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Are Banks still 'Too Big to Fail'? - A market perspective*

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Abstract

This paper aims at deriving the market's assessment as to whether banks worldwide still benefit from a Too Big To Fail (TBTF) subsidy. Such a subsidy reflects the market's expectation of government support in the event of a crisis and results in reduced funding costs for the benefiting bank. To capture this effect, we use two different extensions of the Merton (1974) framework. We find that large banks benefit from a TBTF subsidy, while large nonfinancial firms do not. This subsidy has declined somewhat since the Global Financial Crisis (GFC) but remains larger than before the crisis. These conclusions also hold when considering Contingent Convertible (CoCos) and bail-in bonds as fully loss-absorbing. Moreover, we find differences in the TBTF subsidy across jurisdictions and provide evidence that these can to a large extent be explained by differences in bank health.

Keywords: banking, too big to fail, CreditEdge, CreditGrades

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1 Introduction

During the Global Financial Crisis (GFC) starting in 2007, governments worldwide were forced to rescue large systemic banks, thereby exposing billions of taxpayers' money to risk. Since then, major regulatory efforts have been undertaken to solve this so-called "Too Big To Fail (TBTF)" issue.[1] In line with these regulatory efforts, banks have increased their capital buffers and have taken measures to improve their resolvability in the event of a crisis. Is this sufficient to solve the TBTF issue?

This paper aims at deriving the market's assessment as to whether banks worldwide still benefit from a TBTF subsidy. The latter results in reduced funding costs due to the market's expectation of government support in the event of a crisis.

To capture the market's expectation of government support for a given bank, we use two different extensions of the Merton (1974) framework: the CreditGrades model and Moody's CreditEdge model. Based on the prices of a firm's financial instruments and fundamental data, these models allow estimating a market-implied probability of default. Assuming that the prices of some financial instruments—in our case CDS—consider a TBTF subsidy while the prices of others—equity—do not, one can derive the TBTF subsidy by comparing such market-implied probabilities of default.[2]

While our focus is on large banks, we also study large nonfinancial firms. Based on the analysis of these indicators we reach the following conclusions. First, according to the market's view, the TBTF issue remains unresolved and is specific to financial firms. Although the TBTF subsidy of large banks has fallen since the peak of the GFC, this subsidy is still larger than before the crisis and large banks still benefit from it while large nonfinancial firms do not. This finding also holds when controlling for the impact of Contingent Convertible (CoCos) and bail-in bonds. Assuming that the market assesses these instruments as fully credible, our results still point to a TBTF subsidy, although the magnitude is slightly reduced. Overall, this finding is consistent with the recently published evaluation of the effects of TBTF

[1] These efforts have focused on two fronts: (i) increasing the resilience of large banks to minimise the probability that they experience financial distress and (ii) improving resolution measures to avoid exposing taxpayers' money in case of a bank getting into distress.

[2] We discuss the assumption that share prices do not consider a TBTF subsidy in section 5.

reforms conducted by the Financial Stability Board (FSB). They conclude that the TBTF subsidy has "declined substantially since 2012" but that it "has remained at elevated levels compared to before the crisis."[3]

Second, over most of the period considered, the TBTF subsidy appears to be more pronounced in Europe than in the US. We show that in the CreditGrades model, a large part of this differential is statistically explained by the US banks' better "health", as reflected by their higher leverage ratios and standalone ratings. Nevertheless, there remains a small but increasing differential in favour of European banks since 2017 after controlling for these factors. One cannot rule out at this stage that the market perceives US banks as less likely to be bailed out, other things being equal. This could be the case if, for instance, the market perceived resolution policies in the US as more effective than in Europe.

Third, in times of calm, the interpretation of low indicator values is ambiguous. On the one hand, a low value may imply that the market assesses government support of the bank in the event of a crisis as unlikely. On the other hand, the market may assess the probability that the bank will suffer from financial distress, and, hence, the probability that the bank will actually need financial support, as low. The probability of government support in case of a bank crisis and the probability of such a bank crisis cannot be disentangled as the indicator value is the product of both.[4,5] Because of this identification problem, authorities should not exclusively rely on such TBTF indicators when periodically reviewing the TBTF issue, but rather use them in combination with expert judgement.

The existing literature on measuring a TBTF subsidy can be divided into three broad categories. A first part of the literature focuses on measuring differentials in funding costs or returns between "TBTF firms" vs. "Non-TBTF firms". Acharya, Anginer and Warburton (2016) as an example use US bonds traded between 1990 and 2012 to find that bond credit spreads are sensitive to risk for most financial institutions, but not for the largest

[3]See FSB (2020).

[4]Estrella and Schich (2015) show how the value of sovereign guarantees of bank debt, i.e., the value of the TBTF subsidy, is related to the financial strength and size of the bank and the sovereign. In their model, the better the financial strength of the bank, the lower the value of the TBTF subsidy.

[5]Similarly, a high indicator value may be driven by high levels of individual bank risk but not necessarily by government support. However, given a high indicator value, there must exist at least a certain bailout expectation by the market.

institutions. Moreover, this TBTF relationship between firm size and risk sensitivity of bond spreads is not seen in nonfinancial sectors. More recently, Antil and Sarkar (2018) estimated the implicit government subsidy under various systemic risk measures, with factors constructed from equity returns of large financial firms. They observed an increase in the financial subsidy since the financial crisis, but also found that the market's perception of the sources of systemic risk changes over time (in particular, interconnectedness seems to play an important role currently, whereas size was a key determinant pre-crisis).

Another part of the literature uses the rating uplifts that a financial institution receives from a rating agency due to expectations of government support. Rime (2005) and Ueda and Weder di Mauro (2013), for example, show that large banks benefitted from a TBTF subsidy before and during the GFC. Schich and Toader (2017) analyse rating data between 2007 and 2015 and provide evidence that the TBTF subsidy for a sample of G-SIBs has fallen since the peak of the GFC but that it remains substantial. Over the last few years, however, the major rating agencies have lowered (Moody's) or eliminated (S&P, Fitch) such rating uplifts.[6]

Our paper is part of a third type of study that builds on the above-described bank default models. Jobst and Gray (2013), for example, use inputs from Moody's CreditEdge model to calculate CDS spreads based on stock prices (so-called fair-value CDS) and calculate a market-implied government "contingent liability" for a number of banking sectors. Schweikhard and Tsesmelidakis (2012) and Tsesmelidakis and Merton (2013) use the CreditGrades model and provide evidence of a TBTF subsidy during the 2007-2009 financial crisis. Based on similar approaches, Gudmundsson (2016), Blix Grimaldi et al. (2019) and the Financial Stability Board (2021a) analyse how the TBTF subsidy has evolved since the GFC and conclude that it has decreased overall but remains positive. Berndt, Duffie, and Zhu (2020) build on a structural model to capture the dependence of distance to default on parametric bailout probabilities and on various observable balance-sheet variables. For US G-SIBs, they find large reductions in market-implied probabilities of government bailouts after the Lehman episode, along with big increases in debt nancing costs.

[6]Historical evidence, however, shows that rating agencies can quickly increase the uplift in periods of crisis, if they judge that the likelihood of government intervention has grown. See, e.g., SNB (2016).

Our paper builds on these studies. However, we use different model specifications and show (i) how these TBTF indicators have evolved following the various regulatory measures implemented in the aftermath of the GFC and (ii) how these indicators have reacted to recent market developments since the outbreak of the coronavirus pandemic. Moreover, we expand the analysis by (i) discussing the impact of CoCos and bail-in bonds on the TBTF indicators and (ii) providing insight into the interpretation of such indicators and into geographical as well as cross-sectional variation with respect to the market's TBTF assessment. Our results may, therefore, prove useful for the current debate on bank regulation and the use and interpretation of TBTF indicators based on market prices.

Section 2 describes the methodology and the data used to derive the TBTF indicators. Section 3 presents the results of our analysis. Section 4 analyses these results further with respect to differences across banks and jurisdictions, providing insights into the interaction between the probability of government support in case of a bank crisis and the probability of such a crisis. Section 5 presents some of the limitations of these models, discusses the impact of considering CoCos and bail-in bonds and presents a sensitivity analysis of various parameters. Section 6 concludes.

2 Methodology and Data

The basic assumption behind our approach is that a TBTF subsidy (distortion) may be included in CDS prices, while share prices exclusively reflect economic fundamentals. This assumption is motivated by the fact that, in a crisis, bond investors of TBTF banks are likely to be bailed out and, thus, remain spared from losses, while shareholders are not.[7]

Accordingly, the default probability of a TBTF bank as derived from its CDS prices is expected to be lower than the default probability derived from the firm's share prices. Or, expressed in terms of CDS spreads, the actual CDS spread of a TBTF bank is assumed to be lower than the theoretical spread derived from a bank's share price information. The difference between these two default probabilities or spreads represents the TBTF subsidy of the bank. The higher this difference, the larger the subsidy.

