The Bank-Sovereign Nexus: Evidence from a Non-Bailout Episode*

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Abstract

We explore the interplay between sovereign and bank credit risk in a setting where Danish authorities first let two Danish banks default and then left the country's largest bank, Danske Bank, to recapitalize privately. We find that the correlation between bank and sovereign credit default swap (CDS) rates changed with these events. Following the non-bailout events, the sensitivity to external shocks, proxied by CDS rates on the European banking sector, declined both for Danske Bank and for Danish sovereign debt. After Danske Bank's recapitalization, its exposure to the European banking sector reappeared while that did not happen for Danish sovereign debt. The decoupling between CDS rates on sovereign and private bank debt indicates that the vicious feedback loop between bank and sovereign risk weakened after the non-bailout policies were introduced.

JEL codes: C21, G12, G21, G28.

Keywords: Bailout expectation, risk, CDS, spillover, quantile regression.

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1 Introduction

In the years following the 2007-2008 financial crisis, several countries decided to bail their local banks out, shifting losses from the financial sector to the government. Shortly after the bailout events, the credit risk on many of these countries' sovereign bonds started to rise. Since then, it has been documented that the bank bailouts were an integral factor in fueling sovereign risk, see for instance Ejsing and Lemke (2011). It is hypothesized that the bank bailouts backfired to some extent, as the subsequent rises in sovereign risks weakened the balance sheets of banks and thus re-ignited credit risk in the financial sector, as argued by for instance Acharya et al. (2014) and discussed by Arghyrou and Kontonikas (2012) and Fratzscher and Rieth (2015) in the context of the European sovereign debt crisis.

There are several more studies in this vein. Kallestrup et al. (2016) show that cross-border financial linkages affect sovereign risks to an extent that is beyond what can be explained by the simple exposure to common factors. Alter and Schuler (2012) document that bank bailout programs change the composition of both bank and government balance sheets, transferring risks from the financial sector to the sovereign debt, while Alter and Beyer (2014) find evidence of an increase in bank-to-sovereign and sovereign-to-bank spillovers during the European sovereign crisis, as in Lane (2012). De Bruyckere et al. (2013) show in a sample of European data over the period 2007-2012 that the success of government interventions depends on the type of intervention. Also before the European debt crisis erupted, the bank-sovereign nexus was understood as a potentially problematic issue. For instance, Gray (2009) argued that the feedback and spillover effects between the risk exposures of the banking and sovereign sectors were important, but only incompletely understood.[1]

A typical feature of the existing empirical studies is that they explore episodes where bailouts were undertaken. However, these analyses cannot necessarily say much about the counter-factual scenario, namely what *would* have happened if banks had *not* been rescued, but instead had been left to fail or raise additional capital in the market. We therefore contribute to the existing evidence by exploring one such episode which took place in Denmark. Differently from most of the previous literature on the topic of sovereign and bank credit risk, which primarily has analyzed the problem of contagion at a systemic level, we focus on a single episode where the national authorities let distressed banks default and made the country's largest bank recapitalize privately. In 2011 two Danish banks, Amagerbanken and Fjordbank Mors (Fjordbank, hereafter), defaulted on outstanding bonds. In both cases, senior bond holders incurred substantial losses. The decision not to bail out these banks contrasted with the general Scandinavian practice of the early 1990s, where

[1]Other related studies include Demirgüçport-Kunt and Huizinga (2013) who find that the value of the bank sector increases when the amount of government debt is lower, and Barth and Schnabel (2013) who suggest that banks are not too big to fail, but too systemic to fail and too big to save. The tight link between banks and sovereign credit risks is also increasingly emphasized in the literature on sovereign default, with Gennaioli et al. (2014) and Leonello (2017) as prominent examples.

equity holders took most of the losses as banks collapsed, whereas bond holders were bailed out by the government, see e.g. Honkapohja (2009). The policy also departed from the more recent Danish crisis response in 2009, where the largest bank, Danske Bank, received considerable support. Hence, the string of events was widely interpreted as a sign that Danish authorities were now more determined to impose losses on senior bond holders than history would suggest. For instance, the Financial Times (June 27, 2011) reported on the Fjordbank default: "*This is a tiny bank by international standards – at end-2010 Fjordbank Mors had total assets of DKK 13.2 bln (£1.8 bln) and equity of DKK 0.8 bln (£0.1 bln) – but there are wider implications for the banking system in Denmark and Europe. Following the failure of Amagerbanken, Moody's downgraded the senior ratings of all Danish banks, including Danske Bank, and this latest move underlines the determination of the Danish authorities to impose losses on senior creditors of failing banks.*"[2] The following market-based recapitalization of Danske Bank and restitution of the 2009 funding provided by the government supported this tougher policy stance.

A priori, it is not obvious what the consequences of these policies might be. The above discussion reflects this ambiguity. On the one hand, weaker perceived government guarantees could leave the debt of private banks exposed to external aggregate funding shocks. On the other hand, with a weaker link to the government, bank risk should become less related to aggregate factors affecting the sovereign's solvency, and more dominated by idiosyncratic factors. Likewise, sovereign debt might become more insulated from external disturbances if the government is not expected to support its banks. However, if the lack of perceived bailout guarantees makes banks more vulnerable to external shocks, this could feed back to national balance sheets as the tax base becomes more sensitive to banking crises. Hence, in this paper we seek to characterize how sensitivity to external factors changed for Danish sovereign debt and the main Danish bank, Danske Bank, around the non-bailout events. In particular, we empirically address whether private bank debt became more vulnerable after the non-bailout events and if the evolution of bank and sovereign debt became decoupled. The many possible and opposing effects listed above imply ambiguity on how Danske Bank alone might be affected. A possible explanation is the following: if market participants perceived it to be less likely that Danske Bank, in a state of distress, would be bailed out by the Danish government, the sensitivity of Danske Bank CDS rates to external systemic factors should increase relative to that of CDS rates on Danish sovereign debt. Notably, our strategy rests on the fact that the two defaulting banks were relatively small, and their defaults therefore unlikely to have affected Danske Bank's or the Danish government's sensitivity to external factors via other channels than

[2]Here, there is an analogy to other bailout-events in Europe and how these events have influenced markets through signaling future bailout policy. For instance, Mink and de Haan (2013) study the period after it was made public that Greece might be bailed out, finding abnormal returns on a portfolio of European banks associated with the fact that "*...news about the bailout are a signal of European governments' willingness in general to use public funds to combat the financial crisis...*".

anticipated future bailout policy. Anecdotal evidence from the period of defaults, as in the quote above and presented further below, indicate that this indeed was how market participants interpreted events at the time.

We study the evolution of credit default swap (CDS) rates on the bonds of Danske Bank and on Danish sovereign debt. As Figure 1 shows, the Danske Bank CDS rates did indeed increase after the non-bailout events, in particular after the second event (Fjordbank's default on June 24, 2011). This is consistent with the perception that the two non-bailout episodes indicated a tougher policy stance towards distressed banks. Moreover, a similar pattern is seen for Danish sovereign debt, displayed in Figure 2. At face value this might seem to indicate that the non-bailout policies were unsuccessful, as a reduction in bank guarantees was followed by greater bank and sovereign default risk. However, we also observe that both CDS rates decline toward the end of the sample and have remained low since Danske Bank was recapitalized. Hence, judging the merits of the non-bailout decisions from the immediate CDS responses would give a very different conclusion than a longer-run perspective. Several factors other than the non-bailout events may of course underlie such descriptive patterns, such as the European debt crisis in this specific period. For instance, even the CDS rates on German sovereign debt, by most standards a "safe haven asset", increased in mid-2011, as seen in Figure 3, a movement that obviously was not driven by Danish bailout policies.[3]

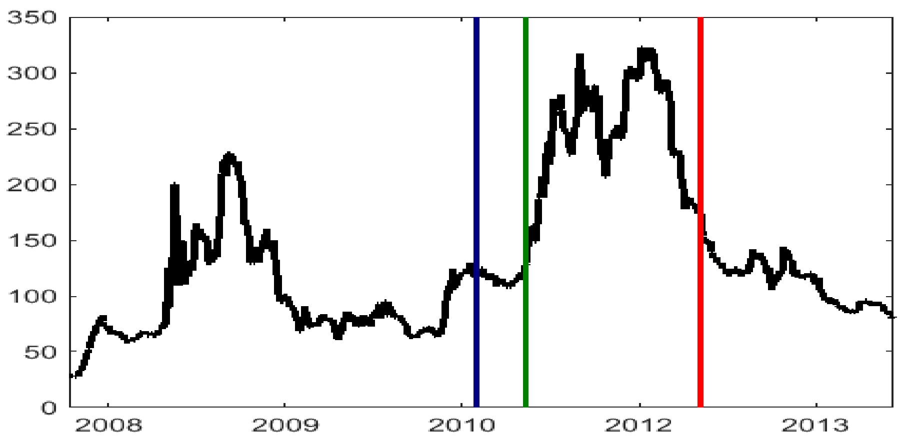


Figure 1: Danske Bank's CDS level. The blue line refers to the default of Amagerbanken, the green line to the default of Fjordbank, and the red line to the recapitalization of Danske Bank.

For these reasons, we do not judge the effects of the non-bailout policies by the levels of CDS rates alone. Instead, we design an indirect testing approach to study the sensitivity

[3]Acharya and Steffen (2015) find evidence that European bailout programs have supported European banks' carry trade behavior by which they load positively on peripheral government bond returns and negatively on German government bond returns used as funding asset, increasing the differences in credit conditions among these countries.

of Danske Bank and Danish CDS rates to international CDS rates around the two non-bailout decisions and the subsequent recapitalization, and ask if they changed after these events. We focus on the dynamics of credit risk on a safe haven asset, as measured by the CDS on German sovereign bonds, and on the dynamics of the CDS index on the European banking sector. If the new non-bailout policy has affected market perceptions of credit risk determinants, that should turn up as time-variation in the regression coefficients of Danske Bank and Danish CDS rates on these variables. Importantly, we here also control for a list of domestic and global factors to limit possible variation in the dynamics from other sources than the change in bailout expectations.

We find that CDS rates on both Danske Bank and Danish sovereign debt became less sensitive to movements in CDS rates on the European banking sector immediately after Amagerbanken and Fjordbank were left to default. Later, after Danske Bank's private recapitalization, the sovereign bonds remained less exposed to EU banking risk than before the non-bailout episodes, whereas Danske Bank's sensitivity reverted to its pre-crisis levels. Hence, the overall effect of the non-bailout policy was to decouple sovereign from banking risk, but only after the private bank was recapitalized. Notably, the above results also emerge when we control for time-varying sensitivity to CDS rates on German sovereign debt. The pattern of co-movement with the safe asset provided by German bonds is quite different from that with EU banking debt: the sensitivities of CDS rates on Danske Bank and Danish sovereign debt to German sovereign debt move together over the period we consider. The default episodes are not associated with a change in co-movement for either assets, while both Danske Bank and Danish sovereign CDS rates respond less to movements in German sovereign CDS rates after the Danske Bank recapitalization.

