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

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Abstract

New contract terms for credit default swaps (CDS) on banks were introduced in 2014 to cover losses from government intervention and related bail-in events. For many large European banks, 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 to resolve distressed banks. We investigate cross-sectional and time series properties of this basis, relative to each bank’s CDS spread. We interpret a general decline in the relative basis as a market price-based signal that governments are less likely to bailout banks in distress, but that banks do not yet have sufficient bail-in debt to protect senior bond holders in case of a credit event.

Keywords: Credit default swaps, banks, government intervention, European Bank Resolution and Recovery Directive

1 Introduction

A credit default swap (CDS) contract on a bond is intended to provide protection against the default of 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 additional changes to CDS contracts to address cases where government actions at ailing banks had affected the payments received by buyers of CDS protection on those banks. 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). The difference in CDS spreads under the 2014 and 2003 definitions reflects the market price of protection against government intervention and certain related consequences of government actions.

The goals of this paper are to explain the government actions addressed by the change in contract definitions; to investigate cross-sectional and time series properties of the difference in CDS spreads under new and old definitions; to identify factors driving the difference in spreads; and to interpret the difference as a signal about what would happen to the bank’s bond holders

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in case of a credit event at the bank. We refer to the difference in CDS spreads under 2014 and 2003 definitions as the *basis*. 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 argue that a general decline in the relative basis reflects a market perception that governments are less likely to bailout distressed banks, but that banks do not yet have sufficient bail-in debt to protect senior bond holders in case of a credit event.

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. We will see that the relative basis may be roughly interpreted as the market-implied conditional probability of a bail-in, given any type of credit event. Somewhat 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.

The new contract terms adopted in 2014 were motivated by cases in which payments to buyers of CDS protection fell far short of the losses incurred by bond holders as a result of government interventions that had not been anticipated in the 2003 definitions.¹ We will review specific incidents that motivated the changes later, but briefly there are two main scenarios in which a 2014 contract might pay more than a 2003 contract: (i) a bank’s creditors may incur losses through a bail-in event that does not qualify as a credit event under 2003 definitions; or, (ii) the event may trigger both types of contracts, but differences in the recovery auctions may lead to different payments to holders of the two types of CDS.

To date, potential failures in the auction process have been the market’s main concern. In the 2013 nationalization of the SNS Reaal bank by the Dutch government, and in the 2014 failure of the Portugese Banco Espírito Santo, both old and new CDS contracts were triggered. But in both cases buyers of CDS protection on subordinated debt received a small fraction of the losses incurred on the debt—in the first case because the Dutch government had expropriated all subordinated debt, and in the second case because of the way the distressed bank was split into “good” and “bad” entities by the Portuguese government.

With the European Union’s Bank Recovery and Resolution Directive (BRRD) (announced in 2014, and effective at the outset of 2016), and similar resolution frameworks expected in Switzerland and other jurisdictions, these sorts of ad hoc interventions are being replaced by a more predictable bail-in regime and lower expectations of government support for distressed banks. Under the BRRD, public funds may not be used to support a distressed bank until at least 8 percent of a bank’s equity and liabilities have been written down. Reduced expectations of government support should make the possibility of a bank defaulting more likely, and lead to a decrease in the relative basis. Previous studies have relied on earlier CDS data and have therefore not been able to use the information in the basis. Schäfer et al. (2016) find that senior CDS spreads under 2003 definitions increase around European bail-in events, which they interpret as the CDS market adapting to a new regime where bail-in becomes more common, as opposed to bailout. Avdjiev et al. (2015) analyze the response of the CDS market to the issuance of different types of CoCo bonds using data of CDS under 2003 definitions. CoCo bonds convert to equity when a certain trigger is breached, for example regulatory capital requirements. It would be interesting to explore whether CDS under 2003 definitions and CDS under 2014 definitions respond differently to CoCos that convert to equity and write-down CoCos.

We are interested in the relative basis between old and new CDS spreads as a market measure of

¹CDS contracts on U.S. reference entities do not ordinarily cover restructuring events. As a consequence, the new definitions introduced in 2014 and discussed here are not relevant to U.S. financial institutions.

the credibility of the evolving bail-in regime and the adequacy of bail-in debt to protect senior bond holders in a credit event. The relative basis may also provide information on a bank's domestic systemic importance because it involves the government's willingness to intervene. By combining the relative basis with a comparison of CDS spreads on senior and subordinated debt, we will argue that a decline in the relative basis in early 2016 signaled a view in the market that, conditional on the bank experiencing a credit event, the bank's losses would be sufficiently large to hit senior creditors. This pattern can arise either because the bank's loss-absorbing capital is insufficient or because the market expects a government bailout in all but the most extreme loss scenarios.

Our analysis focuses on 20 European banks with sufficiently liquid CDS under both 2003 and 2014 definitions. A few general features of the basis and relative basis are evident in the data. In the cross section, we see a strong positive relation between the basis and a bank's CDS spread, indicating that the added protection against a bail-in event is most valuable for riskier banks. We find a negative relation between the conditional cost of protecting senior debt (conditional on any credit event) and the relative basis: the added value of protection against a bail-in is low when losses will exceed the amount that can be absorbed through bail-in debt alone. Since the launch of the new CDS contracts in September 2014, we observe a gradual decline in the average basis. Over the same period we also observe an increase in the ratio of CDS spreads for senior and subordinated debt, again suggesting that junior debt may be insufficient to absorb losses in a credit event.

We develop an econometric model to fit the time series behavior of the relative basis for the 20 banks in our data. We find that a bank's relative basis has a negative loading on the CDS spread for the bank's sovereign, suggesting that a financially weaker sovereign is less likely to trigger a government intervention, conditional on a credit event. We estimate a positive coefficient on a bank's idiosyncratic credit risk, and positive coefficients on dummy variables for Swiss banks (Credit Suisse and UBS) and for institutions identified as global systemically important banks (GSIBs). We test several other variables as well. Our model fits the data quite well, but it leaves unexplained some persistent and potentially important deviations for individual banks.

Beyond the implications investigated in this paper, the changes in CDS definitions highlight how institutional features of the CDS market can contribute to the much studied bond-CDS basis. The bond-CDS basis is the difference in yields observed in bonds and implied by CDS spreads. Factors found to affect the bond-CDS basis in earlier work 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 auction failures that motivated the 2014 definitions point to another feature separating the cash and derivative markets. By better aligning payments to CDS protection buyers with losses to bond holders, the new definitions have reduced the bond-CDS basis for European banks.

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, as well as in anticipation of potential bail-in under BRRD rules. In Section 3, we derive a model to back out the market-implied loss-weighted conditional probability of bail-in, if the bank were to enter distress without receiving a bailout, from observed CDS spreads. In Section 4, we apply the model to subordinated CDS data of 20 European banks. We also investigate to what extent the market-implied loss-weighted conditional probability of a government intervention on a bank is associated with a number of potential risk factors, such as a traditional measure of systemic importance of banks and sovereign CDS spreads. We also assess the effect of the introduction of the BRRD on the CDS market. In Section 5, we derive several market-implied measures of the severity of loss if the bank were to enter distress without receiving a bailout. In Section 6, we apply this model to senior and subordinated CDS data, and study the relationship of the loss severity measures with the conditional probability of bail-in. We study the suitability of our measure in

assessing progress towards ending bailouts in Section 7. We conclude in Section 8.

2 CDS Market and Bail-in

In this section we discuss how the CDS market has changed in response to changes in banking regulation following the financial crisis, particularly with respect to bond bail-in. We review the bail-in events at SNS Bank in 2013, Bankia in 2013, and Banco Espírito Santo/Novo Banco in 2014, in which CDS under the ISDA 2003 rules triggered, but the payout was much smaller than the loss on the underlying bond. We discuss how ISDA responded by changing CDS definitions in 2014.

Since 2009, most CDS contracts on U.S. reference entities do not cover debt restructuring events. We therefore focus on European banks in the following paper. We 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.

2.1 CDS Market and ISDA 2014 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 typically 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:

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

When a credit event occurs, the loss on the bond is determined through an auction process. The CDS then pays out the loss on the bond. We 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. All probabilities extracted from market prizes should be understood as risk-adjusted probabilities or market-implied probabilities. Equation (1) is a simplification that ignores term structure effects. For a more complete discussion, see Duffie and Singleton (1999).

CDS protection under 2014 definitions is more expensive (has a wider spread) than protection under 2003 definitions. The conditional loss and the intensity both contribute to this difference. Any event covered by 2003 CDS is covered by 2014 CDS; but 2014 CDS also cover a new government intervention event to cover bail-ins that might not trigger 2003 contracts. This added event makes the intensity greater for the new contracts than the old contracts. The 2014 definitions also made changes to the CDS auction process to better align the payout to CDS protection buyers with the losses incurred by bond holders.

In Section 2.2, we discuss specific cases of auctions that motivated the changes to the ISDA definitions. These were all cases of bank bail-ins. Each case triggered 2003 CDS contracts; but, as a result of government actions that were not anticipated in the 2003 definitions, the auction process resulted in payments to CDS holders that fell far short of the losses on the bonds. Under 2014 definitions, protection buyers should receive greater payments in these cases, resulting in a wider spread through a higher conditional loss.

The new CDS started trading on Sept. 22, 2014. Currently, both 2003 and 2014 versions of CDS contracts are traded on 20 large European banks. The difference in spreads between the two

contracts — what we call the basis — may be understood as protection against bail-ins: both the change in intensity and the change in conditional loss are driven by bail-in events. This leads us to the following definition:

Definition 1. *Bail-in* refers to an event for which a 2014 CDS pays more than a 2003 CDS.

We make this definition for brevity. It provides a simple way to refer to the factors driving the changes in the CDS definitions. We also need a simple way to refer to cases in which the two contracts trigger and make the same payments. These are credit events for which the 2003 definitions provided adequate protection, so we refer to these simply as defaults:

Definition 2. *Default* refers to an event in which 2003 CDS and 2014 CDS both trigger and result in the same payment to protection buyers.

Figure 1 shows the average 2003 CDS spread and the average basis for each of the 20 banks in our panel. A strong positive, almost linear association on the log-log-scale between the average 2003 CDS spread and the average basis is apparent for most banks. UBS is a notable anomaly, with a basis that is much larger than one would expect from its very low average 2003 CDS spread.

We now outline the changes in ISDA definitions, both with respect to conditional loss and intensity. All of these changes apply to both subordinated and senior CDS, with the exception of the sub-senior cross trigger removal.

2.2 Recovery Interference

Banking regulators may respond to bank distress in various ways. Some of these, such as expropriation and the transfer of debt into a “bad” bank, may interfere with the recovery determined in the CDS market. This reduces the value of 2003 CDS protection. However, when a government expropriates debt, creditors’ claims are voided and they realize losses, but the 2003 CDS may not function as intended because no bonds are available for the auction. Likewise, when a government breaks a bank into “good” and “bad” parts, the 2003 CDS protection may end up referencing the “good” bank, whereas the underlying bond is transferred to the “bad” bank, resulting in poor outcomes for the protection buyer. We will refer to an issue around conditional loss as a *recovery interference*:

Definition 3. We call it a *recovery interference* when a 2003 CDS does not pay out all of the amount lost on the underlying bond, even though a 2003 credit event is declared.

We now discuss asset package delivery issues and debt transfer issues in more detail.

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 bonds suffered a 100 percent loss, subordinated CDS paid out only 14.5 percent. Under 2014 definitions, a near-worthless claim against those subordinated bonds deliverable before expropriation could have been delivered into the auction, yielding full payout.

The new asset package delivery rules should make it more likely that, following an expropriation, the correct recovery rate can be determined. Therefore, 2014 CDS should trade wider relative to their 2003 counterparts, especially so for subordinated CDS.

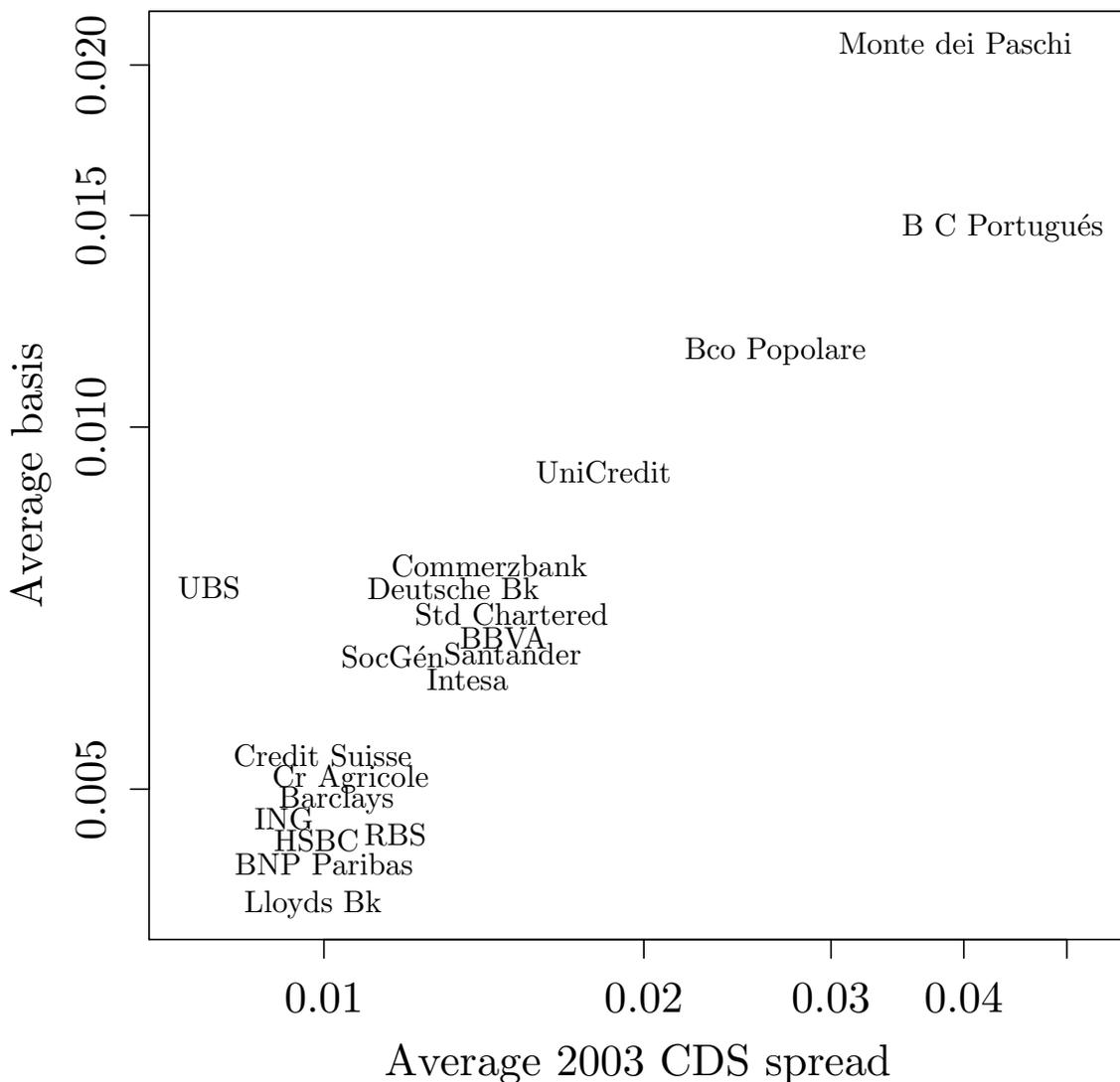


Figure 1: Average across time of 2003 CDS spread and the basis between 2014 CDS and 2003 CDS for each bank (logarithmic axes); note that here and in the following we use spread = (spread in bps)/(10000 bps), so that 0.01 = 100 bps. Bank names are centered at their respective (2003 spread, basis) pair. *Sources: Markit Group Ltd. data and authors' calculations*

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 During Debt Transfers A common resolution following distress is to break the bank up 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 was distressed 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 CDS in the case of a succession event. This change should make 2014 subordinated CDS trade significantly wider than their 2003 counterparts, because of the higher likelihood that subordinated bonds will be available for delivery into the CDS auction after a break up into good and bad bank (J.P. Morgan 2014).

