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Bank structural reform study: Supplementary report 1

Is there an implicit subsidy for EU banks?

November 2014

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1. Summary

PwC have been commissioned by the Association for Financial Markets in Europe (AFME) to undertake a study on the impact of structural reform in the EU banking sector. During the global financial crisis, substantial amounts of public financial support were provided to financial institutions at risk of failure in order to prevent contagion and damage to the functioning of the wider economy. Financial regulators have subsequently defined those banks who pose a systemic risks or were considered Too Big To Fail (TBTF), or Too Important To Fail (TITF) as Globally Systemically Important banks (G-SIBs). The impact of being TBTF on banks' behaviours and potential uncompetitive advantages compared to smaller banks has been a topic of research and discussion since the global financial crisis. Most of this reseach has concentrated on whether G-SIBs benefit from funding advantages, as a consequence of this implicit guarantee.

This Supplementary Report analyses the existence and magnitude of any implicit subsidy for EU banks. Such analysis is required to assess the need for, and benefits of, further reform of the EU banking sector. It also allows a retrospective assessment of any benefits that may already have been achieved through various regulatory reforms.

Focus of this study

When analysing the value of implicit subsidies our focus has been twofold:

- firstly, developing a methodology that improves upon some of the approaches used in previous studies (particularly in the context of previous studies in the EU); and
- secondly, to use this methodology to provide an up to date assessment of the implicit subsidy that might currently exist to the benefit of EU banks, particularly given the progress of regulatory reforms over recent years.

Approaches used to assess implicit subsidies

There have been a substantial number of studies which estimate the value of implicit subsidies using a range of different approaches. There is significant variation in the estimates produced across these studies, depending on the methodology used, the time period considered and the geographical focus (US, EU etc.). The most commonly used approaches focus on cost of funding analysis using econometric techniques and credit ratings analysis.

Econometric analysis has often been used in studies valuing implicit subsidies involving US financial institutions, for example GAO (2014)[1] and Oliver Wyman (2014)[2]. This approach assesses the drivers of bank funding costs and hence isolates the impact of systemic importance on funding costs. A key challenge associated with using econometric analysis is access to good quality detailed financial market data, which is particularly difficult for EU banks compared to the US[3]. There is also a need to ensure that the parameters are correctly specified and the econometric model is robust and passes key regression specification tests.

A credit ratings based approach has often been used in the EU context, for example OECD (2012)[4], IMF (2014)[5] and EC (2014)[6], although a number of studies in the US have also used this approach. This approach relies on

1 'Large Bank Holding Companies: Expectation of Government Support', GAO-14-631.

2 'Do Bond Spreads Show Evidence of Too Big to Fail Effects', Oliver Wyman, available at SSRN 2422769.

3 Systems such as TRACE (Trade Reporting and Compliance Engine) in the US, make over the counter secondary market information more transparent compared to the EU.

4 Schich and Lindh, 'Implicit Guarantees for Bank Debt: Where do we stand?', OECD journal: Financial Market Trends, Vol. 2012, Issue 1.

5 'How Big Is the Implicit Subsidy for Banks Considered Too Important to Fail?', IMF, Global Financial Stability Report, chapter 3.

6 'Economic Review of the Financial Regulation Agenda', European Commission, Commission Staff Working Document, SWD(2014) 158 final.

rating agencies, such as Moody's, Standard and Poors and Fitch, who report a stand-alone as well as a support rating for the financial institutions they cover[7] – and essentially uses the differences between the two ratings to estimate the level of government support. While credit rating based approaches provide useful evidence on credit risk exposure and the level of implied government support for individual financial institutions, they are fundamentally shaped by the judgement of credit ratings agencies. As such, there is no market basis of assessing the impact of the difference between the stand-alone rating and the support rating – as investors price the risk inherent in the overall rating without specifically differentiating between base-line credit assessment (stand-alone) and the support rating.

Moreover, this approach of segmenting overall rating between stand-alone and (government) support rating has been adopted post-financial crisis across financial institutions and has been influenced by the circumstances around the financial crisis (for example, previous bail outs). At some point this explicit difference may no longer be used and the the overall government, political and legislative environment will revert to being one key factor in a companies debt rating. Across other sectors, the government, political and legislative environment already plays an important role in determining a companies credit rating and it is therefore unclear how much this supports ratings compared to the explicit support in the case of banks.

Views of credit rating agencies with regards to trends in the level of government support for TBTF banks have emerged recently – for example, Moody's markedly lowered the support component in its overall ratings of SIBs in November 2013.[8]

Our econometrics analysis therefore attempts to improve on some of the challenges associated with the credit rating based approaches by using market pricing information – analysing statisitical relationship between funding costs and key drivers.

Studies on the current level of implicit subsidies

In the US, the most recent evidence based on studies by GAO and Oliver Wyman (both using econometric techniques), suggests that subsidies did exist during the financial crisis, but they have since declined. The most recent estimate of funding cost advantages for G-SIBs was statistically insignificant (Oliver Wyman) or indeed the effects may have reversed (GAO)[9]. The IMF, using the credit rating based approach (amongst a range of other approaches) and also focusing on the US, notes that the subsidy has been declining in the US[10], consistent with the results from GAO and Oliver Wyman, but that subsidies for financial institutions do still exist and they are at elevated levels compared to the pre-crisis period.

Recent studies in Europe, specifically the UK, show a range of results. Typically they suggest that there has been a decline in implicit subsidies, but the decline is less pronounced than in the US and generally subsidies still exist, as suggested by IMF (2014) and the EC (2014). The IMF finds that implicit subsidies for SIBs in Eurozone economies averaged around 80bps during the peak of the crisis and have since declined to around 50bps more recently (using 2013 data). The EC study calculated a total value for the implicit subsidy of €72-95bn and €58-82bn, for 2011 and 2012 respectively. Although, these results show a reduction between the two years, they suggest that subsidies were still significant in 2012, amounting to approximately 0.5% to 0.8% of EU GDP.

We have used data from Moody's on the stand-alone and support ratings for a range of 50 EU banks over the last 5 years to determine a ratings view on the trends and current level of government support for EU financial

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[7] 'Quantifying the value of implicit government guarantees for large financial institutions', Moody's, *Modelling methodology*, Moody's analytics, 2011.

[8] Moody's (2014), 'Reassessing Systemic Support for EU Banks'.

[9] Oliver Wyman calculate a funding advantage of around 2bps which is statistically insignificant, whereas the GAO study suggests a funding disadvantage of 8bps for large banks (comparing banks with $1trn in assets to those with $10bn in assets). However, as part of their assessment they note that funding differentials cannot be consistently attributed to TBTF perceptions and therefore any results should be interpreted with caution.

[10] The IMF note that subsidies for G-SIBs averaged around 30bps at the peak of the crisis whereas current estimates are close to 15bps.

institutions[11]. The data is consistent with the results of the studies above, suggesting that ratings support has declined in recent years but still exists and is somewhat comparable to pre-crisis levels.

We have not seen any approach that employs an econometric technique to analyse the recent evidence on levels of implicit subsidies in the EU banking sector.

Overall, the evidence on trends and current levels of implicit subsidies is shaped by the methodology used for the assessment. In the US, studies suggest that the level of subsidies has declined overtime, but different approaches support markedly different conclusions on the current levels of subsidies, with econometrics analysis suggesting much smaller subsidies than credit ratings analysis. Similar methodology comparisons are difficult to draw in the context of the EU as, to the best of our knowledge, there is no recent econometric study on the cost of funding for European banks (as there is in the US).

Our preferred approach for estimating implicit subsidies

We use econometric techniques to analyse the relationships between the banks' cost of funding (calculated using the spread of fixed rate senior unsecured debt over a government borrowing cost) and a range of explanatory factors, explicitly including a G-SIB variable which captures the impact on bond spreads for G-SIBs. This approach is consistent with the methodology that has been adopted across some of the previous studies (including Oliver Wyman and GAO) which have explained the relationship between a range of drivers and funding costs differentials across banks of different sizes (and various other related factors such as credit risk). The range of explanatory variables used in our analysis also builds upon the analytical evidence reflected in the research undertaken by some of the other studies (specifically in the US) – our key drivers of funding costs are:

- **Lag of spread** – In our (dynamic) model specification we expect that the bond spread from the previous period has some explanatory power on the spread today. In other words, spread exhibits some persistence over time. We expect the relationship to be positive.
- **Years to maturity** – Years to maturity captures the time remaining in years until a bond's maturity. Although the impact of maturity on spreads will vary with the shape of the yield curve, we expected generally that long-term debt requires a premium in the current environment.
- **Total assets** – Total assets are a core measure of the size of a bank. We have a prior expectation that larger banks have a higher likelihood of benefiting from both economies of scale and TBTF effects. Both of these may reduce funding costs.
- **Leverage** – We define leverage as total liabilities (excluding equity) as a percentage of total assets. Therefore, as this variable increases the bank is said to have higher leverage (a lower proportion of equity relative to total assets). Higher leverage is a measure of a bank's risk and therefore we expect it will lead to a higher cost of funding.
- **Modified Merton (distance to default)** – This represents a measure of default risk. It is calculated using implied share volatility and leverage (where leverage represents the proportion of non-equity funding). For more details on the precise calculation, please refer to Bystrom (2003). As the distance to default increases (as captured by Modified Merton), the cost of funding is expected to decrease.
- **Return on average equity (ROAE)** – ROAE is calculated as earnings from continuing operations divided by average total equity. It is a key business performance measure where higher values signify better performance, and as such we expect that it will be negatively related to the cost of funding.
- **G-SIB variable** – This identifies whether the bank is categorised as a G-SIB. If there are any funding cost advantages, we would expect GSIBs to have a higher likelihood of benefitting from TBTF effects and hence should have a negative relationship with cost of funding.

We use an econometric technique called a system generalised method of moments (GMM) estimator approach, which helps to solve some of the econometric challenges encountered in previous studies which predominantly

[11] We focused on a sample of 50 banks with a range of asset thresholds with market coverage consistent with our base-line econometric specification.

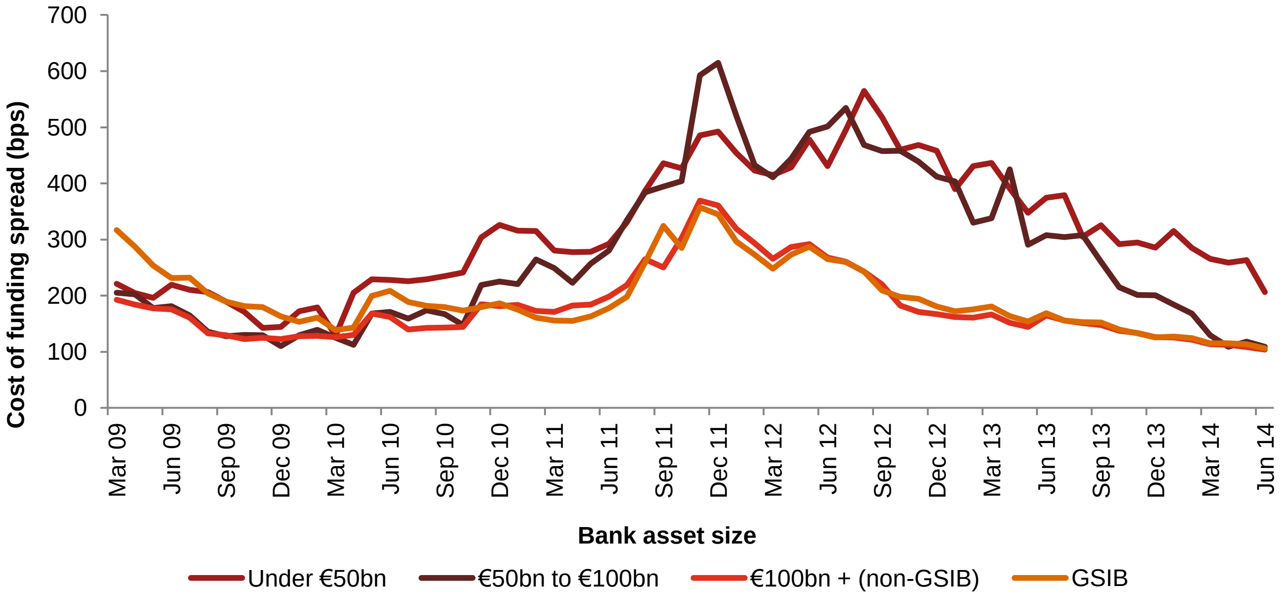
rely on OLS (ordinary least squared) based approaches[12]. One of the key benefits of using the system GMM approach is that it does not specify a particular distribution for the errors, and hence does not depend on the assumption of normality of the error term unlike the simple OLS approach used across other studies. This is important in the context of our analysis due to the presence, in our dataset, of very large or very small banks which may potentially result in the presence of outliers thereby causing the errors to be non-normally distributed.

We focus on a sample of EU banks with assets above €30 billion and cover a range of different countries (including Germany, France, Italy, Spain, Sweden, Switzerland, The Netherlands, and The UK). We use extensive data evidence, covering over 900 bonds across 40+ banks (under our bonds level assessment – as discussed in detail later), analysing spread differentials at both the individual bond level and aggregated bank funding cost level. We perform a range of econometric tests and choose econometric models which pass all regression specification tests and are therefore statistically robust.

Comparison of funding costs

Figure 1 below shows the median spreads on large G-SIBs compared to large non-G-SIBs (€100bn+ assets[13]) and a selection of medium (€50 to €100bn) and relatively smaller sized banks (<€50 bn) over the last five years.

Figure 1: Average funding spread by size cohort



Source: Capital IQ, Datastream, PwC analysis.

Median spreads[14] across large G-SIB banks were higher than those for smaller banks for most of 2009. Between 2010 and 2011, spreads on all banks increased – in part reflecting the greater volatility in financial markets as the Eurozone sovereign debt crisis developed – but spreads on larger banks (with assets of €100 bn+) were markedly below spreads on medium and smaller size banks, and were broadly comparable between G-SIB and

[12] The GMM approach involves using an instrumental variable-based approach where higher lag values of the lagged dependent variable are used as instruments. In contrast to OLS in which the estimator minimises the squared vertical distances between the observation and the mean (the first moment), system GMM minimises the sample average of the second, third and fourth moments: the variance, the skew and the kurtosis. This differencing also serves to eliminate any potential omitted variable bias and unobserved heterogeneity, which means firms' fixed effects, or firm characteristics that are time-invariant, are accounted for. For more details on this approach, please refer to Baum, Schaffer and Stillman (2007), 'Enhanced routines for instrumental variables/generalized method of moment's estimation and testing.' Boston College Economics Working Paper No.667.

[13] Based on total assets reported in the balance sheet.

[14] Calculated as spreads to Government bonds. A Eurozone benchmark is used for all Eurozone banks.

non G-SIB banks. Subsequently, the spreads across the entire sample of banks declined between 2012 and 2013, although throughout the period the trend of larger banks obtaining lower funding costs continued to be considerable (roughly in the order of around 100bps). More recently the spreads for large and medium sized banks have become more aligned, although funding costs for smaller banks are markedly higher.

While it is not possible to draw direct conclusions on the impact of implicit subsidies from this graph, the simple comparison of spreads across banks of different cohorts suggests that bank spreads are now well aligned across a range of banks of varying asset thresholds between €50 to €100 bn+ irrespective of being a G-SIB or non G-SIB. Differences in spreads do exist for relatively smaller size banks. Therefore, the simple comparison of funding costs does not support a lower cost of funding for G-SIB banks purely based on size i.e. being a G-SIB does not reduce funding costs, however, this is too simplistic and there are a range of other factors that might influence credit spreads (maturity of bonds, coupon) hence there is a need for more robust econometric analysis.

Econometric analysis of implicit subsidy

Table 1 below sets out the results from our regression analysis. This model passes all the regression specification tests and covers the most recent time period of January 2013 to June 2014. The key variable of interest is the G-SIB variable which shows the impact on spreads for banks that are G-SIB. The modelled G-SIB coefficient is low and negative, suggesting that G-SIBs have around a 4 bps funding cost advantage compared to banks which are non G-SIB. However, more importantly, the coefficient is statistically insignificant. This suggests that EU G-SIBs do not currently have a funding cost advantage compared to EU banks which are not G-SIB.