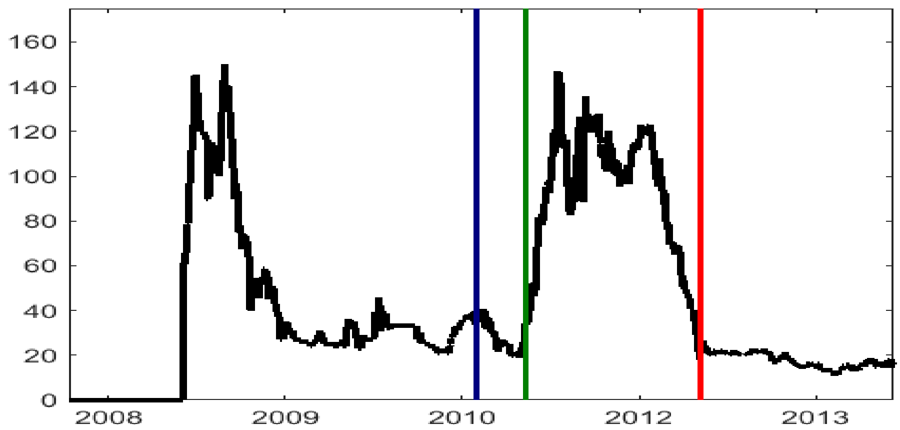


Figure 2: Danish Sovereign CDS level. The blue line refers to the default of Amagerbanken, the green line to the default of Fjordbank, and the red line to the recapitalization of Danske Bank.

Clearly, one may question if the empirical patterns are driven by the non-bailout events or other factors that coincide in time. To shed some light on this issue, we control for an extensive set of variables, including the Danish housing price index and equity prices as domestic variables, as well as market liquidity, oil prices, an index of European bank stock prices, European stock prices and a volatility index as global factors. Danske Bank equity prices are important since bailouts primarily serve to shield debt holders rather than equity holders from losses. Hence, by controlling for swings in the Danske Bank stock price, we isolate the Danske Bank's CDS co-movement with the CDS of the German sovereign debt and of the European banking sector, that is not due to factors that affect the market's valuation of Danske Bank's assets. Similarly, for the Danish sovereign CDS, by controlling for overall equity prices, we control for the market's perception of the state of the Danish economy at large. We also control for European equity indexes, such as STOXX and VSTOXX, as well as macroeconomic indicators, such as the oil index and the liquidity risk in the money market computed as the difference between the 1-month Euribor and the Repo spread. Finally, by controlling for the the European banking sector stock price index, we account for the information it contains on market capitalization and banks' portfolio changes. Thus, we indirectly control for holdings of Danish assets by European banks.

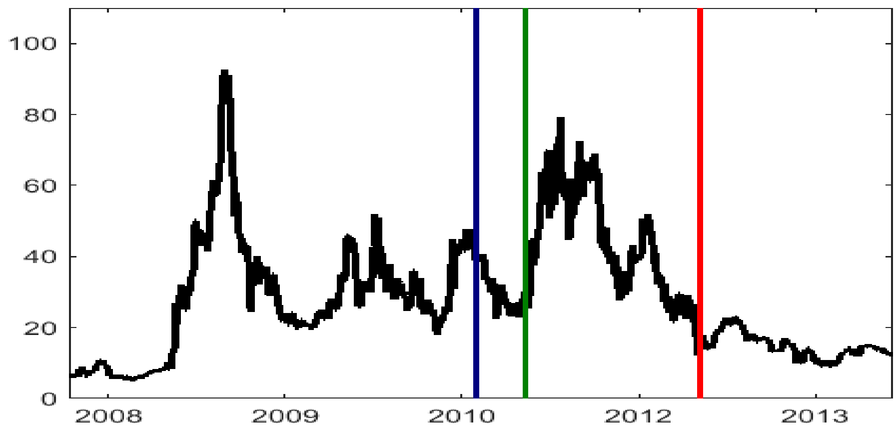


Figure 3: German Sovereign CDS level. The blue line refers to the default of Amagerbanken, the green line to the default of Fjordbank, and the red line to the recapitalization of Danske Bank.

Importantly, we also address non-linearities, as the co-movement between variables could be different in crisis times than in more normal periods. Indeed, bailout events generally take place during extreme market conditions or in exceptional company-specific circumstances. In these situations, the response variables are subject to extremely large realizations and a linear model could produce biased results, see for example Caporin et al. (2018). We therefore extend our analysis with quantile regressions, which facilitate detecting and testing for differential impacts of the explanatory variables across the quantiles of the dependent variable. We apply the method to assess whether the new non-bailout policy had particular effects in different parts of the CDS distribution.[4]

The main findings from the non-linear analysis are consistent with the patterns revealed in the linear regression framework. Conditional upon being in high-volatility times, the co-movement between an average CDS of the larger European banks and Danske Bank CDS is markedly lower after the defaults of Amagerbanken and Fjordbank, whereas the co-movement of Danske Bank CDS and German CDS is stable. The same pattern emerges with Danish sovereign CDS rates. Then, after the Danske Bank recapitalization, the relationship of Danske Bank and Danish sovereign CDS rates with the European banking sector diverges, with a positive significant coefficient for Dansk Bank and a flat zero coefficient for Danish CDS across quantiles. After the Danske Bank recapitalization, (i) CDS levels on both sovereign and private bank debt dropped, and (ii) sovereign and private bank risk were decoupled in their response to international banking risk. Taken together, these observations are consistent with a narrative where the different components of the non-bailout policy choices taken together, including recapitalization, contributed to curb the feedback loop between banking risk and sovereign risk.

This paper is organized as follows. Section 2 provides an overview of the data and the institutional setting, emphasizing how failing banks typically have been dealt with in Scandinavia and the particular events in Denmark that we study. Section 3 describes the results of our analysis applying linear and quantile regressions. Section 4 concludes.

2 Institutional Setting and Data

2.1 Setting and Events

After the real estate crisis in the late 1980s and early 1990s, the Scandinavian governments, particularly in Norway and Sweden, nationalized defaulting banks by creating the system of so-called "bad banks". In a nutshell, the shares of bad banks lost their value while debt was repaid by the government. Hence, stock holders suffered all the losses, whereas bond holders were largely guaranteed, see e.g. Honkapohja (2009). The impression that bank bonds were protected by the government was strengthened during the financial turmoil of 2007-2008, when the governments in Scandinavia, as in many other economies, stepped in to support their largest banks with emergency credit lines. In 2009 the Danish government implemented a credit aid package intended to support Danske Bank, among other financial institutions. In particular, Danske Bank raised a perpetual hybrid loan of 26 billion Danish Krone (DKK) (equivalent to some 4.8 billion US Dollars at the time) with the Danish government, which allowed the bank to maintain its capitalization well above

[4] Quantile regressions have been extensively adopted in treatment effects analysis, typically in clinical trials where the interest is in how subjects respond to a specific treatment.

regulatory requirements (Standard and Poor's, 2012).[5] Despite the support measures of the government, the Danish economy kept deteriorating after 2009, and real estate prices plummeted. The collapse in house prices brought additional problems to the Danish banking sector. In the boom years preceding the crisis, Danish banks had lent massively to property developers, and they were therefore hit hard as property prices collapsed.

On February 6, 2011, the modestly sized Amagerbanken announced it could no longer meet its solvency requirements, as write-downs following the real estate collapse had wiped out its equity. In the end, Amagerbanken's senior bond holders suffered a 41% loss. At the time it was Denmark's 9th largest bank with assets valued at DKK 15,2 billion. The fact that the Danish government chose *not* to bail this 108 year old bank and its senior bond holders out contrasted sharply with previous experience and marked a shift in bailout policy.[6] On June 24, 2011, this restrictive policy line was confirmed when the smaller Fjordbank Mors was left to default, and senior bond holders suffered substantial losses once again, this time with 26% haircuts. The driver of this event was common to that behind Amagerbanken's collapse: bad loans to the construction sector. This was the second bank collapse to trigger a resolution package that involved senior bond losses. At the time, Fjordbank's assets were valued at DKK 7.8 billion by Denmark's bad-bank curating-company Finansiel Stabilitet. This bank was tiny. Yet, as highlighted by the introductory quote from the Financial Times, its default caught international attention by marking Danish authorities' determination to impose losses on senior bond holders.

Danske Bank's direct exposure to the two defaulters was limited. To Amagerbanken, the greater of the two banks, its exposure was below DKK 10 million. In addition, when these two banks collapsed, the remaining Danish banks had to increase funding of the country's deposit guarantee scheme, in order to compensate for the shortfall from Amagerbanken and Fjordbank. Contributions were proportionate to market share, at the time estimated to imply an approximate profit loss of 5 percent (The Independent, June 28, 2011). Taken together, the direct consequences of these defaults for Danske Bank were minor, and this was widely appreciated by markets and the financial press at the time. Still, Danske Bank was downgraded. In their downgrade, Moody's referred to the new government rescue policy: "*Last week's bankruptcy of Amagerbanken demonstrated the willingness and ability of the government to allow depositors and senior creditors of Danish banks to take losses in bankruptcy, where bank operations are continued as a growing concern,"* (Moody's analyst to Financial Times, February 16, 2011).

[5] Danske Bank is the largest bank in Denmark. It serves clients in Finland, Norway, Sweden, and Denmark, with banking, insurance, and asset-management services. As of September 30, 2012, its assets totaled DKK 3.599 billion, equivalent to ca 500 billion Euros. Source: Standard and Poor's (2012).

[6] Financial Times, February 7, 2011, reported: "*Something is interesting in the state of Denmark. Over the weekend, Amagerbanken, a smallish Danish bank filed for bankruptcy. Its assets now have to be transferred to Denmark's bad bank curating-company Finansiel Stabilitet (FS), which has already taken over the assets of a number of failed financial institutions. The Amagerbanken case is special however. Holders of senior unsecured debt and even depositors could face losses.*"

On October 30 2012, Danske Bank initiated a significant recapitalization, with a DKK 7 billion equity rights issue. The recapitalization was a main ingredient in a new three-year plan of the group to improve its earnings capacity. The issue was partly motivated by tighter future regulatory capital requirements, and partly by the fact that the government support measures from 2009 were about to expire while the cost of repaying the government was set to increase sharply after May 2014. Notably, in contrast to the case of the US government support to the local banks, the extraordinary 2009 government measures in Denmark were temporary. They had a precise deadline when funding was supposed to be repaid, in line with EU competition law. Part of the 2009 funding (DKK 2 billion) was repaid already in 2012.

Why did the Danish government let senior bond holders take losses when Amagerbank and Fjordbank failed? This decision was part of the government's "Exit Package" from bank guarantees. It came into force in October 2010. When the crisis hit Denmark in 2008, the government introduced a "Stability Package" with a general state guarantee lasting until September 30, 2010. The Exit Package ended this program, and introduced a detailed plan for how to wind up distressed banks, including a haircut on unsecured loans and deposits above EUR 100,000.[7] The idea was to let creditors carry more of the losses that otherwise would be covered by tax payers. When Amagerbanken and Fjordbanken defaulted, it was the first two times that the government's resolve to follow through on these policies was tested. Clearly, just because the government let two minor banks default on senior loans, it need not follow that the same would *necessarily* apply for a large and more systemically important institution such as Danske Bank. Still, it stands to reason that these events signaled a greater willingness of the government to let senior bond holders take losses also for the main Danish banks. As the above-listed quotes reflect, this interpretation was widely communicated by commentators and financial press at the time. Our empirical exercise is rooted in this interpretation.

