

The Market-Implied Probability of European Government Intervention in Distressed Banks

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Abstract

Exploiting a 2014 change in credit default swap (CDS) contracts on European banks, we find that market expectations of European government support for distressed banks have decreased—an important development in the credibility of financial reforms. CDS contract terms were changed to cover losses from “government intervention” and related bail-in events. For many large European banks, subordinated CDS spreads are available under both the old and new contract terms; the difference (or basis) between the two spreads measures the market price of protection against losses from certain government actions that have mainly imposed losses on subordinated debt holders. Since 2014, the basis has declined, relative to the level of CDS spreads. We argue that this decline in the relative basis reflects a market perception that governments are less likely to protect creditors in an event of financial distress, and that banks do not have sufficient subordinated debt to protect senior bond holders in such an event.

Keywords: Banks, government intervention, government support, bailout, bail-in, European Bank Resolution and Recovery Directive, credit default swaps

1 Introduction

Many regulatory changes following the financial crisis of 2007–09 have sought to reduce the likelihood of financial distress at large, complex financial institutions. Some of these reforms (particularly requirements for bail-in debt and resolution plans) have also sought to reduce the likelihood that governments would provide financial support if such an institution were facing failure. The ability of governments to commit to ending bailouts continues to generate debate. Exploiting a 2014 change in credit default swaps (CDS) on European banks, we find evidence that market expectations of European government support for distressed banks have decreased. This trend marks an important development in the credibility of financial reforms. At the same time, banks do not have sufficient subordinated debt to protect senior bond holders in case of default.

A CDS contract provides the holder of a bond with insurance against default by the issuer of the bond. Various types of events are covered by different contracts, including missed payments, bankruptcy, and restructuring events. In 2014, the International Swaps and Derivatives Association (ISDA), the trade association that defines the terms of CDS contracts, introduced a new “government intervention” event and made related changes to CDS contracts affecting European

banks. The changes were prompted by cases where government actions at ailing banks had indirectly reduced the payments received by buyers of CDS protection on those banks, particularly CDS protection on subordinated debt. For many of the largest European banks, CDS continue to trade under the previous terms (called the 2003 definitions) as well as the new terms (called the 2014 definitions). CDS contracts on U.S. reference entities do not ordinarily cover restructuring events since 2009 (Markit Group Ltd. 2009), so the new definitions introduced in 2014 are not relevant to U.S. financial institutions.

The types of intervention contemplated by the 2014 definitions can broadly be considered bail-in events, in the sense that they impose losses on creditors through government actions, rather than through a missed payment, bankruptcy, or privately negotiated restructuring. Although senior creditors can in principle be bailed in, the government actions that prompted the change in CDS contracts imposed losses on subordinated debt while supporting senior creditors. The difference (or *basis*) between CDS spreads under the 2014 and 2003 definitions reflects the market price of protection against such government actions. For most of our analysis, we work with what we call the *relative basis*, which is the ratio of the basis to the 2014 spread. We will interpret the relative basis as a measure of the market-implied conditional probability of a “contained” bail-in, given financial distress, meaning a scenario in which subordinated debt holders bear losses but senior creditors largely do not. (More precisely, the relative basis measures a *loss-weighted* conditional probability because a CDS spread reflects a loss given default as well as a probability of default.)

This interpretation of the relative basis is strongly supported by a loss severity measure we calculate for each bank. Our loss severity measure is the ratio of the CDS spread on senior debt to the CDS spread on subordinated debt, both using 2014 contract definitions. This ratio measures the market-implied conditional (loss-weighted) probability of a default of senior debt given a default of subordinated debt: this is the conditional probability that credit losses are *not* contained. Across the twenty banks in our sample, the loss severity ratio evolves like the mirror image of the relative basis, consistent with our interpretation of the relative basis. Our loss severity measure relies on the 2014 contract definitions, which eliminated cross-default provisions between senior and subordinated debt in the earlier contract terms. The ratio would be less meaningful if calculated under the 2003 definitions.

If the relative basis reflects the conditional probability that losses are imposed on subordinated debt holders but not on senior creditors, then a decline in the relative basis is consistent with either an increase or a decrease in bailout expectations. This is because a decreased probability of senior creditor bailout, but also an increased probability of subordinated creditor bailout, would imply a reduced likelihood that losses would be borne by subordinated creditors only.

The first of these two explanations (a decreased likelihood of government support) is more plausible, and we provide the following evidence and arguments to support it. First, the various risk factors we test cannot explain the decline in the relative basis, suggesting that the highly synchronized downward trend is due to a common factor spanning multiple European countries and banks; changes in banking regulation offer the most plausible explanation. Under the European Union’s Bank Recovery and Resolution Directive (BRRD), which was announced in 2014 and became effective in 2016, public funds may not be used to support a distressed bank until at least eight percent of a bank’s equity and liabilities have been written down (European Parliament 2014), so market perception reflects a change in policy. This also means that typically a bailout of all bank debt is not legally permitted. Second, we find that senior bondholders have become more likely to suffer losses even in contained bail-ins. If the likelihood of bailout of all bank debt had increased, we would have expected increased support for senior bondholders in contained bail-ins, too. Third, consistent with this policy change (and our interpretation), rating agencies have eliminated ratings uplift for government support of junior instruments. Finally, we also present evidence using default

probabilities, as estimated by Moody’s CreditEdge model, which considers bailout a default event, in support of our interpretation.

Earlier studies have used CDS data to try to infer market perceptions of anticipated government support for financial institutions, but they relied on spreads from before 2014 or overlooked the implications of the changes introduced in 2014. These studies include comparisons of CDS spreads for larger and smaller banks (Volz and Wedow 2009, Barth and Schnabel 2013, Zaghini 2014), and comparisons of Global Systemically Important Banks (G-SIBs) and Domestic Systemically Important Banks (D-SIBs) with banks that are neither (Araten and Turner 2012, Cetina and Loudis 2016). In this literature, narrower CDS spreads are interpreted as evidence of perceived government support, after controlling for other factors. But some bail-in events were not covered under 2003 contract definitions, so narrower CDS spreads could also be explained as an increased risk of loss to bondholders that were not compensated by CDS protection. In other words, based on the earlier contracts alone, narrower CDS spreads could be consistent with either a decrease in expected government support or an increase in the likelihood of a bail-in that was not covered by the earlier contracts.

A different strand of the literature has looked at the response of the CDS market in event studies. Schäfer et al. (2016) find that senior CDS spreads (under 2003 definitions) increased around European bail-in events, which they interpret as the CDS market adapting to a new regime in which bail-in becomes more common. Avdjiev et al. (2015) analyze the response of the CDS market to the issuance of different types of contingent convertible (CoCo) bonds using CDS data under 2003 definitions.

Other studies have directly used equity or bond data. Sarin and Summers (2016) study progress on reducing the riskiness of banks mainly based on realized and implied equity volatility. They find that the riskiness of large banks’ equity has not reduced considerably following the recent financial crisis, which they attribute to a decline in these banks’ franchise value, at least in part caused by new regulation. A study by the U.S. Government Accountability Office (2014) finds that the difference in bond funding costs for large banks in comparison to smaller banks was large during the financial crisis and that it has narrowed considerably since 2011. Ahmed et al. (2015) find that in other industries, too, large firms enjoy lower borrowing costs, and that only during the financial crisis 2008–09 were borrowing costs for large banks unusually low. Measures of systemic risk that use market data include CoVaR (Adrian and Brunnermeier 2016) and SRISK (Acharya et al. 2012).

Much of the literature that looks to market prices for evidence of implicit government support relies on structural models of the type in Merton (1974) and its many extensions. Structural models provide valuable insights, but they can be difficult to apply empirically, given the many assumptions they entail, especially for financial firms. If a structural model finds that large banks have unusually low funding costs, this finding could be due to perceived government support or to weaknesses of the model in explaining the capital structure of large banks. In contrast, our analysis is virtually model-free because it extracts information directly from the difference between two market prices.

Moreover, structural models quantify government support through option value—a bank with a government backstop effectively holds a put option on its assets. As economic conditions improve, the value of this option decreases simply because it moves deeper out-of-the-money. This effect can create the impression of reduced government support, even with no change in government policy. We will argue that the information about losses to creditors that we extract from the relative basis is *conditional* on bank distress. As such, it is not vulnerable to the confounding effect of a general improvement in the economic environment.

The contract changes we exploit are also relevant to the much studied bond–CDS basis, which is the difference in yields observed in bonds and implied by CDS spreads. That 2014 CDS trade higher than 2003 CDS means that a bond–CDS basis for European banks can be partially explained

by the reduced protection against bail-in losses provided under the 2003 definitions. This adds to the list of factors found to affect the bond–CDS basis in earlier work, which include counterparty credit risk, relative liquidity, and bond issuance patterns (De Wit 2006), procyclicality of margin requirements (Fontana 2011) and funding risk and collateral quality (Bai and Collin-Dufresne 2013).

The rest of this paper is structured as follows. In Section 2, we discuss the changes that CDS definitions have undergone in response to the malfunctioning of CDS in the case of past government interventions. In Section 3, we discuss the relative basis and its two contrary interpretations. We provide evidence in Sections 4 and 5 that the decline in the relative basis reflects reduced expectations of government support for European banks in distress due to changes in European banking regulation. We conclude in Section 6.

2 Changes to the CDS Market in Response to Government Intervention

In 2013 and 2014, the European banks SNS Bank, Bankia and Banco Espírito Santo failed. Subordinated CDS under the ISDA 2003 definitions triggered in all of these cases, but the payout to protection buyers was much smaller than the loss on the subordinated bonds due to issues with the 2003 definitions and actions taken by governments in dealing with the failures of these banks. ISDA presented new CDS definitions in 2014 to better align the payouts of CDS with the losses on underlying bonds in government interventions. The changes were also introduced to prepare for the bail-in requirements under the BRRD, which was announced in 2014. Notably, the government actions at SNS Bank, Bankia and Banco Espírito Santo imposed losses on subordinated debt but supported senior debt. New CDS under ISDA 2014 definitions started trading on September 22, 2014. Currently, both 2003 and 2014 versions of CDS contracts are traded on a number of European banks.

2.1 The Basis and the Relative Basis

We begin by defining two central concepts that relate the subordinated CDS under 2003 definitions and the new subordinated CDS under 2014 definitions.¹ We will refer to the spread difference between subordinated 2014 CDS and subordinated 2003 CDS as the *basis*. For convenience, we will also use “basis” to refer to a position that is long a subordinated 2014 CDS and short a subordinated 2003 CDS and thus pays the difference between the two contracts. In other words, when we say that “the basis pays x ” in some event, we mean that x is the difference in payouts of the two CDS in that event. We will furthermore refer to the ratio of basis and subordinated 2014 CDS as the *relative basis*.

Figure 1 shows the evolution of subordinated 2003 and 2014 CDS spreads, their basis, and their relative basis for twenty European banks; we discuss the data source and data quality in detail in Appendix A. Subordinated 2014 CDS trade higher than their 2003 counterparts. While subordinated 2003 and 2014 CDS have tended to go up over most of the sample, their basis has stayed roughly constant. As a result, the relative basis has gone down strongly. In the fall of 2014, the relative basis was slightly over 40 percent on average. Over the course of the first half of 2015, it decreased, on average, to around 30 percent. It stayed roughly constant over the second half of

¹We only consider the “modified-modified” CDS document clause, which is by far the most common and liquid one for European corporations. This document clause specifies that restructuring constitutes a credit event, but that a bond can only be delivered if its maturity date is less than 60 months after the termination of the CDS contract or the reference bond that is restructured.

2015. The relative basis fell strongly in the first quarter of 2016. The average in the summer of 2016 is slightly under 25 percent.

To understand what the decline in the relative basis says about market expectations of government support for European banks, we discuss in detail the changes that ISDA made in 2014 to CDS definitions.

2.2 CDS and Motivation for the 2014 Contract Changes

A credit default swap is intended to cover the buyer of protection against losses if the reference entity named in the contract undergoes certain credit events. Subordinated and senior debt issued by the same bank are covered by separate CDS contracts.

The cost of CDS protection is measured through its spread. The spread is determined by the expected *conditional loss*—the payout that can be expected once the CDS is triggered—and the *intensity*—the probability that the CDS triggers:

$$\text{CDS spread} = \text{conditional loss} \cdot \text{intensity} = (1 - \text{recovery}) \cdot \text{intensity}. \quad (1)$$

This spread should be understood as a risk-adjusted or a market-implied expected loss.²

When a credit event occurs, the loss on the bond is determined through an auction. The CDS then pays out the loss on the bond.³

Government intervention events at SNS Bank in 2013, Bankia in 2013, and Banco Banco Espírito Santo/Novo Banco in 2014 led to large losses for subordinated bondholders through bail-in, but small recoveries in CDS auctions under the 2003 definitions; senior bondholders were mostly spared. These events served as an impetus for the changes implemented in the 2014 definitions. The changes affect both the recovery on the bond that is determined in the auction and the intensity. We discuss these changes in detail in Sections 2.3 and 2.4. The changes are best understood as affecting each of the two factors in (1).