To derive the default probabilities or the theoretical CDS spread, we use bank default model approaches. These approaches are based on Merton's

[7] See section 5 for a discussion of this assumption.

(1974) structural bank default (or credit risk) model, which considers the economic balance sheet of a company. A default occurs when the market value of assets, which follows a stochastic process, falls below the value of the firm's liabilities. The market value of assets is, however, not directly observable. Merton (1974) shows in his model that the firm's equity can be interpreted as a call option on the market value of assets, whereby the value of the firm's liabilities matches the option's strike price. Hence, the market value of assets can be determined using option pricing theory.

The next sections discuss two different TBTF indicators: the CreditGrades indicator (see section 2.1) and the CreditEdge indicator (see section 2.2). These indicators are based on two well-established extensions of the Merton (1974) model and are commonly used in the literature on estimating TBTF subsidies and on analysing how these subsidies evolve. To our knowledge, the CreditEdge approach was the first of these bank default model approaches used in the context of TBTF subsidies (see Moody's (2011)) and was also part of the IMF's TBTF analysis published in its Global Financial Stability Review (IMF (2014) and IMF (2018)). In addition to Moody's CreditEdge approach, we chose to construct a second indicator based on the CreditGrades approach. Compared to CreditEdge, the CreditGrades approach is more transparent and flexible, allowing us to conduct additional analyses and robustness checks. Although both approaches are based on the Merton (1974) model, they differ to some extent. In section 2.3, we describe some of these differences. None of these two approaches is a priori better suited to produce reliable results. Having two similar but different approaches helps to better understand the estimated TBTF subsidies and their dynamics.

2.1 CreditGrades TBTF indicator

The first TBTF indicator is based on a well-established extension of Merton's framework, the CreditGrades model.[8] This model estimates theoretical CDS spreads based on share price information and balance sheet data. As there is no TBTF subsidy assumed in share prices, the modelled CDS spreads—called "fair-value" CDS spreads—are free from a TBTF distortion. The CreditGrades TBTF indicator is then calculated as the difference between these fair-value CDS spreads and the actual CDS spreads. A similar

[8]For a technical description of the model, see Finger et al. (2002).

indicator is also used by Schweikhard and Tsesmelidakis (2012) in a study on the TBTF subsidy for US banks during the GFC.[9]

2.1.1 Overview of the CreditGrades model

CreditGrades extends the classical Merton framework in the sense that it introduces randomness with respect to the default point. The latter, called the default barrier in the CreditGrades framework, is defined as the amount of assets that remain in case of default, LD, where L is the (random) recovery value and D is the firm's debt per share. The random recovery value L follows a lognormal distribution with mean $\bar{L}$ and standard deviation λ. Hence, there exists one additional degree of freedom and one additional source of randomness compared to the classical Merton framework. This feature solves the problem of very low short-term theoretical credit spreads associated with classical structural credit risk models. At the same time, the stochastic nature of the default point takes into account the uncertainty regarding the exact level of leverage at the time a firm actually defaults. The default barrier is given by

$$LD = \bar{L}De^{\lambda Z - \lambda^2/2} \tag{1}$$

A default occurs in the model when the asset value of a firm V is below the default barrier LD. As in the Merton model, the asset value of a firm follows a stochastic process

$$\frac{dV_t}{V_t} = \sigma dW_t + \mu_D dt, \quad V_0 = v \tag{2}$$

where W is a standard Brownian motion independent of the random variable Z; σ is the asset volatility; and μ_D represents the asset drift and $v > 0$. In the CreditGrades model, it is assumed that a firm, on average, issues debt to maintain a steady level of leverage, thus implying an asset drift of zero (i.e., $\mu_D = 0$).

Finger et al. (2002) show that the risk-neutral survival probability P_t that the asset value of a firm (equation 2) does not hit the default barrier

[9] Based on CreditGrades, Schweikhard and Tsesmelidakis find evidence of a structural break in the valuation of US bank debt during the GFC. They contend that a possible explanation is the asymmetric treatment of debt and equity in rescue measures, which tend to favour creditors. Their results corroborate the TBTF hypothesis.

(equation 1) until time t is given by the following approximate closed-form formula

$$P_t = \Phi(-\frac{A_t}{2} + \frac{log(d)}{A_t}) - d\Phi(-\frac{A_t}{2} - \frac{log(d)}{A_t}), \quad (3)$$

where

$$d = \frac{V_0 e^{\lambda^2}}{LD}, \quad (4)$$

$$A_t^2 = \sigma^2 t + \lambda^2. \quad (5)$$

2.1.2 Implementation of the CreditGrades model

We implement the CreditGrades model based on the following inputs:

- The debt per share D is calculated as the sum of short-term borrowing, long-term borrowing and, in the case of banks, customer deposits as a proportion of the number of shares. It excludes other types of liabilities.
- Following Finger et al. (2002), the standard deviation of L, λ, is set to 0.3 and the debt class specific recovery rate R is set to 0.5.
- The mean recovery value $\bar{L}$ is set to 0.25 for banks and 0.6 for nonfinancial firms. These values are in line with values obtained using an optimisation procedure over the entire sample period and the values found in Schweikhard and Tsesmelidakis (0.25 for banks) using a sample period from 2002 to 2010. In section 5.2.1, we discuss the impact of using different parameter values.
- The risk-free interest rate r used is the yearly swap rate in the respective currency.
- The equity volatility σ_s is taken from Moody's (see section 2.2.1). The impact of using an alternative measure of volatility is discussed in section 5.2.3.

As will be shown in section 3, the CreditGrades indicator produces relatively high levels, particularly in times of crisis. Having a random default point in the CreditGrades model introduces uncertainty as to the actual level of a rm's debt per share, which leads to higher short-term spreads. Further, there are several calibration parameters that influence the ultimate level of spreads produced by CreditGrades. As detailed in 5.2.1, one such parameter is the mean recovery rate $\bar{L}$, which has a large impact on the overall level of the indicator. We show that our calibration of this parameter is not only consistent with the existing literature but also with the fact that a negative TBTF subsidy is not meaningful from an economic perspective. Another such key parameter is the debt per share D. Our approach with respect to this parameter comes, on average, very close to that taken by Moody's CreditEdge model (which takes 75% of total liabilities), but is more conservative than other applications of the CreditGrades model.

2.2 CreditEdge (Moody's) TBTF Indicator

To benchmark the results we receive based on the CreditGrades model, we construct a second TBTF-indicator based on Moody's CreditEdge model.[10] The indicator is constructed as the simple difference between two metrics of this model: the "Expected Default Frequencies (EDFs)" and the "CDS-implied Expected Default Frequencies (CDSiEDFs)". The EDFs correspond to the probabilities of default that are extracted from share prices, while the CDSiEDFs correspond to the probabilities of default extracted from CDS prices. A similar indicator is also used by the IMF in the context of its "Financial Sector Assessment Program (FSAP)" and is published in its "Global Financial Stability Report" (IMF (2014) and IMF (2018)).

2.2.1 Overview of the CreditEdge model

Moody's calculates its EDF as follows: in a first step, it estimates the so-called "distance to default (DD)". This measures how far a bank is from defaulting. There, the choices as to how to calculate the equity volatility play an important role. Moody's calculates the latter as the combination of (i) realised volatilities (based on an average over three years), (ii) implicit volatilities (derived from option prices) and (iii) a sector- and a country-specific component. After that, the calculated equity volatility is transformed into an asset volatility taking into account the bank's leverage.

In a second step, for each distance to default calculated in the first step, Moody's allocates a corresponding default probability. For this purpose,

[10] For a technical description of the model, see Moody's Analytics (2015).

Moody's does not use the normal distribution as in the original Merton framework, but rather an empirical distribution derived from its own database of historical defaults. With its update to EDF9 in 2015, Moody's introduced a financial firm-specific DD-to-EDF mapping that uses international financial firm failures between 1987 and 2014. EDF values for financial firms represent the risk of either a default or a government bailout.

To derive their CDSiEDF, Moody's extracts, in a first step, risk-neutral default probabilities from CDS spreads. This requires an assumption with respect to the Loss Given Default (LGD) parameter. In a second step, these risk-neutral default probabilities are translated into real default probabilities, based on an assumption with respect to the market price of risk.

The EDF model is an established industry benchmark for quantitative default risk assessments. Its methodology is applied consistently across firms. A key advantage is that it is calibrated on a global database containing over 11,700 defaults between 1973 and 2014. Such a large calibration dataset enables the model to perform reliably under various market conditions and for a wide range of entities.

2.2.2 Implementation of the CreditEdge model

We use the EDF without further modification as an input in the TBTF indicator. For the CDSiEDF, however, we perform a change to Moody's calculations. Although we use the same methodology, we take a different assumption with respect to the LGD parameter. Moody's determines the LGD in such a way that, for each sector and country, the difference between CDSiEDF and EDF is minimised. In the case of the TBTF indicator described above, this would have the consequence that, by construction, at each point in time, a share of the companies in a specific sector and country would show a (positive) TBTF effect, while for others, the CDSiEDF would exceed the EDF. For that reason, we have replaced Moody's LGD by a fixed LGD of 45%. The assumption of a fixed LGD of 45% is taken from the Foundation IRB approach of the Basel framework.[11] Note that the IMF does not perform such an adjustment in its use of the indicators.