Size, which is proxied by total assets, has a relatively small negative (and statistically insignificant) impact on spreads – suggesting that, on average, as size increases (scaled to €100s of billions), the funding cost spreads should decrease (however, this should be interpreted with caution as it is statistically not different from zero). In essence, our analysis suggests that neither the G-SIB variable nor size (statistically) currently explains the difference in funding cost spreads. Indeed, as set out in the Appendix, this finding is consistent with a range of other model specifications where the G-SIB dummy for the most recent period continues to be statistically insignificant in explaining spreads. Rather we find that credit risk (the 'Modified Merton' variable in Table 1 below) is a more important determinant of funding costs across banks i.e. implying that banks with higher credit risk exposure (i.e. lower distance to default as captured by the Modified Merton metric) are likely to have a higher underlying cost of debt funding. Our model also suggests that the impact of leverage (proportion of non-equity funding) and return on average equity on cost of funding, whilst directionally correct, are statistically insignificant and hence cannot explain differences in funding costs across financial institutions.

Table 1: Econometric outputs from bonds level assessment

Dependent variables (spread to benchmark for individual bonds)	**Coefficients estimates January 2013- June 2014**
Constant	-811.48
Lag of spread	0.57***
Year to maturity	2.83*
Total assets	-1.32
Leverage	981.01
Modified Merton	-124.87*
ROAE	-0.17
GSIB	-4.14
Country dummies	Yes

Dependent variables (spread to benchmark for individual bonds)	Coefficients estimates January 2013- June 2014
Number of observations	8,946
Tests	
Nickell Bias	No
Arellano – Bond test AR (2)	Good
Hansen J test	Good

*Notes: * Significant at 10% level, ** significant at 5% level, *** significant at 1% level*
Source: Capital IQ, Datastream, Bloomberg, Moody's, PwC analysis.

Conclusion

Overall, our analysis suggests that G-SIB banks do not currently benefit from a funding cost advantage compared to other non G-SIBs. The changing regulatory landscape within the EU over the last few years may explain this result. For instance there have been significant regulatory developments with a view to making banks more resilient and therefore less reliant on government support – including the adoption and phased-in implementation of the Capital Requirement Directive (CRD IV) and Capital Requirement Regulation (CRR). Moreover, the European Parliament has voted to adopt the Bank Recovery and Resolution Directive (BRRD), establishing a new framework for managing troubled banks in the European Union (EU), as well as the Single Resolution Mechanism (SRM) regulation, which empowers a Single Resolution Board (SRB) to manage bank resolution in the euro area. While some of these are still evolving and will only be fully implemented in due course, any assessment based on market pricing information does inherently incorporate debt investors' expectations of the impact of these regulatory developments (as spreads capture forward looking expectations of default, and hence take into account the future implementation of regulation).

We note that just because the G-SIB banks do not currently appear to benefit from implicit government support based on our assessment, there is still a possibility that this effect might return during a period of unexpected financial market stress in the future. It is inherently difficult to develop a framework to understand the future impact of unexpected periods of financial market distress, particularly beyond the short-term bank funding horizon[15]. We will only truly know that TBFT and associated implicit subsidies have been eliminated when the new regulatory frameworks are put to test in a bank failure situation.

[15] To the extent that expectations of future market volatility are already priced into spread differences by investors, as they reflect a forward looking perspective, and given the average maturity of bonds in our sample is around 5-7 years, our assessment already incorporates some degree of forward looking view on the future evolution of implicit subsidies.

2. Introduction and Background

2.1. Introduction

PwC has been commissioned by the Association for Financial Markets in Europe (AFME) to undertake a study on the impact of structural reform in the EU banking sector. One part of the study is to analyse the existence, magnitude and evolution of any implicit subsidy for EU banks. The quantification of an implicit subsidy (if any), is a key requirement for the assessment of the need for further reform of the EU banking sector. It also allows a retrospective assessment of the degree of success of that has been achieved through various regulatory reforms to date.

2.2. Background

What are implicit subsidies?

During the global financial crisis, substantial amounts of public financial support were given to financial institutions at risk of failure in order to prevent contagion and damage to the functioning of the wider economy. Financial regulators have subsequently defined those banks who pose a systemic risks or were considered Too Big To Fail (TBTF), or Too Important To Fail (TITF) as Globally Systemically Important banks (G-SIBs). The impact of being TBTF on banks' behaviours and potential uncompetitive advantages compared to smaller banks has been a topic of research and discussion since the global financial crisis. This research has looked as the existence of both explicit subsidies, but also implicit subsidies, where banks benefit from the expectations of government support, even where no financial payments from government are made.

Banks can benefit from implicit subsidies in a number of ways. Banks which are TBTF or are deemed G-SIBs may benefit from a funding cost advantage over comparable banks which are smaller in size or less systemically important. Creditors may be willing to accept lower interest rates on debt issued by these financial institutions if they consider the possibility of government support reduces the likelihood that they could suffer losses.

In addition, depositors may perceive a G-SIB is more likely to receive Government support and may therefore accept a lower rate of interest on their deposits compared to saving with other deposit taking institutions. Suppliers, likewise, may accept less beneficial terms of trade with a G-SIB compared to a smaller or less systemically important bank.

The expectation of government support may also distort markets. In particular, it has been suggested that implicit government support can lead to competitive distortions[16] because those banks that benefit from funding advantages may be more profitable compared to their smaller or less systematically important competitors. They may also be able to achieve faster balance sheet growth and may be incentivised to adopt a higher risk appetite. This is because such banks may be able to benefit from the potential upside returns from high risk strategies, but with reduced downside risk (as a tax-payer funded bail-out provides some protection from downside risks)[17]. Such excessive risk taking and balance sheet growth can increase the likelihood of financial distress and disruption to broader financial markets, as seen in 2008.

While such benefits may accrue to larger banks, the role of sovereigns where these TBTFs are headquartered is also important - banks in Member States with a sovereign more capable of supporting its banks are at an advantage to equally strong banks headquartered in weaker Member States.

In an efficient market, the funding costs for banks should be consistent with their risk profile, where investors bear the full risk of bank failure and return requirements are set accordingly. The regulatory framework,

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[16] For example, see the Turner Review (2009).

[17] In essence, this in the option pricing world this is similar to a put option – where you benefit from the upside and are protected on the downside as market price on the underlying varies overtime. Indeed this approach has been used to value the implicit subsidy – as discussed later in section 3.

through higher capital and liquidity levels, bail-in capital and work on resolution is moving towards the goal of eliminating TBTF. Only when bank investors are fully bearing the risk of bank failure will we be able to conclude that the banking sector is not benefitting from implicit subsidies.

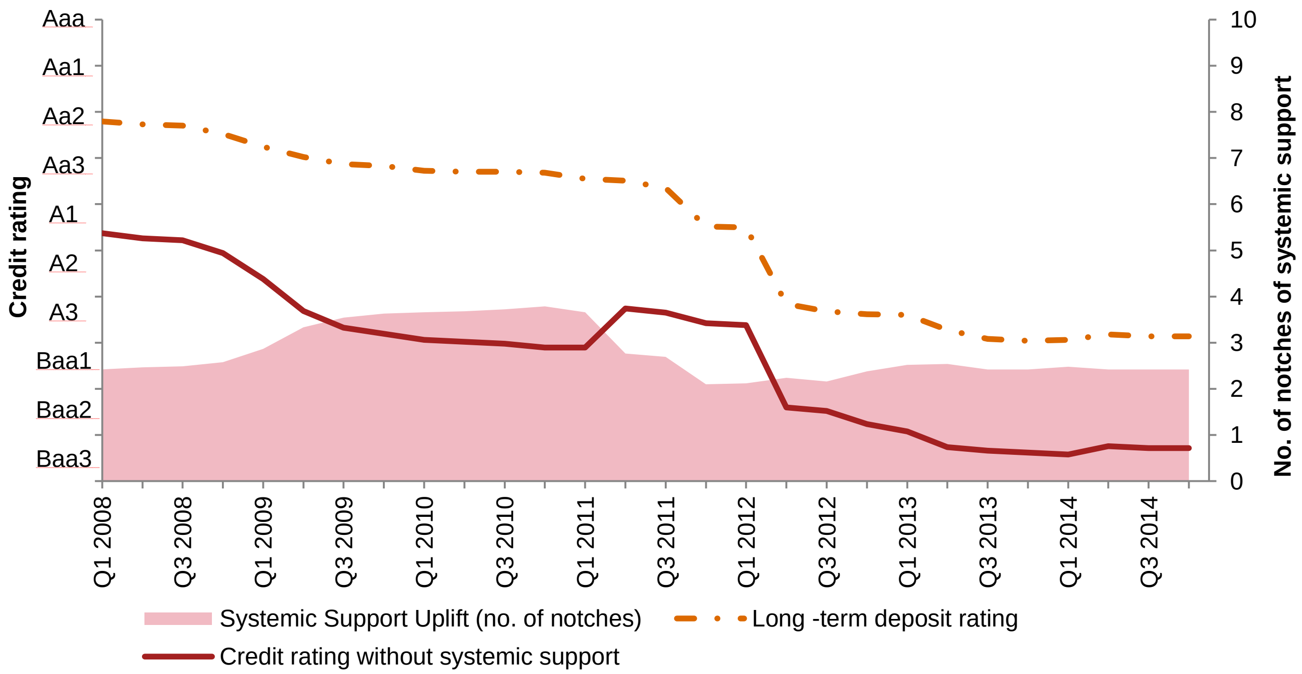
The emerging views of implicit subsides

A number of commentators and studies have pointed to the observation of a cost of funding difference comparing large (TBTF) banks and smaller banks as support to the idea that larger banks have benefitted from implicit subsidies. However, differences in the cost of funding comparing large and small banks do not necessarily show the existence of implicit subsidies. This is because size itself may be helpful in reducing funding costs, absent any implicit government support, due risk diversification and portfolio effects. This has led to alternative views of the extent of implicit subsidies.

Following the financial crisis credit rating agencies adapted their ratings approach to explicitly opine on the degree of government support. This involved assigning a specific uplift for government support. For example, Moody's estimates a base line credit rating (BCA) for banks, which represents a stand-alone rating, as well as a long-term rating, which incorporates their view of the level of government support for the bank. The difference between the two therefore represents the notches of government or systemic support.

Figure 2 below shows the evolution of the stand-alone rating (BCA), support rating (long-term rating) and the level of support notches (the shaded area – calculated as the difference between support and stand-alone rating) across 50 EU banks, based on Moody's data.

Figure 2: Evolution of systemic support uplift for 50 European banks



Source: Moody's, PwC analysis.

This data shows the average amount of systemic support (right-hand axis) was around two notches in Q1 2008, growing to around three to four notches during the 2009 to 2010 period as the impact of the financial crisis intensified. The level of systemic support then declined in 2011; largely as a consequence of deterioration of the fiscal position of many European sovereigns following the sovereign debt crisis restricted their ability to provide support to the banking sector. From 2013 onwards, both the credit ratings with support (see left hand axis) and the level of systemic support have stabilised. Overall, bank credit ratings suggest there has been a declining amount of systemic support since the crisis, however, according to credit ratings some support still exists.

Key drivers of change

A key driver shaping a perceived decline in implicit bank subsidies is the regulatory reform agenda. This aims to improve banks' financial resilience - including the phased-in implementation of the Capital Requirement Directive (CRD IV) and Capital Requirement Regulation (CRR) - as well as implementing frameworks which allow the use of statutory resolution powers to resolve banks in the event of failure and therefore limit tax-payer funded bailouts.

Recently, the European Parliament voted to adopt the Bank Recovery and Resolution Directive (BRRD), establishing a new framework for managing troubled banks in the European Union (EU), as well as the Single Resolution Mechanism (SRM) regulation, which empowers a Single Resolution Board (SRB) to manage bank resolution in the euro area. These texts complete the establishment of a Banking Union in Europe, envisioned as a key contributor to financial and broader economic stability in the region. The BRRD/SRM package seeks to alleviate the cost of bank failures for taxpayers at the expense of shareholders and unsecured creditors, with a very clear expectation that 'bail-in' capital will be utilised, if needed, as part of bank resolutions.

These regulatory developments are expected to impact the probability of default for TBTF banks, through improved financial resilience, but are also through to have influenced the expectations of government support in the event of financial distress and therefore the expectations of implicit subsidy for such banks. Indeed as noted by Moody's[18];

> *"These outlook changes reflect our assessment that, with the BRRD/SRM now adopted and other aspects of the framework in development, the balance of risk has shifted to the downside for banks' senior unsecured creditors. While our (Government) support assessments are unchanged for now, the probability has risen that we will revise them downwards."*

However, Moody's stresses that whilst there is an expectation of revising downward the level of state support; it is unlikely that the state support would cease to exist in entirety at least for now:

> *"If we were convinced that the competing objectives of ensuring financial stability and protecting public funds would be fully met under all scenarios, we would logically withdraw all systemic support from affected banks' ratings. At this stage, though, we are not yet persuaded that the new resolution framework achieves these two objectives fully, and continue to believe that there remains some meaningful probability that national public authorities would provide some form of support to certain troubled banks that would alleviate losses for senior unsecured creditors. The probability of such support provision varies between banks and is reflected in diverse systemic support uplifts embedded in assigned ratings."*

Similarly, Mark Carney, Chairman of the financial stability board, noted in October 2013;[19]

> *"The expectation that systemically important institutions can privatise gains and socialise losses encourages excessive private sector risk-taking and can be ruinous for public finances. . . . Firms and markets are beginning to adjust to authorities' determination to end too-big-to-fail. However, the problem is not yet solved."*

Ending the TBTF phenomenon is high on the list of priorities for the G20's Financial Stability Board. Mark Carney and the FSB have presented a formal proposal to the G20's summit at Brisbane in November 2014 for a global standard, among other things, to deal with cross-border resolution as well as "total loss-absorbing capital", along with minimum requirements for systemically important banks. This so-called TLAC can often include instruments other than common equity, such as subordinated or convertible debt. Higher levels of TLAC would give regulators more confidence that a cross-border bank can fail without causing a crisis. In a

[18] Moody's (2014), 'Reassessing Systemic Support for EU Banks'

[19] Statement to the International Monetary and Financial Committee

recent speech on the 29th Annual G30 International Banking Seminar on "Regulatory work underway and Lessons learned", Mark Carney noted[20]:

> *"Tackling the rampant moral hazard at the heart of the financial system hasn't been easy. And our success can never be absolute. Specifically, we can't expect to insulate fully all institutions from all external shocks, however large. But we can change the system so that systemically important institutions bear the cost of their own actions and the risks they take. After much hard work, and extensive cross-border co-operation, the FSB is on track to agree proposals that, once implemented, will be decisive in achieving that. The use of statutory resolution powers to resolve global systemic banks will finally be possible."*

2.3. Scope of this report

This Supplementary Report specifically focuses on the question of 'implicit subsidy' for EU banks. It develops and implements an approach to analyse and measure the implicit subsidy (if any) received by EU banks.

Our approach for the assessment of the implicit subsidy for EU banks builds on the extensive literature on this topic, with a view to improve on existing methodologies and provide an up to date estimate of the subsidy for EU banks.

As set out in Section 4, we primarily rely on econometric analysis, using a wide range of statistical models and approaches, to analyse the relationship between size and cost of wholesale funding – whilst taking account of a range of other explanatory variables. We focus exclusively on EU and Swiss banks, in particular banks that operate across the following seven countries UK, Germany, Spain, Italy, France, Netherlands and Switzerland.

Our market and bank financial data runs up to the end of June 2014.

2.4. Structure of this report

The remainder of this section is structured as follows:

- **Section 3** reviews previous studies on implicit subsides. It identifies the various approaches that have been used by academics and practitioners alike and sets out the range of findings on estimated subsidies and plausible areas for further improvements in the analysis;
- **Section 4** builds on existing studies to develop an appropriate econometric approach for the assessment of the implicit subsidies, taking into account some of the model specifications and improvements that can be applied to the current established approaches;
- **Section 5** implements our preferred methodology to provide an up to-date estimate of the implicit subsidy across EU banks, taking into account some of the challenges associated with such an assessment.
- **Section 6** concludes with our overall view and assessment of the current levels of implicit subsidy for EU banks and provides comments on possible future trends.
- The **Appendix** includes our bibliography, as well as additional analysis of differences in ratings for different sized banks and differences in funding costs across industries, as well as providing results from a number of different model specifications, including an assessment of the evolution of implicit subsidies across EU banks over the period 2009 to 2013.