2.2 Data

Similarly to Kalbaska and Gatkowski (2012), the evolution of credit risk is analyzed by means of the prices of CDS contracts, obtained from Datastream. We use daily observations of the stock prices (P^{DB}) and CDS rates (CDS^{DB}) of Danske Bank, covering the period December 2007 to April 2014. CDS contracts are designed to transfer the credit exposure of fixed income products between parties. The buyer of a credit default swap receives credit protection from the seller. In doing so, the risk of default is transferred from the holder of the fixed income security to the seller of the swap. Higher CDS values imply higher risk. Hence, the CDS rates proxy for the risk that Danske Bank will default on its debt. We also collect daily data on Danish sovereign CDS rates (CDS^{DK}) with 5-year maturity, along with the German sovereign CDS rates with 5-year maturity (CDS^{DE}),

[7]See IMF (2014) for further details.

and a CDS index for the European banking sector (CDS^{EU}). The latter is computed by Thomson-Reuters as the weighted average CDS spread of the constituents, with weights based on total debt outstanding at the index construction date.[8] We develop our analysis based on the following assumptions:

A1 German bonds are *safe* assets.

A2 The credit risk on Danish sovereign bonds does not influence the credit risk of German bonds and European banks.

A3 The credit risk on Danske Bank bonds does not influence the credit risk of German bonds and European banks.

Assumption A1 is perhaps an exaggeration as there could be risks associated with German debt too (otherwise the CDS price would be zero). This assumption should be interpreted as a statement that German sovereign bonds are safe relative to other bonds. A2 is motivated by the moderate size of the Danish economy and magnitude of its sovereign debt compared to the Germany: German sovereign debt is more than eighteen times larger than the sovereign debt of Denmark.[9] Analogously for assumption A3, the total debt of Danske Bank is less than 1.5% of the total loans of the European banks.[10]

Our strategy is to study the time-variation in the CDS rates of Danske Bank and Danish sovereign debt, and to analyze both the time-variation and the magnitude of the changes in these CDS rates. These evaluations will focus on the response of the target variables to variations in systemic risk in Europe, the latter measured by German and European banks' CDS rates. Therefore, we rely on assumptions A1-A3 to identify the effects of the change in the bailout policy on the dependence of Danske Bank and Danish sovereign CDS rates on German and European CDS rates. In turn, we motivate the assumptions by the relative size of Danske Bank and Danish sovereign bonds compared to the outstanding debt of Germany and of the size of the European banks system. Assumptions A2-A3 implicitly state that it is unlikely that changes in the bailout policy of the Danish Government lead to changes in the exposure to Danish CDS rates by European banks, and that those, consequently, would cause changes in the credit risk of the European banking system (the latter reflected in the CDS index for European banks). For this reason, variations in the German and European CDS rates can be taken as exogenous, thus ruling out the confounding effect mechanically generated by changes in direct holdings of Danish sovereign debt by European banks in response to changes in perceived government guarantees. Nevertheless, assumptions A1-A3 are insufficient to claim that such variation reflects changes in bailout guarantees alone.

[8] We also compute the total connectedness index of Diebold and Yilmaz (2014) on the CDS of the 52 largest European banking institutions, see Figure A.2. Results were qualitatively similar.

[9] In 2014 the GDP of Denmark was about 257 billion Euro and its debt-to-GDP ratio was 44.8%. For Germany, these numbers were 2904 billions and 74.7%, respectively. We recover these data from Eurostat.

[10] In 2014 the total debt of Danske Bank was below 200 billion Euro relative to more than 16 trillion Euro in all of Europe, as reported by Danske Bank and ECB.

For such a claim to hold, changes in exposure to systematic risk caused by other factors, except changes in perceived bailout policy, must be ruled out. To move in this direction, we include a set of controls. We use daily data on five international risk related measures: the return of a stock index for the European banking sector (P^{EU}), the Euro Stoxx 50 Index ($STOXX$), the Euro Stoxx 50 Volatility Index ($VSTOXX$), the Oil price (OIL), and the liquidity risk in the money market computed as the difference between the 1-month Euribor and the Repo spread (LIQ).[11] We also control for Danish house prices, using a monthly Danish house price index ($HOUSE$) that we interpolate to the daily frequency.

3 Empirical Results

3.1 Preliminary analysis

Figure 4 plots stock prices and log-returns ($\Delta \log P^{DB}$) along with log differences of the CDS on Danske Bank ($\Delta \log CDS^{DB}$) and on Danish sovereign debt ($\Delta \log CDS^{DK}$). Both stock prices and CDS levels (see Figures 1-2) display a break after the Fjordbank default in June 2011, with a large drop in stock prices and a large increase in CDS rates. Stock returns and CDS differences are also characterized by high volatility after this event. The effects of the recapitalization of Danske Bank in October 2012 are evident in the CDS, as it returns to its pre-2011 level after the recapitalization. This is natural, as more bank capital implies less risk for bond holders.

Importantly, the patterns in Figure 4 could stem from several other factors than the defaults of Amagerbanken and Fjordbank alone. We therefore study the dynamic interplay between the CDS rates across countries and companies by means of the total connectedness index of Diebold and Yilmaz (2014). The TCI is defined as

$$TCI = \frac{1}{N} \sum_{i,j=1 i \neq j}^{N} \tilde{d}_{i,j}, \tag{1}$$

where N denotes the number of variables in the system, and $\tilde{d}_{i,j}$ is the i, j entry of the standardized connectedness matrix $\tilde{D}$. The matrix $\tilde{D}$ is defined as

$$\tilde{d}_{i,j} = \frac{d_{i,j}}{\sum_{j=1}^{N} d_{i,j}}, \tag{2}$$

with

$$d_{i,j} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H} (e_i A_h \Sigma e_j)^2}{\sum_{h=0}^{H} (e_i' A_h \Sigma A_h' e_i)}, \tag{3}$$

[11] The role of liquidity for credit risk is quite controversial. Early papers, such as Codogno et al. (2003), find a limited impact, while more recent contributions, such as Manganelli and Wolswijk (2009) and Beber et al. (2009), show that "...while the bulk of sovereign yield spreads is explained by differences in credit quality, liquidity plays a nontrivial role...".

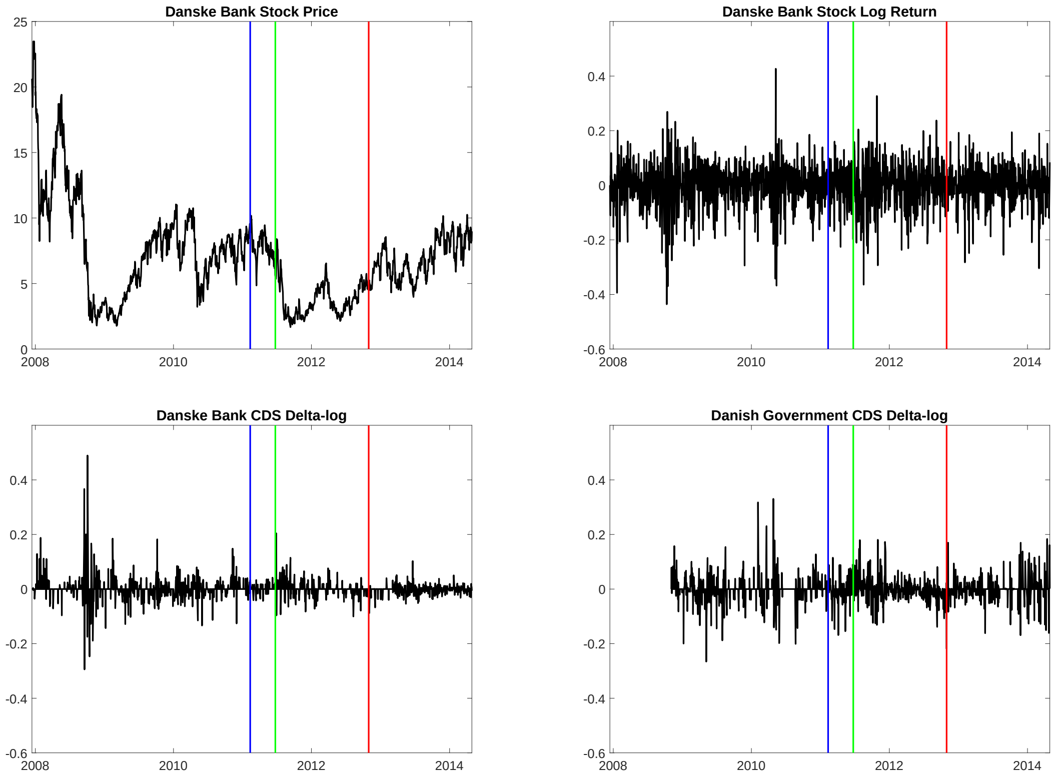


Figure 4: The green line identifies the default of Fjordbank while the red line identifies the recapitalization of Danske Bank.

where A_h is the impulse-response matrix at horizon h associated with a VAR(p) model, Σ is the covariance matrix of the errors, and e_i, e_j are $N \times 1$ selection vectors. By construction, $\sum_{j=1}^{N} \tilde{d}_{i,j} = 1$ and $\sum_{i,j=1}^{N} \tilde{d}_{i,j} = N$. Equation (3) defines the generalized forecast error decomposition, as introduced by Pesaran and Shin (1998).

In words, the TCI measures the average portion over N variables of the forecast error variation of variable i coming from shocks arising from the other $j = 1, \ldots, N-1$ variables of the system. The TCI provides a characterization of the connectedness of a system that is richer than the one obtained by a simple linear correlation coefficient. Indeed, the TCI combines the information coming from both the contemporaneous and the dynamic dependence structure of the system trough Σ and A_h, respectively. Moreover, by estimating the VAR model over rolling windows, it is possible to characterize the evolution of the dependence structure between two or more variables by looking at the variations of the TCI over time. Figure 5 reports the pairwise rolling TCI between $\Delta \log CDS^{DB}$, $\Delta \log CDS^{DE}$, $\Delta \log CDS^{DK}$, and $\Delta \log CDS^{EU}$.[12] After the non-bailout event of Fjordbank and before the recapitalization of Danske Bank, the rolling TCI between $\Delta \log CDS^{DB}$ and

[12]See Figure A.1 in Appendix for rolling window correlations of the same variables.