[11] See Basel Committee on Banking Supervision (2019). Under the foundation approach, senior claims on corporates, sovereigns and banks not secured by recognised collateral will be assigned a 45% LGD.

2.3 Comparison between the CreditGrades and the CreditEdge model

There are several differences between the CreditGrades and the CreditEdge model that need to be taken into account when comparing the results. First, and in our view the most important, the inputs in the CreditGrades indicator are expressed in terms of "risk-neutral" spreads, while in CreditEdge they are expressed in terms of the "real" probability of default. As discussed in section 2.2.1, Moody's transformation of a spread into a real probability of default implies a number of adjustments. Among others, a risk premium calculated using the Market Price of Risk must be deducted from the risk-neutral default probability to obtain the real default probability. As shown in the appendix (see figure 12), this risk-premium adjustment is fairly volatile. As the market becomes more risk averse, this parameter increases accordingly, making the difference between the two default probabilities even larger. We can indeed show that this parameter explains a large part of the difference between the dynamics of the CreditGrades versus the CreditEdge model. The increased risk aversion following the outbreak of the coronavirus pandemic, for instance, is likely to have caused changes in the market price of risk, leading the CreditGrades model to react by more than the CreditEdge model (see section 3).

In addition to this, second, our implementation of CreditGrades uses a time horizon of five years versus a one-year time horizon for CreditEdge. A third difference concerns the default point, which is stochastic in the case of CreditGrades and fixed in the case of CreditEdge. Finally, CreditGrades assumes a normal distribution whereas CreditEdge uses an empirical distribution based on Moody's proprietary default database.

2.4 Sample data

Our sample consists of a peer group of large banks and nonfinancial firms. The peer group of banks includes 13 Global Investment Banks. They share the characteristic of being G-SIB and having a sizable cross-border underwriting and market-making operations.[12] They include Bank of America

[12]Moody's defines and uses this peer group in its analysis. The criteria to identify which banks belong to this group are based on nine publicly available metrics. $https://www.moodys.com/researchdocumentcontentpage.aspx?docid = PBC_1075509$ From the group, we exclude Royal Bank of Scotland (RBS) as the bank was rescued by

(US), Barclays (UK), BNP Paribas (FR), Citigroup (US), Credit Suisse (CH), Deutsche Bank (DE), HSBC Holdings (UK), Goldman Sachs (US), JP Morgan (US), Morgan Stanley (US), Societe Generale (FR), UBS (CH) and Wells Fargo (US). Because of data constrains, we do not include domestically systemically important banks (D-SIBs) in our sample, as CDS, share prices and quarterly balance-sheet information are not regularly available for many of these banks. In addition, our peer group would become less homogenous by adding smaller banks with a different business focus.

As a control group, we also use a sample of nonfinancial firms. The sample includes the largest nonfinancial companies from various sectors. It is composed of three firms from the healthcare sector, namely Novartis (CH), Pfizer (US) and Johnson & Johnson (US), three firms from the consumer sector, namely Nestle (CH), Univlever (UK/NL) and Procter & Gamble (US), as well as AT & T (communication services, US), Apple (technology, US) and Boeing (aerospace, US). As for banks, the choice of firms also reflects data constraints over the sample period.

Our sample covers the period from mid-2001 for CreditGrades or from January 2007 for CreditEdge until June 2020 for both. Firm financial data and market data including share data and CDS prices (5 years for CreditGrades, 1 year for CreditEdge) are extracted from Bloomberg. The firm data is quarterly, but we extrapolate it monthly to use with the market data, which has a monthly frequency.

3 Results

The following sections present the results for both the CreditGrades and the CreditEdge TBTF indicators. We thereby focus on the development of these indicators over time and across banks and compare these indicators to those for nonfinancial firms. Section 5 analyses the impact of taking into account the additional layer of protection that CoCos and bail-in bonds may provide to senior creditors and provides a robustness check to these baseline indicators by discussing the impact of various changes to the analysis.

Figures 1 and 2 show the results based on the CreditGrades and the CreditEdge model for our sample of large banks (median). The blue line corresponds to the information derived from share prices (i.e., median fair-value CDS in the CreditGrades and median EDF in the CreditEdge model)

the government in 2008.

and the green line stems from CDS price information (i.e., median CDS price in the CreditGrades and median CDSiEDF in the CreditEdge model). The difference between these two lines corresponds to the median TBTF subsidy of the sample (red line).

There are similarities and differences between the results of these indicators. Both TBTF indicators are positive for most of the time, implying that the banks in the sample typically benefitted from a TBTF subsidy. This subsidy, especially in the case of CreditGrades, is highly cyclical and strongly increases in crisis periods. This is because, in the eyes of market participants, a TBTF subsidy only becomes relevant in times of crisis. As long as a bank is considered safe, as was, for instance, the case just before the GFC, it is irrelevant for investors whether the bank is TBTF or not, and the indicator values are correspondingly low. If the bank runs into financial difficulties, however, this assessment becomes more important and is reflected in the prices of the bank's instruments.

Put differently, the TBTF subsidy of a bank is influenced by two factors: (i) the probability that a bank gets into financial difficulties and (ii) the probability of government support in a crisis. The TBTF indicator depends on both probabilities and cannot distinguish between the two. This implies that a strongly positive indicator value points to a TBTF subsidy, while a low indicator value in times of calm does not necessarily mean that the market assesses the TBTF problem as solved.[13,14]

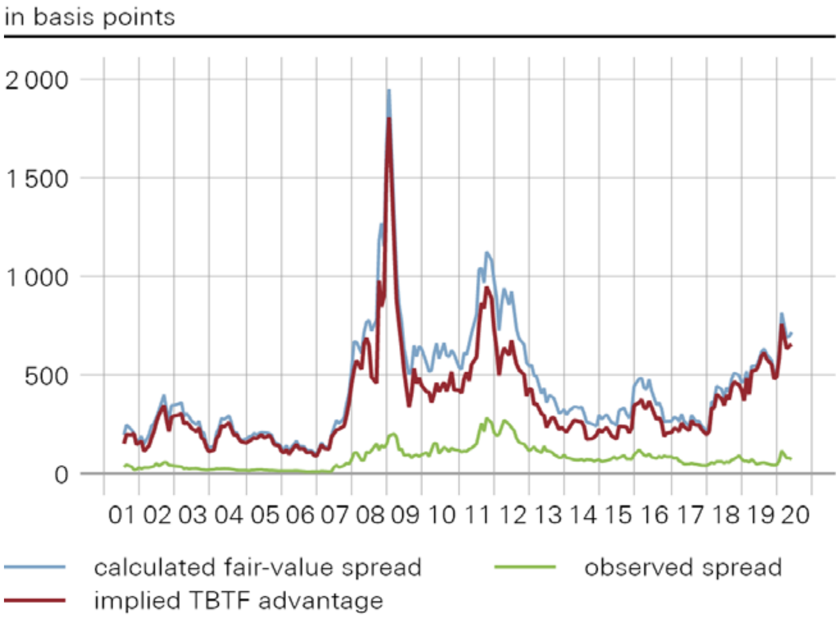
While the pattern of both TBTF indicators is very similar over most of the sample period, it is different since 2018. From 2018 onwards, we observe rising values of the indicator based on the CreditGrades model. After the outbreak of the coronavirus pandemic and the massive actions taken by central banks and governments worldwide to support their economies, this indicator increased sharply, although it has since receded to some extent. The evolution of the indicator based on the CreditEdge model, by contrast, is rather flat since 2018 and shows almost no reaction on average to the outbreak of the pandemic. As discussed in section 2.3, a possible explanation might be

[13]Such a cyclical pattern can also be observed at TBTF indicators based on rating information. As an example of such an indicator, see SNB (2016).

[14]A high indicator value may be driven by high levels of individual bank risk but not necessarily by government support. However, given a high indicator value, there must exist at least a certain bailout expectation by the market. A low indicator level may be driven by low levels of individual bank risk while the market still expects the government to bailout the bank in a crisis.

the increase in the market price of risk which is reflected in the CreditGrades model but not in the CreditEdge model.

Figure 1: CreditGrades, median of bank sample



Sources: Bloomberg, Moody's, author calculations

Figure 3 compares the CreditGrades TBTF indicator across different jurisdictions. It shows a strong increase in the GFC for US banks. For euro area banks, the TBTF indicator increase is even stronger and shows further increases during subsequent crisis periods, such as the 2011-2012 European debt crisis. This geographical differentiation with respect to the degree of the TBTF subsidy is observable throughout the entire sample period. The indicator is currently significantly lower for US banks, while it is higher for Swiss, UK and, in particular, euro area banks. The market seems to assess the probability of US banks getting into financial difficulties and/or of government support for US banks in a crisis as comparatively low with banks in other countries. Given the comparably high leverage ratios of US banks and the fact that US banks are also more advanced in the area of resolution, both interpretations seem sensible. Section 4 provides further analysis on this issue.

