Are European banks still too-big-to-fail?

The impact of government interventions and regulatory reform on bailout expectations in the EU

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Abstract

I investigate the implications of government interventions and regulatory reform on too-big-too-fail expectations in the European banking sector. Evidence from stock returns over the period 1993 to 2016 suggests that large European banks have long benefitted and continue to benefit from implicit government guarantees. I document that investors are willing to accept lower risk-adjusted returns for large bank stocks relative to small bank stocks, because they anticipate that governments absorb part of these stocks' downside risk during financial crises. Recent regulatory reform introducing bail-in and a common standardized resolution framework for European banks were successful in reducing implicit guarantees at first, but became less credible after the effective implementation of these rules came into question in early 2016.

Keywords: European banks, European financial crisis, regulatory reform, too-big-to-fail

JEL Classifications: G12, G18, G21

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1 INTRODUCTION

From an ex post perspective, the bailout of a systemically important bank can be optimal if it ensures overall financial stability by relaxing banks' balance sheet constraints and, by mitigating contagion, limits negative spillovers from the financial sector to output and employment (Bianchi, 2016). Ex ante, however, the anticipation of a government's willingness to rescue major banks provides a state subsidy for these financial institutions through the creation of implicit guarantees.[1] As a consequence, banks which are deemed too-big-to-fail (TBTF) or, more generally, too-important-to-fail (TITF) benefit from favorable funding conditions: When investors expect that part of the negative tail risk of a bank will be absorbed by the taxpayer, they become willing to accept a lower required rate of return for the bank's securities.

In this paper, I explore the asset pricing implications of these TBTF guarantees for the stock returns of banks in the European Union over the period 1993 to 2016. European governments long actively encouraged the emergence of "national banking champions", which could successfully compete with the banking sectors of other European countries (Vives, 2001; Goldstein and Véron, 2011). Figure 1 illustrates the emergence of very large European banks over the time period 1993 to 2016. The figure shows the time evolution in the average total assets of publicly traded European banks according to size quartiles. With a considerable dispersion in total assets already in the early 1990s, large banks especially started to outgrow other banks by multiples from the early 2000s peaking at an average balance sheet of roughly 1.3 trillion USD in 2011.

These large European banks benefitted from two sources of implicit guarantees. First, they were protected by the determination of their national governments to maintain autonomous, large financial sectors in an increasingly international environment. The efforts to protect the national banking sectors yet intensified with the creation of the European Single Market in 1993 and several initiatives to integrate European banking and financial markets, which made national banking sectors increasingly exposed to competition from other European countries. Second and related to the fostering of national banking champions, banks became so large that a failure of such an institution would clearly bear unpredictable repercussions for the financial sector and

[1] Guarantees are implicit, because the government gives no explicit commitment to rescuing large banks. With bailout being ex post optimal, however, governments cannot credibly commit to *not* intervene in the event of negative tail event.

the real economy. Even though governments and central banks remained deliberately vague about their willingness to support failing institutions – a principle which became known as "constructive ambiguity" (Freixas, 1999) – the threat of letting a large financial institution fail was generally perceived non-credible.

Prior to the financial crisis, the implicit protection by governments made investments in stocks of large European bank a comparatively safe strategy. My analysis for European bank stock returns over the period Q1/1993-Q2/2007 suggests that investors were willing to accept lower expected returns for large banks relative to a smaller banks with a comparable risk profile, as they were expecting that European governments would absorb part of the downside risk. I show that the difference in monthly average risk-adjusted returns between banks in the extreme size quartile portfolios is in the magnitude of approximately -1.7% percent per month. This "size anomaly" in equity returns is consistent with similar findings for the US banking sector and a sample of international banks (Gandhi and Lustig, 2015, Gandhi et al., 2017)

Consistent with TBTF expectations arising in the context of European competition, the anomaly is driven by absolute size of banks across European banking sectors, and not by their importance in the domestic banking sector. Results are robust to a number of alternative explanations such as sample selection, a liquidity premium for small banks or the betting-against-beta anomaly (Frazzini and Pedersen, 2014). Also, the size anomaly is distinct from the classical market capitalization effect (Banz, 1981). In accordance with the results of previous studies (Berk, 1997), no size anomaly beyond the classical market capitalization anomaly can be found for non-financial firms.

I furthermore show that paying comparably higher (risk-adjusted) prices for large European bank stocks is rational for investors and can be explained by implicit government guarantees, as large banks indeed provide a hedging role against financial crisis (relative to smaller banks). During the recent financial crisis, a portfolio investing 100 Euros which follows a risk-adjusted strategy going long large stocks and short small stocks gains around 25 Euros in value over the period Q2/2007 to Q1/2010. In Q3/2008, however, the large minus small portfolio shortly loses roughly 30 Euros immediately following the bankruptcy of the US investment bank Lehman brothers in September 2008, before recovering again. The loss in portfolio value is in line with a sudden reversal in investor beliefs, making the failure of a large bank suddenly a possibility in Europe. With no large bank being let fail in Europe, however, investor sentiment soon reverses and large banks continue their outperformance throughout the financial crisis. The outperformance of large banks is in particular notable, given that large banks experienced greater asset write-downs than small ones (Haldane, 2010).

Finally, I evaluate the success of recent regulatory reform at the European level in reducing bailout expectations in the European banking sector. As one of the central lessons learned from the financial crisis, European countries decided to create a new common regulatory framework, which would allow for the restructuring and resolution of even the largest banks in an orderly, swift manner, while at the same time shifting the losses associated with such restructuring or winding-down from the taxpayer to the stakeholder of the firm. Using evidence on the correlation structure between large and small banks, I find that the agreements on the Banking Resolution and Restructuring Directive (BRRD) and the Single Resolution Mechanism (SRM) from 2013 were indeed successful in reducing the relative funding advantage of large banks. However, the reduction in bail-out expectations was only transient. Shortly after the actual introduction of the SRM in the beginning of 2016, policy makers in different European countries were undermining the common framework by openly questioning the applicability of the just agreed restructuring rules. The reduction in credibility was immediately accompanied by the re-emergence of TBTF expectations in stock returns.

This paper makes the following contributions: First, I document a significant size-related funding subsidy for large vis-à-vis small banks for the European banking sector, building on the asset pricing methodology of Gandhi and Lustig (2015). The advantage of using an asset pricing approach is that it allows to capture the average expectation of bailout expectations by using the variation in the entire time series of stock returns. As such, my results circumvent the identification issue of event studies which need a clearly specified event to avoid downward bias in the estimation (Lamdin, 2001). The methodology is also less prone to measuring the possibly quickly evaporating effect of a one-time event, and can capture the persistent presence of (implicit) government guarantees in banks' stock returns through time. The asset pricing model of Gandhi and Lustig (2015) is adapted to a model which more adequately captures the particular features of bank stocks.

Second, in extension to Gandhi and Lustig (2015), Gandhi et al. (2017), I spend considerable effort to document that it is truly size, and not a masked classical market capitalization effect, which is driving the results. Controlling for a number of bank characteristics which offer alternative explanations for a size effect in equity returns, pooled linear regression and quantile regressions indicate that large banks indeed have lower equity returns in normal times, while performing significantly better than small stocks in the lower tail of the return distribution. These results are consistent with the pricing of government guarantees in large bank stocks. The results also indicate that bailout expectations are most closely related to absolute size in the European banking sector, rather than to banks' domestic importance.

Third, I provide evidence on the lack of success of recent regulatory reform in reducing bailout expectations of large banks and ensuring that losses of failing banks are born by stakeholders. In July 2017, the President of the Minneapolis Federal Reserve Bank stated his opinion that recent bailouts in Europe highlighted that TBTF remained alive and well.[2] My results provide empirical evidence for this assessment and highlight that it is questionable that the costs of bailouts were truly transferred from the taxpayer to the financial sector.

The remainder of this paper is organized as follows: Section 2 reviews the related literature. Section 3 provides information on the data selection process. Section 4 describes the empirical strategy. Section 5 documents the pricing of government guarantees in equity returns in the period Q1/1993 - Q2/2007. Section 6 investigates the hedging role of large banks during the financial crisis as well as the impact of recent regulatory reforms on bailout expectations. Section 7 concludes.

2 LITERATURE

TBTF expectations arise when governments are believed to not let large financial institutions fail, because their failure would likely have significant negative repercussions for the financial system and the real economy. The banking literature has extensively discussed how expectations of such future interventions can distort prices and resource allocation: When investors become partially protected from downside risks, investors are willing to request lower compensation for holding a bank's securities and reduce monitoring of banks.

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[2] Reuters, 10 July 2017 "Banks need more equity as bail-in doesn't work –Kashkari". https://www.reuters.com/article/banks-need-more-equity-as-bail-in-doesnt/banks-need-more-equity-as-bail-in-doesnt-work-kashkari-idUSL8N1K12W9

Shareholder maximization can then induce banks to shift into riskier asset classes (Kareken and Wallace, 1978).

This paper contributes to the empirical literature quantifying the funding advantage arising from TBTF. The majority of studies that investigate the impact of implicit government guarantees on funding costs focus on the reductions in the cost of debt. Most of these studies document lower financing costs for large banks in the pre-financial crisis years and during the financial crisis from 2007-09, both in the US and in cross-country studies (e.g., Morgan and Stiroh, 2005; Ueda and Weder di Mauro, 2013; Santos, 2014; Acharya and Mora, 2015). European banks seem to have particularly benefitted from public safety nets (Carbó-Valverde et al., 2013), albeit the fact that the public budget constraints imposed by the European Monetary Union and the loss of national monetary policy through the creation of the European Central Bank (ECB) may have helped reduce implicit guarantees (Sironi, 2003). Recent evidence furthermore suggests that it might be systemic importance rather than balance sheet volume which leads to a reduction in funding costs (e.g., Barth and Schnabel, 2015). Also, when banks grow very large relative to the national economy, they may also become too-big-to-save resulting in an increase in funding costs for these banks (Bertay et al., 2013).

With the focus on historical stock returns, my paper is more closely related to the literature investigating the link between implicit guarantees and the cost of *equity* (e.g., O'Hara and Shaw, 1990; Brewer and Jagtiani, 2013). Mostly using event studies, these papers suggest that shareholders also benefit from TBTF guarantees, as the reduction in tail risk increases the charter value of large banks. This paper instead follows a different empirical strategy of a few previous papers and uses of an asset pricing approach to quantify the size subsidy in bank stock returns: Barber and Lyon (1997) is the first paper, which investigates the size premium for the financial sector without an explicit focus on banks. They find no difference in the pricing of size between publicly traded financial and non-financial firms in the US, when size is measured in terms of market capitalization. In contrast, Gandhi and Lustig (2015) explicitly focus their investigation on US banks rather than on all financial institutions, and find that investors are willing to accept lower risk-adjusted expected returns in exchange for the reduced downside risk during crises. Gandhi et al. (2017) find these pricing advantages generalize to financial institutions in a panel of 31 countries, and that they are more pronounced for countries with deposit insurance, fiscally strong governments and common law countries.

My paper differs from Gandhi and Lustig (2015) and Gandhi et al. (2017) in various aspects. First, the focus of this study lies on bailout expectations for banks in the European Union, which has had a history of raising national banking champions. Europe also exhibits a pronounced dependence on bank finance (Langfield and Pagano, 2016), making TBTF a particular concern. In addition to documenting the importance of size for banks' equity returns, I provide explicit evidence that investors base their assessment of bailout probability on EU-wide rather than domestic importance. Second, I extend their methodology significantly by using an asset pricing model more adequately capturing return dynamics in the banking sector. The analysis is complemented by cross-sectional and quantile regressions to strengthen the evidence that the size effect is distinct from the classical market capitalization effect. Third, I use analyses on the correlation structure in risk-adjusted returns of large versus small stocks to investigate to which degree recent regulatory reform in Europe was successful in reducing bailout expectations in the banking sector. I thus contribute to the recent literature which evaluates the success of regulatory reform in the financial sector (Acharya et al., 2013; Balasubramnian and Cyree, 2014; Schaefer et al, 2017).

Finally, this paper contributes to the broader literature on asset pricing in the financial sector, which does not put a particular focus on TBTF guarantees. Schuermann and Stiroh (2006) find that the classical Fama-French (1993)-factors can explain most of the variation in financial firms' stock returns, while interest rate, credit and liquidity risk contribute only limitedly. Baker and Wurgler (2015) investigate the impact of changing capital requirements in relation with regulatory reforms on stock returns. Adrian et al. (2016) highlight the importance of a banking-sector specific factor as well as ROE and leverage changes for the pricing of financial firms' stocks. This paper adapts the model of Adrian et al. (2016) to the European banking sector by additionally including a sovereign risk factor.

3 Data selection

My sample comprises all publicly traded banks from developed EU countries (excluding Cyprus) which were operating at some point between January 1993 and December 2016. The dataset is built by starting from the entire universe of publicly traded financial firms in European countries between 1973 and 2016, as identified in Bloomberg. Only financial firms which are identified as “banks” are retained in the sample, as only deposit-taking institutions should benefit from implicit bailout guarantees. Note that, in contrast to the US-banking sector, no legal separation between investment and retail banks exists for the banking sectors in developed European countries for the sample period. Quite the opposite, nearly all larger European banks operate as universal banks and are thus protected by some type of deposit insurance scheme.

Equity returns, market capitalization, total asset information and market-to-book ratio are obtained from Datastream for the entire sample period. For stock data, information is collected on an end-of month basis and is denominated in local currency. This is to ensure that exchange rate movements do not influence the analysis (Solnik, 1993). For the Eurozone banks in the sample, this means that pre-1999 stock data information is in local currency (for Greece, pre-2001 information) and in Euro thereafter. I drop all stock returns, for which I do not observe sufficient variation in stock returns. This can be the case, when the bank has been delisted, but stock prices are still quoted as stale values, or the stock is too illiquid given that only a minority of shares is traded on the public exchange.

For market capitalization, total assets and all subsequent balance sheet characteristics, data is provided on a yearly basis as of end of year and denominated in USD to make bank characteristics comparable across countries of different currency. The dataset is furthermore complemented with balance sheet information for the same time horizon for both publicly and non-publicly traded banks from the Bureau van Dijk Bankscope database. The data comprises total assets, equity ratio, return-on-equity, non-interest income ratio and loan to deposit ratio information. Whenever total assets information is unavailable from Datastream, it is substituted by Bankscope information.

Figure 2 shows the evolution in the number of publicly traded banks from developed EU countries across time. The number of banks increases from 8 in 1973 to 122 in 2012 and slightly decreases again to 117 by 2016. In comparison to the US, there are only few publicly traded banks in the developed EU making the analysis vulnerable to outliers. To reduce concerns that results are driven mainly by idiosyncratic shocks, I require that at least 40 publicly traded banks are available at each time point of the analysis. Also, to be able to explore the cross-section of government guarantees in the European Union, I only keep years where at least 8 countries with at least one publicly traded bank are contained in the sample. I also delete from my analysis all securities which are not taking the form of common shares, e.g. preferred stock. In the case that multiple subsidies of a bank are listed, I only keep the ultimate parent in the sample. Finally, I remove all banks, whose balance sheet is smaller than 100 million USD and thereby remove two smaller banks which are outliers in size. After applying all restrictions, the time frame, which is available for analysis, covers the years 1993 to 2016.