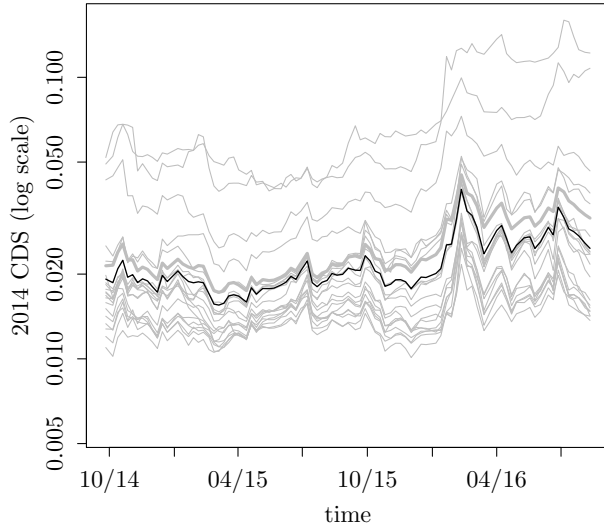
2.3 ISDA 2014 Changes that Affect the Recovery

In some cases, as a result of government actions at ailing banks, the conditional loss determined through CDS auctions was lower than the losses experienced by bond holders. We will call an event where a subordinated 2003 CDS does not pay out all of the amount lost on the underlying bond, as a consequence of government actions, even though a 2003 credit event is declared, a *recovery interference*.

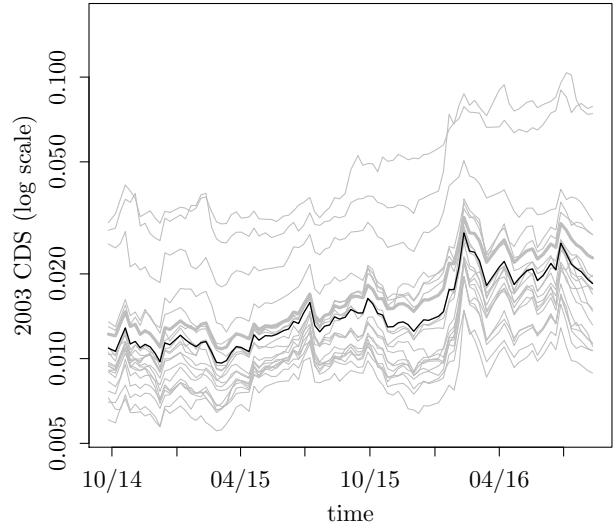
Asset package delivery In the case of SNS bank in 2013, the Dutch government expropriated all subordinated bonds, with no compensation for bondholders. A 2003 credit event was declared by the ISDA committee responsible for making the determination. However, because of the expropriation, no subordinated bonds were available to be delivered into the auction. Senior bonds were used in the subordinated CDS auction as the closest available proxy for the unavailable subordinated bonds, and a recovery of 85.5 percent was determined. As a result, even though subordinated

²Much research has focused on factors that explain CDS spreads. For example, Ericsson et al. (2009) find that the main factors behind CDS spreads under 2003 definitions are firm leverage, equity volatility, and the riskless interest rate.

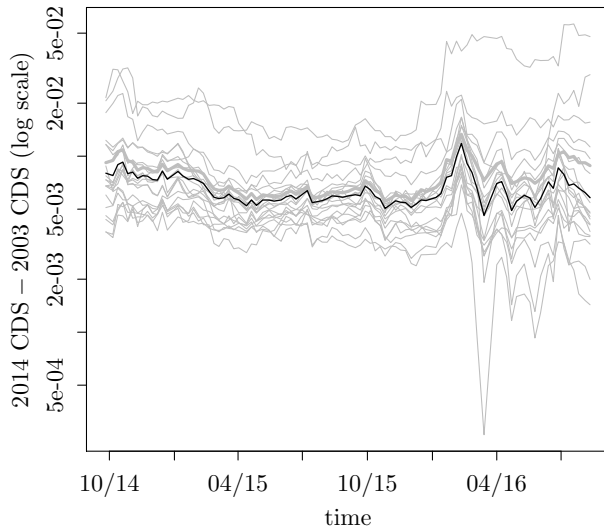
³We refer the reader to Chernov et al. (2013) and Gupta and Sundaram (2013) for more details on the auction process, and to Haworth (2011) for an accessible overview of the 2003 ISDA definitions and their 2009 supplements. Equation (1) is a simplification that ignores term structure effects. For a more complete discussion, see Duffie and Singleton (1999).



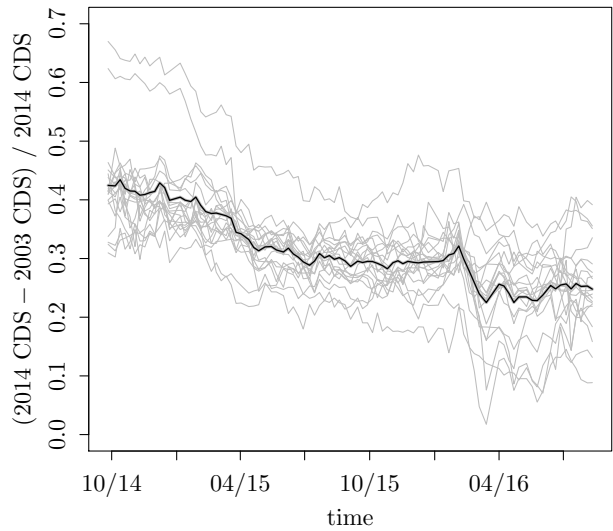
(a) 2014 CDS spreads increased slightly



(b) 2003 CDS spreads increased strongly



(c) The basis stayed roughly constant



(d) The relative basis decreased strongly

Figure 1: Five-year subordinated 2014 CDS and 2003 CDS spreads over time, as well as their absolute basis, all shown in gray, along with the geometric mean at each step in time (black). Also shown is the relative basis for each bank (gray), along with the arithmetic mean at each step in time (black). *Sources: Markit Group Ltd. data and authors' calculations*

bonds suffered a 100 percent loss, subordinated CDS paid out only 14.5 percent. In contrast, under the new “asset package delivery” rules in the 2014 definitions, a near-worthless claim against those subordinated bonds could have been delivered into the auction. These rules makes it more likely that, following a bail-in through expropriation, the correct recovery rate can be determined in the CDS auction.

In a related event in 2011, Northern Rock Asset Management, the government-controlled “bad bank” formed after the failure of Northern Rock (see Shin (2009)), offered to buy back its outstanding subordinated debt below par, and it was able to modify the terms of the debt to allow it to buy any debt not tendered voluntarily. The buyback triggered a restructuring event. With no subordinated bonds outstanding, the CDS auction was based on senior debt, resulting in a high recovery rate and a low payout to CDS protection buyers.

Different treatment of subordinated and senior CDS in debt transfers A common approach to resolution of a distressed bank is to break the bank into a “good” and a “bad” bank. Because subordinated bonds typically become claims on the bad bank, this is a way to implicitly bail in bondholders. As an example, consider the case of Banco Espírito Santo, which failed in September 2014. Subsequently, all senior bonds were moved to Novo Banco, the “good” bank, whereas all subordinated bonds remained liabilities of Banco Espírito Santo, the “bad” bank. Because more than 75 percent of total debt had followed the “good” bank, 2003 ISDA rules mandated that both senior and subordinated CDS now reference the “good” bank — a clause intended to deal with corporate mergers. A 2003 credit event was declared for subordinated CDS at the “good” bank, however, there were no subordinated bonds deliverable in the “good” bank, and senior bonds had to be used instead. Because the “good” bank was well capitalized, with 4.9 billion euros injected by the state, subordinated CDS holders suffered significant losses. A similar issue arose when Bankia became distressed in 2013. With the new 2014 rules, subordinated CDS follow subordinated bonds, and senior CDS follow senior bonds in the case of a succession event.

2.4 ISDA 2014 Change that Affects the Intensity

The government intervention events discussed in the previous section all triggered 2003 CDS. However, when SNS bank’s debt was expropriated, it was not clear ahead of time whether a 2003 credit event would be declared. Furthermore, a government intervention that is expressly contemplated through bail-in language included with bonds, or by law, as is mandated by the BRRD, may not trigger a 2003 CDS. For this reason ISDA has added a new credit event, the *government intervention event*, that triggers 2014 CDS. This event is declared if a government’s action results in binding changes to the underlying bond, for example by reducing its principal, further subordinating it, or expropriation. The addition of this event increases the intensity in Equation (1). We call it a 2014 credit event when either a 2003 credit event or a government intervention event is declared for subordinated CDS.

3 Measuring Progress in European Banking Regulation through the Relative Basis and a Loss Severity Measure

Banking regulators have made efforts in recent years to reduce expectations of government support. We will argue that the decline in the relative basis reflects a market perception that European governments have become less likely to protect creditors in an event of financial distress. To do so,

we first discuss the relative basis in more detail, we then relate it to a measure of the conditional likelihood of losses on senior bonds, and we finally combine it with other data sources.

3.1 The Relative Basis Discriminates Between Intervention and Ordinary Default

The difference in spreads between the subordinated 2014 and 2003 contracts may be understood as protection against certain government interventions, because both the change in intensity and the change in conditional loss are driven by certain bail-in events, as explained in Sections 2.3 and 2.4. We will therefore call an event for which a subordinated 2014 CDS pays more than a subordinated 2003 CDS, which is the case in a recovery interference or an ISDA government intervention event, an *intervention*. We make this definition for brevity. It provides a simple way to refer to the factors driving the changes in the CDS definitions. As discussed in Section 2, post intervention events have been associated with losses on subordinated debt, but, for the most part, not on senior debt.

We also need a simple way to refer to cases in which the two contracts trigger and make the same payments to protection buyers. These are credit events for which the 2003 definitions provided adequate protection. We will call such an event an *ordinary default*.

Figure 2 shows what may happen if a bank were to enter distress, along with the payouts of a subordinated 2003 CDS and the basis. From the perspective of subordinated CDS, the first step is whether subordinated bondholders are bailed out or not following bank distress. In a bailout that includes subordinated bondholders, subordinated bonds do not lose any value, and neither subordinated 2003 CDS nor the basis pay anything. If the government decides against a bailout of subordinated bondholders, a 2014 credit event is determined. Then there are two potential outcomes. The first of these potential outcomes is a 2003 credit event. When a 2003 credit event is declared, either (i) no recovery interference happens, in which case the subordinated 2003 CDS pays L_N , the loss given no recovery interference, and the basis pays zero, or (ii) a recovery interference happens, in which case the subordinated 2003 CDS pays zero, and the basis pays L_A , the loss given a recovery interference. For simplicity, we do not explicitly account for the possibility that a subordinated 2003 CDS may pay out something under a recovery interference, but instead consider such an event implicitly as a probabilistic mixture of the events recovery interference and no recovery interference, given that a 2003 credit event is declared. The second potential outcome is a government intervention event that is not a 2003 credit event. The subordinated 2003 CDS do not even trigger in such a bail-in as may occur under the new BRRD rules. In that case, the subordinated 2003 CDS pays zero, and the basis pays L_G , the loss given a government intervention event that is not a 2003 credit event.

Based on Equation (1), we denote the spread needed to protect against an event \bullet by

$$\mathbb{S}(\bullet) = \mathbb{E}[\text{loss} | \bullet] \mathbb{P}(\bullet).$$

The spread needed to protect against \bullet , given an event \star , is $\mathbb{S}(\bullet | \star) = \mathbb{E}[\text{loss} | \bullet \cap \star] \mathbb{P}(\bullet | \star)$. Here \mathbb{S} , \mathbb{P} , and \mathbb{E} are market-implied spread, probability and expectation, respectively.

In the following we use CDS^{2014} to refer to the subordinated CDS spread under 2014 ISDA definitions, and CDS^{2003} to refer to the subordinated CDS spread under 2003 rules.

From the tree in Figure 2, we see that the spread of a subordinated 2014 CDS is

$$\begin{aligned} CDS^{2014} &= \mathbb{S}(\text{no recovery interference}) + \mathbb{S}(\text{recovery interference}) \\ &\quad + \mathbb{S}(\text{government intervention, no 2003 credit event}) \\ &= \mathbb{S}(\text{ordinary default}) + \mathbb{S}(\text{intervention}). \end{aligned}$$

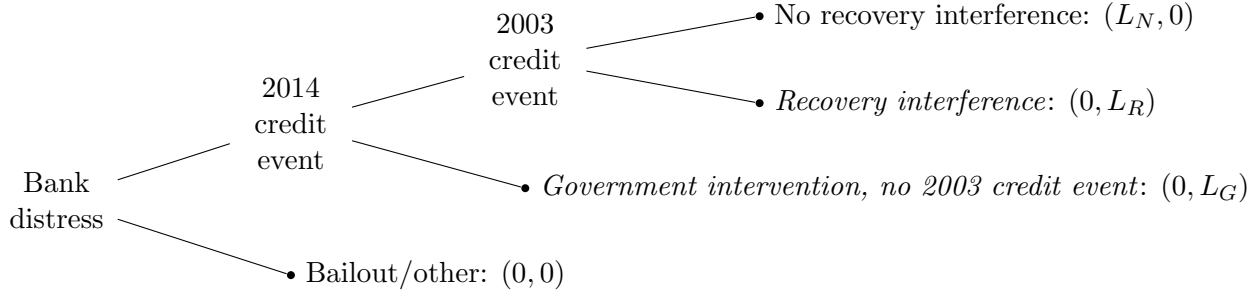


Figure 2: Possible payouts of the subordinated (2003 CDS, basis) pair following a bank distress. Intervention events are highlighted in italics. No recovery interference occurs in an ordinary default event. (The respective event need not be the same for senior CDS. For example, it could happen that losses are imposed on subordinated bondholders, causing a 2014 credit event, but that senior bondholders receive government support.)

The value of the basis is, from its definition in Section 3.1,

$$CDS^{2014} - CDS^{2003} = \mathbb{S}(\text{intervention}).$$

We obtain the conditional probability of an intervention given that a 2014 credit event is declared, weighted with the potentially different sizes of conditional expected losses, as the ratio of basis and CDS^{2014} :

$$\frac{CDS^{2014} - CDS^{2003}}{CDS^{2014}} = \mathbb{S}(\text{intervention} \mid \text{intervention or ordinary default}) \quad (2)$$

$$= \mathbb{S}(\text{intervention} \mid \text{distress, but no bailout of subordinated debt}). \quad (3)$$

The quotient on the left side of (2) is the *relative basis*. It is the spread⁴ that would be necessary to protect against an intervention, if it were certain that a distressed bank would not receive a bailout, but uncertain whether there will be an intervention or an ordinary default. It is a *conditional* measure that is insensitive to changes in the probability of distress. That the relative basis is the ratio of two market-implied spreads also removes most of the influence in the CDS market risk premium that is inherent in basis and subordinated 2014 CDS.

