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Do information contagion and business model similarities explain bank credit risk commonalities?

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Abstract

This paper revisits the credit spread puzzle for banks from the perspective of information contagion. The puzzle consists of two stylized facts: Structural determinants of credit risk not only have low explanatory power but also fail to capture common factors in the residuals. We reproduce the puzzle for European bank credit spreads and hypothesize that the puzzle exists because structural models ignore contagion effects. We therefore extend the structural approach to include information contagion through bank business model similarities. To capture this channel, we propose an intuitive measure for portfolio overlap and apply it to the complete asset holdings of the largest banks in the Eurozone. Incorporating this unique network information into the structural model increases explanatory power and removes a systemic common factor from the residuals. Furthermore, neglecting the network likely overstates the importance of structural determinants.

Keywords: Information contagion, credit spread puzzle, bank business model similarities, portfolio overlap measure, dynamic network effects model.

JEL classifications: G01, G21, C32, C33, C38.

1 Introduction

In this paper, we show that similarities between bank business models constitute an important determinant of how markets value bank default risks. Market participants adjust their credit risk exposures to distressed banks using instruments such as credit default swaps (CDS). A bank's CDS price, therefore, reflects its default risk as it is perceived in the market.[1] In the empirical asset pricing literature, the credit spreads of corporates or banks are mainly modeled using company fundamentals and other structural variables, such as equity returns, the risk-free rate, market volatility, or the slope of the yield curve. However, the seminal paper by Collin-Dufresne et al. (2001) and the subsequent empirical work of Bharath and Shumway (2008); Campbell and Taksler (2003); Ericsson et al. (2009); Fontana and Scheicher (2016) and Zhang et al. (2009) show that structural models have low explanatory power and leave a systematic common factor unexplained. The lackluster performance of variables grounded in economic theory, such as the Merton (1974) model, is commonly referred to as the *credit spread puzzle*. Our main contribution is an empirical framework that suggests an answer to the puzzle by including information contagion into conventional models.

Adopting a network perspective uncovers an intricate relationship between the puzzle and financial contagion. Taken at face value, the structural approach suggests that bank credit risk can only be influenced by bank-specific or system-wide factors. This is challenged by findings of the systemic risk literature, which suggests that contagion can amplify shocks to individual banks by spreading them to other banks. In the presence of contagion effects, it therefore comes as no surprise that the structural model framework systematically misprices the observed credit spreads. Once we allow the credit spread of other relevant banks to inform prices as well, the common factor vanishes and the explanatory power of the structural coefficients is weakened. In other words, the puzzle is bound to occur if credit risk is priced only with respect to idiosyncratic and systematic determinants.

With the purpose of modeling contagion effects in mind, we introduce a network extension to the standard model. The network's nodes represent banks and its edges the relevance to each other's credit spreads. Our key assumption is that banks with similar asset holdings likely follow similar business models and are therefore perceived to be informative about each other. We propose an intuitive measure that establishes the portfolio overlap structure between multiple banks. Its distinguishing feature is that it quantifies one-to-many relationships, rather than one-to-one. More concretely, instead of measuring the similarity of two banks in an isolated fashion, we assess their overlap while considering all other banks in the system. The underlying dataset of bank holdings consists of more than

[1] CDS spreads represent a more accurate measure for credit risk compared to corporate bond yield spreads over a risk free rate (Ericsson et al., 2009). Moreover, Jorion and Zhang (2007) highlight the informational advantage of corporate CDS spreads over stock prices in studying credit contagion.

240,000 unique security identifiers, covering holdings of around €3.2 trillion (ECB, 2015).[2] Applying our method to the complete security holdings of the Eurozone's largest banks grants us new insights into the network structure of the European banking sector.

Our findings can be summarized as follows: We first take a structural approach without networks and replicate the puzzle for CDS spreads of the 22 largest banks in the Eurozone. Surprisingly, in addition to the systematic common factor, the regression residuals also contain an uncaptured factor that distinguishes between the Northern countries (Austria, Belgium, France, Germany and Netherlands) and Southern countries (Italy and Spain). We then construct the network of business model similarities based on portfolio overlaps. Embedding it into the structural regression reveals two novel effects: *structural network effects*, which take place if one bank's CDS changes are affected by another bank's structural credit determinants; and *residual network effects*, which allow idiosyncratic shocks to be correlated according to the network structure. Taking these effects into account allows us to address the two stylized facts of the credit spread puzzle. First, structural network effects increase the share of explained variance by up to 13.4%, on average. Second, the residual network effects greatly reduce the importance of the uncaptured systematic common factor and remove its system-wide nature, while also stripping the dividing characteristic off the North-South factor. Furthermore, most of the structural regression coefficients lose statistical and economic significance while others, such as volatility, gain in importance. These findings indicate that neglecting network effects likely misrepresent the relevance of structural regressors in the extant literature.

Information contagion in banking networks

As the 2008 great financial crisis painfully demonstrated, a bank's financial health may strongly depend on the health of other banks. The financial stability literature studied credit risk with networks and financial contagion occupying center stage (Glasserman and Young, 2015). This literature stresses that banks are part of an interconnected network where risks can cascade throughout the system. Banks thus cannot be analyzed in isolation; rather, they must be understood in relation to other banks.[3] In their seminal contributions, Allen and Gale (2000) model the direct lending exposure between banks wherein the lending relationships determine relevancy. In this set-up, a bank's default risk depends on the banks it has loaned money to. If the borrowing banks face liquidity problems, these problems will ultimately impact the lender. If the lender, in turn, has borrowed money from other banks, distress is passed on along the chain.

In contrast, banks with common asset holdings become the relevant set when contagion is driven by fire-sales. In the model presented by Cifuentes et al. (2005), banks facing sudden

[2] To the authors' knowledge, our analysis is currently the second paper cleared for publication that makes use of the Securities Holdings Statistics on the group level (cf. Hüser et al. (2017)).

[3] In highly interconnected financial systems, idiosyncratic shocks affecting one player's assets may quickly spill over to others, generating systemic risk, see, for instance, Billio et al. (2012), Demirer et al. (2018), Hautsch et al. (2015), Betz et al. (2016) and Blasques et al. (2018).

liquidity needs sell illiquid assets to satisfy capital requirements. The resulting downward price pressure can impact other banks with the same illiquid asset on their books, triggering another round of asset sales, and so on. Duarte and Eisenbach (2018) assess the vulnerability of a bank based on its share of holdings in illiquid, systemic assets. They isolate fire-sale spillovers as the cross-sectional aspect of aggregate vulnerability. This is consistent with the fire-sale framework of Greenwood et al. (2015), who study the indirect vulnerability of banks following the deleveraging of other banks.

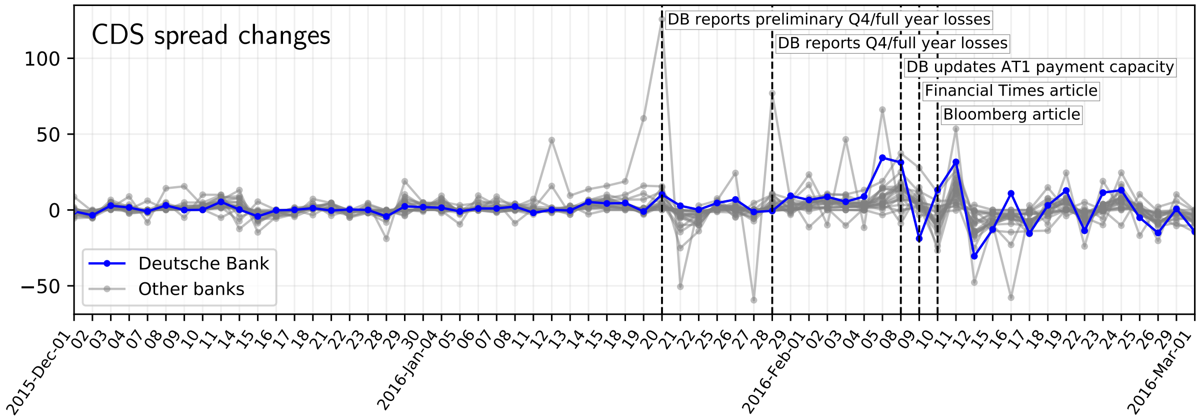
In addition to the mechanisms discussed above, information contagion is based on perceptions, reputations and beliefs. The underlying assumption is that signals about one bank's financial health may not only be informative about that bank's default risk; the signal may also lead to the reassessment of another bank's credit risk. Acharya and Yorulmazer (2008) demonstrate how, when a systematic common factor exists in loan returns because of investments in similar industries, bad news about one bank can be informative of the common factor and, in turn, lead to higher borrowing costs of another bank. If the common factor is less prevalent, then the costs can increase even more because the signal is (relatively) more informative, incentivizing banks to hide in the herd and invest in similar industries. This argument becomes one justification for Ahnert and Georg (2018), who also find that bad news about one bank can be informative about another bank with common exposures, leading to higher overall systemic risk.[4]

To understand the credit risk contained in bank CDS spreads, we argue that structural credit spread models need to account for information contagion. That is, the market's view on a bank's creditworthiness not only depends on its own fundamentals; it also depends on the creditworthiness of other banks. The turmoil following Deutsche Banks (DB) profit warnings in February 2016 serves as a prime example (Figure 1). DB reported a net loss of EUR 2.1 billion for 2015Q4 and EUR 6.8 billion for the full year. In the following weeks, CDS spreads of not only DB but also many other large European banks increased sharply, reflecting a growing concern of investors over the health of European banks in general (Kiewiet et al., 2017). This spread of market unrest is likely due to information contagion, since other European banks did not experience any structural changes during that brief period. Instead, the change in a bank's credit spread might be better explained by a spread change of another bank, which the market deems to be similar enough to be relevant. How relevant that other bank is, depends on how similar the market perceives their businesses to be. For instance, when markets price the CDS of a German savings bank, they are more likely to factor in the spread of other German savings banks than of, say, French investment banks. This story might reverse, however, when markets are instead concerned with the

[4]Furthermore, Slovin et al. (1999) study the externalities in the banking sector following major adverse bank announcements. They find contagion-type effects related to the information contained in dividend reduction announcements of money center banks. A related effect is highlighted by Morrison and White (2013) who study reputational contagion through common regulators. The failure of a bank lowers the perceived quality of the responsible regulator. This signal, in turn, could trigger a run on the other banks that are under the same regulator's umbrella.

Figure 1: Deutsche Bank turmoil in early 2016

This plot depicts the situation surrounding the turmoil due to the loss warnings of Deutsche Bank (DB) regarding Q4 and the full year of 2015. On Jan 20, 2015, DB issued a preliminary results, followed by the full report on Jan 28. As a response to investor concerns, DB updated its payment capacity for Additional Tier 1 coupons on Feb 8. Subsequently, major news outlets published articles relating to DB's situation and spreading market uncertainty.



credit risk of a German investment bank. Thus, business model similarities determine the potential for information spillovers, which do not necessarily align with country borders or bank type classifications.

Bank business model similarities through portfolio overlap

Identifying bank business models, therefore, has been an important goal for both supervisors and academics. A recent study by Cernov and Urbano (2018) highlights the importance and challenges of measuring these similarities for financial stability. These measures are crucial for assessing an institution's riskiness with respect to its peers and for studying the possible impact of new regulations. Methods to group bank business models either rely on quantitative clustering methods, such as k-nearest neighbors, or on qualitative assessments based on bank activities, legal structures, or expert knowledge.

Since business models themselves are abstract and hard to quantify, we focus our attention on bank portfolios instead. A bank's portfolio composition is an observable, numerical characteristic of its business model. Because they have made similar investment, lending, or funding decisions in the past, banks that follow similar business models usually share similar balance sheet structures (Roengpitya et al., 2014, 2017; Lucas et al., 2018; Nucera et al., 2017). For instance, banks adapt their overall strategies and balance sheets to comply with new regulatory environments (Cernov and Urbano, 2018). Similarly, the fire-sale literature studies the implications of the link between asset holdings and business model strategies.

Most relevant to our work, Allen et al. (2012) model information contagion through asset commonalities of banks. The portfolios of banks are the result of a network formation game and the intensity contagion is directly linked to the degree of portfolio overlap the banks share. Coval and Stafford (2007) argue that investors following similar strategies end up with portfolios that are concentrated in similar securities. Thus, they explain, if a bank liquidates its assets in a fire-sale then other banks with similar asset exposures will likely be affected. Hence, only strategy-outsiders are able to absorb these shocks while insiders are vulnerable to each other (Shleifer and Vishny, 1992). Consequently, we consider banks potentially relevant for each other if they share large portfolio overlap.

The remainder of this paper is structured as follows. We first define the baseline model and analyze the credit spread puzzle in the Eurozone. In Section 2, we construct the portfolio overlap measure as a proxy for bank similarities. In Section 3, we derive the Network Effects (NE) model and the Dynamic Network Effects (DNE) model as extensions to the structural regression model. Sections 4 and 5 present the empirical results for the NE and DNE models, respectively, before we conclude.

2 The credit spread puzzle in the Eurozone

In this section we reproduce the credit spread puzzle for the 22 largest banks or banking groups in the Eurozone. These results represent our baseline and set the stage for our subsequent network extension. Our empirical strategy follows the structural approach of Collin-Dufresne et al. (2001) and subsequent authors, who specify a linear structure for CDS spread changes. Since the puzzle was originally studied for U.S. corporate bond spreads, we adapt the set of explanatory variables for the European banks (Fontana and Scheicher, 2016). The banks are located in seven countries: Austria, Belgium, France, Germany, Italy, Netherlands, and Spain.[5] Consequently, the set of structural regressors can be divided into three layers: 1) Europe-wide, 2) country-wide, and 3) bank-specific. Variables included are, amongst others, the slope of the yield curve, stock market performance and leverage (see Table 1). Our analysis spans the period from January 01, 2014, to June 30, 2016, yielding 633 observations. We use the daily 5-year senior, full-restructuring CDS spreads for the dependent variable, as they are the most commonly traded credit derivative contract (Augustin et al., 2014).[6]

Our baseline model stipulates that the credit spread changes are generated by the following linear structure

$$\begin{aligned} \Delta CDS_{i,t} = {} & \gamma_i^1 eurostoxx50_t + \gamma_i^2 \Delta slope_t^{EU} + \gamma_i^3 \Delta vstoxx_t \\ & + \delta_i^1 eqidx_t^C + \delta_i^2 \Delta bond10y_t^C + \delta_i^3 \Delta slope_t^C \\ & + \theta_i^1 eq_{i,t} + \theta_i^2 lev_{i,t} + const_i + e_{i,t}, \qquad \text{with} \quad e_{i,t} \sim N(0, \sigma_i^2). \end{aligned} \tag{1}$$

[5] To maintain confidentiality, we present results for Austria and Germany together as "AT, DE" and Belgium and Netherlands as "BE, NL". For more details on the group structure and country abbreviations, see Table 2 in the Appendix.