Finally, I collect country-level and EU-level macro-economic variables comprising GDP, monthly exchange rates and yields on 10y government bonds from Datastream. I also use bank-level total asset data from Bankscope to derive proxies for the aggregate total assets of the banking sector.[3] Monthly index data on the Bank of America Merrill Lynch AAA Euro Corporate return index is only available from 1996 and collected from Datastream. Monthly Fama-French (1993) factors for European non-financials are obtained from Kenneth French's website. Finally, equity returns, market capitalization and total asset information for non-financial firms are also obtained from Datastream for the entire sample period 1993-2016.[4] Summary statistics for all variables are provided in Table 1.

Note that I limit my analysis to firms from developed EU countries for a number of reasons.[5] First, since the introduction of the European Single Market from January 1993 the European Union has become significantly more financially integrated (Bekaert et al., 2013). In order to give a qualified interpretation of my results, the limitation to this special economic environment appears sensible. Second, my limitation to developed countries relates to the observation that stock markets in emerging markets are only to limited extent comparable to those of developed markets. Third, the limitation is also due to practical reasons. The extension to developed European countries outside of the European Union would mainly entail the inclusion of a large number of Swiss banks (plus two Liechtenstein and three Norwegian banks). The benefit of extending the sample seems

[3] The European Central Bank only provides information for banking sector size from 2007.
[4] To make banks and non-financial firms in the sample comparable in market capitalization, for each year, I eliminate all firms which has a market capitalization less than 95% of the market capitalization of the smallest bank.
[5] Countries included in the sample are Austria, Belgium, Denmark, France, Germany, Greece, Ireland, Italy, Malta, the Netherlands, Portugal, Spain, Sweden and the United Kingdom.

limited, while the possible distortions of capturing characteristics of Swiss banks are large. In addition, the Cypriote banks are removed from the sample, because the stock market before 2006 was very illiquid, the subsequent massive inflow of Russian investments highly distorted the stock market, and the bank run in 2013 essentially left the local banking industry in shatters.

4 EMPIRICAL STRATEGY

Financial crises are high marginal utility states for stockholders. While their occurrence is rare by nature, disasters are associated with large losses for banks and consequently shareholders. As a consequence, the variation of expected loss rates in disaster states affects the cross-section of expected stock returns, because shareholders value better performance in severely bad times especially highly (Wachter, 2013, Gabaix, 2012). Ceteris paribus, implicit government guarantees thus lower the (risk-adjusted) required rate of return on a bank's stock in normal times, exactly because they transfer part of the expected loss in disaster states to the taxpayer. The reduction in funding rates holds true as long as shareholders assume that they can at least partly benefit from a government intervention, i.e., as long as they are not fully wiped out upon a bailout. Building on Gandhi and Lustig (2015), I use an empirical asset pricing methodology to test for the hypothesis of the pricing of implicit government guarantees in European banks' stock returns.

4.1 SIZE ANOMALIES IN AUGMENTED FAMA-FRENCH TIME SERIES REGRESSIONS

Do large banks have persistently lower cost of capital than small banks, even after controlling for all characteristics in which these banks differ apart from size? To test for the pricing of implicit government guarantees in bank returns, I run augmented Fama-French time series regressions. If large European banks indeed benefit from implicit government guarantees, the average risk-adjusted return, i.e. alpha, on a portfolio of small banks should be significantly higher than that of a portfolio of large banks, as severe financial crises are systematic events which cannot be hedged by existing pricing factors (Gandhi and Lustig, 2015, Gandhi et al., 2017).

Consistent with this rationale, I split the sample of banks into bins according to difference measures importance (cf. section 4.2) and run augmented Fama-French regressions on the equally weighted returns on each of these subsets. To be more precise, the usual Fama-French (1993) three factor model is augmented by additional factors, which can help explain the evolution of banks' stock returns

$$f_t = \left[R_t^{Market} - R_t^f, SMB_t, HML_t, \bar{f}_t\right] \tag{1}$$

The first three factors are the standard factors from the Fama-French (1993) three-factor model: the excess return on the market portfolio $R_t^{Market} - R_f$, the Small-Minus-Big (*SMB*) factor and the High-Minus-Low (*HML*) factor. Additional factors $\bar{f}$ capture bank-specific portfolio choices or other risk factors.

Banks are sorted into one of four "systemic risk" quartiles at the end of each year. The least systemically important 25% of banks are assorted into the lowest quartile, the next 25% into the second quartile and so on. Systemic risk measures refers to different measures capturing the domestic or EU-wide importance of bank, which may be associated with a government's willingness to provide a bailout (see Section 4.2). For each systemic risk bin, I calculate monthly equally-weighted returns based on the previous year's systemic risk information. For each systemic risk specification, I then run separate bin-specific augmented Fama-French regressions of monthly excess return on the risk factors identified above,

$$R_t^i - R_t^f = \alpha_i + \beta_i' f_t + \epsilon_t^i \tag{2}$$

where R_t^i is the monthly equally-weighted return in bin *i*. If more systemic banks were indeed more likely to be bailed out, I should expect alphas to be monotonously decreasing across bins, because investors are willing to accept lower returns in exchange for an increased bailout probability. The estimated residuals are correspondingly estimates of the normal risk-adjusted returns on bin *i*, i.e. the returns which are not explained by the included risk factors.

In the baseline specification, $\bar{f}$ comprises the additional factors *FmnF Factor*, *ROE Factor* and *Government Spread*. *FmnF Factor* is the spread between the equally weighted return index of banks in the sample and market return, *ROE Factor* is a banking sector specific ROE factor and *Government Spread* is the spread between the average yield of the 10y government bond in the developed European Union and the yield of the 10y German government bond. The inclusion of the first two factors is motivated by the findings in Adrian et al. (2016), as the augmentation can help alleviate pricing anomalies for financial stocks in standard factor pricing models. *FmNF Factor* captures industry-specific developments in the banking sector vis-à-vis non-financial firms. Equal weighting ensures that the returns of large banks are not over-weighted in the sample. The *ROE-factor* is derived by sorting banks into four bins based on end-of-year return on equity and defined as the difference in equally-weighted returns of the highest and lowest bin. It captures risk appetite in the financial sector, as intermediaries take risk to meet ROE targets (Adrian et al., 2016).

The inclusion of the *Government Spread* Factor is motivated by two observations. First, sorting banks at the EU-level leads to different presence of European countries across bins, because certain countries are characterized by the presence of many large banks (e.g., UK), whereas others are not. One concern might be that results are driven by the allocation of banks from stronger, more developed economies into the larger bins. Indeed, if banks from more fragmented financial markets or less developed economies demand higher risk premiums in relation to increased risk or reduced liquidity, this would also explain monotone intercepts across intercepts. Second, large banks act as dealer banks for the primary market issuance of government bonds and hold considerable amounts of sovereign debt in banking and trading book. Having a strong home bias makes banks more exposed to home country-specific variation in sovereign bond prices (Battistini et al., 2014). The evolution of the *Government Spread* Factor helps alleviate these concerns:. The bin-specific loading on this sovereign-risk factor captures the equally-weighted exposure of banks in a bin to country-specific risk factors.

I explicitly choose equally rather than value-weighted returns. My goal is to detect a systemic risk effect which goes beyond the usual market capitalization effect. Value-weighting would by construction overweight high market cap banks in the systemic risk bin, and distinguishing a market capitalization effect from a size effect becomes harder. Also, value-weighting potentially overweighs certain countries with banks of large market capitalization. As such, any effect may be due to different risk premiums in relation with differentials in economic development. Finally, there is only a limited number of publicly traded banks in the European banking sector. Equal-weighting ensures that any measured effect is not due to the relative overweighting of some large banks.

4.2 MEASURING IMPORTANCE

Key to the investigation is the distinction of more from less systemically important banks. I choose different specifications of systemic risk capturing different types of domestic or EU-wide importance of bank. For each of these specifications, I sort banks into four systemic risk quantiles and run augmented Fama-French time series regressions, as described in Section 4.1.

The simplest approach to measuring a bank's systemic importance is by ranking it according to its market capitalization (*mcap*) or total assets (*ta*) among all developed EU countries. This builds on the fundamental TBTF argument, where the failure of a larger banks poses a significant risk of contagion. It is also consistent with European governments raising and fostering banking champions, which were competing in an international environment. Out of total assets and market capitalization, total assets is likely the better measure of size, because the government presumably cares more about the entire bank, rather than only about the value of equity. Also, market capitalization captures expectations about the riskiness of future cash flows which is only indirectly connected to a bank's size (Berk, 1997).

At the same time, however, both measures suffer from being in absolute terms and thus do not take into account the country-specific importance of a bank. In fact, it is (usually) the domestic government which bails out a bank. While a bank may be considered non-systemic at the European level, it may in fact be quite large importance at the national level and thus profiting from immense government guarantees. Banks are thus ranked according to the share of total assets in the domestic banking sector (*ta_bs*), the rank in the domestic banking sector according to total assets (*ta_ct*) or market capitalization (*mcap_ct*). I also investigate domestic rankings, where only the largest bank per country is assigned to bin 4, and all other banks are equally distributed across bins 1-3 (*ta_ct4*).[6] Alternatively, while a bank may be small for the entire European economy, it might be too large relative to the domestic economic output and thus in fact be too large to be saved. To capture the fiscal capacity of a government to rescue a bank, I calculate the size (in form of total assets or market capitalization) relative to home country's domestic product (*ta_gdp*; *mcap_gdp*).

[6] I require that there have to be at least four publicly traded banks per country in order for banks from a country to be included into the specification.

Finally, it may not always the largest banks which are the most systemic (Barth and Schnabel, 2013). I therefore expand my analysis to a more sophisticated measure of systemic risk building on Basel Committee systemic importance indicator (Basel Committee on Banking Supervision, 2011, 2013). The BIS systemic risk indicator is used to identify globally systemically important banks (G-SIBS) and relies on more complex characteristics such as interconnectedness and cross-border exposure. Based on balance sheet data from Bankscope I derive a proxy for the BIS systemic risk indicator (*bis_sc*)[7]. It is only available for a limited number of banks, for which this information is available and which are generally very large. The calculations are detailed in Table A1.

4.3 Bin-specific characteristics

Table 1 presents the time series average of annual cross-sectional summary statistics per bin under different size specifications.[8] All data is winsorized at the 5% confidence interval with the exception of market capitalization and total assets.[9] The table highlights one limitation of this study is the focus on very large banks. Even in the smallest bin, banks a relatively large, both in terms of market capitalization and total assets. For example, when banks are sorted according to total assets at the EU-level, the time series average of the cross-sectional mean of banks in the smallest bin is still 3.6 bn. USD. As a consequence, any approximation of the pricing advantages with being protected by implicit government guarantees is likely an estimate at the lower bound of the true value of government guarantees. Nonetheless, there is also advantages to the sample choice. With only large banks being included in the sample, sufficient liquidity of the stock is ensured. Also, it may be assumed that all banks in the sample are sufficiently diversified, mitigating concerns that any observed effect may arise from idiosyncratic shocks.

Given my choice for country- and EU-level sorting, it should furthermore be not surprising that banks assigned to bin 4 are considerably larger under total asset sorting in absolute terms relative to sorting in relative terms (i.e., at country-level). A bank with considerable domestic importance may be small from an international

[7] The BIS-Score itself is only available from 2011.

[8] Break points between bins may be overlapping, because banks are assorted into bins on a yearly basis. The large standard deviation is due to the strong right-skewedness of some fundamentals.

[9] I explicitly decide to not winsorize size measures, because it is exactly the effect of very large banks which I want to capture.

perspective. Finally, the table underlines that not only size displays monotonicity across bins. Market-to-Book ratio, leverage, return-on-equity and non-interest income ratio are all related to size. For example, being larger in terms of total assets is both at the EU-level sorting and country-level sorting associated with lower market-to-book ratio and a lower equity ratio. The empirical strategy will adequately control for these differences in characteristics.

Note that the systemic risk measures are highly correlated. For instance, the correlation between total assets and market capitalization over the entire sample period is at 77%. A large banks is likely to have a higher market capitalization, simply because its book equity is large. Table A2 shows that this, naturally, carries over to the bin assignment. The table shows the pairwise correlation between bin assignments. Exemplarily, table A3 also presents the bin banks are assigned to on average throughout the sample period, when allotted according to absolute total assets (i.e. at EU-level). Generally, rankings among market capitalization and total assets at country-level and at EU-level are highly correlated, respectively. Total assets/GDP and domestic market share are also very likely to co-move, while the association with the BIS score is looser (likely due to the limited data availability). The correlation highlight that a careful investigation is required to pin down, which characteristic is associated with bailout expectations.

5 TBTF IN EUROPEAN BANKS' STOCK RETURNS UNTIL 2007

I begin my analysis by investigating the implications of systemic importance for the pricing of European bank stocks in the years prior to the financial crisis. For the time period Q3/1993-Q2/2007, augmented Fama-French time regressions suggest that investors are willing to accept lower expected returns on the stocks of systemically important banks relative to those of less systemic banks, after controlling for all alternative explanations in which way these stocks may differ. The funding cost advantage is associated with absolute size in the European banking sector and not relative size in the domestic banking sector or more sophisticated measures of systemic importance such as the BIS score. The effect is also different from the classical market capitalization effect (Banz, 1981). Results from quantile regressions and the time series evolution of residuals corroborate that investors are willing to pay higher prices for larger bank stocks, exactly because they tend to outperform small bank stocks during financial crises. I conduct the same analysis for non-financial firms and find that stock returns of non-financial firms do not exhibit a similar size anomaly.

5.1 Baseline Regression: Decreasing alpha across bins

I start by conducting augmented Fama-French time series regressions under my preferred baseline specification. I regress monthly excess returns for each systemic risk portfolio on the three Fama-French (1993) factors *MktRF, SMB* and *HML*, the banking sector factors *FmnF-Factor* and *ROE Factor* as well as the sovereign risk factor *Government Spread*.

5.1.1 The importance of size for risk-adjusted portfolio returns

Table 2 shows the results for baseline times series regression, when banks are sorted into systemic risk bins according to total assets at the EU level (*ta*). Each column reports the estimated coefficients, their statistical significance and the adjusted R2 for one bin, ranging from smallest (Column 1) to largest size (Column 4). The intercept estimate *Constant* is the average risk-adjusted excess return, which is not explained by the risk factors. Column 5 finally shows the regression results for a long-short position going long 1 unit in the largest bin and short 1 unit the smallest bin. Standard errors are Newey-West (1987)-adjusted for heteroscedasticity and autocorrelation.

