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Discussion Paper Series nr: 14-03

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# Measuring too-big-to-fail funding advantages from small banks' CDS spreads

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March 2014

**Abstract**

Large banks derive a funding advantage from being too-big-to-fail, while small banks do not. To estimate the funding advantage we explain the CDS spreads of small banks in six major European countries during the crisis by market fundamentals and bank-specific characteristics. Next, we extrapolate and predict the CDS spreads of large banks. The difference between the predicted and the observed spread is then interpreted as the funding advantage and amounts to 67 basis points for large banks and 121 for GSIFIs.

**Keywords**: Too big to fail, credit default swaps, bank funding, costs of crisis

**JEL classification**: G01, G21, G24, G28, H12

**Acknowledgements**
We would like to thank Ferry Haaijen for assistance in compiling the dataset and Remco Mocking and Skander Van den Heuvel for useful suggestions. Naturally, all mistakes are ours. The data used is proprietary and cannot be shared, but program files are available upon request.

# 1 Introduction

The financial crisis has refueled the discussion on the possible misallocation of resources in the economy caused by too-big-to-fail (TBTF) banks. Lenders to large institutions know that they are likely to receive a bail-out and will therefore demand a lower risk premium from these institutions. Because society covers the losses of such banks whenever operations turn out badly, these institutions have little incentive to make a welfare-optimal trade-off between risk and return and as a result take on too much risk (Altunbas et al., 2011) or strive to increase in size in order to become TBTF (Brewer and Jagtiani, 2009).

A potential solution to this problem may lie in tougher regulation and more supervision for larger banks: globally systemically important financial institutions (GSIFI) are obliged to have a higher leverage ratio and are subject to a stricter and more frequent supervision. An alternative solution, which goes back to Pigou, calls for a tax on banks related to the benefits they exact from society by being TBTF. We propose a method to calculate the funding advantage that banks derive from being TBTF and do so for a sample of large European banks. In our method the TBTF advantage evolves over time. This allows for an assessment of the effectiveness of tougher regulation in pushing back the TBTF advantage, or alternatively may also help in setting the right Pigouvian tax.

Using market fundamentals and bank characteristics, we explain the CDS spreads of small banks, which we assume not to be TBTF, and use the estimated coefficients to predict CDS spreads for larger banks, which are TBTF. Subsequently, we subtract the actual from the predicted CDS spreads for large banks and identify the difference as the advantage large banks derive from being TBTF (henceforth: TBTF advantage). We use bank-specific characteristics together with market fundamentals to explain and predict CDS spreads.

This study belongs to the strand of literature that quantifies the TBTF advantage for banks from CDS spreads. Using CDS data has two main advantages. First, unlike credit rating uplifts[5], CDS data reflect default risk much more accurately. Second, differences in liquidity, important for bond yield estimates[6], are less of an issue for CDS models (Kroszner, 2013).

We extend the literature in several ways. First, we focus on banks in France, Germany, Italy, the Netherlands, Spain and the United Kingdom, whereas most of the literature focuses on US institutions (Tsessmelidakis and Merton, 2012). Second, while most previous studies focus on the period prior to the financial crisis (Völz and Wedow, 2011), we study the period from 2008 to 2011. This is relevant, as the advantage banks derive from being too-big-to-fail is largest when it matters most: during a crisis. Third, previous studies concentrated primarily on GSIFIs and neglected the TBTF subsidies for large banks which do not qualify as such (Li et al., 2011). We estimate the TBTF advantage for both groups. Fourth, our estimation

[5] For studies using credit uplifts, see Bijlsma and Mocking (2012), Ueda and Weber di Mauro (2012), Haldane (2010), Haldane (2012), Noss and Sowerbutts (2012) and Schich and Lindh (2012)
[6] For studies using bond spreads, see Acharya et al. (2013) and Stogin et al. (2013)

method does not rely on a structural pricing model to predict CDS spreads, as in Li et al. (2011) and Tsessmelidakis and Merton (2012), but is fully empirical.

Our results show a robust average TBTF advantage of 67 basis points (bp) for the sample of large banks from 2008 till 2011. Further, we find that the largest banks in the sample, the GSIFIs, have a TBTF advantage which is on average another 54bp higher than the rest of the large banks. These results are in line with empirical work by Acharya et al. (2013), who use bond spreads and find a TBTF advantage for GSIFIs of up to 120bp in 2009, and Bijlsma and Mocking (2012), who combine bond spreads with credit ratings and find a TBTF advantage for European banks ranging between 10bp in early 2008 and 100bp in 2011. Results using structural pricing equations vary widely: Li et al. (2011) and Tsessmelidakis and Merton (2012), who estimate a pricing equation for CDS spreads and find TBTF advantages of respectively 50bp for US and European banks and 200-350bp for US financial institutions. The latter two papers are closest to ours as they use CDS spreads as well, they however use structural models to predict from fundamentals what the CDS price should be, whereas we extrapolate from small banks.

This paper is organized as follows. Section 2 discusses our methodology and Section 3 describes the data. In Section 4 we summarize the results, followed by a discussion of their robustness in Section 5. Section 6 examines the day-to-day evolution of the TBTF advantage and links it to recent events and Section 7 concludes.

# 2 Methodology

We explain the CDS spreads of small banks, which we assume not to be TBTF, from market fundamentals and bank characteristics and use the estimated coefficients to predict CDS spreads for larger banks, which are TBTF. Since governments help out institutions that are systemically important within their jurisdiction (Acharya et al., 2013; Eising and Lemke, 2011), we use the size of the bank relative to GDP, rather than its absolute size, to determine whether a bank is small.

Our main challenge here is to explain the CDS spreads of banks sufficiently well. For this, we follow Kroszner (2013) and take bank specific characteristics and correct for effects of size that are unrelated to the TBTF advantage into account. We do not take liquidity into account; as we are working with CDS data instead of bond data, liquidity is less of an issue. Furthermore, following the literature on explaining CDS spreads we add market-based next to accounting-based variables as such a hybrid model explains most of the variation (Das et al., 2009; Otker-Robe and Podpiera, 2010).

Thus, our regression equation for the CDS spreads of small European banks has the following form:

$$CDS_{it} = \beta_0 + \beta_1 X_t + \beta_2 Y_{it} + \varepsilon_{it}, \qquad (1)$$

where $CDS_{it}$ refers to the CDS spread of bank i at time t, $X_t$ refers to market fundamentals at time t, and $Y_{it}$ denotes bank i's balance sheet characteristics at time t. Our main regression is estimated using a pooled OLS, to capture the between-bank heterogeneity. Standard errors are corrected for heteroskedasticity and autocorrelation.

In the set of market fundamentals we include sovereign risk, implied market volatility and the European financial sector equity index. Higher sovereign risk premia indicate funding difficulties for the sovereign. First, a financially strained government's ability to bail-out its banks is limited. Even though small banks will not be bailed out, an insolvent sovereign increases the probability of a banking, sovereign or currency crisis, which has severe negative effects for small banks as well. Second, the value of government bond holdings decreases whenever sovereign risk premia increase. This negatively impacts the balance sheets of banks. We thus expect sovereign risk to affect bank CDS spreads positively.

The implied market volatility measures general uncertainty in the market. Ericsson et al. (2009) provides evidence in support of market volatility as a determinant of CDS spreads. We expect the bank risk premia to increase with market volatility. Contagion and spillover effects are important in the banking sector and according to Zhang et al. (2005) they can be captured using an equity index. The financial sector equity index captures the condition of the financial industry and since it is highly correlated with the general stock index ($\rho$=0.84), it also proxies the general market conditions. We expect that a positive change in this variable will result in lower CDS spreads.