[6] See Ericsson et al. (2009) for the advantages of using CDS spreads over calculated credit spreads.

Table 1: Data on independent variables

Variable	Description	Frequency
Europe-wide		
$eurostoxx50$	Log-returns of EuroStoxx50	Daily
$slope^{EU}$	10-year Euro swap rate minus 3-month EURIBOR	Daily
$vstoxx$	EuroStoxx50 Volatility (VSTOXX)	Daily
Country-wide		
$eqidx^{C}$	Log-returns of equity indices (ATX, BEL20, DAX, IBEX35, CAC40, FTSE MIB, AEX)	Daily
$bond10y^{C}$	10-year sovereign bond yield	Daily
$slope^{C}$	10-year minus 2-year sovereign bond yields	Daily
Bank-specific		
eq	Log-differences of stock prices, if available (see Table 2)	Daily
lev	Leverage ratio ($Tier1\ captial_{i,t}/Total\ exposure\ measure_{i,t}$)	Quarterly*

*We interpolate the quarterly data to match the daily frequency of other regressors.

Note that this yields N times K bank-specific regression coefficients and that the covariance matrix is heteroskedastic with $\Sigma = \text{diag}(\sigma_1^2, ..., \sigma_N^2)$. Furthermore, the empirical application also includes lagged versions of dependent and independent variables.[7]

2.1 Empirical evidence

Table 3 presents the regression results of the linear baseline model. Due to confidentiality reasons, we present the results as group averages. We also present the anonymized regression coefficients in density plots of Figure 6 and the associated p-values in the histograms of Figure 17 (Appendix).

For Europe-wide regressors, we find that the sign and magnitude of the group averages are mostly homogeneous. In line with previous research, higher equity returns and proxy for the yield curve slope are associated with lower credit spreads while the opposite holds for volatility indicators.[8] For country-specific regressors, the group averages are more heterogeneous. Once again, we rediscover a North-South division where Italian and Spanish bank spreads respond similarly to their countries' 10-year bond yields and yield curve slopes, while the Austria, Belgium, France, Germany and Netherlands point to the opposite direction. For the bank-specific regressors, the (lagged) equity returns are consistently negative. The constant is insignificant for all banks. The lack of significance for leverage is likely explained by its interpolated nature due to its low reporting frequency.

Furthermore, we confirm the two stylized facts of the credit spread puzzle: the group R^2 values range from 28.3% (Austria, Germany) to 48.5% (Italy) with an total average of

[7] We explored other variables such as sector-specific equity indices or Eurozone interbank lending rates, country-specific volatility proxies. The empirical results remain qualitatively the same.

[8] Note that the parentheses of Table 3 contain average p-values for each group and hence cannot used directly for the rejection of the null hypothesis.

36.5%. These values are slightly higher than what Collin-Dufresne et al. (2001) found for U.S. corporate bonds. To determine whether this indicates a good model performance we turn our attention to the residuals. In Figure 3, demonstrates that this is not the case, since we find a systematic common factor across all banks. This factor alone explains 35.63% of the residual variance, while the first four components together make up 53.02%. Interestingly, the second component seems to capture country-specific effects, even though the regression model already includes country-specific regressors. Upon closer inspection, the component draws a line between Northern and Southern Eurozone members. Thus, this component curiously reflects a North-South divide that is not a feature of the country-specific regressors. Fontana and Scheicher (2016) find a similar division for European sovereign CDS spreads.

2.2 Absence of credit contagion

These findings make intuitive sense from the perspective of credit contagion. The linear structure of the baseline model leaves little room for contagion effects between banks and countries. Changes in a bank's credit risk can only be due to bank-specific, country-wide or Europe-wide determinants. This means, however, that commonalities between banks within or across country borders, are left for the residuals. The North-South factor we find belongs to this category.

The absence of contagion effects between banks also provides an explanation for the systematic common factor. As the Collin-Dufresne et al. (2001) concluded, the systematic factor withstands a host of explanatory variables in their "kitchen sink" approach. This is consistent with the contagion perspective, since the additional variables still belong to the three layers of credit determinants. In contrast, once we allow for contagion effects, credit risk may propagate across banks and countries, which can ultimately reach systematic proportions.

In the following sections, we propose a network extension to the structural approach. The network reflects our assumption that banks are more likely to pass on credit risk to institutions with similar business models. This introduces a channel for credit contagion that lies between the three layers of structural credit spread determinants.

Figure 2: Regression results of baseline model

Each plot depicts the estimated baseline coefficients as density plots. The thin black lines mark the value of each regression coefficient from equation 1. The triangles locate the average coefficient value.

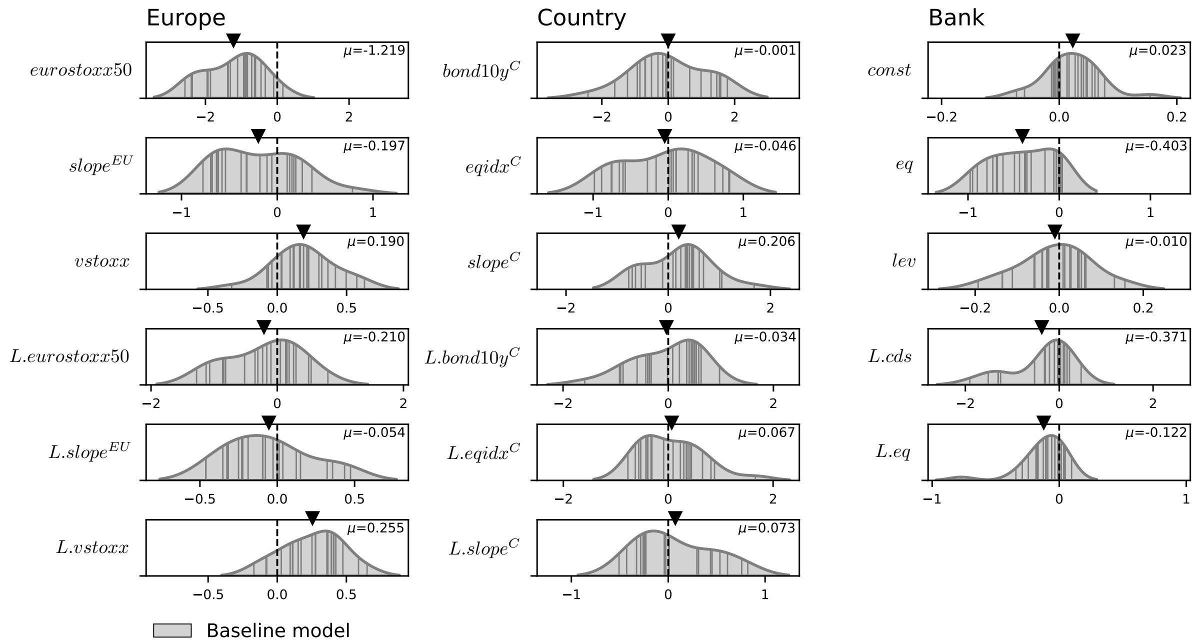
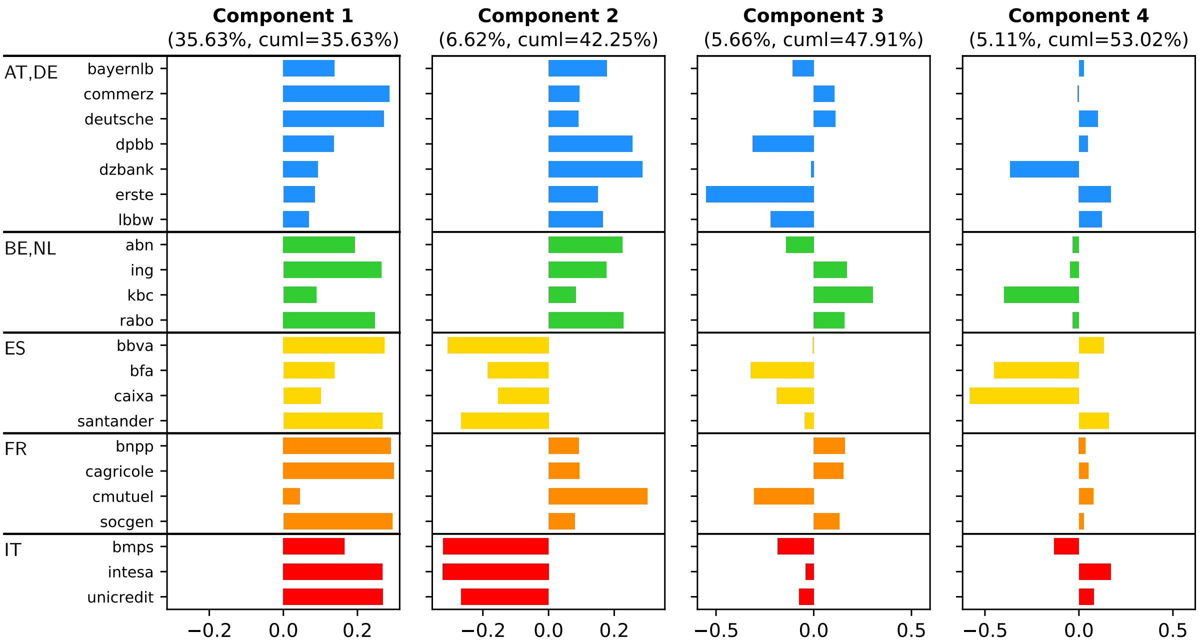


Figure 3: Principal components analysis of baseline residuals

This graph presents the coefficients of the four largest principal components of the baseline model residuals. We see that the first component is a systematic factor that affects all banks. Furthermore, the second component is a North-South factor that assigns positive values to Austria, Belgium, Germany, France, Netherlands and negative values to Italy, Spain.



3 Network of bank similarities

The systemic risk literature has extensively studied channels of contagion, such as portfolio overlap and common asset exposures, especially in the context of fire-sales. While portfolio overlap are important in our model, their main purpose is to model information contagion due to similar business model, not to capture actual fire-sales. However, if the market believes that one bank is vulnerable to another bank's rapid deleveraging efforts, then this belief would again constitute information contagion. The systemic risk literature is therefore closely related and highly relevant. For instance, Wagener (2010) highlights that, although portfolio diversification is desirable for individual institutions, it is dangerous on a macro level as it increases portfolio overlap among banks and therefore exposes them to the same risks. Similarly, Caccioli et al. (2014) study a network model with overlapping portfolios and leverage. In their model, a system may become unstable if a critical threshold for leverage is crossed, resulting in system-wide contagion. Finally, Cont and Schaanning (2018) use portfolio overlap to quantify a bank's mark-to-market losses resulting from the deleveraging decisions of another bank. Other studies provide empirical models that can be used for stress-tests. Greenwood et al. (2015), for example, study how banks that are seemingly unrelated can contaminate other banks because of indirect vulnerabilities to deleveraging externalities. They estimate their model with balance sheet data from the European Banking Authority. Finally, Poledna et al. (2018) propose a systemic risk measure that relies on portfolio overlap, which they calculate using the complete security holdings of major Mexican banks.

We develop a regression-based overlap measure that quantifies partial correlations between portfolio structures.[9] Intuitively, our measure asks how much the knowledge of one bank's portfolio helps in predicting the contents of another bank's portfolio, relative to all remaining banks. For instance, the measure would assign a high overlap between two German Landesbanken and a low overlap between a Landesbank and some other bank type. This captures the fact that the holdings of one Landesbank is likely to be much more predictive of another Landesbank's holdings, compared to banks that follow an entirely different business model. Our proposed measure has three distinct properties:

Property 1: Non-negativity. The measure is either zero when banks have no assets in common or positive if they share at least one asset. A negative overlap has no economic interpretation.

Property 2: Relativity. The measure varies with banks and assets in the system. A bank with high overlap with all other banks may lose its central position once we include new banks and/or new assets.

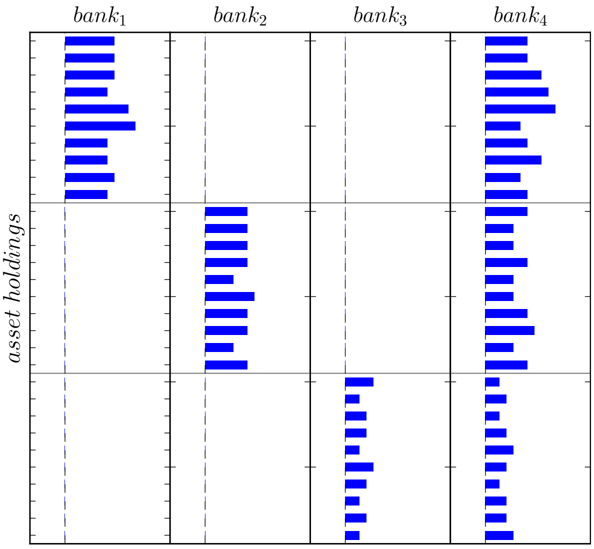
[9] These correlations do not refer to correlations between the portfolios returns. Instead, we are interested in how similar portfolios are in structure, i.e. whether the portfolios contain the same types and quantities of securities. This is partly motivated by the fact that banks' portfolios contain many securities for which price information is patchy. Conventional price correlation measures ignore such exposures.

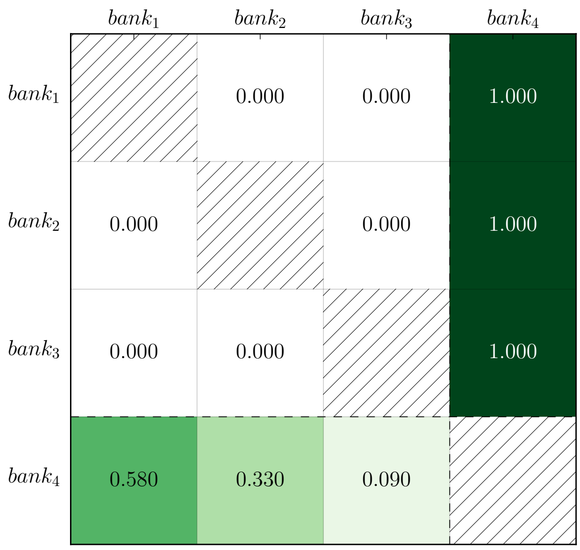
Property 3: Asymmetry. If a bank holds a portfolio and all other banks only hold partitions thereof, then that bank can have a larger overlap with regards to one of the other banks than vice versa.