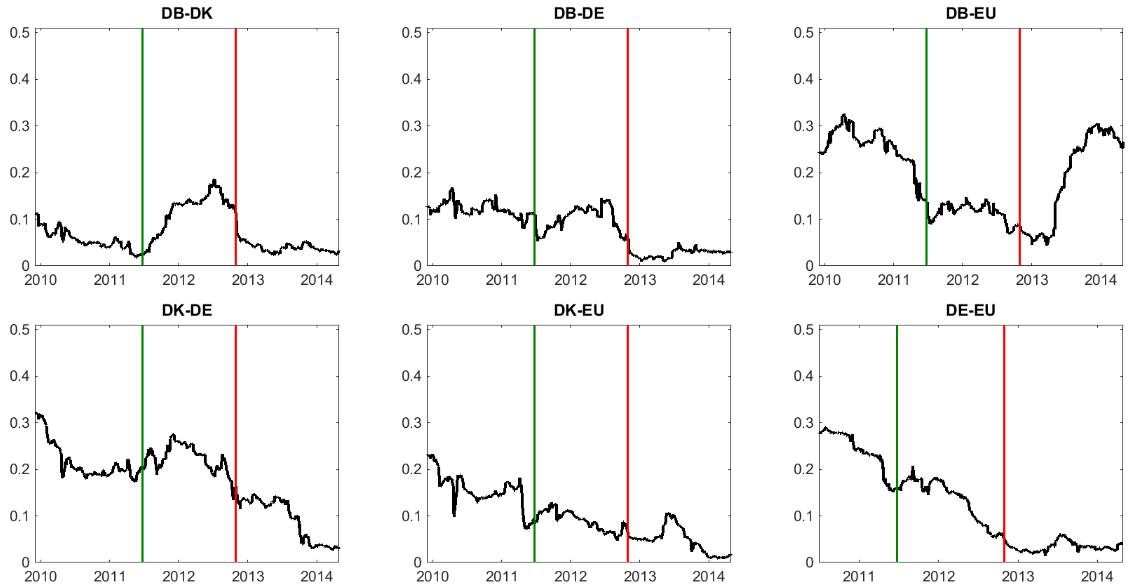


Figure 5: Rolling total connectedness index (one-year window) between the delta-logs of CDS on Danske Bank (DB), Danish sovereign debt (DK), German sovereign debt (DE), and the European banking sector (EU). The green line identifies the default of Fjordbank, while the red line denotes the recapitalization of Danske Bank. The total connectedness index is computed as in Diebold and Yilmaz (2014), based on a VAR with two lags (p=2) and a horizon of $H = 12$ days for the impulse-response functions.

$\Delta \log CDS^{DK}$ increased, but only after a decline at the beginning of the sample. After the recapitalization, the TCI index plunged and remained low and stable until the end of the sample. A similar pattern also arises from the TCI of $\Delta \log CDS^{DB}$ and $\Delta \log CDS^{DE}$. The connectedness between $\Delta \log CDS^{DB}$ and $\Delta \log CDS^{EU}$, the latter capturing systemic risk of other European banks, increases toward the end of the period, while it is very low between 2011 and 2012. This indicates that after the recapitalization, the dynamic behavior of credit risk associated with Danske Bank is connected to that of the rest of the European banking sector. Finally, the graphs in the bottom panels of Figure 5 display a general downward trend of the TCI between the CDS of Danish, German and the European banking sector without notable breaks after the recapitalization of Danske Bank.

3.2 Dependence on systemic risk after the non-bailout episodes

In order to further explore the relation between credit risk in the Danish economy and the European system before and after the non-bailout events, we study the sensitivity of Danske Bank and Danish sovereign CDS rates to movements in the CDS rates on European banks and German sovereign debt, $\Delta \log CDS_t^{EU}$ and $\Delta \log CDS_t^{DE}$. We first consider a linear specification of the following form:

$$\Delta \log CDS_t^i = \alpha_j^i + \beta_{j,1}^i \Delta \log CDS_t^{DE} + \beta_{j,2}^i \Delta \log CDS_t^{EU} + \delta_j^{i,\prime} W_t + \varepsilon_t, \tag{4}$$

where $i = DB, DK$. DB stands for Danske Bank and DK for Denmark, and the dependent variable is the log change in the CDS of Danske Bank or Danish sovereign debt; ε_t is the error term; and $j = 1, 2, 3$ refer to the three periods we consider. These are: the period up to the default of Fjordbank (from December 18, 2007 to June 24, 2011), the period between the default and the recapitalization of Danske Bank (from June 25, 2011 to October 30, 2012), and the period after the recapitalization (from November 1, 2012 to April 29, 2014).

Note that we do not consider linear relations between the CDS of Danske Bank and the CDS of Danish Sovereign debt. Under assumptions A1 to A3, the German Sovereign and European Banks' CDS are exogenous variables for Danske Bank and Danish Sovereign variables, thus supporting the appropriateness of regressors included in equation (4). Differently, Danske Bank and Danish Sovereign are likely to be endogenous to each other thus challenging the validity of estimates from a linear regression as in equation (4). We further note that we choose to use the Fjordbank default and not that of Amagerbanken, as it was only after the Fjordbank event that the CDS of Danske Bank reacted, indicating that the second event was more strongly associated with a change in expected future bailout policy.[13] The main covariates are the log changes of German CDS and the log changes of the European banking sector CDS. The vector W_t contains a number of control variables, such as the log-return of Danske Bank equity, the log-return of a stock index for the European banking sector computed by Thomson-Reuters, $\Delta \log P_t^{EU}$, and the changes in the Danish housing index ($\Delta \log HOUS$). Furthermore, W_t contains other financial variables related to international risks that are used as additional controls, $\Delta \log OIL_t$, $\Delta \log STOXX_t$, $\Delta \log VSTOXX_t$, and ΔLIQ_t.

Table 1 reports the estimates of regression (4), for DK and DB in columns 1 and 2 respectively. Quantitatively, the reported coefficient estimates are to be interpreted in percent. For instance, our estimates imply that in period one (P1), a one percent increase in CDS_t^{DE} was associated with a 0.125 percent contemporaneous increase of CDS_t^{DK}. We provide further interpretation of the magnitudes involved below. The estimated coefficients on $\Delta \log CDS_t^{DE}$ are significantly positive in the two regressions, both in the first period and in the second period. Moreover, the values of the coefficients in the two sample periods are very similar. The credit risk on debt issued by both Danske Bank and the Danish government co-move with the German CDS rate, suggesting the relationship of the two assets with the safe haven has been constant. The coefficients' signs make economic sense, since a general increase in global risk is likely to raise riskiness of Danske Bank and the Danish and German sovereign debts at the same time. In P3, the series of $\Delta \log CDS_t^{DE}$

[13] We also run a set of standard Chow-type tests on the covariates in equation (4) to evaluate our event-driven choice of splitting the sample. We verify that the pre-default period coefficients are equivalent, at the 1% level (p-value 0.04), to those obtained by running the model (4) on the data between the defaults. We also compare the latter coefficients to those obtained by a regression on the data between the Fjordbank default and the racapitalization. Now the null is rejected at the 1% level, but with a p-value very close to the boundary (p-value 0.014). We thus read this as evidence supporting our choice. Tests for equality of coefficients among other periods always lead to a clear rejection of the null.

has hardly moved, see Figure 3, which might explain why both the coefficients are close to zero here. To provide further perspective on the magnitudes involved, we standardize $\Delta \log CDS_t^{DK}$, $\Delta \log CDS_t^{DB}$ and $\Delta \log CDS_t^{DE}$, so that our estimates can be evaluated in units of standard deviations. When doing so, the estimates for Danish sovereign debt become 0.4, 0.3 and 0.04, while for Danske Banks' CDS they are 0.08, 0.08, and -0.004, for P1, P2 and P3 respectively.[14]

The evidence is different when focusing on co-movements with the European banking sector CDS. The coefficients for both regressions are all positive, but with large differences across periods and between the two dependent variables. For $\Delta \log CDS_t^{DK}$, we observe a substantial decrease of the coefficient in the second period for both dependent variables, from 0.286 to 0.053 and from 0.756 to 0.146 for DK and DB respectively. Then, after Danske Bank's recapitalization (P3), the co-movement between $\Delta \log CDS_t^{DB}$ and $\Delta \log CDS_t^{EU}$ rebounded. In stark contrast, this did not happen for $\Delta \log CDS_t^{DK}$, where the last-period coefficient on $\Delta \log CDS_t^{EU}$ is significant only at the 10% level. If we again standardize coefficients so that magnitudes can be gauged in units of standard deviations, we observe that these estimated changes in how $\Delta \log CDS_t^{DB}$ and $\Delta \log CDS_t^{EU}$ co-move with $\Delta \log CDS_t^{EU}$ are considerable. In P1, a one standard deviation increase in $\Delta \log CDS_t^{EU}$ was associated with an 0.59 standard deviation increase in $\Delta \log CDS_t^{DB}$ and an 0.46 standard deviation increase in $\Delta \log CDS_t^{DK}$. After the recapitalization, in P3, the same numbers are 0.32 for Danske Bank and only 0.12 for Danish sovereign debt.[15] Alternatively, in monetary terms, our estimates mean that if the price of the European banking CDS increased by one Euro in P1, it would cost an extra 32.50 cents to insure 100 Euros of Danske Bank debt, and an extra 43.68 cents to insure 100 Euros of Danish sovereign debt. In P3, these extra costs would be 52.96 cents for Dansk Bank debt, and only 11.45 cents for Danish sovereign debt. In sum, we therefore interpret our estimated changes in co-movement as economically significant, in particular the decoupling of how CDS's on Danske Bank and Danish sovereign debt respond to movements in European banking CDS rates.

These findings indicate that the exposure of Danske Bank and Danish government debt to international shocks decreased after the default of Fjordbank. We interpret this decline in co-movement as a sign that after the non-bailout episode, the systemic component became relatively less important than the *idiosyncratic* (company specific) component of Danske Bank's perceived riskiness. The pattern is consistent with the hypothesis that under a regime with a strong implicit bailout guarantee, bank debt is ultimately backed by the government and hence only sensitive to systemic risk, not idiosyncratic risk, even if the

[14] If we standardize by standard deviations computed period-by-period instead of over the full sample, the resultant coefficients for periods P1 to P3 are 0.34, 0.36, and 0.07 for $\Delta \log CDS_t^{DK}$, and 0.06, 0.12, and -0.006 for $\Delta \log CDS_t^{DB}$.

[15] If we standardize by standard deviations computed period-by-period instead of over the full sample, the resultant coefficients for periods P1 to P3 are 0.39, 0.11, and 0.14 for $\Delta \log CDS_t^{DK}$, and 0.48, 0.19, and 0.35 for $\Delta \log CDS_t^{DB}$.