In addition, bank-specific characteristics play a key role in driving CDS spreads. The vector of bank characteristics consists of the leverage ratio, the non-performing loans ratio, bank non-interest cost efficiency and change in adjusted assets. The leverage ratio accounts for capital adequacy. We expect higher capital adequacy to have a negative effect on bank risk. Aunon-Nerin et al. (2002) and Ericsson et al. (2009) find evidence that bank leverage has significant explanatory power – a higher leverage ratio is associated with lower risk.

The non-performing loans ratio gives the proportion of loans that is non-performing and proxies bank health and asset quality. The higher the ratio, the higher the bank risk. Chiaramonte and Casu (2013) examine the effect of balance sheet characteristics on CDS spreads in the periods before, during and after the financial crisis, and find that loan-loss reserve to gross loans is the only significant variable in all three periods.

The cost ratio is given by the bank's operating cost relative to its size and is used in many studies as a measure for bank operating efficiency (Allen et al., 2006; Demirguç-Kunt and Levine, 2011; Demirguç-Kunt and Huizinga, 2011; Baselga-Pascual et al., 2013). When banks increase in size towards their optimal level, they realize economies of scale which come from higher efficiency and reduction in the operating costs. This variable captures to some extent these economies of scale while at the same time it is not influenced by the TBTF advantage that comes with larger size. This is because the TBTF advantage is observed mainly in reduction of the bank funding costs. We expect a positive size.

The change in adjusted assets measures size variation within banks over time and serves as a proxy for risky behavior. Banks may engage in risky investments in order to increase their size or for short-term gains. During the crisis however many banks decided to downsize and reduce their exposure to risky assets in response to the high market uncertainty. Therefore, a positive sign of the variable is expected.

Under the assumption that large banks enjoy TBTF advantage while small ones do not, we predict the size of the CDS spreads of large banks if implicit guarantees were absent. The out-of-sample predictions are obtained through extrapolation:

$$CDS(predicted)_{jt} = \widehat{\beta_0} + \widehat{\beta_1}X_t + \widehat{\beta_2}Y_{jt}, \quad (2)$$

where a hat denotes the estimated coefficient from equation (1).

Then, we subtract the actual CDS spreads of the big banks, including the TBTF advantage, from the predicted value, without the TBTF advantage, and interpret the difference between the two as the TBTF advantage

$$\Delta CDS_{jt} = CDS(predicted)_{jt} - CDS_{jt}. \quad (3)$$

A positive difference implies that large banks pay a lower risk premium on their funding than they would, if they would not have had implicit government guarantees.

Note that, unlike Das et al. (2009) and Otker-Robe and Podpiera (2010), we do not include a distance to default measure based on stock volatility as this variable is influenced by banks' TBTF status and might therefore generate biased results for the TBTF advantage. This is in line with Tsesmelidakis and Merton (2013), who argue that the value of the equity of large banks is positively affected by their TBTF status. This comes from the lower debt interest rate paid by these banks at the time of issuance which leads to a higher return on equity and consequently to a higher equity value.

# 3 Data description

The analysis concentrates on European banks from six countries (France, Germany, Italy, the Netherlands, Spain and the United Kingdom) and covers the period from 2008 to 2011. The sample consists of 54 banks in total which we divide in 3 groups. The 25 banks whose assets to GDP ratio is up to 10% are defined as small. Following the FSB, we categorize 13 banks as globally systemically important financial institutions (GSIFI). The remaining 16 banks in our sample, which are larger than 10% of GDP but are not GSIFIs, are labeled large. Appendix 1 contains a list of the banks in each category with their total asset size, in billions and relative to domestic GDP, and their average CDS spread over the period. We will vary the definition of a small bank in robustness checks.

Bank risk is captured by the 5-year mid-quote CDS spread on senior bonds from Markit with daily frequency. Here mid-quote reflects the average of the bid and ask prices and 5-year is both the most liquid and the benchmark maturity in the market. Similarly, sovereign risk is measured by the senior 5-year mid-quote government CDS spread. The log of the implied volatility index (VIX) accounts for market volatility and the log of the EU 600 Banks equity index proxies for the condition of the European financial industry. Both variables are obtained from Datastream and have daily frequency. Additionally, in the robustness check we will use the logarithm of US dollar/Euro exchange rate and the European iTraxx CDS index, both measured in basis points on a daily basis from Datastream.

The bank specific characteristics - leverage ratio, bad loans ratio, cost ratio and change in assets - are from Bankscope and have a yearly frequency. The leverage ratio is defined as Tier 1 capital (equity plus reserves minus intangible assets) divided by total assets, the bad loans ratio as the reserves for impaired loans relative to gross loans, the cost ratio as overhead (non-interest expenses) divided by total assets and the change in assets (Δ assets) is the change in percent of adjusted assets (total minus intangibles). Additionally, in the robustness checks we will use the liquidity ratio and the return on assets. The liquidity ratio is given by liquid assets over short-term funding and return on assets is net income over adjusted assets.

And finally, in additional robustness checks, we use three country-specific macroeconomic variables: the government gross debt as a percentage of GDP (debt), the government surplus to GDP ratio and the GDP growth rate, all obtained from Eurostat with an annual frequency. Table 1 summarizes all the variables, Table 2 provides summary statistics for the bank specific variables, Table 3 for the country-specific variables and Table 4 for the market fundamentals that are neither country nor bank specific.

Note that while the financial market variables are available with a daily frequency, the macroeconomic and bank-specific variables have annual frequency. For the analysis of our main results, we use averages of the daily variables to avoid autocorrelation in the error terms. This procedure may lead to time inconsistency as the annual data, which is mostly end-of-period balance sheet data, is then used to explain the over-the-year-averaged daily observations. To mitigate this, we construct the daily averages from the observations of the last quarter of each year only.

**Table 1:** Variable description and data source

| Variable | Description | Source |
|---|---|---|
| **bank risk** | 5-year bank CDS spread (bp) | Markit |
| **financial equity index** | EU 600 bank stock price index (logarithm x 100) | Datastream |
| **VIX** | implied volatility (logarithm x 100) | Datastream |
| **sovereign risk** | 5-year sovereign CDS spread (bp) | Markit |
| **cost ratio** | overhead/adjusted assets (%) | Bankscope |
| **Δ assets** | yearly change in adjusted assets (%) | Bankscope |
| **bad loans ratio** | loan loss reserve /gross loans (%) | Bankscope |
| **leverage ratio** | Tier 1 capital / total assets (%) | Bankscope |
| **liquidity ratio** | liquid assets / deposits short-term funding (%) | Bankscope |
| **ROA** | net income /adjusted assets (%) | Bankscope |
| **Δ equity** | yearly change in equity (%) | Bankscope |
| **$/€ rate** | exchange rate (logarithm x 100) | Datastream |
| **iTraxx** | EU CDS iTraxx index (bp) | Datastream |
| **Debt** | government debt (% of GDP) | Eurostat |
| **surplus** | government surplus (% of GDP) | Eurostat |
| **Δ GDP** | yearly change in GDP (%) | Eurostat |
| **1/assets** | 1/total assets (bln) | Bankscope |