We define the overlap measure $\mu_{i,j}$ between banks i and j for a system $B = \{bank_1, ..., bank_N\}$. Each $bank_i$ holds a portfolio of assets that is represented by a random vector in an L-dimensional asset space. In the remainder of this section we derive the overlap measure. We start with the overlap between two banks and extend the concept for N banks.

Figure 4: Hypothetical financial sector with four banks

This hypothetical example shows how the asset holdings of a banking system translate into a portfolio overlap network. Left: A financial system with four banks and 30 assets. Each column represents a bank portfolio and the blue bars indicate the amount a banks holds of a certain asset. Right: The portfolio overlap matrix W that results from applying Algorithm 1 to the asset holdings on the left panel. We can see that the W is asymmetric and row-normalized.





3.1 Derivation

It is instructive to begin with a system with two banks $B = \{bank_i, bank_j\}$. An obvious candidate for the overlap measure is the correlation coefficient between both vectors of observed holdings, $\mu_{i,j} = \rho_{i,j} = \text{corr}(bank_i, bank_j)$. Although this choice is intuitive and simple, it can violate the desirable non-negativity property.[10] As a remedy, we take the squared correlation coefficient. This is, in fact, the R^2 from a simple regression of $bank_i$ on $bank_j$ with no constant. The overlap measure is then $\mu_{i,j} = \rho^2_{i,j} = R^2$, which is, by definition, always non-negative.

$$bank_i = bank_j\beta + u_i.$$

[10]For example, if $bank_i = [1, 1, 1, 0, 0, 0]$ and $bank_j = [0, 0, 0, 1, 1, 1]$, the correlation is exactly -1. For a more elaborate example, consider the hypothetical system in the Appendix. The correlation between $bank_4$ and $bank_5$ would violate the non-negativity property as well, since $\rho_{4,5} = \text{corr}(bank_4, bank_5) < 0$.

In a general system with N banks $B = \{bank_1, ..., bank_N\}$, a natural extension is to calculate $\mu_{i,j}$ for all i and j pairs. However, this approach results in symmetric overlap measures, that is $\mu_{i,j} = \mu_{j,i}$. But symmetry is not desirable if the ultimate purpose of the measure is to capture information contagion among banks. To illustrate, consider the hypothetical system with four banks in Figure 4, left panel. For this illustration, we abstract from the effects of exogenous credit spread determinants. If we observe a drop of $bank_1$'s credit spread, then this drop can only be due to information spillover from $bank_4$. At the same time, if we observe a deterioration of $bank_4$'s creditworthiness, this information spillover can be partly ascribed to each of the other three banks. Symmetry would imply that both cases are informationally equivalent, which is not the case. For a more concrete example for why symmetry is undesirable, recall that perceived vulnerability to fire-sales also constitutes a type of information contagion. Clearly, $bank_4$ is most central as its portfolio shares common assets with all other banks while the other banks' portfolios only hold partitions of $bank_4$. If $bank_4$ suddenly needs to raise money, it could be a knock-on effect from either of the other banks liquidating their assets in a fire-sale. Conversely, if one of the other banks has to liquidate its assets, this portfolio adjustment can only be due to deleveraging efforts of $bank_4$. Asymmetry is therefore a crucial property of the overlap measure and differs from other proposed measures, such as Cont and Schaanning (2018).

Returning to the derivation, the coefficient of determination serves as a useful starting point for constructing such an asymmetric measure. Similar to the two-bank situation, we can calculate the R_i^2 from a multiple regression of each $bank_i$ on all remaining banks,

$$bank_i = \sum_{j \neq i} bank_j \beta_j + u_i.$$

This coefficient R_i^2 measures how well $bank_i$'s portfolio is *jointly* explained by the portfolios of all other banks. However, we are interested in the individual contributions of the banks on the right-hand side. A decomposition of the R_i^2 into $N-1$ separate *partial*-$R_{i,j}^2$ would reflect the *relative importance* of $bank_j$ in explaining $bank_i$, compared to its peers. Denoting the decomposition function with d, we have $d(R_i^2) := [R_{i,1}^2, ..., R_{i,j}^2, ..., R_{i,N}^2]$. Note that we define a bank's overlap with itself as zero, $R_{i,i}^2 = 0$. These partial-R^2 capture the essence of our portfolio overlap measure. They are, by construction, non-negative; allow the overlap measure to be asymmetric; and depend on which banks and assets are considered in their calculation.[11] To compute the overlap relationships for the entire system, we repeat this exercise for all banks. Each repetition yields a row vector of partial-R^2. Stacking these results in the portfolio overlap matrix W.

[11] While R^2 decomposition is not a trivial task, the statistical literature on relative importance and variable selection has proposed several methods for it. We refer the reader to the Appendix for the algorithm and accompanying technical discussion of our overlap measure.

$$W := \begin{bmatrix} d(R_1^2) \\ \vdots \\ d(R_i^2) \\ \vdots \\ d(R_N^2) \end{bmatrix} = \begin{bmatrix} [\, 0 & \cdots & R_{1,j}^2 & \cdots & R_{1,N}^2 \,] \\ & \vdots & & \vdots & \\ [R_{i,1}^2 & \cdots & 0 & \cdots & R_{i,N}^2] \\ & \vdots & & \vdots & \\ [R_{N,1}^2 & \cdots & R_{N,j}^2 & \cdots & 0 \,] \end{bmatrix} \tag{2}$$

To calculate the portfolio overlap network according to Algorithm 1, we use the reported holdings data from the Securities Holdings Statistics (SHS). This data is reported on a quarterly basis and covers each of the 22 banks' holdings in about 240,000 unique securities, identified by their International Securities Identification Number (ISIN). For confidentiality reasons, the networks cannot be shown here. The networks experience only slight variations between quarters and have many within-country but few between-country overlap.

4 Analytical framework

Now that we have established an empirical measure of the underlying similarity network, we return to the original task of finding a potential answer to the credit spread puzzle. Our econometric model extends the structural regression model of Collin-Dufresne et al. (2001) with network effects. The main difference is that we do not only regress a bank's CDS changes on structural variables; we also regress on a weighted average of CDS changes of all other banks in the system. The weights correspond to the similarity a bank shares with all other banks, as derived in the previous section. A scalar parameter determines the importance of these added network effects. We interpret this parameter as network intensity. If the intensity is zero, the model reverts back to the structural regression model where banks are independent. Otherwise, information contagion takes place and CDS prices become functions of one another, depending on their similarities. This functional dependency holds for all CDS contracts, such that information can spillover from bank to bank. To ensure that this spillover process converges, we assume that its effect attenuates with each round. The speed of convergence is determined by the network intensity parameters.

We model these rounds as successive linear transformations with the portfolio overlap network W.[12] This iterative nature imitates the learning or price discovery process studied in the financial literature, where traders act under bounded rationality and imperfect knowledge. Most relevant to our work, Routledge (1999) shows how information diffusion based on adaptive or evolutionary learning across multiple periods can lead to a Grossman and Stiglitz (1980) type rational equilibrium. The success of this process crucially relies on the monotonic selection dynamic, where traders imitate better strategies more frequently than bad ones. Viewing the financial market as a complex system, Hommes (2008) studies

[12] This transformation matrix can be understood in the same manner as the input-output matrix from the Leontief model. Instead of sectors producing goods by combining goods from other sectors, our outputs are CDS prices resulting from the weighted combinations of other CDS prices.

bounded rational traders that improve their strategies either with adaptive learning or evolutionary selection. Using a simple cobweb model, he shows that the market price can converge to the rational expectations equilibrium in both cases.

In this section, we construct a framework that embeds the network W into established credit spread models. While the baseline model (1) analyzes the credit spread of each bank individually, the network approach takes a holistic view of the system. In other words, the CDS spreads of the banks are priced jointly. We therefore stack the N equations and collect all K regressors into one regressor matrix:

$$y_t = X_t\beta + e_t, \qquad \text{with} \quad e_t \sim N(0, \Sigma). \tag{3}$$

We first introduce extensions with constant network effects and later on, introduce time-variation in these effects.

4.1 Network effects model

As discussed in the introduction, we distinguish between two types of network effects, namely *structural network effects* and *residual network effects*. Correspondingly, we embed the same network W into the baseline model (1) in two ways.

Structural network effects refer to changes in one bank's credit risk that are due to changes in a neighboring bank's credit risk. To incorporate this effect, we extend the baseline model (1) by allowing $y_{i,t}$ to be influenced by other $y_{j,t}$:

$$y_t = \rho W y_t + X_t\beta + e_t. \tag{4}$$

Here, $\rho \in (-1, 1)$ is the *structural network intensity*. If $\rho = 0$, the structural network effects model (4) reverts back to the baseline (1). The overlap matrix W is calculated according to Algorithm 1, described in the Appendix. By repeatedly inserting (4) into itself, it becomes clear how information spillovers happen through W.

$$\begin{aligned} y_t &= \rho W y_t + X_t\beta + e_t \\ &= \rho W(\rho W y_t + X_t\beta + e_t) + X_t\beta + e_t \\ &= \rho W(\rho W(\rho W y_t + X_t\beta + e_t) + X_t\beta + e_t) + X_t\beta + e_t \\ &= \cdots = \lim_{m\to\infty} \sum_{n=1}^{m} [\rho W]^n (X_t\beta + e_t) \end{aligned} \tag{5}$$

The process in equation (5) converges to a fixed point if the largest eigenvalue of ρW is smaller than one in absolute value. Since W is row-stochastic by construction, its largest eigenvalue is exactly equal to one and, therefore, the invertibility condition reduces to

$|\rho| < 1$. In this case, we can express the model in explicit form.

$$\begin{aligned} y_t &= (I_N - \rho W)^{-1} X_t \beta + (I_N - \rho W)^{-1} e_t \\ y_t &= Z X_t \beta + Z e_t \\ y_t &= Z X_t \beta + \epsilon_t \qquad \text{with} \quad \epsilon_t \sim N(0, Z \Sigma Z^\top) \end{aligned} \tag{6}$$

Here, $Z = (I_N - \rho W)^{-1}$ is the structural network component. Note that it affects both regressors and errors. We also define the reduced form errors $\epsilon_t = Z e_t$ as *dirty* model errors, as their covariance matrix $Z \Sigma Z^\top$ is not diagonal. This differentiates them from *clean* model errors e_t.

Economic interpretation The last line in equations (5) contains the keystone of our model: In the limit, the endogenous structure vanishes and the dependent variable can be isolated from the independent variables. Economically, this model stipulates that the observed CDS prices are the *consensus* prices of the market participants. This consensus finding process is driven by the information contagion about the underlying banks. The course of the spillover process is determined by the portfolio overlap network W, while its duration is controlled by the network intensity ρ. Thus, (4) stipulates that one bank's CDS price depends on the CDS prices of its peers. But if we follow this logic to the end, then the price in (6) ultimately depends on both the exogenous credit determinants of its peers and their idiosyncratic errors.

This has two important implications. First, this framework establishes a channel between one bank's credit risk and another bank's credit determinant. Secondly, even though the clean model errors e_t are independently distributed with diagonal covariance matrix Σ, the dirty model errors ϵ_t are 'tainted' from the contagion process and have a covariance structure $Z \Sigma Z^\top$. This relaxes the independence assumption of the baseline model and introduces heteroskedasticity and cross-correlations among idiosyncratic bank shocks. At the same time, since the covariance structure is determined by the similarity matrix W, we can decompose the estimated covariance matrix into a network component $\hat{Z}$ and the cleaned error component $\hat{\Sigma}$.

Residual network effects While structural network effects introduce contagion into both regressors and residuals, the residual network effects model only does so for the latter. This specification is therefore well-suited to capture contagion effects that are not driven by structural determinants, such as during times of market stress. To differentiate between both effects, we use λ to denote the residual network intensity.

$$y_t = X_t \beta + u_t \qquad \text{with} \quad u_t = \lambda W u_t + e_t \tag{7}$$

Under the condition that $|\lambda| < 1$ we can write the model into explicit form.

$$\begin{aligned} y_t &= X_t\beta + (I_N - \lambda W)^{-1} e_t \\ y_t &= X_t\beta + \Lambda e_t \\ y_t &= X_t\beta + \epsilon_t \qquad \text{with} \quad \epsilon_t \sim N(0, \Lambda\Sigma\Lambda^\top) \end{aligned} \tag{8}$$

Here, $\Lambda = (I_N - \lambda W)^{-1}$ denotes the residual network component. Note that the structural network effects and residual network effects are identical if the data-generating process does not contain any exogenous determinants.

Lastly, we define a general network effects (NE) model that contains both network effects.

$$y_t = \rho W y_t + X_t\beta + u_t \qquad \text{with} \quad u_t = \lambda W u_t + e_t \tag{9}$$

Under the same invertibility conditions we can reformulate (9) into the explicit form

$$\begin{aligned} y_t &= (I_N - \rho W)^{-1} X_t\beta + (I_N - \rho W)^{-1}(I_N - \lambda W)^{-1} e_t \\ y_t &= Z X_t\beta + Z\Lambda e_t \\ y_t &= Z X_t\beta + \epsilon_t \qquad \text{with} \quad \epsilon_t \sim N(0, Z\Lambda\Sigma\Lambda^\top Z^\top) \end{aligned} \tag{10}$$

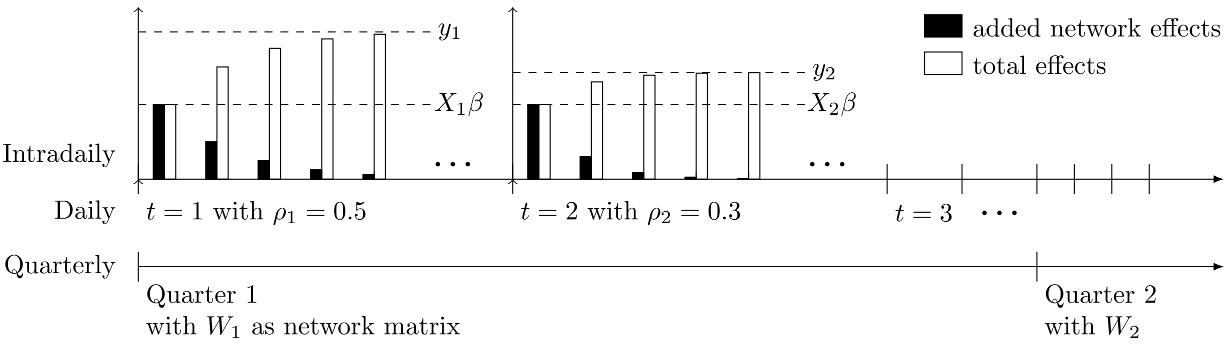
4.2 Dynamic network effects model

Since we suspect that the intensity of information contagion does not remain constant across time, we introduce time variation in the network effects $\rho_t W_t$ and $\lambda_t W_t$, respectively. We assume that the time dynamics are primarily driven by the intensity parameters ρ_t and λ_t. In fact, they vary on the same daily frequency as the credit spreads y_t, while W_t varies only on a quarterly frequency. Figure 5 shows an overview of the temporal structure in the model.