2.3 ISDA 2014 Changes that Affect the Intensity

The bail-in events discussed in Section 2.2 all triggered 2003 CDS. However, when SNS bank’s debt was expropriated, it was unclear whether a 2003 credit event would be declared. Furthermore, a bail-in 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 change affects the intensity part in Equation (1). We therefore define:

Definition 4. A *2014 credit event* occurs when either a 2003 credit event or a government intervention event, as discussed below, is declared.

Government Intervention Event 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. Importantly, a government intervention event is declared even if the bail-in is expressly contemplated in the terms of the bond. For a reference, see Markit Research (2014).

Market participants believed that at the time of introduction the government intervention clause would have little to no effect on CDS spreads, but that with time the government intervention clause would have a widening effect on 2014 spreads (J.P. Morgan 2014, Usher and Whitmore 2014).

For Swiss banks only, the market expects that CoCo bonds are deliverable into the subordinated CDS auction, because Swiss law requires all newly issued subordinated bonds to have contingent

features (J.P. Morgan 2014). This may have a widening effect on the basis for Swiss banks as compared with similar other European banks.

A second government action at Novo Banco, in December 2015, turned out not to qualify even as a 2014 credit event (Bird and Whittall 2016). This was a transfer of debt from the “good” bank to the “bad” bank. The ISDA determinations committee ultimately ruled that debt transfers are not covered by the government intervention event.

Removal of the Sub–Senior Cross Trigger This change affects only senior CDS. Under 2014 definitions, senior CDS do not automatically trigger when subordinated CDS trigger, whereas this is the case under 2003 definitions. This change likely reduces senior 2014 CDS spreads, compared with their 2003 counterparts, because the 2014 senior CDS is less likely to get triggered.

2.4 Discussion

To summarize, a basis between 2014 CDS and 2003 CDS can arise for two reasons, corresponding to the two factors in the CDS spread in Equation (1)—the recovery rate and the event intensity. Changes in auction rules should increase the payout to protection buyers following certain bail-in events. The addition of the government intervention event expands the scope of events covered by CDS to ensure that bail-in events trigger CDS protection. The added event should become particularly important in the future with the implementation of the BRRD.

3 Conditional Probability of Subordinated Debt Bail-in

Much research has focused on the determinants of CDS spreads. For example, Ericsson et al. (2009) find that the main factors behind CDS spreads are firm leverage, equity volatility, and the riskless interest rate. However, while such factors drive the price of credit risk, they do not disentangle the outcomes when risk is realized. In this section, we show how to infer the loss-weighted conditional probability of a bail-in that is implicit in the observed difference between subordinated 2003 and subordinated 2014 CDS spreads. We also discuss what aspects of systemic importance of a bank this quantity measures.

3.1 Model

In order to differentiate CDS payouts in different scenarios, we introduce the following notation for various events:

Definition 5. Let F denote an event of bank distress, B denote a bailout, C denote the event that a 2003 CDS triggers. Also, let G denote the event where an ISDA government intervention event from Section 2.3 occurs, which means that 2014 CDS pays, but a 2003 credit event is not declared. Furthermore, let R be the recovery interference event from Definition 3.

Definition 6. Let CDS^{2014} denote the subordinated CDS spread under 2014 ISDA definitions, and CDS^{2003} denote the subordinated CDS spread under 2003 rules. We refer to the spread difference $CDS^{2014} - CDS^{2003}$ as the *basis*.

For convenience, we will also use “basis” to refer to a position that is long a 2014 CDS and short a 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 use Definition 7 to simplify notation, based on Equation (1).

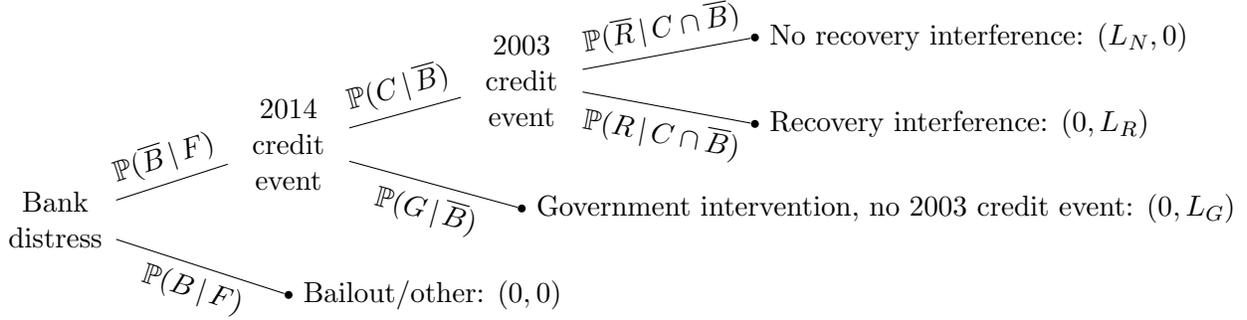


Figure 2: Possible payouts of the (2003 CDS, basis) pair following a bank distress
Source: authors' analysis

Definition 7. We denote the spread needed to insure against an event \bullet by

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

The spread needed to insure against \bullet , given an event \star , is $\mathbb{S}(\bullet \mid \star) = \mathbb{E}[\text{loss} \mid \bullet \cap \star] \mathbb{P}(\bullet \mid \star)$.

We show what may happen if a bank were to enter distress in Figure 2, along with the payouts of CDS^{2003} and the basis. From the perspective of CDS, the first step is whether bondholders are bailed out or not following bank distress. In a bailout, bonds do not lose any value, and neither 2003 CDS nor the basis pay anything. If the government decides against a bailout, 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 CDS^{2003} pays L_N , the loss given no recovery interference, and the basis pays zero, or (ii) a recovery interference happens, in which case CDS^{2003} 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 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 2003 CDS do not even trigger in such a bail-in as may occur under the new BRRD rules. In that case, the CDS^{2003} pays zero, and the basis pays L_G , the loss given G .

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

$$\begin{aligned} CDS^{2014} &= [L_N \mathbb{P}(\bar{R} \mid C \cap \bar{B}) \mathbb{P}(C \mid \bar{B}) + L_R \mathbb{P}(R \mid C \cap \bar{B}) \mathbb{P}(C \mid \bar{B}) + L_G \mathbb{P}(G \mid \bar{B})] \mathbb{P}(\bar{B} \mid F) \mathbb{P}(F) \\ &= [\mathbb{S}(\bar{R} \mid C \cap \bar{B}) \mathbb{P}(C \mid \bar{B}) + \mathbb{S}(R \mid C \cap \bar{B}) \mathbb{P}(C \mid \bar{B}) + \mathbb{S}(G \mid \bar{B})] \mathbb{P}(\bar{B} \mid F) \mathbb{P}(F). \end{aligned}$$

Here and in the following we use $\bar{\bullet}$ to denote the complement of \bullet . The value of the basis is

$$\begin{aligned} CDS^{2014} - CDS^{2003} &= [L_R \mathbb{P}(R \mid C \cap \bar{B}) \mathbb{P}(C \mid \bar{B}) + L_G \mathbb{P}(G \mid \bar{B})] \mathbb{P}(\bar{B} \mid F) \mathbb{P}(F) \\ &= [\mathbb{S}(R \mid C \cap \bar{B}) \mathbb{P}(C \mid \bar{B}) + \mathbb{S}(G \mid \bar{B})] \mathbb{P}(\bar{B} \mid F) \mathbb{P}(F), \end{aligned}$$

and the value of a 2003 CDS is

$$\begin{aligned} CDS^{2003} &= L_N \mathbb{P}(\bar{R} \mid C \cap \bar{B}) \mathbb{P}(C \mid \bar{B}) \mathbb{P}(\bar{B} \mid F) \mathbb{P}(F) \\ &= \mathbb{S}(\bar{R} \mid C \cap \bar{B}) \mathbb{P}(C \mid \bar{B}) \mathbb{P}(\bar{B} \mid F) \mathbb{P}(F). \end{aligned}$$

We obtain the conditional probability of a bail-in 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} :

$$\frac{CDS^{2014} - CDS^{2003}}{CDS^{2014}} = \frac{L_R \mathbb{P}(R | C \cap \bar{B}) \mathbb{P}(C | \bar{B}) + L_G \mathbb{P}(G | \bar{B})}{L_N \mathbb{P}(\bar{R} | C \cap \bar{B}) \mathbb{P}(C | \bar{B}) + L_R \mathbb{P}(R | C \cap \bar{B}) \mathbb{P}(C | \bar{B}) + L_G \mathbb{P}(G | \bar{B})} \quad (2)$$

$$= \frac{\mathbb{S}(R | C \cap \bar{B}) \mathbb{P}(C | \bar{B}) + \mathbb{S}(G | \bar{B})}{\mathbb{S}(\bar{R} | C \cap \bar{B}) \mathbb{P}(C | \bar{B}) + \mathbb{S}(R | C \cap \bar{B}) \mathbb{P}(C | \bar{B}) + \mathbb{S}(G | \bar{B})} \quad (3)$$

$$= \mathbb{S}(R \cup G | C \cup G). \quad (3)$$

$$= \mathbb{S}(\text{bail-in} | \text{distress} \cap \text{no bailout}). \quad (4)$$

Recall that we defined a bail-in to be an event in which the 2014 CDS pays more than the 2003 CDS, which is $R \cup G$ in Figure 2. The quotient on the left side of (2) is the *relative basis*. It is the spread that would be necessary to insure against bail-in, if it were certain that a 2014 CDS was going to trigger, but uncertain whether there will be a bail-in or not. We choose the relative basis as the quantity of interest because it contains new information, namely what would happen if a bank were to enter distress, independent of the distress probability. The probability of the no-bailout event cancels when we consider the relative basis rather than the basis itself. In addition, because we take the ratio of two market-implied spreads, most of the influence of the CDS market risk premium is removed.

If we were to make the simplifying assumption of a fixed recovery rate whenever a CDS triggers, then the effect of conditional losses would cancel in (3), and this conditional spread could be interpreted as the conditional probability $\mathbb{P}(R \cup G | C \cup G)$. 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. This pattern is in line with a report by J.P. Morgan (Elizalde et al. 2009), which 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.

3.2 Relative Basis Measures Aspects of Systemic Importance

It is tempting to interpret the relative basis as a measure of systemic importance. However, care must be taken in doing so. It is national governments that decide how to respond to distressed banks, especially whether they decide to let a distressed bank default. Their decisions may be guided by national concerns, so the relative basis is at best a measure of national, rather than global, systemic importance. To understand to what extent the relative basis is a measure of national importance, we consider the representation in (4). We see that the relative basis informs about what may happen if a bank were to enter distress *without bondholders receiving a bailout*, in which case a 2014 credit event is declared. If, for example, default would become more likely, and bailout less likely, that would reduce the relative basis. This would be in line with interpreting the relative basis as a measure of systemic importance. If, however, bail-in were to become more likely, and bailout less likely, that would increase the relative basis. This is the opposite of the way we would expect a measure of systemic importance to respond.

A better measure of national importance would be the spread on a hypothetical contract

$$\mathbb{S}(\text{bank does not default} | \text{distress}),$$

which is the spread needed theoretically to protect against the event that a bank will not default given that it enters distress. This quantity decomposes as follows:

$$\mathbb{S}(\text{bank does not default} \mid \text{distress}) = \text{relative basis} \cdot \mathbb{P}(\text{no bailout} \mid \text{distress}) + \mathbb{S}(\text{bailout} \mid \text{distress}). \quad (5)$$

Here we interpret $\mathbb{S}(\text{bailout} \mid \text{distress})$ as the cost of the potential bailout, if the bank were to enter distress. We see that it is possible for $\mathbb{S}(\text{bank does not default} \mid \text{distress})$ to be large even if (4) is small—exactly in the situation where a bank’s systemic importance is so high that the respective government chooses to bail bondholders out rather than to risk any disruptions to the bank’s access to funding.

The relative basis in (4) does contain considerable insight, however. A high value is indicative of national importance, since it means that default is unlikely given distress. A low value indicates one of two extremes: (i) the bank is not important, and the national government would decide to let it default if it were to enter distress, or (ii) the bank is so important that the government would choose to bail the bank out if it were to enter distress, unless losses are so large that default becomes the only option.

The relative basis could always be interpreted as a measure of national importance if either the probability of a bailout were low, or the conditional probability of a bail-in were strongly positively related with the conditional probability of a bailout. However, that may not be the case. We will discuss the relationship between bail-in and bailout in more detail in Section 7.

4 Bail-In Probability and Subordinated Debt

In this section, we infer the loss-weighted conditional probability of a bail-in for each bank, if it were to enter distress. We consider an econometric model to determine to what extent potential risk factors can explain this conditional probability. We also investigate time series effects and how they may relate to changes in governmental policy, such as the introduction of the BRRD.