**Table 2:** Summary statistics bank-specific variables

| Variable | All banks | Small banks | Large banks | GSIFIs |
|---|---|---|---|---|
| **bank CDS spread** | 208 | 259 | 188 | 152 |
| | (191) | (250) | (143) | (94) |
| **bank assets/GDP ratio (%)** | 31.2 | 5.1 | 26.2 | 79.6 |
| | (37.4) | (2.8) | (24.3) | (34.7) |
| **bank adjusted assets (bln)** | 472 | 90.3 | 348 | 1250 |
| | (540) | (6.42) | (159) | (502) |
| **cost ratio** | 1.2 | 1.3 | 1.1 | 1.3 |
| | (0.6) | (0.7) | (0.5) | (0.4) |
| **Δ adjusted assets** | 3.7 | 3.7 | 2.1 | 5.9 |
| | (20.8) | (27.6) | (11.4) | (18.0) |
| **bad loans ratio** | 2.3 | 2.2 | 2.3 | 2.5 |
| | (1.5) | (1.5) | (1.6) | (1.3) |
| **leverage ratio** | 4.1 | 4.5 | 4.0 | 3.6 |
| | (1.7) | (1.9) | (1.7) | (1.4) |
| **liquidity ratio** | 41.6 | 34.2 | 40.8 | 54.5 |
| | (33.3) | (35.9) | (27.4) | (33.0) |
| **ROA** | 0.09 | -0.02 | 0.10 | 0.23 |
| | (0.68) | (0.88) | (0. 54) | (0. 38) |
| **Δ equity** | 16.5 | 14.5 | 21.4 | 13.3 |
| | (77.2) | (54.3) | (114.0) | (40.1) |
| **1/assets** | 0.011 | 0.022 | 0.004 | 0.001 |
| | (0.020) | (0.026) | (0.003) | (0.0004) |

Note: Mean values on top and standard deviations in parenthesis below

**Table 3:** Summary statistics country-specific variables

| Variable | France | Germany | Italy | Netherlands | Spain | United Kingdom |
|---|---|---|---|---|---|---|
| **sovereign risk** | 69 | 36 | 192 | 53 | 174 | 73 |
| | (44) | (14) | (131) | (25) | (97) | (13) |
| **debt** | 80 | 76 | 115 | 62 | 56 | 70 |
| | (6.8) | (6.0) | (5.5) | (2.7) | (11.4) | (12.3) |
| **surplus** | -5.8 | -2.1 | -4.0 | -3.8 | -8.7 | -8.5 |
| | (1.7) | (1.7) | (1.0) | (2.3) | (2.5) | (2.5) |
| **Δ GDP** | 1.5 | 1.7 | 0.2 | 1.0 | 0.2 | -3.6 |
| | (2.4) | (3.7) | (2.6) | (3.2) | (2.9) | (9.4) |

Note: Mean values on top and standard deviations in parenthesis below

**Table 4:** Summary statistics market fundamentals

| Variable | |
|---|---|
| **financial equity index** | 521 |
| | (20) |
| **VIX** | 351 |
| | (35) |
| **$/€ rate** | 31.8 |
| | (4.3) |
| **iTraxx** | 132 |
| | (40) |

Note: Mean values on top and standard deviations in parenthesis below

# 4 Results

Table 5 shows the regression in equation (1) for banks that have assets over GDP ratios up to 7%, 10%, 15% and 20% respectively. The highlighted column shows our preferred specification (10%). The financial equity index, sovereign risk, the change in assets and the leverage ratio turn out to be significant. The VIX, the cost ratio and the bad loans ratio are not individually statistically significant. In all cases we observe joint significance of the explanatory variables.

An increase in the index indicates general improvement of the condition of the financial sector in Europe and thus reduces individual bank risk through contagion and spillover effects. A 1% increase in the index leads to a reduction of bank risk with 1.49bp on average. The size of the effect increases if we increase the cut-off for small banks.

Sovereign risk has a statistically significant effect on bank risk: for small banks an increase in sovereign risk with 1bp results in an equal change of bank risk. The size of the coefficient does not change substantially as we increase the size of the banks in the sample. This implies that bank risk exposure to sovereign risk does not vary with size of the bank. These results are in line with the findings of Alter and Schuler (2012) and Demirgüç-Kunt and Huizinga (2011).

The change in assets is significant as well, but only when the cut-off level is at 10% assets over GDP. Below that level, a 1% decrease in assets over GDP will lower bank risk by 0.71bp. The sign implies that banks that reduce their size have lower CDS spreads. This is the case when banks facing severe risks scale back in response. See Demirgüç-Kunt and Huizinga (2011) for a discussion.

Finally, the leverage ratio negatively affects bank risk: a 1%-point increase in the leverage ratio yields a 25bp lower bank CDS spread. This implies that banks with higher Tier 1 capital relative to their assets are considered less risky. The effect is relatively stable. A similar relationship between bank risk and leverage ratio has been reported by Annaert et al. (2013) and Ericsson et al. (2009).

The $R^2$ of the regressions varies around 40%. A direct comparison with previous papers is obscured by differences in the sample, data frequency, variable choice and methodology. Das et al. (2009), who use a combination of balance-sheet and market variables to explain bank CDS spreads, but focus on the pre-crisis period, find $R^2$ of around 60%. Chiaramonte and Casu (2013), who use only balance sheet data with a quarterly frequency, show an $R^2$ of around 60% pre- and post-crisis and 49% during the crisis. It turns out, 2008 is characterized by unprecedented volatility which causes bank CDS spreads to be driven by market sentiments instead of fundamentals. For comparative purposes, we re-estimate our main specification excluding 2008 and find an $R^2$ of 63% (results in Appendix 5, column 9).

**Table 5**: Regression results, dependent variable: CDS spread of small banks

| | **assets/GDP ≤7%** | **assets/GDP ≤10%** | **assets/GDP ≤15%** | **assets/GDP ≤20%** |
|---|---|---|---|---|
| **fin. equity index** | -1.23 | -1.49** | -1.74*** | -1.87*** |
| | (0.73) | (0.65) | (0.55) | (0.56) |
| **VIX** | 0.052 | 0.02 | -0.03 | -0.17 |
| | (0.74) | (0.58) | (0.45) | (0.39) |
| **sovereign risk** | 1.087*** | 1.073*** | 1.022*** | 1.104*** |
| | (0.37) | (0.34) | (0.34) | (0.34) |
| **cost ratio** | 5.016 | 4.669 | -3.217 | -9.697 |
| | (34.5) | (32.2) | (28.8) | (27.0) |
| **Δ assets** | 0.659*** | 0.712*** | 0.515 | 0.495 |
| | (0.17) | (0.19) | (0.38) | (0.37) |
| **bad loans ratio** | 24.53 | 24.26 | 13.55 | 9.207 |
| | (19.7) | (18.8) | (17.0) | (16.4) |
| **leverage ratio** | -24.01* | -24.77** | -20.04** | -20.03** |
| | (11.6) | (10.4) | (9.24) | (8.79) |
| **constant** | 820.5 | 960.9** | 1102.0*** | 1236.1*** |
| | (535.9) | (426.6) | (359.9) | (367.6) |
| *N* | 63 | 79 | 106 | 119 |
| *# banks* | 22 | 25 | 32 | 36 |
| $R^2$ | 0.308 | 0.394 | 0.401 | 0.412 |
| adj. $R^2$ | 0.220 | 0.335 | 0.358 | 0.375 |
| F | 5.199 | 6.996 | 7.317 | 8.132 |

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

From the highlighted column in Table 5 we predict the CDS spreads of large banks using equation (2) and subtract the observed CDS spread to obtain the TBTF advantage. Table 6 shows the average TBTF advantage. The GSIFIs enjoy a TBTF advantage from 156 bp in 2008 to 109 bp in 2011 while for the large banks it remains relatively constant of around 70bp. On average GSIFIs receive a TBTF advantage that is 50bp larger than the one for large banks.

**Table 6:** Average TBTF advantage in bp

| Year | GSIFIs | Large Banks |
|---|---|---|
| **2008** | 156 | 74 |
| **2009** | 104 | 64 |
| **2010** | 114 | 72 |
| **2011** | 109 | 55 |
| **Mean** | 121 | 67 |

Appendix 2 presents the TBTF advantage for each bank in the group of the GSIFIs. The table shows that on average all banks receive a TBTF advantage ranging from 62bp for the Dutch ING to more than 190bp for the Italian UniCredit. For most banks the TBTF advantage remains relatively constant throughout the period, even though decreases occur as well. The decrease is most substantial for Lloyds and Commerzbank. These banks were forced by their governments to downsize and to reduce their international exposure in exchange for government aid. As a result, the Financial Stability Board (FSB) removed them from the list of GSIFIs in 2012. UniCredit exhibited the highest TBTF advantage throughout the period.