		$\Delta \log CDS_t^{DK}$	$\Delta \log CDS_t^{DB}$
α	P1	0.000	0.000
	P2	0.000	0.001
	P3	0.001	0.001
$\Delta \log CDS_t^{DE}$	P1	0.125^a	0.049^c
	P2	0.095^a	0.048^b
	P3	0.013	-0.002
$\Delta \log CDS_t^{EU}$	P1	0.286^a	0.756^a
	P2	0.053^a	0.146^a
	P3	0.075^c	0.412^a
$\Delta \log P_t^{EU}$	P1	-0.169^b	-0.260
	P2	-0.084	0.066
	P3	-0.128^c	-0.108
$\Delta \log P_t^{DB}$	P1	-0.006	0.040
	P2	-0.116^b	-0.130
	P3	-0.076	-0.074
$\Delta \log HOUSE_t$	P1	-1.106	-2.571^c
	P2	-1.374^b	-0.919
	P3	-1.874^b	-3.840^c
LIQ_t	P1	0.063	0.134
	P2	-0.025	0.016
	P3	0.057	0.277
OIL_t	P1	-0.018	0.089
	P2	-0.028	-0.037
	P3	-0.147^b	-0.007
$\Delta \log STOXX_t$	P1	0.097	0.238
	P2	-0.091	-0.105
	P3	0.094	-0.479^b
$\Delta \log VSTOXX_t$	P1	0.009	0.117
	P2	-0.112^b	-0.130
	P3	-0.069	-0.085
Adj R2		0.348	0.248

Table 1: Linear Regression Results: OLS estimation results for Danish Sovereign CDS log differences, $\Delta \log CDS_t^{DK}$ and Danske Bank CDS log differences, $\Delta \log CDS_t^{DB}$. The explanatory variables are: log differences of German CDS, $\Delta \log CDS_t^{DE}$; log differences of a CDS index for the European banking sector computed by Thomson-Reuters, $\Delta \log CDS_t^{EU}$; log differences of a stock index for the European banking sector computed by Thomson-Reuters, $\Delta \log P_t^{EU}$; log-returns on Danske Bank stocks, $\Delta \log P_t^{DB}$; differences of Danish real estate index, $\Delta HOUSE_t$; the liquidity risk in the money market computed as the difference between the 1-month Euribor and the Repo spread, LIQ_t; oil price, OIL_t; log-returns on the Euro Stoxx 50 Index, $\Delta \log STOXX_t$; log-returns on the Euro Stoxx 50 Volatility Index, $\Delta \log VSTOXX_t$. The coefficients are period-specific and refer to the three periods we consider in the analysis (P1, P2, and P3), namely: from the beginning of the sample up to the default of Fjordbank; from the default up to the recapitalization of Danske Bank; from the recapitalization up to the end of the sample. Significant coefficients, computed with the Newey-West standard errors, are indicated as follows: 1%=a, 5%=b, and 10%=c. The last row reports the adjusted R-squared coefficients.

latter risk may be far greater than the former.[16] Once the bailout guarantee is weakened,

[16] See for example Brunnermeier and Oehmke (2013) for an analysis of belief distortions in the presence

holders of bank bonds become more strongly exposed to idiosyncratic risks instead of systemic risks. Before its recapitalization, Danske Bank's idiosyncratic risks were likely perceived as considerable. Notably, also the Danish sovereign CDS became less tightly correlated with the foreign banking sector after letting Fjordbank default, indicating that once bailouts were less likely, banking risk became less important for perceived sovereign risk. Importantly, after the recapitalization of Dansk Bank was finalized, the coefficients for the two parties diverge: for Danske Bank the coefficient increases toward the value it had before Fjordbank defaulted, whereas for the Danish CDS, it remains low. This indicates some success of the policy changes: the recapitalization leaves Danske Bank less exposed to idiosyncratic factors, and hence its perceived riskiness is again primarily driven by the credit risk of the international banking sector, but the recapitalization has no such effect for the Danish government. With weaker perceived bailout guarantees, the government remains less exposed to the international banking sector although its largest bank still is.

Note that the above results hold when we control for both Danish house prices and for Danske Bank equity prices. In particular, the Danish housing market appears to be negatively correlated with the credit risk on Danish sovereign bonds and Danske Bank, especially after the recapitalization of the latter. This might suggest a re-established negative dependence between the probability of defaults and the market prices of the underlying/collateral assets, such as real estate. Notably, the Danish CDS rates are negatively related with the returns on the equity of the European banking sector only in the first and third period, while they are disconnected between the default of Fjordbank and the recapitalization of Danske Bank. The other control variables are often insignificant, and we observe hardly any change in the coefficients on the controls that proxy for global risk factors.

3.3 Credit risk under different market conditions

Bailout events typically occur during extreme market conditions or under exceptional company-specific circumstances. In these scenarios our object of interest, the credit risk of bonds, might reach extreme values. Consequently, it might display a correlation structure with the credit risk on bonds issued by other European countries that differs from the patterns observed in normal times. Our linear regression approach from the previous section ignores such possible different market conditions, and might therefore provide a distorted picture of the underlying movements in the data. Hence, we extend the analysis to assess if the time-variation in default-risk sensitivities occurred in particular parts of the distribution of credit risk. We are especially interested in evaluating if the variations in the sensitivities are more pronounced in the tails, so as to understand if there are different responses in more turbulent periods than under normal circumstances.

of a bailout guarantee.

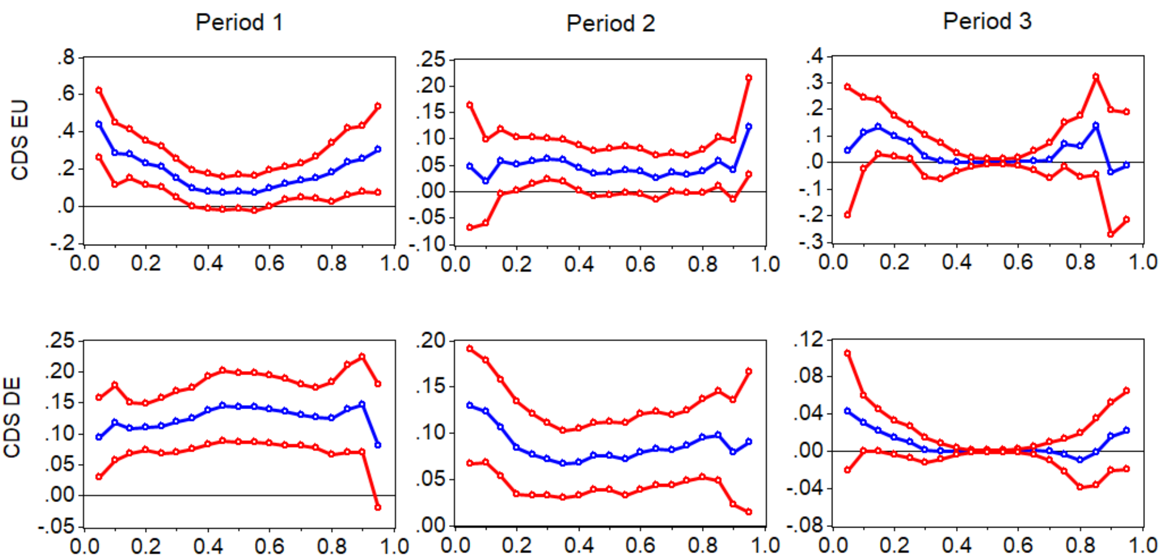
To this end we adopt a quantile regression method where we hypothesize that a specific quantile of the density of the target variable (the CDS-change) is a linear function of a set of covariates. In recent years, financial applications of quantile regression methods have become increasingly common, see for instance Boyson et al. (2010), Baur (2013), and Caporin et al. (2018), among many others. We thus consider the quantile regression estimation of model (4), where the estimated parameters are associated with a specific quantile (τ). This allows recovering the τ-quantile of the dependent variable conditional on the set of covariates. The model is defined as

$$Q_\tau\left(\Delta \log CDS_t^i\right) = \alpha_{j,\tau}^i + \beta_{j,1,\tau}^i \Delta \log CDS_t^{DE} + \beta_{j,2,\tau}^i \Delta \log CDS_t^{EU} + \delta_{j,\tau}^{i,\prime} W_t, \qquad (5)$$

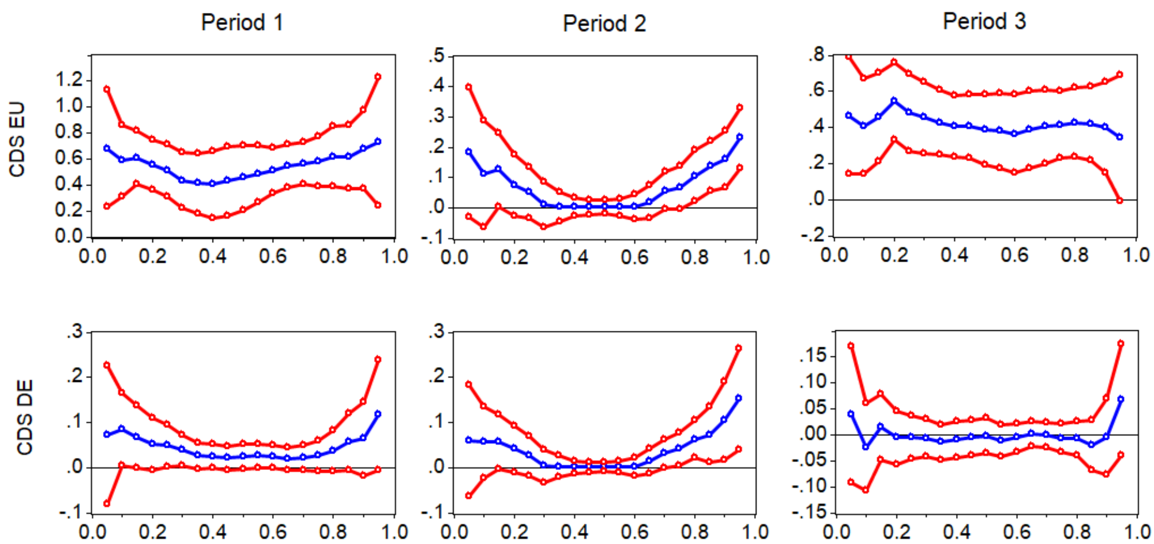
where $i = DB, DK$, and $j = 1, 2, 3$ refer to the three sub-samples we consider. Similarly to the linear case, W_t contains several explanatory/control variables and is included in all model specifications considered in this section. The quantile regression specification is comparable in terms of regressors to that of equation (4). Therefore, the parameters of interest are still the same as those in (4), but they are now separately estimated for each particular quantile τ. For details on quantile regression estimation, see Koenker (2005). In our analysis, we consider values of τ ranging from 5% to 95% with a 5% step. We note that, as discussed in Caporin et al. (2018), quantile regression offers an important feature in the presence of omitted variables and endogeneity problems. Quantile regression parameters might be biased, such as other estimation methods, due to either endogeneity or omitted variables. However, if we compare the equality of the parameters for the variable of interest across quantiles, the bias, under the hypothesis that the bias is not a function of the quantiles, will cancel out, and tests to verify equality across quantiles or symmetry are valid.

First, we consider the quantile regression for the CDS of Danish sovereign bonds. Panel a) of Figure 6 (and Table A.1 in Appendix) shows that the coefficients associated with the German CDS and the CDS of EU banks. The main result when applying the linear regression is robust to quantile regression: the coefficient on the European banking sector drops across periods and it is not significant at almost any quantile in period three. Hence, the dependence between riskiness of Danish government debt and risk of the foreign banking sector has disappeared after the non-bailout episodes, while it was present before the non-bailout events. The coefficients are approximately zero for some of the central quantiles. The coefficient on German sovereign CDS follows a similar patter across the three periods. Overall, the combined non-bailout and recapitalization events were associated with a clear break in the relation between Danish sovereign risk and the covariates, indicating that sovereign risk became less closely related to other risk factors.