This frequency is primarily dictated by the data availability. However, even if a daily frequency were available, a lower frequency is desirable for two reasons: First, banks are not likely to change their profiles significantly over time. Roengpitya et al. (2014) point out that most of the 108 banks they investigate remain in the same classification. Commercial banks switched between retail to wholesale funding before and after the crisis, but this happened in a period of six years. In their subsequent study about model popularity and transitions, Roengpitya et al. (2017) use the bank-year as their time unit and find that in the period from 2006 to 2015, European banks switched business models on average 1.25 times. Thus, even though models are not static, they certainly do not shift from one day to the next. Second, if W_t were to change daily along with ρ_t and λ_t, we would face an endogeneity problem in the estimation. The data-generating process assumes that information contagion happens for given perceptions of the bank similarities. If the underlying

Figure 5: Timeline overview of DNE model

This figure outlines the three frequencies in the DNE model. The overlap matrix W, which proxies the bank business model similarities, is obtained at the beginning of each quarter, the CDS spreads are daily, and the contagion process takes place within each day. The bar charts depict the geometric convergence behind the network effects from (5). The left panel ($t = 1$), describes how network effects (black) are added to the initial $X_1\beta$ until they converge to the observed CDS y_1, i.e. the total effects (white).



similarities were to change as a result of information spillovers, then simultaneity will lead to biased estimates of the network effects.

To model and estimate the dynamic intensity parameters ρ_t and λ_t we treat them as latent state variables within a state-space framework (Durbin and Koopman, 2012). For the network models to be invertible we need to ensure that ρ_t and $\lambda_t \in (-1, 1)$. Hence, we do not model the time-dynamics directly but instead model two state variables α_t^1, α_t^2. These, in turn, drive the intensities $\rho_t = \Phi(\alpha_t^1)$ and $\lambda_t = \Phi(\alpha_t^2)$ through a logistic transformation function $\Phi : \mathbb{R} \to (-1, 1)$. The final state-space model which we call dynamic network effects (DNE) model, is described below.

Dynamic network effects (DNE) model

Observation equation

$$y_t = Z_t X_t \beta + \epsilon_t \qquad \text{with} \quad \epsilon_t \sim N(0, \hat{\Omega}_t),$$

with $\hat{\Omega}_t = Z_t \Lambda_t \Sigma \Lambda_t^\top Z_t^\top$ and network components $Z_t = (I - \rho_t W_t)^{-1}$, $\Lambda_t = (I - \lambda_t W_t)^{-1}$ and diagonal covariance matrix Σ.

State equations

$$\alpha_t^1 = c_1 + T_1 \alpha_{t-1}^1 + \eta_t^1 \qquad \text{with} \quad \eta_t^1 \sim N(0, \sigma_1^2),$$
$$\alpha_t^2 = c_2 + T_2 \alpha_{t-1}^2 + \eta_t^2 \qquad \text{with} \quad \eta_t^2 \sim N(0, \sigma_2^2),$$

with $\rho_t = \Phi(\alpha_t^1)$ and $\lambda_t = \Phi(\alpha_t^2)$ where $\Phi : \mathbb{R} \to (-1, 1)$ is a logistic transformation.

The DNE model assumes a dynamic covariance structure and constitutes an alternative way of modeling multivariate stochastic volatility. Compared to conditional correlation models (Engle, 2002), the main benefit of the DNE model is that it is primarily determined by the observed similarity matrix W_t. This separates cross-sectional dynamics from the temporal dynamics in the network intensity parameters ρ_t, λ_t. This structure facilitates the interpretation of the model outputs and gives an economic meaning to the similarity network W_t.

Estimation methodology While the Kalman filter can be used to estimate the linear baseline model, with regression coefficients as constant state variables, the DNE model is highly nonlinear due to the contagious process in the observation equation. Furthermore, the model includes heteroskedasticty and stochastic volatility, since the time-varying network effects also affect the residuals. These properties make the estimation a challenging task and linear estimators like the Kalman filter are not applicable. Approximating nonlinear filters, such as the extended or unscented Kalman filter, do not perform satisfactorily either, mostly due to the stochastic volatility (Wang et al., 2018). Therefore, we estimate our nonlinear state-space model with a smooth marginalized particle filter, based on the smooth particle filter (Malik and Pitt, 2011; Doucet et al., 2001) and the marginalized particle filter (Casella and Robert, 1996; Andrieu and Doucet, 2002). This simulation-based filter is able to cope with all of the DNE model's properties and has the best performance in our setting. The plot of estimated log-likelihoods is in the Appendix, Figure 16. We discuss details of this estimator's performance and its finite sample properties compared to alternative methods using an extensive simulation study in the companion paper Wang et al. (2018).

5 Empirical evidence for network effects

In addition to the estimation output of the baseline model, the NE model also produces estimates for the latent network intensity parameters, $\hat{\rho} = 0.458$ and $\hat{\lambda} = -0.093$.[13] These correspond to a structural multiplier effect of 1.844 and residual multiplier effect of 0.915. Economically, this means that the structural network effects had a moderate to strong, amplifying effect, while the residual network effects had a weak, dampening effect on credit contagion.

Our first main result is depicted in Figure 8: After accounting for network effects, the largest component in the clean residuals only accounts for 21.36% of residual variance, representing a drop of 40% versus its baseline counterpart (35.63%). Furthermore, all four components account jointly for 40.08%, compared to 53.02% in the baseline. Most importantly, the first component loses its systematic nature. Its loadings are not strictly positive for all banks anymore, and some of them are very close to zero or even change signs. Moreover, the second component (North-South) loses its distinctive character as its values become more erratic with no clear pattern. This means that the overlap network

[13] The $\hat{\rho}$ is statistically significant on a 1% level while the $\hat{\lambda}$ is not significantly different from zero.

both explains most of the unobserved, systematic residual component and accounts for North-South effect that eluded the structural regressors.

Our second main result relates to how the regression coefficients adjust in response to the network effects. The violin plots in Figure 6 visualize this difference for each coefficient.[14] After including network effects, the structural coefficients drop in importance. The density distributions become less dispersed and move closer to zero. Compared to the baseline model, bank-specific regressors such as leverage, lagged CDS spread changes and lagged equity returns become significantly less important. The constant remains irrelevant for all banks. The 10-year sovereign bond yield coefficients concentrate around zero and are among the few variables which gain in statistical significance due to the network effects. Hence, neglecting constant network effects likely overstates the importance of structural regressors.

The better fit is also reflected by the higher share of explained variances in Figure 7.[15] The R^2_{dirty} based on prediction errors ranges from 29.9% (AT,DE) to 49.0% (IT) with an overall average of 37.2%, which is only slightly higher than in the baseline model. We do not expect this improvement to be large, because the prediction errors, or dirty model residuals, still contain contagion effects. After filtering out the contagion effects, the R^2_{clean} based on clean residuals ranges from 36.7% (AT,DE) to 63.9% (IT) with an average of 48.2%, which is by 11.7% percentage points higher than in the baseline model. A suite of residual diagnostics (6, Appendix) indicate that constant network effects mostly affect the cross-sectional correlations in the residuals.

[14]In the Appendix, Figure 18 displays the change in statistical significance and Table 4 lists the grouped regression results.

[15]The R^2 depends on how we compute sum of squared residuals. In the baseline model, we compute the R^2 using prediction errors, $\hat{e}_t = y_t - \hat{y}_t$. In the NE model, however, prediction errors contain network effects (see equation (10)). We refer to them as 'dirty' model residuals, $\hat{\epsilon}_t$. Filtering out these effects yields 'clean' model residuals, $\hat{e}_t$.

$$\textit{dirty model residuals (prediction errors)} \qquad \hat{\epsilon}_t = y_t - \hat{y}_t = \hat{Z}_t \hat{\Lambda}_t \hat{e}_t$$

$$\textit{clean model residuals} \qquad \hat{e}_t = \hat{\Lambda}_t^{-1} \hat{Z}_t^{-1} \hat{\epsilon}_t$$

The two types of residuals lead to two corresponding R^2_{dirty} and R^2_{clean}.

Figure 6: Regression results of NE model

The violin plots compare the baseline and NE model results. Each each thin black line marks the anonymized coefficient value of one bank and the triangles locate the average. After modeling constant network effects, the cleaned coefficients lose in economic significance. Figure 18 (Appendix) shows the corresponding p-values.

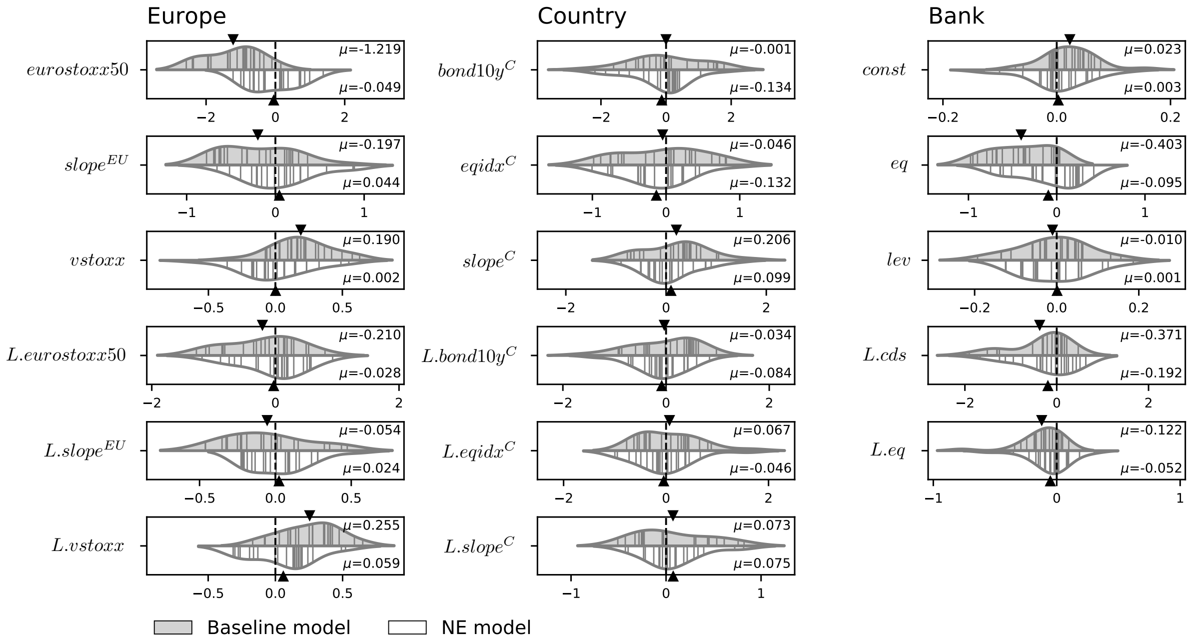


Figure 7: Coefficients of determination of the NE model

The bar plots describe the estimated R^2 values for the baseline model in comparison to the network effects model. We show both dirty and clean R^2 for each banking group. See footnote 15 on page 19 on the distinction between 'clean' and 'dirty' R^2.

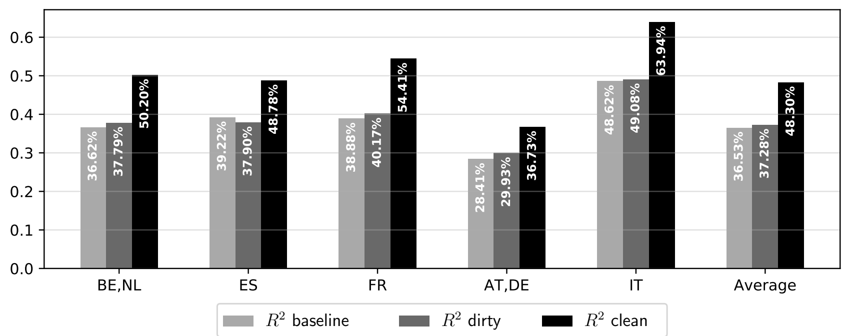
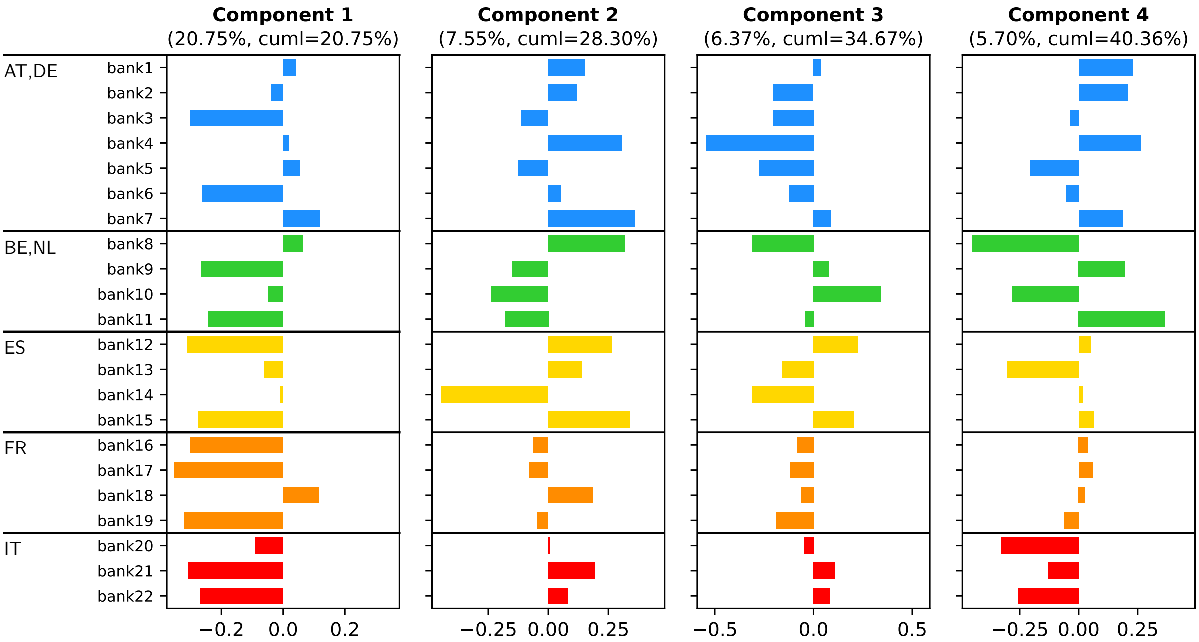


Figure 8: Principal components analysis of NE residuals

This graph presents the coefficients of the four largest principal components of the NE model residuals. We see that the first component loses its systematic nature and explains a fifth of the residual variance (21.36%), compared to its baseline counterpart (35.63%). Furthermore, the second component loses its North-South factor structure. The banks are anonymized and randomly positioned in each group.