# 5 Robustness

This section presents the robustness checks on our results. We examine the robustness of our results from four different perspectives - estimation procedure, sample selection, model specification and time consistency. We conclude that our results are robust and show limited sensitivity to changes in the model specification and estimation. Further, the robustness checks show that the variation in bank CDS spreads is mostly explained by bank-specific characteristics while market variables capture time-specific effects.

## 5.1 Estimation procedure

In order to find the correct estimation procedure, we apply two econometric tests. First, we use the Hausman test to see whether random or fixed effects specification is more efficient. The result shows that at 5% confidence level a random effects specification is preferred ($p > \chi^2 = 0.06$). Second, we conduct Hausman-Wu test for endogeneity to determine whether a pooled OLS or a random effects specification is justifiable. Except for the VIX, the variables are strictly exogenous. A random effects model can lead to biased and inconsistent estimators if strict exogeneity does not hold for all predictors. Therefore, we proceed with pooled OLS estimation under the assumption of contemporaneous exogeneity.

For comparison however, we also estimated the model with a fixed and random effects specification. The results of the regressions are presented in Appendix 3, Table A3.1a and their extrapolation results are shown in Table 7. In a correctly specified model, random effects and pooled OLS should lead to similar results – this is also the case here. Despite some differences, all three models show evidence in support of the existence of TBTF advantage for both group of banks. Again, the TBTF advantage is larger for GSIFIs.

Next we add yearly dummies to account for time-fixed effects. Since our market variables vary only through time but not cross-sectionally, they become redundant when we add time-fixed effects. The regression outcome, available in Appendix 3, Table A3.1a is very similar to the pooled OLS estimation. The estimates of the TBTF advantages is almost identical to the ones from the preferred specification. This shows that the variation in bank CDS spreads is driven by the bank-specific variables while the market variables control for time effects.

Further, to verify that we are not discarding relevant information by averaging the daily data, we apply a 2-step approach to estimate the regression coefficients. First, we regress daily bank CDS spreads on daily market fundamentals. Second, we regress the last-quarter averages of the residuals on the bank specific characteristics with yearly frequency. We use the coefficients derived from the two steps to estimate the TBTF advantage. The results of the regressions are presented in Appendix 3, Table A3.1b and the results of the extrapolations are available in Table 5. The estimates are in line with the main specification.

**Table 7:** Average TBTF advantage in bp, estimation procedure

| Model | Estimation procedure | GSIFIs | Large Banks |
|---|---|---|---|
| **1** | Pooled OLS | 121 | 67 |
| **2** | FE | 71 | 25 |
| **3** | RE | 95 | 48 |
| **4** | time FE | 120 | 67 |
| **5** | 2-Step | 109 | 54 |

## 5.2 Sample selection

We also check if our results are sensitive to sample selection. We re-estimate our model using 2 types of cut-off criteria - relative and absolute bank size. For the first type we choose four options – assets/GDP ratio of up to 7%, 10%, 15% and 20%. The regression estimations were already presented and discussed in Section 3, Table 3, and we saw that the coefficients remained stable with the change of the specification. For the second type there are also three categories – assets < 100 bln, assets < 200 bln and assets < 300 bln. The regression results are available in Appendix 3, Table A3.2. The coefficient estimates are in line with the main specification. Further, Table 8 summarizes the TBTF advantage for GSIFIs and large banks for all specifications. The large banks TBTF advantage remains stable at around 70 bp, whereas the GSIFI TBTF advantage declines as the cut-off level increases.

Also, we check if our results are robust if we use smaller time span of the crises. We exclude 2008 from our analysis. The regression output is presented in Appendix 3, Table A3.2. The estimates are similar to the extended time-period specification. The $R^2$ of the regression shows that the explanatory power of the model is substantially higher when 2008 is not included.

**Table 8:** Average TBTF advantage in bp, sample selection

| Model | Selection criterion | # banks | GSIFIs | Large Banks |
|---|---|---|---|---|
| **1** | assets/GDP ≤ 7% | 22 | 130 | 73 |
| **2** | assets/GDP ≤ 10% | 25 | 121 | 67 |
| **3** | assets/GDP ≤ 15% | 32 | 98 | 62 |
| **4** | assets/GDP ≤ 20% | 36 | 89 | 62 |
| **5** | assets < 100bln | 18 | 191 | 130 |
| **6** | assets < 200bln | 25 | 135 | 89 |
| **7** | assets < 300bln | 31 | 98 | 55 |
| **8** | excl. 2008 | 25 | 137 | 84 |

## 5.3 Additional variables

Next, we deviate from our main specification by adding additional explanatory variables. We present the regression results in Appendix 3, Table A3.3 and the resulting TBTF advantage in Table 9.

First, we add four bank specific variables. Following Chiaranonte and Casu (2013), we add the liquidity ratio and return on assets. Also, we add change in equity. We expect that an increase in these variables will reduce bank CDS spreads. These variables do not have a statistically significant effect on bank risk and the average TBTF advantages are similar to our main specification. In addition, the convex relationship between CDS spreads and bank size in our sample (see Figure A3.1 in Appendix 3) may partly be due to economies of scale that arise if large banks are better diversified. To capture this effect, we include 1/ total assets.[7] The variable is significant at 10% level of significance and has a positive effect on CDS spreads, which implies that when banks increase in size, their CDS spreads decrease. The estimated TBTF advantages for GSIFIs are nevertheless in line with previous results.

Next, we proceed by adding two variables that capture market fundamentals: the dollar-euro exchange rate and the European non-financial corporate iTraxx CDS index. Appreciation of the euro signifies improvement in the economic performance and confidence in Europe and reduces bank risk. The same is true for the reduction in corporate non-financial risk measured by the iTraxx CDS index. These variables do not have a statistically significant effect on bank risk and the average TBTF advantages are similar to our main specification.

Further, we add three variables that capture country specific fundamentals: government debt as a percentage of GDP, the government surplus and the change in GDP. An increase in debt is associated with lower ability of the sovereign to bail-out troubled banks. Here, however the variable is significant and has a negative sign (see Appendix 3, Table A3.3). This

[7] Including the level of assets in the regression will lead to negative predicted CDS spreads for the largest banks.

result could be driven by banks which, in response to the high government debt, lower their risk profiles by increasing the amount of equity they hold. Next, the increase of government surplus and the GDP are signals for growth and economic improvement and are expected to reduce bank risk. These variables do not have a statistically significant effect on bank risk. The average TBTF advantages derived from the three regressions are similar to our main specification.

**Table 9:** Average TBTF advantage in bp, variable selection

| Model | Variable added | GSIFIs | Large Banks |
|---|---|---|---|
| **1** | Liquidity | 100 | 62 |
| **2** | ROA | 102 | 60 |
| **3** | Δ equity | 118 | 69 |
| **4** | 1/assets | 105 | 51 |
| **5** | $/€ rate | 120 | 67 |
| **6** | iTraxx | 121 | 67 |
| **7** | Debt | 128 | 80 |
| **8** | Surplus | 128 | 70 |
| **9** | Δ GDP | 122 | 67 |

## 5.4 Time matching

In our main specification, we average the daily financial variables (bank risk, sovereign risk, etc.) over the last quarter of the year and use these side-by-side in our regression with end-of-year balance sheet variables. Especially for the dependent variable, there may be a time mismatch, as the balance sheet variables are not known yet. In the fourth quarter, however, the market may have quite accurate expectations of year-end balance sheet variables.

To assess whether this is an issue, we use averages of bank risk, the financial equity index, the VIX and sovereign risk over other quarters (Q3, Q4, Q1 next year, Q2 next year) and over the entire year and reestimate our model. The regression outputs are in Appendix 3, Table A3.4 and the results from the TBTF advantage estimates are presented in Table 10. The results in all cases remain stable.