4.1 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. For many of the smaller European banks, CDS are traded too rarely to give good daily, or even weekly, spread quotes. We select only banks for which data quality is judged “B” or higher—indicating at least moderate data quality—according to Markit’s data quality rating on at least 97 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 20 banks that satisfy this data quality requirement; their names are given in Figure 1. Only on a very few days does their data quality fall 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. We confirm that for these banks quoted spreads from Markit closely match spreads at which trades happen in Appendix A, using anonymized data of actual CDS trades from 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 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.

4.2 Market-Implied Loss-Weighted Conditional Probability of a Bail-in

In Figure 3, we show how subordinated 2003 CDS, 2014 CDS, their basis, and their relative basis have evolved over time. While 2003 and 2014 CDS have tended to go up over most of the time window, their basis has stayed roughly constant. The relative basis—the share of the total 2014 CDS spread that it costs to protect against a bail-in, see Equation (4)—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 2015. The relative basis has fallen strongly again against an improving market climate in the spring of 2016, to little over 20 percent on average in the spring of 2016.

We show how the relative basis has been developing for each of the banks in Figure 4. The banks that systematically deviate most in terms of their likelihood of bail-in, if they were to enter distress without receiving a bailout, are Banco Comercial Português, where a bail-in has recently become conditionally much less likely than the European average; Credit Suisse, where at first it was conditionally very likely, but now extremely unlikely; and UBS, where a bail-in was always conditionally much more likely than average.

4.3 Econometric Model

The relative basis may be associated with a number of risk factors. We discuss several such risk factors in Section 4.4. We specify the following hierarchical model, for banks $i = 1, \dots, n$ at times $t = 1, \dots, T$:

$$\frac{CDS_{it}^{2014} - CDS_{it}^{2003}}{CDS_{it}^{2014}} = \alpha + \delta_i + \beta^T (\text{risk factors})_{it} + \tau_{it} + \varepsilon_{it}. \quad (6)$$

Here 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 choose 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.

Our panel contains only 20 banks and about a year-and-a-half 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 as well as sampling in Appendix C.1. The coefficient of determination for this model, using the risk factors from the next section, and including random effects and Gaussian processes, is 0.977.

4.4 Potential Risk Factors

We consider a number of potential risk factors, and examine how they may relate to the relative basis. We divide the risk factors into three groups:

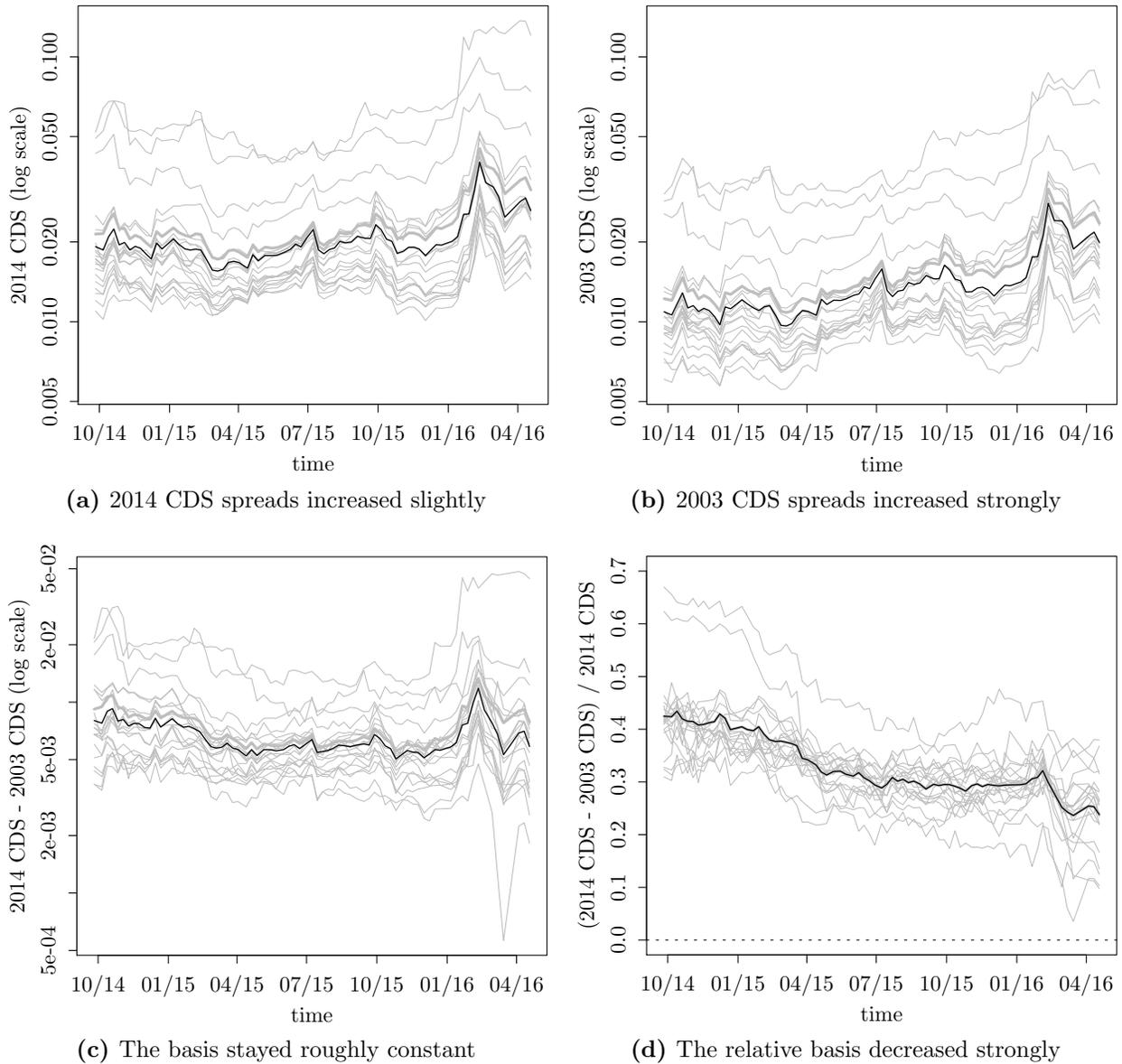


Figure 3: Five-year subordinated CDS^{2014} and CDS^{2003} spreads over time, as well as their absolute basis, all shown in gray, along with the geometric mean at each step in time (black). Also shown is the relative basis for each bank (gray), along with the arithmetic mean at each step in time (black). *Sources: Markit Group Ltd. data and authors' calculations*

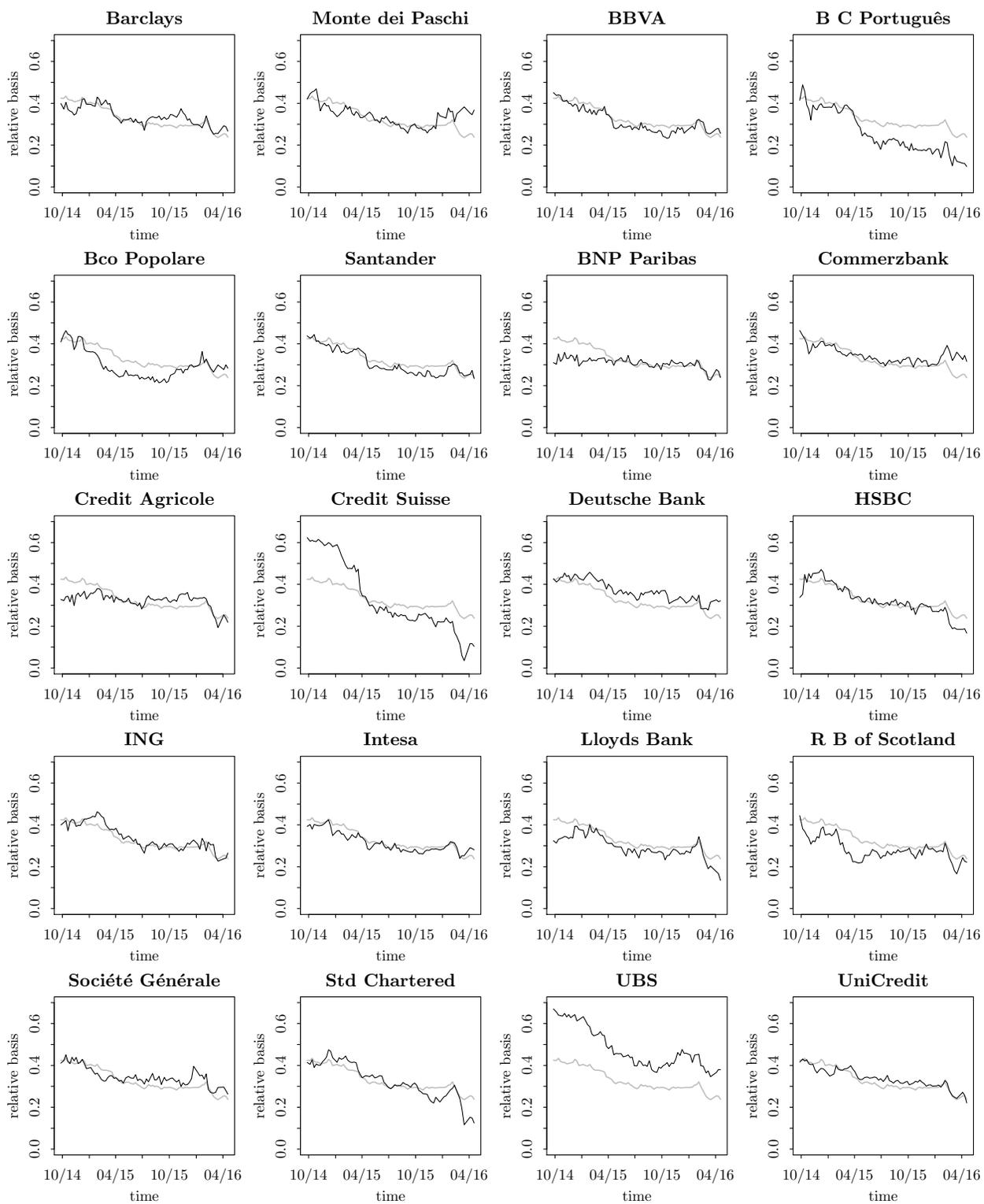


Figure 4: The relative basis for each bank (black) and, for comparison, the average relative basis across all banks (gray). *Sources: Markit Group Ltd. data and authors' calculations*

1. Government-specific factors

- 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: 25 bps, Germany: 9 bps, Italy: 95 bps, Netherlands: 11 bps, Portugal: 157 bps, Spain: 74 bps, Switzerland: 20 bps, United Kingdom: 21 bps. See the evolution of the sovereign CDS spreads in Figure 5.
- The latent effect that changes in banking regulation, such as the BRRD introduction, has over time.

2. Bank-specific factors

- Whether the bank would have a significant capital shortage in case of a large drop in the market. For this purpose, Brownlees and Engle (2015) 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 Brownlees and Engle (2015):

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

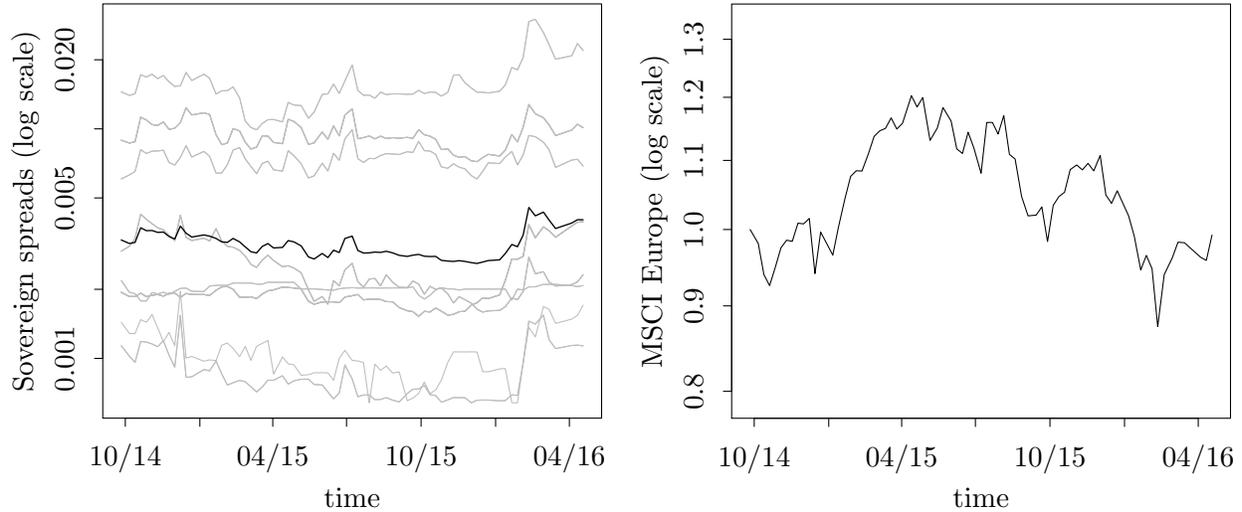
It is the share in capital shortage that bank i would face relative to all other banks if a systemic event were to happen. We obtain SRISK data from V-Lab (2016). Its estimates are based on an asymmetric volatility and correlation framework, with $k = 0.08$ and the assumption that worldwide stock markets 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 20 banks, on a log scale:

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

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 a bail-in, 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 4.

- 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 bail-in. We list the scores in Table 4 in the Appendix.
- The bank’s raw systemic importance score, divided by the respective country’s gross domestic product (in trillion euro), as a measure of bank riskiness relative to country size.



(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: Bloomberg data and authors' calculations*

Figure 5: Sovereign CDS spreads and MSCI Europe Index over time

- Whether the bank is partially or wholly state-owned at the time of writing. Commerzbank, Lloyds Bank, and Royal Bank of Scotland are partially state-owned. Governments may be more or less likely to bail-in bondholders of banks in which they hold equity.

3. Market factor

- 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 default of a financial institution. These data are from MSCI.

4.5 Findings

We separate our findings into three groups: first, several risk factors are statistically significantly associated with the relative basis; second, the relative basis has fallen strongly since the introduction of 2014 CDS in September 2014; third, for many banks the relative basis deviates significantly from what would be predicted based on the risk factors alone.