Panel b) of Figure 6 shows the coefficients associated with the German CDS and the CDS of EU banks (and Table A.2 in the Appendix). The relationship with the German CDS changes over the three periods. In the first period, the relationship is present through-



(a) Danish Sovereign CDS



(b) Danske Bank CDS

Figure 6: Variation of regression coefficients across quantiles. The dependent variables are the Delta-log of the Danish sovereign CDS (DK) and the Delta-log of Danske Bank CDS (DB). The displayed covariates are the Delta-log of the Germany sovereign CDS (DE) and the Delta-log of the CDS on the European banking sector (EU). The three columns refer to the three subsamples we consider (P1, P2, P3). The plot reports the estimated coefficients across quantiles and the 95% confidence interval obtained by boostrapping and the OLS coefficients (red-line) with 95% confidence interval (red-dashed line).

out the quantile distribution. In period two, it is only present for upper quantiles, while for period three it disappears for all quantiles. Hence, the removal of the implicit bailout guarantee made Danske Bank riskier, and its correlation with the German CDS vanished. The only exception is those instances when the CDS on Danske Bank were in the riskiest quantile (right tail) in the second period. In this case, a positive increase in the German CDS was positively associated with the perceived credit risk of Danske Bank. The coefficient associated with the CDS on the European bank system is always positive and significant in the first period. In the second period, the coefficients are substantially smaller than in the first period, and significant for the upper quantiles only. This aligns with the prior hypothesis that the large bank's credit risk becomes more dominated by idiosyncratic factors when bailout is less likely, factors which were considerable for Danske Bank before the recapitalization. After the recapitalization, these idiosyncratic risks necessarily fall in magnitude, and the coefficient on European-wide banking risks increases across all quantiles, returning to values comparable to those of period one. Therefore, the quantile regressions confirm the evidence in the linear regression model and show a divergence of the relationship between Danish sovereign CDS and the CDS on the European bank that vanishes after the recapitalization, and between Danske Bank CDS and the CDS on the European bank that returns to pre-defaults levels.

To statistically validate the previous graphical evidence, we consider a testing procedure based on the estimates of the quantile regression model (5). The approach we follow comes from the extensive use of quantile regression methods in treatment effects analysis typical of clinical trials, where the interest lies in the response of subjects to a specific treatment. Quantile regression allows detecting the so-called quantile treatment effect that postulates a possible different impact of the treatment across quantiles. Direct estimation of the quantile treatment effect is possible by means of dummies that identify treated subjects. In this way, it is possible to disentangle the different impacts of the treatment: the absence of impact when dummy coefficients all are zero across quantiles; a simple location shift, with dummy coefficients that are constant across quantiles; the scale shift case, where dummy coefficients are symmetric; and the location and scale shift, where coefficients are neither constant across quantiles nor symmetric. In our setting, we might identify two different treatments: the absence of a government bailout and the recapitalization. Our interest is whether these treatments affect the relation between CDS changes and the various covariates.[17] We thus rewrite the model in (5) in the following way:

The estimation of model (5) for a given quantile τ allows testing a null hypotheses of

[17]We also consider a version of the test associated with a model specification in which the covariates $\Delta \log CDS_t^{DE}$ and $\Delta \log CDS_t^{EU}$ and the intercept are excluded. Results are qualitatively similar.

parameter stability across periods. We thus proceed to test the null hypotheses

$$\begin{aligned} i) \qquad & \mathcal{H}_0 : \beta_{1,\ell,\tau} = \beta_{2,\ell,\tau} \quad \text{vs} \quad \mathcal{H}_1 : \beta_{1,\ell,\tau} \neq \beta_{2,\ell,\tau}, \\ ii) \qquad & \mathcal{H}_0 : \beta_{1,\ell,\tau} = \beta_{3,\ell,\tau} \quad \text{vs} \quad \mathcal{H}_1 : \beta_{1,\ell,\tau} \neq \beta_{3,\ell,\tau}, \end{aligned}$$

for $\ell = 1, 2$ for DE and EU, respectively. The Wald-type test statistics can be easily derived given the asymptotic properties of quantile regression estimators, see Koenker (2005). The

	Danske Bank				Denmark			
	$\Delta \log CDS_t^{DE}$		$\Delta \log CDS_t^{EU}$		$\Delta \log CDS_t^{DE}$		$\Delta \log CDS_t^{EU}$	
τ	P2	P3	P2	P3	P2	P3	P2	P3
0.05	0.418	0.261	**0.000**	**0.008**	0.902	**0.753**	**0.046**	0.440
0.10	0.874	**0.011**	**0.006**	0.114	0.619	**0.072**	**0.004**	0.345
0.15	0.938	**0.000**	**0.003**	**0.087**	0.820	0.260	**0.000**	0.336
0.20	0.395	**0.000**	**0.007**	**0.067**	0.780	0.135	**0.000**	0.934
0.25	0.255	**0.000**	**0.012**	**0.038**	0.480	**0.089**	**0.000**	0.832
0.30	0.140	**0.000**	0.123	**0.059**	0.184	**0.075**	**0.000**	0.884
0.35	**0.063**	**0.000**	0.491	0.128	0.206	**0.070**	**0.001**	0.905
0.40	**0.038**	**0.000**	0.526	0.137	0.103	0.114	**0.002**	0.988
0.45	**0.042**	**0.000**	0.491	0.142	0.156	0.229	**0.002**	0.894
0.50	**0.052**	**0.000**	0.456	0.118	0.109	0.230	**0.001**	0.678
0.55	**0.039**	**0.000**	0.578	0.159	0.089	0.066	**0.000**	0.516
0.60	**0.086**	**0.000**	0.289	**0.065**	0.145	0.105	**0.000**	0.314
0.65	0.128	**0.000**	**0.057**	**0.019**	0.777	0.329	**0.000**	0.250
0.70	0.124	**0.000**	**0.037**	**0.023**	0.639	0.254	**0.000**	0.226
0.75	0.203	**0.000**	**0.050**	0.241	0.564	0.157	**0.000**	0.214
0.80	0.413	**0.000**	**0.096**	0.229	0.408	0.139	**0.000**	0.210
0.85	0.311	**0.000**	**0.057**	0.433	0.718	**0.073**	**0.000**	0.236
0.90	0.163	**0.002**	**0.025**	**0.046**	0.487	0.235	**0.002**	0.179
0.95	0.876	0.292	0.153	**0.040**	0.664	0.565	**0.051**	0.218

Table 2: P-values of the Wald test for zero restrictions for the coefficients of the main covariates in equation (5). The null hypothesis is that covariates impact on the dependent variables ($\Delta \log CDS_t^{DB}$ and $\Delta \log CDS_t^{DK}$) equally across periods, as in equations (4) and (5). Column P2 compares the estimates in the second period in our analysis to estimates in the baseline first period, the null hypothesis in (4); column P3 compares estimates in the third period to estimates in the baseline first period, as in the null hypothesis (5). The covariates that we restrict and test are $\Delta \log CDS_t^{DE}$ and $\Delta \log CDS_t^{EU}$. Bold numbers indicate p-values below 10%.

results to the left in Table 2 confirm the graphical evidence and imply that we can reject the null of equal coefficients for most quantiles when comparing the first to the third period. Moreover, the coefficient changes for the German sovereign CDS are statistically significant across the quantile distribution. This is also supported by the evidence on the left-right panel of Figure 6. The Wald test for Danske Bank shows that the coefficients on German sovereign debt are significantly different only in the lower end of the quantile distribution, and these differences are primarily significant for period 3. In contrast, for period 2 the coefficients on European banks are significantly different from period 1 across the quantile distribution, while the difference is insignificant for period 3. This is the same pattern as we saw in Figure 6.

To further dissect the empirical findings, we perform two specification tests on the outcomes of the quantile regression in equation (5). First, we verify coefficient stability across quantiles (the so-called "slope equality test"), contrasting the coefficients of the median with the coefficients of the upper 90% and 95% quantiles. The null hypothesis is the equality of the quantile regression coefficients at the three quantile levels, and its rejection suggests that the covariates have different impact at different quantiles of the dependent variable. Table 3 reports results for the two dependent variables, Danish Government CDS and Danske Bank CDS, for tests of stability of the coefficients associated with German CDS and European bank CDS in the three periods. In the case of the Danish sovereign CDS, we detect equality across quantiles, thus no effect associated with the change in government policy. The finding is expected, and the government default risk as well as the risks perceived by bond holders are unaffected by the policy change. The results are different for Danske Bank CDS. In the first period the coefficients associated with the three variables are stable across quantiles. For the second period, however, the coefficients for $\Delta \log CDS_t^{DE}$ and $\Delta \log CDS_t^{EU}$ are not stable, and the null is rejected. The evidence is opposite for the third period where the null hypothesis of coefficient stability is not rejected for any variable.

Second, we focus on a test that evaluates the symmetry of coefficients. In particular, this test evaluates if the slopes of the coefficients change when moving from the left side of the median to the right side. Similarly to the previous set of tests considered, we are interested in evaluating if there is an asymmetric response after specific events. The quantile symmetry test is based on 0.05, 0.10, 0.50, 0.90, 0.95 quantiles, and the null hypothesis is symmetry in the impact of the covariates on the dependent variable, i.e., $\beta(0.05) + \beta(0.10) + \beta(0.90) + \beta(0.95) = 4\beta(0.5)$, where $\beta(\tau) = [\beta_{1,\tau}, \beta_{2,\tau}, \ldots, \beta_{N,\tau}]'$ is the vector of parameters at a given quantile. The results reported in Table 3 provide a clear answer: as for the slope tests, the rejections only occur in the second period for the German CDS and European banking CDS.

The change in perceived bailout policy associated with the two defaults increases the idiosyncratic risk of Danske Bank, but if the Danske Bank CDS is in its upper tail, then increases in the German CDS and European banking CDS will affect Danske Bank, as one might expect. For the other two periods, the responses are more uniform across quantiles. Therefore, it seems that the defaults of Amagerbanken and Fjordbank in the second period resulted in a location and scale shift; the recapitalization of Danske Bank restored normality for Danske Bank. Similarly to the slope equality test, we do not note

Danish Sovereign CDS					
	Slope Equality		Symmetry		
	DE	EU	Interc.	DE	EU
P1	0.167	0.074	0.880	0.066	**0.000**
P2	0.923	0.145	0.882	0.302	0.182
P3	0.553	0.930	0.995	0.135	0.869

Danske Bank CDS					
	Slope Equality		Symmetry		
	DE	EU	Interc.	DE	EU
P1	0.319	0.323	0.488	0.201	0.214
P2	**0.019**	**0.000**	0.195	**0.026**	**0.003**
P3	0.206	0.885	0.701	0.098	0.984

Table 3: Quantile regression specification tests (p-values) for slope equality on quantiles 0.50, 0.90, and 0.95 (columns 1, 2 and 3), and symmetry on quantiles 0.05, 0.10, 0.50, 0.90, and 0.95 (columns 4, 5 6 and 7) for the first period (row P1), the second period (row P2), and the third period (row P3). Results in the first panel refer to Danish sovereign (DK) and in the second panel to Danske Bank (DB) CDS with either Germany sovereign (DE) and European banking sector (EU) CDS among the regressors. Bold numbers indicate p-values below 5%.

significant asymmetries in the Danish Government case, apart for the asymmetry to the European banking CDS in the first period.