**Table 10:** Average TBTF advantage in bp, time selection

| Model | Quarter | GSIFIs | Large Banks |
|---|---|---|---|
| **1** | Q1 next year | 145 | 83 |
| **2** | Q2 next year | 114 | 70 |
| **3** | Q3 same year | 97 | 75 |
| **4** | Q4 same year | 121 | 67 |
| **5** | Q1-Q4 same year | 100 | 75 |

## 5.5 Combined robustness

In general, our results are robust against the variations considered above and vary to a limited extent across the different specifications. Here, we combine the robustness checks of the previous subsections in all possible ways by picking randomly a specification, the sample selection and the set of explanatory variables. In addition, we leave out a small and a big bank in every draw to see whether our results are driven by outliers[8]. After making this choice we explain the small bank CDS spreads using the chosen specification, sample and set of variables and use the coefficients to calculate the TBTF advantage.

We repeat this process 10,000 times and plot the average TBTF advantage in a histogram in Figure 1. We see that our estimates are consistent. The TBTF advantage for the large banks is slightly over 60bp on average while for GSIFIs it is around 100bp and shown in Table 11.

**Figure 1:** TBTF Advantage in bp, Monte Carlo simulation

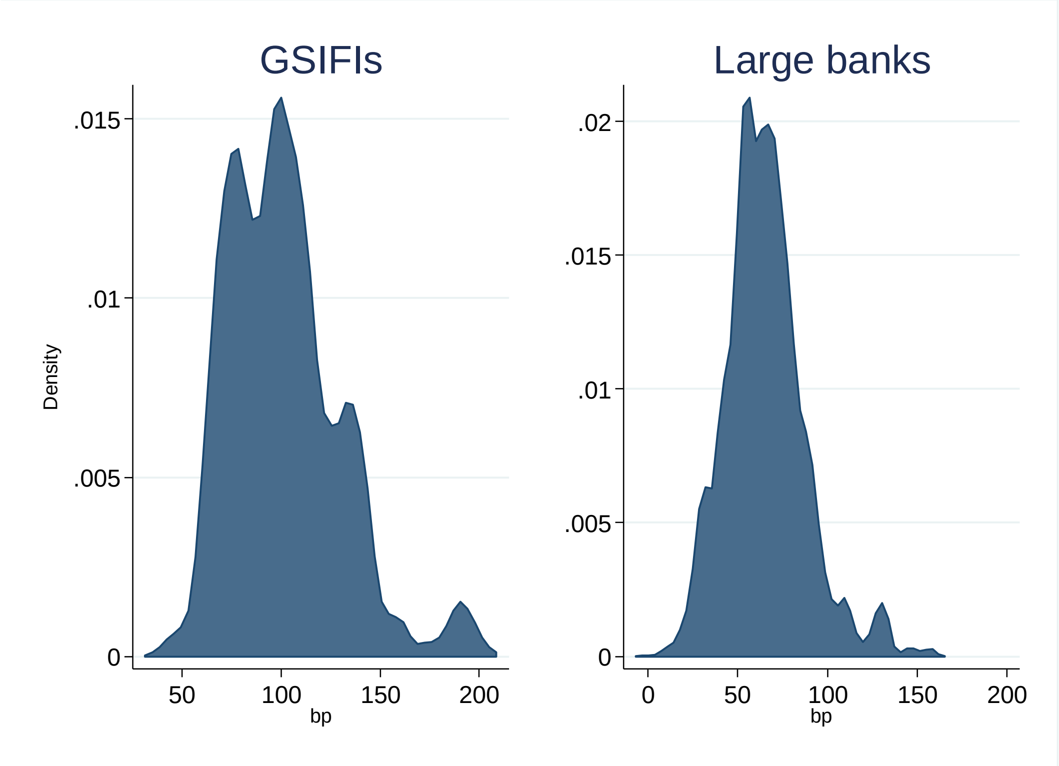


**Table 11:** TBTF advantage in bp, Monte Carlo simulation

| | GSIFIs | Large Banks |
|---|---|---|
| **mean** | 101 | 65 |
| **standard deviation** | 28 | 22 |
| **90% CI** | 64-147 | 30-106 |

# 6 Day-to-day TBTF advantage

To assess the stability of our results within the year and provide insight into how the TBTF advantage evolves over time, we extrapolate our estimations that explain bank risk in the

[8] The options include random versus pooled OLS specification as well as all the options listed in tables 8, 9 and 10.

last quarter of every year in two ways. First, we extrapolate to a daily frequency. For this we use the coefficients estimated on the annual sample and apply these on the financial variables with a daily frequency (the financial equity index, the VIX and the sovereign risk). Second, we extend this extrapolation outside the last quarter of the year and span the entire year.

Figure 2 shows the actual and the predicted CDS spreads for banks with an assets/GDP ratio up to 10%. It turns out that within the last quarter, the match of the predicted CDS spread with the actual spread is quite good. Outside of the last quarter, the match is good for the variation of the spread, however the prediction of the level of the average spread is less good, and especially so for the first three quarters of 2008. This indicates that there are time-fixed effects which we have corrected the predictions in Figure 2 for by using quarterly dummies.

**Figure 2**: Actual vs predicted CDS spreads (banks with asset/GDP≤10%)

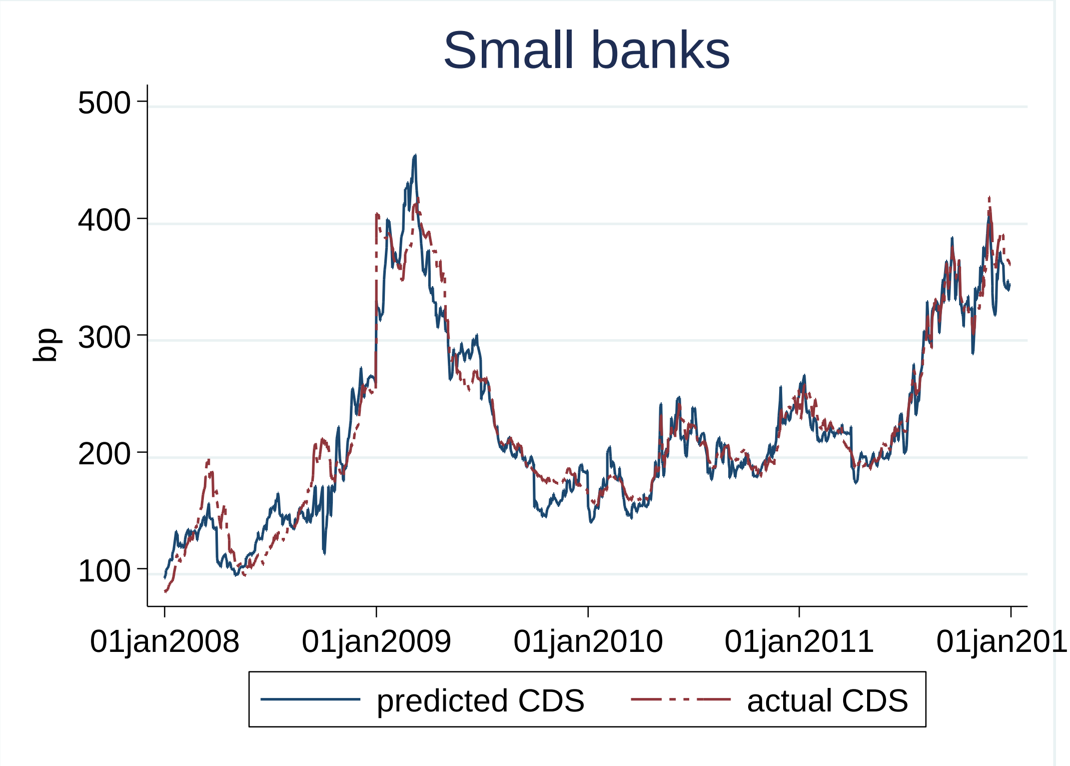


Figure 3 presents the mean daily TBTF advantage for large banks and GSIFIs. The predicted CDS include the quarterly dummies from Figure 2.[9] First, the average the TBTF advantage remains positive throughout the entire period. There are two moments in this period in which the TBTF advantage for both groups of banks becomes very low. The first one is in March 2008 when Bear Sterns suffered a bank run and the second is in September 2008 when Lehman Brothers filed for bankruptcy. Both events led to substantial uncertainty regarding the TBTF status of large financial institutions. Swiftly however, governments provided financial support for the banks, which reduced uncertainty and lead to an in the

[9] We are interested in the difference between the actual and predicted CDS spread for large banks, so when we correct the predictions for the small banks for time fixed effects we have to correct the predictions for the large banks.

increase in the size of the TBTF advantage in the months that followed. Second, we see that there is a persistent difference in the TBTF advantage between GSIFIs and large banks in favor of the GSIFIs.