Relationship between Risk Factors and Relative Basis The parameter estimates for the econometric model from Equation (6) are given in Table 1. The likely range for the coefficient on raw GSIB score is between roughly -0.1 and 0.6, suggesting that large banks may have a higher

Table 1: Parameter estimates for the model in Equation (6). *Sources: Markit Group Ltd. data and authors' calculations*

Parameter	Posterior mean	Posterior SD	95 % CI	$\frac{\text{posterior mean}}{\text{posterior SD}}$
Intercept α	0.32	0.04	(n.m.)	(n.m.)
$\beta_{\text{GSIB score}}$	0.23	0.16	[−0.08, 0.55]	1.4
$\beta_{\text{GSIB score / GDP}}$	0.18	0.15	[−0.12, 0.47]	1.2
$\beta_{\text{Partially state-owned}}$	0.03	0.05	[−0.06, 0.13]	0.7
$\beta_{\text{Idiosyncratic}}$	0.15	0.01	[0.12, 0.17]*	11.9
β_{CAPE}	−0.004	0.001	[−0.007, −0.001]	−2.9
$\beta_{\text{Sovereign spread}}$	−2.82	0.77	[−4.33, −1.30]*	−3.6
$\beta_{\text{Relative SRISK}}$	0.11	0.17	[−0.22, 0.43]	0.6

In this table an interval is starred if it does not overlap zero; the respective parameter may then be considered statistically significantly different from zero. n.m. = not meaningful.

likelihood of going through a bail-in, if they were to enter distress without receiving a bailout, but considerably uncertainty remains as to the size of the effect because of the limited number of banks in our data set. The results for the coefficient on bank size relative to country size are qualitatively similar. It is surprising that being partially state-owned shows hardly any association with the conditional probability of a bail-in. The posterior mean estimate on idiosyncratic stress is 0.15, meaning that doubling a particular bank’s subordinated 2014 CDS spread is associated with an increase in the relative basis of 9 percent, all else equal. This could be because a bank that is in a considerably worse 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, without a bank default. The posterior mean estimate for CAPE is −0.004. A possible explanation is that letting a bank default becomes more of an option when financial markets are in good shape. Lastly, we find that a 0.01 increase in a country’s sovereign CDS spread is associated with a reduction in the relative basis of 0.028. This suggests that a government in a weaker financial and/or political position is less likely to intervene on 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 government credit risk weakens the financial sector due to the reduced value of government guarantees and bond holdings. The estimated coefficient on relative SRISK is very small and not statistically distinguishable from zero.

Overall Downward Time Trend In Figure 6, we show the overall time trend in the relative basis. We capture the overall downward trend by, at each point in time, taking the mean across banks of the Gaussian processes in the econometric model in Equation (6), $\frac{1}{20} \sum_{i=1}^{20} \hat{\tau}_{it}$. The average relative basis was slightly over 40 percent in the fall of 2014 and it has fallen almost 20 percent since, net of the effect of changes in risk factors. We interpret the overall downward trend in the relative basis as a reflection of increased credibility in the market that governments will refrain from bailing out banks. The requirement of resolution planning and living wills for large European banks makes orderly failure by distressed banks more plausible. Another factor in the downward trend could be that the BRRD has streamlined government intervention in a way that reduces the

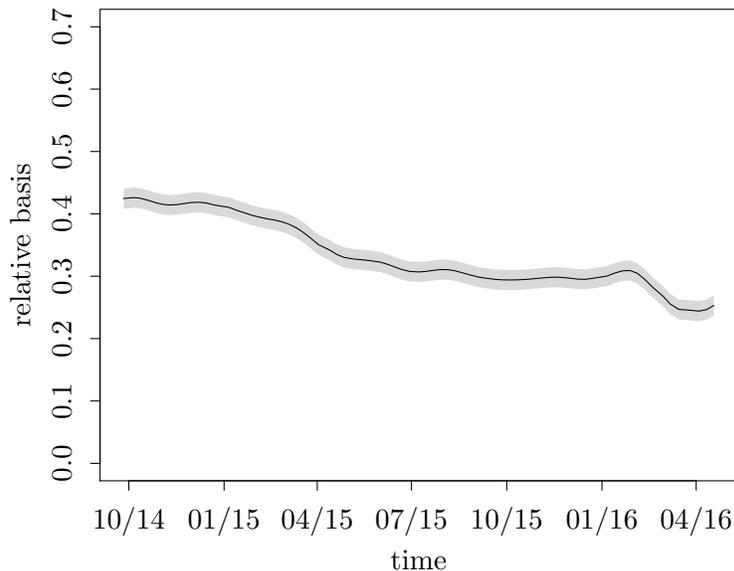


Figure 6: Average time trend in the relative basis net of risk factor effects, $\frac{1}{20} \sum_{i=1}^{20} \hat{\tau}_{it}$, shifted to start from the observed average relative basis on Sept. 22, 2014; posterior mean estimate along with 68 percent credible intervals. *Sources: Markit Group Ltd. data and authors' calculations*

chance of a recovery interference following a bail-in. However, this effect is likely not large, as we will discuss in Section 6.

In Figure 7 we also 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 3. For reasons we return to later, the decline in the relative basis at these four banks from the United Kingdom may signal a greater perceived likelihood that they would be allowed to 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.

Persistent Idiosyncratic Deviations In Figure 8, we assess how much a given bank's market-implied loss-weighted conditional probability of a bail-in deviates from what would be expected based on the risk factors and the overall downward trend alone. We include the overall downward trend as a systematic risk factor 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 a bail-in 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 default. Also for Banco Comercial Português, the relative basis is unexpectedly low, suggesting a high likelihood of default, if it were to enter distress and not receive a bailout.

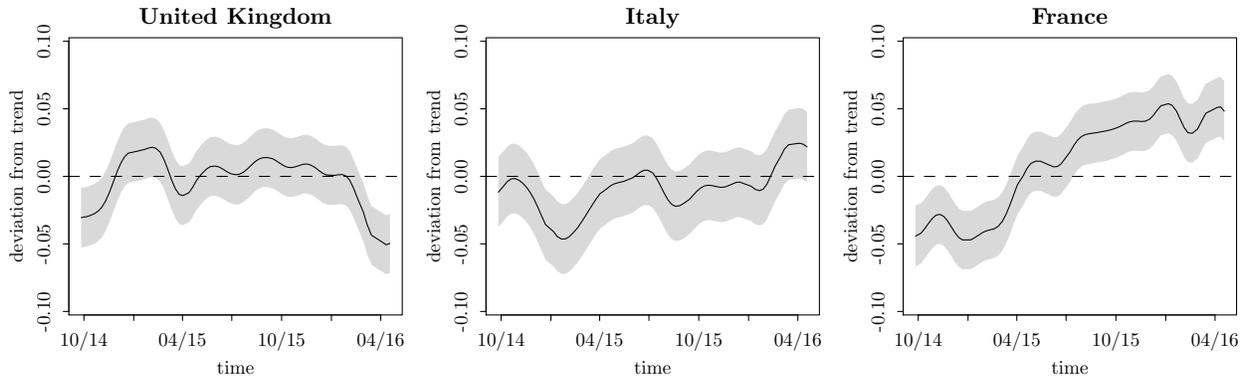


Figure 7: Time trend in the idiosyncratic deviation from the overall downward trend, $|\{i \in \text{country}\}|^{-1} \sum_{i \in \text{country}} (\hat{\delta}_i + \hat{\tau}_{it}) - \frac{1}{20} \sum_{i=1}^{20} \hat{\tau}_{it}$, for each of the countries with three or more banks in the data set, namely 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*

Note the conditionality on the no-bailout event, particularly when interpreting the relative basis for individual banks. For example, if a bank were likely to be bailed out, a small relative basis could be reflective of a tail event where losses would be too large to make a bailout, or even a bail-in, affordable, and the bank would default instead.

These persistent idiosyncratic deviations occur even though our model (6) 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 other factors that are not captured by traditional measures of systemic importance.

Sensitivity of These Findings to How We Define Bail-in In Definition 1, we assume that every bail-in causes either a recovery interference or a government intervention event for subordinated CDS. If, however, there could be bail-ins for which subordinated CDS under 2003 definitions correctly pay the amount lost on the underlying bond, then the relative basis would underestimate the chance of a bail-in. Then, for example, the overall downward trend in the relative basis could also be due to a reduced likelihood that bail-in will interfere with the workings of subordinated CDS under 2003 definitions. This could be due to the BRRD, which reduces the discretion of governments in how they handle bail-ins, which may in turn increase the chance that a subordinated 2003 CDS can pay out the correct amount. The evidence we present in the next section suggests that this is not the main factor behind the downward trend in the relative basis.

5 Conditional Probability of Senior Debt Bail-in

In this section we relate the relative basis to a measure of how severe losses would be in a default or a bailout. This will allow us to confirm that the decline in the relative basis that we observe in the previous section is indeed fundamentally informative, and not, for example, caused by unobserved features of the CDS auction. The approach that we develop in this section will also enable us to learn how likely it is that a bail-in would be associated with losses on senior bonds. It will furthermore allow us to compare the size of expected losses across senior and subordinated bonds. We will be able to identify the effect of the loss-weighting on the relative basis, and thereby to learn

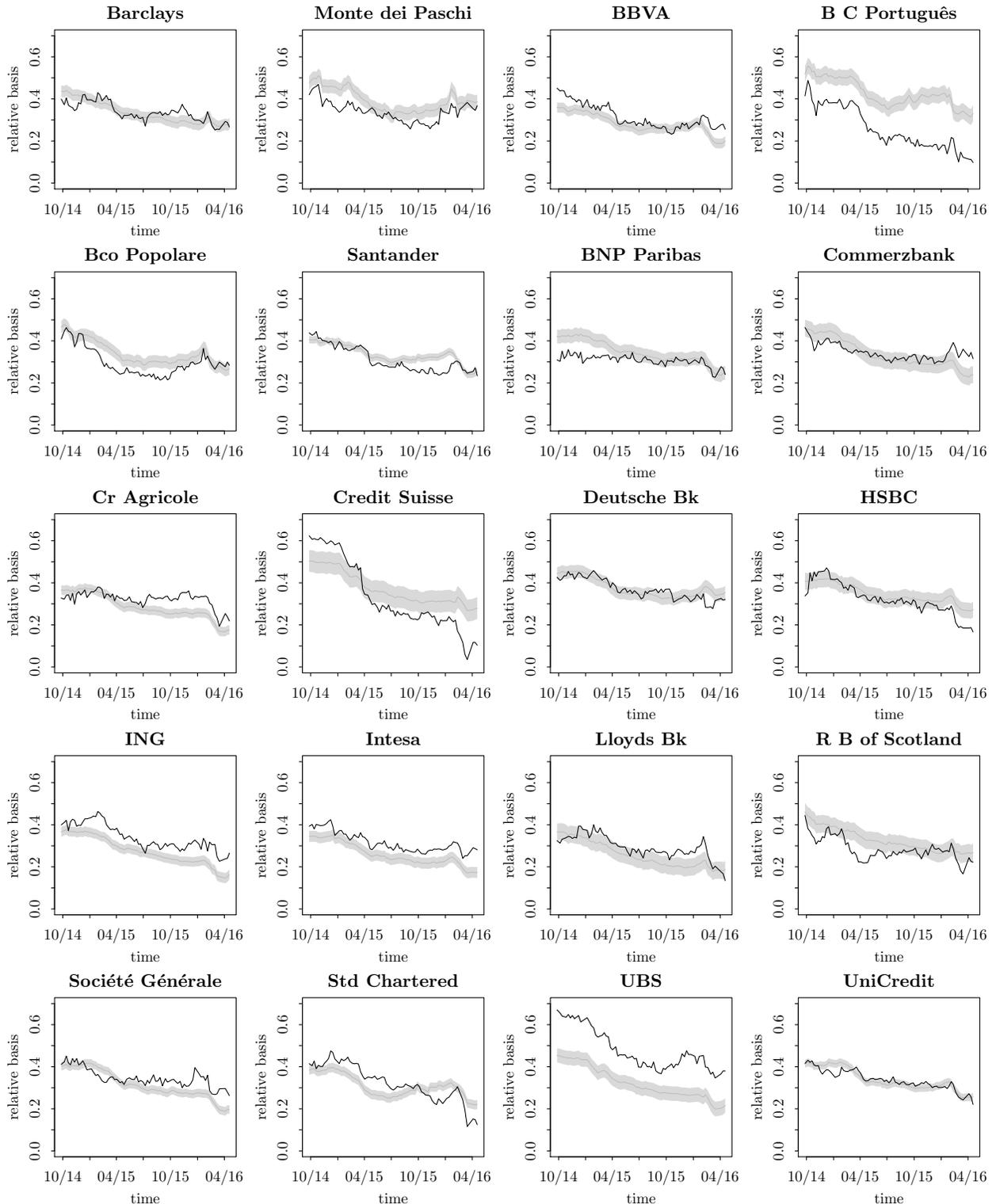


Figure 8: Time trend in the model predictions, $\hat{\alpha} + \hat{\beta}^T (\text{risk factors})_{it} + \frac{1}{20} \sum_{j=1}^{20} \hat{\tau}_{jt}$, (gray, posterior mean estimate, along with 68 percent credible intervals) and the observed relative basis (solid), for each bank. We include the overall 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*

whether the decline in the relative basis is due to changes in the conditional losses or changes in the conditional bail-in probability. We discuss the model in this section, and apply it to combined subordinated and senior CDS data in Section 6.

We begin with some definitions. As we did with subordinated debt, we will use the terms “bail-in” and “default” to refer to specific events defined through CDS:

Definition 8. With *senior bail-in* we will refer to an event where there are losses on senior bonds at the same time that a sub bail-in occurs. With *senior default* we will refer to an event where there are losses on senior bonds at the same time a sub default occurs.

This means that

$$\begin{aligned}\mathbb{S}(\text{senior bail-in}) &= \mathbb{S}(\text{losses on senior bonds} \mid \text{sub bail-in}) \mathbb{P}(\text{sub bail-in}), \\ \mathbb{S}(\text{senior default}) &= \mathbb{S}(\text{losses on senior bonds} \mid \text{sub default}) \mathbb{P}(\text{sub default}).\end{aligned}$$

We interpret a senior bail-in as an event where the government imposes losses on senior bondholders, and not only subordinated bondholders. This happened, for example, in the case of the Danish bank Amagerbanken in 2011 and in the bail-in of banks in Cyprus in 2013. We interpret a senior default as an event where there is no bail-in, and where losses are so large that the default of subordinated bonds alone cannot absorb all of the losses. A senior bail-in can only occur when there is also a sub bail-in, and a senior default can only occur when there is also a sub default.