[20] Mark Carney (2014), 'Regulatory work underway and lessons learned', Speech at the 29th Annual G30 International Banking Seminar, Washington D.C 12th October 2014.

3. Review of previous studies

3.1. Review of previous approaches

Since the financial crisis of 2008, and subsequent intervention in the financial sector by Governments in many developed economies, there has been a growing body of literature which seeks to determine whether an implicit subsidy for financial institutions deemed 'too big to fail' (TBTF) exists. This section reviews previous studies which have estimated the size of such implicit subsidies. It summarises some of the key approaches that have been used, the challenges of the associated approaches and the key findings from their research.

From our review of previous studies we have identifies four groups of approaches. These are:

- Credit default swaps ("CDS") spreads
- Contingent claims approaches
- Acquisition valuations
- Cost of funding, which in turn has been approached from a number of perspectives, including simple comparisons, credit ratings and econometric analysis.

Most studies rely on cost of funding based approaches, either using an econometrics technique or more simplistic approaches that aim to identify funding differences based on specific metrics (for example size). In the next section we take these approaches in turn.

3.1.1. Observed vs fair value CDS spreads

A number of studies and market participants estimate the implicit subsidy benefits using data on CDS spreads[21] – in particular comparing the observed CDS spreads with fair-value CDS spreads. In principle, observed CDS spreads capture the credit risk profile of financial institutions – taking into account both the probability of bank default and the likelihood of government support in the event of distress. In comparison, fair value CDS spreads, which are computed using equity volatility and expected default frequencies[22], only capture the probability of default[23]. Therefore, fair-value CDS spreads (FVS) can be compared directly with observed CDS spreads where the difference can be used to interpret the expectation of Government support.

Moody's (2011) compares their estimate of fair-value CDS spreads to observed market CDS spreads for a number of US and EU banks and finds that CDS spreads for larger US banks were lower than those at other US institutions by 23bps pre-crisis, rising to 56bps post-crisis. In dollar terms they estimate that this premium for the top 20 US banks (by asset size) is equivalent to \$170bn, and is \$293bn for the top 20 European banks[24].

Also utilising this approach, IMF (2014) finds that in advanced economies implicit subsidies for systemically important banks (SIBs) averaged around 30bps over the past nine years, reaching approximately 60bps in 2009, a figure consistent with that of Moody's. Additionally, they find that subsidies have grown again in recent years for European economies; however, they attribute this to the market turmoil during the sovereign debt crisis rather than any failure of regulatory initiatives. In the United States, the CDS approach shows that implicit subsidies have dropped sharply from 2009 peaks.

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[21] CDS spreads are the price of insuring against default. The buyer of a CDS has to make periodic payments to the seller of the contract - and in the event of default - the seller must pay the par value of the contract to the buyer.

[22] Moody's model default as the point to which the market value of a firm's assets falls below its liabilities payable. Expected default frequency is estimated using three key components: market value of assets, level of the firm's obligations, and asset volatility.

[23] A key assumption underlying this framework is that in the event of distress equity holder's value is entirely lost i.e. only debt holders receive the benefits of government support.

[24] Assuming their governments back half of their total liabilities.

A key disadvantage of this approach is that the methodology is heavily reliant upon the calculation of the fair-value CDS spread; in practice determining parameters such as expected default frequencies is very challenging and estimation methodologies heavily rely upon assumptions (for example the assumption that equity holders are not bailed-out) that are used in the fair value calculation. Moreover, the CDS spreads vary considerable by maturity and in addition to credit risk might also reflect premium for other risk parameters – for example CDS spreads can also factor in some counterparty risk – which might bias any results focusing on this approach.

3.1.2. Contingent claims approaches

Contingent claims analysis aims to quantify the expected value of government support to the banking sector (or financial institutions within) by modelling future asset values of the banking sector under different market scenarios. Given a shock to asset values of a significant size, the government may need to intervene to bring asset values back up to some minimum acceptable threshold to ensure system wide stability and reduce broader financial market contagion. In essence, this can be conceived in the context of option pricing framework (which was the approach used to quantify the impact by Oxera (2011)) where the bank (or the sector in general) can be perceived to hold a put option on the underlying asset values with the exercise price being equal to the minimum acceptable asset (or equity) threshold. As the financial market volatility increase and the value of underlying assets drop below the minimum threshold, the banks can exercise the option and redeem the asset value to the acceptable levels.

A key challenge with such an assessment is sensitivity around some of the key assumptions, for example around determining the probability of a shock of the requisite threshold which cause market distress and declining asset values as well as the parameters for the various inputs within the option pricing Black Scholes model. Oxera (2011), on behalf of RBS, in its assessment of the implicit subsidies used such a framework and estimated a central scenario for annual forward-looking state support in the UK of 8bps per pound of assets, corresponding to an annual value transfer from the state of £5.9bn. Following Oxera's study, the Bank of England reviewed the analysis[25] in their 2012 report on implicit subsidies and found that under a different set of assumptions, for example using alternative distribution for asset prices as opposed to the normal distribution assumed by Oxera, the subsidy could vary considerably and could be as high as 175bps, corresponding to an annual subsidy of £122.5bn.

As the Bank of England's analysis shows, one key drawback of this approach is the sensitivity of the analysis to the various assumptions. Additionally, there are a number of other challenges with this framework:

- It assumes that the payment from the state only needs to restore asset values up to an arbitrarily set systemic trigger threshold and no more, in a market with low confidence, a larger injection may be needed to stabilise markets;
- Calculating the probability of large asset shocks is notoriously difficult, and the approach of using share prices has a endogeneity problem, particularly if share prices already incorporate investor expectations of implicit government support;
- The distribution of asset prices is a key input and a number of studies have shown that asset prices do not follow normal distributions; and
- Most importantly, it presumes government support in the event of a large shock. As the regulatory reform programme is implemented, the presumption of government support should reduce or be eliminated.

3.1.3. Acquisition valuations

Another approach to quantifying the value of TITF affects is to study valuations of banks in merger acquisitions. Brewer and Jagtiani (2011)[26], using data from the 'merger boom' period of 1991 to 2004 in the US, found that acquisitions had higher premiums where post-merger the combined organisation had over $100bn in assets. The $100bn threshold is assumed to represent the level at which institutions begin to benefit from TITF subsidies. Based upon eight merger deals during the 1991 to 2004 period that resulted in the size of the new

[25] See Noss and Sowerbutts (2012)

[26] Brewer and Jagtiani (2011), 'How Much Did Banks Pay to Become Too-Big-To-Fail and to Become Systemically Important', *Working paper no.11-37*, Federal Reserve Bank of Philadelphia.

organisation exceeding the $100bn asset size mark, they estimate that the size of 'added merger premiums' was at least $15bn. The authors then suggest that this $15bn estimate is only a fraction of the total TITF benefits that banks may receive, as the premiums only relate to the shareholders of the bank and therefore do not cover any benefits that debt holders may receive. Furthermore, the authors apply their regression approach to estimate the impact of crossing this $100bn size threshold on both abnormal stock market returns and the cost of funds (measured using bond data). Their findings suggest that abnormal returns are higher and cost of funding is lower above the size threshold.

Although the regression approach used by Brewer and Jagtiani to estimate merger premiums has the advantage of controlling for other variables that may be causing high premiums, key drawbacks are that the observed period is outdated and the sample includes very few mergers that meet the somewhat arbitrary $100bn post-merger asset criteria.

3.1.4. Cost of funding approaches

The most extensively used approach in the studies we have reviewed focus on cost of funding, which are also known as 'funding advantage' models. The cost of funding advantage can typically be estimated in a number of different ways:

- Comparisons of spread differences on traded debt or deposit rates on money market accounts between large and small banks and evolution of such differences over time – including event analysis. These techniques traditionally are quite simplistic and generally do not rely on sophisticated models and/or econometric techniques for such an assessment – rather they focus on assessment of market pricing data on wholesale or retail funding liabilities to infer trends on underlying implicit subsidies.
- Credit ratings based approaches which review the differences in credit risk profile across banks of different sizes. This approach exploits the differences between two sets of credit ratings provided by ratings agencies. The first rating is a 'standalone' rating, which reflects a banks intrinsic financial strength. The second rating is a 'support' rating which also incorporates the possibility of government support in the event of bank failure. Converting the rating differential between the two ratings into a yield estimate, using either market pricing frameworks or using established empirical/academic evidence, allows estimation of the funding cost advantage from the implicit government subsidy. Other credit rating based approaches analyse the relationship between long-term ratings and support ratings using econometric models – to determine the level of uplift and hence the associated subsidy.

Using econometric techniques to analyse funding cost differences across banks, generally focuses on a segment of bank liabilities (including deposits). Typically these studies estimate a funding advantage in terms of spread or deposit rate differentials and convert it into a monetary value by extrapolating it to the relevant bank liabilities. Some of the econometric models also use CDS spreads or credit ratings as a proxy for funding cost differences (with the presumption being that any differences in funding costs should be related to CDS spreads as both capture credit risk). Principally, econometric approaches seek to establish whether larger financial institutions, or G-SIBs, have a cost of funding advantage by examining the relationship between cost of funding and a host of other explanatory variables – including size, credit risk, income etc. Modelling the cost of funding as function of size, or systematic importance, and controlling for other factors allows the analysis to isolate the impact of different factors on funding costs. We now review the various studies that fall under the categories set out above.

Comparisons of funding costs

A number of the earlier studies which assessed cost of funding advantages associated with systemically important banks were relatively simplistic in their approach. Baker and McArthur (2009)[27] for example, measured the spread difference between the cost of funds for smaller banks and those with assets greater than $100bn[28] in the US - associating the difference to perceived benefits from size and hence systemic importance. They found that the spread difference between small and large banks was 0.29% for the period 2000 to 2007, but from Q4 2008 to Q2 2009 it had risen to 0.78%. Translating this increase into monetary comparable

[27] Baker and McArthur (2009), 'The Value of the "Too Big to Fail" Big Bank Subsidy', Issue Brief, The Centre for Economic Policy Research.

[28] Using data provided by the Federal Deposit Insurance Corporation (FDIC) on the cost of funds.

suggested a government subsidy of $34.1bn per year for the 18 bank holding companies (BHCs) in the US with more than $100bn in assets.

While this approach does have the advantage of simplicity, the $100bn threshold selection appears to be arbitrary, rather than an output of the analysis, and there are a number of other characteristics that might explain the spread differentials across banks, which should ideally be controlled for as part of such an assessment.

Credit rating approaches

The credit rating based approaches have been widely used in the literature. Haldane (2010) analysed the average rating differences between 'standalone' and 'support' credit ratings for both large and small UK banks over the 2007 to 2009 period. He found that for large banks the average ratings difference for the period was 3.4 notches, while for small banks it was 1.5 notches. These credit rating notches were then converted into yield differentials by analysing historical yield spreads across a spectrum of credit ratings and subsequently into a monetary measure of the implicit subsidy by multiplying the number of basis points by the value of each bank's rating sensitive liabilities. Haldane concluded that the size for the implicit subsidy was £55bn for large banks and £4bn for small banks over the 2007 to 2009 period; leading to the conclusion that large banks account for over 90% of the implicit subsidy.

Two of the more recent studies following Haldane (2010) that have specifically focused on Europe are Schich and Lindh (2012) and European Commission (2014). Schich and Lindh (2012) study 123 large banks spanning 17 European countries. Similar to Haldane, they use reported rating differences between AICR (all-in credit rating) and adjusted-SACR (stand-alone credit rating) provided by Moody's. The 'adjusted' prefix on SACR refers to non-governmental support factors such as parental support being included. Therefore, the remaining difference between AICR and adjusted-SACR should be solely attributable to government and systemically motivated support. Across their range of European countries, Schich and Lindh find that the yearly reduction in funding costs can range between $43bn and zero[29], where the aggregate of the large banks in most countries receive yearly funding cost reductions of under $10bn. They also compare their own findings to that of Haldane (2010). They calculate the total funding advantage for 14 UK banks as being just under $10bn for 2012; far lower than the estimates by Haldane for 13 UK banks over the 2007-2009 period (£59bn). They attribute these differences to the more recent time period studied as well as the choice of debt measure. Whereas Haldane scaled his funding advantage in monetary terms using 'ratings sensitive liabilities' (excluding deposits but including unsecured wholesale borrowing) Schich and Lindh scale their funding advantage by using 'outstanding debt'.

The European Commission's analysis of the implicit subsidy was very similar in approach to that of Schich and Lindh (2012). They also used credit rating differences, and studied a sample of 112 EU banks, suggesting that this sample constituted 60-70% of the total bank assets in the EU over the period 2011-12. The findings of this study were provided at the aggregate EU level. The total implicit subsidy was calculated as €72-95bn and €58-82bn, for 2011 and 2012 respectively. Although these results show a reduction between the two years the subsidy's size is still large, amounting to approximately 0.5% to 0.8% of EU GDP.

In April 2014, the IMF published its Global Financial Stability Report, in which it reviewed the size of implicit guarantees. It also applied a credit ratings based approach[30] when valuing implicit subsidies for large banks. The IMF's methodology was slightly different compared to some of the other studies, using an ordered probit regression model with the overall credit rating (long-term rating) used as the dependent variable (each credit rating notch is assigned a discrete number). The support level provided by the rating agencies (again each support level was assigned a discrete number), fundamental characteristics of the bank (such as the common equity ratio and return on assets) and sovereign ratings of the country were used as explanatory variables. This approach allows the estimation of the impact of a one notch increase in support rating on the overall long term (target) credit rating (and hence the level of rating uplift). This can then be multiplied by the average support level for each bank in the sample to determine the average rating uplift. Overall, the IMF study finds that subsidies for US systemically important banks (SIBs) are somewhat above their pre-crisis levels. Subsidies

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[29] For the year 2012.

[30] Based on the work of Ueda and Weder di Mauro (2013).

remain higher than pre-crisis levels for the euro area, but for the UK and Switzerland current subsidy levels are close to pre-crisis levels. However, the IMF's analysis, based on this credit ratings approach, shows that subsidies are trending downwards in all advanced economies, perhaps with the exception of Switzerland, where subsidies have levelled off after falling very fast post-crisis.

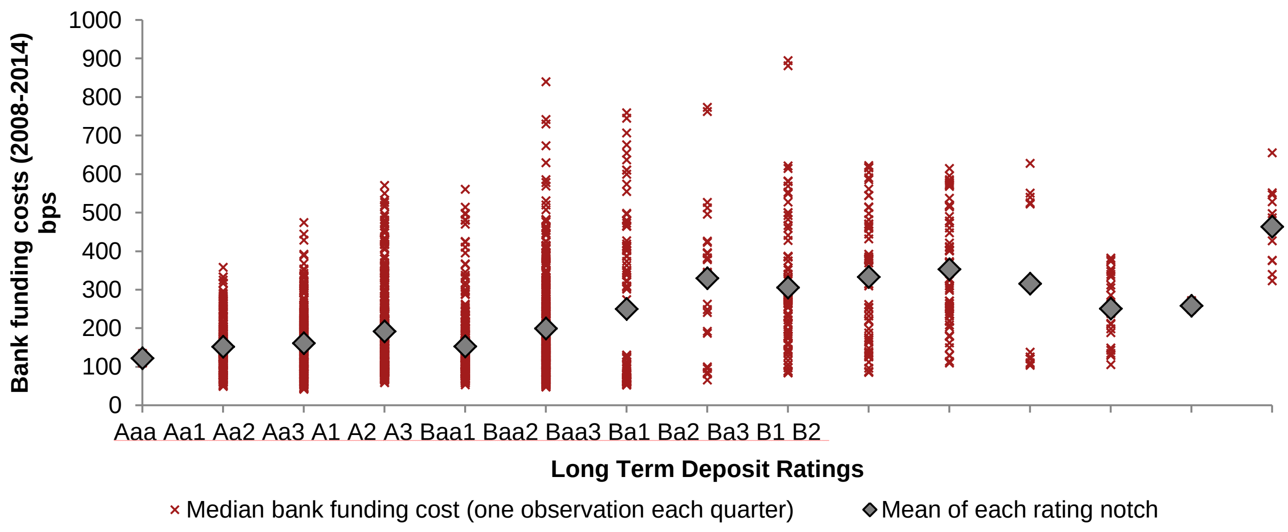
While credit rating based approaches provide useful evidence on credit risk exposure and the level of implied government support for individual financial institutions, they are fundamentally shaped by the judgement of credit ratings agencies. As such, there is no market basis of assessing the impact of the difference between the stand-alone rating and the support rating – as investors price the risk inherent in the overall rating without specifically differentiating between base-line credit assessment (stand-alone) and the support rating.