To interpret these results, we conduct a regression of the daily TBTF advantage of GSIFIs and large banks on the daily logarithm of the VIX, the sovereign risk, the quadratic term of the sovereign risk and the bank spread. The results are presented in Table 12 and show positive correlation between the TBTF advantage and the VIX and negative correlation with the bank CDS spread. The effect of the sovereign risk on the TBTF advantage follows an inverted U-shape. This shows that above certain level of sovereign risk, the state can no longer provide guarantees for the banking sector. The inverse relation between the bank spread and the TBTF advantage shows that when bank CDS spreads decrease, the TBTF advantage increases. This effect is likely driven by the private-to-public risk transfer mechanism, particularly for banks which enjoy strong implicit or explicit government guarantees. The results are similar for both groups of banks.

**Figure 3:** Day-to-day TBTF advantage

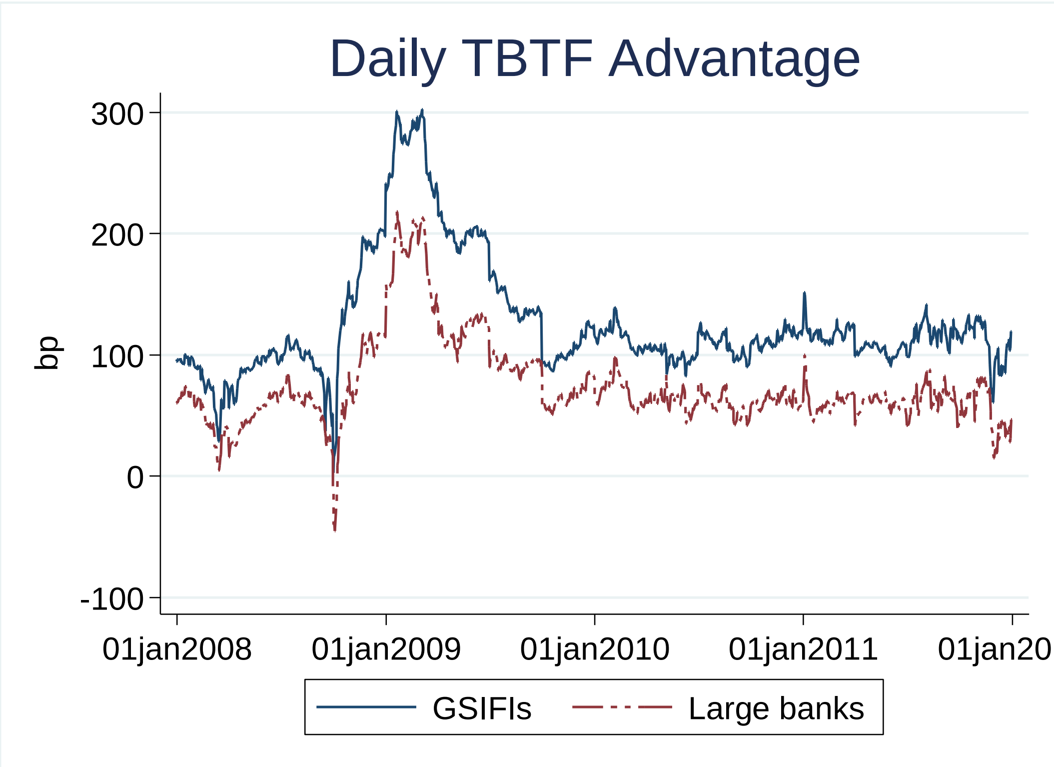

**Table 12:** Explaining the TBTF advantage

| | **GSIFIs** | **Large banks** |
|---|---|---|
| **VIX** | 1.290*** | 1.162*** |
| | (0.11) | (0.18) |
| **sovereign risk** | 0.809** | 1.061*** |
| | (0.27) | (0.35) |
| **sovereign risk^2** | -0.0000265 | -0.000216 |
| | (0.00042) | (0.00060) |
| **bank risk** | -0.798*** | -0.874*** |
| | (0.092) | (0.078) |
| **constant** | -255.2*** | -243.3*** |
| | (27.1) | (41.8) |
| *N* | 10166 | 12299 |
| $R^2$ | 0.531 | 0.669 |
| adj. $R^2$ | 0.531 | 0.668 |
| F | 143.8 | 60.58 |

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

# 7 Discussion and conclusion

We find that big banks have enjoyed an advantage from being TBTF from 2008 till 2011. The GSIFIs banks enjoy a funding advantage of on average 121bp, while the other large banks enjoy a funding advantage of 67bp. This advantage is relatively constant from the end of 2009 onward. In 2008 the TBTF advantage became almost zero during the Bear Stern bank run and the Lehman bankruptcy, while increasing sharply when government rescue schemes were put in place.

Our results are in line with previous studies which also measure the TBTF funding advantage (Li et al., 2011; Bijlsma and Mocking, 2012; Acharya et al., 2013). Due to differences in specifications, samples of years and banks and measurements of bank risk, it is difficult to compare results directly. The only exception to some extent is the research conducted by Li et al. (2011) as they use a similar approach based on CDS spreads. They find a TBTF premium of 50bp on average for the GSIFIs relative to all other banks in the post crisis period in Europe. This result is close to our estimate of average 54bp TBTF advantage for the GSIFIs over large banks in our sample of six European countries in the period 2008-2011.

A rough but simple method to assess the market value of the TBTF advantage in euro terms is to multiply the TBTF advantage by the uninsured fraction of the outstanding bank liabilities. Assuming that the proportion of insured debt is 30%, the average amount of uninsured liabilities per bank is 847bln euro for GSIFIs and 232bln euro for the large banks. This implies that the average yearly TBTF advantage per bank in euro terms is 10.2bln for GSIFIs and 1.6bln for the large banks in the period 2008-2011[10].

Our findings show that implicit government guarantees lead to a substantial funding advantage for large financial institutions. Although policy makers have recently undertaken several measures to tackle this issue, the problem continues to exist. Our analysis provides a way to measure the progress in reducing the TBTF advantage. An important challenge for policymakers is to reduce the TBTF advantage for large banks while at the same time stimulating banks to provide credit in an efficient and stable way.

[10] This estimate is based on the 5-year CDS spread. For a normal yield curve the advantage is overstated if the liabilities have a shorter maturity and understated if the liabilities have a longer maturity.