The spreads we identify in the following are: first, the loss-weighted conditional probability of any credit event in senior bonds, given that there is any credit event in subordinated or senior bonds,

$$\mathbb{S}(\text{senior bail-in} \cup \text{senior default} \mid \text{any 2014 credit event}); \quad (7)$$

second, the loss-weighted conditional probability of a bail-in of senior bonds, given a bail-in of subordinated bonds,

$$\mathbb{S}(\text{senior bail-in} \mid \text{sub bail-in}); \quad (8)$$

third, the loss-weighted conditional probability of a default on senior bonds, given a default on subordinated bonds,

$$\mathbb{S}(\text{senior default} \mid \text{sub default}); \quad (9)$$

fourth, the loss-weighted conditional probability of a bail-in of senior bonds, given that there is any credit event in subordinated or senior bonds,

$$\mathbb{S}(\text{senior bail-in} \mid \text{any 2014 credit event}); \quad (10)$$

and, fifth, the loss-weighted conditional probability of a default of senior bonds, given that there is any credit event in subordinated or senior bonds,

$$\mathbb{S}(\text{senior default} \mid \text{any 2014 credit event}). \quad (11)$$

We make an assumption.

Assumption 1. A credit event for senior CDS cannot occur without a credit event for subordinated CDS.

Then the spreads in (7), (10) and (11) equal

$$\begin{aligned}\mathbb{S}(\text{senior bail-in} \cup \text{senior default} \mid \text{any sub 2014 credit event}), \\ \mathbb{S}(\text{senior bail-in} \mid \text{any sub 2014 credit event}), \\ \mathbb{S}(\text{senior default} \mid \text{any sub 2014 credit event}).\end{aligned}$$

5.1 Conditional Probability of Senior Debt Losses

Let $CDS_{\text{senior}}^{2014}$ denote the senior CDS spread under ISDA 2014 definitions. Then the spread in (7) is

$$\mathbb{S}(\text{senior bail-in} \cup \text{senior default} \mid \text{any sub 2014 credit event}) = \frac{CDS_{\text{senior}}^{2014}}{CDS^{2014}}. \quad (12)$$

Under Assumption 1, this ratio is always between zero and one. A value close to one indicates that, conditional on a loss to subordinated debt, senior debt would experience a similar loss, in percent.

5.2 Conditional Probability of Senior Debt Bail-in

We now identify the spreads in (8) to (11). We cannot directly infer the loss-weighted conditional probability of bail-in for senior debt, the way we did for subordinated debt in Section 3, because the basis between senior 2014 spreads and senior 2003 spreads is affected by other elements of the 2014 definitions. As discussed in Section 2.3, the 2014 definitions removed the sub-senior cross trigger. This means that a senior 2003 CDS will trigger whenever a subordinated 2003 CDS triggers, but a senior 2014 CDS will trigger only in case of an event that directly affects the senior debt. Nevertheless, by making two relatively mild assumptions, we will be able to infer several quantities of interest.

We begin by expressing Equation (12) as

$$\begin{aligned} \frac{CDS_{\text{senior}}^{2014}}{CDS^{2014}} &= \mathbb{S}(\text{senior bail-in} \mid \text{sub bail-in}) \mathbb{P}(\text{sub bail-in} \mid \text{any sub 2014 credit event}) \\ &\quad + \mathbb{S}(\text{senior default} \mid \text{sub default}) \mathbb{P}(\text{sub default} \mid \text{any sub 2014 credit event}). \end{aligned} \quad (13)$$

We see that the total loss severity can be decomposed into the sum of loss severity in a bail-in and loss severity in a default, weighted with the respective conditional probability. We know that $\mathbb{P}(\text{sub default} \mid \text{any sub 2014 credit event}) = 1 - \mathbb{P}(\text{sub bail-in} \mid \text{any sub 2014 credit event})$.

We will use the shorthands

$$\begin{aligned} b &= \mathbb{S}(\text{senior bail-in} \mid \text{sub bail-in}), \\ d &= \mathbb{S}(\text{senior default} \mid \text{sub default}). \end{aligned}$$

These are measures of the loss severity in a bail-in and the loss severity in a default from (8) and (9), respectively.

We express

$$\mathbb{P}(\text{sub bail-in} \mid \text{any sub 2014 credit event}) = \frac{\text{relative basis}}{w} = \frac{1}{w} \frac{CDS^{2014} - CDS^{2003}}{CDS^{2014}}, \quad (14)$$

$$\mathbb{P}(\text{sub default} \mid \text{any sub 2014 credit event}) = 1 - \mathbb{P}(\text{sub bail-in} \mid \text{any sub 2014 credit event}). \quad (15)$$

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

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

We find

$$\begin{aligned} w^{-1} &= \mathbb{P}(\text{sub bail-in} \mid \text{any sub 2014 credit event}) \\ &\quad + \frac{L_{\text{sub default}}}{L_{\text{sub bail-in}}} \mathbb{P}(\text{sub default} \mid \text{any sub 2014 credit event}). \end{aligned} \quad (16)$$

We see that w is increasing in the ratio of loss given bail-in and loss given a default, and that w equals one if the conditional losses are equal.

Plugging (14) and (15) into Equation (13) yields, for each bank i and point in time t ,

$$\frac{CDS_{\text{senior } it}^{2014}}{CDS_{it}^{2014}} = \frac{b_{it}}{w_{it}} \frac{CDS_{it}^{2014} - CDS_{it}^{2003}}{CDS_{it}^{2014}} - \frac{d_{it}}{w_{it}} \frac{CDS_{it}^{2014} - CDS_{it}^{2003}}{CDS_{it}^{2014}} + d_{it}. \quad (17)$$

We find an approximate solution to this underdetermined system of equations by making two Assumptions.

Assumption 2. Values for b that are close in time are similar to each other. Likewise, values for d that are close in time are similar.

This assumption ensures that the parameters are identifiable at all. We make this assumption precise directly following Equation (18).

Assumption 3. w_{it} changes linearly with time, separately for each bank.

This assumption is needed because, locally in time, the separate effects of b_{it} and w_{it} are only weakly identifiable. This assumption is much weaker than the commonly made assumption that all conditional losses are equal, which we discussed at the end of Section 3.1. Under Assumption 3, the conditional losses of bail-in and default may be different, and they may even differ across banks and, linearly, over time.

To incorporate Assumptions 2 and 3, we express (17) as a regression model,

$$\frac{CDS_{\text{senior } it}^{2014}}{CDS_{it}^{2014}} = \frac{b_{it}}{w_{it}} \frac{CDS_{it}^{2014} - CDS_{it}^{2003}}{CDS_{it}^{2014}} - \frac{d_{it}}{w_{it}} \frac{CDS_{it}^{2014} - CDS_{it}^{2003}}{CDS_{it}^{2014}} + d_{it} + \epsilon_{it}. \quad (18)$$

We place so-called random walk priors on b_{it}/w_{it} and d_{it} , and allow w_{it} to change linearly over time for each bank; see Assumption 3. We discuss the details of the prior and hyperprior specification and of the Markov chain Monte Carlo sampling in Appendix C.2.

This model yields estimates for the loss-weighted conditional probabilities of senior bail-in given subordinated bail-in and of senior default given subordinated default from (8) and (9), respectively:

$$\begin{aligned} \mathbb{S}(\text{senior bail-in} \mid \text{sub bail-in})_{it} &= b_{it}, \\ \mathbb{S}(\text{senior default} \mid \text{sub default})_{it} &= d_{it}. \end{aligned}$$

Finally, we obtain the loss-weighted conditional probabilities of senior bail-in (10) and default (11) given any 2014 credit event as

$$\begin{aligned} \mathbb{S}(\text{senior bail-in} \mid \text{any 2014 credit event})_{it} &= \mathbb{S}(\text{senior bail-in} \mid \text{sub bail-in})_{it} \mathbb{P}(\text{sub bail-in} \mid \text{any sub 2014 credit event})_{it} \\ &= \frac{b_{it}}{w_{it}} \frac{CDS_{it}^{2014} - CDS_{it}^{2003}}{CDS_{it}^{2014}}, \\ \mathbb{S}(\text{senior default} \mid \text{any 2014 credit event})_{it} &= \mathbb{S}(\text{senior default} \mid \text{sub default})_{it} \mathbb{P}(\text{sub default} \mid \text{any sub 2014 credit event})_{it} \\ &= d_{it} \left(1 - \frac{1}{w_{it}} \frac{CDS_{it}^{2014} - CDS_{it}^{2003}}{CDS_{it}^{2014}} \right). \end{aligned}$$

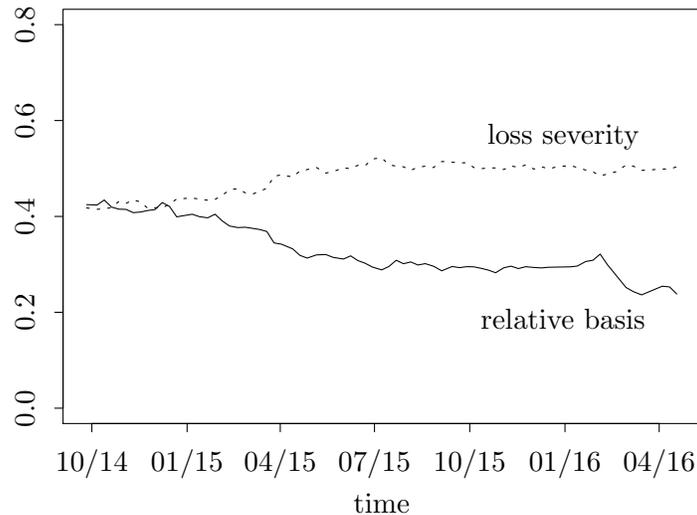


Figure 9: Average trend across all banks in $\mathbb{S}(\text{senior bail-in} \cup \text{senior default} \mid \text{any 2014 credit event})$ from (12) and average trend in the relative basis. *Sources: Markit Group Ltd. data and authors’ calculations*

6 Losses on Senior Debt Given Losses on Subordinated Debt

We now infer the market-implied spreads for senior bail-in and default using the approach outlined in Sections 5.1 and 5.2. We also infer the loss weighting that enters the relative basis. Data quality for senior CDS spread quotes under both 2003 and 2014 clauses is high; 89 percent of quoted spreads have a Markit data quality rating of “AA” or “A,” and no quotes are rated less than “B.” We confirm the close correspondence between quoted spreads and traded spreads in Appendix A.

6.1 Spread for Losses on Senior Debt Given Losses on Subordinated Debt

Figure 9 shows the average trend in $\mathbb{S}(\text{senior bail-in} \cup \text{senior default} \mid \text{any 2014 credit event})$ from (7) across the 20 European banks, along with the relative basis from (2). We see that it has become more likely that senior bonds would also suffer losses, which means that the capacity of subordinated capital to absorb losses has decreased as expectations of government support have decreased. The general upward trend in this loss severity measure may indicate that changes in banking regulation have made it possible to impose larger losses on bondholders, instead of bailing them out. A different explanation would be that generally banks’ business models have become riskier relative to their capital structure. However, this interpretation seems to go against the strong emphasis in banking regulation over the last years on improving the capital buffers at banks.

A striking finding is that there is a strong positive association between the size of losses and the chance of default, if a bank were to enter distress without receiving a bailout. The empirical correlation between changes in the relative basis (2) and changes in the loss severity measure (12) is -0.54 . In Figure 10 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 -0.73 . The picture that emerges is that the market has reduced its expectation of government support for a bank facing large losses, but that banks do not yet have sufficient loss-absorbing capital to protect senior creditors in the event of such losses.

That the relative basis — which is calculated based on 2003 and 2014 CDS — and the size of losses — which is calculated using CDS under 2014 definitions only — show such strong comovement suggests that the changes in the relative basis really are fundamentally informative, and not, for example, caused by unobserved features of the CDS.

The interpretation of the loss severity measure is, like the interpretation of the relative basis, confounded by the conditionality on the non-bailout event, especially when analyzing bank-specific trends. For example, if bailout were to cover all but the largest losses, extreme values of $\mathbb{S}(\text{senior bail-in or senior default} \mid \text{any 2014 credit event})$ are possible. While the relative basis for Credit Suisse went from 60 percent to roughly 10 percent over the time horizon studied, the loss-weighted conditional probability that senior bonds would suffer losses if subordinated bonds were to suffer losses went approximately from 0.3 to 0.8. This could either be due to a strongly increased riskiness of Credit Suisse’s business model relative to its capital structure, or due to a strongly increased bailout probability.

Most banks are in line with the general trend in both the relative basis and in the severity of loss given distress, see Figure 10. Exceptions are again Banco Comercial Português and Credit Suisse — for which the market implies that they would default, and that losses would be large, if they were to enter distress without receiving a bailout — and UBS — for which the market implies that the conditional probability of a government interference is unusually high, and that senior bonds are less likely to be hit than typical for other banks, if it were to enter distress without receiving a bailout.

6.2 The Source of the Negative Correlation Between the Relative Basis and the Loss Severity Measure

We now investigate what the reason for the strong negative correlation between the relative basis and the loss severity measure is. For this purpose, we examine $\mathbb{S}(\text{senior bail-in} \mid \text{sub bail-in})$ from (8) and $\mathbb{S}(\text{senior default} \mid \text{sub default})$ from (9). These spreads serve as weights in the representation of the loss severity measure in (13), with $\mathbb{P}(\text{sub bail-in} \mid \text{any sub 2014 credit event})$ serving as the mixture proportion between these two spreads. Figure 11 shows the averages for $\mathbb{S}(\text{senior bail-in} \mid \text{sub bail-in})$ and $\mathbb{S}(\text{senior default} \mid \text{sub default})$ over time. We see that the market implies that a default on senior debt typically involves larger losses than the bail-in of senior bonds, with average spreads of 0.60 and 0.33, respectively. These spreads are approximately constant over time. We find that cross-sectionally, too, $\mathbb{S}(\text{senior bail-in} \mid \text{sub bail-in})$ and $\mathbb{S}(\text{senior default} \mid \text{sub default})$ show little association with the relative basis, with empirical correlations of 0.17 and -0.14 , respectively. Thus, changes in $\mathbb{P}(\text{sub bail-in} \mid \text{any sub 2014 credit event})$, which serves as the mixture proportion in the representation in (13), must be responsible for the strong association between the loss severity measure and the relative basis. This means that bail-in typically covers smaller losses, whereas under larger losses the bank defaults or receives a bailout. Furthermore, this suggests that the market has not become more nervous about disruptions in a default scenario.