The IMF study notes that credit ratings can often be slow to adjust, and since its publication Moody's have announced that they are updating the bank rating methodology to reflect a, "fundamental shift seen in the banking industry and its regulation"[31]. The European Commission's analysis also noted that from a forward-looking perspective, the rating agency Fitch, "estimates that BRRD is likely to further weaken the sovereign support."

Moreover, this approach of segmenting overall rating between stand-alone and (government) support rating has been adopted post-financial crisis across financial institutions and has been influenced by the circumstances around the financial crisis (for example, previous bail outs). At some point this explicit difference may no longer be used and the the overall government, political and legislative environment will revert to being one key factor in a companies debt rating. Across other sectors, the government, political and legislative environment already plays an important role in determining a company's credit rating and it is therefore unclear how much this supports ratings compared to the explicit support in the case of banks.

The relationship between credit rating and funding cost is not clear cut. Figure 3 below shows the variation in debt funding costs across banks' bonds according to their rating (which includes elements of systemic support) [32]. This suggests that on average as rating improves, funding costs decrease; however, bonds with similar ratings can have markedly different funding costs and we therefore consider it is inherently difficult to assess the impact of any systemic support within banks using ratings analysis.

Figure 3: Bank funding cost spread and long-term (support) rating



Source: Moody's, PwC analysis

31 Moody's (2014), 'Reassessing Systemic Support for EU Banks'.

32 For information on the bond spread data used see section 4.2.1.

Econometric approaches focusing on funding cost analysis

Econometric approaches aim to link funding cost differences (or proxies such as CDS spreads) across cohorts of banks to a range of fundamental factors, including size, default risk, income etc. and thereby capture a more precise estimate of any benefits associated with underlying implicit subsidies. This approach represents a popular strand of funding advantage models and has featured prominently in implicit subsidy studies. All the studies covered as part of the current review focus on the US banking market, as we haven't identified studies that adopt such an approach in the EU context. The specific funding component used to test for implicit subsidies varies between studies, however, it generally falls under three broad categories:

- Wholesale funding focusing on traded debt – senior or subordinated (or indeed a combination of both);
- Retail funding where the focus is on money market deposit accounts; and
- Measure of credit risk which might be broadly aligned with trends in funding costs or act as a reasonable proxy (CDS spreads).

Although the funding component varies across studies, the underlying framework is broadly similar. It typically determines whether the independent variables such as size, or degree of systemic importance of a bank, can lead to different costs of funding (the dependent variable) across financial institutions after controlling for other key factors. The additional factors which are used as regression controls generally tend to fall under instrument characteristics (for example coupon rate, bid-ask spread, trade size), bank characteristics (for example leverage, credit risk) and macroeconomic conditions (for example market volatility).

Econometric models that focus on wholesale funding generally use cost of debt financing as the dependent variable (usually senior unsecured debt). Although debt financing in general (and senior unsecured debt in particular) might present a relatively small component of bank's total liabilities, there is a large amount of market pricing information on this segment of wholesale funding, which helps to improve the statistical robustness of the analysis. In particular, market information for banks' debt funding is richest is the US (compared to the EU) where systems such as TRACE (the Trade Reporting and Compliance Engine) enhance transparency, as a result the majority of studies in this space have been for US financial institutions.

Such an econometric approach was conducted by Balasubramanian and Cyree (2014)[33]. Their approach employed an econometric methodology[34], an approach we will go onto discuss in more detail below. Examining bond spreads in the six months before and after the passage of Dodd-Frank act; they found that funding advantages for the largest banks fell by around half following the passage of the act.

Acharya, Anginer and Warburton (2013)[35] (AAW) prepared another such study on US financial firms. They studied a wide sample of major financial institutions covering depository institutions, non-depository institutions, brokers, exchanges, insurance carriers and holding and other investment offices over the period 1990 to 2010. They focus on all US issued bonds (removing those which have equity or derivative features, warrants and floating interest rates) and use the spread to benchmark[36] as the dependent variable. Using a range of explanatory variables including bond characteristics, bank risk factors[37] and macroeconomic factors, and applying fixed effects regression approach, they find that firms in the top 90th percentile by assets have a funding advantage of 28bps on average over the 1990 to 2010 period. The subsidy was as high as 120bps in 2009, declining fractionally from this peak in 2010. In monetary terms they calculated this implicit subsidy to be between $20bn and $100bn per annum.

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[33] Balusubramanian and Cyree (2014), 'Has market discipline on banks improved after the Dodd-Frank Act?' *Journal of Banking & Finance,* vol.41, pp.155-166.

[34] The authors applied a Generalized Method of Moments (GMM) approach.

[35] Acharya, Anginer and Warburton (2013), 'The End of Market Discipline? Investor Expectations of Implicit State Guarantees', March 2013.

[36] Calculated as the difference between the yield on the bond and the yield on its corresponding benchmark treasury bond

[37] Bond characteristics include time to maturity, issue rating and issue size; bank characteristics include Merton distance to default, leverage, return on assets, market-to-book value and maturity mismatch.

Following the approach of AAW, Oliver Wyman (2014) provided an updated analysis of US financial institutions, covering the period 2009 to 2013. They argue that this more up to date period should have most relevance for assessing whether post-crisis financial reforms have impacted perceived TBTF subsidies. Focusing on US BHCs which have significant commercial or investment banking activities (specifically excluding those banks which have asset management and/or insurance business), they analyse the relationship between senior unsecured debt (fixed rate and no options attached) and a host of explanatory variables using a pooled Ordinary Least Squares (OLS) framework. The key variable in their regression specification is a G-SIB dummy which reflects whether a bank is categorised as globally systemically important, the summary results for the coefficient on this G-SIB dummy is shown in the table below.

Table 2: G-SIB funding advantage in the US as measured by Oliver Wyman (2014)

Year	2009	2010	2011	2012	2013
Impact on bond funding cost (bps) for GSIB status	-137bps	-79bps	-57bps	-36bps	+8bps
Significant at 5% level?	Yes	Yes	Yes	Yes	No

Source: Oliver Wyman (2014).

Based upon their bond sample from 42 BHCs, totalling $440bn in value, they find that there has been a gradual but economically significant impact from reforms targeted at the TBTF issue. Specifically they find that funding advantage for those BHCs that are categorised as G-SIBs relative to other BHCs, declines from 137bps in 2009, to 57bps in 2011, and was statistically insignificant in 2013. Moreover, they also find a number of other interesting relationships across a range of other explanatory variables – for instance they find distance to default and market to book ratio as statistically significant driver of funding cost differences across banks. While their finding suggests that there is no G-SIB impact in 2013 on bank funding costs, they note that this in itself is not conclusive evidence of a lack of TBTF impact – nonetheless they argue that assuming impact of different size thresholds are effectively captured by the size variable than any other benefit over and above size (for example being denominated a G-SIB) should effectively be captured by the G-SIB dummy. Moreover, they also undertake a separate specification where they use an additional dummy to reflect banks that have assets in excess of a $100 billion but are non G-SIBs – this specification does not materially affect their results and the G-SIB dummy still continues to be insignificant in 2013. They also aggregate the data at the bank level and repeat the analysis – with the results broadly consistent across the two samples. One drawback of this study is the use of an OLS specification in their regressions, which is vulnerable to endogeneity issues.

An even more recent study in the US was released by GAO in July 2014. The institutional focus for this study was once again on US BHCs, and the measure of funding costs was the bond yield spreads[38] on senior unsecured debt that were ‘plain vanilla’[39]. The period under review by GAO was 2006 to 2013[40]. For each year between 2006 and 2013 GAO ran 42 different econometric models, where the number of model permutations was driven by different combinations of explanatory variables, in each case using a simple OLS regression. The key findings of this study was that in 2008 funding cost advantages were estimated to be between 17bps to 630bps for larger BHCs, but that in 2013 estimates ranged from a 196bps cost advantage to a 63bps cost disadvantage – suggesting that the implicit subsidy benefit may have actually reversed. However, an additional finding of the study was that most models for 2013 still showed a funding advantage for larger BHCs when credit conditions akin to those in 2008 were applied. Overall, this study lends support to hypothesis that financial reforms have reduced the expectation of government support for larger financial institutions; however, there remains uncertainty on the level of implicit support during periods of financial distress.

[38] Spreads over benchmark treasury securities

[39] ‘Plain vanilla’ bonds are those that have a fixed coupon, bullet maturity and no options such as convertibility.

[40] Over this period the number of bank holding companies with senior unsecured bond outstanding which met the relevant bond criteria, ranged from 22 to 31, with the number of bonds in the sample varying between 166 and 510

There are a number of challenges associated with the interpretation of outputs from econometric models such as those specified above, which need to be considered when looking at the evolution of funding cost advances for large banks overtime. In particular, Goldman Sachs (2013)[41] raises a number of interesting issues. Firstly they state that the funding advantage is greater for non-bank financials than it is for banks, therefore where studies use a broad universe of bonds and issuers, the funding advantage is inflated above levels that are attributable to banks. For example, the AAW study cited above uses a very broad set of financial institutions in their analysis, and subsequently may have this bias present in their sample. Secondly, they find that bonds issued by larger banks have higher levels of liquidity, and that the advantages of superior liquidity can explain some of the observed funding advantages. Another shortcoming of this field of research that Goldman Sachs highlight is that few banks issue bonds in the first place, and the fact that those that do are predominantly the largest banks means that we are not truly comparing large to small banks, rather, larger and 'less' large banks. This shortcoming is consistent with GAO's report, which shows that a very small proportion of US BHCs had plain vanilla senior unsecured bonds outstanding.

Goldman Sachs (2013) conduct their own analysis and find that for bond-issuing US banks, the six largest had a small funding advantage between 1999 and 2007 of 6bps. They find that this advantage did widen during the crisis, but has since reversed and has become a disadvantage (consistent with GAO study). However, this analysis appears to only consider the spread differential on bonds between the largest and smallest banks without controlling for other factors and therefore could omit other drivers of funding costs. The Goldman Sachs study also compares funding advantages in other industries to show that banks are not unique. Their analysis finds that in many other industries larger firms enjoy even larger funding advantages over their smaller peers than they do in banking; calling into question the ability to attribute funding advantages to implicit Government support.

A key critique of the econometric approaches discussed thus far is that they typically rely on traded bonds which only represent a small proportion of a bank's overall funding, and hence the focus of these studies is too narrow. Below we conclude our review of cost of funding approaches by reviewing studies that consider other large components of bank funding.

There are a number of different studies which focus on retail funding (i.e. deposits) when trying to capture funding benefits associated with G-SIBs. For example, Jacewitz and Pogach (2013)[42] use branch level data in the US on deposit rates offered to assess cost of funding advantages for G-SIB banks over the period 2005-2010. In order to separate 'large' from 'small' banks, this study defines large banks as having greater than $200bn in assets. For each bank, a 'risk premium' measure is calculated which reflects the differences in interest rates offered on money market deposit accounts (MMDAs) with a minimum deposit of $25,000 versus MMDAs with a minimum deposit of $100,000[43]. This is used as the dependent variable. They use an OLS regression framework, and they find that larger banks pay approximately 40bps lower risk premiums compared to smaller banks after controlling for other risk factors. Another finding was that these differences diminished once the insurance deposit limit was raised.

Oliver Wyman (2014b)[44] update Jacewitz and Pogach study to provide more up to date estimate of the implicit subsidy using the same approach. As the deposit insurance limit was raised from $100,000 to $250,000 in 2008, they calculate the premium as the difference between interest rates offered on $100,000 MMDAs and $250,000 MMDAs after this time period. As above, these premiums are then modelled as a function of bank risk factors and bank size. Using this updated branch level dataset, they find that the funding advantage for the largest banks amounts to just 4bps over the 2010-12 period. However, they note that funding cost differentials are likely to incorporate non-TBTF effects, for example, they find that large banks have a funding advantage on accounts that are explicitly insured, and hence should be unrelated to TBTF issues.

[41] Goldman Sachs (2013), 'Measuring the TBTF effect on bond pricing', Global Markets Institute

[42] Jacewitz and Pogach (2013), 'Deposit rate advantages at the largest banks', FDIC working paper.

[43] Up until in Q42008 MMDA accounts that require a minimum deposit of $100,000 were only partially insured by FDIC, whereas the $25,000 MMDAs were fully insured.

[44] Oliver Wyman (2014b), 'Do Deposit Rates Show Evidence of Too Big to Fail Effects', Available at SSRN 2412852.

While studies focusing on retail funding generally represent a broader proportion of overall bank liabilities (hence reflect an improvement on approaches that focus entirely on wholesale funding), they face a number of different challenges. Firstly, the minimum deposit sizes on the MMDAs studied are on the threshold of the deposit insurance limit, therefore, as there is no information on the amount of deposits that are held beyond the minimum requirement for the account, it is difficult to assess the proportion of deposits which are exposed in the event of bank failure. Secondly, consumer behaviour in savings markets can be influences by other products or product features, for example, consumers may opt to bundle many products with one provider for convenience or because they can achieve some preferential rate on another product for doing so. Thirdly, the deposit rate a bank chooses to offer is a multifaceted decision that depends on the objectives of the bank e.g. to manage their balance sheet, and/or whether to expand into new markets. Fourthly, this approach assumes consumers are very active and diligent in comparing rates offered and assessing the riskiness and size of institutions. Numerous market studies have shown that a significant proportion of consumers are 'sticky' and don't respond rapidly to deposit rate changes[45]. Lastly, as shown in Oliver Wyman's analysis, a large number of banks do not offer a higher interest rate on MMDA accounts with larger minimum deposits (partially insured), this issue is particularly acute when comparing $100,000 and $250,000 MMDAs.

3.2. Summary of the estimate of implicit subsidies

In the immediate aftermath of the crisis, many studies confirmed the hypothesis that an implicit subsidy does exist. This finding was consistent across different regions and different methodologies although the estimated size of the subsidy did vary considerably.

Table 3 below summarises estimates of the implicit subsidy for a large range of previous studies – some of which we have covered in our discussion above.

Table 3: summary of implicit subsidy estimate from previous studies

Author	Year	Time frame	Region	Methodology	Estimate (bps)	Monetary estimate	Comments
Baker and McArthur	2009	2000 - 2009	US	Cost of funding	29bps to 78bps	$6bn to $34bn	Based on FDIC cost of funds data
Haldane (BoE)	2010	2007 - 2009	UK	Credit rating differentials	-	£11bn to £107bn	High estimates for 2009
Moody's	2011	2001 - 2010	US and Europe	Fair value CDS spreads	23bps to 56bps	$170bn (US) $293bn (Europe)	Estimates based on top 20 largest banks, high estimates for the post –crisis period
Oxera	2011	NA	UK	Option pricing	8bps	£5.9bn	-
Ueda and Weder di Mauro	2013	2007 - 2009	Global	Credit rating differentials, econometrics	60bps to 80bps	-	Use an ordered choice model rather than a simple credit rating comparison
Schich and Lindh	2012	2007 – 2012	Europe	Credit rating differentials	-	$0bn to $43bn	Subsidy size varies across countries, estimates at March 2012

[45] For the UK a recent example has been FCA (2014), 'Cash savings market study: interim report'; and for the Netherlands, another recent example is ACM (2014), 'Barriers to entry into the Dutch retail banking sector'.