Figure 4 compares the CreditEdge TBTF indicator across different jurisdictions. As for the CreditGrades TBTF indicator, it shows that the TBTF

Figure 2: CreditEdge, median of bank sample

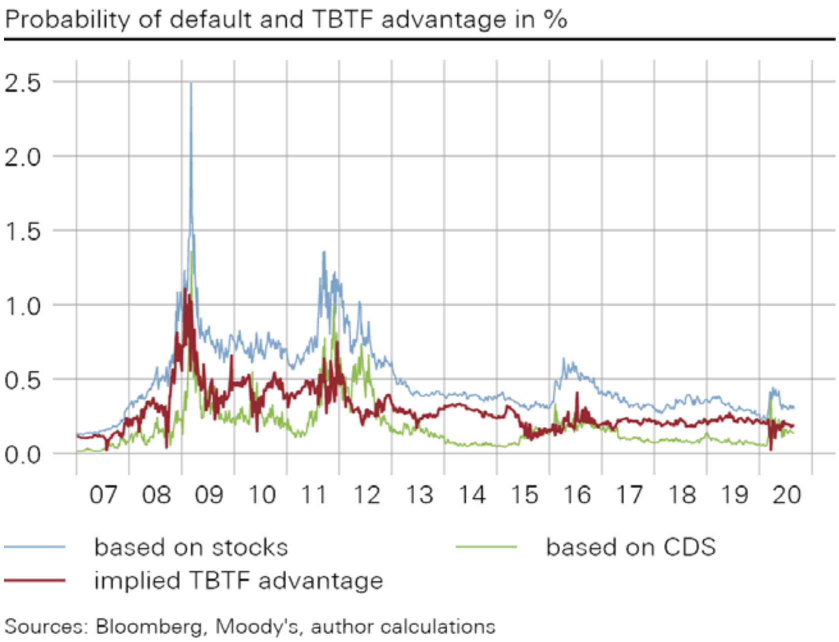
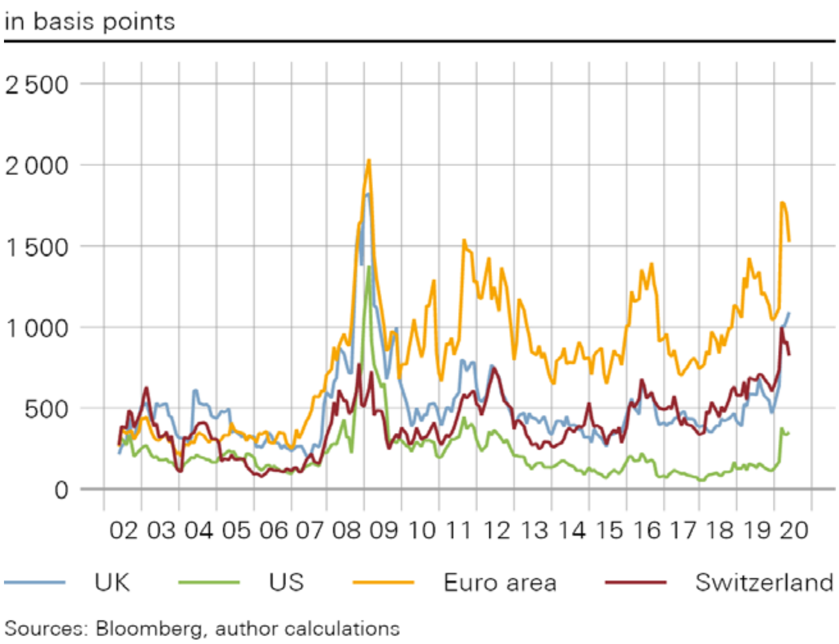


Figure 3: CreditGrades: international comparison of TBTF advantage



subsidy has been strongest for US banks during the peak of the GFC and has been quite high for euro area banks in the 2011-2012 period. Until 2016, the indicator values differ in their level across jurisdictions. Since then, and in contrast to the CreditGrades indicator, the median TBTF subsidy of the different jurisdictions have become very similar. With the outbreak of the coronavirus pandemic, however, a more pronounced differentiation across jurisdictions is again observable (see Figure 4). While the indicator increases strongly for UK banks and slightly for US banks, it decreases for euro area banks and for Swiss banks after a jump in the first quarter of 2020.

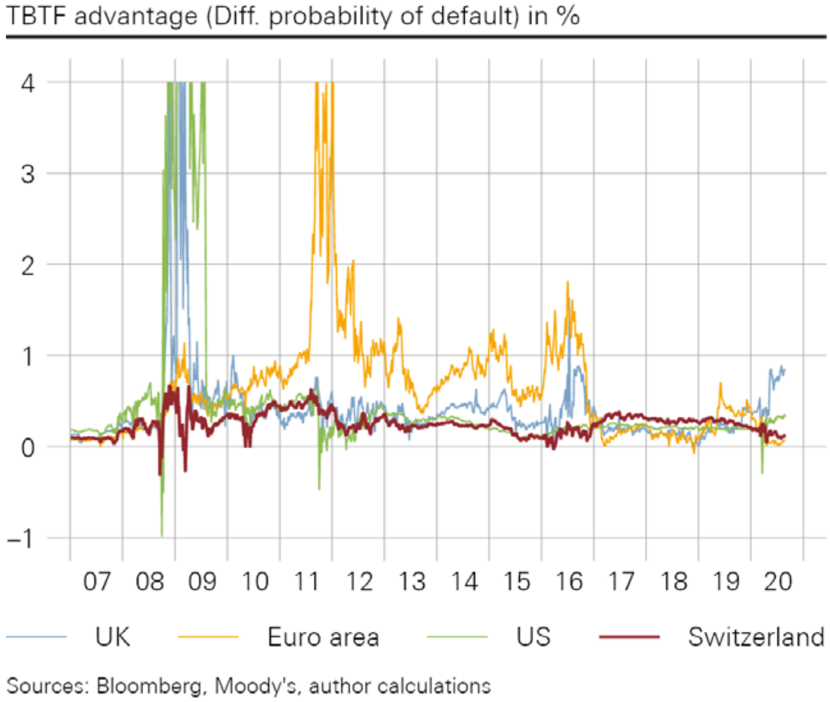
Another output from the model is that, for several G-SIBs at the beginning of crisis periods, the CreditEdge TBTF indicator falls into negative territory. Figure 2 shows that these shifts in negative territory mostly occur in times where CDSiEDF and CDS prices abruptly increase. From an economic point of view, a negative TBTF premium is not meaningful: the market either considers a bank as TBTF or not. The occurrence of negative values in the TBTF indicator is due to two factors illustrated in Figure 13 in the appendix. First, the true asset volatility can only be approximated, since it is not observable, as outlined above. This approximation relies, among other things, on historical moving averages and is hence not sufficiently reactive at the beginning of a crisis. As a consequence, EDFs might react more slowly to new information than CDSiEDFs.[15] Secondly, CDS spreads do react instantaneously. Hence, there is an asymmetry in the reactivity of the model parameters compared to the real data. We provide some further insight on the choice of the volatility in section 5.2.3.

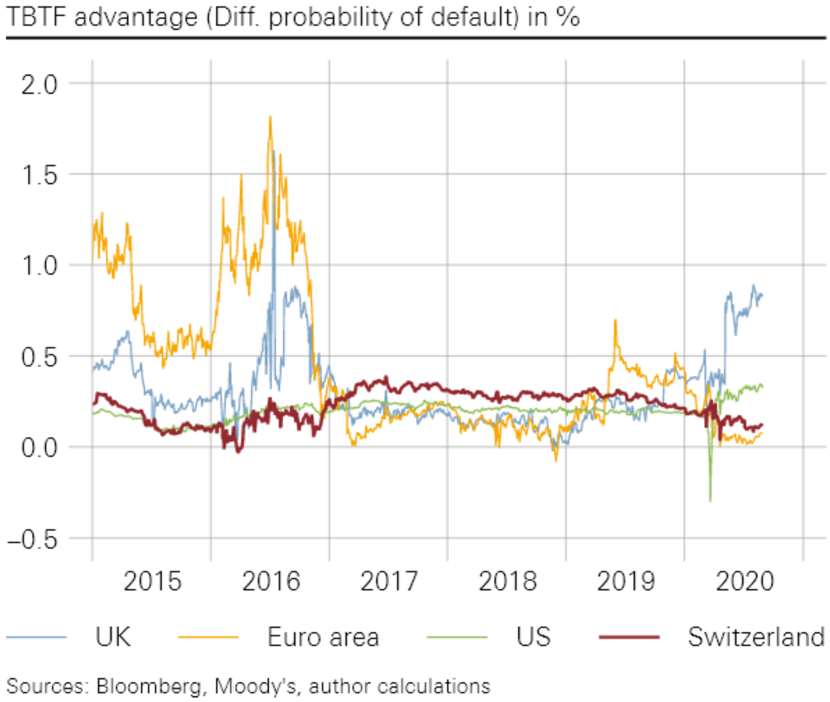
Figures 5 and 6 present the TBTF indicators for nonfinancial firms based on both the CreditGrades and the CreditEdge model. As expected, the indicators for these firms differ considerably from the ones for the large banks and do not show any TBTF subsidy.