3.2 As the Relative Basis Decreased the Likelihood of Losses on Senior Bonds Increased

We discussed at the beginning of Section 2 that past intervention events have been associated with losses to subordinated debt but support for senior debt. We therefore want to understand how the decline in the relative basis relates to loss expectations for senior debt in a 2014 credit event.

⁴If one were to make the simplifying assumption of a fixed recovery rate whenever a CDS triggers, then the effect of conditional losses would cancel in (2) (and (3)), and this conditional spread could be interpreted as the conditional probability $\mathbb{P}(\text{intervention} \mid \text{intervention or ordinary default})$. This is a useful if rough interpretation to keep in mind. In practice, market assumptions for the sizes of conditional losses are often blunt (Schuermann 2004, Altman 2006). For example, Markit, which aggregates recovery rate quotes from several sources, quotes a “recovery” of exactly 20 or 40 percent on most days for the banks in our panel, with only rare, small deviations from these values. A report by J.P. Morgan (Elizalde et al. 2009) notes that it is common practice to fix the recovery rate at 20 or 40 percent, and to derive a “calibrated” default probability from market data.

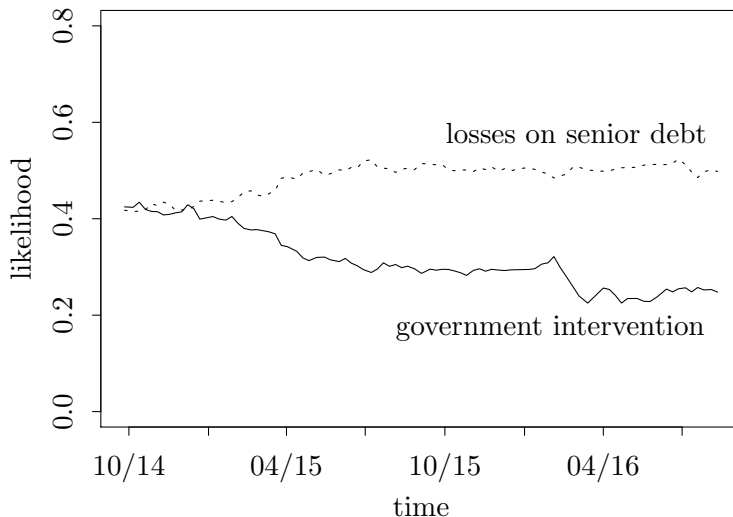


Figure 3: Average trend across all banks in $\mathbb{S}(\text{losses on senior debt} \mid \text{any 2014 credit event})$ from (4) and average trend in the relative basis, $\mathbb{S}(\text{intervention} \mid \text{any 2014 credit event})$. The results using medians are nearly identical. *Sources: Markit Group Ltd. data and authors' calculations*

We consider the ratio of senior 2014 CDS, which we denote by $CDS_{\text{senior}}^{2014}$, and subordinated 2014 CDS as a measure of how likely it is that senior bonds would suffer losses in a 2014 credit event. This ratio has an interpretation as a conditional spread:

$$\frac{CDS_{\text{senior}}^{2014}}{CDS^{2014}} = \mathbb{S}(\text{losses on senior debt} \mid \text{any 2014 credit event}). \quad (4)$$

This ratio is always between zero and one, under the assumption that senior debt has strict priority over subordinated debt. A value close to one indicates that, conditional on a loss to subordinated debt, senior debt would experience a similar loss, in percent. A value close to zero indicates that losses in a 2014 credit event would be contained to subordinated bonds.

Figure 3 shows the average trend in $\mathbb{S}(\text{losses on senior debt} \mid \text{any 2014 credit event})$ from (4) across the twenty European banks in our panel, along with the average trend in the relative basis from (2). Data quality for senior CDS spread quotes from Markit under the 2014 clause is very high; the details are in Appendix A. We see that it has become more likely that senior bonds would also suffer losses in a bank failure without bailout. The increase in the loss severity measure also means that the capacity of subordinated debt to absorb losses has decreased.

We find a strikingly close positive association between the size of losses and the chance of ordinary default, if a bank were to enter distress without receiving a bailout of subordinated debt. The empirical correlation between changes in the relative basis (2) and changes in the loss severity measure (4) is -0.47 . In Figure 4 we show the same analysis for individual banks, where we see that this pattern also holds for individual time series. The pattern holds cross-sectionally as well, with an empirical correlation of -0.76 across the whole panel.

This close association between the relative basis and the loss severity measure means that the relative basis is a measure of the likelihood that losses in a distress would tend to be contained to subordinated bonds, if there is no bailout of subordinated debt.

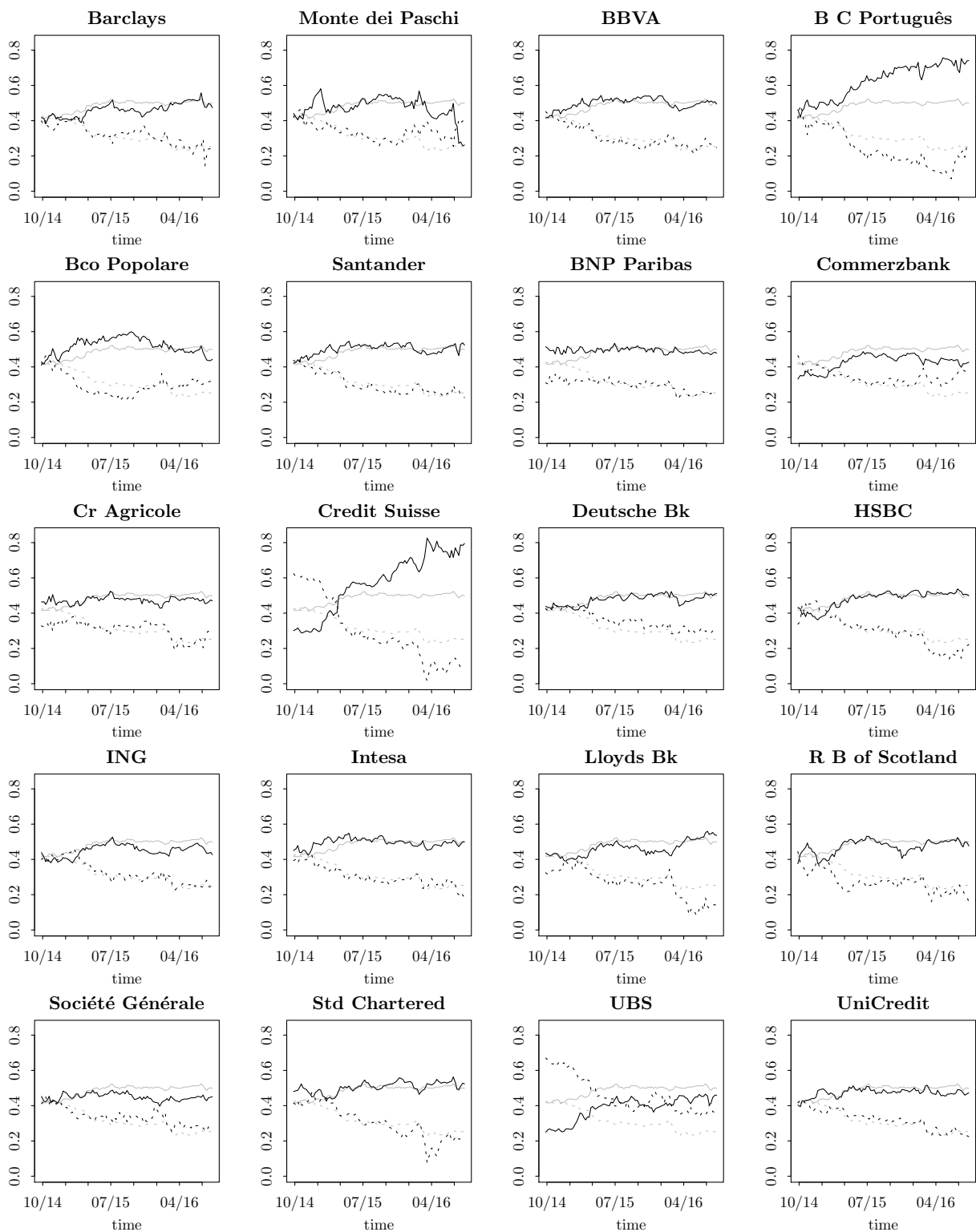


Figure 4: Individual trends in $S(\text{losses on senior debt} \mid \text{any 2014 credit event})$ from (4) (black, solid) and the relative basis (black, dotted), along with average spread across banks (gray, solid) and average relative basis across banks (gray, dotted); anomalies are Banco Comercial Português, Credit Suisse, UBS and recently Monte dei Paschi. *Sources: Markit Group Ltd. data and authors' calculations*

3.3 Reduced Market Expectations of Government Support Due to Reforms in European Banking Regulation

To understand whether the significant decline in the relative basis, and the increased conditional likelihood of losses on senior bonds, signify reduced market expectations of government support for distressed banks due to changes in European banking regulation, we need to address three questions: (i) whether the decline in the relative basis is fundamentally informative about changed loss expectations in bank distress, (ii) whether the decline in the relative basis is due to changes in banking regulation, and (iii) what the decline in the relative basis says about the likelihood of government support for banks in distress.

Regarding (i), it could be that the decline in the relative basis is due to unobserved features of subordinated 2003 CDS, or an increased liquidity premium in subordinated 2003 CDS. However, that the relative basis—which is calculated based on 2003 and 2014 CDS—and the loss severity measure from Section 3.2—which is calculated using CDS under 2014 definitions only—show such strong comovement dispels these potential concerns.

Regarding (ii), it could furthermore be that the decline in the relative basis is due to changes in banks’ capital structures, or changes in risk factors. However, we find in Section 4 that the synchronized decline in the relative basis across banks cannot be explained by capital structure changes or natural candidates for risk factors. This leaves changes in banking regulation, such as the BRRD, as the likely cause.

Regarding (iii), the decline in the relative basis is consistent with two contrary interpretations (compare Figure 2). It could be that banks entering distress increasingly are expected to undergo ordinary default, instead of intervention or bailout, meaning that expectations of government support especially for senior creditors have decreased—this would be a success for banking regulators. However, the opposite is also possible: it could be that bailouts that include subordinated debt have recently replaced interventions (which offer support only for senior bondholders), and that governments would cover all but the largest losses—this would mean that the expected vulnerability of the European financial system has increased or retrogressed to worse practices in the treatment of systemically important institutions. Thus, the key question is whether bailouts that include subordinated debt have replaced interventions. We provide evidence in Section 5 that the conditional likelihood of bailouts that include subordinated debt has not increased since 2014.

4 The Downward Trend in the Relative Basis Is Likely Due to Changes in Banking Regulation

In this section we investigate whether changes in banks’ capital structures or natural candidates for risk factors can explain the downward trend in the relative basis; compare the discussion in Section 3.3. That neither can explain the strong and highly synchronized downward trend in the relative basis suggests changes in banking regulation, such as the introduction of the BRRD, as the likely cause.

4.1 Levels of Senior Debt, Subordinated Debt and Equity Have Changed Little

We have seen that the relative basis is closely associated with the loss severity measure. An explanation for changes in the loss severity measure could be that banks have markedly changed their levels of subordinated or senior debt, or their levels of the most junior financing (junior subordinated debt and equity). However, Figure 5 shows that, on average and as a share of risk-weighted assets, neither has changed much. The median ratio of subordinated debt to total

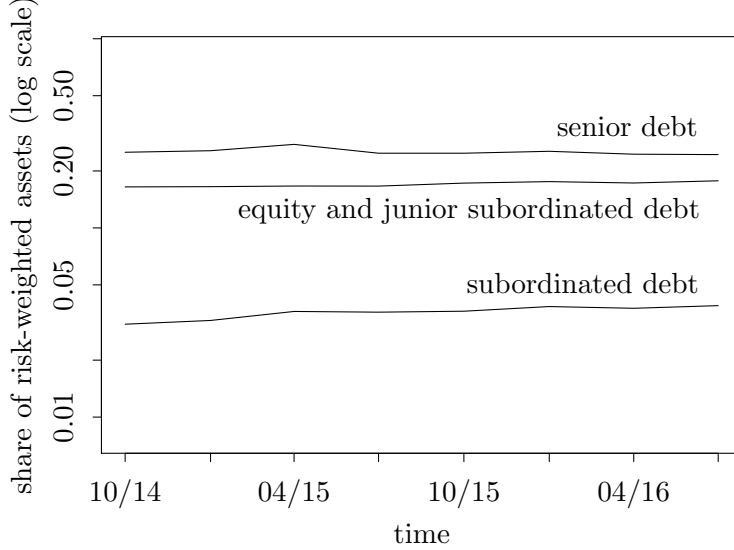


Figure 5: Senior debt, subordinated debt and sub-subordinated financing as a percentage of risk-weighted assets; average across all banks over time. *Sources: S&P Global Market Intelligence data and authors’ calculations*

risk-weighted assets was 2.8 percent in the fall of 2014, and increased by a median of 0.7 percent since then. At the same time, the ratio of senior debt to total risk-weighted assets had a median change of zero. Its median level was 20 percent in the fall of 2014. The median ratio of equity and junior subordinated debt to risk-weighted assets was 16.4 percent in the fall of 2014, and it increased by a median of 1.1 percent since. That all of these ratios have not changed much suggests that they are not responsible for the considerable changes in the loss severity measure and the relative basis across banks over the same time horizon.

