model estimated using Feasible GLS with panel specific corrections for heteroskedasticity and AR1. The daily variance estimates are calculated using a Glosten-Jagannathan-Runkle GARCH (1,1) model (Glosten, *et al.*, 1993; Zakoian, 1994), using all data available back to 1990, estimated using quasi-maximum likelihood estimation. All data available from 1990 forward are used to generate volatility forecasts, with exponentially declining weights used to apply greater importance to recent observations. All bank level variables drawn from the BankScope database for each bank, with the exception of the G-SIB dummy (sourced from Financial Stability Board, 2015). All variables are measured as per cent with the exception of total assets which is the log of USD in thousands. National HHI Index (Herfindahl-Hirschman Index) calculated from BankScope, regulatory quality drawn from the world governance index (Kaufmann, *et al.*, 2010). Interest rate data from the IMF International Financial Statistics. Structure ratio measures the ratio of stock market turnover per annum divided by domestic credit provided per annum and is sourced from the IMF International Financial Statistics. GDP per capita and growth in GDP per capital are also sourced from the IMF International Financial Statistics.