We also observe an interesting pattern between the spreads $\mathbb{S}(\text{senior bail-in} \mid \text{sub bail-in})$ and $\mathbb{S}(\text{senior default} \mid \text{sub default})$. Figure 12 shows for each bank the respective averages. Banks differ considerably particularly in whether a bail-in would also hit senior bonds, with spreads taking values from slightly over zero to almost one-third, but also in whether a default would hit senior bonds. An empirical negative correlation of -0.41 between these two quantities is apparent. This inverse association may appear counterintuitive, since it means that a bank for which losses on senior bonds would be high in a bail-in tends to have lower losses on senior bonds in a default, and *vice versa*. An explanation for this negative correlation could be that a bail-in is a viable option if only smaller

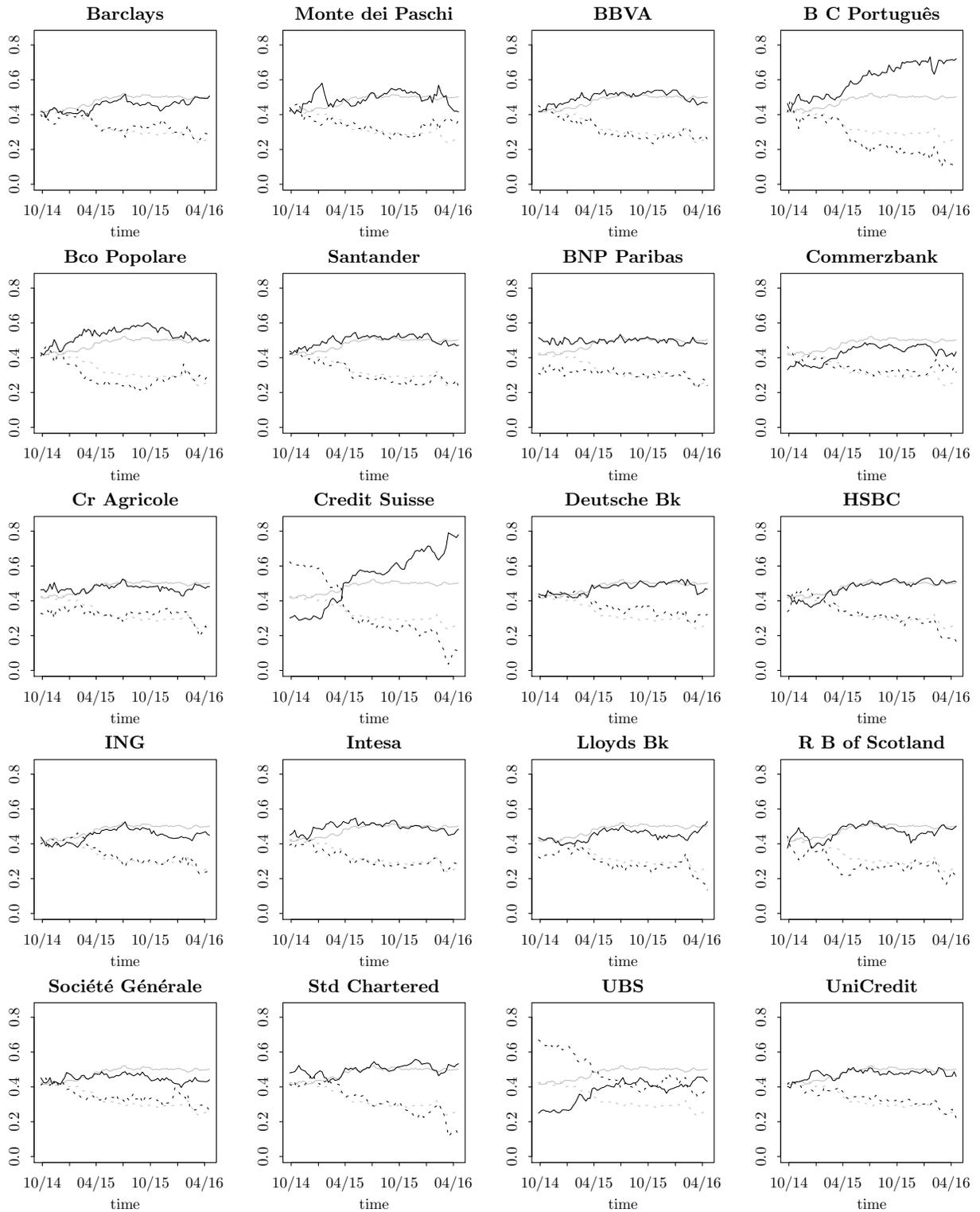


Figure 10: Individual trends in $\mathbb{S}(\text{senior bail-in} \cup \text{senior default} \mid \text{any 2014 credit event})$ from (12) (black, solid) and the relative basis (black, dotted), along with average spread across banks (gray, solid) and average relative basis across banks (gray, dotted); anomalies are Banco Comercial Português, Credit Suisse and UBS. *Sources: Markit Group Ltd. data and authors' calculations*

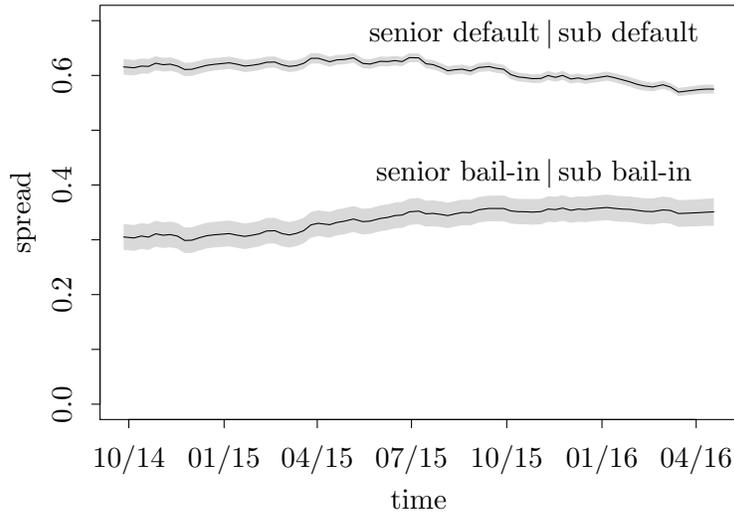


Figure 11: Average of $\mathbb{S}(\text{senior default} \mid \text{sub default})$ as well as $\mathbb{S}(\text{senior bail-in} \mid \text{sub bail-in})$ over time, posterior mean estimate along with 68 percent credible intervals. These spreads function as weights in (13). The figure shows that they are roughly constant. *Sources: Markit Group Ltd. data and authors' calculations*

losses are expected, which likely do not hit senior bonds, whereas default becomes a more serious option if losses are large, in which case senior bonds will also be hit significantly. Taking this idea a step further, banks for which a bail-in is more viable may be expected to undergo the bail-in early enough that the larger losses that would occur in a disorderly default can be avoided.

6.3 Comparison of Senior and Subordinated Spreads for Bail-in and Default Conditional on Distress without Bailout

Figure 13 shows the joint development of the average spreads, conditional on a 2014 credit event, for subordinated bail-in (the relative basis from (2)), subordinated default (1 – relative basis), senior bail-in (from (10)), and senior default (from (11)). We see that the market implies that default of both subordinated and senior debt has become more likely with time, while the bail-in of subordinated and senior bonds has become less likely, given distress without bailout.

The chance that a senior bond would be bailed in, if a bank were to enter distress without a bailout, is about twenty percent on average, and it has slightly declined with time. That this decline occurs more slowly than the decline in the spread for subordinated bail-in, given a 2014 credit event, is explained by the increased loss-weighted probability of senior bail-in given a subordinated bail-in; compare Figure 11. At the same time, the chance that senior bonds would default, if a bank were to enter distress without a bailout, has on average increased from approximately 0.2 to approximately 0.4 from the fall of 2014 to the spring of 2016. The spread for senior default is now higher than the spread for sub bail-in, both conditional on a 2014 event, because default has become more likely with time and losses on senior bonds are severe in a default.

In Figure 16 in Appendix E we show how the spreads $\mathbb{S}(\text{senior bail-in} \mid \text{any 2014 credit event})$ and $\mathbb{S}(\text{senior default} \mid \text{any 2014 credit event})$ evolve for each bank over time.

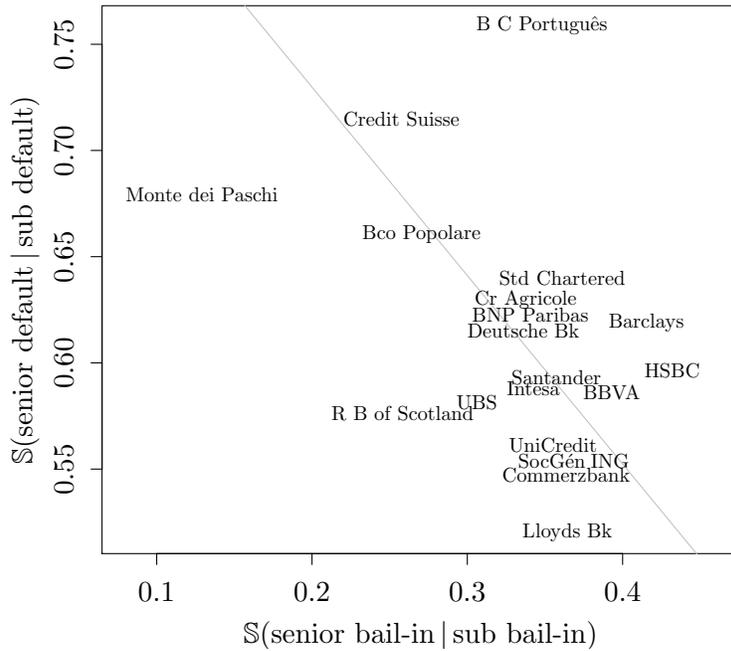


Figure 12: Average in $\mathbb{S}(\text{senior bail-in} | \text{sub bail-in})$ as well as $\mathbb{S}(\text{senior default} | \text{sub default})$ for each bank; also shown is the standardized major axis (first principal component based on empirical correlation matrix). *Sources: Markit Group Ltd. data and authors' calculations*

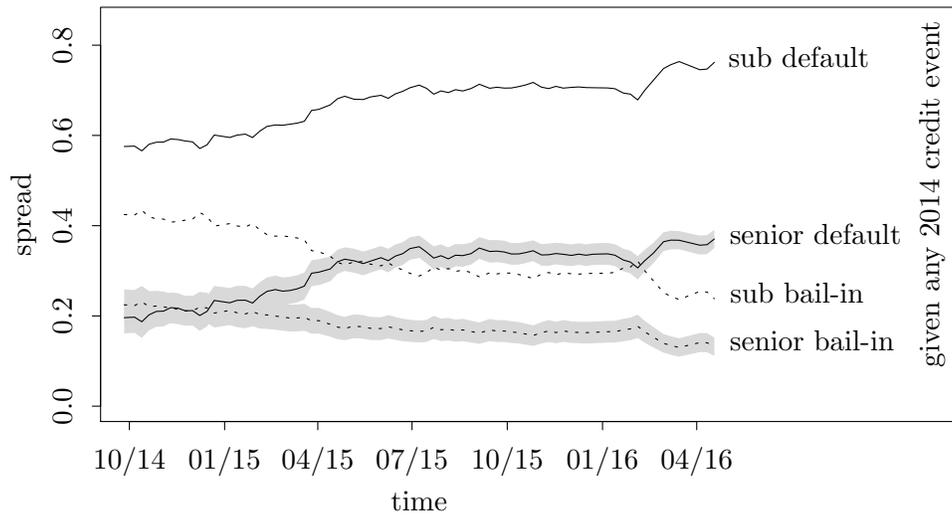


Figure 13: Average of $\mathbb{S}(\text{sub default} | \text{any 2014 credit event}) = 1 - \text{relative basis}$, $\mathbb{S}(\text{senior default} | \text{any 2014 credit event})$ (posterior mean estimate along with 68 percent credible intervals), as well as $\mathbb{S}(\text{sub bail-in} | \text{any 2014 credit event}) = \text{relative basis}$ and $\mathbb{S}(\text{senior bail-in} | \text{any 2014 credit event})$ (posterior mean estimate along with 68 percent credible intervals). *Sources: Markit Group Ltd. data and authors' calculations*

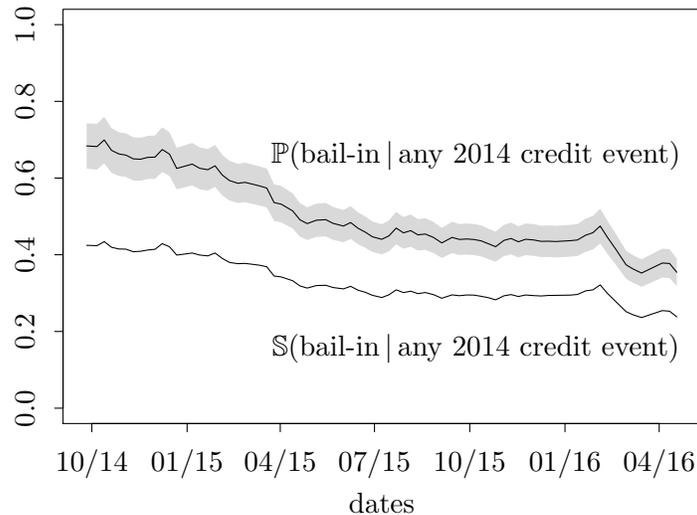


Figure 14: Average conditional probability of sub bail-in (with with 68 percent credible intervals), and relative basis (loss-weighted average conditional probability of sub bail-in), given distress without bailout. *Sources: Markit Group Ltd. data and authors’ calculations*

6.4 Comparing Losses on Subordinated Bonds in a Bail-in and a Default

We find that for subordinated bonds, too, a default would typically involve larger losses than a bail-in. The average value for w from the model in (17) is 0.73 across banks and over time, and the average value for the ratio of expected loss in a sub default to expected loss in a sub bail-in, $L_{\text{sub default}}/L_{\text{sub bail-in}}$ from (16), is 1.84.

We determine the conditional probability of sub bail-in, given distress but no bailout, by plugging the relative basis (the loss-weighted conditional probability of bail-in) and the estimates for w_{it} into Equation (14). See the comparison between the conditional probability of sub bail-in and the relative basis in Figure 14, averaged over all banks. We find that the conditional probability of a bail-in has only recently fallen below one-half. The relative basis is considerably lower due to the loss-weighting. In Figure 17 in Appendix E we show the same comparison for each bank.