4.2 Natural Candidates for Risk Factors Cannot Explain The Downward Trend

In this part we relate the relative basis to a number of risk factors to see if the downward trend can be explained by natural candidates for risk factors. We find that some of these risk factors are significantly associated with the relative basis, but that they cannot explain the strong and synchronized downward trend.

Econometric Model We specify the following hierarchical model, for banks $i = 1, \dots, n$ at times $t = 1, \dots, T$:

$$\frac{CDS_{it}^{2014} - CDS_{it}^{2003}}{CDS_{it}^{2014}} = \alpha + \delta_i + \beta^T (\text{risk factors})_{it} + \tau_{it} + \varepsilon_{it}. \quad (5)$$

We discuss the potential risk factors further below. The δ_i denote random intercepts that allow us to capture systematic level deviations in a bank’s relative basis from what would be predicted based on the risk factors alone. We do not use fixed effects because they would be able to exactly account for all cross-sectional variation, and therefore not allow us to identify the effect of risk factors that are constant over time (perfect multicollinearity). We place a mean-zero Gaussian process prior on $(\tau_{i1}, \dots, \tau_{iT})$, for each bank i , to account for potential systematic time trends in each bank’s

relative basis that cannot be explained by changes in the risk factors.⁵

Our panel contains only twenty banks and about two years of data. This means that the amount of information available to identify cross-sectional effects is limited, whereas the effect of variables that are observed continuously over time can be identified much more accurately.

We choose all prior and hyperprior distributions on the parameters in this hierarchical model as weakly informative (Gelman et al. 2014, Sections 2.9 and 5.7), meaning that they are wide enough to not affect inferences, but informative enough to improve numerical stability. We discuss the details of prior and hyperprior choice and the Monte Carlo sampling in Appendix C.1.

Potential Risk Factors We consider a number of natural candidates for risk factors, and examine how they may relate to the relative basis. In addition to these risk factors, changes in banking regulation, such as the BRRD, could also have an effect over time.

- General risk affinity in the market, which we will measure by the cyclically adjusted price–earnings ratio *CAPE* (Campbell and Shiller 1988) of the MSCI Europe Index, which is defined as the price of the index divided by the ten-year average of inflation-adjusted index earnings. The idea behind *CAPE* is that stock prices movements are too large to be explained by changed expectations about future dividends, and must therefore mostly be due to changes in the general risk premium; see Shiller (1981). In favorable market circumstances the economy is more resilient and may therefore better withstand the ordinary default of a financial institution. These data are from MSCI.
- The sovereign five-year CDS spread, which is a measure of the respective government’s financial strength and political stability. The average spreads over the time horizon we study are as follows. France: 27 bps, Germany: 11 bps, Italy: 107 bps, Netherlands: 14 bps, Portugal: 182 bps, Spain: 80 bps, Switzerland: 21 bps, United Kingdom: 24 bps. See the evolution of the sovereign CDS spreads in Figure 6.
- Whether the bank would have a significant capital shortage in case of a large drop in the market. For this purpose, Acharya et al. (2012) define SRISK as the expected capital shortfall conditional on a systemic event: $SRISK_i = \mathbb{E}[kA - E \mid \text{large drop in market}]$, where A is assets, E is equity and k is the regulatory percentage of assets to be held in equity. We will use as a risk factor the relative SRISK, as suggested in Acharya et al. (2012):

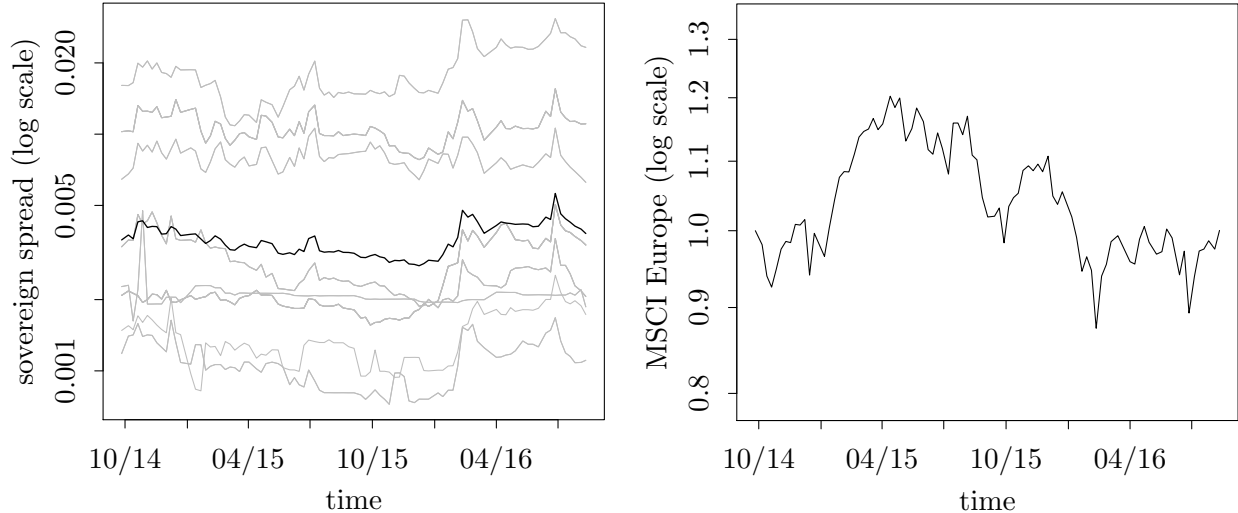
$$\frac{SRISK_i}{\sum_{j=1}^{20} \max(SRISK_j, 0)}.$$

It is the share in capital shortage that bank i would face relative to all other banks if a systemic event were to happen. We obtain SRISK data from V-Lab (2016). Its estimates are based on an asymmetric volatility and correlation framework, with $k = 0.08$ and the assumption that worldwide stock markets fall 40 percent over a six months period.

- Idiosyncratic stress of the bank. We measure this by the difference between the 2014 CDS spread of bank i and the average 2014 CDS spread across all twenty banks, on a log scale:

$$\text{idiosyncratic stress}_{it} = \ln(CDS_{it}^{2014}) - \frac{1}{20} \sum_{j=1}^{20} \ln(CDS_{jt}^{2014}).$$

⁵The estimates for the coefficients on the time-varying risk factors are robust to specifying the δ_i in the model in (5) as fixed effects (which makes all other time-constant effects drop out due to perfect multicollinearity). The estimates are also robust to adding another Gaussian process as the main trend across all banks (which makes the τ_{it} model the deviation of each bank’s relative basis from the main trend).



(a) Sovereign CDS spreads (gray) over time, along with geometric mean (black); Portugal has the highest sovereign CDS spread, followed by Italy and Spain. *Sources: Markit Group Ltd. data and authors' calculations*

(b) MSCI Europe Index, normalized to start at one in September 2014. *Sources: MSCI data and authors' calculations*

Figure 6: Sovereign CDS spreads and MSCI Europe Index over time

A bank with idiosyncratic stress of larger than zero is likely to fail when other banks are not in distress, whereas a bank with idiosyncratic stress lower than zero is more likely to enter distress in a market-wide crisis. It is meaningful to include idiosyncratic stress as a predictor of the relative basis because the information provided by the idiosyncratic stress — how high a bank's CDS spread is relative to other banks — is considerably different from the information in the relative basis — which measures the conditional likelihood of an intervention, and where scaling of the spreads cancels out because spreads appear in both numerator and denominator. We list the average idiosyncratic stress for each bank in Table 3 in Appendix D.

- The bank's raw systemic importance score in 2014, divided by 1000. This score is based on the Basel Committee on Banking Supervision's GSIB scorecard of systemic importance indicators of size, interconnectedness, substitutability, complexity, and cross-jurisdictional activity. This allows us to learn to what degree the Basel systemic importance score is an indicator of intervention. We list the scores in Table 3 in Appendix D.
- The bank's raw systemic importance score, divided by the respective country's gross domestic product (2014, in trillion euro), as a measure of bank riskiness relative to country size.
- Whether the bank is partially or wholly state-owned. Commerzbank, Lloyds Bank and Royal Bank of Scotland were partially state owned for our whole sample. Governments may be more or less likely to support bondholders of banks in which they hold equity.

The parameter estimates for the model in (5) are given in Table 1, and the hyperparameter estimates in Table 4 in Appendix E. We find that only three coefficients are statistically significantly different from zero. The posterior mean estimate on idiosyncratic stress of 0.16 means that doubling a particular bank's subordinated 2014 CDS spread is associated with an increase in the relative basis of ten percent, all else equal. This could be because a bank that is in a considerably worse

Table 1: Parameter estimates for the model in Equation (5). *Sources: Markit Group Ltd. data and authors' calculations*

Parameter	Posterior mean	Posterior SD	95 % CI	$\frac{\text{posterior mean}}{\text{posterior SD}}$
$\beta_{\text{GSIB score}}$	0.26	0.17	[-0.07, 0.58]	1.5
$\beta_{\text{GSIB score / GDP}}$	0.14	0.17	[-0.18, 0.47]	0.85
$\beta_{\text{Partially state owned}}$	0.04	0.05	[-0.07, 0.14]	0.7
$\beta_{\text{Idiosyncratic}}$	0.16	0.01	[0.14, 0.18]	14.7
β_{CAPE}	-0.005	0.001	[-0.008, -0.003]	-2.5
$\beta_{\text{Sovereign spread}}$	-1.67	0.67	[-2.99, -0.35]	-2.5
$\beta_{\text{Relative SRISK}}$	0.21	0.16	[-0.11, 0.53]	1.3

state than its competitors may experience a capital shortage from relatively minor, idiosyncratic losses. Losses that are not too large can be absorbed by bailing in subordinated debt.

The posterior mean estimate for CAPE is slightly negative. A possible explanation is that letting a bank undergo ordinary default becomes more of an option when financial markets are in good shape.

Lastly, we find that a 100 bps increase in a country's sovereign CDS spread is associated with a reduction in the relative basis of 170 bps. This suggests that a government in a weaker financial and/or political position is less likely to intervene in its banks. This adds another dimension to the research of Acharya et al. (2014), who find a feedback loop between sovereign and bank credit risk, because the bailout of banks increases government credit risk, and increased sovereign credit risk weakens the financial sector due to the reduced value of government guarantees and bond holdings.

The positive estimates on GSIB and GSIB/GDP could indicate that more systemically important banks have a higher likelihood of interventions; however, because the panel contains only twenty banks, these cross-sectional estimates are very noisy. The marginal association of SRISK with the relative basis is negligible.

In Figure 7 we show the overall time trend in the relative basis, as captured by $20^{-1} \sum_{i=1}^{20} \hat{\tau}_{it}$, which is the mean across banks at every point in time of the Gaussian processes in the econometric model in Equation (5). We compare that time trend with the average relative basis at each point in time. We see that the patterns match almost perfectly, which means that the risk factors cannot explain the downward trend. This figure supports the view that changes in banking regulation, such as the BRRD, may be the driving forces behind the decline.

We show the same analysis at the level of individual banks in Appendix F. For some banks, the likelihood of intervention differs considerably from what would be expected based on the risk factors and the general downward trend alone.

This model also allows us to study country-specific trends in the relative basis. In Figure 8 we show the average trend in $\hat{\delta}_i + \hat{\tau}_{it}$ for the five banks from the United Kingdom, the four banks from Italy, and the three banks from France, each with the European average subtracted out. Recently, the relative basis has declined for banks in the United Kingdom, whereas it has increased in Italy and France. This effect appears to be driven by declines in the relative basis at Lloyds Bank and Standard Chartered, and, to a lesser extent, at HSBC and Royal Bank of Scotland. All the banks in our panel saw their CDS spreads rise in the first quarter of 2016; see Figure 1. For reasons we return to later, the decline in the relative basis at these four banks from the United Kingdom

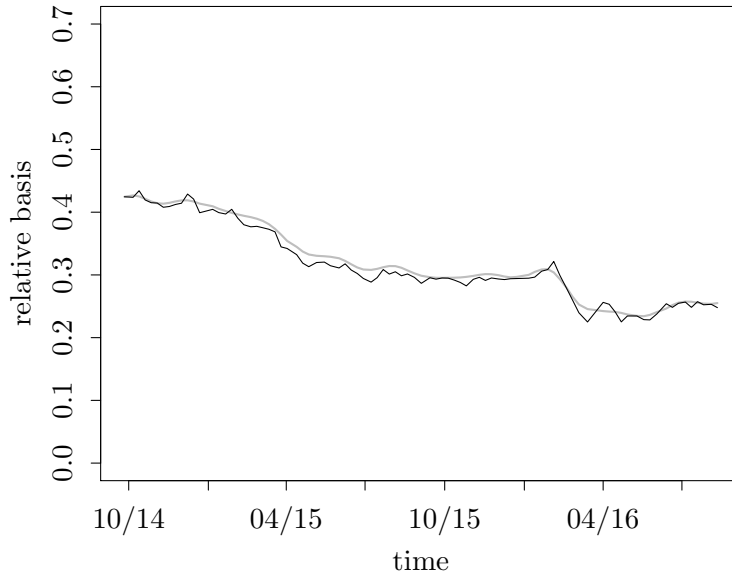


Figure 7: Average time trend in the relative basis with risk factor effects subtracted out, $\frac{1}{20} \sum_{i=1}^{20} \hat{\tau}_{it}$, shifted to start from the observed average relative basis on September 22, 2014; posterior mean estimate (gray). Also shown is the observed average relative basis across all banks (black). This shows that natural candidates for risk factors do not explain the downward trend. *Sources: Markit Group Ltd. data and authors' calculations*

may signal a greater perceived likelihood that they would be allowed to undergo ordinary default if their condition worsened. Standard Chartered conducts most of its business outside the United Kingdom and may therefore be viewed as least likely to receive government support. We discuss the effects of the “Brexit” vote in detail in Appendix G.