4 Conclusion

New regulations, such as the proposed "bail-in" clauses in Europe, limit the scope for governments to bail their banks out from financial distress. These regulations are at least partly motivated by the hypothesis that bailouts might fuel sovereign risk and backfire as greater sovereign riskiness weakens banks' balance sheets and thus re-ignites credit risk in the financial sector. We shed light on this channel in a setting where the authorities decided to let distressed banks default and left the main bank to recapitalize privately. Our evidence suggests that the no-bailout policy helped curb the feedback loop between bank and sovereign risk and reduce the exposure of the government to external conditions in the banking sector. This conclusion is based on an indirect testing approach. In particular, the methodology relies on both linear regressions and quantile regressions, where the latter also accounts for possible asymmetries between crisis periods and normal times. We also present quantile regressions as a treatment effect approach. The purpose of this approach is to study whether the new policy was associated with a location shift, a slope shift, or both. The latter turns out to be the case.

Our analysis offers empirical support of regulation policies that limit bailouts of senior debt holders and encourage market based solutions, such as recapitalization. It also provides new tools, based on indirect testing and quantile regressions, to investigate the interplay between sovereign and private banking risks.

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A Additional Figures and Tables

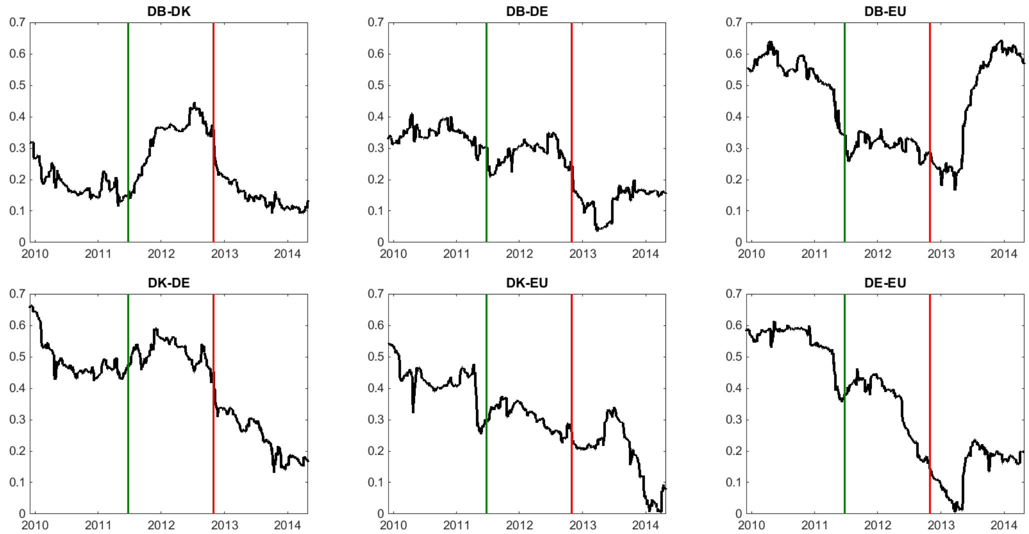

Figure A.1: Rolling correlations (one-year window) between the CDS delta-logs of Danske Bank (DB), Danish Sovereign (DK), Germany Sovereign (DE) and European banking sector (EU). The green line identifies the default of Fjordbank while the red line identifies the recapitalization of Danske Bank.

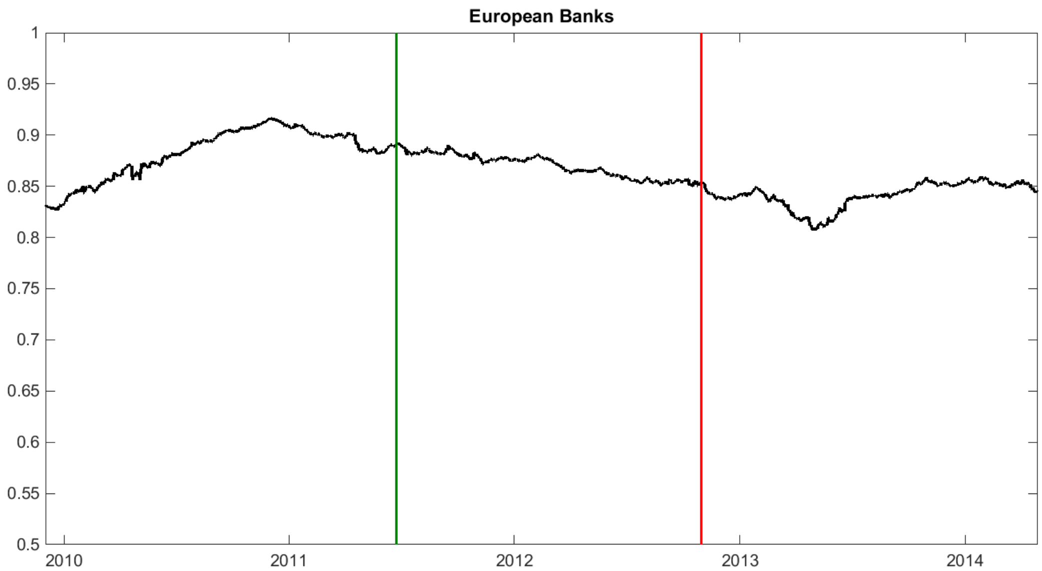

Figure A.2: Rolling total connectedness index (one-year window) between the CDS delta-logs of the 52 largest European institutions. The green line identifies the default of Fjordbank while the red line identifies the recapitalization of Danske Bank. The total connectedness index is computed as in Diebold and Yilmaz (2014), based on a VAR with two lags (p=2) and an horizon of $H = 12$ days for the impulse-response functions.

	α			$\Delta \log CDS_t^{EU}$			$\Delta \log P_t^{EU}$			$\Delta \log CDS_t^{DE}$			$\Delta \log P_t^{DB}$		
	P1	P2	P3	P1	P2	P3	P1	P2	P3	P1	P2	P3	P1	P2	P3
0.05	-0.023^a	-0.019^a	-0.013^a	0.440^a	0.047	0.042	0.063	0.102	-0.393	0.093^a	0.129^a	0.042	-0.277	-0.025	-0.048
0.10	-0.015^a	-0.014^a	-0.008^a	0.282^a	0.018	0.111	0.017	-0.054	-0.146	0.117^a	0.123^a	0.030^b	-0.216^c	-0.068	-0.157
0.15	-0.011^a	-0.011^a	-0.005^a	0.281^a	0.057	0.134^b	0.000	-0.030	-0.091	0.108^a	0.106^a	0.022^c	-0.130	-0.058	-0.176
0.20	-0.009^a	-0.009^a	-0.003^a	0.232^a	0.052^b	0.100^b	0.008	-0.046	-0.105	0.111^a	0.084^a	0.014	-0.085	-0.087	-0.051
0.25	-0.007^a	-0.006^a	-0.002^b	0.211^a	0.059^a	0.078^b	-0.015	0.051	-0.036	0.113^a	0.076^a	0.010	-0.095^c	-0.081	-0.066
0.30	-0.004^a	-0.005^a	0.000	0.148^a	0.062^a	0.024^a	-0.038	-0.006	0.000	0.119^a	0.072^a	0.001	-0.076	-0.068	-0.022
0.35	-0.002^a	-0.004^a	0.000	0.096^c	0.059^a	0.004	-0.046	-0.004	-0.001	0.124^a	0.066^a	0.000	-0.056	-0.076	-0.002
0.40	-0.001	-0.003^a	0.000	0.078	0.045^b	0.001	-0.049	0.008	0.000	0.137^a	0.069^a	0.000	-0.037	-0.065	-0.001
0.45	0.000	-0.002^a	0.000	0.069	0.034	0.000	-0.032	0.031	0.000	0.144^a	0.075^a	0.000	-0.019	-0.053	0.000
0.50	0.000	-0.001^b	0.000	0.075	0.037	0.002	-0.030	0.007	0.000	0.142^a	0.076^a	0.000	-0.011	-0.051	-0.001
0.55	0.000	0.000	0.000	0.071	0.042	0.003	-0.047	-0.009	0.001	0.143^a	0.072^a	0.000	-0.022	-0.057	-0.002
0.60	0.001	0.001	0.000	0.096	0.039	0.005	-0.065^c	0.004	-0.001	0.139	0.080^a	0.000	-0.014	-0.077	-0.002
0.65	0.002^a	0.003^a	0.000	0.122^a	0.026	0.006	-0.093^b	0.004	0.001	0.135^a	0.083^a	0.001	-0.020	-0.110^c	-0.004
0.70	0.003^a	0.004^a	0.000	0.138^a	0.036^c	0.008	-0.135^a	-0.050	0.001	0.131^a	0.082^a	0.000	-0.020	-0.151^a	-0.009
0.75	0.004^a	0.005^a	0.002^b	0.153^a	0.033^c	0.068	-0.167^a	-0.063	-0.021	0.126^a	0.087^a	-0.004	-0.023	-0.168^a	-0.061
0.80	0.006^a	0.007^a	0.004^a	0.179^b	0.039^c	0.059	-0.177^b	-0.095	-0.066	0.125^a	0.095^a	-0.010	-0.017	-0.111	-0.099
0.85	0.010^a	0.010^a	0.006^a	0.239^a	0.057^b	0.137	-0.106	-0.133	-0.177	0.140^a	0.097^a	-0.001	0.033	-0.148	-0.077
0.90	0.016^a	0.013^a	0.009^a	0.254^a	0.041	-0.039	-0.309^b	-0.132	-0.259	0.147^a	0.079^a	0.016	-0.022	-0.122	-0.067
0.95	0.024^a	0.020^a	0.014^a	0.303^a	0.123^a	-0.014	-0.308^c	-0.397^b	-0.395^c	0.080	0.090^b	0.022	0.031	-0.083	-0.112

Table A.1: Quantile regression results for the log changes of the CDS on Danish sovereign bonds across a range of quantiles (first column). See Table 1 for explanatory variables. Significant coefficients are indicated as follows: 1%=a, 5%=b, and 10%=c.