Our results broadly confirm the findings of the current literature. The dynamics of the TBTF subsidies are in line with similar studies such as Schweikhard and Tsesmelidakis (2012), Tsesmelidakis and Merton (2013) or, more recently, the analysis produced by the FSB in its evaluation of the effect of TBTF reforms (see FSB (2020) and (2021a)). The TBTF subsidies for banks peaked during the GFC, declined after a second peak during the European debt crisis but remained at elevated levels compared to the period before the GFC. As the FSB (see FSB (2021b)), we also find an increase

[15] See Moody's (2010) for an explanation on this point.

Figure 4: CreditEdge: international comparison of TBTF advantage





in our TBTF indicator based on the CreditGrades model after the outbreak

Figure 5: CreditGrades: TBTF indicator for nonfinancial firms

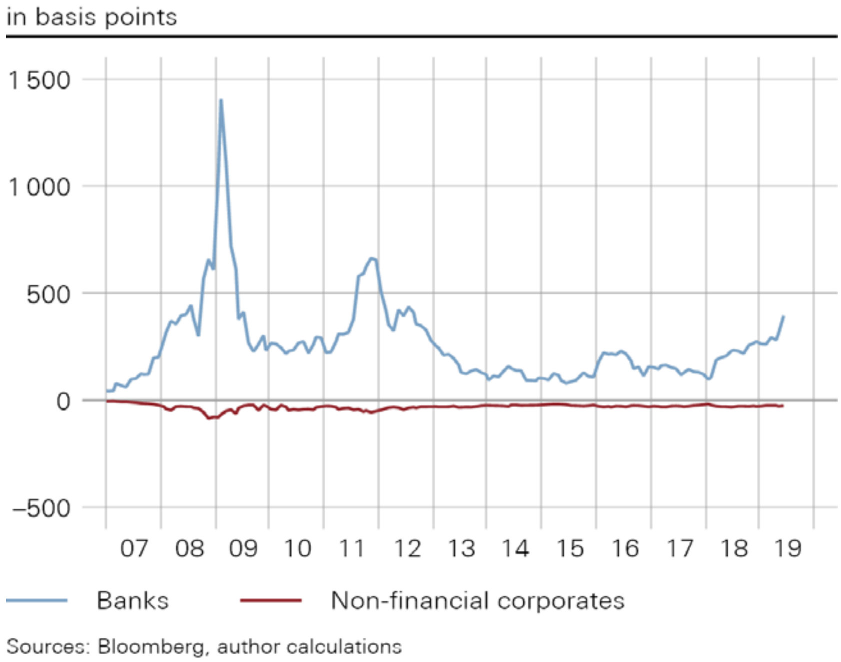
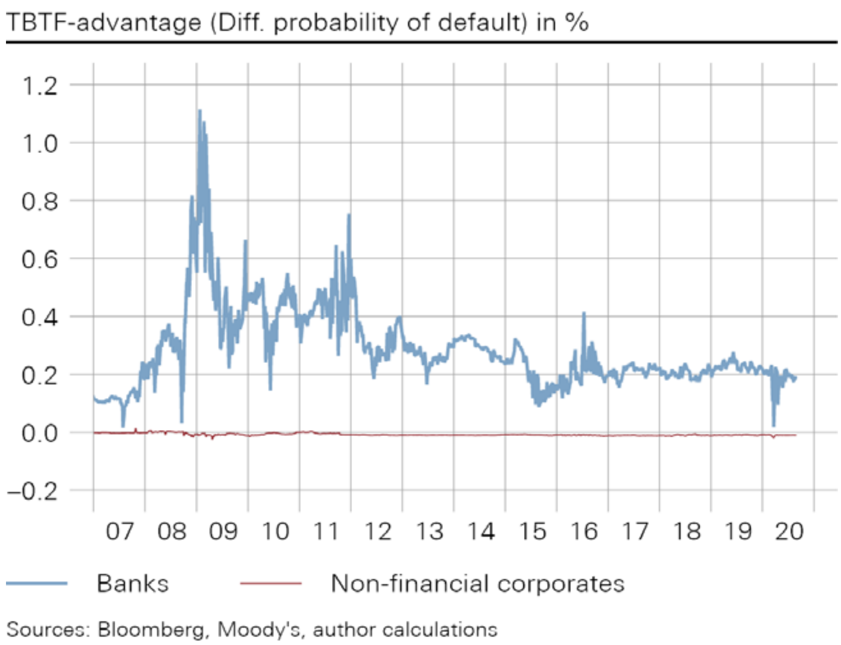


Figure 6: CreditEdge: TBTF indicator for nonfinancial firms



of the coronavirus pandemic. Moreover, the level of the TBTF subsidies is of similar magnitude as in these studies. As in the case of Schweikhard and Tsesmelidakis, we did not find any evidence for a TBTF subsidy for nonfinancial firms.

4 Understanding differences across banks and jurisdictions

As discussed in section 1, the interpretation of the TBTF indicator is ambiguous, as it includes both the likelihood that a bank will need support and the likelihood that the government will provide such support. To better understand the indicator, we attempt in the following to identify how much of these effects contribute to the TBTF indicator. The first type of effect can be summarised as "bank health" effects. The healthier the bank (the better capitalised and more profitable), the less likely it is to need support. The second effect depends both on a government's "capacity" (how able is the government to provide support) and its "willingness" to intervene. The ability of a government to provide support chiefly depends on its credit strength. Given that in our sample of Western European and US banks, all governments are rated AAA, this factor does not vary across the sample. In contrast, one cannot exclude that the willingness to provide support might vary across jurisdictions. This depends, in turn, on the effectiveness of the resolution framework in place.

To shed some light on what drives differences across banks in their TBTF advantage, we present regressions of the following form:

$$TBTF_{i,t} = \alpha_t + \kappa_i + \beta LevRat_{i,t} + \gamma Rating_{i,t} + u_{i,t} \tag{6}$$

where $TBTF_{i,t}$ is the TBTF subsidy of bank i in quarter t according to the CreditGrades model; $LevRat_{i,t}$ is the banks' leverage ratio defined as the ratio of Tier 1 capital to total assets (i.e., a measure of capital adequacy); and $Rating_{i,t}$ is a bank's standalone rating (Moody's Bank Financial Strength Rating) translated into a numerical scale (from 1 to 17).[16] α_t and κ_i are

[16] We have also conducted an alternative specification, where we use the bank's price to book ratio (PBR) instead of the rating. PBR are a good proxy for the market assessment on banks' profitability. However, this analysis is merely done for the purpose of robustness, since the PBR could be "mechanically" linked with the TBTF effect.

quarter and bank fixed effects, which are added in some specifications, and $u_{i,t}$ represents the error term. We report standard errors that are two-way clustered by bank and quarter.[17]

Table 1 shows our regression results, based on our sample of global G-SIBs with quarterly data since 2007. Column (1) does not feature any fixed effects. It shows that per one percentage point higher leverage ratio, the TBTF subsidy falls by about 1.3 percentage points. Per one notch improvement in ratings, the subsidy falls by 0.6 percentage points. These two variables statistically explain a substantial part of the variation in the TBTF subsidy.

Column (2) adds bank fixed effects (meaning only time-series variation is used) while column (3) adds time fixed effects (meaning only cross-sectional variation is used). In both cases, the regression coefficients remain significant and quite stable. The adjusted R^2 values indicate that constant differences across banks explain a large part of the variation (column 2) although within-bank changes in LR and ratings still have incremental explanatory power (as indicated by the "within" adj. R^2). Somewhat surprisingly, time fixed effects are a relatively small contributor to the adjusted R^2 in column (3)—most of the variation is explained by differences in bank characteristics in the cross-section.

In column (4), where both time and bank fixed effects are added, the two explanatory variables retain the same sign but lose statistical significance, presumably because there is not much residual variation remaining. However, when further adding year-by-country fixed effects in column (5), which means that we allow for time variation that differs across countries (e.g., due to different macroeconomic conditions), the leverage ratio again becomes significant. In other words, within a given country in a given year, if a bank has a T1 leverage ratio that is 1 percentage point above its own average, this reduces its estimated TBTF subsidy by about 0.9 percentage points—an economically and statistically significant effect.

Similar regressions also allow us to study whether the differences across jurisdictions that are shown in figure 3 can be explained by differences in the bank characteristics across these jurisdictions, or whether, instead, there appear to be "residual jurisdiction effects" that could reflect differences in regulation or the market's perception of sovereign support.