5 Evidence that Bailouts of Subordinated Debt in Distressed Banks Have Not Become More Likely

In this section we provide four pieces of evidence that bailouts that include subordinated debt have not become more likely in distressed banks; compare the discussion in Section 3.3.

5.1 The BRRD Legally Requires Some Bail-in Before Bailout

The BRRD, which became effective in 2016, mandates that eight percent of a bank’s liabilities need to be bailed in before a government may inject funds. In typical cases, this means that subordinated debt can no longer be bailed out legally. While BRRD rules do not directly apply to Switzerland, Norway and Liechtenstein, market expectations are that their national resolution frameworks will treat failing banks similarly (Moody’s 2015b). Politicians and regulators may feel compelled to circumvent bailout bans in times of stress. However, for example the discussion around troubled Italian banks in the summer of 2016 shows that this is not trivial in the case of the BRRD (The Economist 2016).

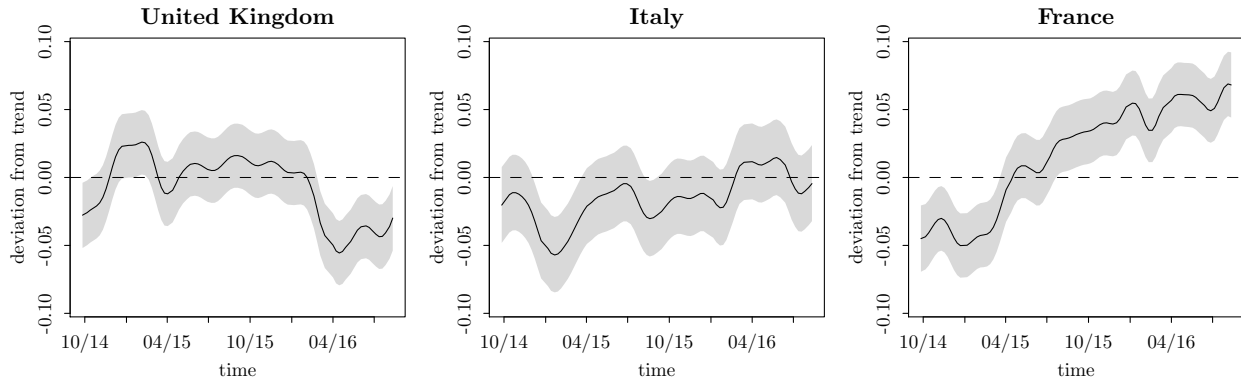


Figure 8: Time trend in the idiosyncratic deviation from the overall downward trend, $|\{i \in \text{country}\}|^{-1} \sum_{i \in \text{country}} (\hat{\delta}_i + \hat{\tau}_{it}) - \frac{1}{20} \sum_{i=1}^{20} \hat{\tau}_{it}$, for each of the countries with three or more banks in the data set, namely the United Kingdom with five banks, Italy with four banks, and France with three banks; posterior mean estimate along with 68 percent credible intervals. *Sources: Markit Group Ltd. data and authors' calculations*

5.2 Losses on Senior Debt Have Become More Likely Even in Interventions

Senior bondholders tend to receive some government support in interventions; see the discussion in Section 3.2. If government support for distressed banks' bondholders had increased so much that even the bailout of subordinated debt had become more likely, then one would expect that governments would increasingly support senior bondholders in interventions, too. However, we find below that the likelihood that senior bonds would suffer in an intervention has increased. This suggests that rather governments find themselves to be more able to impose losses on senior bondholders recently instead of bailing them out.

To show this, we aim to identify the spread for losses on senior bonds, given an intervention in subordinated bonds,

$$\mathbb{S}(\text{losses on senior debt} \mid \text{sub intervention}) =: v, \quad (6)$$

and the spread for losses on senior bonds, given an ordinary default on subordinated bonds,

$$\mathbb{S}(\text{losses on senior debt} \mid \text{sub ordinary default}) =: d. \quad (7)$$

We cannot directly calculate these spreads the way we did for subordinated debt in Section 3.1.⁶ Nevertheless, by making only two relatively mild assumptions, we will be able to infer them. We begin by expressing the senior–sub ratio from (4) as the sum of loss severity in an intervention and loss severity in an ordinary default, weighted with the respective conditional probability:

$$\begin{aligned} \frac{CDS_{\text{senior}}^{2014}}{CDS^{2014}} &= \mathbb{S}(\text{losses on senior debt} \mid \text{sub intervention}) \\ &\quad \times \mathbb{P}(\text{sub intervention} \mid \text{any sub 2014 credit event}) \\ &\quad + \mathbb{S}(\text{losses on senior debt} \mid \text{sub ordinary default}) \\ &\quad \times \mathbb{P}(\text{sub ordinary default} \mid \text{any sub 2014 credit event}). \end{aligned} \quad (8)$$

⁶This is because ISDA made a change to senior CDS definitions in 2014 that is not related to intervention: it removed the sub–senior cross trigger. While a senior 2003 CDS triggers whenever a subordinated 2003 CDS triggers, a senior 2014 CDS will trigger only in case of an event that directly affects senior debt. This decreases the value of a senior 2014 CDS, and has no effect on subordinated CDS.

We also express

$$\mathbb{P}(\text{sub intervention} \mid \text{any sub 2014 credit event}) = \frac{\text{relative basis}}{w} = \frac{1}{w} \frac{CDS^{2014} - CDS^{2003}}{CDS^{2014}}, \quad (9)$$

and we know that

$$\begin{aligned} \mathbb{P}(\text{sub ordinary default} \mid \text{any sub 2014 credit event}) \\ = 1 - \mathbb{P}(\text{sub intervention} \mid \text{any sub 2014 credit event}). \end{aligned} \quad (10)$$

To understand the role of w , consider the simplified representation of the relative basis

$$\begin{aligned} \frac{CDS^{2014} - CDS^{2003}}{CDS^{2014}} &= \frac{L_{\text{sub intervention}} \mathbb{P}(\text{sub intervention})}{L_{\text{sub intervention}} \mathbb{P}(\text{sub intervention}) + L_{\text{ordinary default}} \mathbb{P}(\text{ordinary default})} \\ &= w \mathbb{P}(\text{sub intervention} \mid \text{any sub 2014 credit event}). \end{aligned}$$

From

$$\begin{aligned} w^{-1} &= \mathbb{P}(\text{sub intervention} \mid \text{any sub 2014 credit event}) \\ &+ \frac{L_{\text{sub ordinary default}}}{L_{\text{sub intervention}}} \mathbb{P}(\text{sub ordinary default} \mid \text{any sub 2014 credit event}) \end{aligned} \quad (11)$$

we see that w is increasing in the ratio of loss given an intervention and loss given an ordinary default, and that w equals one if the conditional losses are equal.

Plugging (9) and (10) into Equation (8) yields, for each bank i and point in time t ,

$$\frac{CDS_{\text{senior } it}^{2014}}{CDS_{it}^{2014}} = \frac{v_{it}}{w_{it}} \frac{CDS_{it}^{2014} - CDS_{it}^{2003}}{CDS_{it}^{2014}} - \frac{d_{it}}{w_{it}} \frac{CDS_{it}^{2014} - CDS_{it}^{2003}}{CDS_{it}^{2014}} + d_{it}. \quad (12)$$

This is an underdetermined system of equations. We make two assumptions to ensure identifiability.

Assumption 1. Values for v that are close in time are similar to each other. Likewise, values for d that are close in time are similar.

We make this assumption precise further below.

Assumption 2. w_{it} changes linearly with time, separately for each bank.

This assumption is needed because, locally in time, the separate effects of v_{it} and w_{it} are only weakly identifiable. This assumption is far weaker than assuming, for example, that all conditional losses are equal. Under Assumption 2, the conditional losses of intervention and ordinary default may be different, and they may even differ across banks and, linearly, over time.

We obtain estimates for the $v_{it} = \mathbb{S}(\text{losses on senior debt} \mid \text{sub intervention})_{it}$ from (6) as well as the $d_{it} = \mathbb{S}(\text{losses on senior debt} \mid \text{sub ordinary default})_{it}$ from (7) by expressing (12) as a regression model, with an error term ε_{it} . We incorporate Assumptions 1 and 2 in this regression model by placing so-called random walk priors on v_{it}/w_{it} and d_{it} , and allowing w_{it} to change linearly over time for each bank. We discuss the details of the prior and hyperprior specification and of the Markov chain Monte Carlo sampling in Appendix C.2.

Figure 9 shows the averages for $\mathbb{S}(\text{losses on senior debt} \mid \text{sub bail-in})$ and also the averages for $\mathbb{S}(\text{losses on senior debt} \mid \text{sub ordinary default})$ over time. We see that the market implies that an ordinary default typically involves larger losses on senior debt than an intervention, with average spreads of 0.60 and 0.39, respectively. We show the results separately for each bank in Figure 12

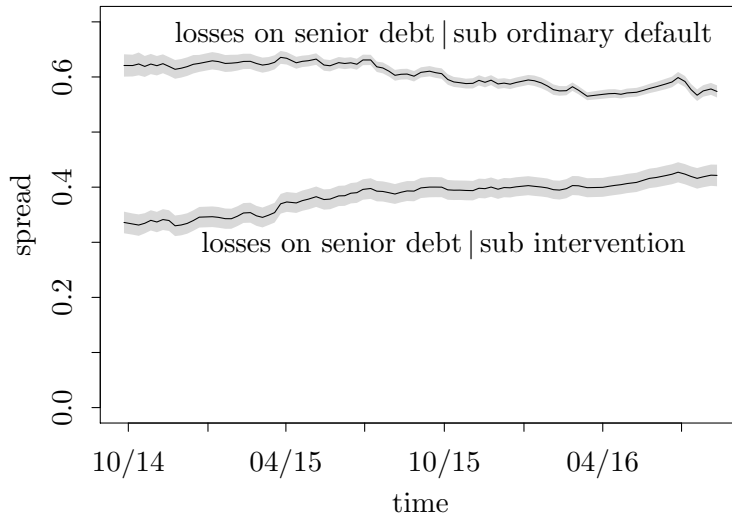


Figure 9: Average of $\mathbb{S}(\text{losses on senior debt} \mid \text{sub ordinary default})$ as well as $\mathbb{S}(\text{losses on senior debt} \mid \text{sub intervention})$ over time; posterior mean estimate along with 68 percent credible intervals. These spreads function as weights in (8). The figure shows that $\mathbb{S}(\text{losses on senior debt} \mid \text{sub intervention})$ increased slightly over time, and the other spread stayed roughly constant. *Sources: Markit Group Ltd. data and authors' calculations*

in Appendix H. The average spread for losses on senior debt given sub ordinary default is approximately constant over time at a high level. This suggests that the market has not become more nervous about disruptions in an ordinary default scenario. The average spread for losses on senior debt given sub intervention is lower, but surprisingly large, and it has increased considerably. This means that the market expects that governments have become less likely to support senior creditors in an intervention, and that the current levels of subordinated debt do not suffice to cover the expected losses in an intervention.

5.3 Relationship between Relative Basis and Likelihood of Bailout

If bailouts that include subordinated debt had been replacing interventions systematically, then we should observe a strong negative correlation between the relative basis and the conditional likelihood of bailout of subordinated debt. This is because a shift of probability mass from interventions to bailouts that include subordinated debt reduces the relative basis. However, we find in the following that the correlation is weak.

The conditional likelihood of a bailout that includes subordinated debt is

$$\begin{aligned} & \mathbb{S}(\text{bailout incl sub debt} \mid \text{distress}) \\ &= \frac{\mathbb{S}(\text{ordinary default} \cup \text{intervention} \cup \text{bailout incl sub debt}) - \mathbb{S}(\text{ordinary default} \cup \text{intervention})}{\mathbb{S}(\text{ordinary default} \cup \text{intervention} \cup \text{bailout incl sub debt})}. \end{aligned} \tag{13}$$

We cannot measure (13) directly because $\mathbb{S}(\text{ordinary default} \cup \text{intervention} \cup \text{bailout incl sub debt})$ is not observable in the market. However, we can use Moody's KMV model to estimate a bank-specific spread that includes bailouts of subordinated debt. This is possible because the KMV model includes bailout as a default event, and because it uses the counterfactual that losses in a bailout of subordinated debt are not zero but the average for interventions or ordinary defaults.

A complication is that the KMV model estimates a spread calculated under the real-world measure, $\mathbb{S}^{\text{physical}}(\text{ordinary default} \cup \text{intervention} \cup \text{bailout incl sub debt}) = L_{\text{distress}}^{\text{physical}} \cdot \mathbb{P}^{\text{physical}}(\text{distress})$. In contrast, a spread \mathbb{S} is market implied, which means that it can be expected to include a risk premium. We address this issue further below.

We obtain annualized five-year estimates of $\mathbb{P}^{\text{physical}}(\text{distress})$ for all banks and points in time from Moody’s KMV CreditEdge model, which is based on the general approach of Merton (1974). Although the approach of Merton (1974) generates a risk neutral probability of distress, KMV CreditEdge is calibrated to match historical distress probabilities and is therefore under the physical measure. The real-world default probability estimates range from significantly less than 0.01 for banks such as UBS, Lloyds Bank and HSBC up to above 0.08 for Banca Monte dei Paschi di Siena.