Intercepts decrease monotonically across bins from 0.658% in the quartile of smallest banks to a - 1.020% in the quartile of largest banks. The intercept in the smallest bin is significantly positive at the 10%-level, while the alpha in the largest bin is negative at the 1%-level. A portfolio that goes long large and short small banks has a negative alpha of -1.678%, with the intercept being significant at the 1%-level. The results suggest that large European banks have significantly lower risk-adjusted returns than small banks.

The relatively lower funding costs of large banks in risk-adjusted excess returns need not show up in non-risk-adjusted returns, as the loading on the other factors may have countervailing effects. Indeed, market beta increases from 0.969 in bin 1 to 1.210 in bin 4. Accordingly, the portfolio going long large stocks and short small stocks displays a positive beta of 0.241, which is significant at the 10% significance level. The increase of betas across systemic risk bins coincides with the findings of Gandhi and Lustig (2015) for the US banking sector and is likely related to the considerably higher leverage of large banks relative to small banks. The coefficient on the SMB factor is size-dependent as well, going from positive and significant 0.0.384 in bin 1 to -0.511 in bin 4, with the difference being strongly significant at the 1%-level. The effect is consistent with the usual market valuation effect for non-financial corporates, where firms with small size in terms of market capitalization face a higher cost of capital than large firms. Previous studies find that for non-financial firms the market capitalization effect is completely unrelated to total assets, but driven by the discount factor and the riskiness of future cash flows.[10]

The coefficient estimates on the HML factor also exhibits a certain size dependence with loadings going from a small negative coefficient of -0.109 in the smallest bin to approximately 0.22 in bin 3 and bin 4. The difference of coefficients between bin 1 and 4 is significant at the 5%-level. Such size dependence is also present for the sovereign risk factor, for which loadings decrease monotonously from an insignificant -0.017 in bin 1 to a highly significant 0.974 in bin 4. This suggest that larger banks are significantly more exposed to sovereign risk than smaller banks, either due to direct holdings of risky sovereign debt, higher exposure to loan markets in these countries or for other mentioned reasons.

In contrast, the coefficient estimate on banking sector factor *FmnF Factor* is highly significant and approximately equal across bins. The difference between bin 1 and bin 4 is 0.138 and non-significant. The result is in line with the banking sector factor capturing the average industry dynamics relative to those of non-financial firms. The ROE-Factor *ROE Factor* finally displays no clear pattern across bins indicating that risk-taking to meet ROE targets is not systematically related to size.

5.1.2 ALTERNATIVE MEASURES OF SYSTEMIC IMPORTANCE

When bank stocks are sorted into portfolios according to total assets, systemic importance is measured relative to the European banking sector as a whole. An alternative hypothesis is, however, that implicit government guarantees arise in the context of domestic importance rather than absolute size. It is also possible that the SMB factor derived from non-financial firms only imperfectly captures the market capitalization effect for financial firms. Finally, size is only an imperfect measure of systemic importance and it may be rather the

[10] Berk (1997) uses double-sorting to show that for non-financial firms of the same market capitalization, total assets size has no additional impact on equity returns.

inherent complexity or other systemic characteristics, which determine investors' anticipation of the governments' willingness to support a specific failing bank. To understand which characteristics drive investors' bail-out expectations, banks are thus sorted into systemic risk bins according to the share of total assets in the domestic banking sector (*ta_bs*), the rank in the domestic banking sector according to total assets (*ta_ct, ta_ct4*), total assets relative to GDP (*ta_gdp)*, market capitalization at the European level (*mcap*), the rank in the domestic banking sector according to market capitalization (*mcap_ct*) and the (approximated) BIS-Score (*bis_sc*).

Table 3 provides intercept estimates for bin assignment under different specifications of systemic risk. While intercepts decrease strongly when sorting banks according to total assets (*ta*), neither sorting according to domestic along total assets (*ta_ct*, *ta_ct4*), shows a discernible monotonic evolution of intercepts across portfolios 1 to 4. The difference in coefficient estimates between bin 1 and bin 4 is insignificant. When sorting according to market share (*ta_bs*), intercepts do decrease from 0.656 in bin 1 (significant at the 5%-level) to -0.595 in bin 4 (significant at the 10%-level), with the difference also being significant at the 1%-level. However, the intercept estimate for bin 4 is considerably smaller than under total asset sorting and intercept estimates do not decrease monotonically, with average risk-adjusted returns being smaller in bin 2 than in bin 3.[11] For sorting according to size per GDP (*ta_gdp*), the decrease in intercepts is similar to that of assortment according to total assets, but less pronounced.

When sorting banks according to market capitalization at the European level (*mcap*), similar results are obtained as when sorting according to total assets, with intercepts decreasing from a highly significant 0.876 for bin 1 to significant and negative -0.708 for bin 4, the difference being highly significant. The results are

[11] In a banking sector with many large banks, the market share of each of these banks is smaller than in countries with a single large bank. Despite bearing considerable risk for financial stability at home and in Europe, this technically makes it assignment to a smaller bin under market share sorting more likely and attenuates the bin-specific pricing advantage. This is, for instance, the case for the UK with the Royal Bank of Scotland, Lloyds, Barclays and HSBS all being very large banks.

also present when sorting according to market capitalization at the country level, but the results are less pronounced. For sorting according to BIS-Score, alphas exhibit no strong evolution across systemic risk bins.[12]

Taken together, the results suggests that absolute size rather than country-level measures of systemic importance is associated drives bailout expectations. However, the results do not yet allow to distinguish whether the funding advantage in equity is truly related to TBTF expectations, or is simply the classical market capitalization effect for the banking sector.

5.2 SIZE OR MARKET CAPITALIZATION?

Time series regressions for portfolio sorts along one dimension cannot resolve the question, whether TBTF (i.e., bank size) or the classical market capitalization are the explanation behind declining intercepts across size bins. Also, while the results from section 5.1 indicate that the size advantage is driven by perceived importance in the European Union, rather than at the domestic level, the high correlation between these measures inhibits a definite conclusion. A double-sorting strategy, such as in Berk (1997), would be preferable to pin down the culprit behind decreasing intercepts across bins. However, for the sample of European banks, double-sorting is not a viable strategy given the limited number of publicly traded banks and the high correlation between market capitalization and total assets.

Following Cochrane (2005), I thus use cross-sectional pooled OLS regressions, which allow to simultaneously include market capitalization and total assets as well as other measures of systemic risk to investigate their differential impact on bank stock returns. For the period Q1/1993-Q2/2007, I regress bank-level excess returns on lagged log market capitalization, one lagged measure of systemic risk and lagged bank characteristics comprising the loading on several traded factors, the book-to-market ratio and the return on equity

$$R_{it} = \alpha + \lambda_{\beta}' \beta_{it} + \gamma_{size} \cdot size_{it} + \gamma_{controls}' \, controls_{it} + \epsilon_{it} \tag{3}$$

[12] While being conceptually appealing, the investigation for the BIS score suffers from limited data availability. Only the largest bank report the accounting information which is necessary to approximate the BIS Score. As such, the sample of banks is limited to the very largest banks to be distributed across systemic risk bins, limiting the informative value for the cross-section of bank sizes. As a result, the BIS score is excluded from the subsequent investigation.

where α is the common intercept estimate across all stocks, β_i are bank-level betas on different traded factors, *size* contains different measures of systemic importance and *controls* contains book-to-market and ROE as further control variables. β_i comprises betas for the Europe-wide market excess return β_{Market}, the spread of the equally-weighted average of bank stock returns over the market excess return β_{FmnF} and the excess return of the 10y German government total return index over the risk-free rate β_{Term}. Standard Errors are Newey-West (1987)-adjusted for heteroscedasticity and autocorrelation. Fixed effects are not included into the regression as they would suggest a predictable trend in individual stock returns. Also, the size effect in bank stock returns arises from the cross-sectional variation in size rather than from within variation.

The variable of interest is $size_{it}$. I am interested in two questions. First, what is the impact of systemic importance beyond the ordinary market capitalization effect related to cash flow riskiness? Second, which systemic risk measure most adequately captures investors' assessment of the relevant characteristic driving governments' bailout decisions? To be able to answer these question, I insert multiple measures of systemic risk in combination with log market capitalization into Equation (3). I orthogonalize market capitalization to total assets (as well as other measure of systemic risk) using a Gram-Schmidt orthogonalization procedure to separate the size component in market capitalization from the future cash flow component. If cash flow expectations were the driver between reduced equity costs for large banks, the estimated coefficient on total asset should be insignificant. To furthermore reduce concerns of trailed multi-collinearity, I also orthogonalize the book-to-market ratio.[13]

Table 4 presents the results for pooled OLS regression, when systemic risk is measured in terms of log total assets (Column 1), total asset per GDP (Column 2), the share of total assets in the domestic banking sector (Column 3), a dummy indicating whether the bank is the largest or second largest bank in the domestic banking sector (Column 4) or the BIS Score (Column 5). Across all specifications, the price of risk for log market capitalization is negative and highly significant corroborating that the classical market capitalization effect is

[13] Orthogonalization between systemic risk measure, market capitalization and book-to-market leaves all other coefficient estimates unchanged, because the orthogonalization merely reallocates the variation between these variables, while leaving the combined correlation structure untouched. As such, orthogonalization can be understood as a double sorting strategy.

as relevant for the banking sector as it is for the non-financial sector. In addition, however, the coefficient estimate on log total assets in is negative and significant as well (Column 1). At the mean, a 1% percent increase in total assets decreases expected returns by 0.128% per month. This is consistent with the expectation that larger banks have lower cost of capital in normal times. Of the other systemic risk measure, only the BIS Score has similar explanatory power for stock returns (Column 5), while the coefficient estimates on all other systemic risk measures are negative, but insignificant. This is in line with the results from the time series regression which indicated that importance at the EU-level rather than the country-level drives down the cost of capital.

The coefficient estimates for all other characteristics are in line with standard theory: Higher book-to-market ratios and higher market beta are associated with higher expected returns and are significant across all specifications. The coefficient estimate on ROE is positive, but marginally non-significant.

I run a number of robustness checks for pooled OLS regressions. First, I follow Adrian et al. (2017) who suggest that first differences in leverage may in addition to return on equity affect the cross-section of stock returns. I include first differences in leverage, but obtain virtually unchanged results and the results are therefore not reported. To mitigate concerns that the effect arises as a result of the fragmentation of European markets in the early part of the sample, I also run regressions with country-level market indices rather than a Europe-wide market index to control for the fact that especially in the earlier time of the panel, European markets were still fragmented. The results are also unchanged and are also not reported.

5.3 THE RELATIVE HEDGING ROLE OF LARGE BANKS

A systematic structure in alphas across bins implies that there is a bin-related tail risk factor which is priced by investors, but not spanned by the existing risk factors. Under the TBTF-rationale, small banks outperform large banks in normal times, conditional on controlling for systematic risk factors. If there is a certain probability of disaster, investors are willing to accept a lower cost of capital from systemically important bank, because they anticipate that with a certain likelihood governments will not let these banks fail. In turn, one should observe that large banks are outperforming relative to small banks during crisis times. In the following, systemic risk will be measured by total assets, as it was identified in the previous analysis as the most likely indicator associated with implicit government guarantees.

5.3.1 Time series variation in hedged large-minus-small portfolio

Figure 3 provides graphical support for the hedging role large banks take. The figure shows 12-month moving averages of the spread between normal risk-adjusted returns of banks in the smallest bin minus those of banks in the largest bin, with bank being sorted according to total assets (bottom figure). The normal risk-adjusted returns are the residuals from the baseline Fama-French time series regression in Section 5.1. In addition, the figure also contains the evolution of the Economic Sentiment Indicator (top figure).

During normal times, when economic sentiment is improving, small banks are outperforming large banks and the spread is positive. When a crisis hits, however, the opposite occurs. The cost of protection becomes more expensive, when disaster probability increases, i.e. just before the outbreak of an (anticipated) banking crisis. Just before the crisis, the spread between the cost of capital for large and small banks widens. This is the case both for the recession following the Mexican peso crisis from end 1994 as well as the 1998 Ruble and subsequent LTCM crisis. Shortly before the crisis outbreak, the spread starts in fact widening, with smaller banks requiring a relatively higher discount. This is perfectly in line with large banks become more attractive as a (relative) hedge, when the likelihood of a disaster hitting the domestic banking sector increases.

5.3.2 Quantile Regressions

Quantile regressions provide further evidence for the hedging role large banks provide relative to small banks, while additionally allowing to differentiate between the market capitalization effect related to the riskiness of banks' future cash flows and TBTF expectations related to size.

Classical least squares regressions, like in Section 5.2, estimate the impact of regressors on the dependent variable at the mean. To understand, however, whether investors are willing to pay more for a large bank stock because of their outperformance during crises times, the entire distribution of stock return needs to be analyzed. Quantile regressions allow to identify the impact of size on returns at any pre-specified percentile of the return distribution, while controlling for other bank characteristics. It can thus be verified that large bank stocks provide the anticipated protection in the lower tail of the expected return distribution, while underperforming when returns are at medium or high levels.

I run quantile regressions of quarterly excess returns on characteristics from previous periods on measures of systemic importance and other bank characteristics

$$r_{i,t+k}^{q} = \alpha + \lambda_{\beta,q}'\beta_{it} + \gamma_{size,q}'size_{it} + \gamma_{controls,q}'controls_{it} + \epsilon_{it,q} \quad (4)$$

for a wide range of percentiles of the stock return distribution [0.05, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 0.95]. β_{it} and *controls* are defined as before for pooled OLS regressions. *Size* again contains one systemic risk measure as well the orthogonalized log market capitalization. Standard errors are robust and obtained via 100 bootstraps.[14]

I test the following two hypotheses: First, if size was indeed a proxy for implicit government support, large banks should be outperforming small banks in bad times while underperforming in normal or good times. Second, the effect is likely to be non-linear, where size likely only starts to matter from a certain threshold.

To test hypothesis 1, I first run quantile regressions for the entire cross-section of banks on measures of systemic risk and market capitalization. If TBTF-expectations were indeed influencing returns, the effect of size on the lower percentiles of the return distribution should be positive, while the effect should be negative for the upper percentiles. The results for quantile regression on total assets are presented in Figure 4 which contains coefficient estimates from quantile regressions (solid line), their 90%-confidence interval (grey-shaded area) as well as the OLS estimate (dashed line) and its 90% confidence interval (dotted line).

I find that the effect of total assets is monotonically decreasing across expected return percentiles. While large banks significantly outperform small banks in the lower tail of the distribution, i.e. during times when performance in the banking sector is generally poor, they are associated with significant lower returns in the upper tail. Interestingly, the effect arises only from the 70%-percentile, indicating that government protection may only become important when markets performing very well and the burst of a market bubble is anticipated.

[14] I use only 100 bootstraps due to computational intensity of the calculations.

The coefficient estimates for market capitalization are of similar magnitude along percentiles for both specifications.

Next, I further eliminate concerns that the observed effect mainly arises from market capitalization. To do so, I split the sample according to market capitalization quartiles and run separate quantile regressions for each of these quartiles. The split serves the following purposes. First, by splitting the sample into subsamples of similar market capitalization, the effect of market capitalization on expected return should be even less pronounced than by mere orthogonalization. Second, I can more easily capture the importance of size across bins. In other words: Conditional on having approximately the same market capitalization, I can investigate what impact size has on expected stock returns. Figure 5 shows the results for all market capitalization quantiles.