6 Empirical evidence for dynamic network effects

Arguably, if network effects exist, they are unlikely to remain constant over time. We therefore estimate the DNE model and Figure 9 shows the estimated time-varying intensity parameters for both structural and residual network effects. The averages of both intensity parameters ($\hat{\mathbb{E}}[\hat{\rho}_t] = 0.101$ and $\hat{\mathbb{E}}[\hat{\lambda}_t] = 0.165$) differ substantially from their constant counterparts ($\hat{\rho} = 0.458$ and $\hat{\lambda} = -0.093$) and these correspond to a structural multiplier effect of 1.113 and a residual multiplier effect of 1.197.

Compared to the constant specification, both time-varying parameters have predominantly amplifying effects. Nonetheless, both series also exhibit brief periods of dampening effects. The negative spikes in one network effect are often associated with opposite spikes in the other effect. For instance, on Jan 2, 2015, we observe structural network effects of 0.572 and residual network effects of -0.564. In the context of the DNE model, this means that the amplification effects are almost exclusively affecting the structural component $Z_t X_t \beta$, while cancelling each other out in the residual component $Z_t \Lambda_t e_t$. In contrast, we also observe periods where we do not detect any network effects, for example between Jul 24 and Aug 3, 2015 where $\hat{\rho}_t$ averages to -0.003 and $\hat{\lambda}_t$ to 0.011. Finally, towards the end of 2016, we see a build up of amplification effects for both network parameters. This preceeds the Deutsche Bank turmoil period, which we discuss in more detail at the end of this section.

As with the constant network effect model, we present the estimated coefficients in a violin plot (Figure 10).[16] The results are mostly similar to the constant case, with a few notable differences. For the country-wide regressors, the inclusion of yields almost identical results. In addition to the 10-year sovereign bond yield, the lagged slope of the sovereign yield curve becomes more significant as well. Other country regressors become statistically less significant.

On the European level, the results are quite different. The equity index *eurostoxx*50 (lagged and contemporaneous) still loses in economic importance, but less than in the constant case. More interestingly, the volatility variable *vstoxx* becomes more important and gains in statistical significance. The same holds to a lesser degree for the lagged slope. This is the opposite of the constant case and indicates that the baseline results underestimate the relevance system-wide volatility.

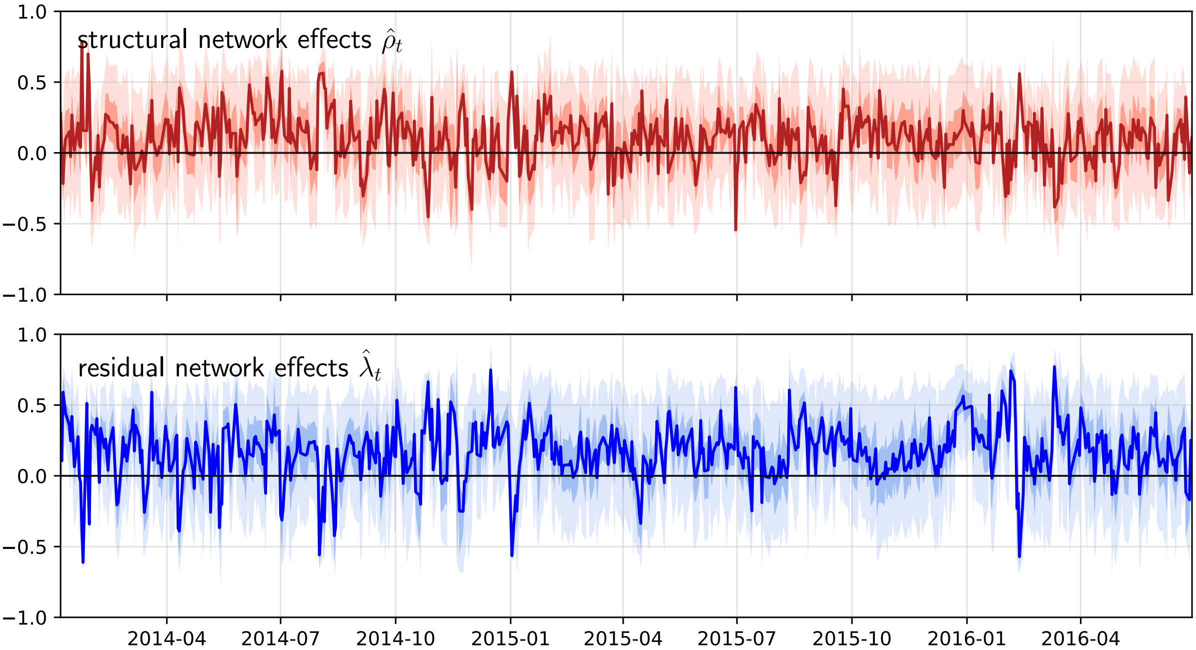
The bank-specific regressors behave in a similar fashion. The estimated coefficients for equity returns, leverage and the lagged CDS spread changes move closer to zero with increased statistical evidence. However, this happens to a lesser degree than in the constant case. The constant remains insignificant.

The coefficients of determination also paint a similar picture as the constant case. The R^2_{dirty} ranges from 31.3% (AT,DE) to 50.9% (IT) with an average of 39.4%, compared to 36.5% in the baseline. The R^2_{clean} ranges from 38.2% (AT,DE) from 64.5% (IT) with an average of 48.2%, which is 13.4% higher than in the baseline model. Thus, allowing the

[16] In the Appendix, Figure 19 displays the change in statistical significance and Table 5 lists the grouped regression results.

Figure 9: Estimated network intensities ρ_t and λ_t

Estimated intensity parameters of the DNE model using a smooth marginalized particle filter: Structural network effects ρ_t (top, red) and residual network effects λ_t (bottom, blue). The 90% (50%) asymmetric confidence interval is demarcated with the light (dark) areas.



network effects to follow a stochastic process strictly improves explanatory power.

This residual component analysis leads similar results as in the NE model, with only minor additional improvements (Figure 12). After accounting for dynamic network effects, the largest residual component accounts only for 19.75% of residual variance, compared to 21.36% in the constant case. Furthermore, all four components explain 38.77% jointly, compared to 40.08% in the NE model. As before, the first and second components lose their distinct systemic and country structures. This leads us to conclude that dynamic network effects do improve model performance, but only marginally. Table 6 (Appendix) presents further residual diagnostics.

Figure 10: Regression results of DNE model

The violin plots compare the baseline and DNE model results. Each each thin black line marks the anonymized coefficient value of one bank and the triangles locate the average. After modeling constant network effects, the cleaned coefficients lose in economic significance with the exception of the *vstoxx*. Figure 19 (Appendix) shows the corresponding p-values.

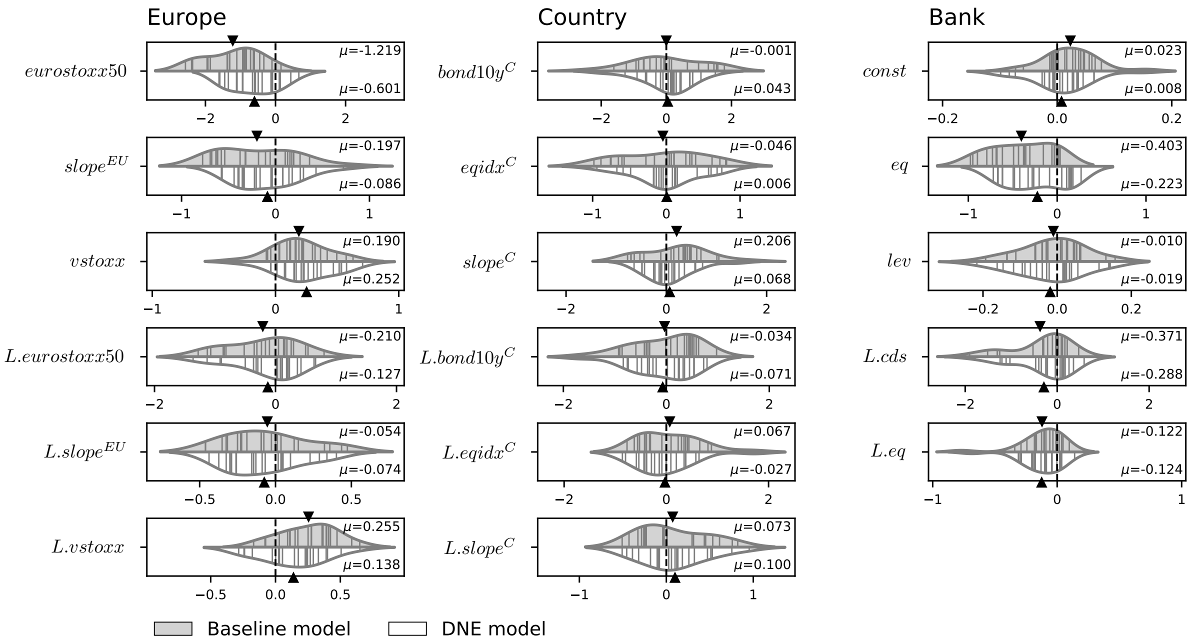


Figure 11: Coefficients of determination of the DNE model

The bar plots describe the estimated R^2 values for the baseline model in comparison to the dynamic network effects model. We show both dirty and clean R^2 for each banking group. See footnote 15 on page 19 on the distinction between 'clean' and 'dirty' R^2.

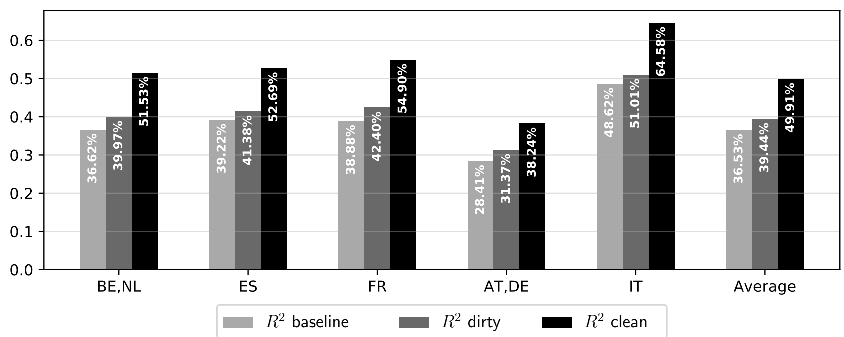
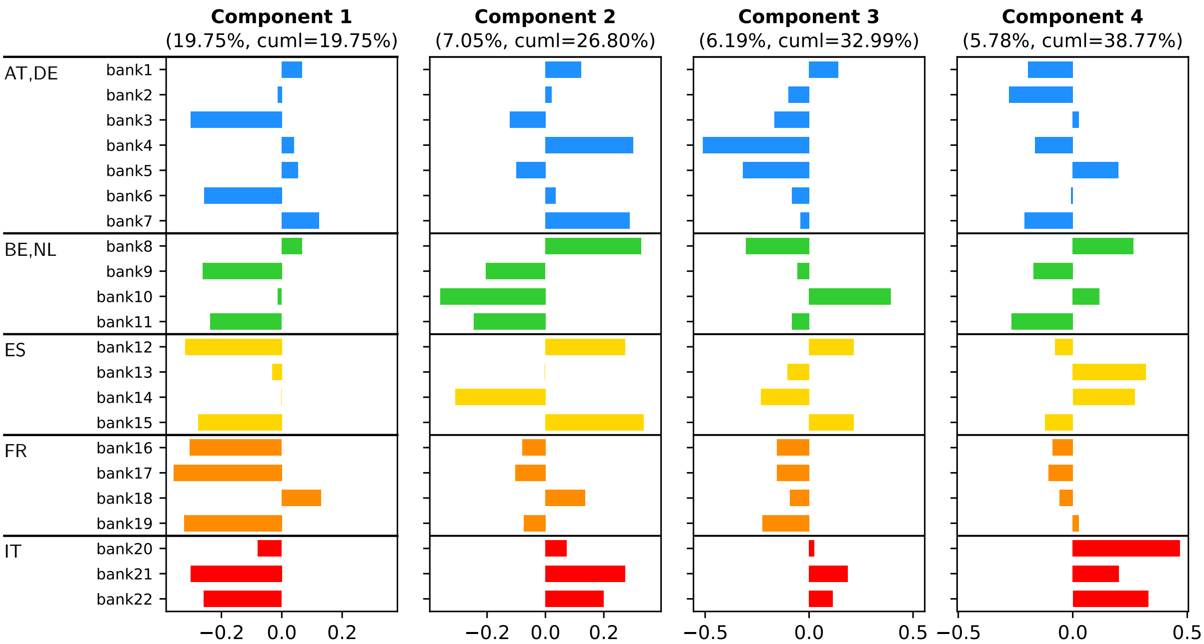


Figure 12: Principal components analysis of DNE residuals

This graph presents the coefficients of the four largest principal components of the DNE model residuals. We see that the first component loses its systematic nature and explains a fifth the residual variance (19.75%), compared to its NE counterpart (21.36%) or baseline counterpart (35.63%). Furthermore, the second component loses its North-South factor structure. The DNE model does outperform the NE model, but only slightly. The banks are anonymized and their position randomized within each group.