[17]Two notes on these specifications: first, the number of clusters in the bank dimension is low, but inference was not qualitatively altered with bootstrapped standard errors. Second, a Hausmann test indicated that fixed effects should be preferred over random effects panel models in this application.

Table 1: Regression of the TBTF advantage on different variables

	(1)	(2)	(3)	(4)	(5)
Tier 1 Leverage Ratio	-1.331***	-1.131**	-1.208***	-0.091	-0.882**
	(0.217)	(0.498)	(0.247)	(0.487)	(0.386)
Ratings	-0.612***	-0.438*	-0.833***	-0.469*	-0.331
	(0.170)	(0.222)	(0.226)	(0.247)	(0.228)
Constant	18.972***	16.046***	20.634***	10.750**	13.571***
	(2.658)	(4.506)	(2.771)	(4.545)	(3.061)
Nr banks	15	15	15	15	15
Bank FE	No	Yes	No	Yes	Yes
Quarter FE	No	No	Yes	Yes	Yes
Country X Year FE	No	No	No	No	Yes
Adj. R-squared	0.419	0.587	0.563	0.754	0.809
Adj. R-squared (within)	0.419	0.061	0.494	0.043	0.032
Observations	794	794	794	794	794

Standard errors (two-way clustered by bank and quarter) in parentheses.

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

The regression specification is now

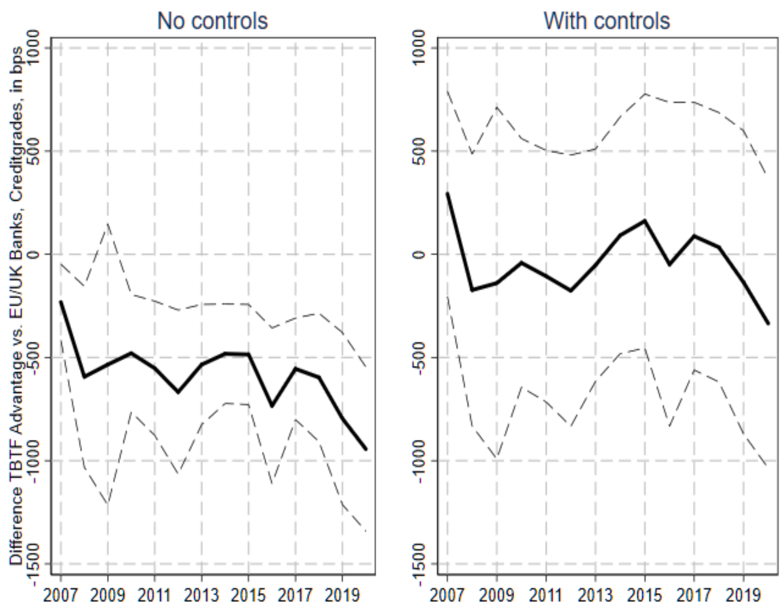
$$TBTF_{i,t} = \alpha_t + \beta LevRat_{i,t} + \gamma Rating_{i,t} + \theta_t US_i + \mu_t CH_i + u_{i,t} \qquad (7)$$

where US_i is a dummy that equals 1 for US banks, and CH_i a dummy that equals one for Swiss banks. The coefficients on these dummies are allowed to vary by year. Their evolution shows the annual estimated differences in the TBTF subsidy for US banks and Swiss banks relative to the other (EU and UK) banks, which are the omitted category in the regression. We estimate these differences both without controlling for leverage ratios and ratings (left panel) and when these controls are added (right panel). Estimated coefficients are shown in figure 7 for the US banks and in figure 8 for the Swiss banks.

The left panel of figure 7 simply illustrates what was already shown in figure 3: the TBTF subsidy is much smaller for US banks than EU/UK banks, especially in the aftermath of the crisis. However, the right panel illustrates that after differences in leverage and ratings are controlled for, there is no systematic difference. This implies that the smaller TBTF subsidy of US banks can statistically be explained by their lower leverage and better standalone ratings. Similarly, for the Swiss banks, the estimated residual TBTF subsidy becomes smaller when adding the control variables, especially after 2013. However, since there are only two Swiss banks in the sample, the confidence intervals are quite wide.

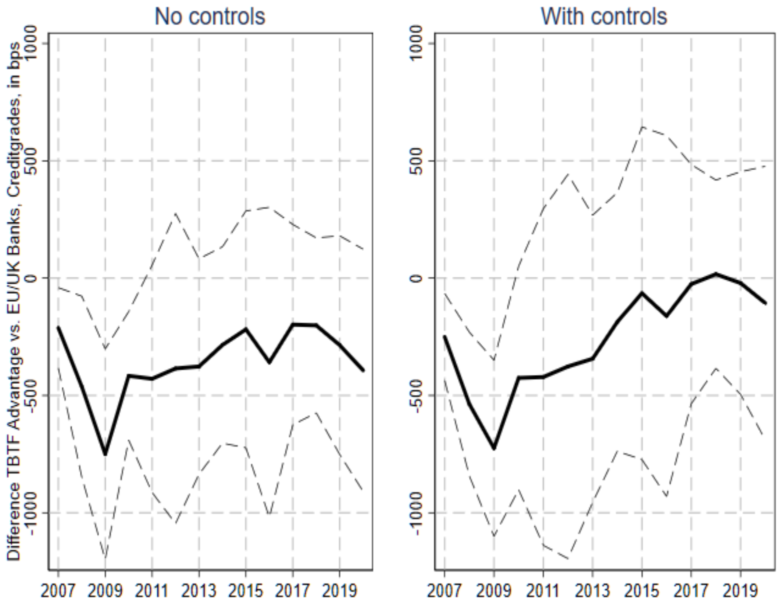
In sum, we draw the following conclusions from this analysis. First, differences in bank observable characteristics are able to explain part of the variation in the TBTF subsidy, with regression coefficients that are in line with economic intuition, and sizeable explanatory power (as indicated by the R^2 values). The second part of the analysis suggests that differences in the TBTF subsidy across jurisdictions can, to a large extent, be explained by differences in bank health. In particular, the large differential in favour of the European banks since the end of the crisis is significantly smaller when controlling for the aforementioned observables. Nevertheless, and bearing in mind the large confidence interval, we note that directionally, the differential has been increasing since 2017 (i.e., European banks benefit from a larger advantage even when accounting for controls). Given that resolution frameworks are only being implemented in Europe and the US, one cannot exclude at this stage that the market considers the US resolution framework as being comparatively more effective or credible. However, more time and additional analyses will be needed to further assess this conclusion.

Figure 7: Difference in TBTF subsidy: US versus EU and UK banks



Note: left panel shows estimated θ_t and 95% confidence interval from regression $TBTF_{i,t} = \alpha_t + \theta_t US_i + \mu_t CH_i + u_{i,t}$. Right panel shows the same from regression $TBTF_{i,t} = \alpha_t + \beta LVG_{i,t} + \gamma RTG_{i,t} + \theta_t US_i + \mu_t CH_i + u_{i,t}$.

Figure 8: Difference in TBTF subsidy: Swiss versus EU and UK banks



Note: left panel shows estimated μ_t and 95% confidence interval from regression $TBTF_{i,t} = \alpha_t + \theta_t US_i + \mu_t CH_i + u_{i,t}$. Right panel shows the same from regression $TBTF_{i,t} = \alpha_t + \beta LVG_{i,t} + \gamma RTG_{i,t} + \theta_t US_i + \mu_t CH_i + u_{i,t}$.

5 Discussion

The TBTF indicators presented in this paper are subject to several caveats. First, data availability is limited. This applies to both the length of the sample period and the sample size. For instance, data on share and CDS prices are usually not available for smaller banks. Hence, due to these data limitations, a crosscheck of our findings with results for smaller banks not considered TBTF is not possible.

Second, there might exist some factors that are not considered in the model but that may affect the prices of financial instruments and, therefore, also the TBTF indicators.

- Share prices, for example, might also be distorted by TBTF expectations. In the GFC, bank shareholders also benefitted from the government support measures taken worldwide. Empirical studies indeed show that share prices embody expectations of the TBTF subsidy (Gandhi and Lustig (2015), Gandhi, Lustig and Plazzi (2016), Kelly, Lustig and Van Nieuwerburgh (2016) and Antill and Sarkar (2018)). However, based on historical experience, a possible TBTF distortion seems to be especially relevant with respect to prices for debt instruments. Despite extensive support measures, shareholders suffered from massive stock price declines, while debtholders were spared from any losses. Moreover, not taking into account a possible TBTF distortion in share prices implies an underestimation of the actual TBTF subsidy by the two TBTF indicators. If a TBTF distortion is present, the default probability or the fair-value CDS spread derived from share prices is lower than fundamentally justified, which, in turn, lowers the value of our TBTF indicator.

- Similar, CDS prices may also contain counterparty credit risk premia. In this case too, not taking into account counterparty credit risk premia implies an underestimation of the "true" TBTF advantage. Counterparty credit risk premia increase CDS premia and default probabilites derived from these premia, which in turn reduce the TBTF subsidy measured by our indicators.