With size and market capitalization being so highly correlated, the variation of size within each bin is limited. Despite this shortcoming, the figures show the positive impact of size on returns in the lower return percentiles and negative impact in upper return percentiles. The effect is relatively similar across bins, with the exception of bin 2, where no clear effect can be determined. Interestingly, contrary to what one might expect, the differential between the positive effect of size in the lower percentiles and the negative effect in the upper percentiles is most pronounced for banks in bin 3. Keeping in mind that banks in bin 4 are already very large, the incremental value of being larger in this bin may be less pronounced than for the smaller banks in bin 3. Note that the effect of market capitalization on returns is similar to the quantile regression for the full sample. The effect on is muted across bins 1 - 3, except for the uppermost percentiles.

5.4 Robustness Checks

The results from the baseline specification are robust to using alternative model specifications, controlling for a number of alternative factors which explain the cross-section of stock returns. The results corroborate that the observed monotonicity across bins is indeed due to the size effect rather than the omission of other factors, which could alternatively account for the cross-section of stock returns in the banking sector.

5.4.1 Gandhi and Lustig (2015)-specification

I first show that the result is robust to using the asset pricing specification proposed in Gandhi and Lustig (2015) rather than the baseline specification in Section 5.1. In the specification according to Gandhi and Lustig (2015), the Fama-French three-factor model is augmented by two bond risk factors controlling for maturity transformation risk and credit risk. The factor mat_t controls for maturity transformation risk and is the excess return of a 10y German government bond over the risk-free rate. The rationale behind including the factor is that banks can be interpreted as managing fixed income portfolios, which are characterized by the maturity structure of assets and liabilities (Flannery and James, 1984). The credit risk of assets arguably also matters for the cross-section of the cost of capital (Longstaff and Myers, 2009). To control for credit risk, the excess return of the Bank of America Merrill Lynch AAA Euro Corporate return index is included. The index is available from 1996 only, which restricts the analysis to the time period Q1/1996 - Q2/2007. To again control for different country-specific exposure, the sovereign risk factor is included as an additional risk factor.

The estimated intercepts for the period Q1/1993-Q2/2007 are presented in Table 5. The results are similar to the baseline regression. Intercepts decrease monotonically across bins, when banks are sorted according to total assets and market capitalization at EU-level as well as for market capitalization at country-level. Under total asset sorting, a portfolio going long small banks and shorting large banks earns significant negative returns of -1.094%. For sorting according to market capitalization, such an investments yields a strongly significant negative return of -1.272%. Sorting according to the market share in the domestic banking sector and size per GDP brings forth a similar effect, albeit not being as strong as for the other specifications. For all other specifications, no clear size effect can be detected. Note that the explanatory power of the Gandhi and Lustig (2015)-specification is significantly lower than under the baseline specification. The substitution the two banking sector factors *FmnF Factor* and *ROE Factor* with the maturity transformation risk factor mat significantly decreases the explanatory power of the regression. The adjusted R2 ranges between 30% and 50% instead of between 58% and 87%. Also, and in contrast to Gandhi and Lustig's result for the US banking sector, intercepts are usually positive across bins highlighting that banks on average command a higher risk premium than non-financial stocks.

5.4.2 FURTHER ROBUSTNESS CHECKS

Bin specific summary statistics highlight that small and large banks differ along a number of characteristics. Is these characteristics mirror underlying pricing factors which are not spanned by the factors included in the model specification, they may explain the differences in intercepts of large versus small banks, albeit not being related to TBTF. To control for such alternative explanations, I construct a number of factors based on bank characteristics. These include leverage, banking-sector book-to-market ratios, loan-to-deposit ratios and non-interest income ratio. Factors are constructed by sorting banks into four bins according to the relevant characteristic and defining the factor as the spread between equally-weighted returns of the highest bin minus the equally-weighted return of the lowest bin. I add each of these factor to the baseline regression one at a time.

A further explanation why stocks of large banks are relatively more costly than small bank stocks is that these stocks are more liquidly traded. To control for the liquidity advantage of large bank stocks, I include the Pastor-Stambaugh (2003) liquidity factor as an additional factor. Also, I run an alternative, where I include the betting-against-beta factor of Frazzini and Pedersen (2014) to exclude the possibility that the funding advantage of large banks is driven by the low risk anomaly. Finally, I run robustness checks to see whether the results are driven by the privatization of French banks in the 1990s or the large presence of UK banks in the sample.

Table A4 presents the intercept estimates for the LMS portfolio, which goes long more systemic stocks and short less systemic stocks under different model choices and for different measures of systemic risk. The result corroborate that being large, both in terms of total assets and market capitalization, is associated with a significant funding advantage.

5.4.3 No size effect for Non-Financial firms

Next, I ensure that the size effect is indeed specific to the banking sector. Large banks benefit from government guarantees because of the anticipated contagious effects their failure has for the banking system. Investors assume that governments are willing to support systemic banks to prevent that a failure of an important bank causes unpredictable repercussions throughout the financial system. Non-financial firms are far less interconnected than banks and there is no immediate need for the bailout of a single firm. Indeed, Berk (1997) use double sorting along market capitalization and total assets to show that for the sample of publicly traded US non-financial firms over the time period 1967 to 1987, that there is no size effect beyond the market capitalization effect for non-financial firms' equity returns. Gandhi and Lustig (2015) similarly show for a sample of US firms that non-financial firm display no monotonicity across size bins, when firms are sorted according to total assets and the standard risk factors are accounted for.

I test for the presence of a size anomaly in non-financial firms' stock return by running Fama-French time series regressions for non-financial European firms. I regress monthly excess returns for size-sorted portfolios on the three Fama-Fama factors. Non-financial firms are sorted into four bins according to total assets at the European level (*ta*), at the domestic level (*ta_ct*, *ta_ct4*), total assets to GDP (*ta_gdp*), as well as market capitalization at the European level (*mcap*) and the domestic level (*mcap_ct*). There is no natural equivalent to the BIS score of systemic importance, given that this is an indicator explicitly designed for the particular sources of systemic risk in the banking sector. The intercepts for each specification are presented in Table 6. In contrast to the large funding for large banks, I do not find a funding advantage for large non-financial firms – neither at the European nor at the national level.

The finding is corroborated by results for pooled OLS regressions. Table 7 shows the results for pooled OLS regressions, when non-financial stocks returns are regressed on market capitalization, total assets or total asset per GDP, betas and book-to-market ratio. In contrast to case of bank returns, the coefficient on total assets is positive and significant. In other words, for a non-financial firm, being larger appears to be associated with higher rather than lower risk. The result also contradicts the previous finding of Berk (1997) who found no explanatory power of size for stock returns beyond the ordinary market capitalization effect for a sample of US non-financial firms. Possibly being a specificity of European stock markets, the effect deserves further investigation, but goes beyond the banking focus and scope of this paper. The coefficient estimate on total assets per GDP is also positive, but insignificant.

6 The Financial Crisis and Regulatory Reform

In the next step, I expand my sample to include the financial crisis and the recent regulatory reform period. I uncover that especially large banks seem to have benefited from implicit government protection during the financial crisis and were taking the expected role of as a hedge against the downturn. Further evidence suggest that regulatory reform creating a unified European framework for bail-in were only temporarily effective in reducing bail-out expectations, but suffer from lack of credibility. I exclude the sovereign debt crisis from my analysis, because of the dominant role sovereign risk played during this period. I also concentrate my subsequent analysis on systemic importance being measured in terms of total assets, following the evidence from the previous section.

6.1 OUTPERFORMANCE OF LARGE BANKS DURING THE FINANCIAL CRISIS

For the financial crisis period until about end-2009 the results are fully in line with large bank stocks acting as a (relative) hedging devices against crisis times, where failure of financial institutions become more likely. When governments are more willing to bail out large or, more generally, systemically important banks, these banks should be outperforming banks which are deemed less important for financial stability in times of financial turmoil. This is exactly what can be observed for the period Q3/2007-Q1/2010.

I first rerun the baseline time series regression (2) for total asset sorting, but extended to Q1/2010 and including a dummy variable for the months in the financial crisis period Q3/2007-Q1/2010. The coefficient estimate on the dummy variable captures the bin-specific intercept for the financial crisis period. I pick Q3/2007 as the beginning of the crisis period, because the termination of withdrawals from three hedge funds by BNP Paribas in August 2007 is widely considered to mark the beginning of the financial crisis. Q1/2010 is chosen as endpoint to separate the estimation from the sovereign debt crisis period.

Table 8 shows the results for augmented Fama French regressions under the baseline specification with the banking sector *FmnF Factor,* the banking sector *ROE-factor* ROE and the spread of the average EU-sovereign yield over the German yield *Government Spread*. Portfolios are again ranked from smallest (Bin 1) to largest (Bin 4), and the last column contains the portfolio going long large stocks and short small stocks. Matching the results for the shorter sample period up until Q2/2007, estimated intercept *Constant* are monotonically decreasing across intercepts. Importantly, however, coefficient estimates on the dummy variable are *in*creasing across size bins. The coefficient estimate on *Dummy Financial Crisis* is -0.456 for bin 1 and increased to 0.505 for bin 4. The difference between the first and fourth bin is 0.961, but insignificant over the short time horizon, for which the coefficient is estimated.

To understand better the performance of large banks during the financial crisis, I track the value evolution of a portfolio investing 100 Euro at the beginning of the financial crisis going long large stocks and short small stocks and adjusting for the risk factors. The portfolio replicates an investment based on the risk-adjusted returns in Column 5 of Table 3. Figure 6 shows the evolution of such a portfolio graphically, when the investments is taken at end-July 2007 and is held until end-March 2010, Table 9 provides the corresponding numbers. The table differentiates between the evolution of a portfolio on the simple spread between large and small banks (i.e. without risk-adjustment) in Column 1, and with risk-adjustment in Column 2 under assignment according to total assets and in Columns 3 and 4 for assignment according to market capitalization. The unhedged size portfolio maintains almost a constant value over the entire time period, under both measures of sizes. This highlights the strong co-movement in bank stocks during the financial crisis. However, when controlling for the risk factors specified in (2), the hedged large minus small portfolio gains almost 25 Euros over the course of the financial crisis under total assets sorting, and 5 Euros under market capitalization sorting highlighting the outperformance of large stocks vis-à-vis-small stocks. The results corroborate that the outperformance of large banks during the financial crisis is indeed due to the implicit guarantees associated with being TBTF. The conjecture is also supported by the time series evolution of the portfolio value: While large banks start outperforming relative to small firms from the beginning of the financial crisis from August 2007, the relation reverses after the bankruptcy of Lehman Brothers in September 2008. From September 2008 to February 2009, the large minus small portfolio loses roughly 30 Euros, before recovering again. The loss in portfolio value is in line with a sudden reversal in investor beliefs, making the failure of a large bank suddenly a possibility in Europe as well. Subsequently, however, the fear turned out to be unsubstantiated for Europe, where no large bank was let fail until end-2009 and large banks started outperforming relative to small banks again from March 2009. The short-term reversal in investor beliefs also explains the non-significance on the coefficient estimate for *Dummy Financial Crisis* in Column 5 of Table 8.

6.2 THE EFFECT OF REGULATORY REFORM ON BAILOUT EXPECTATIONS

In a final step, I investigate whether recent regulatory reform aimed at reducing implicit government guarantees for the European banking sector were indeed credible and successful in reducing the bailout expectations of investors. Evidence from the co-movement in the risk-adjusted returns of small and large banks suggests that regulatory reform was at first perceived as eliminating the tail risk subsidy for large banks. However, discussions about a possible bailout for Deutsche Bank in 2016 outside the just agreed resolution framework for Europe and public guarantees for the Italian banking sectors significantly reduced the credibility of the common resolution framework.

6.2.1 Regulatory Reform in Europe

The massive amount of tax payer money deployed for the rescue of European banks during the financial crisis highlighted the ex post fiscal costs associated with implicit guarantees. Table A3 highlights the banks, which received recapitalizations from their respective governments from 2007, in bold. Not surprisingly, the majority of publicly traded banks receiving recapitalizations by their respective governments are large and assigned to the third or fourth size bucket. Exactly because banks were shielded from downside risk, they were willing to load up on this risk to benefit from its upside, while the downside was borne by the taxpayer. What exacerbates the issue was that European countries did not have adequate insolvency regimes, which could deal with the ordered resolution of large financial institution.

As one of the central lessons learnt from the financial crisis, European governments decided to create a new regulatory framework, which would allow for the restructuring and resolution of even the largest banks in an orderly, swift manner, while at the same time shifting the losses associated with such restructuring or winding-down from the taxpayer to the stakeholder of the firm. The idea was to eliminate TBTF by making banks resolvable and having investors bear the down-side risk with making risky investments. As a consequence, and following previous regulatory initiatives at the national level, European regulators put forth the Bank Recovery and Resolution Directive (BRRD) for the European Union and the Single Resolution Mechanism (SRM) for the Eurozone. The regulatory reform process at the European level started with the unanimous agreement by the EU finance ministers on the BRRD in July 2013 and concluded with the introduction of the SRM in January 2016, including the bail-in provisions.

The initiatives harmonized tools and procedures in the recovery and resolution process for credit institutions in the EU and instituted common rules for bail-in across Europe. The harmonized legal framework for rescue and resolution was introduced to reduce legal insecurity, limiting national government's discretion in bailing out their national banking champions and to increase transparency for market participants. Specifically, with the introduction of an explicit bail-in scheme, European governments wanted to send a clear signal to market participants: Prior to using the tax payers money to rescue systemic relevant institutions, shareholders will have to cover the losses first, other stakeholders such as junior debt holders and the financial industry will follow and only in case these resources will not prevent a financial turmoil the government can step in for support as an ultimate solution.

Investors are willing to accept lower (risk-adjusted) returns for the stocks of large banks relative to smaller banks in normal times if they believe that implicit government guarantees shield these stocks (at least partly) from downside risk during crisis times. The BRRD and the SRM should have decreased the relative hedging value of large banks, if they were successful in reducing investors' expectations that governments will absorb the downside risk of large banks. Thus, if the regulation has been successful in eliminating investors' expectations of the taxpayer absorbing large stocks' downside risk, the funding advantage of large banks should disappear.

6.2.2 Correlation Analysis in stock movement

Standard asset pricing techniques are not directly suited to track a change to the funding advantage of large banks associated with regulatory reform, because sufficiently long time horizons are required to accurately estimate the intercept for time series regressions. Using daily rather than monthly stock returns does not help to estimate alphas more accurately. However, shortening the estimation window does help to estimate **second** moments. Thus, I subsequently resort to the analysis of the time series variation in the *correlation* structure of risk-adjusted returns to derive a statement about the success of regulatory reform for bank stocks.