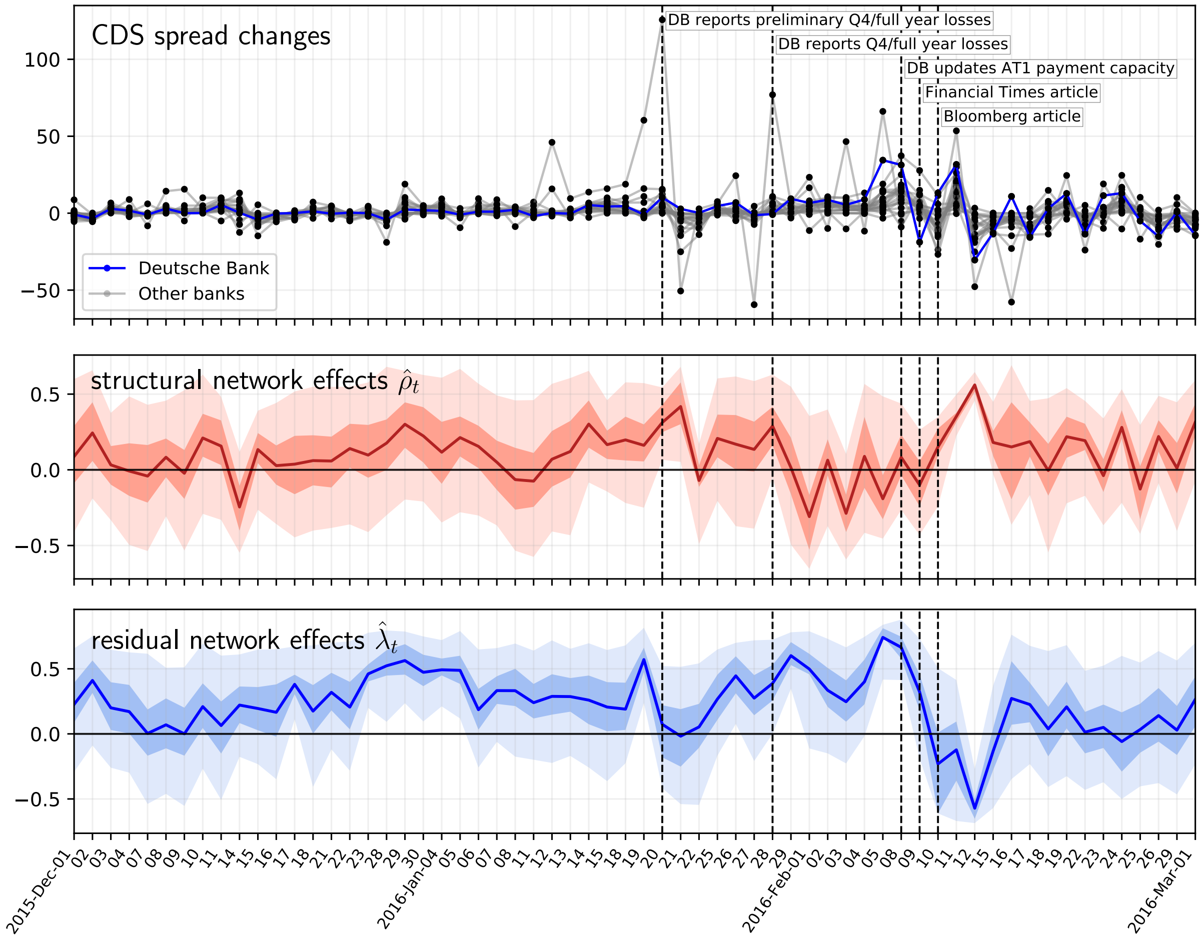


6.1 Dynamic network effects during the Deutsche Bank turmoil

To illustrate how the DNE model captures signals in a period of market turmoil, we show the dynamics of CDS prices and parameter estimates together in Figure 13. In the period around Deutsche Bank's profit warnings in early 2016, we see that the dynamics of both network effects react differently to the market commotion. After the DB's preliminary report on Jan 20, 2016, the residual network effects steadily increase and reflect co-movements that are not explained by the structural regressors themselves or contagion effects originating from them. Economically, this means that markets start to demand higher premia for the increasing credit risk of European banks. But this risk is still regarded as contained and localized rather than an aggregated risk factor. The build-up continues until DB announces to increase payment capacity for coupons on Feb 8, and media outlets begin to cover the market-wide effects in the equity, bond, and CoCo markets. As a result, structural network effects start to take over, while residual effects simultaneously drop in importance. This indicates that credit contagion has shifted from the residuals to the structural component. The market has now digested the new information and concluded that there is information in the structural regressors that merit a re-evaluation of the risk outlook. This corroborates the analysis in Kiewiet et al. (2017) which focuses on the market's ability to price contingent convertible bonds in an uncertain environment.

Figure 13: Network effects during the Deutsche Bank turmoil

The two network effects capture the market commotions in different ways. After the DB's preliminary report, the residual network effects steadily increase and indicate co-movements that are not explained by the structural regressors themselves or contagion effects set off by them. This build-up continues until DB announces to increase payment capacity for coupons and media outlets begin to cover the market-wide effects. As a result, structural network effects dominate and partly offset the residual effects. This indicates that contagion effects are now primarily driven by structural regressors.



7 Conclusion

In this paper, we investigate whether incorporating business model similarities into the modeling of the credit spreads of the 22 largest banks in the Eurozone improves risk capture. Earlier models explain the credit spread based on structural regressors only, such as equity returns, market volatilities, and spot rates. These models suffer from low explanatory power and fail to capture a systemic common factor. We attribute their poor empirical performance – the *credit spread puzzle* – to the omission of contagion effects in the models. Such contagion could be driven by business model similarities, either real or perceived by the market. However, including such effects into linear regressions is challenging because contagion mechanisms are self-reinforcing and nonlinear. To address this limitation, we augment the existing models with a portfolio overlap network, positing that common asset exposures of banks are a reasonable measure of business model similarity. We construct the network by applying an R^2-decomposition method on the banks' complete holdings data.

This leads to two extensions, the Network Effects (NE) model and Dynamic Network Effects (DNE) model. Both incorporate the overlap network and measure how important it is with intensity parameters. The difference is that the DNE model has time-varying intensities. If the network represents the vehicle that credit risk uses to spread from bank to bank, then the intensity represents the fuel that determines how far the vehicle can go. We obtain several surprising results with this modeling approach.

First, while the traditional model yields an R^2 for the European banks of 36.5% on average, the NE model leads to a R^2 that is only slightly higher, averaging 37.2%. After removing contagion effects in the residuals, the resulting average 'clean' R^2 goes up to 48.2%, an increase of 11.7% percentage points compared to the baseline model.[17] We attribute the increased explanatory power to the NE model's *structural network effects*. These effects include other banks as endogenous regressors, which ultimately still depend on the structural variables through the network. In addition, we find that the structural regressors of the NE become less important compared to the baseline. The DNE model, which has time-varying network effects, improves these findings even further, albeit only slightly. The average R^2_{clean} amounts to 49.9%. Surprisingly, while the regression coefficients generally become less relevant as in the NE model, the volatility index increases in importance under the DNE model. Thus, neglecting network effects, whether constant or dynamic, likely overstates the importance of most structural regressors. It is interesting to note that, although banks are presumably unaware of exactly how much portfolio overlap they have with other banks, CDS premia nonetheless seem to correctly price this contagion risk. It should therefore be in the interest of regulators to monitor this risk channel. Market participants could benefit from these insights if they can find a reliable measure of business sector similarity – which would seem feasible.

Second, the residuals of traditional models contain uncaptured common factors. A principal component analysis reveals that the first component is a systematic factor that affects all banks, responsible for 35.63% of the remaining variance. The second component contains country-specific blocks, which is surprising since the structural regressors already contain country-specific determinants. Upon closer inspection, this component differentiates between Northern countries (AT, BE, FR, DE, NL) and Southern countries (ES, IT). The NE and DNE models are constructed to capture these *residual network effects*. A subsequent residual component analysis confirms that the first component loses its systematic nature and only explains 21.36% (NE) and 19.75% (DNE) of the remaining variance, and the second component also loses its North-South structure. The largest four components jointly explain 40.08% (NE) and 38.77% (DNE) compared to 53.02% in the baseline. These findings imply that the bank similarity network helps us shed light on an aspect of credit risk that has eluded the structural regressors.

[17]See footnote 15 on page 19 on the distinction between 'clean' and 'dirty' R^2.

Lastly, the DNE allows us to measure the importance of the network effects over time. The structural network intensity oscillates around a constant mean of about $\hat{\mathbb{E}}[\hat{\rho}_t] = 0.101$ (corresponding to a multiplier of 1.113). At the same time, the residual network intensity revolves around $\hat{\mathbb{E}}[\hat{\lambda}_t] = 0.165$ (multiplier of 1.197). During the market stress period of early 2016, these intensities reach up to 0.561 (multiplier of 2.28) for the structural effects and 0.741 (multiplier of 3.86) for the residual effects. The time-varying nature tells us that network effects respond to or predict periods of financial distress. In the period following the Deutsche Bank's negative earnings announcements that spread throughout the continent, we find that there was a consistent build up of residual correlations not captured by the structural variables. This transitioned into a period where contagion effects were predominantly driven by structural regressors. The intensities also help us understand the contagion mechanism in details, for instance, by tracking how shocks to individual banks or Europe-wide variables find their way through the system during calm or volatile times.

In conclusion, we find that credit contagion and the credit spread puzzle are tightly connected. Neglecting the network component likely over- or underestimates the importance of structural regressors and fails to capture important common factors. The proposed NE/DNE framework is able to integrate these effects into established credit spread models and helps us resolve the puzzle for the largest banks in the Eurozone. The DNE model performs better than the NE model in every regard, as it allows for network effects to vary over time. But the improvements are slight, indicating that accounting for constant network effects is already sufficient to realize almost all of the benefits. Nonetheless, the dynamic model does provide valuable insights into the contagion mechanism during stress periods. Note that doubtlessly other contagion channels, such the interbank lending channel or market liquidity conditions, play important roles in contagion as well. Thus, our results highlight the need for more research on the network effects in credit risk.

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8 Appendix

Table 2: Bank groups and data availability

Bank	Abbreviation	Group	CDS data	Stock price
KBC Bank NV	kbc	BE,NL	01 Jan 2014	01 Jan 2014
ABN AMRO Bank NV	abn	BE,NL	01 Jan 2014	20 Nov 2016
ING Group	ing	BE,NL	01 Jan 2014	01 Jan 2014
Rabobank	rabo	BE,NL	01 Jan 2014	Not listed
BNP Paribas	bnpp	FR	01 Jan 2014	01 Jan 2014
Groupe BPCE	bpce	FR	02 Jul 2015	Not available
Crédit Agricole	cagricole	FR	01 Jan 2014	01 Jan 2014
Crédit Mutuel	cmutuel	FR	01 Jan 2014	Not available
Société Generale	socgen	FR	01 Jan 2014	01 Jan 2014
Erste Bank Group AG	erste	AT,DE	01 Jan 2014	01 Jan 2014
Bayerische Landesbank	bayernlb	AT,DE	01 Jan 2014	Not listed
Commerzbank AG	commerz	AT,DE	01 Jan 2014	01 Jan 2014
Deutsche Bank AG	deutsche	AT,DE	01 Jan 2014	01 Jan 2014
Deutsche Pfandbriefbank AG	dpbb	AT,DE	01 Jan 2014	01 Jan 2014
DZ Bank AG	dzbank	AT,DE	01 Jan 2014	Not listed
Landesbank Baden-Württemberg	lbbw	AT,DE	01 Jan 2014	Not listed
Norddeutsche Landesbank	nordlb	AT,DE	09 May 2014	Not listed
Banca Monte dei Paschi di Siena SpA	bmps	IT	01 Jan 2014	01 Jan 2014
Intesa Sanpaolo SpA	intesa	IT	01 Jan 2014	01 Jan 2014
UniCredit SpA	unicredit	IT	01 Jan 2014	01 Jan 2014
Banco Bilbao Vizcaya Argentaria SA	bbva	ES	01 Jan 2014	01 Jan 2014
BFA Tenedora de Acciones SAU	bfa	ES	01 Jan 2014	01 Jan 2014
CaixaBank SA	caixa	ES	01 Jan 2014	01 Jan 2014
Santander Group	santander	ES	01 Jan 2014	01 Jan 2014

A Portfolio overlap measure

The statistical literature on relative importance and variable selection has proposed several methods for R^2 decomposition.[18] In multiple regression analysis, these methods help us understand how much explanatory power a regressor contributes in relation to all other regressors. Essentially, we are interested in how similar a particular bank's portfolio is to a stressed bank's portfolio, relative to the portfolios of all other banks. Translated into a variable selection problem, we are interested in the predictive power of a bank's portfolio regarding the stressed bank portfolio structure, compared to the remaining portfolios.

A.1 Algorithm

Algorithm 1 details the steps to compute the portfolio overlap measure $\mu_{i,j}$. The basic idea is best illustrated in the context of a multiple regression of y on X: If the columns

[18] For a review of such methods we refer to Grömping (2015). Our measure is closest to Genizi (1993) as discussed in Johnson (2000).

of X are mutually disjoint, then the R^2 of this regression is simply the sum of the R^2 of regressing y on each column of X, separately. However, this does not hold when the columns of X are not orthogonal. The idea is instead to use the nearest orthogonal matrix Z of X.[19] Since Z is orthogonal, we can apply the same logic as before and regress y on Z, the orthogonal counterpart of X. However, this will give us the contributions of Z. Since were are interested in the contributions of X, the algorithm involves a further projection of X onto Z. For more details we refer to Johnson (2000).

To obtain the portfolio overlap matrix W, we repeat Algorithm 1 as described in equation (2). The result for the hypothetical portfolios is presented in Figure 4 and 14, right panels. Note that the matrix satisfies all desired properties 1-3 and is by construction row-stochastic, i.e. each row adds up to one. This system is constructed to have three distinct features. First, the holdings of $bank_1$-$bank_3$ and $bank_4$-$bank_6$ form two disjoint groups. Second, the holdings of $bank_1$,$bank_2$ ($bank_4$,$bank_5$) are positively (negatively) correlated. Third, the holdings of $bank_3$ and $bank_6$ are randomly drawn: Their first halves follow $U[0, 10]$ while their second halves follow $U[10, 20]$.