Author	Year	Time frame	Region	Methodology	Estimate (bps)	Monetary estimate	Comments
Noss and Sowerbutts (BoE)	2012	NA	UK	Various	8ps to 175bps	£5.9bn to £122.5bn	Based on contingent claims (option pricing) approach
Jacewitz and Pogach	2013	2005 – 2010	US	Deposit rates, econometrics	40bps	-	Risk premia based on uninsured MMDAs for large versus small banks
Tsesmelidakis and Merton	2013	2007 – 2010	US	Bond spreads, econometrics	-	$365bn	Wealth transfer estimated for shareholders and debt holders
Acharya, Anginer and Warburton	2013	1990 - 2010	US	Bond spreads, econometrics	28bps to 120bps	$20bn to $100bn	Lower estimate for the 1990 to 2010 period, high estimate for 2009 specifically
Goldman Sachs	2013	1999 - 2013	US	Bond spreads	31bps	-	Estimate the average for 1999 to 2013. Estimates are higher for periods for market stress
European Commission	2014	2011 - 2013	EU	Credit rating differentials	-	€59bn to €95bn	2012 estimates lower than those for the 2011
Oliver Wyman	2014	2006 - 2012	US	Deposit rates, econometrics	4bps	-	An update for Jacewitz & Pogach. Note that estimate is likely to incorporate non TBTF effects
GAO	2014	2006 – 2013	US	Bond spreads, econometrics	(63)bps to 196bps in 2013	-	Estimates for 2008 range from 17bps to 630bps. Negative figure represents a funding disadvantage
Oliver Wyman	2014	2009 - 2013	US	Bond spreads, econometrics	137bps to 0bps	-	High estimate for 2009 and statistically insignificant from zero for 2013
IMF (a)	2014	2003 - 2013	Global	Bond spreads	25bps	-	Estimate for advanced economies over the 2003 – 2013 period
IMF (b)	2014	2005 - 2013	Global	CDS Spreads	30bps to 60bps	-	Low estimate based on 2005 to 2014, high estimate for 2009
IMF (c)	2014	2003 - 2013	Global	Credit rating differentials	15bps to 60bps	$15bn to $100bn	Low estimates based on US and high estimates based on the Euro Area

Source: Various.

The banking landscape has been altered by new legislation. Landmark examples are the Dodd-Frank Act in the US and the Bank Recovery and Resolution Directive (BRRD) in the EU. The introduction of this new legislation, which (amongst other issues) is targeted towards removing TBTF, is expected to have had some impact on the evolution of the implicit subsidy across different regions overtime. In a large part, the regulatory reform agenda is still evolving and the new framework are still to be fully implemented– therefore at this stage there might still be some continued uncertainty around their precise impact.

Overall, studies from the United States suggest that there has been a steeper reduction in the size of implicit subsidies compared to other regions. In particular, the latest US studies that use econometric techniques around funding cost analysis suggest that the implicit subsidies may have reduced significantly or indeed are non-existent. Evidence from recent studies in Europe, specifically UK, somewhat vary, but on average suggest that whilst there has been a decline, it is less pronounced than that in the US and in most part implicit subsidies still exist. For example, recent studies by IMF (2014) and European Commission (2014) show that although there may have been declines since peak levels, an implicit subsidy still remains. However, both of these studies employ a credit rating methodology, and to the best of our knowledge there is no up to date econometric cost of funding studies for Europe and the UK (as there is in the US) – which should provide a more robust estimate of trends in such implicit subsidies.

3.3. Conclusion

Overall, we find that each approach has its own merits and drawbacks. CDS approaches are market driven, and therefore can be estimated using the most up to date market data, however they are heavily reliant upon the formulation of a 'fair-value CDS spread'. Option pricing approaches try to directly estimate government support levels and by varying inputs are able to generate range of scenarios – however, these inputs are difficult to calibrate and can lead to significantly different results. Moreover, the approach assumes the existence of Government support – the very thing we are trying to test for.

Credit rating approaches allow for simple quantification of government support and their evolution can be tracked over time, but their key drawback is that the support differential is not directly priced.

Econometric approaches (for example those that focus on OLS techniques) using spreads on senior debt and a range of explanatory variables including size, have the advantage of being able to control for bank specific characteristics that may drive directly observed funding costs. However, their weakness is that data quality and coverage generally varies across markets (also for example focusing on a specific segment of liabilities like senior debt does not necessarily represent a complete picture of bank's funding). Econometric models are seldom perfect (whether OLS or more sophisticated specifications) and can suffer from model specification issues (such as endogeneity) and struggle to pass regression specification tests. Nonetheless, for our study, we consider econometric techniques as more appropriate when assessing and valuing implicit subsidies

There is consensus that implicit subsidies have fallen since the depths of financial crisis, however evidence points towards steeper reductions in the US. One factor that may be driving this apparent divergence between US and European implicit subsidies is a lack of up to date studies on European economies using an econometric approach similar to those used in the US. In Section 4 we set out our methodology in more detail, covering areas where we think our model specification helps us deal with some of the challenges that previous studies might have faced as well as some of the shortcoming of our proposed approach.

4. Valuing the implicit guarantee

4.1. Our proposed methodology

In Section 3 we reviewed in detail some of the previous studies that have estimated the size of implicit subsidies that TBTF financial institutions benefit from. The magnitude of the subsidies, and indeed the trends over time, are particularly driven by the underlying methodology and the time period considered – with each approach having its own merits and drawbacks. Therefore any study that attempts to value such subsidies needs to take into consideration the advantages and disadvantages of various approaches and some of the key assumptions that shape the overall outcomes.

Our preferred approach uses an econometric assessment, but this does have its own challenges, particularly around some of the econometric model specification issues and related input variables (discussed in more detail later). For example, Oliver Wyman (2014) noted when applying statistical models on, "limited and noisy data to differentiate highly correlated effects and interdependent relationships"[46]. However, using an appropriate econometric technique can improve on the robustness of the sample results and help deal with some of these key issues – allowing us to control for the effect of different explanatory variables and specifically analyse the impact of key bank characteristic (for example being designated as a G-SIB) on funding costs. Moreover, as stated above in the context of the EU, econometric analysis which has focused on cost of funding across financial institutions to analyse the impact of size (and other variables) has not been undertaken recently.

4.2. Funding cost data

We estimate the cost of funding from the wholesale market sources, using the spreads on fixed rate senior unsecured debt[47]. This is consistent with a wide range of studies in the EU, and the US, which have focused on wholesale funding when valuing implicit subsidies. There are a number of benefits associated with using traded debt spreads compared to other options (for example deposit rates, CDS spreads or credit ratings which have been used across a number of different studies) including:

- Bonds are traded and priced in secondary financial markets, so timely market driven information about changes in their yield spreads are easily observable. In contrast deposit rates are not easily observable, particularly on a consistent basis across the EU.
- Bond yield spreads represent a direct measure of banks' funding costs; as opposed to credit ratings which represent an indirect estimate.
- Bond holders are more likely to benefit from government support in the event of financial distress, compared to shareholders, as they are a higher ranking creditor in the event of failure. This means any benefits associated with implicit subsidies are most likely to be concentrated on senior (unsecured) debt holders. By contrast equity holders are likely to be highly diluted and therefore receive less benefit from government support. Therefore, for the purpose of our assessment we consider a class of senior (unsecured) debt holders as an appropriate source of bank funding.
- Bank holding companies with a wide variety of sizes issue bonds, including some with less than $8-10 billion in assets. In contrast, CDS spread coverage is less exhaustive.

A number of studies in the US have used deposit rates information on money market deposit accounts when valuing implicit subsidies (as they represent a large proportion of overall liabilities) relying on very granular branch level data for rates quoted on relatively homogenous MMDA products. Replicating this type of dataset for the EU would be very difficult. To the best of our knowledge, data on a standardised set of savings products across our countries of interest, whose minimum deposit levels are greater than the amounts covered by Deposit Guarantee Schemes, is not available. These deposit rate studies also had several drawbacks of their own

[46] Oliver Wyman (2014), pg.2

[47] Without any options attached to the bond.

as highlighted in section 3.2, particularly in the EU context, where differences in markets, consumer behaviours and regulation imply limited relevance for direct comparisons. Therefore, despite deposits compromising a large part of bank funding structure, it would be very difficult to extract information relating to any implicit subsidies that may exist within this segment within the EU.

Whilst we consider a wholesale funding focus (using senior unsecured debt) to be appropriate in the EU context, there are also a number of challenges associated with this approach that should be recognised. Firstly, senior (fixed-rate) unsecured debt may only represent a relatively small proportion of bank funding – implying the need for extrapolation to a broader funding cost base. Differences in bond characteristics might also imply limited comparability across different bonds. IMF (2014) raised specific concerns around this approach, for example, yields reflecting differences in the characteristics of bonds. As set out in the data section, we aim to address this issue by selecting a set of 'plain vanilla' bonds to ensure maximum comparability. Moreover, yield spreads do not solely reflect credit risk, but also capture other things like liquidity risk which in principle should be controlled for as part of the assessment. Schich and Lindh (2012) also raised concerns such as accounting for liquidity premia and sovereign credit risks as part of the assessment. Whilst these challenges do impact the inference we can draw from our analysis, we aim to control for as many of these effects in our regression specification – which we discuss in more detail in the following sections.

While some of these challenges may impact the precise extrapolation and valuation of any implicit guarantee, they are less of a concern in detecting any implicit guarantee within this area of bank funding. For this reason we focus on the detection of implicit guarantee, rather than extrapolating to an absolute value, as other studies have done.

4.3. Choosing the right econometric approach

Many of the studies we have reviewed seek to quantify the spread advantage of large financial institutions using a panel data approach. The panel often consists of a dependent variable observed at the firm or bank level, usually bond spreads or other variables that reflects cost of funding (at the retail or wholesale level), and a range of independent variables covering different bond, bank and macro level drivers or controls.

However, in most cases, very little explanation is provided with regard to the choice of econometric approach (for example Pooled Ordinary least squared (POLS) vs ordinary least squared (OLS) etc.). Much of the existing research uses a POLS regression approach. However, this method is vulnerable to endogeneity problems, which can stem from three different sources:

- **Measurement error:** this issue can be overcome by carefully choosing the variables used in the econometric model to ensure accuracy;
- **Reverse causality:** this is known as simulateaity and occurs when there is a circular relationship between the dependent and independent variables. Specifically this implies that the dependent variable is influencing an explanatory variable which biases the coefficients and reliability of the model;
- **Omitted variables:** often many variables which influence a dependent variable are unobserved or immeasurable, meaning they are omitted from the specifitcation. If these factors are correlated with an explanatory variable and not accounted for in the model, this can bias the results.

Firstly, in the context of looking at the impact of bank size on bond spread, there is likely to be reverse causality between some explanatory variables, for example bank return on average equity (ROAE), and the dependent variable i.e. bond spread. In principle, a high cost of debt can lead to lower ROAE (and vice versa) which in turn can influence the yield on traded debt (and hence the spreads). This problem of reverse causality violates a strong assumption required to use the OLS approach, i.e. where the current observations of the explanatory variable (e.g. ROAE) are independent of past values of the dependent variable. If this is not corrected for, the estimates derived for the impact of size on the bond spread is said to be biased. Similarly, certain variables, such as the bond spread, can be highly correlated with their past values. Hence, our proposed econometric methodology will need to account for both these challenges: reverse causality and the dynamic nature of key relationships.

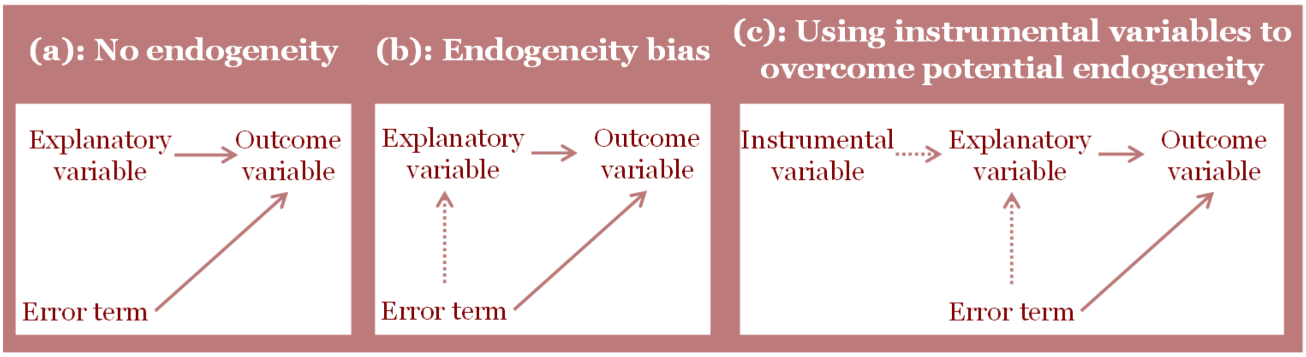
Secondly, bond spreads could be influenced by unobserved (and hence omitted) bank-specific characteristics, such as managerial ability or the legal environment around potential claims. Our review of the literature suggests that the bond spread tends to be influenced by a range of factors, not all of which are observable or measurable. These fixed effects may be banks characteristics, which are time-invariant, and can directly influence the dependent variable. This means that our chosen methodology should account for banks' fixed effects. The central principle behind the fixed effects (FE) approach is that there is some factor at each firm level which may bias the dependent variable due to correlation between the error term and the explanatory variables. FE models serve to remove the time-invariant characteristics of the independent variables in order to mitigate omitted variable bias and generate unbiased and efficient estimators.

While we have seen evidence in previous studies using FE models, which help to mitigate unobserved heterogeneity, nonetheless there are residual problems. Firstly, the approach fails to overcome the problems of reverse causality and endogeneity identified above (Nickell, 1981)[48]. Secondly, related to the first point, there is a need to introduce a dynamic element to the standard fixed effects framework to capture the dynamic nature of some of the relationships, i.e. including the first lag of the dependent variable as an additional explanatory variable is deemed inappropriate and will result in inconsistent estimates in the case of a FE model (Wooldridge, 2002)[49].

Figure 4 illustrates the concept of endogeneity and how this can be mitigated using an instrumental variable approach. Panel (a) shows that in the absence of endogeneity, both the explanatory variable and the error term are correlated with the outcome variable, but not with one another. The error term typically accounts for, among other things, the influence of omitted variables on the dependent variable. As long as the omitted variables (i.e. error term) are uncorrelated with the independent variables – in this case for example the bank ROAE – an OLS regression will produce unbiased estimates. However, endogeneity arises when the omitted variables (or the error term) are in fact correlated with the independent variables (panel (b)), which biases the estimates using the OLS approach.

In our analysis, we include the lag of the dependent variable (i.e. bond spread) as an additional explanatory variable; however, the lag of the bond spread is correlated with the error term in the model by construction which leads to endogeneity. One potential strategy to overcome these issues is to use an instrumental variable (IV) approach combined with fixed effects (Shepherd, 2009)[50]. This would require the use of an instrument, which is a variable that is strongly correlated with the potentially endogenous explanatory variable but also uncorrelated with the error term in the model. The instrument should only influence the dependent variable through the potentially endogenous explanatory variable, as shown in panel (c) of Figure 4.

Figure 4: Explaining endogeneity



A good instrument must fulfil two criteria. Firstly, the instrument must be valid, meaning that the instrument must be independent of the error term. [51] Secondly, the instrument must be relevant, meaning that the instrument must have some explanatory power over the potentially endogenous variable.[52] In reality, finding an

[48] Nickell (1981) 'Biases in Dynamics Models with Fixed Effects' Econometrica, Vol.49, No. 6, 1417-1426.

[49] Wooldridge, J. (2002), "Econometric Analysis of Cross Section and Panel Data", MIT Press.

[50] Shepherd (2009) 'Development Consultant Dealing with Endogeneity' Trade Economist & International www.Developing-Trade.com.

[51] It is measured by the Sargan/Hansen J test of exogeneity.

[52] The Kleibergen Paap under-identification test measures the strength of this correlation.

appropriate instrument that meets both the above criteria can be a considerable challenge, however, we use a number of specification tests to check the validity of our instrumental variables.