Decreasing and significant intercepts across size bins indicate that there is a size-dependent pricing factor which is priced by investors, but not spanned by the existing pricing factors. I follow Gandhi and Lustig (2015) and use principal component analysis on risk-adjusted returns to construct a size factor on which small banks load positively and large banks negatively and which moves cyclically. I find that the first principal of normal risk-adjusted returns on size-sorted portfolios has loadings which depend monotonically on size, which is in line with their results.[15] The weights **w** on the first principal component $PC_t^1 = w_1{}'\epsilon_t$ are given by

$$w_1 = [0.661, 0.038, -0.499, -0.557].$$

The weights of the principal components mirror the monotonicity of intercepts across size bins, making the principal component the candidate factor to explain the relative price advantage of large stocks. The weight on the third bin is quite negative as well, underlining that implicit government guarantees were not only limited to the very largest banks. The first principal component explains 37.4% of the variation in residual returns, meaning that roughly 40 percent of variation in the residuals is explained by size.

The results from the principal component analysis highlight that in principle, large banks underperform when small banks over-perform (relative to the overall development in the banking sector) and vice versa. The size factor introduces a negative correlation between small and large banks stocks, once the overall market movement is controlled for by the factor *FmnF Factor*. To test for the effect of regulatory reform on bailout expectations, it is thus adequate to test for changes in the dependence structure between risk-adjusted returns of small and large stocks.

I measure the dependence structure between small and large stocks in two ways. First, I run time series regressions of daily equally weighted excess returns $R_t^4 - R_t^f$ of bin 4 in the baseline specification, but additionally including the equally weighted excess returns R_t^1 of bin 1 as an explanatory variable,

$$R_t^4 - R_t^f = \alpha_4 + \beta_4' f_t + \gamma \cdot \left(R_t^1 - R_t^f\right) + \epsilon_t^4.$$

The coefficient estimate on R_t^1 is the (conditional) Pearson correlation between normal returns of bin 1 and bin 4, after controlling for the known factors which contemporaneously drive returns of small and large banks. Second, I use Spearman's rank correlation as an alternative, non-parametric measure for the dependence

[15] In fact, Gandhi and Lustig (2015) find in their analysis that the second principal component of risk-adjusted returns can be interpreted as this size factor, while the first principal component is a factor, on which all bins load equally making it likely that this is a banking industry-specific factor. My specification explicitly controls for banking-sector specific dynamics by including the factor *FmnF Factor* into to the analysis.

structure between stock returns of small and large banks which is scale invariant and not affected by the marginal distribution of each return series (Patton, 2012). Both measures are estimated over rolling windows of 120 days (backward-looking), advancing in 30 day-steps. I use bootstrapping to obtain 95% confidence intervals.

The correlation analysis is preferred to an event study to investigate the effect of the announcement of major regulatory reform on bailout expectations in the banking sector for a number of reasons. First, regulatory reforms both in the US and the European Union were negotiated over a long time horizon. As such no clear event can be identified which can be identified as surprise announcement to the extent of bail-in of large banks. Instead, it appears plausible that the changing attitude of regulators towards bail-in was communicated to the public in a continuous flow of information. For an event study, reliable results can only be produced if the event, where new information is revealed, is clearly identified (Lamdin, 2001). Second, and relatedly, the process of regulatory reform is a continuous process which is highly related to the credibility of the regulator. While investors may perceive an initial signal of the regulator as credibly curtailing the bailout probabilities of large banks, only the firm application of the rules can fasten these beliefs in the long horizon. With the event study only considering a short window around a regulatory announcement, it is inadequate to capture subsequently changing beliefs.

Figure 7, Panel A shows a time series plot of rolling 120-day conditional Pearson correlation between the returns of bin 1 and bin 4 under total asset sorting. Panel B shows a time series plot of the corresponding rolling 120-day rank correlation. The gray area indicates the corresponding 95% confidence interval. The correlation estimates are comparable under both dependence measures, with the correlation varying mostly between -0.10 and -0.50 for the early part of the sample and throughout the financial and also the sovereign debt crisis corroborating the results from the principal component analysis. The estimates are almost continuously significantly different from zero.

In contrast, the regulatory reform period is associated with a structural break in the correlation structure of residual returns. With the agreement on the BRRD on the EU-summit by 27 in June 2013 and the presentation of the SRM by the European Commission in July 2013, the opposite performance of small and large bank stocks abates. The correlation between small and large stocks becomes insignificant approximately with the approval of the SRM Regulation by the EU Parliament in April 2014 (120-day backward looking windows). I also test for a break in the correlation structure between returns of small and large stocks and estimate the unknown breakpoint following the “sup” test proposed in Patton (2012). The structural break in the correlation is estimated to take place in April 2014 and is significant at 1% level. The month coincides with the decision of the EU parliament in favor of the SRM. As such, the introduction of the new framework can be interpreted as indeed being credible in reducing investors’ expectations that large banks would also in future benefit from government interventions.

The reduction in bail-out expectations is only transient, however. Shortly after the actual introduction of the SRM in the beginning of 2016, the negative correlation between small and large stocks re-emerges, both under Pearson and Spearman’s rank correlation. The re-emergence of the opposite performance in risk-adjusted returns is coinciding with policy makers in different European countries undermining the common framework and thereby critically reducing the credibility of the just agreed resolution rules. From January 2016, the Italian government started criticizing the new regulatory regime as causing “an increase in instability, rather than stability”.[16] Italy was especially facing the issue that a bail-in was particularly affecting retail investors which had been previously encouraged to take out risky debt by the banks instead of traditional deposits. In January, the Italian government agreed with the EU-commission on state guarantees for their banking sector to help banks offload non-performing loans. Also from January 2016, concerns surfaced about the viability of Deutsche Bank following a record loss in 2015 and with the prospect of further litigation charges.[17] The case of Deutsche Bank raised the question whether the resolution of the very largest banks could be handled in the framework of the new resolution mechanism. From February 2016, first newspaper articles raised the

[16] Financial Times, 11 February 2016 “Bank turmoil: are Europe’s new bail-in rules to blame?” https://www.ft.com/content/8ad2ed98-d0a0-11e5-986a-62c79fcbcead
[17] Financial Times, 21 January 2016 “Charges to push Deutsche Bank to €6.7bn loss” https://www.ft.com/content/06b856d2-bfb7-11e5-9fdb-87b8d15baec2

possibility of a bailout of Deutsche Bank outside of the resolution regime culminating in rumors that the German government was preparing a bailout.[18]

7 Conclusion

My analysis for European banks stocks over the period 1993-2016 supports the hypothesis that large European banks have long benefitted and likely continue to benefit from sizeable bailout guarantees. I document that size reduces the cost of capital significantly for the pre-crisis period, even after carefully controlling for the classical market capitalization pricing anomaly. Quantile regressions support the hypothesis that investors are willing to accept lower expected returns for large bank stocks in exchange for the protection that these banks enjoy in downturns. The evidence from Section 6 furthermore indicates that TBTF implications persisted to be important throughout the financial and sovereign debt crisis.

For the post-crisis period, I also find some evidence for continued pricing of bailout guarantees. However, the evidence is considerably weaker and has to be interpreted with care. The findings for this later period highlight the limits of an asset pricing methodology in capturing recent changes in regulatory and institutional frameworks, when beliefs about the long-running nature of these changes are continuously updated. A definite statement about the success of recent regulatory reforms by the means of asset pricing can only be made, once sufficient data become available.

My results bear important implications for the future design of the European banking regulation. Implicit bailout guarantees shield large banks from downside risk and allow them to engage in riskier portfolio choices. The long-lasting prevalence of too-important-to-fail in the European banking sector can only be reduced, if legislation aimed at curtailing bailout expectations is implemented credibly.

[18] Financial Times, 23 February 2016 “Is the era of bank bailouts over? Nobody knows” https://www.ft.com/content/8c8835f8-d96a-11e5-a72f-1e7744c66818

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Figures

Figure 1: **Evolution of mean total assets per size quartiles**
The figure shows the evolution of mean total assets of publicly traded banks in developed countries of the European Union between 1993 and 2016, averaged within size quartiles.

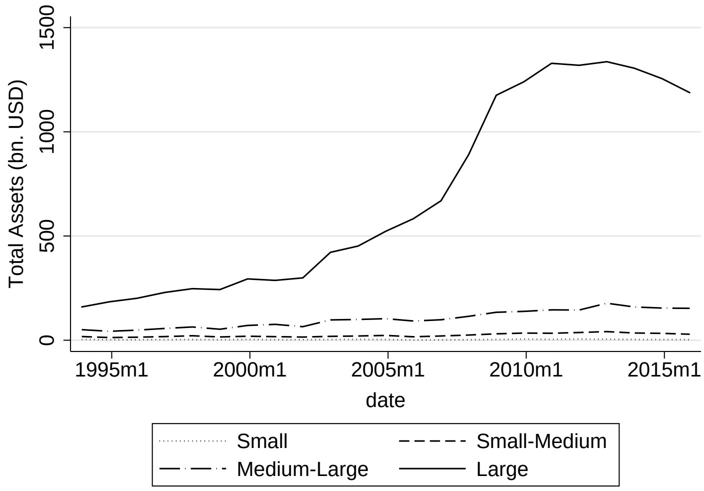


Figure 2: **Evolution of number of publicly traded banks between 1970 and 2016**
The figure shows the number of publicly traded banks in developed countries of the European Union between 1970 and 2016.

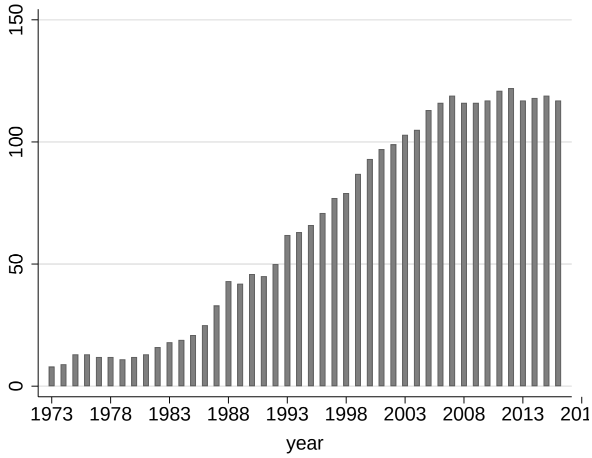
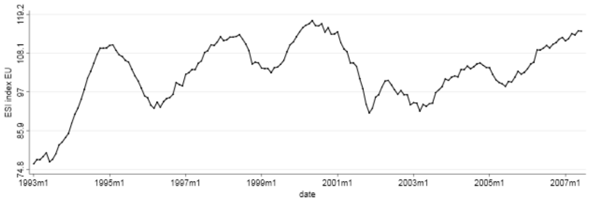
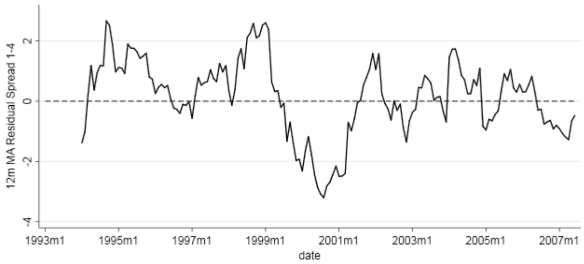


Figure 3: **Residual Spread Bin 1 - Bin 4**
The graphs show 12 month moving averages of the residual spread between equally-weighted returns of banks in bin 1 and bin 4 under different size specifications.



(a) EU Sentiment Index



(b) Residual spread

Figure 4: **Quantile Regression for time period Q1/1993 - Q2/2007**
The figure shows results from quantile regressions of equity excess returns on size and bank-level characteristics. Depicted are coefficient estimates from quantile regressions for percentiles $[0.05, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 0.95]$ (solid line), their 90%-confidence interval (grey-shaded area) as well as the OLS estimate (dashed line) and its 90% confidence interval (dotted line). Size is measured in form of log total assets and the orthogonalized market capitalization. Bank-level characteristics include betas on the market excess return β_i^{Market}, on the Spread of the equally-weighted average of bank stock returns over the market excess return β_i^{FmNF}, on the excess return of the respective sovereign yield $\beta_i^{\text{Sov Yield}}$ as well as bank characteristic *Book-to-Market* and *ROE*. Betas are estimated simultaneously via rolling time-series regressions for daily data over the preceding year. Market Capitalization and Book-to-Market are orthogonalized via the Gram-Schmidt orthogonalization method. Standard errors are robust and obtained via 100 bootstraps.

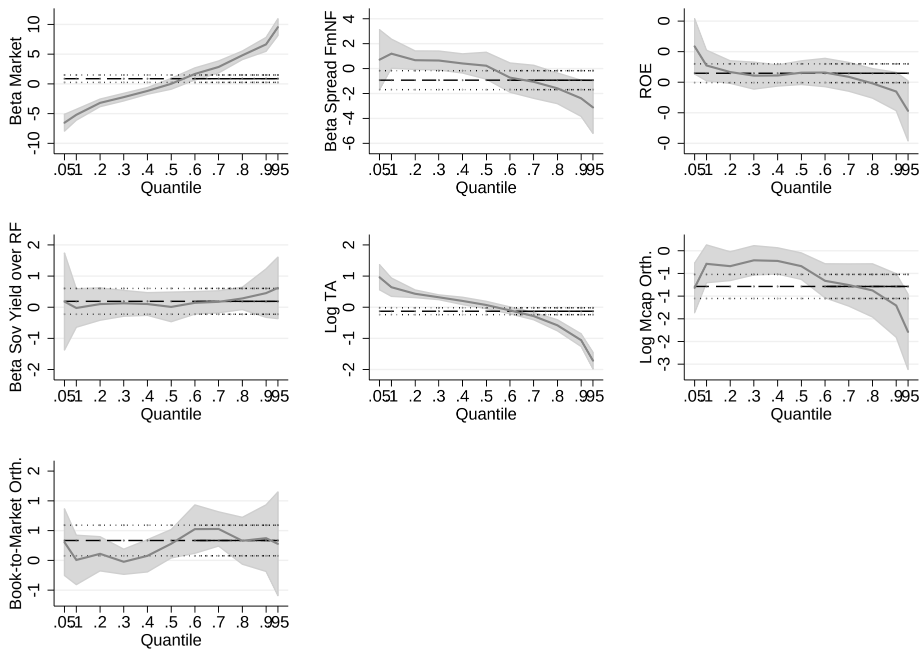
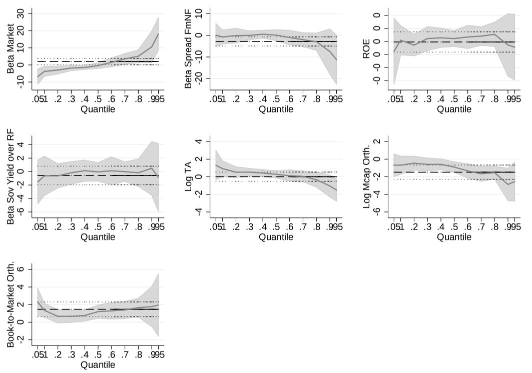
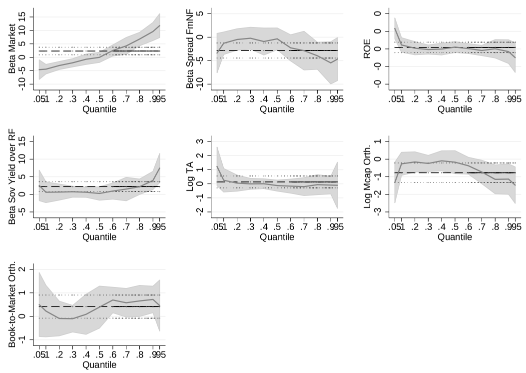