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## Appendix 1 Bank characteristics

**Table A1.1:** Bank characteristics per bank

| category | country | bank | assets (€ bln) | assets/GDP (%) | CDS (bp) |
|---|---|---|---|---|---|
| **GSIFI** | France | BNP Paribas | 1993 | 103 | 142 |
| | France | Crédit Agricole | 1604 | 83 | 165 |
| | France | Société Générale | 1104 | 57 | 187 |
| | Germany | Commerzbank | 750 | 30 | 149 |
| | Germany | Deutsche Bank | 1843 | 74 | 129 |
| | Italy | UniCredit | 906 | 58 | 249 |
| | Netherlands | ING | 923 | 157 | 135 |
| | Spain | Santander | 1166 | 111 | 208 |
| | Spain | BBVA | 553 | 52 | 219 |
| | United Kingdom | Barclays | 1712 | 102 | 137 |
| | United Kingdom | HSBC | 910 | 54 | 93 |
| | United Kingdom | Lloyds | 997 | 59 | 207 |
| | United Kingdom | Royal Bank of Scotland | 1567 | 93 | 174 |
| **large** | France | BFCM | 388 | 20 | 152 |
| | France | Dexia | 361 | 19 | 396 |
| | France | DZ Bank | 392 | 16 | 122 |
| | France | Natixis | 468 | 24 | 183 |
| | Germany | Bayerische Landesbank | 321 | 13 | 169 |
| | Germany | LBBW | 386 | 16 | 169 |
| | Italy | MPS | 231 | 15 | 278 |
| | Italy | Intesa | 619 | 40 | 216 |
| | Netherlands | ABN AMRO | 390 | 66 | 156 |
| | Netherlands | Rabobank | 660 | 112 | 86 |
| | Netherlands | SNS Real | 80 | 14 | 247 |
| | Spain | BANESTO | 118 | 11 | 117 |
| | Spain | CIC | 237 | 12 | 118 |
| | Spain | Banco Popular | 129 | 12 | 429 |
| | Spain | LA CAIXA | 275 | 26 | 204 |
| | United Kingdom | NatWest | 420 | 25 | 218 |
| | United Kingdom | Nationwide Building Society | 216 | 13 | 147 |
| | United Kingdom | Standard Chartered | 379 | 22 | 110 |
| **small** | France | LCL | 111 | 6 | 166 |
| | Germany | Bremer Landesbank | 34 | 1 | 150 |
| | Germany | Co-operative Bank | 55 | 3 | 273 |
| | Germany | Deutsche Postbank | 209 | 8 | 135 |
| | Germany | HSH Nordbank | 154 | 6 | 205 |
| | Germany | IKB Deutsche Industriebank | 33 | 1 | 390 |
| | Germany | Landesbank Berlin | 134 | 5 | 157 |
| | Germany | Helaba | 167 | 7 | 167 |
| | Germany | LBBW | 60 | 2 | 55 |
| | Germany | NORD/LB | 231 | 9 | 161 |
| | Italy | Banca Italease | 13 | 1 | 247 |
| | Italy | BPM | 49 | 3 | 252 |
| | Italy | Mediobanca | 75 | 5 | 97 |
| | Netherlands | AEGON | 7 | 1 | 186 |
| | Netherlands | NIBC Bank | 29 | 5 | 267 |
| | Spain | Banco de Sabadell | 93 | 9 | 421 |

| | | | | | |
|---|---|---|---|---|---|
| | Spain | Banco Popolare | 131 | 8 | 355 |
| **small** | Spain | Bankinter | 56 | 5 | 403 |
| | Spain | CAM | 75 | 7 | 457 |
| | Spain | Novacaixa Galicia | 73 | 7 | 404 |
| | United Kingdom | Northern Rock | 81 | 5 | 282 |
| | United Kingdom | Skipton | 17 | 1 | 196 |
| | United Kingdom | Yorkshire Building Society | 33 | 2 | 178 |

## Appendix 2 TBTF Advantage per bank

**Table A2.1: TBTF Advantage per GSIFI (bp)**

| country | bank | 2008 | 2009 | 2010 | 2011 | mean |
|---|---|---|---|---|---|---|
| **France** | BNP Paribas | 208 | 129 | 143 | 125 | 151 |
| **France** | Crédit Agricole | 200 | 124 | 140 | 178 | 160 |
| **France** | Société Générale | 136 | 86 | 122 | 66 | 103 |
| **Germany** | Commerzbank | 121 | 131 | 67 | 6 | 81 |
| **Germany** | Deutsche Bank | 113 | 73 | 109 | 88 | 96 |
| **Italy** | UniCredit | 220 | 158 | 185 | 213 | 194 |
| **Netherlands** | ING | 102 | 55 | 27 | 64 | 62 |
| **Spain** | BBVA | 144 | 84 | 106 | 155 | 122 |
| **Spain** | Santander | 123 | 91 | 152 | 171 | 134 |
| **United Kingdom** | Barclays | 147 | 98 | 122 | 99 | 116 |
| **United Kingdom** | HSBC | 192 | 131 | 141 | 163 | 157 |
| **United Kingdom** | Lloyds | 167 | 137 | 97 | -29 | 93 |
| **United Kingdom** | Royal Bank of Scotland | 151 | 54 | 71 | 115 | 98 |

## Appendix 3 Robustness

**Table A3.1a**: Regression results, different specifications

| | Pooled OLS | FE | RE | Time FE |
|---|---|---|---|---|
| **fin. equity index** | -1.49** | 0.21 | -0.73 | - |
| | (0.65) | (0.97) | (0.66) | |
| **VIX** | 0.02 | 0.13 | 0.26 | - |
| | (0.58) | (0.55) | (0.63) | |
| **sovereign risk** | 1.073*** | 2.192*** | 1.489*** | 1.086*** |
| | (0.34) | (0.31) | (0.22) | (0.35) |
| **cost ratio** | 4.669 | 195.0 | 26.78 | 4.333 |
| | (32.2) | (158.0) | (50.9) | (32.5) |
| **Δ assets** | 0.712*** | 0.794*** | 0.563*** | 0.669*** |
| | (0.19) | (0.26) | (0.12) | (0.21) |
| **bad loans ratio** | 24.26 | -74.26*** | 0.505 | 23.73 |
| | (18.8) | (21.1) | (12.0) | (19.6) |
| **leverage ratio** | -24.77** | 18.31 | -14.03 | -24.96** |
| | (10.4) | (15.1) | (8.87) | (10.4) |
| **constant** | 960.9** | -272.2 | 410.1 | 243.8*** |
| | (426.6) | (861.1) | (555.6) | (44.3) |
| *N* | 79 | 79 | 79 | 79 |
| $R^2$ | 0.394 | 0.734[1] | 0.6450[1] | 0.396 |
| F | 6.996 | 74.38 | | 5.923 |
| Wald chi2(7) | | | 101.40 | |

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, [1] within $R^2$

**Table A3.1b**: Regression results, different specifications

| | Step 1 | Step 2 | Main specification |
|---|---|---|---|
| **fin. equity index** | -0.202 | | -1.49** |
| | (0.43) | | (0.65) |
| **VIX** | 1.555** | | 0.02 |
| | (0.66) | | (0.58) |
| **sovereign risk** | 0.695** | | 1.073*** |
| | (0.26) | | (0.34) |
| **cost ratio** | | 12.01 | 4.669 |
| | | (24.8) | (32.2) |
| **Δ assets** | | 0.586** | 0.712*** |
| | | (0.28) | (0.19) |
| **bad loans ratio** | | 21.18 | 24.26 |
| | | (13.6) | (18.8) |
| **leverage ratio** | | -18.13 | -24.77** |
| | | (11.6) | (10.4) |
| **constant** | -226.4 | -23.20 | 960.9** |
| | (365.3) | (33.4) | (426.6) |
| *N* | 28238 | 91 | 79 |
| $R^2$ | 0.131 | 0.064 | 0.394 |
| adj. $R^2$ | 0.131 | 0.021 | 0.335 |
| F | 26.35 | 1.848 | 6.996 |