We also obtain estimates of the annualized five-year real-world expected loss given default for subordinated debt, $L_{\text{distress}}^{\text{physical}}$, from Moody’s KMV LossCalc model. LossCalc is a regression model that uses historical data on recoveries together with predictors such as industry, credit cycle stage, debt type, and the probability of distress. In LossCalc a bailout event is assigned losses that would be expected under a distress that is not a bailout (Moody’s Analytics 2016). The estimates for the loss given distress on subordinated bonds, $L_{\text{distress}}^{\text{physical}}$, show relatively little variation across banks and time around their mean of 80 percent. This relatively high number means that distress would typically wipe out most of a bank’s subordinated debt.

We now investigate the correlation between the conditional likelihood of bailout that includes subordinated debt and the relative basis. As discussed at the beginning of this analysis, if bailouts that include subordinated debt had systematically replaced interventions, then this correlation should be strongly negative. We cannot directly plug the estimates from the KMV model for $\mathbb{S}^{\text{physical}}(\text{ordinary default} \cup \text{intervention} \cup \text{bailout incl sub debt})$ into (13), because then we would be subtracting market-implied from real-world spreads. Instead, we define

$$b = \frac{\mathbb{S}^{\text{physical}}(\text{ordinary default} \cup \text{intervention} \cup \text{bailout incl sub debt})}{\mathbb{S}(\text{ordinary default} \cup \text{intervention})} = \frac{L_{\text{distress}}^{\text{physical}} \cdot \mathbb{P}^{\text{physical}}(\text{distress})}{CDS^{2014}}. \quad (14)$$

This quantity takes a large value when the probability of bailout that includes sub debt is high and/or the risk premium is low, and it takes a small value when the probability of such a bailout is low and/or the risk premium is high (recall that the KMV physical probabilities treat bailouts as defaults). Empirically, we find that b is typically much smaller than one, with average values for the banks ranging from 0.29 for UBS and 0.32 for Banco Comercial Português to 0.98 for Société Générale and 1.02 for Commerzbank, with a mean across all banks of 0.68.

We address the complication that b also depends on the risk premium by taking, for each bank, the average value of b over time, which marginalizes out this dependency. Likewise, we calculate the average relative basis over time, separately for each bank.

We find that the empirical correlation between the bank-averages for b and the bank-averages for the relative basis is 0.02. Given the small sample size of only twenty banks, the uncertainty about the true correlation is relatively high, as captured by a 95 percent confidence interval that ranges from -0.43 to 0.46 . Hence, we also perform correlation analyses with the panel data in Appendix I. Both within and across time series we find only a very small negative correlation on average. This suggests that bailouts that include subordinated debt have not systematically replaced interventions.

5.4 Rating Agencies Removed or Lowered Uplift for Government Support in Bank Bond Ratings

Rating agencies have eliminated their ratings uplift on all junior instruments in expectation of reduced government support for such instruments following recent changes in banking regulation; see, for example, Moody's (2015a) and Standard & Poor's (2015). This development is consistent with our interpretation of the decline in the relative basis as reflecting reduced expectations of government support.

6 Conclusion

The European Union has formalized the role of bond bail-in in resolving distressed banks through the BRRD. Contemporaneously, ISDA has introduced new definitions for the CDS market in 2014 to cope with the complications surrounding bond bail-in. Using data of CDS trading under old and new ISDA definitions, we find reduced market expectations of support for senior bondholders in bank failures where at most senior bondholders, but not subordinated bondholders, receive a bailout.

We have provided evidence that bailouts that include subordinated debt have not become more likely conditionally over the same time horizon; this suggests that expectations of government support for banks in distress have decreased. We have furthermore provided evidence that natural candidates for risk factors cannot explain the highly synchronized downward trend in the relative basis; this leaves changes in banking regulation as the likely cause.

We conclude from these findings that changes in European banking regulation, such as the BRRD, have reduced expectations of government support for ailing banks. This development represents important progress in the credibility of financial reforms aimed at reducing perceived government guarantees for large banks.

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References

- Acharya, Viral, Itamar Drechsler, and Philipp Schnabl, "A pyrrhic victory? Bank bailouts and sovereign credit risk," *The Journal of Finance*, 2014, 69 (6), 2689–2739.
- , Robert Engle, and Matthew Richardson, "Capital Shortfall: A New Approach to Ranking and Regulating Systemic Risks," *The American Economic Review*, 2012, 102 (3), 59–64.
- Adrian, Tobias and Markus K Brunnermeier, "CoVaR," *American Economic Review*, 2016, 106 (7), 1705–1741.
- Ahmed, Javed, Christopher W Anderson, and Rebecca Zarutskie, "Are the Borrowing Costs of Large Financial Firms Unusual?," *U.S. Office of Financial Research Working Paper*, 2015.
- Altman, Edward I, "Default recovery rates and LGD in credit risk modeling and practice: an updated review of the literature and empirical evidence," *New York University, Stern School of Business*, 2006.

- Araten, Michel and Christopher M. Turner**, “Understanding the funding cost differences between Global Systemically Important Banks (G-SIBs) and non-G-SIBs in the United States,” *Available at SSRN 2226939*, 2012.
- Avdjiev, Stefan, Patrick Bolton, Wei Jiang, Anastasia Kartasheva, and Bilyana Bogdanova**, “Coco bond issuance and bank funding costs,” *Bank for International Settlements and Columbia University working paper*, 2015.
- Bai, Jennie and Pierre Collin-Dufresne**, “The cds–bond basis,” in “AFA 2013 San Diego Meetings Paper” 2013.
- Barth, Andreas and Isabel Schnabel**, “Why banks are not too big to fail—evidence from the CDS market,” *Economic Policy*, 2013, 28 (74), 335–369.
- Brooks, Stephen P and Andrew Gelman**, “General methods for monitoring convergence of iterative simulations,” *Journal of Computational and Graphical Statistics*, 1998, 7 (4), 434–455.
- Campbell, John Y and Robert J Shiller**, “Stock prices, earnings, and expected dividends,” *The Journal of Finance*, 1988, 43 (3), 661–676.
- Cetina, Jill and Bert Loudis**, “The influence of systemic importance indicators on banks credit default swap spreads,” *Journal of Risk Management in Financial Institutions*, 2016, 9 (1), 17–31.
- Chernov, Mikhail, Alexander S Gorbenko, and Igor Makarov**, “CDS auctions,” *Review of Financial Studies*, 2013, 26 (3), 768–805.
- Duffie, Darrell and Kenneth J Singleton**, “Modeling term structures of defaultable bonds,” *Review of Financial studies*, 1999, 12 (4), 687–720.
- Elizalde, Abel, Saul Doctor, and Yasemin Saltuk**, “Bond–cds basis handbook,” *JP Morgan European Credit Derivatives Research*, 2009.
- Ericsson, Jan, Kris Jacobs, Rodolfo Oviedo et al.**, “The determinants of credit default swap premia,” *Journal of Financial and Quantitative Analysis*, 2009, 44 (1), 109–132.
- European Parliament**, *Directive 2014/59/EU of the European Parliament* 2014. <http://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32014L0059&from=EN>.
- Fontana, Alessandro**, “The negative cds–bond basis and convergence trading during the 2007/09 financial crisis,” *Swiss Finance Institute Research Paper*, 2011, (11-41).
- Gelman, Andrew**, “Prior distributions for variance parameters in hierarchical models (comment on article by Browne and Draper),” *Bayesian Analysis*, 2006, 1 (3), 515–534.
- , **John B Carlin, and Hal S Stern**, *Bayesian Data Analysis*, Vol. 3, Taylor & Francis, 2014.
- Gupta, Sudip and Rangarajan K Sundaram**, “CDS Auctions and Informative Biases in CDS Recovery Rates,” *Available at SSRN 1942727*, 2013.
- Haworth, Helen**, “A guide to Credit Events and auctions,” Technical Report, Credit Suisse 2011.
- Hoffman, Matthew D and Andrew Gelman**, “The No-U-Turn Sampler: Adaptively Setting Path Lengths in Hamiltonian Monte Carlo,” *Journal of Machine Learning Research*, 2014, 15, 1593–1623.
- Markit Group Ltd.**, “The CDS Big Bang: Understanding the Changes to the Global CDS Contract and North American Conventions,” Technical Report, Markit Group Ltd. 2009.
- Merton, Robert C**, “On the pricing of corporate debt: The risk structure of interest rates,” *The Journal of Finance*, 1974, 29 (2), 449–470.
- Moody’s**, *Moody’s concludes reviews on 13 global investment banks’ ratings* 2015. https://www.moodys.com/research/Moodys-concludes-reviews-on-13-global-investment-banks-ratings-PR_326277.
- , *Ratings will reflect declining probability of government support for European banks* 2015. https://www.moodys.com/research/Moodys-Ratings-will-reflect-declining-probability-of-government-support-for-PR_320732.
- Moody’s Analytics**, “Moody’s Analytics RiskCalc LGD: LossCalc v4.0 Model,” Technical Report, Moody’s Analytics Quantitative Research Group 2016.

- Rasmussen, Carl Edward and Chris Williams**, *Gaussian processes for machine learning*, MIT Press, Cambridge, MA, 2006.
- Sarin, Natasha and Lawrence H Summers**, “Have big banks gotten safer?,” *BPEA Conference Draft*, 2016.
- Schäfer, Alexander, Isabel Schnabel, and Beatrice Weder**, “Bail-in Expectations for European Banks: Actions Speak Louder than Words,” *CEPR Discussion Paper No. DP11061*, 2016.
- Schuermann, Til**, “What do we know about Loss Given Default?,” *Wharton Financial Institutions Center Working Paper No. 04-01*, 2004.
- Shiller, Robert J**, “Do Stock Prices Move Too Much to be Justified by Subsequent Changes in Dividends?,” *American Economic Review*, 1981, 71 (3), 421–36.
- Shin, Hyun Song**, “Reflections on Northern Rock: the bank run that heralded the global financial crisis,” *The Journal of Economic Perspectives*, 2009, 23 (1), 101–119.
- Stan Development Team**, “Stan: A C++ Library for Probability and Sampling, Version 2.9.0,” 2015. <http://mc-stan.org/>.
- Standard & Poor’s**, *Most European Bank Ratings Affirmed Following Government Support And ALAC Review* 2015. https://www.globalcreditportal.com/ratingsdirect/renderArticle.do?articleId=1490042&SetArtId=357748&from=CM&nsl_code=LIME&sourceObjectId=9428729&sourceRevId=1&fee_ind=N&exp_date=20251202-00:52:42.
- The Economist**, *Italian banks: Crisis and opportunity* 2016. <http://www.economist.com/news/finance-and-economics/21701755-brexit-vote-has-sideswiped-italys-banksand-testing-europes-new-rules>.
- U.S. Government Accountability Office**, *Large Bank Holding Companies: Expectations of Government Support* 2014. <http://www.gao.gov/products/GAO-14-621>.
- V-Lab, NYU Stern – The Volatility Institute** 2016. <http://vlab.stern.nyu.edu>.
- Volz, Manja and Michael Wedow**, “Does banks’ size distort market prices? evidence for too-big-to-fail in the CDS market,” *Available at SSRN 1367534*, 2009.
- Wit, Jan De**, “Exploring the CDS–bond basis,” *National Bank of Belgium working paper*, 2006, (104).
- Zaghini, Andrea**, “Bank bonds: size, systemic relevance and the sovereign,” *International Finance*, 2014, 17 (2), 161–184.

A Description of the CDS Quote Data

We consider subordinated five-year 2003 and 2014 CDS spreads, starting on Sept. 22, 2014, the date of the introduction of the 2014 CDS, to April 18, 2016. These data are from Markit, and we already used them in Figure 1. For many of the smaller European banks, subordinated CDS are traded too rarely to give good weekly, or even daily, spread quotes. We select only banks for which subordinated data quality is judged “B” or higher — indicating at least moderate data quality — according to Markit’s data quality rating on at least 95 percent of quote days (which include some public holidays). Markit judges data quality by the number of sources that provide spread quotes, as well as competitiveness, liquidity and transparency of the market. We are left with twenty banks that satisfy this data quality requirement; their names are given in Figure 10. Only on a very few days their data quality falls below “B.” Data quality is highly similar for subordinated 2003 and 2014 CDS, across all banks — even those banks that are not included in our final data set because of insufficient data quality. This suggests that our sampling according to the data quality rating is outcome-independent.

For senior CDS, 85 percent of quoted spreads have a Markit data quality rating of “AA” or “A,” and only 0.3 percent are rated less than “B.”

We confirm that for these banks quoted spreads from Markit closely match spreads at which actual trades happen in Appendix B, using anonymized data of actual CDS trades confirmed

through The Depository Trust & Clearing Corporation (DTCC). Lastly, we subsample the panel data to a weekly frequency to reduce the effect of potential short term autocorrelation in Markit’s spread quotes.

We note that the CDS market is somewhat technically driven, because CDS can be used to both hedge against default, and to hedge against the spread of other CDS, bonds or counterparty exposures. Hedging spread changes with subordinated 2003 CDS may be perceived as slightly cheaper than hedging with 2014 CDS. At the same time, switching from old 2003 CDS to new 2014 CDS may cause wide bid–ask spreads during the time of transition. We find in Section 3.2 that neither of these technical factors has a large impact on the quotes we study.

B Establishing Quote Validity

Our analysis uses quoted rather than transacted spreads. While these quotes are not tradable, they are a composite of tradable quotes submitted by market makers in European financial reference entities. As market makers have been known to shade surveys to favor their own interests, for example in the recent LIBOR scandal, we seek to verify that the quotes are accurate indicators of the spreads at which trades will occur.