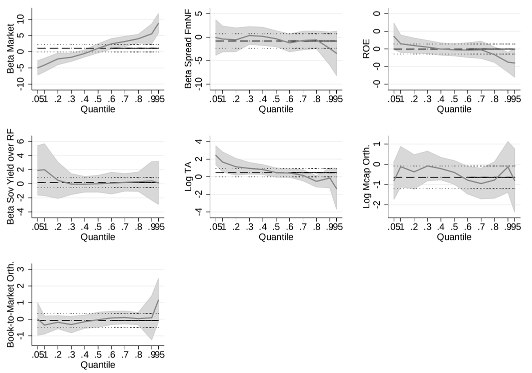
Figure 5: **Quantile Regression on Total Assets in Market Capitalization Deciles Q1/1993-Q2/2007**
The figure shows results from quantile regressions of equity excess returns on size and bank-level characteristics, under market capitalization splits. Depicted are coefficient estimates from quantile regressions for percentiles $[0.05, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 0.95]$ (solid line), their 90%-confidence interval (grey-shaded area) as well as the OLS estimate (dashed line) and its 90% confidence interval (dotted line). Size is measured in form of log total assets and the orthogonalized market capitalization. Bank-level characteristics include betas on the market excess return β_i^{Market}, on the Spread of the equally-weighted average of bank stock returns over the market excess return β_i^{FmNF}, on the excess return of the respective sovereign yield $\beta_i^{\text{Sov Yield}}$ as well as bank characteristic *Book-to-Market* and *ROE*. Betas are estimated simultaneously via rolling time-series regressions for daily data over the preceding year. Market Capitalization and Book-to-Market are orthogonalized via the Gram-Schmidt orthogonalization method. Standard errors are robust and obtained via 100 bootstraps.



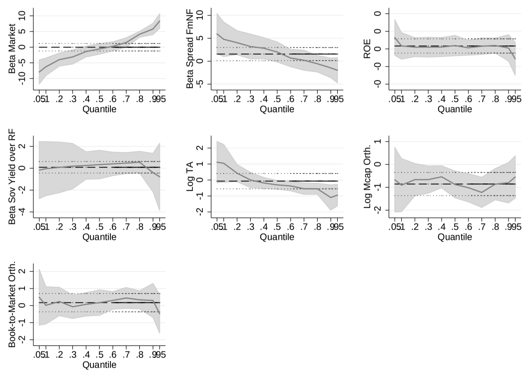
(a) Quartile 1



(b) Quartile 2



(c) Quartile 3



(d) Quartile 4

Figure 6: **Perfomance of hedged portfolio goin long large and short small stocks**
The figure shows the performance of hedged portfolio investing 100 Euro in a portfolio going long large stocks and short small stock. The portfolio is adjusted for exposure to the risk factors.

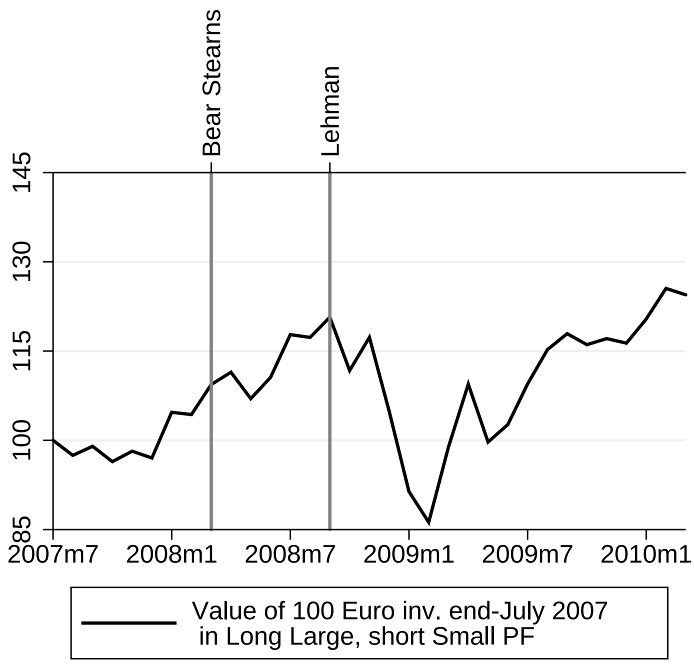
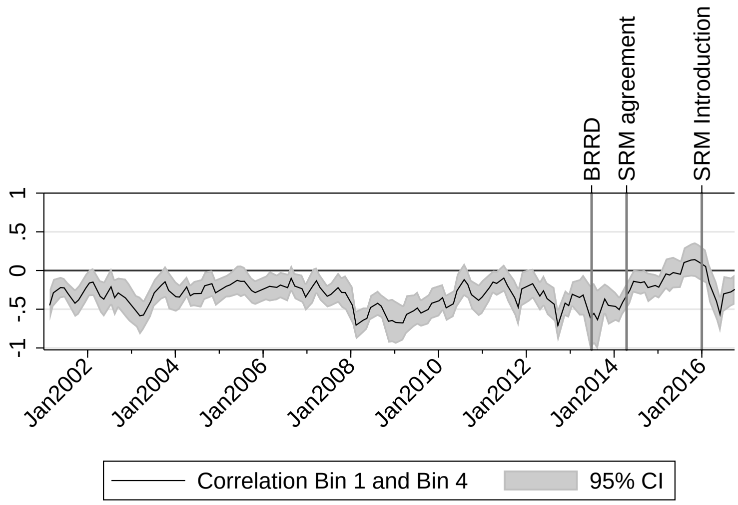
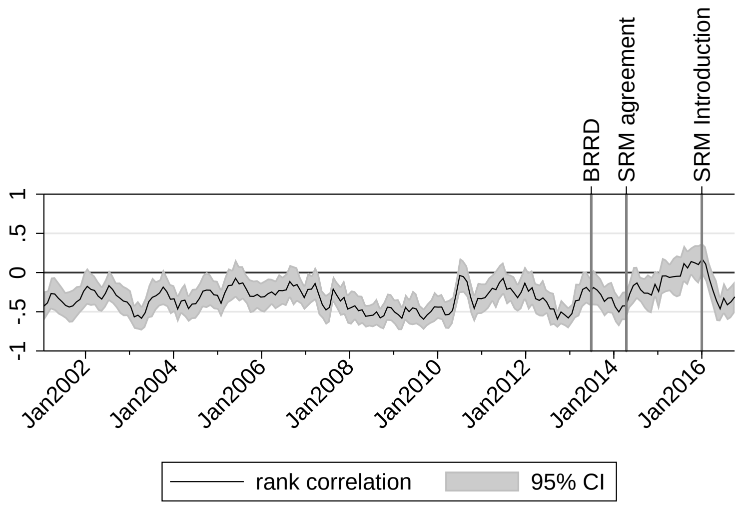


Figure 7: **Correlation Analysis**
The figure shows 120-day backward-looking rolling estimates for Pearson's and Spearman's rank correlation between risk-adjusted standardized return in bin 1 and bin 4, when banks are assigned to bins under total asset sorting. The solid line tracks the 120-day backward-looking correlation estimates, the gray-shaded areas are the corresponding 95% confidence interval.



(a) Correlation-based



(b) Rank-based

Tables

Table 1: **Summary Statistics**

Variable	N	Mean	Median	SD	Min	Max
Banks						
Stock return (%)	21,993	0.48	0.17	12.13	-89.25	294.34
Total Assets (bn. USD)	1,703	218.67	39.13	484.96	0.11	3450.25
Market cap (bn. USD)	1,707	11.32	2.60	23.59	0.00	217.80
Total Assets/GDP	1,703	0.20	0.05	0.31	0.00	2.16
Market Cap/GDP	1,707	0.01	0.00	0.02	0.00	0.12
TA/TA Banking Sector	1,703	0.06	0.02	0.10	0.00	0.77
BIS Score (Proxy)	887	49.94	10.27	79.98	0.01	556.26
Market-to-Book	1,567	1.65	1.37	1.81	-17.57	34.16
Return on Equity	1,632	1.82	10.60	176.33	-5369.40	98.14
Equity/Total Assets	1,397	0.09	0.08	0.11	-0.09	1.05
Non-Interest Income/Gross Revenues	1,394	0.59	0.53	0.59	-0.69	9.42
Non-Financials						
Stock return, non-financials (%)	425,292	0.75	0.00	28.65	-100.00	13163.94
Total Assets, non-financials (bn. USD)	33,717	4.56	0.31	18.92	0.00	441.64
Market cap, non-financials (bn. USD)	33,281	2.98	0.23	11.31	0.00	237.37
Total Assets/GDP, non-financials	33,717	0.00	0.00	0.01	0.00	0.26
Market Cap/GDP, non-financials	33,281	0.00	0.00	0.01	0.00	0.67
Macro Variables						
Nominal GDP (bn. USD)	288	903.09	428.16	917.98	6.37	3757.46
Total Assets Banking Sector (bn. USD)	253	968.56	385.21	1393.32	4.47	8731.91

Table 2: **Cross-sectional summary statistics for selected size measures**
The table displays time series averages of annual cross-sectional summary statistics for banks in different size bins. The table presents average mean (*mean*), standard deviation (*sd*), minimum (*min*) and maximum (*max*) values for the distribution of variables, with the average taken across years 1993-2016

Bin	**1**		**2**		**3**		**4**	
Bin Assignment: Total Assets (bn. USD.)	**mean**	**sd**	**mean**	**sd**	**mean**	**sd**	**mean**	**sd**
Total Assets (bn. USD)	3.60	3.48	25.01	13.92	105.63	69.35	754.49	746.35
Marketcap (bn. USD)	0.55	0.70	2.10	2.14	6.69	5.03	36.30	36.56
Total Assets/GDP	0.01	0.03	0.06	0.08	0.24	0.23	0.50	0.41
Mcap/GDP	0.00	0.00	0.01	0.01	0.02	0.02	0.03	0.02
TA/TA Banking Sector	0.07	1.23	1.58	22.93	0.13	0.28	0.15	0.28
Market-to-Book	1.71	0.95	1.45	0.85	1.43	0.79	1.36	0.73
ROE	11.16	9.78	9.93	8.56	10.63	9.48	10.33	8.30
Equity/Total Assets	0.10	0.09	0.11	0.07	0.08	0.06	0.07	0.04
Non-Interest Income/Gross Revenues	0.52	0.50	0.53	0.35	0.51	0.34	0.67	0.40
Bin Assignment: Market cap (bn. USD.)	**mean**	**sd**	**mean**	**sd**	**mean**	**sd**	**mean**	**sd**
Total Assets (bn. USD)	6.75	12.04	29.71	31.14	114.77	119.53	717.48	757.09
Marketcap (bn. USD)	0.31	0.26	1.73	1.07	6.02	3.96	35.67	35.69
Total Assets/GDP	0.02	0.05	0.07	0.14	0.22	0.22	0.50	0.41
Mcap/GDP	0.00	0.00	0.00	0.01	0.01	0.02	0.03	0.03
TA/TA Banking Sector	0.01	0.03	0.11	1.28	1.61	22.67	0.15	0.30
Market-to-Book	1.41	0.87	1.61	0.91	1.45	0.84	1.50	0.76
ROE	8.83	9.20	10.74	9.59	10.86	9.13	11.67	8.07
Equity/Total Assets	0.09	0.08	0.10	0.06	0.09	0.06	0.08	0.05
Non-Interest Income/Gross Revenues	0.43	0.42	0.62	0.41	0.50	0.35	0.65	0.40
Bin Assignment: Total Assets (country-ranking)	**mean**	**sd**	**mean**	**sd**	**mean**	**sd**	**mean**	**sd**
Total Assets (bn. USD)	12.95	25.97	84.23	155.35	298.06	511.39	714.00	826.82
Marketcap (bn. USD)	1.14	2.04	4.78	7.88	14.11	17.60	36.64	42.90
Total Assets/GDP	0.02	0.05	0.08	0.14	0.20	0.23	0.51	0.45
Mcap/GDP	0.00	0.00	0.01	0.01	0.01	0.01	0.03	0.03
TA/TA Banking Sector	0.01	0.03	0.03	0.07	0.06	0.10	0.19	0.31
Market-to-Book	1.76	0.98	1.48	0.86	1.39	0.79	1.37	0.75
ROE	11.07	9.29	10.22	9.39	10.09	8.70	10.20	8.44
Equity/Total Assets	0.12	0.08	0.09	0.07	0.08	0.06	0.08	0.05
Non-Interest Income/Gross Revenues	0.58	0.42	0.52	0.45	0.55	0.42	0.58	0.38
Bin Assignment: TA/TA Banking Sector	**mean**	**sd**	**mean**	**sd**	**mean**	**sd**	**mean**	**sd**
Total Assets (bn. USD)	6.85	9.70	49.10	58.68	393.15	577.99	446.82	676.77
Marketcap (bn. USD)	0.67	0.83	3.74	6.48	20.79	33.84	20.90	25.84
Total Assets/GDP	0.00	0.01	0.03	0.03	0.24	0.22	0.55	0.38
Mcap/GDP	0.00	0.00	0.00	0.00	0.01	0.02	0.03	0.02
TA/TA Banking Sector	0.00	0.03	0.02	0.10	0.07	0.26	1.88	23.32
Market-to-Book	1.62	0.89	1.47	0.89	1.44	0.81	1.48	0.79
ROE	10.36	8.71	10.00	8.84	10.19	9.08	11.48	9.81
Equity/Total Assets	0.12	0.08	0.10	0.06	0.08	0.05	0.06	0.05
Non-Interest Income/Gross Revenues	0.59	0.50	0.57	0.32	0.64	0.40	0.45	0.36
Bin Assignment: BIS Score	**mean**	**sd**	**mean**	**sd**	**mean**	**sd**	**mean**	**sd**
Total Assets (bn. USD)	47.33	90.41	83.74	127.80	200.56	220.62	949.24	889.00
Marketcap (bn. USD)	2.94	5.53	5.02	5.81	13.24	15.93	44.29	43.72
Total Assets/GDP	0.11	0.20	0.25	0.41	0.33	0.38	0.49	0.34
Mcap/GDP	0.01	0.01	0.01	0.02	0.02	0.03	0.03	0.02
TA/TA Banking Sector	0.06	0.10	0.13	0.20	0.11	0.13	0.10	0.07
Market-to-Book	1.37	0.70	1.43	0.73	1.47	0.79	1.46	0.79
ROE	8.95	8.26	11.45	7.53	11.53	9.35	10.84	8.39
Equity/Total Assets	0.08	0.08	0.09	0.06	0.09	0.05	0.08	0.04
Non-Interest Income/Gross Revenues	0.37	0.43	0.44	0.31	0.60	0.26	0.72	0.35

Table 3: **Baseline specification: Bin-specific time-series regressions for equally-weighted excess returns of European commercial banks (Q1/1993-Q2/2007)**
The table displays the coefficient estimates of bin-specific OLS regressions for equally-weighted excess returns, when banks are sorted into bins **according to total assets at the EU-level**. Excess returns are regressed on the Fama and French (1993)-Factors, the Market excess return *MktRF*, Small-minus-Big *SMB* and High-minus-Low *HML*, as well as the excess return of a financial market index over the market index *FmNF*, the ROE-factor *FROE* and the excess return of the average 10y government yield of countries in the sample. The column 'Long large, short small' is the excess return on a portfolio strategy going long the largest bin and short the smallest bin. P-values are displayed in brackets. *,**, and *** indicate significance at the 10%, 5% and 1%-significance level. Standard errors are Newey and West (1987)-adjusted for heteroskedasticity and autocorrelation.