7 Bailout, Bail-in, and Default

Banking regulators have made efforts in recent years to end bailouts, and to reduce the systemic importance of banks. We want to understand whether the market perceives these efforts to be successful. The general decline that we observe in the relative basis would be consistent with three explanations (compare Figure 2). (i) It could be that banks entering distress increasingly are expected to undergo default, instead of bail-in. (ii) Banks that would in the past have received a bailout are now expected to undergo default. Both of these cases would be a success for banking regulators. However, (iii) it could be that bailouts have recently replaced bail-ins, implying that the expected vulnerability of the European financial system has increased or retrogressed to worse practices in the treatment of systemically important institutions. We will provide evidence in the following that bailouts have not systematically crowded out bail-ins in distressed banks and, therefore, our measure can be used to study market expectations of the treatment of systemically important firms if they become distressed.

First, we observe that the association between the relative basis and the respective sovereign CDS spread is negative; see Table 1. This suggests that a bail-in becomes relatively more likely when the sovereign is more able to afford a bailout. One may infer from this that bail-ins crowd out bailouts. A weakness of this argument is that other factors, such as good governance, could limit bailout risks and lead to prudent public finance without any causal connection between public finance and bailout risk.

Second, if (iii) were the case, then we should observe a strong negative correlation between the relative basis and the likelihood of bailouts given distress. This is because a shift of probability mass from bail-ins to bailouts reduces the relative basis. We investigate in the following whether such a strong correlation can be observed in the market. We will find that the correlation is weak.

Ideally, we would use

$$\mathbb{S}(\text{bailout} \mid \text{distress}) = \frac{\mathbb{S}(\text{default} \cup \text{bail-in} \cup \text{bailout}) - \mathbb{S}(\text{default} \cup \text{bail-in})}{\mathbb{S}(\text{default} \cup \text{bail-in} \cup \text{bailout})}$$

as a measure of the likelihood of bailout. A large difference would indicate a high likelihood of bailout. But only $\mathbb{S}(\text{default} \cup \text{bail-in}) = CDS^{2014}$ can be observed directly in the market. We can, however, estimate $\mathbb{S}^{\text{physical}}(\text{default} \cup \text{bail-in} \cup \text{bailout})$ and use it as a proxy for $\mathbb{S}(\text{default} \cup \text{bail-in} \cup \text{bailout})$. While this solves the problem that $\mathbb{S}(\text{default} \cup \text{bail-in} \cup \text{bailout})$ is not observable, it makes it more difficult to compare the spreads with and without bailout risk. This is because a spread \mathbb{S} is market implied, which means that it can be expected to include a risk premium. In contrast, $\mathbb{S}^{\text{physical}}$ is a spread calculated under the real-world measure, which means that it does not contain a risk premium.

We define

$$r = \frac{\mathbb{S}^{\text{physical}}(\text{default} \cup \text{bail-in} \cup \text{bailout})}{\mathbb{S}(\text{default} \cup \text{bail-in})} = \frac{L_{\text{distress}}^{\text{physical}} \cdot \mathbb{P}^{\text{physical}}(\text{distress})}{CDS^{2014}}. \quad (19)$$

This quantity takes a large value when the bailout probability is high and/or the risk premium is low, and it takes a small value when the bailout probability is low and/or the risk premium is high.

In practice, $\mathbb{P}^{\text{physical}}(\text{distress})$ and $L_{\text{distress}}^{\text{physical}}$ need to be estimated, which introduces some estimation error. 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. CreditEdge is based on the general approach of Merton (1974). Additionally, it uses a mapping from distance to default to probability that is specific to financial firms, but not specific to individual banks. CreditEdge considers bailout a distress event, meaning that an increased probability of bailout increases $\mathbb{P}^{\text{physical}}(\text{distress})$. Although the approach of Merton (1974) generates a risk neutral probability of distress, the mapping step of 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 0.07 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 0.8. This relatively high number means that distress will typically wipe out most of a bank's subordinated debt.

We combine $L_{\text{distress}}^{\text{physical}}$ and $\mathbb{P}^{\text{physical}}(\text{distress})$ to generate $\mathbb{S}^{\text{physical}}(\text{default} \cup \text{bail-in} \cup \text{bailout})$ under the counter-factual that losses given bailout are not zero but in fact the average for bail-ins or default as predicted by LossCalc. This is a bank-specific estimate, under the physical measure, of credit spread. Specifically, the appropriate spread that the bank would have, absent bailouts, if total distress probability were unchanged.

Empirically, we find that r 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 0.99 and 1.02 for Commerzbank and Deutsche Bank, with a mean across all banks of 0.68. This means that subordinated 2014 CDS are relatively expensive when compared with the underlying real-world probabilities of default and loss expectations.

We marginalize out the dependency of r on the risk premium by taking, for each bank, the average value of r over time. Likewise, we calculate the average relative basis over time, separately for each bank. We find that the empirical correlation between these two quantities is -0.04 . Given the small sample size of only 20 banks, the uncertainty about the true correlation is relatively high, as captured by a 95 percent confidence interval that ranges from -0.48 to 0.41 . Hence, we also perform correlation analyses with time series data in Appendix F. Both within and across time series we find a very small negative empirical correlation.

That the correlation between r and the relative basis is only very weakly negative provides evidence that bailouts do not systematically crowd out bail-ins. This gives us confidence that the relative basis can be used as a measure of national systemic importance. In particular, this suggests that the overall decline in the relative basis means that the national systemic importance of banks has reduced on average in response to changes in European banking regulation.

8 Conclusion

The European Union has formalized the role of bond bail-in in resolving distressed banks through the BRRD. Contemporaneously, ISDA has introduced new mechanisms and terms for the CDS market to cope with the complications surrounding bond bail-in. We have used CDS quotes under old and new ISDA definitions to determine the loss-weighted conditional probability of a bail-in on 20 European banks, if they were to enter distress without receiving a bailout. We find that this conditional probability has decreased, from about 40 percent in the fall of 2014 to about 20 percent in the spring of 2016. This downward trend is consistent with the notion that changes in banking regulation, such as living wills, indeed allow a more orderly default of distressed banks, and thereby reduce the pressure to bail distressed banks out. While markets are still convinced these 20 banks will not be allowed to fail in all circumstances, this sharp reduction represents meaningful progress. This is consistent with the regulatory decision to designate 17 of these 20 firms as either globally or domestically systemically important.

We furthermore find that the market-priced likelihood of a bail-in is associated with being systemically relevant, and with high idiosyncratic stress. At the same time, a lower likelihood of government intervention is associated with higher sovereign CDS spreads. Systematic differences remain between banks regarding their probability of bail-in if they were to enter distress, without receiving a bailout, which cannot be explained by the risk factors considered. These deviations suggest that market participants expect governments may decide to act on banks not only based on how systemically important they are. We also find that the bail-in of senior bonds remains unlikely, whereas the default of senior bonds has become more likely, if banks were to enter distress without receiving a bailout.

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A 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 Sept. 1, 2014 and Feb. 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

Table 2: Assessing the relationship between traded spreads and same day quoted spread. *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	1.08	1.05	1.00	1.04
	(0.09)	(0.003)	(0.02)	(0.002)
Intercept	0.26	0.24	-0.11	0.18
	(0.40)	(0.01)	(0.08)	(0.01)
Sample size	73	2487	269	4020
Coefficient of determination	0.67	0.98	0.94	0.99

(standard errors in parentheses)

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 $\epsilon_{i,t}^j$:

$$s_{i,t}^j = \alpha_0 + \beta_0 q_{i,t}^j + \epsilon_{i,t}^j. \quad (20)$$

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. 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 20 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.

It is not the case that quotes are mechanically set at observed transaction prices, even when only one trade occurs in a day. They are constructed from surveys of market makers and so are usually averages of quotes provided by multiple dealers, many of which have not traded on that day. Because the market may take time to disseminate the price of risk, market quotes may reflect transactions with some delay. It could also be that traders may wish to distort quotes away from fundamentals but find it more difficult to do so on days where there are traded transactions as a reference price. This makes quoted spreads closer to fundamentals on days when trades occur. To understand the average quoted to traded spread relationship we need to compare quoted spreads on days not contaminated by this problem. We proxy for this with the previous day's quotes. On the previous trading day traders could not know with certainty that the following day they would trade. Therefore, the prior day quotes are unlikely to be biased by the prices of the trade on the following business day. As an alternative to the model in Equation (20), we consider transacted spreads as a function of the quoted price on the previous trading day:

$$s_{i,t}^j = \alpha_0 + \beta_0 q_{i,t-1}^j + \epsilon_{i,t}^j.$$

The regression results in Table 3 show that that the coefficients on lagged quoted expected losses and contemporaneous expected losses are highly similar.

Table 3: Assessing the relationship between traded spreads and previous day quoted spread. Sources: *Markit Group Ltd., 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	1.07	1.04	1.00	1.04
	(0.08)	(0.004)	(0.02)	(0.002)
Intercept	0.18	0.19	-0.07	0.17
	(0.36)	(0.02)	(0.09)	(0.01)
Sample size	70	2385	266	3895
Coefficient of determination	0.73	0.96	0.92	0.97

(standard errors in parentheses)

B Raw Global Systemically Important Bank (GSIB) Score and Partial State Ownership

Table 4 shows each bank's raw GSIB score and whether it is partially state owned, as discussed in Section 4.4. 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 that uses total risk-weighted assets as the predictor.

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 4.3 and 5.2.

C.1 Model in Equation (6) in Section 4.3

As the prior distributions we choose:

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

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.

Table 4: Raw GSIB Score and Partial State Ownership. Sources: Banks' 2014 disclosure reports for globally financially important institutions, The Volatility Laboratory of the NYU Stern Volatility Institute (<https://vlab.stern.nyu.edu>), and authors' calculations

Raw GSIB score, mean idiosyncratic stress and mean relative SRISK				
Barclays Bank plc	United Kingdom	349	-0.3	0.11
Banca Monte dei Paschi di Siena SpA	Italy	22	1.0	0.01
Banco Bilbao Vizcaya Argentaria SA	Spain	90	0.0	0.02
Banco Comercial Portugués SA	Portugal	45*	1.0	0.00
Banco Popolare SC	Italy	47*	0.6	0.01
Banco Santander SA	Spain	208	0.0	0.05
BNP Paribas	France	405	-0.3	0.13
Commerzbank AG	Germany	107	0.1	0.04
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	0.12
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	0.07
Société Générale	France	210	-0.1	0.09
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

SRISK is a market implied measure of the capital a firm is expected to need in the event of another financial crisis (Acharya et al. (2012)).

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 et al. (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 Equation (18) in Section 5.2

We place the priors

$$\epsilon_{it} \sim_{\text{i.i.d.}} \text{normal}(0, \sigma^2),$$

$$b_{it}/w_{it} \mid b_{i(t-1)}/w_{i(t-1)} \sim_{\text{i.i.d.}} \text{normal}(b_{i(t-1)}/w_{i(t-1)}, \sigma_{b/w}^2), \quad \text{for all } i, \text{ and } t = 2, \dots, T, \quad (21)$$

$$d_{it} \mid d_{i(t-1)} \sim_{\text{i.i.d.}} \text{normal}(d_{i(t-1)}, \sigma_d^2), \quad \text{for all } i, \text{ and } t = 2, \dots, T, \quad (22)$$

$$w_{it} = \frac{T-t}{T-1} w_{i1} + \frac{t-1}{T-1} w_{iT}, \quad \text{for all } t = 2, \dots, T-1.$$

Here (21) and (22) are so-called random walk priors, which limit the size of jumps between adjacent values. As hyperprior distributions for σ , $\sigma_{b/w}$, 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.

D Hyperparameter Estimates for the Model in Equation (6) in Section 4.3

The hyperparameter estimation results are in Table 5. 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

Table 5: Hyperparameter estimates for the model in Equation (6). *Sources: Markit Group Ltd. data and authors' calculations*

Parameter	Posterior mean	Posterior SD	95 % CI
σ_δ (random intercepts SD)	0.07	0.02	[0.04, 0.10]
η (GP variation)	0.06	0.003	[0.06, 0.07]
ρ (GP lengthscale)	6.6	0.4	[5.9, 7.4]
σ (noise SD)	0.013	0.0004	[0.013, 0.014]

level differences persist in the relative basis across banks, but that levels also change over time. The Gaussian process lengthscale of roughly 1.5 months indicates that the relative basis does typically not undergo rapid level changes.

E Additional Figures

Figure 15 shows the trends in $\mathbb{S}(\text{senior default} \mid \text{sub default})$ and $\mathbb{S}(\text{senior bail-in} \mid \text{sub bail-in})$, otherwise discussed in Section 6.2, for each bank over time. For most banks the spreads have stayed approximately constant. Exceptions are Credit Suisse and Banco Comercial Português, for which the market implies in the spring of 2016 that both a bail-in and a default would hit senior bonds unusually strongly, and Banca Monte dei Paschi di Siena, for which the market implies that a bail-in would likely not hit senior bonds, if these banks were to enter distress without receiving a bailout.

Figure 16 shows, for each bank, the time trends in $\mathbb{S}(\text{senior default} \mid \text{any 2014 credit event})$ and $\mathbb{S}(\text{senior bail-in} \mid \text{any 2014 credit event})$, otherwise discussed in Section 6.2. Again, Credit Suisse is a significant anomaly, for which markets now imply that senior CDS would likely go through a major default, if Credit Suisse were to enter distress without receiving a bailout. A similar pattern holds for Banca Monte dei Paschi di Siena.

Figure 17 shows, for each bank, the comparison between conditional probability of sub bail-in and loss-weighted conditional probability of sub bail-in (relative basis), otherwise discussed in Section 6.4. An anomaly is Barclays, for which a bail-in would often involve relatively small losses, as compared with a default. For Banca Monte dei Paschi di Siena the ratio of losses in a sub bail-in to losses in a sub default is roughly one, making conditional probability of bail-in and the relative basis roughly equal.

F Bailout, Bail-in, and Default over Time

In Section 7 we find cross-sectional evidence that bailouts do not crowd out bail-ins. 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.

Figure 18 shows the evolution of the empirical r_{it} from Equation (19), along with their average trend. The empirical correlation of the common trend with CAPE, discussed in Section 4.4, is 0.65, which suggests that the trend is to a large extent explained by changes in the risk premium, and not changes in the bailout probability.