We obtained anonymized data of CDS trades recorded by The Depository Trust & Clearing Corporation (DTCC). These are all trades where at least one of the counterparties is based in the United States. We consider transactions that occur between September 1, 2014 and February 12, 2016. We focus in our sample on confirmed initial trades which reference subordinated debt and are roughly five years at inception. In other words, we exclude canceled transactions, as the information content of those may be misleading. We also ignore other DTCC transaction classifications such as Assignment, Amendment, Backload, Exit, Increase, and Terminate because these transactions largely embed information that follow trade inception. As we aim to compare information content from transaction execution to market quotes, only initial trades are relevant.

We do not expect quoted spreads and transacted spreads to align perfectly for several reasons. First among these are differences in upfront payment conventions. Typically, the upfront of a CDS contract reflects the difference between market spreads and a fixed coupon spread the contract pays. To the extent the upfront is higher, the fair value spread will be lower. Sometimes, market participants transact an upfront different than the one that reflects this difference in spreads. We delete trades where we can observe intentional deviations from the market price, specifically those trades whose fair value spreads are exactly 100, 300 and 500 basis points. Additional sources of discrepancy between market quoted spread and transacted spread are differences in contract maturities, choice of nonstandard coupon payment and swap termination dates, nonstandard transaction sizes, and adjustments for counterparty risk since the market is over the counter and not anonymous. To address these issues, we standardize market-quoted maturities to correspond to those of each contract and assume that each CDS terminates on the international money market (IMM) date closest before, or upon, the transacted termination date. We ensure that each transaction’s base currency, seniority, and documentation clause take the same value for each quote.

We obtain, for each bank i and point in time t the transacted spread, $s_{i,t}^j$, and the quoted spread, $q_{i,t}^j$, where we use j to denote that there may be multiple trades for a bank on a given day. We model the transacted spread–quoted spread relationship as linear, with error term $\varepsilon_{i,t}^j$:

$$s_{i,t}^j = \alpha_0 + \beta_0 q_{i,t}^j + \varepsilon_{i,t}^j. \quad (15)$$

We run this regression independently four times: for subordinated 2003 CDS, for subordinated 2014 CDS, for senior 2003 CDS, and senior 2014 CDS. We show the estimation results in Table 2.

Table 2: Assessing the relationship between traded spreads and quoted spreads. *Sources: Markit Group Ltd. data, DTCC data and authors' calculations*

	Regression 1	Regression 2	Regression 3	Regression 4
	Traded sub 2003 spread	Traded sub 2014 spread	Traded senior 2003 spread	Traded senior 2014 spread
Slope on quoted spread	1.05 (0.08)	1.05 (0.00)	1.02 (0.01)	1.05 (0.00)
Intercept	0.10 (0.37)	0.25 (0.01)	0.01 (0.07)	0.21 (0.00)
Sample size	81	3139	287	5905
Coefficient of determination	0.67	0.99	0.94	0.99

(standard errors in parentheses)

We find a strong relationship between same day quotes and transacted prices. The coefficient of determination is high or very high in all of the regressions. The estimated slopes on the quoted spreads are close to one. That the sample size is relatively low for subordinated 2003 CDS reflects that they are less frequently traded. At the same time, Markit obtains quotes from all dealers, whereas DTCC coverage is limited to trades in which at least one counterparty is based in the United States. Another reason that Markit assesses data quality for subordinated 2003 CDS for the twenty banks we study as high could be that many dealers are willing to quote 2003 subordinated CDS spreads (high liquidity), but only few, potentially nonstandard, trades are executed.

C Prior and Hyperprior Distributions and Sampling Diagnostics

We now discuss the choice of prior and hyperprior distributions as well as the details of the Markov chain Monte Carlo sampling for the regression models in Sections 4.2 and 5.2.

C.1 Model in Equation (5) in Section 4.2

As the prior distributions we choose:

$$\begin{aligned}
 \alpha &\sim \text{normal}(0, 1), \\
 \delta_i &\stackrel{\text{i.i.d.}}{\sim} \text{normal}(0, \sigma_\delta^2), \\
 \beta &\sim \text{normal}(\mathbf{0}, \text{diag}(5^2)), \\
 (\tau_{i1}, \dots, \tau_{iT}) &\stackrel{\text{i.i.d.}}{\sim} \mathcal{GP}(\mathbf{0}, k), \\
 \varepsilon_{it} &\stackrel{\text{i.i.d.}}{\sim} \text{normal}(0, \sigma^2).
 \end{aligned}$$

Here $\mathcal{GP}(\mathbf{0}, k)$ denotes a Gaussian process prior that has zero mean and covariance function

$$k(a, b) = \eta^2 \exp(-(a - b)^2 / \rho^2).$$

For a reference on Gaussian processes priors, see Rasmussen and Williams (2006). The parameter η controls the variation of the Gaussian process, which cannot be large because of the boundedness of the relative basis. The parameter ρ controls the average length scale of the process, here in weeks due to the subsampling. We set the prior standard deviation for the elements of β to five because a change in sovereign spread of one percent likely does not result in a change in the relative basis of much more than five percent. Since government spread is measured on the smallest scale by far, it likely also has the largest regression coefficient.

We choose the following hyperprior distributions:

$$\begin{aligned}\sigma &\sim \text{half-Cauchy}(0, 0.1), \\ \sigma_\delta &\sim \text{half-Cauchy}(0, 0.1), \\ \eta^2 &\sim \text{half-Cauchy}(0, 0.1), \\ \rho^2 &\sim \text{half-Cauchy}(0, 100).\end{aligned}$$

Here we set a prior mean absolute deviation for the noise level σ and the random effects standard deviation σ_δ of 0.1, considering that the relative basis itself is approximately lower-bounded at 0 and that it cannot exceed 1. Half-Cauchy prior distributions are generally recommended as priors on standard deviations or variances in hierarchical models, for example in Gelman (2006).

We draw Markov-Chain Monte Carlo samples from the posterior distribution using the No-U-Turn sampler (Hoffman and Gelman 2014), a variant of Hamiltonian Monte Carlo, implemented in the software Stan (Stan Development Team 2015). For each of 15 separate chains, we draw 2,500 samples following a burn-in phase of 2,500 samples, for a total of 37,500 Monte Carlo samples. We check that after warm-up the chains have converged to their stationary distribution using the statistic \hat{R} (Brooks and Gelman 1998); it takes a value of less than 1.1 for all parameters, which indicates good mixing of the Markov chains. For each parameter, the effective sample size drawn is greater than 100, and typically much larger than that. For all parameters the posterior distribution is significantly more concentrated than the prior distribution, in an area of the parameter space that is likely under the prior, which implies that the prior distributions did not influence the inferences in any meaningful way.

C.2 Model in Section 5.2

We place the priors

$$\begin{aligned}\varepsilon_{it} &\overset{\text{i.i.d.}}{\sim} \text{normal}(0, \sigma^2), \\ \frac{v_{it}}{w_{it}} \mid \frac{v_{i(t-1)}}{w_{i(t-1)}} &\overset{\text{i.i.d.}}{\sim} \text{normal}\left(\frac{v_{i(t-1)}}{w_{i(t-1)}}, \sigma_{v/w}^2\right), \quad \text{with } \frac{v_{it}}{w_{it}} \geq 0, \quad \text{for all } i, \text{ and } t = 2, \dots, T, \quad (16)\end{aligned}$$

$$\begin{aligned}d_{it} \mid d_{i(t-1)} &\overset{\text{i.i.d.}}{\sim} \text{normal}(d_{i(t-1)}, \sigma_d^2), \quad \text{with } d_{it} \geq 0, \quad \text{for all } i, \text{ and } t = 2, \dots, T \quad (17) \\ w_{it} &= \frac{T-t}{T-1}w_{i1} + \frac{t-1}{T-1}w_{iT}, \quad \text{with } w_{it} \geq 0, \quad \text{for all } t = 2, \dots, T-1.\end{aligned}$$

Here (16) and (17) are so-called random walk priors, which limit the size of jumps between adjacent values. As hyperprior distributions for σ , $\sigma_{v/w}$, σ_d and σ_w we place independent half-Cauchy(0,1) distributions.

We draw 2,500 Markov-chain Monte Carlo samples each using five chains, following a burn-in phase of equal length, for a total sample size of 12,500. The effective sample size for each of the parameters is at least in the hundreds. The statistic \hat{R} takes a value close to 1, which indicates very good mixing of the Markov chains. The effect of the positivity constraints is limited.

D Raw global systemically important bank (GSIB) Score and Partial State Ownership

Table 3 shows each bank’s raw GSIB score and whether it is partially state owned, as discussed in Section 4.2. The raw GSIB scores are our own calculations based on the banks’ disclosure reports

for globally financially important institutions in 2014. Banco Comercial Português and Banco Popolare do not make these reports publicly available. We impute their raw GSIB score using a linear regression with total risk-weighted assets as the predictor.

E Hyperparameter Estimates for the Model in Equation (5) in Section 4.2

The hyperparameter estimation results are in Table 4. All credible intervals contain the mode of the distribution. The lower bounds of the credible intervals for the random intercepts standard deviation and for the Gaussian process variation are considerably above zero, which suggests that level differences persist in the relative basis across banks, but that levels also change over time. The Gaussian process lengthscale of roughly six weeks indicates that the relative basis does typically not undergo rapid level changes.

F The Observed and Predicted Relative Basis for Individual Banks

Figure 10 shows how much a given bank’s spread for an intervention deviates from what would be expected based on the risk factors and the overall downward trend alone. We include the overall downward trend because it may be explained by changes in banking regulation. We find that the two Swiss banks show the most striking deviations from what the model would predict based on the risk factors alone. UBS has a surprisingly high relative basis throughout the whole period — and therefore is unexpectedly likely to experience an intervention if it were to enter distress without being bailed out. For Credit Suisse, the relative basis starts out similarly high but market expectations have changed drastically, such that its relative basis is now near zero — suggesting that, if Credit Suisse were to enter distress without receiving a bailout, it would most likely undergo ordinary default. Also for Banco Comercial Português, the relative basis is unexpectedly low, suggesting a high likelihood of ordinary default, if it were to enter distress and not receive a bailout.

These persistent idiosyncratic deviations occur even though our model (5) accounts for traditional measures of systemic importance, such as SRISK and GSIB score. This suggests that whether a government decides to take action on a distressed bank depends on strongly idiosyncratic factors or unobserved political factors, which are not captured by traditional measures of systemic importance.

G Case Study: “Brexit” Vote

The United Kingdom voted on June 23, 2016 to leave the European Union. The vote came as a surprise, with most polls before voting day suggesting a narrow win for “remain.” This provides a rare opportunity for us to observe the market reaction to expected changes in governmental policy.

2014 spreads increased strongly for all banks, with an average of 16 percent (log difference between average of two weeks before and average of two weeks following the Brexit vote). This is in line with the strong decline in European stock markets, and the fall of the British Pound after the Brexit vote. We assess how unusual an increase in spreads of this size is by comparing it with all other changes over a time horizon of same length between September 2014 and August 2016. We find that spreads increased more strongly than around the Brexit vote only in six percent of other time windows of the same width.

Table 3: Each bank's origin, raw GSIB score, mean idiosyncratic stress and mean relative SRISK, as defined in Section 4.2. Sources: *Banks' 2014 disclosure reports for globally financially important institutions and authors' calculations*

Bank	Country	Raw GSIB score	Mean idiosyncratic stress	Mean relative SRISK
Barclays Bank plc	United Kingdom	349	-0.3	0.10
Banca Monte dei Paschi di Siena SpA	Italy	22	1.1	0.01
Banco Bilbao Vizcaya Argentaria SA	Spain	90	0.0	0.02
Banco Comercial Português SA	Portugal	45*	1.1	0.00
Banco Popolare SC	Italy	47*	0.6	0.01
Banco Santander SA	Spain	208	0.0	0.05
BNP Paribas	France	405	-0.4	0.12
Commerzbank AG	Germany	107	0.1	0.03
Credit Agricole SA	France	186	-0.3	0.11
Credit Suisse Gp AG	Switzerland	270	-0.3	0.04
Deutsche Bank AG	Germany	360	0.0	0.11
HSBC Bank plc	United Kingdom	438	-0.4	0.05
ING Bank NV	Netherlands	132	-0.4	0.04
Intesa Sanpaolo SpA	Italy	80	0.0	0.02
Lloyds Bank plc	United Kingdom	76	-0.4	0.03
Royal Bank of Scotland plc	United Kingdom	213	-0.2	0.06
Société Générale	France	210	-0.2	0.08
Standard Chartered Bank	United Kingdom	142	0.0	0.03
UBS AG	Switzerland	189	-0.3	0.02
UniCredit SpA	Italy	165	0.3	0.05