A key motivation of this study is to potentially overcome the issues that might have been encountered in previous studies by adopting an econometric approach that accounts for these problems, and to improve the credibility of our results. [53]

In the context of the current analysis, we believe a dynamic panel system generalised method of moments (GMM) estimator is appropriate. The GMM approach involves using an instrumental variable-based approach where higher lag values of the lagged dependent variable are used as instruments. In contrast to OLS in which the estimator minimises the squared vertical distances between the observation and the mean (the first moment), system GMM minimises the sample average of the second, third and fourth moments: the variance, the skew and the kurtosis.[54] The GMM approach overcomes the difficulty of instrument identification as it works by using lagged historical variables in differences as instruments for the endogenous variables in the level regression (and vice versa), since lagged values are less likely to be influenced by current shocks. This differencing also serves to eliminate any potential omitted variable bias and unobserved heterogeneity, which means firms' fixed effects, or firm characteristics that are time-invariant, are accounted for.[55]

The system GMM approach does not specify a particular distribution for the errors, and hence does not depend on the assumption of normality of the error term unlike the simple OLS approach. This is important in the context of our analysis due to the presence, in our dataset, of very large or very small banks which may potentially result in the presence of outliers thereby causing the errors to be non-normally distributed. This is another reason why the system GMM approach is preferable. To ensure the statistical robustness of our specifications, first, the instruments used must be valid. Our study uses various statistical tests to ensure that our specifications are not affected by problems of under-identification or weak-identification, as proposed by Baum, Schaffer and Stillman (2007)[56]. Second, the correct number of lags must be used. When testing for the correct number of lags (levels and differences), we ensured the model(s) fulfilled certain criteria:

- **Nickell bias test:** the magnitude of the coefficient of the lagged dependent variable (e.g. bond spread) from the system GMM estimation approach must be smaller than that when computed using OLS, but greater than when computed using a fixed effects model, such that OLS>GMM>FE . Hsiao (1986)[57] argues that the OLS coefficient of the lagged dependent variable is expected to suffer from an upward bias due to the fact that it ignores specific effects, while Nickell (1981)[58] argues that the coefficient in a fixed effects model is likely to be downward biased. Hence, Blundell and Bond (1998) rationalise that a plausible parameter estimate should lie within the two estimates;
- **The Arellano:** Bond test for autocorrelation: tests the null hypothesis that the model does not suffer from autocorrelation; this test is applied to the differenced residuals or error term. We expect the AR test of order 1 to be rejected in our dynamic model by construction. However, we want the AR (2) test to not be rejected, to ensure that autocorrelation is not evident in the model. [59]
- **The Hansen J test for instrument validity:** assesses the null hypothesis that the model is correctly specified and the over-identifying restrictions are valid; it tests if the instruments as a group are exogenous, ensuring the validity of the instruments. The Sargan[60] test also tests for instrument validity, but it is not

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[53] Our use of "robust" in this context is in reference to statistical robustness, i.e. statistical methods and results that are not unduly affected by deviations of statistical assumptions (e.g. non-normality, homoskedaticity).

[54] Kurtosis is a measure of the "peakedness" of the probability distribution.

[55] Monte Carlo analysis has shown that such an approach consistently produces better quality results

[56] Baum, Schaffer and Stillman (2007), 'Enhanced routines for instrumental variables/generalized method of moment's estimation and testing.' *Boston College EconomicsWorking Paper No.667.*

[57] Hsiao, C. (1986) 'Analysis of panel data' Cambridge: Cambridge University Press

[58] Nickell (1981), 'Biases in Dynamic Models with Fixed Effects' Econometrica, Vol.49, No. 6, pp.1417-1426.

[59] Tests for autocorrelation, also known as serial correlation, in which the error term in time t is correlated with the error term in time t-n; this reduces the efficiency of estimators. The AR(1) test checks for correlation between the value of the current dependent variable and its value one period ago; the AR(2) tests for correlation between the value of the dependent variable and its value two periods ago.

[60] Tests for correlation between the instrument and the error term.

robust to heteroskedasticity, unlike the Hansen test. Thus, in the study, we only report the results of the Hansen test due to the presence of heteroskedasticity in our model[61]. The criterion is that the Hansen J[62] test result is greater than 0.05, but less than 0.9, such that 0.05>x>0.9, meaning we would be unable to reject the null hypothesis of exogeneity. In addition to testing for instrument validity, Roodman (2009)[63] contends that the test can also be viewed as a test of structural specification; omitting important variables may move components of variation into the error term and make them correlated with the instruments, where they may not be in the correct model;

Our system GMM model specification also applies the 'two-step' command to ensure that the model is robust to panel-specific autocorrelation and heteroskedasticity, and the 'collapse' command to avoid instrument proliferation.[64]

However, whilst the System GMM framework helps to deal with some of the issues identified above – some challenges remain. A notable limitation of our study relates to the use of the lags of the variables found to be endogenous as instruments. Although this is a perfectly legitimate approach and indeed a technique which is widely used in many published studies, it is still the case that using lags is more of an ad hoc statistical solution. Finding instruments other than the lags remains the best approach in dealing with endogeneity. The results from the dynamic panel GMM models or indeed any results based on the instrumental variable approach where lagged variables are used as instruments tend to be in general highly sensitive to the choice of the instrument matrix used.

An important word of caution about the Hansen J test is that, although robust to the presence of heteroskedasticity, this test can be weakened by the use of many instruments. We mitigate this issue by using the rule of thumb which consists in using fewer instruments than groups (Rodman, 2009). For example, in our analysis based on banks, if the number of banks in the dataset in 30, then we use less than 30 instruments.

In the next section we discuss the data and sources underlying our analysis.

4.4. Data collected for econometric analysis

We set out below some of the key data parameters and associated assumptions underlying our analysis.

Countries included in the sample

More coverage across countries increases sample size and number of observations and therefore the potential validity and specification of our econometric models. However, data coverage is poor across a large number of European countries on banks' funding costs and our range of explanatory variables. In selecting countries for our study, we opted to include those European countries where at least one bank with G-SIB status was located. Based on the Financial Stability Board's[65] latest update these countries were the UK, France, Germany, Netherlands, Italy, Spain, Sweden and Switzerland. This approach should be sufficient to capture G-SIB impact (and hence more EU countries are not strictly required).

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[61] Tested by the xttest3 command on Stata.

[62] The Hansen test is used to assess the validity of the instruments, the null hypothesis assuming the instruments are valid. The Hansen test is robust to heteroskedasticity, unlike the Sargan test.

[63] Roodman (2009), 'Practitioners' Corners, A note on the Theme of Too Many Instruments', *Oxford Bulletin of Economics and Statistics, Vol.*71, Issue 1.

[64] Instrument proliferation can cause two problems (Roodman, 2009): 1. By being numerous, instruments can over fit instrumented variables, failing to expunge their endogenous components and biasing coefficient estimates towards those from non-instrumenting estimators. 2. Instrument proliferation also leads to imprecise estimates of the optimal weighting matrix used in the two-step variants of DGMM and SGMM estimations. In order words, the standard errors in two-step GMM will tend to be severely downward biased. We therefore use the "collapse" option in Stata to mitigate this problem. See Windmeijer (2005).

[65] http://www.financialstabilityboard.org/publications/r_131111.pdf

Selection criteria for banks

A wide selection criteria increases the potential statistical robustness of the analysis, but the data quality and availability is markedly lower for smaller banks. The inclusion of a large array of smaller banks might have also required a wider range of explanatory variables to capture funding cost differences at smaller banks. We used a number of selection criteria when including banks in our sample, following a series of steps which are laid out below:

- **First,** we screened for financial institutions in each country using S&P Capital IQ. Starting with an initial broad search criteria, focusing on all institutions that were primarily classified as 'banks' of 'diversified financials' in our countries of choice;
- **Second,** we filtered down to those institutions whose primary activity was either retail or investment banking (excluding for example private banks and asset managers); and
- **Last,** we truncated the sample to banks that as of 2013 has approximately €30bn or more in assets[66].

This overall list gave us a sample of over 85 banks, however, the precise number of banks used across any given regression specification varies as the data coverage across the sample of bank was not consistently available overtime.

Selection criteria for bonds

For the sample of selected banks, we source bonds issued using Thomson Reuters. Using bond specific information from Thomson Reuters and S&P Capital IQ we then isolated a specific subset of bonds that meet the following criteria:

- Were denominated as senior unsecured;
- Had a fixed coupon;
- Had no options attached;
- There were no explicit guarantees; and
- Had at least more than one year to maturity at issue.

For each of these bonds Thomson Reuters provided data on the spread of the bond yield to that of its relevant government benchmark. Benchmarks are selected on a currency basis, so for example for Euro denominated bonds, we use a European Monetary Union benchmark[67] as opposed to country specific benchmarks. This allows greater consistency across the data set. However, to capture sovereign risk factors and isolate spread differences associated with country domicile, we use country dummies in the model specification.

Time period of data collection

We obtained these spreads monthly, using the yields on the final day of each month for the period January 2009 to June 2014. Whilst we cover the entire period, our focus and key conclusions are drawn from the recent period of January 2013 to June 2014.

Regression specification and choice of explanatory variables

Data for explanatory variables has been sourced from S&P Capital IQ. Where it was available, explanatory variable data was sourced at a quarterly frequency. Group level data is used for explanatory variables whereas funding cost data is drawn from bank issuers which may either be the group holding company or a subsidiary. We adopt a general to specific modelling approach when choosing the explanatory variables. This implies starting with a large pool of independent variables for our econometric model and then thinning down

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[66] Although some Cantonal banks in Switzerland met these criteria, they were excluded from this study as they are government owned institutions.

[67] The selection criteria for the EMU benchmark is by choosing the lowest yield on a 1 month moving average amount the relevant country benchmark indices, this approach applies to all tenors.

explanatory variables based on model specification tests, statistical analysis and data availability[68]. An explanation of our key explanatory variables, and the expected theoretical relationship with debt spreads, are summarised in the table below.

Table 4: List of variables used in the econometric model

Variable	Expected Relationship	Description
Lag of spread	Positive	In our dynamic specification we expect that the bond spread from the previous period has some explanatory power on the spread today. In other words, spread exhibits some persistence over time.
Years to maturity	Positive	Years to maturity captures the time remaining in years until the bond's maturity date. Although this relationship will vary with the shape of the yield curve, we expected generally that long-term debt requires a premium in the current environment.
Total Assets	Negative	Total assets are a core measure of the size of a bank. We have a prior expectation that larger banks have a higher likelihood of benefiting from both economies of scale and TITF effects. Both of these may reduce funding costs.
Leverage	Positive	We define leverage as total liabilities as a percentage of total assets. Therefore, as this variable increases the bank is said to have higher leverage (a lower proportion of equity relative to total assets). Higher leverage is a measure of a bank's risk and therefore we expect it will lead to a higher cost of funding.
Modified Merton	Negative	A measure of default risk. It is calculated using implied volatility and leverage (where leverage represents the proportion of non-equity funding). For more details on the precise calculation, please refer to Bystrom (2003)
ROAE	Negative	ROAE is calculated as earnings from continuing operations divided by average total equity. It is a key business performance measure where higher values signify better performance, and as such we expect that it will be negatively related to the cost of funding.
GSIB	Negative	This is a binary identification mechanism (dummy variable) to categorising G-SIB banks. If there are any implicit subsidies, we would expect GSIBs to have a higher likelihood of benefitting from TBTF effects and hence should have a negative relationship with cost of funding. Its size may decrease over time though as markets stabilise and regulatory changes materialise.

Our choice of variables is consistent with other studies; however, as part of our assessment we consider a wide range of model specifications with a differing array of explanatory variables not mentioned above. For the purpose of this report, we show results from model specifications which have passed the various regression specification tests. We report the results from some of the other models which use different permutations and combinations of explanatory variables in the Appendix. For example, one of the permutations uses proxies for the retail and wholesale segments of the business, specifically we used net interest income as a percentage of total assets to capture the retail business and total trading assets as a proportion of total assets to reflect the wholesale segment, to capture the impact on wholesale funding of different business units[69]. A challenge with using these additional specifications is the limited data availability and consistency of data overtime – implying

[68] The data quality in our sample does vary considerably overtime for the range explanatory variables – which in itself has influenced on the selection and inclusion of some of these variables in the model. This is an issue especially when one of our aims is to analyse the evolution of the relationship between GSIB and cost of funding over time. For the time periods where these gaps exist, it becomes very challenging to explore the nature of the relationship of interest.

[69] We also attempted to capture the impact on wholesale funding of the degree of diversification across geographical markets, however, there was very limited data overtime to capture the effect of this metric on spreads.

the model outputs are not as robust and hence difficult to interpret. Some of these model specifications are also set out in the Appendix.

Following the empirical model in Campbell and Taksler (2003), and our selection of explanatory variables, we estimate the following panel data based regression to analyse how the size of a bank affects the spread on its bonds. The key variable of interest in the specification is the G-SIB dummy, which in principal reflects the impact of G-SIB specification on debt spreads for senior unsecured debt.

$$\begin{aligned} Spread_{i,b,t} = \alpha_i + \beta_1 Lag\ of\ spread_i + \beta_2 Years\ to\ maturity_{i,b,t} + \beta_3 Total\ assets_{i,b.t} \\ + \beta_4 Leverage_{i,t} + \beta_5 Modified\ Merton_t + \beta_6 ROAE + \beta_7 GSIB \\ + Country\ dummies + \varepsilon_{i,b,t} \end{aligned}$$

Input data consistency/quality

In order to assess the econometric effect of size on the costs of funding, we analyse the cost of funding at the level of individual bonds as well as averaging at the bank level across different European countries. Any implicit government subsidy is likely to reside at the bank level (and hence for all its funding sources). However, longer dated funding may not benefit to such an extent (particularly as the regulatory reform programme continues). This means that bond level analysis is more flexible and inherently uses a larger number of data points – thus suggests improved robustness of the sample.

Bond level analysis has typically been the focus of previous studies; however, for completeness most studies also undertake a bank level analysis. Our motivation to average the cost of funding at the bank level is twofold. First, different banks have different numbers of bonds in our sample; hence averaging makes our sample more representative and avoids the results being influenced by the existence of few banks with large number of bonds in the sample. Second, for a number of banks, the data on costs of funding might appear across only selected time periods – implying they would be dropped from the sample of bonds for the representative period. Averaging across bank level allows us to account for all the available information on the cost of funding over the given period. Therefore, for completeness, we use both models but have a preference for the bond level analysis. Across the period Q1 2009 to Q2 2014, our 'plain vanilla' bond sample, comprises approximately 1,000 bonds with a value of approximately €500bn.

The data quality varies over time, with more recent data (2012 onwards) generally being more consistent and of higher quality compared to previous periods – across both the dependent and the explanatory variables. Further back in time, the data availability tends to worsen, particularly as data on now matured bonds is less available.

On average, our analysis also suggests that the quality of European market data, compared to the US market, is consistently lower - perhaps suggesting why there is limited focus on econometric techniques in the EU context. Focusing on listed banks only (or inclusion of variables which restrict the sample scope to such banks) further reduces the number of observations across some of the explanatory variables[70]. In order to address issues surrounding data availability and the subsequent gaps in our dataset, we use both a complete (balanced) panel and incomplete (unbalanced) panel dataset at the bonds and banks level. Each of these are explained below:

- **Complete dataset** – the same number of observations of dependent variables (either at the bond level or the bank level) are consistently observed over time i.e. the sample of bonds or banks over time remains constant (although coverage of explanatory variables changes across individual years)
- **Incomplete dataset** – individual observations of the dependent variable (either at the bond level or the bank level) can drop in and out of the sample overtime – implying the sample does not consistently include the same sets of bonds (or banks). In principle, this implies that for any given year the number of bond (or bank) observations can vary as bonds mature or are not specifically priced during the period (similar to above coverage of explanatory variables changes across individual years).

[70] For example, some of our constructed variables such at the Modified Merton Distance-to-Default require raw data which are only available for institutions that are listed on the stock market (i.e. Table 2 in our data visualisation section shows how over 7,000 observations are lost when the Modified Merton is included in the model).

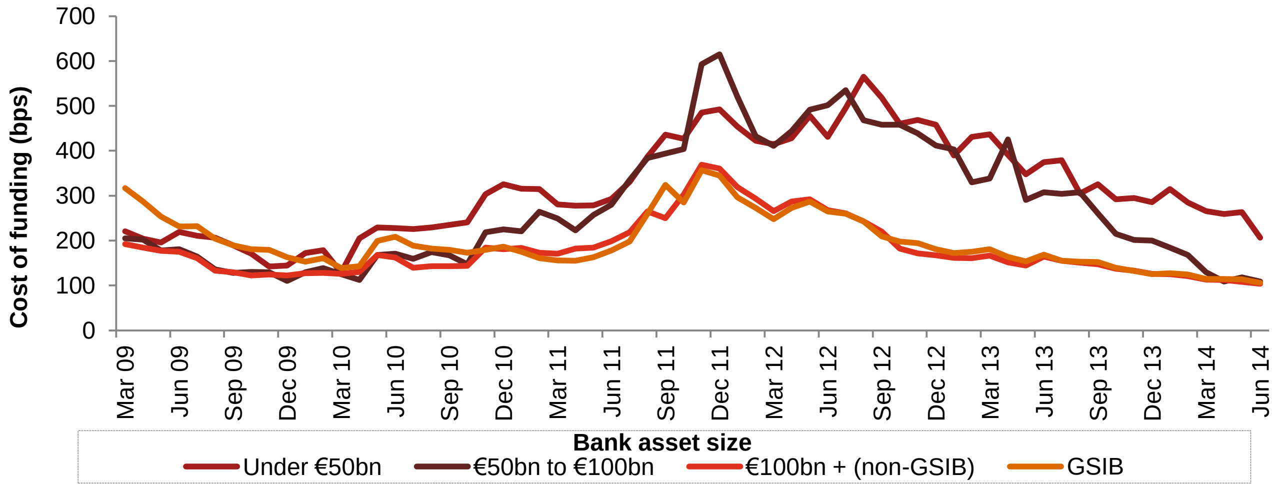
By construction, the constraints we put around the data to generate a dataset that is complete means that the incomplete dataset has invariably more observations[71]. The rational for using both of these data format is to ensure that our results are not merely driven by our sample selection methodology as well as that we have enough observations to build a credible econometric model.