	$\Delta \log HOUSE_t$			LIQ_t			OIL_t			$\Delta \log STOXX_t$			$\Delta \log VSTOXX_t$		
	P1	P2	P3	P1	P2	P3	P1	P2	P3	P1	P2	P3	P1	P2	P3
0.05	0.682	-0.004	1.755	0.061	-0.072	-0.415	-0.047	-0.140	-0.228^{c} c	0.404	-0.234	0.182	-0.315^{c}	-0.053	-0.004
0.10	-1.309	-0.224	1.235	0.001	-0.025	-0.222	-0.046	-0.109	-0.205^{a}	0.170	-0.122	0.255	-0.255^{b}	-0.067	-0.149
0.15	-1.531	0.170	-0.523	0.021	-0.041	-0.078	-0.029	-0.070	-0.185^{a}	0.166	-0.101	0.250	-0.146^{c}	-0.056	-0.169
0.20	-1.433^{c}	-0.955	-0.836	0.020	-0.040	-0.158	-0.024	0.055	-0.125^{c}	0.144	-0.091	-0.029	-0.079	-0.075	-0.052
0.25	-0.945	-0.646	-0.606	0.023	-0.021	-0.094	-0.020	0.042	-0.093	0.119	-0.070	0.017	-0.098^{c}	-0.064	-0.065
0.30	-0.463	-0.357	-0.338	0.016	-0.010	-0.011	-0.014	0.029	-0.024	0.083	-0.080	0.006	-0.079	-0.049	-0.024
0.35	-0.293	-0.656	-0.033	0.007	-0.018	-0.005	-0.009	0.018	-0.004	0.052	-0.070	0.000	-0.054	-0.055	-0.002
0.40	-0.176	-0.804	-0.001	0.000	-0.026	0.000	-0.004	0.016	-0.003	0.028	-0.142	0.000	-0.035	-0.053	-0.001
0.45	-0.114	-0.774^{c}	0.001	0.002	-0.009	0.000	-0.002	0.001	-0.002	0.010	-0.156	0.000	-0.017	-0.045	0.000
0.50	-0.097	-0.832^{c}	0.013	0.002	-0.015	-0.001	-0.001	0.008	-0.002	0.003	-0.107	0.000	-0.007	-0.035	-0.001
0.55	-0.125	-1.033^{c}	0.013	0.006	-0.010	-0.001	-0.002	-0.006	-0.006	0.012	-0.136	0.001	-0.020	-0.034	-0.002
0.60	-0.296	-1.100^{c}	0.018	0.008	-0.010	0.000	0.000	0.007	-0.015	-0.004	-0.109	0.002	-0.010	-0.061	-0.002
0.65	-0.391	-1.099^{c}	-0.014	0.010	0.008	0.005	0.001	0.010	-0.012	-0.002	-0.077	0.004	-0.017	-0.100	-0.004
0.70	-0.504	-1.268^{b}	-0.063	0.007	0.030	0.016	-0.007	0.005	-0.008	-0.027	-0.021	0.016	-0.011	-0.138^{b}	-0.007
0.75	-0.512	-0.984	-1.251	0.013	0.035	0.095	-0.006	-0.008	-0.031	-0.013	0.016	0.132	-0.009	-0.152^{b}	-0.049
0.80	-0.798	-1.361	-1.897	0.017	0.046	0.142	-0.018	-0.056	-0.100	0.019	-0.145	0.163	0.000	-0.116	-0.082
0.85	-0.760	-1.902^{c}	-1.887	0.018	0.060	0.344	-0.052	-0.079	-0.078	0.075	-0.136	0.238	0.071	-0.162^{c}	-0.048
0.90	-2.779	-2.784^{b}	-2.539	0.125	0.087	0.127	-0.087	-0.118	-0.022	0.114	-0.265	0.161	0.013	-0.149	-0.024
0.95	-4.352^{c}	-3.965^{c}	-6.072 c	0.220^{b}	-0.064	0.812	-0.146^{c}	-0.157	-0.048	0.161	-0.330	0.187	0.100	-0.087	-0.087

Continue Table A.1.

	α			$\Delta \log CDS_t^{EU}$			$\Delta \log P_t^{EU}$			$\Delta \log CDS_t^{DE}$			$\Delta \log P_t^{DB}$		
	P1	P2	P3	P1	P2	P3	P1	P2	P3	P1	P2	P3	P1	P2	P3
0.05	-0.046^a	-0.033^a	-0.019^a	0.682^a	0.183^c	0.464^a	-0.245	-0.041	-0.093	0.072	0.060	0.039	-0.160	0.023	-0.274
0.10	-0.030^a	-0.019^a	-0.013^a	0.586^a	0.112	0.406^a	-0.056	0.047	-0.022	0.085^b	0.056	-0.024	-0.222	-0.182	0.080
0.15	-0.019^a	-0.013^a	-0.008^a	0.611^a	0.125^b	0.455^a	-0.092	-0.100	-0.112	0.068^c	0.058^c	0.014	0.020	-0.125	-0.019
0.20	-0.014^a	-0.008^a	-0.006^a	0.560^a	0.074	0.548^a	-0.071	-0.044	-0.028	0.053^c	0.042	-0.005	-0.093	-0.069	0.097
0.25	-0.009^a	-0.005^b	-0.004^a	0.512^a	0.051	0.480^a	-0.010	-0.069	0.024	0.049^b	0.026	-0.004	-0.094	-0.073	0.009
0.30	-0.005^a	-0.001	-0.004^a	0.434^a	0.010	0.456^a	0.007	-0.008	-0.029	0.038^b	0.003	-0.006	-0.102	-0.012	-0.029
0.35	-0.003^a	0.000	-0.003^a	0.411^a	0.003	0.429^a	0.017	-0.001	-0.008	0.026^c	0.002	-0.014	-0.076	-0.006	-0.041
0.40	-0.002^a	0.000	-0.001	0.403^a	0.002	0.405^a	0.011	0.001	-0.023	0.026^c	0.001	-0.009	-0.048	-0.003	0.013
0.45	-0.001^c	0.000	-0.001	0.430^a	0.002	0.408^a	0.015	0.000	-0.020	0.021	0.001	-0.006	-0.030	0.001	-0.012
0.50	0.000	0.000	0.000	0.455^a	0.002	0.388^a	0.018	0.001	-0.027	0.024^c	0.001	-0.002	-0.039	0.000	0.001
0.55	0.001^b	0.000	0.001	0.485^a	0.002	0.384^a	0.004	-0.001	-0.054	0.026^b	0.001	-0.011	-0.026	0.000	0.014
0.60	0.002^a	0.000	0.001^c	0.509^a	0.003	0.364	-0.010	0.001	-0.081	0.026^b	0.002	-0.005	-0.066	0.000	-0.026
0.65	0.004^a	0.001	0.003	0.550	0.020	0.387^a	-0.035	-0.001	-0.045	0.020	0.014	0.002	-0.086	0.008	-0.077
0.70	0.006^a	0.004^a	0.003^a	0.566^a	0.057^c	0.404	-0.086	-0.001	-0.037	0.022	0.031^c	0.000	-0.104^c	0.001	-0.104
0.75	0.008^a	0.006^a	0.005^a	0.586^a	0.068^c	0.416^a	-0.096	-0.011	-0.038	0.027	0.041^b	-0.006	-0.102	-0.041	-0.138
0.80	0.012^a	0.011^a	0.007^a	0.621^a	0.105^b	0.429^a	-0.060	0.011	0.020	0.038	0.063^a	-0.006	-0.084	-0.043	-0.082
0.85	0.019^a	0.017^a	0.009^a	0.617^a	0.138^a	0.422^a	-0.183	0.164	0.062	0.057^c	0.073^b	-0.019	-0.126	-0.189	-0.108
0.90	0.026^a	0.024^a	0.013^a	0.674^a	0.161^a	0.402^a	-0.187	0.152	0.053	0.064	0.105^b	-0.004	-0.053	-0.394^c	-0.048
0.95	0.046^a	0.034^a	0.019^a	0.731^a	0.230^a	0.343^c	-0.815^b	-0.233	-0.308	0.117^c	0.152^a	0.068	-0.244	-0.435^c	-0.251

Table A.2: Quantile regression results for the log changes of the CDS of Danske Bank across a range of quantiles (first column). See Table 1 for explanatory variables. Significant coefficients are indicated as follows: 1%=a, 5%=b, and 10%=c.

	$\Delta \log HOUSE_t$			LIQ_t			OIL_t			$\Delta \log STOXX_t$			$\Delta \log VSTOXX_t$		
	P1	P2	P3	P1	P2	P3	P1	P2	P3	P1	P2	P3	P1	P2	P3
0.05	1.259	-2.585	-7.926^{c} c	-0.046	0.086	0.644	0.317	0.164	-0.026	0.377	-0.012	-0.704	-0.141	0.161	-0.389
0.10	0.523	-2.157	-5.907^{b}	0.038	0.030	0.288	0.177	-0.025	-0.211	0.236	0.086	-0.953^{b}	-0.235	-0.157	0.023
0.15	0.703	-2.242	-3.809^{c}	-0.054	0.037	-0.009	0.059	-0.053	-0.089	-0.086	0.021	-0.525^{b}	0.022	-0.099	-0.026
0.20	0.069	-2.265^{c}	-3.430^{c}	-0.030	0.012	0.161	0.018	-0.113	-0.088	0.108	-0.173	-0.633^{a}	-0.066	-0.067	0.083
0.25	0.076	-1.845^{c}	-2.336	-0.018	0.003	0.353	-0.028	-0.056	-0.038	0.066	-0.088	-0.495^{a}	-0.099	-0.069	0.003
0.30	0.198	-0.161	-1.791	-0.007	0.000	0.360^{c}	-0.024	-0.014	-0.038	0.092	-0.010	-0.430^{b}	-0.106	-0.010	-0.037
0.35	0.153	-0.069	-1.462	-0.001	-0.001	0.324^{c}	-0.035	-0.010	-0.009	0.090	-0.012	-0.356^{c}	-0.072	-0.006	-0.041
0.40	-0.061	-0.049	-1.458	0.010	-0.001	0.249	-0.019	-0.007	0.020	0.055	-0.013	-0.373^{b}	-0.040	-0.003	0.017
0.45	-0.106	-0.003	-1.820	0.013	-0.001	0.206	-0.023	-0.003	0.005	0.056	-0.015	-0.325^{c}	-0.018	0.001	-0.002
0.50	-0.629	0.013	-1.421	0.016	-0.001	0.117	-0.006	-0.002	-0.011	0.091	-0.013	-0.366^{b}	-0.025	0.001	0.010
0.55	-0.939	0.014	-0.622	0.021	-0.001	0.124	-0.017	-0.002	-0.026	0.087	-0.013	-0.363^{b}	-0.009	0.001	0.019
0.60	-1.379^{c}	0.032	1.076	0.024	-0.001	0.141	-0.016	-0.004	-0.049	0.157^{c}	-0.017	-0.272^{c}	-0.041	0.002	-0.021
0.65	-1.498^{c}	0.005	1.506	0.024	-0.004	0.083	-0.005	-0.011	-0.051	0.186^{c}	-0.059	-0.242^{c}	-0.049	0.022	-0.070
0.70	-1.731^{c}	-0.137	1.321	0.032	0.004	0.132	-0.033	-0.037	-0.031	0.192^{c}	-0.147	-0.239^{c}	-0.068	0.034	-0.099
0.75	-2.842^{b}	-0.016	-0.026	0.039	0.022	0.211	-0.078	-0.051	0.044	0.188	-0.101	-0.170	-0.054	-0.010	-0.126
0.80	-3.738^{b}	0.585	-0.641	0.057	0.055	0.054	-0.113^{c}	-0.062	0.097	0.136	-0.226	-0.247	-0.035	-0.034	-0.065
0.85	-3.754	1.022	-0.569	0.080	0.092	0.129	-0.092	-0.086	0.168	0.251	-0.185	-0.337	-0.067	-0.190	-0.114
0.90	-7.551^{b}	-0.603	-2.946	0.109	0.180^{c}	0.255	-0.110	-0.039	0.319	0.284	0.014	-0.466^{c}	0.013	-0.453^{b}	-0.064
0.95	-8.724^{b}	-0.632	-3.497	0.143	0.250^{c}	0.404	-0.262	-0.238	0.426	1.093^{c}	0.026	-0.290	-0.074	-0.506^{c}	-0.288

Continue Table A.2.