We visualize this contagion process in Figure 15. Panel (a) is the graphical representation of the portfolio overlap network from Figure 14 while panel (b) demonstrates how a bank's demise spreads to its neighbors in an iterative fashion, according to the portfolio distances. With each round the network intensity decays geometrically. Panel (b) can also be viewed as the impulse response function of the network for a given shock.[20]

Algorithm 1: Portfolio overlap measure

Let $y = bank_i$ be the $S \times 1$ regressand and $X = [bank_j]_{j \neq i}$ the $S \times (N-1)$ regressor.

1. Calculate $R_{XX} = \frac{1}{S} X^\top X$ and $R_{Xy} = \frac{1}{S} X^\top y$.
2. Estimate $c = R_{XX}^{-1/2} R_{Xy}$ where $R_{XX}^{1/2}$ denotes the matrix square root of R_{XX}.
3. Calculate raw overlap measure for all regressors $bank_j$ with $j \neq i$.
$$\mu^*_{i,j} = \sum_{k=1}^{N-1} [R_{XX}]^2_{j,k} c_k^2$$
4. Set overlap measure between $bank_i$ and $bank_j$ to zero if they are disjoint.
$$\mu_{i,j} = \begin{cases} \mu^*_{i,j} & \text{if } y^\top X_j \neq 0, \\ 0 & \text{otherwise.} \end{cases}$$
5. Collect overlap measures in $1 \times (N-1)$ row vector and normalize with $\bar{\mu}_i = \sum_{k \neq i} \mu_{i,k}$.
$$\mu_i = \frac{1}{\bar{\mu}_i} [\mu_{i,1}, \cdots, \mu_{i,N-1}].$$

[19] The closeness between two matrices is measured using the Frobenius norm. The matrix Z can be determined either using singular value decomposition (Fabbris, 1980) or by using the matrix square root (Genizi, 1993).

[20] An interactive visualization can be found at http://dieter.wang/contagionchain.

Figure 14: Hypothetical financial sector with six banks

This idealized example shows how the asset holdings of a banking system translate into a portfolio overlap network. Left: A hypothetical financial system with six banks and 40 assets. Each column represents a bank portfolio and the blue bars indicate the amount a banks holds of a certain asset. Right: The portfolio overlap matrix that results from applying Algorithm 1 to the asset holdings on the left panel. We can see that the resulting matrix is asymmetric and row-normalized.

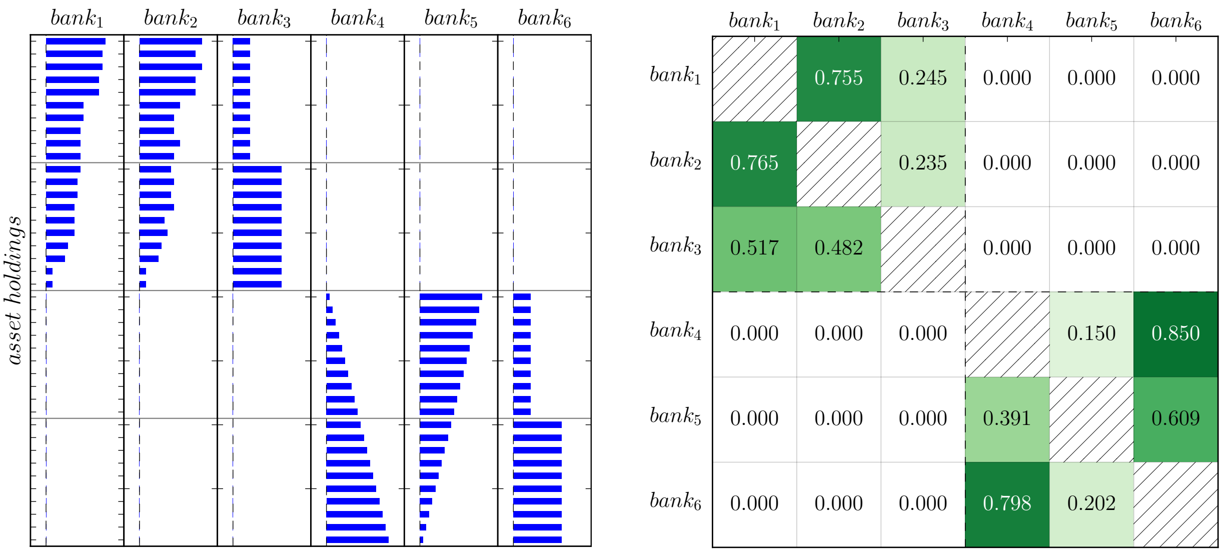


Figure 15: Visual representation of contagion process

This visualization depicts the contagion process of equation (5) for the portfolio overlap network of Figure 14. Each column represents one round of contagion. The assumed network intensity is $\rho = 0.7$.

(a) Chord diagram   (b) Contagion process

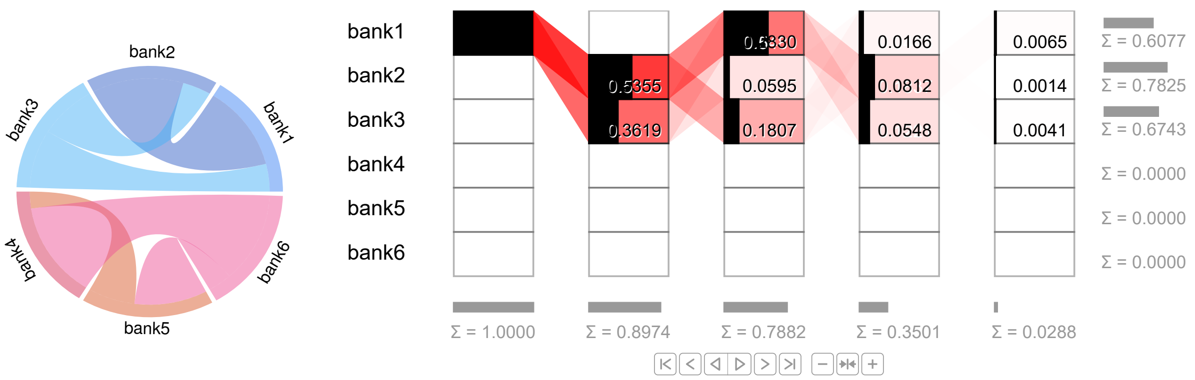


Table 3: Regression results of baseline model

This table presents the regression coefficients of each country group (see Table 2). For confidentiality reasons, we present group averages. Note that the parentheses contain average p-values and therefore do not lend themselves for hypothesis testing. The bottom rows present the average R^2 coefficient of each group.

		Average	Country group				
Scope	Variable	All banks	BE,NL	ES	FR	AT,DE	IT
Europe	*eurostoxx*50	-0.9941	-0.7913	-0.6494	-1.7427	-0.9150	-0.9102
		(0.202)	(0.105)	(0.445)	(0.000)	(0.198)	(0.329)
	$slope^{EU}$	-0.197	-0.134	-0.387	-0.556	0.291	-0.690
		(0.580)	(0.743)	(0.684)	(0.571)	(0.579)	(0.276)
	vstoxx	0.190	0.244	0.151	0.203	0.056	0.464
		(0.740)	(0.686)	(0.679)	(0.875)	(0.876)	(0.449)
	*L.eurostoxx*50	-0.210	-0.894	0.225	-0.278	-0.290	0.400
		(0.478)	(0.094)	(0.565)	(0.690)	(0.543)	(0.467)
	$L.slope^{EU}$	-0.054	-0.110	-0.376	-0.160	0.271	-0.168
		(0.608)	(0.813)	(0.223)	(0.764)	(0.633)	(0.603)
	L.vstoxx	0.255	0.237	0.416	0.297	0.154	0.245
		(0.522)	(0.544)	(0.391)	(0.524)	(0.595)	(0.526)
Country	$bond10y^C$	-0.001	-0.348	1.117	0.034	-1.150	1.608
		(0.228)	(0.423)	(0.011)	(0.705)	(0.072)	(0.000)
	$eqidx^C$	-0.046	0.085	-0.748	0.155	0.246	-0.236
		(0.463)	(0.435)	(0.087)	(0.603)	(0.707)	(0.282)
	$slope^C$	0.206	0.399	-0.529	0.373	0.764	-0.598
		(0.337)	(0.377)	(0.392)	(0.439)	(0.378)	(0.023)
	$L.bond10y^C$	-0.034	0.394	0.563	-0.310	-0.648	0.400
		(0.330)	(0.517)	(0.342)	(0.164)	(0.351)	(0.260)
	$L.eqidx^C$	0.067	0.737	-0.279	0.304	-0.029	-0.458
		(0.487)	(0.456)	(0.568)	(0.483)	(0.565)	(0.280)
	$L.slope^C$	0.073	-0.234	-0.204	0.514	0.305	-0.278
		(0.479)	(0.549)	(0.676)	(0.128)	(0.629)	(0.294)
Bank	*const*	0.023	-0.012	0.035	-0.009	0.040	0.057
		(0.944)	(0.976)	(0.922)	(0.979)	(0.957)	(0.894)
	eq	-0.403	-0.178	-0.435	-0.681	-0.278	-0.579
		(0.180)	(0.698)	(0.169)	(0.000)	(0.076)	(0.028)
	lev	-0.010	-0.102	-0.054	0.054	0.008	0.041
		(0.883)	(0.811)	(0.874)	(0.920)	(0.935)	(0.843)
	L.cds	-0.371	-0.564	-0.670	-0.171	-0.363	0.001
		(0.690)	(0.394)	(0.647)	(0.896)	(0.716)	(0.849)
	L.eq	-0.122	-0.213	-0.051	-0.130	-0.049	-0.253
		(0.871)	(0.865)	(0.912)	(0.923)	(0.917)	(0.689)
R^2	Baseline	0.365	0.365	0.392	0.388	0.283	0.485
	Entities	22	4	4	4	7	3

Table 4: Regression results of NE model

This table presents the regression coefficients of each country group (see Table 2). The estimated network intensity parameters are $\hat{\rho} = 0.458$ and $\hat{\lambda} = -0.093$. These correspond to a structural multiplier effect of 1.844 and residual multiplier effect of 0.915. For confidentiality reasons, we present group averages. Note that the parentheses contain average p-values and therefore do not lend themselves for hypothesis testing. The bottom rows present the average R^2 coefficient of each group.

		Average	Country group				
Scope	Variable	All banks	BE,NL	ES	FR	AT,DE	IT
Europe	$eurostoxx50$	-0.339	-0.544	-0.248	-0.551	-0.174	-0.287
		(0.292)	(0.542)	(0.663)	(0.016)	(0.210)	(0.040)
	$slope^{EU}$	-0.048	-0.011	-0.233	-0.338	0.368	-0.436
		(0.658)	(0.813)	(0.740)	(0.754)	(0.539)	(0.527)
	$vstoxx$	0.073	0.087	0.093	0.107	-0.066	0.308
		(0.812)	(0.835)	(0.734)	(0.922)	(0.871)	(0.626)
	$L.eurostoxx50$	-0.069	-0.597	0.132	0.044	-0.100	0.288
		(0.573)	(0.541)	(0.767)	(0.772)	(0.540)	(0.189)
	$L.slope^{EU}$	0.011	-0.038	-0.179	-0.112	0.249	-0.063
		(0.726)	(0.774)	(0.630)	(0.812)	(0.690)	(0.779)
	$L.vstoxx$	0.120	0.122	0.206	0.163	0.063	0.082
		(0.620)	(0.727)	(0.564)	(0.575)	(0.647)	(0.593)
Country	$bond10y^C$	-0.032	-0.232	0.694	0.102	-0.914	1.143
		(0.201)	(0.227)	(0.116)	(0.418)	(0.216)	(0.000)
	$eqidx^C$	-0.090	-0.097	-0.269	-0.044	-0.054	0.013
		(0.595)	(0.477)	(0.697)	(0.708)	(0.681)	(0.304)
	$slope^C$	0.117	0.216	-0.320	0.158	0.531	-0.456
		(0.554)	(0.648)	(0.496)	(0.738)	(0.520)	(0.372)
	$L.bond10y^C$	-0.071	0.306	0.268	-0.192	-0.544	0.240
		(0.409)	(0.273)	(0.604)	(0.277)	(0.393)	(0.571)
	$L.eqidx^C$	-0.003	0.529	-0.169	-0.004	-0.114	-0.229
		(0.625)	(0.535)	(0.632)	(0.655)	(0.633)	(0.702)
	$L.slope^C$	0.074	-0.195	-0.080	0.371	0.263	-0.199
		(0.558)	(0.322)	(0.659)	(0.470)	(0.676)	(0.612)
Bank	$const$	0.007	-0.029	0.008	-0.010	0.025	0.035
		(0.948)	(0.962)	(0.898)	(0.978)	(0.971)	(0.939)
	eq	-0.320	-0.115	-0.416	-0.518	-0.202	-0.473
		(0.277)	(0.555)	(0.373)	(0.009)	(0.253)	(0.223)
	lev	-0.003	-0.084	-0.047	0.059	0.014	0.038
		(0.905)	(0.893)	(0.867)	(0.884)	(0.950)	(0.914)
	$L.cds$	-0.224	-0.420	-0.255	-0.100	-0.297	0.084
		(0.648)	(0.574)	(0.462)	(0.860)	(0.632)	(0.762)
	$L.eq$	-0.069	-0.120	0.086	-0.100	-0.020	-0.282
		(0.862)	(0.873)	(0.875)	(0.942)	(0.909)	(0.654)
R^2	Baseline	0.365	0.365	0.392	0.388	0.283	0.485
	Dirty	0.372	0.377	0.379	0.401	0.299	0.490
	Clean	0.482	0.501	0.487	0.544	0.367	0.639
	Entities	22	4	4	4	7	3

Table 5: Regression results of DNE model

This table presents the regression coefficients of each country group (see Table 2). The averages of both network intensity parameters ($\hat{\mathbb{E}}[\hat{\rho}_t] = 0.101$ and $\hat{\mathbb{E}}[\hat{\lambda}_t] = 0.165$) are close to their constant counterparts ($\hat{\rho} = 0.458$ and $\hat{\lambda} = -0.093$). These correspond to a structural multiplier effect of 1.113 and residual multiplier effect of 1.197. For confidentiality reasons, we present group averages. Note that the parentheses contain average p-values and therefore do not lend themselves for hypothesis testing. The bottom rows present the average R^2 coefficient of each group.