4.4.1. Data visualisation

In this section, we present selected data statistics and chart some of the key relationships in our dataset. This exercise allows us to identify key features of the dataset that ultimately shape the outcome from our analysis.

Figure 5 below shows the median spreads on large G-SIBs banks compared to large non-G-SIB banks (€100bn+) and a selection of medium and small sized banks (by assets) over the last 4-5 years.

Figure 5: Median spread by cohort



Source: Capital IQ, Datastream, PwC analysis.

The exhibit shows that median spreads across G-SIB banks were above other banks in early 2009 (larger non-G-SIB as well other bank of different sizes) but declined over time and were lowest across the sample for a very brief period in mid-2011. Since then, the spreads on G-SIB banks rose for a brief period and were actually higher than comparable spreads for large non G-SIB banks at the end of 2011 (but lower than other banks). From 2012 to the end of 2013 spreads for larger banks (G-SIB and non G-SIB) were consistently below comparable spreads for banks with lower asset thresholds. More recently, the spreads have continued to decline across the entire sample of banks – and current spreads for G-SIB banks are comparable to (or even slightly above) spreads for large non G-SIB banks and banks with assets in the €50 to €100bn threshold (large to medium size entities). However, spreads for these banks are markedly lower than comparable spreads for smaller banks with assets below €50 billion. Whilst it is difficult to draw direct conclusions on the precise value of implicit subsidies from this graph, the simple evolution of spreads across banks of different cohorts suggests that bank spreads are actually quite aligned for banks above a certain threshold for example above €50 billion in this case (irrespective of G-SIB or non G-SIB categorisation), however, marked differences exist between funding costs for smaller banks below that threshold. We analyse similar funding cost differences between large and small institutions across a range of other sectors in Appendix 1.

Figure 6 below shows the cost of funding and asset size across a range of banks included in our sample.

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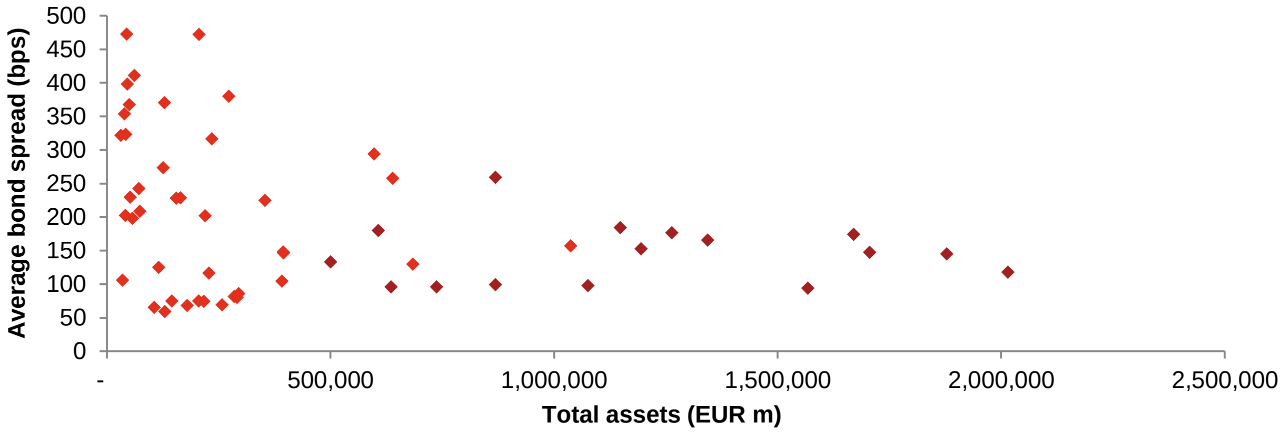
[71] As set out above, we use a range of explanatory variables and run various different permutations and combinations of the explanatory variables across our econometric model specifications at the bond and bank level (for complete and incomplete data set). Overall, this exercise resulted in running over 700 econometric specifications.

Figure 6: Cost of funding and total assets: GSIB and non-GSIB (2013-2014)

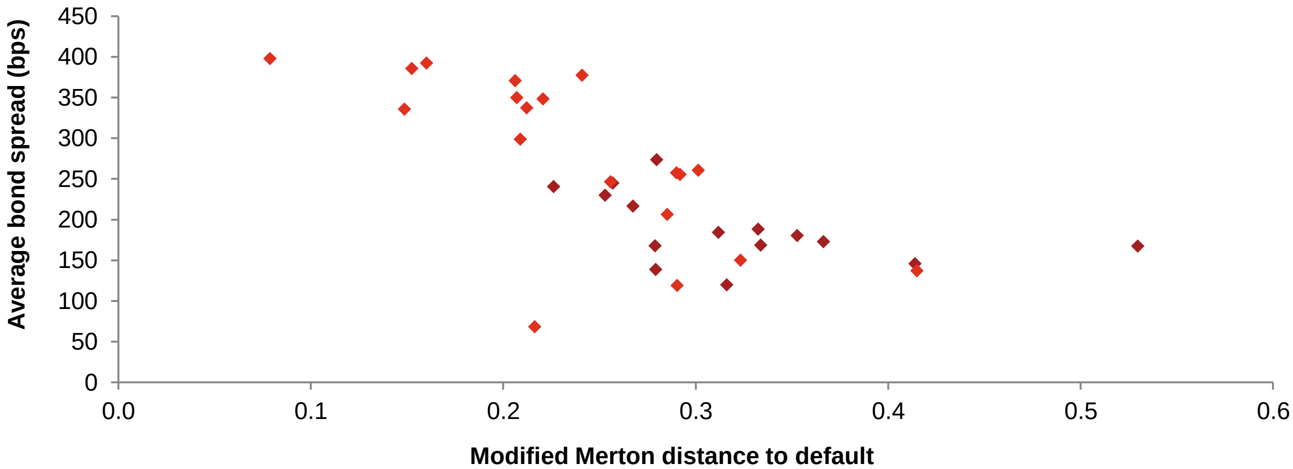


Note: The dots highlighted in red represent European G-SIB banks.
Source: Capital IQ, Datastream, PwC analysis.

Figure 6 suggests significant variation in cost of funding across relatively smaller banks of comparable sizes. This is driven by banks with both low and high funding costs. At the low end, this is explained by a cohort of small German banks having a relatively low cost of funding and at the high end banks from countries with weaker sovereigns and weaker macroeconomic conditions (e.g. Italy). This shows that factors other than size are significant drivers of bond spreads across banks in the sample. We look at evidence from credit rating agencies (Moody's) on linking size with level of systemic support in Appendix 2.

Figure 7 below shows the relationship between cost of funding and credit risk (proxied by the Modified Merton distance to default metric).

Figure 7: Scatter plot of cost of funding and Modified Merton distance to default



Note: The dots highlighted in red represent European G-SIB banks.
Source: Capital IQ, Datastream, PwC analysis.

Compared to assets, the relationship between the risk profile and the cost of funding is clearly visible. Credit risk appears to be a key driver of spreads – as the Modified Merton distance-to-default measure increases (i.e. you are further away from point of default) the cost of debt continually decreases. This is consistent with market expectations, as bond spreads reflect the credit risk profile of financial institutions.

5. What is the impact of the implicit guarantee?

In this Section we set out the results from our econometric analysis of implicit government support in the EU banking sector. As set out in Section 4 above, we use a System GMM approach to account for the dynamic nature of the analysis as well as to improve on some of the model specification issues identified in our review of other studies. We also utilise a number of regression specification tests to ensure our estimates are efficient and unbiased.

As part of our analysis, we have used a wide range of econometric models using different permutations and combinations of data sets (i.e. complete vs incomplete datasets) at both the bonds and banks' level as well as an array of explanatory variables covering the relevant time period (some of which are set out in the sub-appendix 2).

Our key conclusions are drawn from modelling outputs which have passed the key specification tests (as set out above for example including Nickell bias test, Hansen test and Arellano-Bond test) and hence are statistically robust. We deliberately do not report on the various other models that were developed as part of the assessment either because the results are already captured in the model(s) covered (and hence there is no additional value add in terms of reporting them separately) or they did not pass the specification tests over the entire period (or segments within).

Specifically, we find the bond level assessment using a complete data set and the bank level analysis using an incomplete dataset (as the complete dataset would be too small) are statistically robust using the explanatory variables set out in Section 4 above. However, the period covered by the two models vary, particularly the bond level assessment does not pass the specification tests for period prior to 2013 (largely because we lose a large number of bonds in the sample)[72]. Nonetheless, given the key areas of interest, and hence the focus of this study, is on the current level of any implicit subsidy in the EU, we consider the bonds level assessment as our preferred approach given the greater granularity of the underlying data. We turn to this next.

For the analysis over the period 2009 to 2014, we switch to the bank data (weighted average of funding cost across all available bonds), using an incomplete dataset – which is covered in more detail in the Appendix.

Table 5 below shows the results from the econometric analysis covering the most recent period using the complete dataset at the bonds level. As set out in the table below, the model passes the key specification tests for 2013-2014 (the results for previous period are not reported as they do not pass these tests) with a large number of observations over the sample period (calculated as number of bonds in a period (monthly) multiplied by the number of periods):

- **Nickell bias:** The model passes the Nickell bias test as the coefficient of the lag spread for the Pooled OLS (0.81) is greater than the comparable estimate under System GMM (0.57) which in turn is above the output under the FE model (0.28).
- **Arellano:** Bond test AR (2): We find a p-value of 0.36 which suggests that the null hypothesis that the model does not suffer from autocorrelation cannot be rejected.
- **Hansen J test:** We find a p-value of 0.064 which suggests that the null hypothesis that the model is correctly specified and the instruments are valid cannot be rejected.

[72] Bonds used were active at the time of data extraction; therefore, for earlier time periods fewer data points are available.

Table 5: Econometric outputs from bond level assessment using a complete dataset

Dependent variables	Coefficients estimates Jan 2013 to June 2014
Constant	-811.48
Lag of spread	0.57***
Year to maturity	2.83*
Total assets	-1.32
Leverage	981.01*
Modified Merton	-124.87*
ROAE	-0.17
GSIB	-4.14
Country dummies	Yes
Number of observations	8,946
Tests	
Nickell Bias	No
Arellano – Bond test AR (2)	Good
Hansen J test	Good

*Notes: * Significant at 10% level, ** significant at 5% level, *** significant at 1% level*
Source: PwC analysis. Stata code available on request

The key variable of interest is the G-SIB dummy which shows the impact on spreads for banks that are categorised as a G-SIB. According to this analysis, the G-SIB coefficient is low and negative implying G-SIBs on average have a 4 basis point lower funding cost compared to other banks which are non G-SIB, after explaining for other factors. However, the coefficient is statistically insignificant. This suggests that G-SIBs do not currently have a funding cost advantage compared to non G-SIBs. Size, which is proxied by total assets (scaled to 100s of billions), has a relatively small negative (and again statistically insignificant) impact on spreads – suggesting that, on average, as size increases, spreads decrease (however, this should be interpreted with caution as it is statistically not different from zero). In essence, our model suggests that neither the G-SIB dummy nor size (statistically) explains the difference in spreads. Indeed, as set out in the Appendix, this finding is consistent with a range of other model specifications where the G-SIB dummy for the most recent period continues to be statistically insignificant in explaining spreads.

In essence, the G-SIB dummy captures benefits of being designated a G-SIB and any benefits purely arising from size (across the array of different thresholds) are already captured in the size variable. Since our designated G-SIBs have asset sizes towards the top-end of the spectrum for asset size threshold across the sample of banks, there is a potential risk that the size effect for banks with significantly large asset portfolios is masked by the (coefficient of the) G-SIB dummy (however, we note that the size effect is not significant in explaining spread differecnes across banks for the purpose of our analysis).

The insignificant G-SIB effect could alternatively be interpreted as showing that the entire EU banking sector benefits from implicit support. However, we consider expectations of the likelihood of smaller (and not systematically important) banks receiving such government support as low and counter to the public policy of not bailing out banks.

The key conclusions across some of the other variables are specified below:

- As leverage increases (represented by the proportion of non-equity used to fund assets), the spread to benchmark increases – the coefficient is statistically significant at 10% level. This implies that as leverage increases by one percentage (i.e. the proportion of non-equity used to fund asset goes from 0.95 to 0.96), the spread increases by around 9.8 basis points.
- Credit risk, as captured by Modified Merton distance to default, is a statistically significant driver of spread differences. Essentially, as distance to default increases spread decreases. This is consistent with evidence presented in Section 4 which maps the negative relationship between spreads and distance to default (as captured by the Merton's metric). It also supports our expectations that an efficient bank funding market should price differences in credit risk.
- As the return on average equity increases, the spread decreases. However, it is statistically insignificant in explaining spreads.
- Given our focus on spreads relative to currency specific benchmarks, we also use country dummies to identify differences in sovereign risk and hence the spreads across our representative sample of countries. The model calculates country dummy impact relative to a benchmark country (in our case Germany) and suggests that the cost of funding differential is statistically significant and lowest for banks located in the Netherlands (compared to Germany). The model does not suggest statistically significant difference in cost of funding across countries such as France, Sweden, UK, Spain and Switzerland. It is important to interpret the results with caution as data limitations underlying the model specification and the inclusion of specific banks within the sample might influence these outcomes.

6. Conclusion

Our approach

We use a dynamic framework and System GMM approach to analyse the relationship between banks' cost of funding and size (as well as a number of other factors), explicitly factoring in a G-SIB variable to capture the impact on spreads for designated G-SIBs.

We consider a range of explanatory variables, analysing spread differentials at both bonds and bank level using different data sets (complete and incomplete); choosing econometric models which pass all the regression specification tests and hence are statistically robust. We consider our proposed System GMM approach to be robust as it improves upon some of the key model and parameter specification issues (for example endogeneity and omitted variable bias). However, we are conscious that certain challenges still remain and the approach itself is not perfect (for example finding instruments other than the lag of spreads remains the best approach in dealing with endogeneity). The results from the dynamic panel GMM models or indeed any results based on the instrumental variable approach where lagged variables are used as instruments tend to be in general highly sensitive to the choice of the instrument matrix used.

Our results

Our primary conclusions are drawn from bond level specification which uses a complete data set for the January 2013 to June 2014. The analysis suggests that G-SIBs in the EU currently do not benefit from an implicit subsidy as we find the coefficient for the G-SIB dummy to be statistically insignificant. Moreover, the evidence suggests G-SIBs face a slightly lower funding cost (of around 4 bps) compared to non-G-SIBs. These findings appear to be broadly consistent with evidence found by Oliver Wyman in the US. Indeed, the evolution of spreads across banks of different sizes (as set out in Figure 7 above) suggests that current funding costs across banks within certain size thresholds, G-SIBs as well as non G-SIBs, are comparable and the difference only arises compared to banks with much smaller asset portfolios. Furthermore, we find credit risk and leverage as consistent and material factors in explaining funding costs. We find size (total assets) and return on average equity as statistically insignificant in explaining spreads.

Our conclusions on the statistical insignificance of the G-SIB dummy, from a range of different model specifications which all pass the regression specification tests (although with varying degree of statistical robustness, some of which are set out in the appendix), are consistent with the model above in that we do not find any evidence of cost of funding advantages for banks that are designated as G-SIBs.