Baseline regression (ta,Q1/1993-Q2/2007)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Bin 1	Bin 2	Bin 3	Bin 4	Long large short small
MktRF	0.978***	0.951***	1.057***	1.194***	0.216*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.085)
SMB	0.406**	0.042	-0.279***	-0.590***	-0.995***
	(0.038)	(0.553)	(0.009)	(0.000)	(0.001)
HML	-0.094	0.091	0.214***	0.189*	0.283
	(0.509)	(0.122)	(0.002)	(0.057)	(0.104)
ROE Factor	0.008	-0.122***	-0.014	0.047	0.038
	(0.924)	(0.000)	(0.764)	(0.519)	(0.785)
FmnF Factor	0.998***	0.956***	0.994***	1.142***	0.144
	(0.000)	(0.000)	(0.000)	(0.000)	(0.320)
Government Spread	-0.028	0.162	0.591***	0.994***	1.021**
	(0.932)	(0.169)	(0.002)	(0.001)	(0.048)
Constant	0.667*	0.026	-0.323	-1.055***	-1.722***
	(0.068)	(0.860)	(0.146)	(0.002)	(0.003)
Observations	174	174	174	174	174
Adj. R2	0.697	0.825	0.821	0.811	0.179
Avg. # Banks in bin	15	14	15	14	

pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: **Baseline specification: Intercept estimates for bin-specific time-series regressions for equally-weighted excess returns of European commercial banks (Q1/1993-Q2/2007)**

The table displays the intercept estimates of bin-specific OLS regressions for equally-weighted excess returns under all size specifications. Banks are sorted into bins according to total assets at the EU-level (*ta*), total assets per total assets in the banking sector (*ta_bs*), total assets at the country-level (*ta_ct*), total assets at the country-level, when only the largest bank is assigned to bin 4 (*ta_ct4*), total assets per domestic GDP (*ta_gdp*), market capitalization at the EU-level (*mcap*), market capitalization at the country-level (*mcap_ct*), and the BIS Score (*bis_sc*). Excess returns are regressed on the Fama and French (1993)-Factors, Market excess return *MktRF*, Small-minus-Big *SMB* and High-minus-Low *HML*, as well as the excess return of a financial market index over the market index *FmNF* the ROE-factor *FROE* and the excess return of the average 10y government yield of countries in the sample. The column 'Long large, short small' is the excess return on a portfolio strategy going long the largest bin and short the smallest bin, respectively. P-values are displayed in brackets. *,**, and *** indicate significance at the 10%, 5% and 1%-significance level. Standard errors are Newey and West (1987)-adjusted for heteroskedasticity and autocorrelation.

Bin		**1**	**2**	**3**	**4**	**LMS**
taquantile	Intercept	0.667*	0.026	-0.323	-1.055***	-1.722***
	p-value	(0.068)	(0.860)	(0.146)	(0.002)	(0.003)
	Adj. R2	0.697	0.825	0.821	0.811	0.179
ta_bsquantile	Intercept	0.665**	-0.390**	-0.343	-0.619**	-1.283***
	p-value	(0.017)	(0.043)	(0.195)	(0.043)	(0.007)
	Adj. R2	0.727	0.846	0.842	0.766	0.188
ta_ctquantile	Intercept	0.431	-0.285	-0.151	-0.180	-0.611
	p-value	(0.126)	(0.315)	(0.563)	(0.555)	(0.164)
	Adj. R2	0.795	0.764	0.798	0.804	0.229
ta_ct4quantile	Intercept	0.389	-0.274	-0.267	-0.067	-0.456
	p-value	(0.122)	(0.322)	(0.349)	(0.828)	(0.287)
	Adj. R2	0.812	0.780	0.810	0.786	0.197
ta_gdpquantile	Intercept	0.689**	-0.287	-0.362	-0.754**	-1.443***
	p-value	(0.028)	(0.190)	(0.160)	(0.011)	(0.005)
	Adj. R2	0.707	0.823	0.868	0.789	0.184
mcapquantile	Intercept	0.880***	-0.367	-0.390	-0.745**	-1.625***
	p-value	(0.002)	(0.142)	(0.163)	(0.017)	(0.001)
	Adj. R2	0.710	0.772	0.827	0.811	0.226
mcap_ctquantile	Intercept	0.501*	0.035	-0.228	-0.588*	-1.088**
	p-value	(0.085)	(0.907)	(0.343)	(0.063)	(0.023)
	Adj. R2	0.779	0.743	0.833	0.807	0.149
mcap_ct4quantile	Intercept	0.441*	-0.024	-0.397	-0.453	-0.894**
	p-value	(0.093)	(0.931)	(0.136)	(0.132)	(0.048)
	Adj. R2	0.792	0.744	0.837	0.813	0.166
bis_scquantile	Intercept	-0.214	-0.294	-0.298	-0.406	-0.193
	p-value	(0.636)	(0.172)	(0.274)	(0.176)	(0.739)
	Adj. R2	0.576	0.803	0.803	0.802	0.175

Table 5: **Pooled OLS regression Q1/1993 - Q2/2007**
The table displays the result from pooled OLS regressions of equity excess returns on size and bank-level characteristics. Size is measured in form of log market capitalization, log total assets, total assets/GDP, BIS score, the log transform of total assets/total assets in the banking sector, rank in the local banking sector or an orthogonalization thereof. Bank-level characteristics include betas on the market excess return β_i^{Market}, on the Spread of the equally-weighted average of bank stock returns over the market excess return β_i^{FmNF}, on the excess return of the respective sovereign yield and on the excess return of the 10y German government total return index over the risk-free rate β_{it}^{Term} as well as bank characteristic *Book-to-Market* and *ROE*. Betas are estimated simultaneously via rolling time-series regressions for daily data over the preceding year. Market Capitalization and Book-to-Market are orthogonalized via Gram-Schmidt orthogonalization method. Standard errors are Newey and West (1987)-adjusted for heteroskedasticity and autocorrelation.

VARIABLES	(1) Log TA orth	(2) TA/GDP orth	(3) TA/BS orth	(4) Rank orth	(5) BIS Score orth
Beta Market	0.875**	0.755*	0.841*	0.773*	0.030
	(0.035)	(0.077)	(0.056)	(0.065)	(0.959)
Beta Spread FmNF	-0.927*	-0.905	-1.003*	-0.934*	0.994
	(0.087)	(0.100)	(0.078)	(0.085)	(0.201)
Log Mcap Orth.	-0.787***	-0.602***	-0.552***	-0.630***	-0.448**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.032)
Book-to-Market Orth.	0.334**	0.594***	0.622***	0.613***	0.691***
	(0.042)	(0.001)	(0.001)	(0.001)	(0.003)
Log TA	-0.128*				
	(0.069)				
ROE	0.029	0.015	0.018	0.018	0.046*
	(0.127)	(0.422)	(0.357)	(0.331)	(0.094)
Beta Sov Yield over RF	0.189	0.206	0.205	0.209	-0.300
	(0.367)	(0.331)	(0.330)	(0.320)	(0.643)
TA/GDP		-0.496			
		(0.308)			
TA/BS			-1.500		
			(0.361)		
Dummy largest bank				-0.055	
				(0.866)	
Dummy 2nd largest bank				-0.056	
				(0.862)	
BIS Score					-0.003*
					(0.073)
Constant	1.686**	0.774**	0.730**	0.718**	-0.080
	(0.016)	(0.018)	(0.029)	(0.031)	(0.847)
Observations	6,464	6,464	6,464	6,514	2,080
Lags	4	4	4	4	4

pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: **Robustness Check under Gandhi and Lustig (2015)-specification: Intercept estimates for bin-specific time-series regressions for equally-weighted excess returns of European commercial banks (Q1/1996-Q2/2007)**

The table displays the intercept estimates of bin-specific OLS time series regressions for equally-weighted excess returns under all size specifications. Banks are sorted into bins according to total assets at the EU-level (*ta*), total assets per total assets in the banking sector (*ta_bs*), total assets at the country-level (*ta_ct*), total assets at the country-level, when only the largest bank is assigned to bin 4 (*ta_ct4*), total assets per domestic GDP (*ta_gdp*), market capitalization at the EU-level (*mcap*), market capitalization at the country-level (*mcap_ct*), and the BIS Score (*bis_sc*). Excess returns are regressed on the Fama and French (1993)-Factors, Market excess return *MktRF*, Small-minus-Big *SMB* and High-minus-Low *HML*, the excess return on a total return index for 10y German government bonds *Return German gov TRI spread* and the excess return of the average 10y government yield of countries in the sample. The column 'Long large, short small' is the excess return on a portfolio strategy going long the largest bin and short the smallest bin, respectively. P-values are displayed in brackets. *,**, and *** indicate significance at the 10%, 5% and 1%-significance level. Standard errors are Newey and West (1987)-adjusted for heteroskedasticity and autocorrelation.

Bin		**1**	**2**	**3**	**4**	**LMS**
taquantile	Intercept	1.320***	0.656*	0.575	0.226	-1.094***
	p-value	(0.002)	(0.067)	(0.120)	(0.594)	(0.008)
	Adj. R2	0.445	0.430	0.521	0.545	0.215
ta_bsquantile	Intercept	1.164***	0.473	0.496	0.652	-0.511
	p-value	(0.001)	(0.270)	(0.203)	(0.106)	(0.153)
	Adj. R2	0.447	0.456	0.497	0.534	0.157
ta_ctquantile	Intercept	1.131***	0.531	0.700	0.771	-0.360
	p-value	(0.003)	(0.158)	(0.116)	(0.118)	(0.335)
	Adj. R2	0.516	0.473	0.454	0.474	0.216
ta_ct4quantile	Intercept	1.103***	0.563	0.668	0.773	-0.329
	p-value	(0.003)	(0.154)	(0.153)	(0.101)	(0.357)
	Adj. R2	0.520	0.441	0.465	0.528	0.248
ta_gdpquantile	Intercept	1.184***	0.575	0.465	0.546	-0.638*
	p-value	(0.001)	(0.150)	(0.266)	(0.162)	(0.079)
	Adj. R2	0.447	0.455	0.498	0.571	0.210
mcapquantile	Intercept	1.436***	0.675*	0.432	0.168	-1.268***
	p-value	(0.000)	(0.062)	(0.271)	(0.687)	(0.001)
	Adj. R2	0.402	0.469	0.552	0.530	0.218
mcap_ctquantile	Intercept	1.200***	0.652*	0.654*	0.443	-0.757*
	p-value	(0.003)	(0.099)	(0.096)	(0.343)	(0.060)
	Adj. R2	0.473	0.491	0.489	0.474	0.159
mcap_ct4quantile	Intercept	1.133***	0.659*	0.538	0.532	-0.601
	p-value	(0.003)	(0.074)	(0.231)	(0.234)	(0.114)
	Adj. R2	0.479	0.476	0.499	0.506	0.180
bis_scquantile	Intercept	1.152***	0.584*	0.491	0.574	-0.578
	p-value	(0.007)	(0.094)	(0.270)	(0.205)	(0.120)
	Adj. R2	0.326	0.448	0.458	0.469	0.177

Table 7: **Results for non-financial firms: Fama-French Regressions**
The table shows results for Fama-French time-series regressions and cross-sectional regressions for non-financial firms. Panel A presents intercept estimates of bin-specific OLS regressions for equally-weighted excess returns of non-financial firms. Non-financial firms are sorted into bins according to breakpoints derived for banks at a yearly basis. Equally-weighted excess returns are regressed on the Fama and French (1993)-Factors, Market excess return *MktRF*, Small-minus-Big *SMB* and High-minus-Low *HML*. The column 'Long large, short small' is the excess return on a portfolio strategy going long the largest bin and short the smallest bin, respectively. P-values are displayed in brackets. *,**, and *** indicate significance at the 10%, 5% and 1%-significance level. Standard errors are Newey and West (1987)-adjusted for heteroskedasticity and autocorrelation. Panel B displays the result from pooled OLS regressions of equity excess returns of non-financial firms on size and firm-level characteristics. Size is measured in form of log market capitalization, log total assets, total assets/GDP or an orthogonalization thereof. Firm-level characteristics include betas on the market excess return β_i^{Market} and on the excess return of the respective sovereign yield as well as firm-specific *Book-to-Market* and *ROE*. Betas are estimated via rolling time-series regressions for daily data over the preceding year. Market Capitalization and Book-to-Market are orthogonalized via Gram-Schmidt orthogonalization method. Standard errors are Newey and West (1987)-adjusted for heteroskedasticity and autocorrelation.