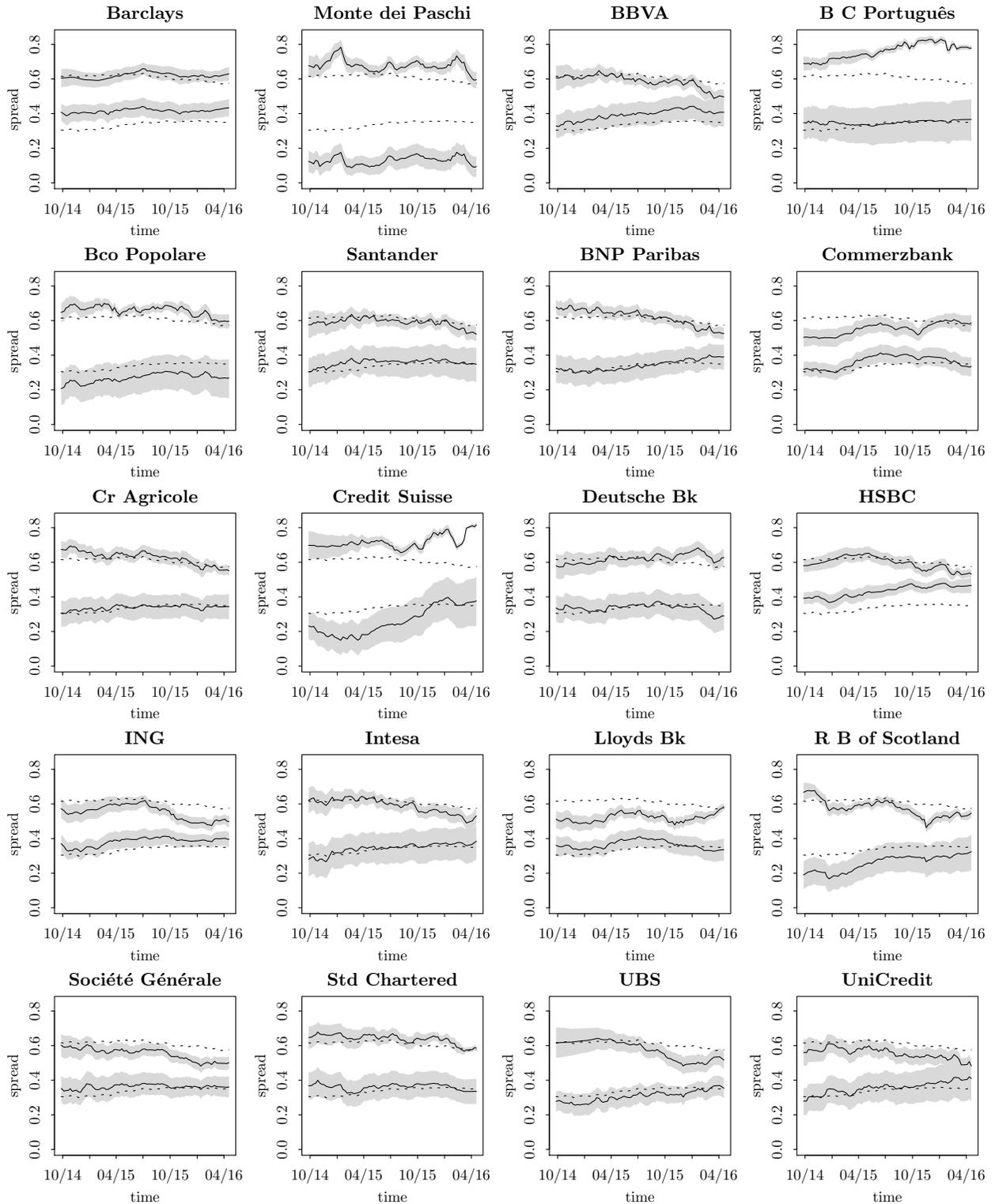


Figure 15: Individual trends in $\mathbb{S}(\text{senior default} | \text{sub default})$ (top solid line, posterior mean estimate along with 68 percent credible intervals) as well as $\mathbb{S}(\text{senior bail-in} | \text{sub bail-in})$ (bottom solid line, posterior mean estimate along with 68 percent credible intervals); also shown are the respective averages across all banks (top and bottom dotted line). *Sources: Markit Group Ltd. data and authors' calculations*

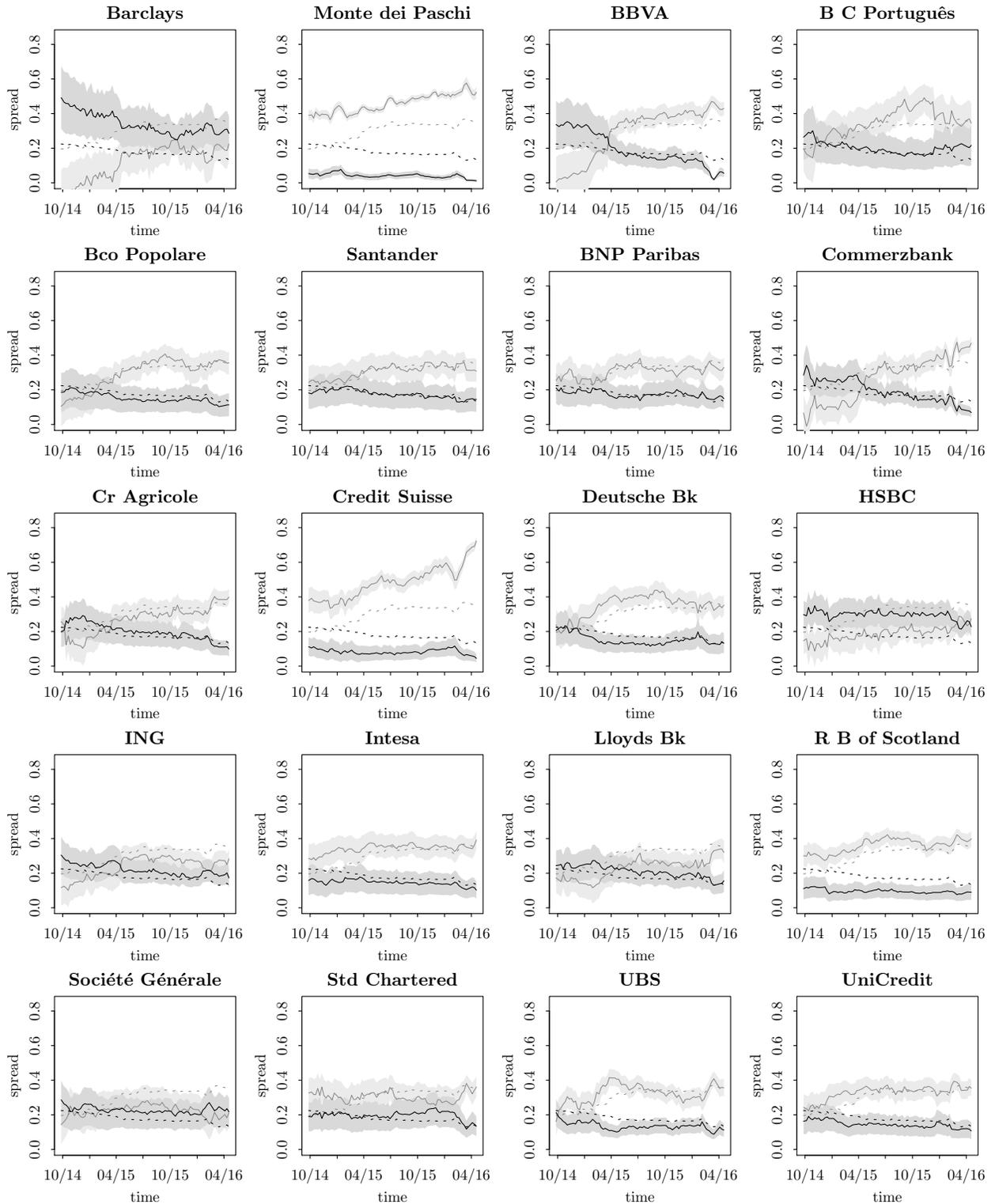


Figure 16: Individual trends in $\mathbb{S}(\text{senior default} \mid \text{any 2014 credit event})$ (top solid line in gray, posterior mean estimate along with 68 percent credible intervals) as well as $\mathbb{S}(\text{senior bail-in} \mid \text{any 2014 credit event})$ (bottom solid line, posterior mean estimate along with 68 percent credible intervals); also shown are the respective averages across all banks (top and bottom dotted line in gray and black, respectively). *Sources: Markit Group Ltd. data and authors' calculations*

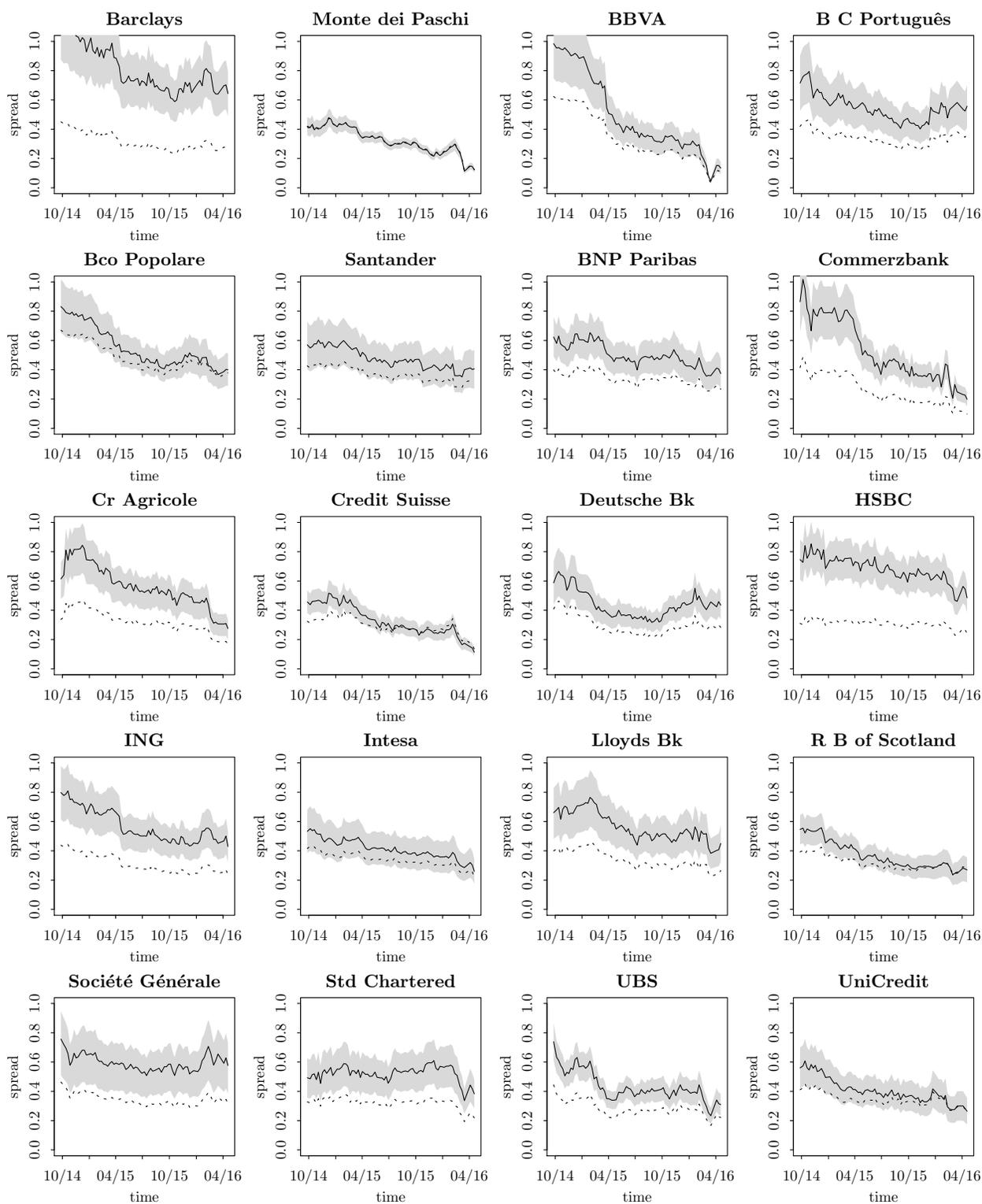


Figure 17: Conditional probability of sub bail-in (top line with with 68 percent credible intervals), and relative basis (loss-weighted average conditional probability of sub bail-in, dotted line), for each bank, given distress without bailout. *Sources: Markit Group Ltd. data and authors' calculations*

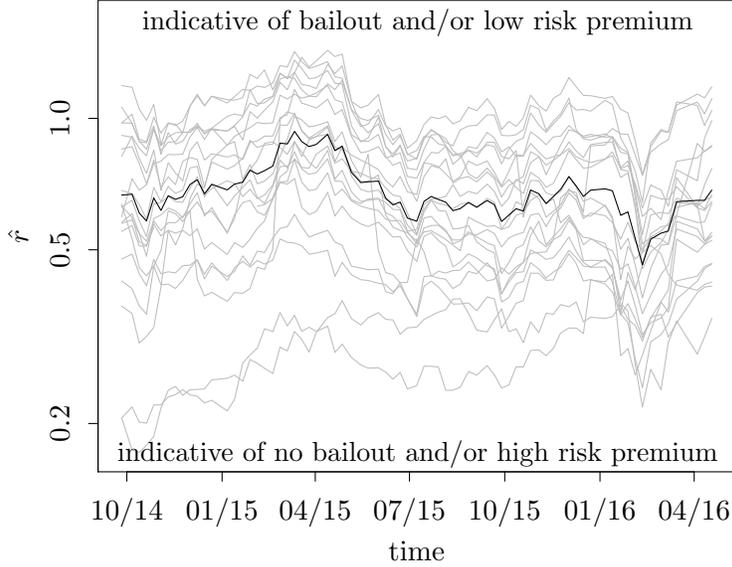


Figure 18: The empirical r_{it} in Equation (19), for each bank over time (gray), along with the average across all banks over time (black). *Sources: Markit Group Ltd. data and authors' calculations*

We normalize r_{it} with respect to the time trend:

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

This quantity is independent of any shared risk premium across banks, but also independent of any common trend in the r_{it} that could be attributed to changes in the bailout probability. This measure tells us how likely bailout is for a given bank i , relative to how likely bailout 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:

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

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

We find that the empirical correlation between the empirical $r_{it}^{\text{normalized}}$ and the normalized relative basis is -0.05 . This means that firms with a larger than average conditional chance of bail-in have a slight tendency to also have a larger than average conditional chance of bailout. We also analyze, separately for each bank, the empirical correlation between changes over time in the empirical $r_{it}^{\text{normalized}}$ and changes over time in the normalized relative basis. We find these correlations between changes to range from -0.42 to -0.03 , with a mean of -0.26 , which is consistent with only a slight tendency for bailouts to crowd out bail-ins.