- A bank's capital and liability structure differ from those of other firms, not least because of various bank regulatory measures. In recent years, for example, banks have built up a considerable amount of CoCos and/or bail-in bonds as these instruments play an important role in the authorities' attempts worldwide to solve the TBTF issue. Assuming that the market believes in the proper functioning of these instruments, Section 5.1 shows that not taking into account these instruments implies, overall, a moderate overestimation of the actual TBTF subsidy. However, recent instances of bailouts, despite the existence of a bail-in framework, such as in the case of Monti dei Paschi in 2016, leave some doubts as to whether these instruments will in practice fulfil their role as an additional protection layer.[18]

Third, as in any other model, the TBTF indicators depend on the underlying assumptions of the CreditGrades and the CreditEdge model. The level of the indicator, in particular, reacts sensitively to changes in the underlying model parameters. Critical assumptions include those related to the LGD parameter, the distribution parameters of the default barrier such as $\bar{L}$, Moody's historical default data base and the volatility of the assets. In section 5.1, we discuss the possible impact of assuming that CoCos and bail-in bonds are fully loss-absorbing. Section 5.2 shows how a variation in certain parameters affects the TBTF indicators. In both cases, we illustrate the sensitivity of the results by focusing on one or both of the Swiss G-SIBs, UBS and Credit Suisse.

5.1 Impact of CoCos and bail-in bonds

In line with the TBTF regulations, large international banks have been issuing large amounts of CoCos and bail-in bonds over the past few years. In the banks' balance sheets, these instruments are classified as debt. However, in the liability structure of a bank, CoCos and bail-in bonds are subordinated to senior bonds, either structurally or statutorily. These means that in case of a bail-in or an insolvency, these instruments offer an additional layer of protection to senior creditors. Bail-in debt accounts for the largest share of a bank's Total Loss-Absorbing Capacity (TLAC). In our previous calculations, these instruments are by definition included in the banks' debt which increases the default barrier in the model when deriving the probability of default based on equity prices. As a consequence, and assuming that the

[18]See "A bailout of Monte dei Paschi is not enough", Financial Times, 23 December 2016 (https://www.ft.com/content/7df5a074-c92a-11e6-9043-7e34c07b46ef).

market believes in the proper functioning of these instruments, the probability of default derived from equity prices and, hence the TBTF subsidy, might be overestimated in the baseline TBTF indicator.

To provide an upper bound of such a possible overestimation, we constructed adjusted CreditGrades TBTF indicators where CoCos and bail-in bonds have been reclassified from debt to equity. With this reclassification, the debt per share D and in turn the default point LD become smaller. Note that we do not perform a change to the asset volatility σ_s. The reason is that σ_s is not purely based on the equity volatility and the relation of debt and equity, but contains several components, as outlined in Section 2.1.2. Hence, our adjusted indicators represent only a rough approximation of considering the additional layer of protection stemming from CoCos and bail-in bonds.

Nevertheless, our approximation shows that large banks currently still benefit from a TBTF subsidy even when correcting for the impact of CoCos and TLAC (which includes CoCos and bail-in bonds). Figure 9 presents the adjusted CreditGrades TBTF indicators for Credit Suisse, with delta CoCo (delta TLAC) showing the indicator when all CoCo (all TLAC) instruments are reclassified as equity. The differences in basis points (average in 2018) presented in table 2 for Credit Suisse and UBS show that the TBTF indicator corrected for CoCo bonds is still very close to the baseline TBTF indicator and somewhat lower when adjusting for all TLAC instruments. As banks continue to build on their TLAC, we expect this effect to become larger.

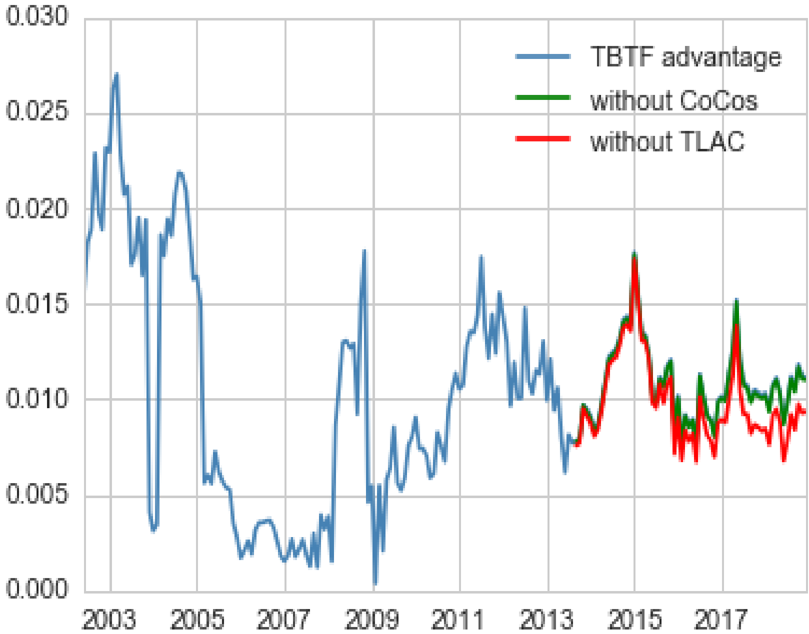
Table 2: Impact on TBTF subsidy of reclassifying TLAC as equity (in bps.)

	UBS	Credit Suisse
Contingent Convertible Bonds (CoCos)	1	2
Total Loss Absorbing Capacity Instruments (TLAC)	10	19

5.2 Sensitivity analysis

The following sections discuss some of the parameter choices in the baseline specification.

Figure 9: Impact of bail-in bonds and CoCos: CreditGrades TBTF indicator (Credit Suisse)



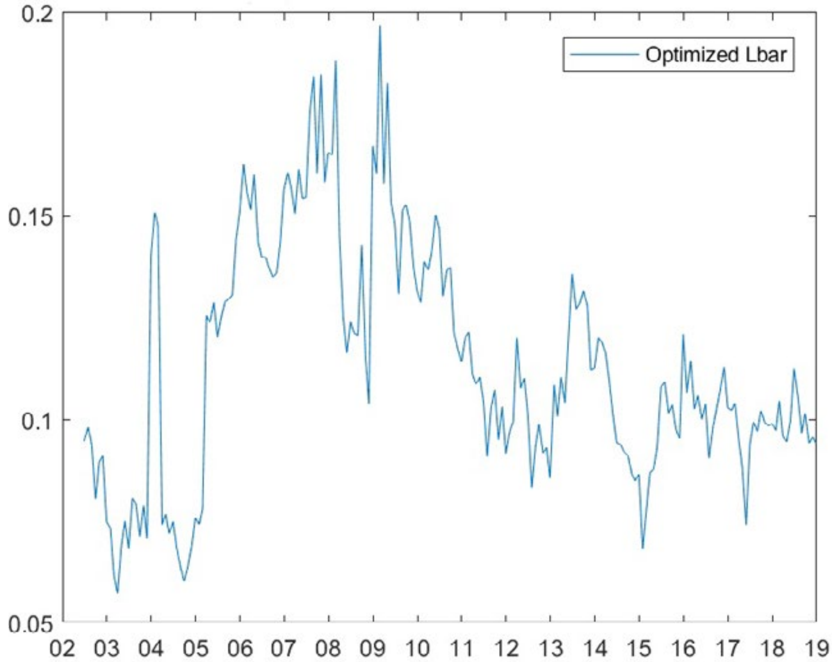
5.2.1 Choice of $\bar{L}$

A variation in the mean recovery value $\bar{L}$ (CreditGrades) or in the LGD (CreditEdge) affects the level of the TBTF indicators: the higher these parameters, the higher the TBTF indicators. As mentioned in sections 2.1 and 2.2, the parameters in the baseline specification are in line with the academic literature and/or industry standards (e.g., the assumption concerning $\bar{L}$) or assumptions made for regulatory purposes (e.g., the LGD assumption in the Foundation IRB approach of the Basel framework).

The parameter $\bar{L}$ in the CreditGrades model is a latent variable that cannot be directly observed. In some sense, it exhibits similarities with the implied volatility in an asset pricing framework.

In our calibration, we assume $\bar{L}$ to be constant over time. This implies that if $\bar{L}$ changed systematically, we would not capture this dynamic in the model. When optimising $\bar{L}$ to match the CDS prices, however, we observe a significant variation of the parameter (implied $\bar{L}$), depending on the bank and time point (see figure 10). In our view, this reflects the variation in the TBTF premia and not the variation of the model parameter. Further, we observe no structural breaks in the series of implied $\bar{L}$.