Panel A

Bin		**1**	**2**	**3**	**4**	**LMS**
taquantile	Intercept	0.658**	0.436*	0.402*	0.417*	-0.241*
	p-value	(0.023)	(0.057)	(0.086)	(0.063)	(0.080)
	Adj. R2	0.579	0.618	0.592	0.601	0.621
ta_ctquantile	Intercept	0.637**	0.448*	0.367	0.457**	-0.179
	p-value	(0.024)	(0.056)	(0.121)	(0.040)	(0.224)
	Adj. R2	0.598	0.595	0.596	0.609	0.655
ta_ct4quantile	Intercept	0.534**	0.489**	0.402*	0.495*	-0.039
	p-value	(0.043)	(0.038)	(0.079)	(0.064)	(0.876)
	Adj. R2	0.608	0.601	0.595	0.562	0.407
ta_gdpquantile	Intercept	0.505**	0.387	0.544**	0.481**	-0.024
	p-value	(0.046)	(0.133)	(0.020)	(0.038)	(0.822)
	Adj. R2	0.606	0.588	0.600	0.594	0.642
mcapquantile	Intercept	0.672**	0.409*	0.469*	0.396*	-0.276*
	p-value	(0.014)	(0.096)	(0.051)	(0.089)	(0.074)
	Adj. R2	0.542	0.603	0.597	0.614	0.537
mcap_ctquantile	Intercept	0.615**	0.426*	0.451*	0.455**	-0.160
	p-value	(0.015)	(0.091)	(0.057)	(0.046)	(0.207)
	Adj. R2	0.564	0.599	0.597	0.621	0.612

Table 8: **Results for non-financial firms: Pooled OLS regressions**

Panel B

VARIABLES	(1) Log TA orth	(2) TA/GDP orth
Beta Market	-0.729**	-0.905***
	(0.017)	(0.003)
Log TA	0.138***	
	(0.000)	
Beta Sov Yield over RF	0.153	0.160
	(0.132)	(0.125)
Log Mcap Orth.	-0.545***	-0.030
	(0.000)	(0.538)
Book-to-Market Orth.	0.074	0.265***
	(0.175)	(0.000)
TA/GDP		2.517
		(0.260)
Constant	0.457***	1.370***
	(0.009)	(0.000)
Observations	115,629	115,629
Lags	4	4

pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: **Baseline specification: Bin-specific time-series regressions for equally-weighted excess returns of European commercial banks (Q1/1993-Q1/2010)**
The table displays the coefficient estimates of bin-specific OLS regressions for equally-weighted excess returns, when banks are sorted into bins **according to total assets at the EU-level**. Excess returns are regressed on the Fama and French (1993)-Factors, the Market excess return *MktRF*, Small-minus-Big *SMB* and High-minus-Low *HML*, as well as the excess return of a financial market index over the market index *FmNF*, the ROE-factor *FROE* and the excess return of the average 10y government yield of countries in the sample. *Dummy Financial Crisis* is a dummy variable taking value 1 in the period Q3/2007-Q1/2010 and 0 else. The column 'Long large, short small' is the excess return on a portfolio strategy going long the largest bin and short the smallest bin. P-values are displayed in brackets. *,**, and *** indicate significance at the 10%, 5% and 1%-significance level. Standard errors are Newey and West (1987)-adjusted for heteroskedasticity and autocorrelation.

Baseline regression (ta,Q1/1993-Q1/2010)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Bin 1	Bin 2	Bin 3	Bin 4	Long large short small
MktRF	0.866***	0.857***	1.138***	1.242***	0.376***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SMB	0.419***	-0.016	-0.252***	-0.570***	-0.989***
	(0.009)	(0.819)	(0.004)	(0.000)	(0.000)
HML	-0.131	0.022	0.240***	0.220**	0.351**
	(0.314)	(0.699)	(0.000)	(0.016)	(0.023)
ROE Factor	0.027	-0.111***	-0.055	0.045	0.018
	(0.751)	(0.000)	(0.249)	(0.497)	(0.896)
FmnF Factor	0.871***	0.872***	1.076***	1.238***	0.367**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.025)
Government Spread	-0.075	0.116	0.616***	0.994***	1.069**
	(0.809)	(0.377)	(0.001)	(0.001)	(0.030)
Dummy Financial Crisis	-0.456	-0.491	0.217	0.505	0.961
	(0.466)	(0.388)	(0.731)	(0.400)	(0.405)
Constant	0.831**	0.187	-0.438*	-1.126***	-1.957***
	(0.023)	(0.298)	(0.056)	(0.001)	(0.001)
Observations	207	207	207	207	207
Adj. R2	0.731	0.848	0.875	0.866	0.249
Avg. # Banks in bin	16	16	16	15	

pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10: **Evolution of portfolio investing 100 Euro at end-July 2007 in a Long Large, Short Small Portfolio**
The table shows the time series evolution of a portfolio strategy investing 100 Euro in a Large minus small portfolio in July 2007. Portfolio returns are calculated based on the simple ("Value") or hedged ("Hedged Value") strategy going long large banks and short small banks. Size is determined based on total assets (Total Assets) or market capitalization (Market cap).

Date	(1) **Value (Total Assets)**	(2) **Hedged Value (Total Assets)**	(3) **Value (Market cap)**	(4) **Hedge Value (Market cap)**
Jul-07	100.00	100.00	100.00	100.00
Aug-07	99.98	97.47	99.99	98.31
Sep-07	100.00	99.00	100.01	99.07
Oct-07	99.98	96.41	100.00	97.05
Nov-07	100.00	98.17	100.04	99.58
Dec-07	99.98	97.04	100.01	98.74
Jan-08	100.00	104.71	100.01	104.65
Feb-08	99.96	104.33	99.96	103.46
Mar-08	99.98	109.38	100.00	110.67
Apr-08	100.02	111.44	100.06	113.78
May-08	99.96	107.00	100.00	109.06
Jun-08	99.93	110.57	99.97	113.66
Jul-08	99.99	117.76	100.02	119.54
Aug-08	99.99	117.30	100.00	117.28
Sep-08	99.96	120.69	99.97	121.72
Oct-08	99.85	111.73	99.84	109.83
Nov-08	99.85	117.31	99.84	114.27
Dec-08	99.75	104.89	99.74	101.13
Jan-09	99.55	91.40	99.58	92.75
Feb-09	99.41	86.23	99.44	87.11
Mar-09	99.63	98.89	99.59	93.45
Apr-09	99.81	109.44	99.76	104.70
May-09	99.73	99.72	99.68	94.43
Jun-09	99.71	102.65	99.68	97.86
Jul-09	99.85	109.48	99.78	101.03
Aug-09	99.95	115.23	99.79	101.85
Sep-09	99.96	117.93	99.75	99.69
Oct-09	99.90	116.07	99.70	97.92
Nov-09	99.90	117.10	99.72	99.13
Dec-09	99.91	116.33	99.71	97.61
Jan-10	99.88	120.39	99.66	100.52
Feb-10	99.90	125.53	99.67	103.30
Mar-10	99.95	124.46	99.74	105.18

Appendix

Table A1: **BIS Score approximation**
The table displays the calculation of BIS Scores according to the official methodology (Basel Committee on Banking Supervision, 2011, 2013) in column 1, 2 and 3 as well as approximations used in this paper. For each indicator, the score for a given bank is calculated by dividing the individual bank amount by the aggregate amount summed across all banks in the sample for the given indicator. The score is then weighted by the indicator weighting within each category. Then, all the weighted scores are added.

Category (overall weight)	**Individual indicator**	**Weight**	**Proxy**	**Weight**
Cross-jurisdictional activity (20%)	Cross-jurisdictional claims	10%	Proxied by foreign subsidiaries	30%
	Cross-jurisdictional liabilities	10%		
Size (20%)	Total exposures (cf. (Basel Committee on Banking Supervision 2013))	20%	Total Assets (Bankscope)	30%
Interconnectedness (20%)	Intra-financial system assets	6.67%	Loans and advances to banks (Bankscope)	10%
	Intra-financial system liabilities	6.67%	Deposits from Banks (Bankscope)	10%
	Securities outstanding = total value of debt and equity securities	6.67%	Securities Outstanding (Bankscope)	10%
Substitutability/ financial institution infrastructure (20%)	Assets under custody	6.67%	Not sufficient data coverage	0%
	Payments activity	6.67%	No BankScope correspondance	0%
	Underwritten transactions in debt and equity markets	6.67%	No BankScope correspondance	0%
Complexity (20%)	Notional amount of over-the-counter (OTC) derivatives	6.67%	No BankScope correspondance	0%
	Level 3 assets	6.67%	Not sufficient data coverage in BankScope	0%
	Trading and available-for-sale securities	6.67%	Trading and AfS Securities (Bankscope)	10%

Table A2: **Correlation table for bin assignment**
The table displays the correlation between being assigned to a certain bin under different systemic risk measures.

	Mcap	Mcap (ctry)	TA	TA (ctry)	TA/BS	TA/GDP	BIS Score	BIS Score (ctry)
Mcap	1							
Mcap (country-level)	0.73	1						
Total Assets	0.87	0.68	1					
Total Assets (country-level)	0.69	0.87	0.74	1				
TA/Banking Sector	0.69	0.67	0.73	0.71	1			
TA/GDP	0.75	0.67	0.8	0.72	0.91	1		
BIS Score	0.73	0.6	0.77	0.62	0.41	0.56	1	
BIS Score (country-level)	0.54	0.73	0.6	0.78	0.63	0.61	0.65	1

Table A3: **Average bin assignment, when banks are ranked at EU-level according to total assets**

The table displays the bin a bank is on average assigned to during the period 1993-2016, when banks are sorted into bins according to total assets at the EU-level. Banks that were supported by a recapitalizaton in the 2007-2016 period are in bold.

Bin 1	**Bin 2**	**Bin 3**	**Bin 4**
bks bank (AT)	oldenburgische landesbank (DE)	**erste group bank** (AT)	**kbc group** (BE)
comdirect bank (DE)	jyske bank (DK)	**raiffeisen bank international** (AT)	**commerzbank** (DE)
dab bank (DE)	sydbank (DK)	**aareal bank** (DE)	deutsche bank (DE)
merkur bank (DE)	**banco de valencia** (ES)	**deutsche pfandbriefbank** (DE)	danske bank (DK)
umweltbank (DE)	bankinter (ES)	landesbank bl.holding (DE)	banco santander (ES)
djurslands bank (DK)	bolsas y mercados espanoles (ES)	banco de sabadell (ES)	**bankia** (ES)
gronlandsbanken (DK)	**credit agr.ile de france** (FR)	banco espanol de credito (ES)	bbv.argentaria (ES)
hvidbjerg bank (DK)	**credit agricole brie picardie** (FR)	banco popular espanol (ES)	**caixabank** (ES)
jutlander bank (DK)	paragon group of cos (GB)	**liberbank** (ES)	**bnp paribas** (FR)
kreditbanken (DK)	tullett prebon (GB)	icap (GB)	cic (FR)
lollands bank (DK)	**agri.bank of greece** (GR)	standard chartered (GB)	**credit agricole** (FR)
ringkjobing landbobank (DK)	emporiki bank of greece (GR)	**alpha bank** (GR)	natixis (FR)
salling bank (DK)	**tt hellenic postbank** (GR)	**eurobank ergasias** (GR)	**societe generale** (FR)
skjern bank (DK)	banca carige (IT)	**national bank of greece** (GR)	barclays (GB)
spar nord bank (DK)	banca piccolo crdt. valtell (IT)	**bank of ireland** (IE)	hbos (GB)
totalbanken (DK)	banca popolare di sondrio (IT)	**permanent tsb** (IE)	hsbc holding (GB)
vestjysk bank (DK)	banco di sardegna rsp (IT)	Banco di Desio e della Brianza (IT)	**lloyds banking group** (GB)
aldermore group (GB)	credito bergamasco (IT)	banca nazionale lavoro (IT)	**royal bank of scotland group** (GB)
arbuthnot banking group (GB)	credito emiliano (IT)	**banca popolare di milano** (IT)	**depfa bank** (IE)
bgeo group holding (GB)	finecobank spa (IT)	**banca popolare emilia romagna** (IT)	intesa sanpaolo (IT)
brewin dolphin (GB)	mediobanca bc.fin (IT)	**banco popolare** (IT)	unicredit (IT)
close brothers group (GB)	van lanschot (NL)	unione di banche italian (IT)	**abn amro group** (NL)
evolution group (GB)	**banco bpi** (PT)	**banco comr.portugues** (PT)	nordea bank (SE)
shawbrook group (GB)		**banco espirito santo** (PT)	
attica bank (GR)		seb (SE)	
bank of piraeus (GR)		svenska handbanken (SE)	
banca finnat euramerica (IT)		swedbank (SE)	
banca generali (IT)			
banca intermobiliare (IT)			
banca popolare etruria lazio (IT)			
banca profilo (IT)			
bnc.di desio e della brianza (IT)			
credito artigiano (IT)			
avanza bank holding (SE)			
hq (SE)			
nordnet (SE)			

Table A4: **Robustness Check with Liquidity factor: Intercept estimates for bin-specific time-series regressions for equally-weighted excess returns of European commercial banks (Q1/1996-Q2/2007)**

The table displays the intercept estimates of bin-specific OLS regressions for equally-weighted excess returns under all size specifications. Banks are sorted into bins according to total assets at the EU-level (*ta*), total assets per total assets in the banking sector (*ta_bs*), total assets at the country-level (*ta_ct*), total assets at the country-level, when only the largest bank is assigned to bin 4 (*ta_ct4*), total assets per domestic GDP (*ta_gdp*), market capitalization at the EU-level (*mcap*), market capitalization at the country-level (*mcap_ct*), and the BIS Score (*bis_sc*). Excess returns are regressed on the Fama and French (1993)-Factors, Market excess return *MktRF*, Small-minus-Big *SMB* and High-minus-Low *HML*, as well as the excess return of a financial market index over the market index *FmNF* the ROE-factor *FROE* and the excess return of the average 10y government yield of countries in the sample as well as the Pástor and Stambaugh (2003) liquidity factor. The column 'Long large, short small' is the excess return on a portfolio strategy going long the largest bin and short the smallest bin, respectively. P-values are displayed in brackets. *,**, and *** indicate significance at the 10%, 5% and 1%-significance level. Standard errors are Newey and West (1987)-adjusted for heteroskedasticity and autocorrelation.

	lvg	**banking sector MtB**	**LtD Ratio**	**Pastor-Stambaugh**	**BAB**
	LMS	LMS	LMS	LMS	LMS
taquantile	-1.038**	-1.726***	-1.471**	-1.708***	-1.168*
	(0.020)	(0.002)	(0.011)	(0.003)	(0.090)
	0.449	0.182	0.287	0.149	0.195
ta_bsquantile	-0.824*	-1.280***	-1.395***	-1.162**	-1.394**
	(0.057)	(0.009)	(0.005)	(0.019)	(0.014)
	0.319	0.190	0.207	0.189	0.184
ta_ctquantile	-0.203	-0.617	-0.454	-0.538	-0.497
	(0.606)	(0.159)	(0.276)	(0.242)	(0.341)
	0.375	0.245	0.293	0.189	0.226
ta_ct4quantile	-0.127	-0.457	-0.446	-0.361	-0.171
	(0.753)	(0.286)	(0.306)	(0.421)	(0.734)
	0.296	0.194	0.192	0.158	0.201
ta_gdpquantile	-0.852*	-1.439***	-1.393***	-1.391***	-1.324**
	(0.066)	(0.006)	(0.008)	(0.006)	(0.019)
	0.400	0.186	0.184	0.165	0.180
mcapquantile	-1.119**	-1.618***	-1.373***	-1.602***	-0.869*
	(0.013)	(0.002)	(0.003)	(0.002)	(0.095)
	0.388	0.245	0.348	0.180	0.264
mcap_ctquantile	-0.607	-1.093**	-0.897**	-1.056**	-0.818
	(0.151)	(0.024)	(0.038)	(0.035)	(0.125)
	0.339	0.157	0.237	0.089	0.151
bis_scquantile	0.096	-0.183	0.177	-0.123	1.006
	(0.849)	(0.751)	(0.735)	(0.846)	(0.123)
	0.213	0.206	0.388	0.130	0.257