* imputed

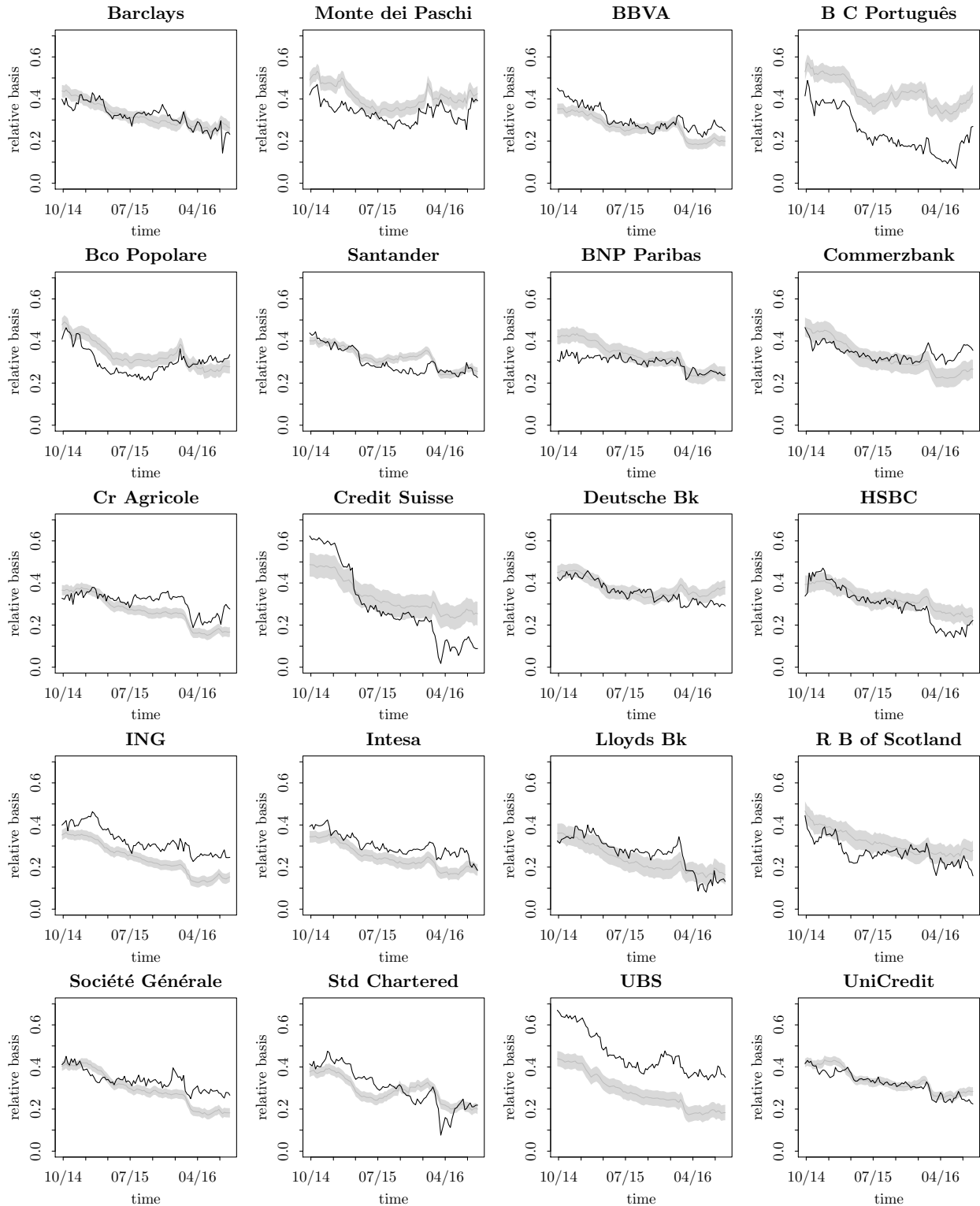


Figure 10: Time trend in the model predictions, $\hat{\alpha} + \hat{\beta}^T (\text{risk factors})_{it} + \frac{1}{20} \sum_{j=1}^{20} \hat{\tau}_{jt}$, (gray, posterior mean estimate, along with 68 percent credible intervals) and the observed relative basis (solid), for each bank. We include the overall downward trend because it may be explained with changes in banking regulation. We exclude the individual random effects and Gaussian process estimates, since these capture systematic but unexplained variation. *Sources: Markit Group Ltd. data and authors' calculations*

Table 4: Hyperparameter estimates for the model in Equation (5). *Sources: Markit Group Ltd. data and authors' calculations*

Parameter	Posterior mean	Posterior SD	95 % CI
σ_δ (random intercepts SD)	0.08	0.02	[0.05, 0.11]
η (GP variation)	0.07	0.003	[0.06, 0.07]
ρ (GP lengthscale)	6.2	0.2	[5.8, 6.7]
σ (noise SD)	0.013	0.0003	[0.013, 0.014]

Table 5: United Kingdom income as share of total income for banks in the United Kingdom, and relative change in the relative basis around the Brexit vote. *Sources: Banks' 2015 annual reports, Markit Group Ltd. data and authors' calculations*

Bank	United Kingdom income share	relative change in relative basis
Standard Chartered	< 5 %	-5 %
HSBC	26 %	11 %
Barclays	48 %	8 %
Royal Bank of Scotland	88 %	11 %
Lloyds Bank	95 %	23 %

The relative basis increased only slightly around the Brexit vote, with an average of three percent (again using log differences over the same time window as above). This means that the market does not expect for Brexit to, on average, have a significant change on governmental policy regarding distressed banks. However, we find that banks that generate a large share of their income (2015 numbers) inside the United Kingdom have a higher increase in their relative basis; see Table 5 for a comparison of geographical income source and change in relative basis. For example, the log difference in the relative basis for Lloyds Bank, which generates nearly all of its income inside the United Kingdom, is a very large 23 percent. This suggests that government support has increased in the United Kingdom for banks that are truly dependent on the home market.

Figure 11 shows a strong correlation of 0.61 between changes in 2014 spreads and changes in the relative basis around Brexit. This high correlation may suggest that banks that are affected by Brexit are expected to have increased government support. The correlation is stronger than the correlation observed in 88 percent of comparable time windows in our data set.

H Additional Figures

Figure 12 shows for each bank over time $\mathbb{S}(\text{losses on senior debt} \mid \text{sub ordinary default})$ and also $\mathbb{S}(\text{losses on senior debt} \mid \text{sub intervention})$, otherwise discussed in Section 5.2. For most banks the spreads have stayed approximately constant. Exceptions are Credit Suisse and Banco Comercial Português, for which the market implies in the summer of 2016 that both an intervention and an ordinary default would hit senior bonds unusually strongly, and Banca Monte dei Paschi di Siena, for which the market implies that an intervention would likely not hit senior bonds, if these banks were to enter distress without receiving a bailout.

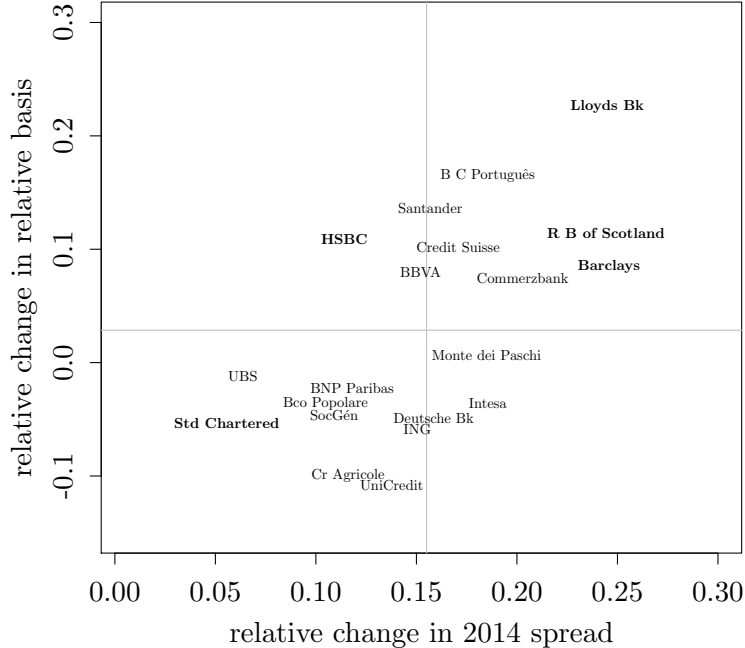


Figure 11: Relative change in 2014 spread and relative change in relative basis around the “Brexit” vote. Banks from the United Kingdom are in boldface. Each gray line is the respective average of the changes of all banks. *Sources: Markit Group Ltd. data and authors’ calculations*

I Time Series Relationship between Relative Basis and Conditional Likelihood of Subordinated Debt Bailout

In Section 5.3 we find cross-sectional evidence that bailouts that include subordinated debt do not crowd out interventions. In the following we analyze the association over time between how likely a bank is to be bailed in and how likely it is to receive a bailout. We will conduct this analysis on a relative scale, to remove the shared influence of a potentially time-varying risk premium.

The empirical correlation of the average trend in the empirical b_{it} from Equation (14) with CAPE, discussed in Section 4.2, is 0.61; this suggests that the trend is to a large extent explained by changes in the risk premium, and not changes in the probability of bailouts that include subordinated debt.

We normalize b_{it} with respect to the average trend:

$$b_{it}^{\text{normalized}} = \frac{b_{it}}{20^{-1} \sum_{i=1}^{20} b_{it}}.$$

This quantity is independent of any shared risk premium across banks, but also independent of any common trend in the b_{it} that could be attributed to changes in the bailout probability. This measure tells us how likely bailout that includes subordinated debt is for a given bank i , relative to how likely bailout that includes subordinated debt is on average for all other banks in our data set, at a given point in time. By construction, its average at each point in time is one.

Similarly, we normalize the relative basis to remove any aggregate trend from it:

$$\text{normalized relative basis}_{it} = \frac{\text{relative basis}_{it}}{20^{-1} \sum_{i=1}^{20} \text{relative basis}_{it}}.$$

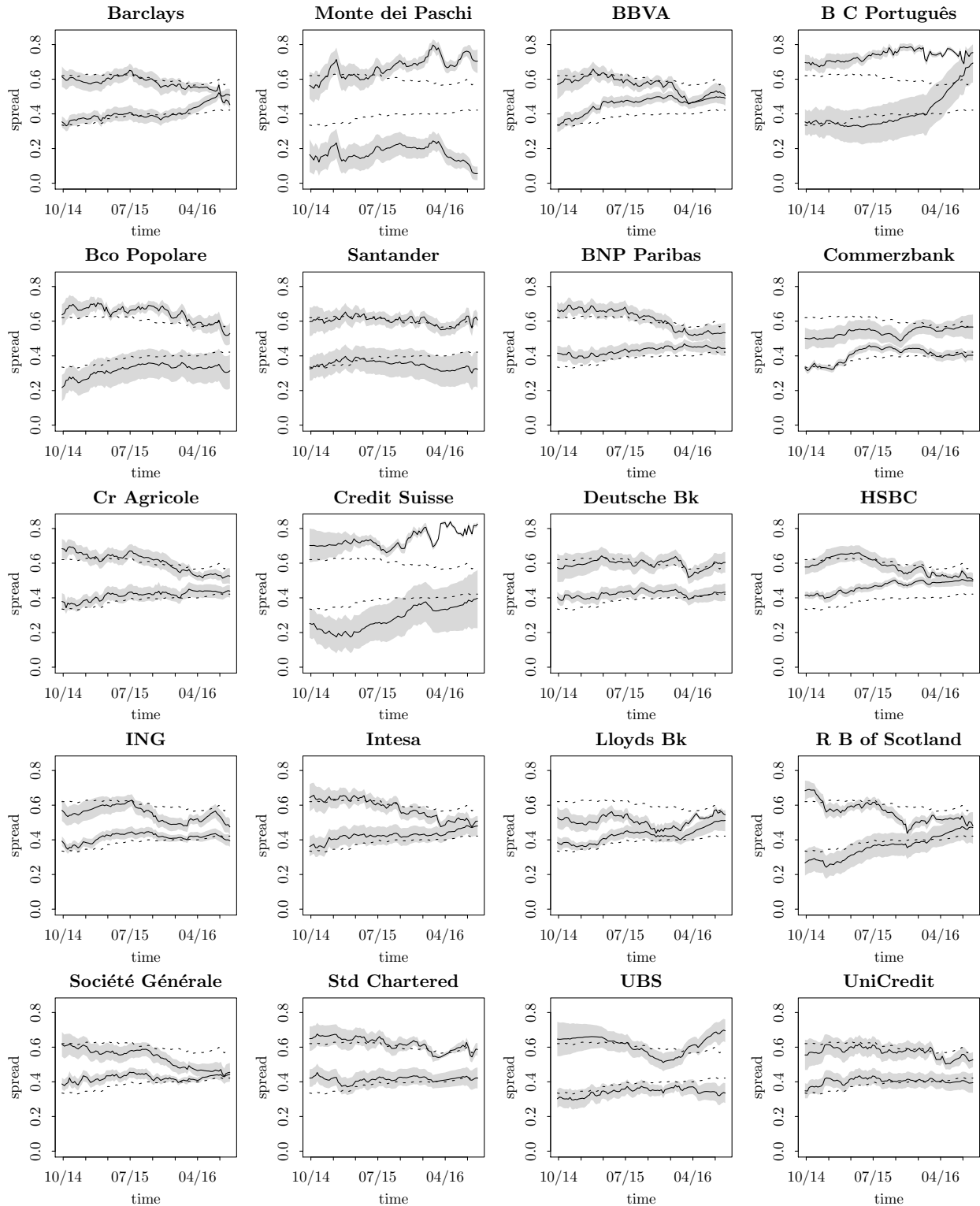


Figure 12: Individual trends in $\mathbb{S}(\text{losses on senior debt} \mid \text{sub ordinary default})$ (top solid line, posterior mean estimate along with 68 percent credible intervals) as well as $\mathbb{S}(\text{losses on senior debt} \mid \text{sub intervention})$ (bottom solid line, posterior mean estimate along with 68 percent credible intervals); also shown are the respective averages across all banks (top and bottom dotted line). *Sources: Markit Group Ltd. data and authors' calculations*

The normalized relative basis measures how likely intervention is for a given bank i , relative to how likely intervention is on average for all other banks, at a given point in time.

We find that the empirical correlation between the empirical $b_{it}^{\text{normalized}}$ and the normalized relative basis is 0.02. This means that firms with a larger than average conditional chance of intervention have no tendency to also have a larger than average conditional chance of bailout that includes subordinated debt. We also analyze, separately for each bank, the empirical correlation between changes over time in the empirical $b_{it}^{\text{normalized}}$ and changes over time in the normalized relative basis. We find these correlations between changes to range from -0.42 to 0.035 , with a mean of -0.25 , which is consistent with at most a slight tendency for bailouts that include subordinated debt to crowd out interventions.