Figure 10: Implied $\bar{L}$ obtained by matching CDS spreads for Credit Suisse



As discussed in section 3, a negative TBTF value is not meaningful from an economic perspective, conditional on TBTF firms being correctly identified. However, when calibrating $\bar{L}$, one must also take into account that fair value CDS might react more slowly to new information than CDS. We must, therefore, allow some tolerance for negative values of the TBTF subsidy. Our sensitivity analysis shows that the lower the value of $\bar{L}$, the more often the TBTF indicator will be negative. This is shown in the upper part of the table 3. For an $\bar{L}$ of 0.25, as in our baseline specification, the TBTF indicator is negative in 6% of the observations overall, with some variations across jurisdictions. For a lower value of $\bar{L}$, we obtain 22% of negative observations and for a higher value, we obtain 1%. In the lower part of the table, we follow the converse approach, which we call "Negative at Risk". There, we calculate the values of $\bar{L}$ that correspond to the TBTF subsidy being negative 5% or 10% of the instances respectively. An $\bar{L}$ of 0.24 (0.23) would be compatible with the TBTF indicator being negative in 5% (10%) of the observations.

This analysis shows the large sensitivity of the TBTF indicator to the $\bar{L}$ parameter. It also shows that the value of 0.25 for $\bar{L}$ that is used in the existing literature and in our baseline is also a reasonable choice for our analysis, as the number of negative observations remains, on average, within an acceptable confidence interval.

Table 3: Sensitivity to the variation of $\bar{L}$
and Negative at Risk approach

	Europe	CH	EU	US	overall
$\bar{L}$					
0.20	6%	11%	6%	29%	22%
0.25	2%	1%	3%	11%	6%
0.30	0%	0%	1%	7%	1%
Negative at Risk					
5%	0.18	0.21	0.18	0.31	0.24
10%	0.15	0.19	0.14	0.27	0.23

5.2.2 Choice of LGD

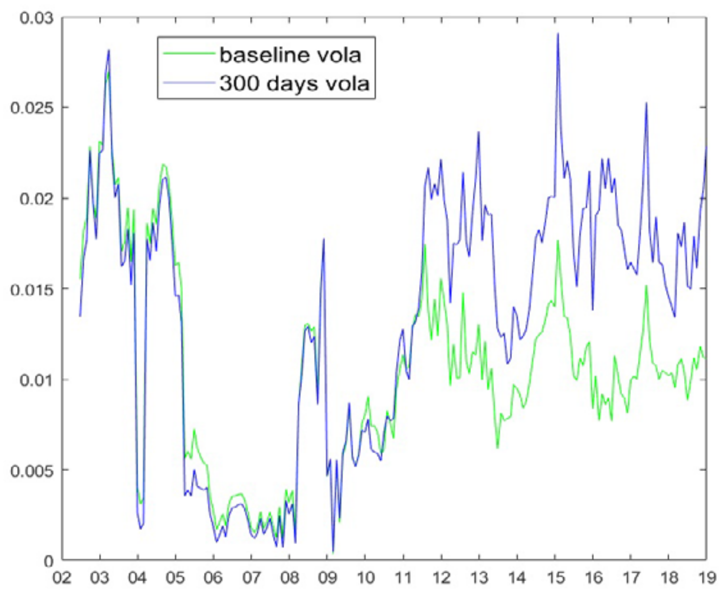
For the CDSiEDF, we take a different assumption than Moody's with respect to the LGD parameter. As discussed in section 2.2.1, Moody's approach in determining the CDSiEDF implies that the LGD parameter varies significantly. For the reasons mentioned in section 2.2.2, however, we chose to fix this parameter in our baseline specification to 45%, a level that is consistent with the assumptions made for regulatory purposes (e.g., the LGD assumption in the Foundation IRB approach of the Basel framework).

An analysis of the historical bank default data from the US Federal Deposit Insurance Company (1986-2017) shows that the average losses to creditors are somewhat cyclical and tend to increase in times of crisis. However, this increase is contained. The average loss rate in 2008-2010 is about seven percentage points higher than the long-term average. This variation is far lower than the variation in the LGD parameter observed in the Moody's approach.

5.2.3 Choice of σ

Merton-type models are known to react sensitively to variations in asset volatility. The latter critically depends on the way equity volatility is calculated. Figure 11 compares the impact of the following alternative methods in calculating equity volatility on the CreditGrades TBTF indicators: (i) volatility as used by Moody's (baseline specification); and (ii) historical volatility based on an average over 300 days. The chart shows that the way equity volatility is calculated affects the degree of fluctuation in the indicator: greater volatility implies a higher fair value CDS and hence a larger TBTF subsidy. We observe that the use of historical 300-day volatilities would, in this example, lead to significantly larger TBTF subsidies.

Figure 11: CreditGrades TBTF indicator: Baseline volatility measure vs. historical volatility



5.2.4 Analysis with endogenous recovery rates R

In our approach, we use external recovery rates but the Merton framework produces its own endogenous recovery rates. In the following, we analyse these endogenous recovery rates in more detail. To achieve that, we use properties of log-normal random variables that allow for a closed form computation of the expected shortfall and, hence, enable us to compute not only the probability of default (PD) in a Merton framework, but also the LGD. The approach reads as follows: the estimation of the PDs relies on a computation of the share of paths that cross the default threshold and, hence, lead to an asset value below the default threshold. The estimation of the model-endogenous LGD relies on a more detailed analysis of the paths that cross the default threshold. We only analyse a setting where defaults can occur at final maturity to keep the analytic tractability. Focusing on the "default paths", we compute the average asset value given the default. The relative difference between this quantity and the default threshold is the model-endogenous LGD. This quantity strongly depends on the volatility in the model and, to a lesser extent, on the default threshold. We provide a numerical example below for two volatility levels and two PDs (see table 4). The selected PDs correspond to the current average ratings of the two large Swiss banks. In both cases, the endogenous recovery rate levels are high compared to regulatory and literature benchmarks. The strong increase of the recovery rate with decreasing volatility is due to the Gaussian nature of the approach. The probability of a path that crosses the default threshold ends up far away from the default threshold decreases as the volatility decreases. Overall, these elements, and in particular the high level of the endogenous recovery rates compared to the usual benchmarks, suggest that a Merton approach might not be an ideal methodology for LGD estimation.

Table 4: model endogenous recovery rates

σ	0.2	0.2	1	1
ρ	0.14%	1.10%	0.11%	0.14%
Recovery rate	95.0%	93.5%	74%	78%

6 Conclusion

In this paper, we present two indicators based on structural credit risk models that allow for a quantification of the TBTF subsidy. The construction of these indicators is nontrivial and relies on assumptions that are not easily verifiable. For that reason, we present arguments for the plausibility of the model choices and a sensitivity analysis for the key parameters. We conclude that a TBTF subsidy for large international banks is currently still observable, larger today compared to before the GFC and specific to financial firms. These conclusions also hold when considering CoCos and other TLAC instruments as fully loss absorbing (a conservative approach with respect to the size of the TBTF subsidy).

A recurring challenge in most approaches that attempt to measure the TBTF subsidy is the identification issue outlined above. Our models simultaneously measure the probability of a bank needing support (which itself depends on the bank's health) and the conditional probability of it receiving support if needed. In our regression analysis, we have attempted to isolate bank health effects from other effects for the CreditGrades model. We find that a very large part of the differential in favour of the European banks (i.e., a larger TBTF subsidy) compared to the US banks is statistically attributable to bank health factors. Nevertheless, the remaining differential has been increasing since 2017. Given that resolution frameworks are just being implemented in Europe and the US, at this state, it cannot be excluded that the market considers the US resolution framework as comparatively more effective or credible. More time and additional analyses will be needed to further assess this conclusion.

7 Appendix

Figure 12: Implied risk premium adjustment in Moody's CDSiEDF

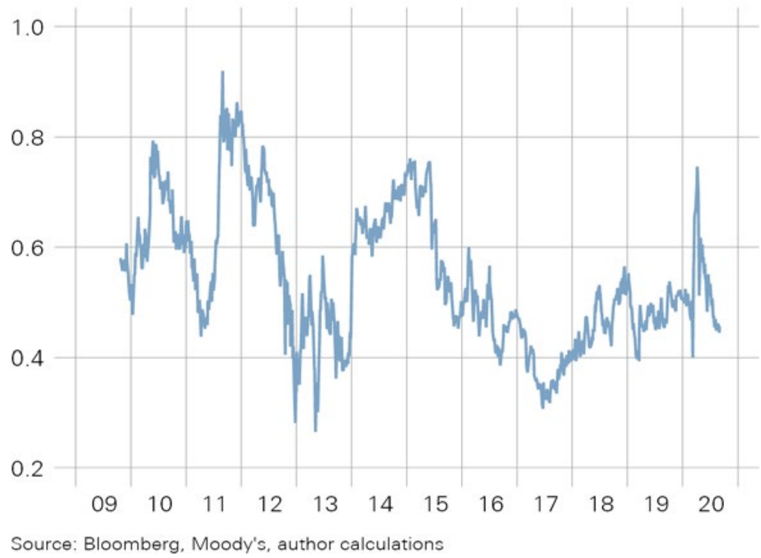


Figure 13: Reaction of EDF vs. asset volatility (UBS)

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