For one of the model extensions based on using incomplete dataset at the banks level, we analyse the evolution of spread differentials and hence the cost of funding benefit for G-SIB banks. Our analysis suggests that, whilst G-SIB banks might have benefited from a funding cost advantage in 2009 (consistent with a range of evidence across other studies), some of the other observed relationships are inconsistent with expectations (for example the model does not appear to suggest that credit risk is a key driver of spreads which is inconsistent with the results from all the other model specifications for the current period), we are therefore less clear on the evolution of the trend overtime and caution interpreting historical results. Our key finding therefore focuses on the current level of the subsidy, as opposed to its historical evolution overtime.

Comparison to other approaches

Compared to our econometric assessment, evidence from credit rating agencies approaches suggests that while the level of systemic support has declined significantly compared to crisis levels (due in part to the deteriorating financial health of sovereigns following the sovereign debt crisis in Europe), some level of implicit subsidies still remains and is broadly comparable to pre-crisis levels. The difference of results is indeed consistent with some of the other studies, for example in the US, where GAO/Oliver Wyman find little evidence of any implicit subsidies using econometric techniques whereas IMF suggests subsidies still exist using credit rating based approaches over the same time period. This further stresses the point that the underlying approach, its consistency and appropriateness in the context of the analysis are key drivers of the assessment. We favour econometric techniques over credit rating based approaches as we consider the former to be more robust and based more directly on market information.

Future evolution of the implicit guarantee

The changing regulatory landscape within the EU over the last few years can explain our view on the value of implicit subsidies. For instance there have been significant regulatory developments with a view to making banks more resilient and therefore less reliant on government support – including the adoption and phased-in implementation of the Capital Requirement Directive (CRD IV) and Capital Requirement Regulation (CRR). Moreover, the European Parliament has voted to adopt the Bank Recovery and Resolution Directive (BRRD), establishing a new framework for managing troubled banks in the European Union (EU), as well as the Single Resolution Mechanism (SRM) regulation, which empowers a Single Resolution Board (SRB) to manage bank resolution in the euro area. Whilst some of these are still evolving and will only be fully implemented in due course, any assessment based on market pricing information would inherently incorporate investors' expectations of the impact of these regulatory developments – which we have attempted to capture as part of our study.

We note that just because the G-SIB banks do not appear to currently benefit from implicit government support based on our assessment, there is still a possibility that this effect might return during periods of unexpected financial market stress in the future. To the extent that expectations of future market volatility are already priced in spread differences by investors, as they reflect a forward looking perspective, and given the average maturity of bonds in our sample is around 5-7 years, our assessment already incorporates the impact of expected financial market volatility that is broadly consistent with investor expectations over this period.

It is inherently difficult to develop a framework to understand the future impact of unexpected periods of financial market distress, particularly beyond the short-term bank funding horizon. We will only truly know that TBFT and associated implicit subsidies have been eliminated when the new regulatory frameworks are put to test in a banking failure situation.

Appendices

Appendix 1 – Bibliography

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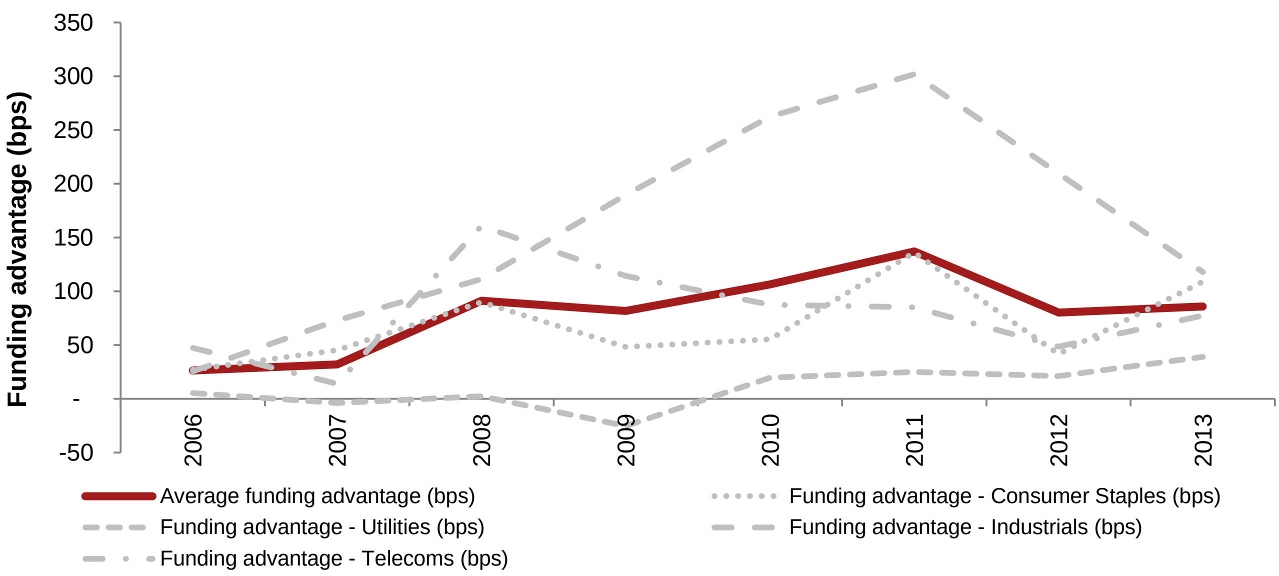
Appendix 2 – Funding cost differences across other sectors

The difference in cost of funding between large and small firms is not specific to financial sector. For comparability, we look at evidence on spreads across large and small UK firms covering a range of sectors other than financial services. To analyse the funding differences for firms across these sectors we compare the average bond spreads of the top 25% to the bottom 50% by revenues (i.e. the difference in spreads between these two cohorts of institutions)[73]. Whilst not directly comparable to the Figure 7 above in the main body of the report (which sets out the spreads across large and small financial institutions), the evidence presented in Figure 8 below[74] suggests that, on average, funding cost differences exist between large and small firms in other sectors similar to financial institutions.

This is consistent with the evidence presented by Goldman Sachs (2013) discussed in Section 3.

Figure 8: Funding advantage and size across a range of UK sectors



Source: Capital IQ, Datastream

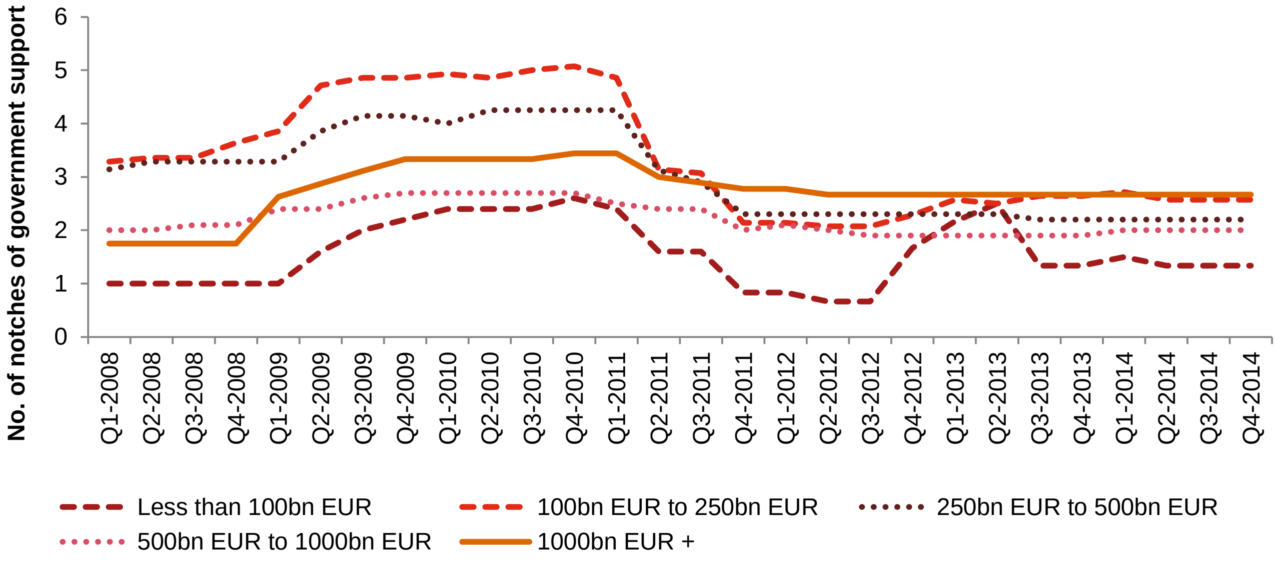
[73] Given the differences in asset intensity across some of these sectors, we consider revenues to be a more appropriate measure when benchmarking size.

[74] *For each year we calculate the funding advantage based on the end of year bond spreads.*

Appendix 3 – Size and level of systemic support – evidence from Moody's

In this Appendix we set out data from credit rating agency - Moody's – showing the variation in the amount of government support for different sized banks (captured as number of uplift notches to the banks' stand-alone rating). This is shown in Figure 9 below, covering 50 EU banks).

Figure 9: Government support by asset sizes



Source: Moody's, PwC analysis.

While relatively smaller banks have benefitted the least from the level of credit rating support over time, historically mid to large banks benefitted more from credit rating support compared to the largest banks in the sample[75]. For example, from 2008-2010, banks with asset sizes between €100bn and €500bn received the highest levels of credit rating support. More recently (over the last 2-3 years), the largest banks appear to be benefitting the most and the smallest ones the least, however, the relationship between asset size and credit rating support is less clear in the intervening asset tranches. More importantly, the perceived amount of systemic support is not substantially different between the largest banks and other banks with large asset portfolios (however, it is markedly above smaller banks).

[75] The largest group of banks, those with over €1trn in assets, have received a stable level of systemic support over the past three years, of approximately 2.75 notches.

Appendix 4 – How has the implicit subsidy evolved overtime?

Our analysis at the bank level using an incomplete data set (as well as a number of different permutations in the next-appendix) allows us to analyse the evolution of the coefficients of the various parameters in our specification overtime. Table 6 below shows the results from this specification. As suggested, similar to the bond level analysis set out in section 5, the model passes the various regression specification tests for each year in the sample suggesting it is robust and correctly specified. The number of observations is relatively low (calculated as the number of banks in a period (monthly) multiplied by the number of periods), but still supports sufficient statistical robustness.

Table 6: Regression outputs from bank level assessment using an incomplete data set

Spread	2009	2010	2011	2012	2013
Constant	-112.62	-28.88	215.12	36.71	56.14
Lag of spread	0.81***	0.79***	0.98***	0.89***	0.94***
Year to maturity	-0.29	-1.70	6.91***	-0.57	-0.23
Total assets	2.73*	0.45	-0.31	0.05	0.17
Leverage	178.04	121.96	-222.60	3.46	-55.998
Modified Merton	-58.99	-94.11	-144.10***	-44.72	-1.37
ROAE	-0.08	-0.61	-0.04	-0.12**	-0.04
GSIB	-27.38**	-7.33	5.36	-10.88	-0.58
Country dummies	No	No	No	No	No
Number of observations	273	349	371	386	612
Tests					
Nickell Bias	Passed	Passed	Passed	Passed	Passed
Arellano – Bond AR (2)	Good	Good	Good	Good	Good
Hansen test	Good	Good	Good	Good	Good

Source: Capital IQ, Datastream, analysis.

Similar to the model in Section 5, the G-SIB dummy is low and negative for the most recent period and more importantly is statistically insignificant. For example, the analysis suggests that in 2012, the G-SIB banks had a funding advantage of 11 bps whereas in 2013 the advantage reduced to around 0.6 bps – however, none of these numbers are statistically significant. Indeed, the evidence for the most recent period (specifically 2013) is consistent with studies that have employed a broadly comparable approach in the US, for example Oliver

Wyman (2014), which suggest an estimate of around 2-4bps for G-SIB banks. However, going back to 2009, the model suggests that G-SIB banks had a statistically significant (at the 10% level) cost of funding benefit of 27 bps – whilst lower than comparable estimates from other studies (IMF, EC in the EU and others in the US), this nonetheless supports the view that G-SIB banks had lower funding costs compared to other non-GSIBs in 2009 at the peak of the financial crisis.

While our model clearly sets out the impact of G-SIB specification on cost of funding at the two spectrums of the time periods considered, the evidence across the intervening years is mixed – with the model suggesting that G-SIB cost of funding benefit actually was lower in 2010 and eventually G-SIBs actually faced a funding disadvantage in 2011 before returning to an advantage again in 2012. It is important to note that none of the estimates are statistically significant. Therefore, whilst we are comfortable in our conclusions that there does not appear to be a current cost of funding benefit for G-SIB banks compared to 2009, we can't be sure of the evolution of this benefit overtime and hence would like to caution any interpretation based solely on these results. Moreover, the challenges associated with linking the coefficient on the G-SIB dummy with existence of an implicit subsidy discussed above are equally relevant in the context of the current discussion.

The key conclusions across some of the other variables are specified below:

- The coefficient for total assets is low and positive for 2009-2010 (and significant at the 10% level for 2009), then turns negative in 2011 and is subsequently positive again in 2012-2013. However, it is statistically insignificant throughout this period (except 2009) – implying there is no clear relationship between size and funding costs under this specification. Such a relationship may exist, but could be masked by a range of other factors used in the model. The positive impact of size on spreads (specifically in 2009) might suggest that larger banks are perceived too risky by investors and in part might be explained by the significant focus of regulatory reform agenda and the cost of compliance for these instructions.
- The coefficient for leverage is statistically insignificant over time, although the most recent estimates are negative for 2013 (and 2011) which is contrary to expectations and unexplained (although the fact that its statistically insignificant implies it has limited relevance). Given our definition of leverage (proportion of funding that is non-equity financed), we would expect a positive relationship with cost of funding as is the case from 2009, 2010 and 2012 (although the coefficient is quite low).
- Credit risk is a statistically significant driver of spreads in 2011; however, more recently in 2013 it is statistically insignificant. In particular the estimate in 2011 captures the broader risk associated with euro-zone crisis and impact on credit markets. Moreover, the model suggests that its effect has reduced overtime as markets have calmed (data extraction is prior to market turbulence in October 2014), however, the result is different from the model above where we find credit risk to be a statistically significant driver of spreads.
- Return on average equity has a low negative (as expected) and insignificant impact on spreads, across all years except 2012 where the effect is significant at 5% level.

Appendix 5 – Alternative regression specifications

Table 7 and Table 8 below shows a number of additional model specifications, using different explanatory variables (net interest income, traded assets and both net interest income and traded assets) for the most recent period, based on bonds (complete data) and a banks (incomplete data) level assessment, respectively. In general, the G-SIB dummy is not (statistically) significantly different from zero in the most recent period, is not influenced by the introduction of additional variables. Furthermore, the new variables are largely insignificant and where they are significant (see Table 2) the model does not pass all the regression specification tests.

Table 7: Bond complete data

Spread	2013	2013	2013
Constant	-818.31	-778.64	-785.91
Lag of spread	0.57***	0.57***	0.57***
Year to maturity	2.84*	2.78**	2.78**
Total assets	-1.31	-0.77	-0.77
Leverage	987.73*	954.60	961.61
Modified Merton	-125.32*	-137.85**	-138.04**
ROAE	-0.18	-0.17	-0.18
GSIB	-4.14	-0.28	-0.41
Traded Assets	-	-42.47	-41.39
Net Interest Income of Asset	400.11**	-	386.20**
Country dummies	Yes	Yes	Yes
Number of observations	8,622	8,946	8,946
Tests			
Nickell Bias	No	No	No
Arellano – Bond AR (2)	Passed	Passed	Passed
Hansen test	Passed	Passed	Passed

Source: Capital IQ, Datastream, analysis

Table 8: Banks incomplete dataset

Spread	2013	2013	2013
Constant	64.83	40.97	50.54
Lag of spread	0.95***	0.95***	0.95***
Year to maturity	-0.22	-0.29	-0.25
Total assets	0.05	0.19	0.05
Leverage	-66.51	-40.97	-52.86
Modified Merton	0.28	-1.04	0.97
ROAE	-0.04	-0.04	-0.04
GSIB	-1.56	-0.64	-1.997
Traded Assets	10.898	-	13.20
Net Interest Income of Asset	-	308.22	342.53
Country dummies	No	No	No
Number of observations	612	594	594
Tests			
Nickell Bias	No	No	No
Arellano – Bond AR (2)	Passed	Passed	Passed
Hansen test	Passed	Passed	Passed

Source: Capital IQ, Datastream, analysis.