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

**Table A3.2**: Regression results, different selection criteria

| | assets < 100bln | assets < 200bln | assets < 300bln | excl. 2008 |
|---|---|---|---|---|
| **fin. equity index** | -1.05 | -1.48** | -1.624*** | -0.27 |
| | (1.17) | (0.68) | (0.57) | (1.03) |
| **VIX** | 0.74 | 0.26 | 0.04 | 0.95 |
| | (0.99) | (0.63) | (0.43) | (0.99) |
| **sovereign risk** | 1.152*** | 1.105*** | 0.982*** | 1.297*** |
| | (0.34) | (0.34) | (0.32) | (0.26) |
| **cost ratio** | 19.50 | 10.96 | -1.812 | -8.299 |
| | (42.4) | (33.9) | (27.5) | (25.7) |
| **Δ assets** | 0.593** | 0.773*** | 0.553 | 0.635** |
| | (0.21) | (0.23) | (0.37) | (0.24) |
| **bad loans ratio** | 31.44 | 21.84 | 14.44 | 10.87 |
| | (20.7) | (17.7) | (17.0) | (11.9) |
| **leverage ratio** | -41.83*** | -30.94** | -22.20** | -32.24** |
| | (12.6) | (11.5) | (9.00) | (13.1) |
| **constant** | 565.8 | 903.6* | 1035.4*** | 75.74 |
| | (834.9) | (490.3) | (359.4) | (840.5) |
| $N$ | 53 | 80 | 105 | 61 |
| $R^2$ | 0.446 | 0.411 | 0.386 | 0.626 |
| adj. $R^2$ | 0.359 | 0.354 | 0.341 | 0.577 |
| F | 7.392 | 7.249 | 6.577 | 11.57 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Table A3.1a: Regression results, different specification robustness

**Table A3.3:** Regression results, different variables selection

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| **fin. equity index** | -1.57*** | -1.439** | -1.37* | -1.285* | -1.63** | -1.66 | -2.24*** | -1.73** | -1.73** |
| | (0.55) | (0.63) | (0.71) | (0.64) | (0.69) | (1.86) | (0.68) | (0.66) | (0.74) |
| **VIX** | 0.04 | -0.03 | 0.04 | 0.204 | 0.11 | | -0.51 | 0.25 | -0.02 |
| | (0.60) | (0.57) | (0.58) | (0.66) | (0.48) | | (0.48) | (0.58) | (0.62) |
| **sovereign risk** | 1.017*** | 1.036*** | 1.125*** | 1.141*** | 1.081*** | 1.069*** | 1.048*** | 0.964*** | 1.048*** |
| | (0.33) | (0.35) | (0.34) | (0.30) | (0.35) | (0.34) | (0.34) | (0.28) | (0.33) |
| **liquidity** | -0.828** | | | | | | | | |
| | (0.38) | | | | | | | | |
| **cost ratio** | -12.54 | 0.994 | 8.554 | 4.420 | 4.495 | 4.845 | 18.80 | 3.202 | 5.438 |
| | (31.2) | (28.4) | (33.7) | (30.4) | (32.6) | (32.1) | (30.4) | (32.9) | (32.0) |
| **Δ assets** | 0.567** | 0.755*** | | 0.783*** | 0.679*** | 0.710*** | 0.734*** | 0.627*** | 0.653*** |
| | (22.3) | (0.17) | | (0.20) | (0.21) | (0.19) | (0.17) | (0.22) | (0.22) |
| **bad loans ratio** | 25.95 | 17.71 | 18.74 | 31.00 | 23.86 | 24.18 | 35.78* | 27.13 | 24.54 |
| | (18.8) | (15.1) | (19.1) | (21.2) | (19.6) | (19.2) | (18.9) | (18.8) | (18.9) |
| **leverage ratio** | -23.57** | -18.56* | -25.72** | -30.16** | -24.92** | -24.86** | -15.44 | -24.56** | -24.33** |
| | (10.4) | (10.5) | (11.5) | (11.0) | (10.4) | (10.3) | (10.2) | (10.3) | (10.6) |
| **ROA** | | -44.51 | | | | | | | |
| | | (32.2) | | | | | | | |
| **Δ equity** | | | 0.22 | | | | | | |
| | | | (0.30) | | | | | | |
| **1/assets** | | | | 1120.2* | | | | | |
| | | | | (611.0) | | | | | |
| **$/€ rate** | | | | | 1.856 | | | | |
| | | | | | (3.53) | | | | |
| **iTraxx** | | | | | | -0.0810 | | | |
| | | | | | | (1.19) | | | |
| **debt** | | | | | | | -3.015*** | | |
| | | | | | | | (1.01) | | |
| **surplus** | | | | | | | | -5.728 | |
| | | | | | | | | (5.34) | |
| **Δ GDP** | | | | | | | | | -1.65 |
| | | | | | | | | | (1.83) |
| **constant** | 1041.3** | 945.7** | 895.1* | 769.9 | 944.0** | 1068.0 | 1690.9*** | 981.2** | 1100.1** |
| | (374.3) | (444.5) | (441.7) | (472.4) | (420.5) | (1120.2) | (380.4) | (422.7) | (508.7) |
| *N* | 79 | 79 | 79 | 79 | 79 | 79 | 79 | 79 | 79 |
| $R^2$ | 0.417 | 0.420 | 0.388 | 0.418 | 0.395 | 0.394 | 0.465 | 0.401 | 0.396 |
| adj. $R^2$ | 0.350 | 0.354 | 0.327 | 0.351 | 0.326 | 0.335 | 0.404 | 0.332 | 0.327 |
| F | 5.772 | 13.58 | 6.233 | 7.008 | 6.060 | 7.028 | 15.99 | 6.726 | 6.451 |

1. **liquidity**
2. **ROA**
3. **Δ equity**
4. **1/assets**
5. **$/€ rate**
6. **iTraxx**
7. **debt**
8. **surplus**
9. **Δ GDP**

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

**Table A3.4:** Regression results, different time selection

| | 1st quarter next year | 2nd quarter next year | 3rd quarter same year | 4th quarter same year | all quarters included |
|---|---|---|---|---|---|
| **fin. equity index** | -13.05** | -3.030* | 1.221 | -1.489** | -1.179* |
| | (5.93) | (1.49) | (1.12) | (0.65) | (0.61) |
| **VIX** | -9.942** | -0.431 | 3.582* | 0.02 | 2.693* |
| | (4.03) | (0.40) | (2.04) | (0.58) | (1.50) |
| **sovereign risk** | 0.401 | 0.823 | 1.104*** | 1.073*** | 0.851* |
| | (0.89) | (0.53) | (0.33) | (0.34) | (0.45) |
| **cost ratio** | 23.66 | 18.28 | -1.217 | 4.669 | -11.06 |
| | (38.9) | (29.0) | (28.2) | (32.2) | (35.9) |
| **Δ assets** | 0.649** | 0.355 | 0.613** | 0.712*** | 0.332 |
| | (0.27) | (0.23) | (0.28) | (0.19) | (0.42) |
| **bad loans ratio** | 30.18 | 22.85 | 26.36 | 24.26 | 33.16 |
| | (26.1) | (20.5) | (17.1) | (18.8) | (20.7) |
| **leverage ratio** | -18.61 | -21.69* | -20.57 | -24.77** | -12.70 |
| | (11.6) | (11.1) | (12.3) | (10.4) | (15.8) |
| **constant** | 10278.1** | 1906.4** | -1685.4 | 960.9** | -130.0 |
| | (4430.4) | (756.1) | (1255.3) | (426.6) | (533.4) |
| *N* | 54 | 54 | 79 | 79 | 79 |
| *# banks* | 21 | 21 | 25 | 25 | 25 |
| $R^2$ | 0.147 | 0.207 | 0.420 | 0.394 | 0.283 |
| adj. $R^2$ | 0.017 | 0.087 | 0.361 | 0.335 | 0.212 |
| F | 2.364 | 2.378 | 7.554 | 6.996 | 11.53 |

**Figure A3.1:** Bank CDS spreads and total assets