		Average	Country group				
Scope	Variable	All banks	BE,NL	ES	FR	AT,DE	IT
Europe	$eurostoxx50$	-0.911	-1.075	-0.721	-1.306	-0.931	-0.522
		(0.212)	(0.311)	(0.291)	(0.000)	(0.412)	(0.055)
	$slope^{EU}$	-0.244	-0.168	-0.279	-0.448	0.171	-0.498
		(0.648)	(0.650)	(0.722)	(0.664)	(0.760)	(0.451)
	$vstoxx$	0.423	0.428	0.361	0.441	0.250	0.633
		(0.542)	(0.515)	(0.593)	(0.698)	(0.662)	(0.260)
	$L.eurostoxx50$	-0.113	-0.768	0.138	0.098	-0.365	0.332
		(0.524)	(0.306)	(0.717)	(0.640)	(0.541)	(0.430)
	$L.slope^{EU}$	-0.180	-0.205	-0.421	-0.247	0.157	-0.182
		(0.552)	(0.658)	(0.173)	(0.604)	(0.716)	(0.631)
	$L.vstoxx$	0.232	0.170	0.448	0.236	0.096	0.212
		(0.524)	(0.678)	(0.370)	(0.479)	(0.632)	(0.482)
Country	$bond10y^{C}$	0.335	-0.035	0.827	0.257	-0.655	1.282
		(0.176)	(0.312)	(0.062)	(0.365)	(0.157)	(0.000)
	$eqidx^{C}$	-0.002	0.005	-0.261	0.235	0.277	-0.266
		(0.612)	(0.550)	(0.631)	(0.589)	(0.727)	(0.580)
	$slope^{C}$	-0.024	0.194	-0.356	0.084	0.458	-0.502
		(0.528)	(0.668)	(0.486)	(0.821)	(0.569)	(0.128)
	$L.bond10y^{C}$	0.086	0.506	0.538	-0.321	-0.632	0.341
		(0.340)	(0.558)	(0.359)	(0.227)	(0.212)	(0.372)
	$L.eqidx^{C}$	-0.049	0.525	-0.107	-0.138	-0.002	-0.521
		(0.558)	(0.610)	(0.782)	(0.720)	(0.524)	(0.162)
	$L.slope^{C}$	0.035	-0.334	-0.152	0.560	0.343	-0.240
		(0.438)	(0.534)	(0.705)	(0.068)	(0.437)	(0.474)
Bank	$const$	0.012	-0.018	0.027	-0.005	0.029	0.028
		(0.944)	(0.976)	(0.891)	(0.966)	(0.966)	(0.940)
	eq	-0.397	-0.135	-0.461	-0.615	-0.266	-0.507
		(0.214)	(0.722)	(0.137)	(0.000)	(0.151)	(0.072)
	lev	-0.031	-0.122	-0.063	0.018	-0.004	0.015
		(0.832)	(0.753)	(0.817)	(0.922)	(0.858)	(0.830)
	$L.cds$	-0.364	-0.574	-0.599	-0.195	-0.353	-0.097
		(0.682)	(0.381)	(0.639)	(0.860)	(0.705)	(0.845)
	$L.eq$	-0.188	-0.224	-0.128	-0.230	-0.078	-0.282
		(0.810)	(0.824)	(0.866)	(0.856)	(0.888)	(0.642)
R^2	Baseline	0.365	0.365	0.392	0.388	0.283	0.485
	Dirty	0.394	0.399	0.413	0.423	0.313	0.509
	Clean	0.499	0.515	0.526	0.549	0.382	0.645
	Entities	22	4	4	4	7	3

Figure 16: Comparison of log-likelihoods

We compare the log-likelihoods of the baseline, NE and DNE models. The log-likelihoods were estimated with maximum likelihood, using the smooth marginalized particle filter with 200 particles. We used stratified resampling to prevent particle degeneracy.

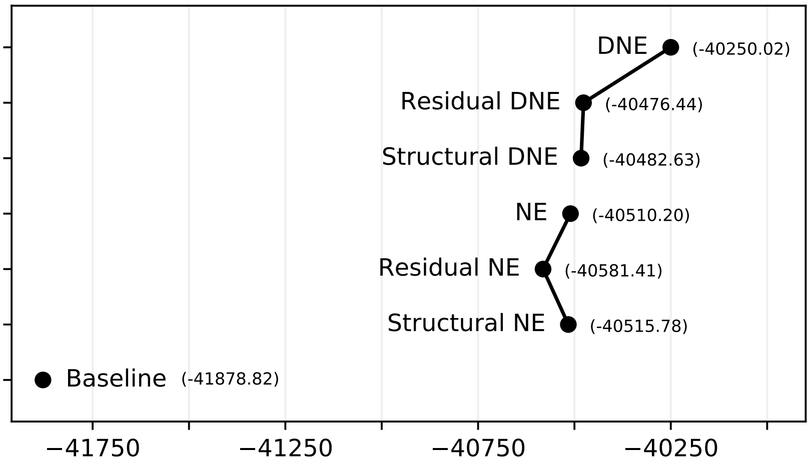


Figure 17: Regression results of baseline model

Each histogram describes the p-values of the baseline model regression coefficients. The red line demarcates the 5% significance level. The triangles locate the average p-value.

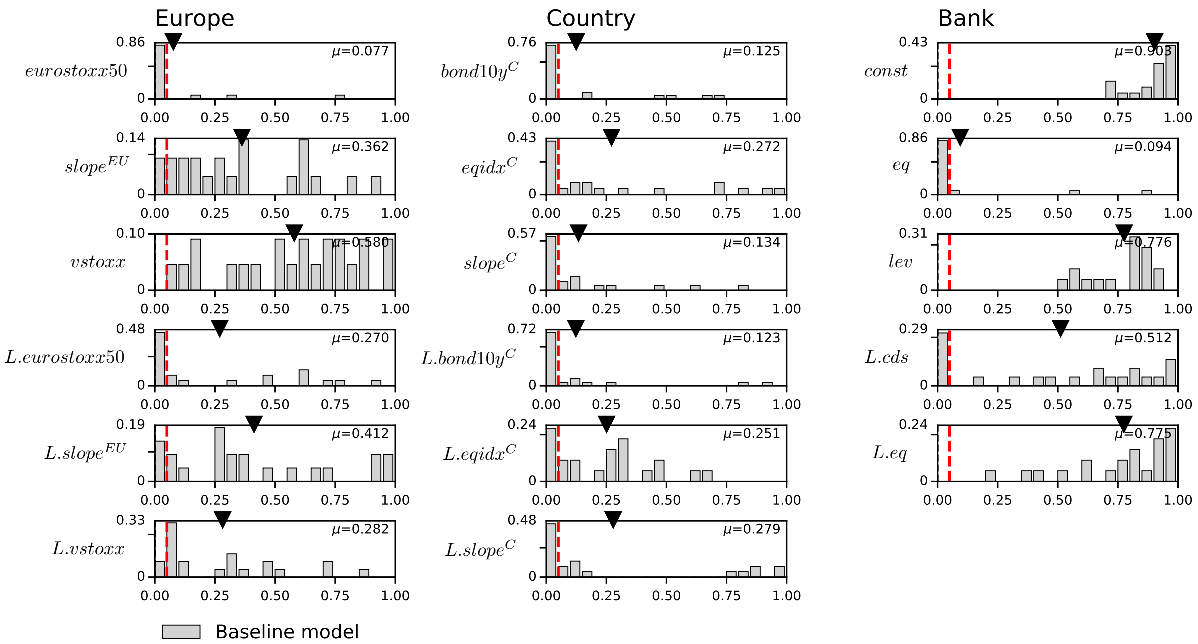


Figure 18: Regression results of NE model

Each histogram describes the p-values of the baseline model regression coefficients. The red line demarcates the 5% significance level. The triangles locate the average p-value.

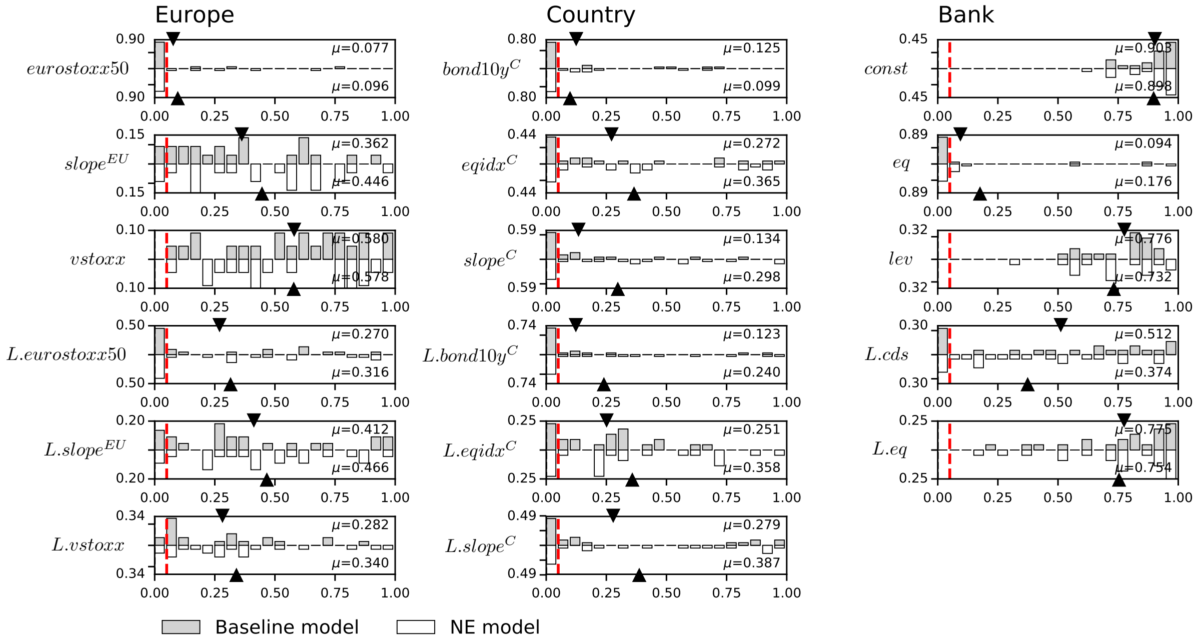
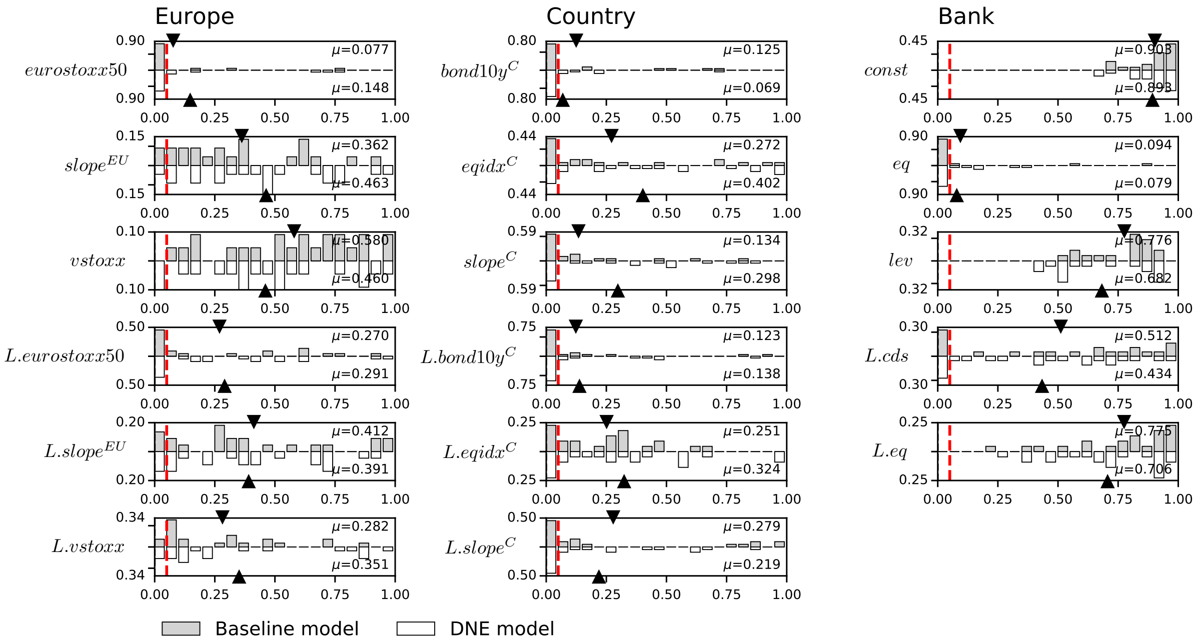


Figure 19: Regression results of DNE model

Each histogram describes the p-values of the baseline model regression coefficients. The red line demarcates the 5% significance level. The triangles locate the average p-value.



A.2 Residual diagnostics

Network effects model

The left panel of Table 6a shows how the average correlation of a bank's residuals with all other banks drops from 0.306 to 0.118 while also becoming less dispersed. On the right panel of Table 6a we see a more similar effect for the squared residuals, dropping from 0.177 to 0.114. In the center, Table 6b, we tabulate the test statistics and p-values of a Ljung-Box test for autocorrelation. The results show that the residuals become more autocorrelated after including network effects. When we examine the autocorrelation structure (not shown here) we find that the autoregressive coefficients become negative or more negative for all banks. At the bottom, Table 6c displays the results of ARCH-LM tests for conditional heteroskedasticity. Different from the increasing serial autocorrelation, we find less residual clustering for all countries, with the exception of Spain. Nonetheless, the tests fail to find evidence for ARCH effects in the same country groups as in the baseline (i.e. Austria, France and Germany). This suite of tests leads us to conclude that constant network effects mostly affect the cross-sectional correlations in the residuals.

Dynamic network effects model

The DNE model lowers average (squared) residual correlations (Table 6a) further than the NE model, but the improvements are almost indistinguishable from the constant case. The tests for serial autocorrelation (Table 6b) are qualitatively similar to the NE model, but the average p-value indicates that we cannot reject the null hypothesis of uncorrelated errors on the 10% significance level anymore. We also find that tests for conditional heteroskedasticity (Table 6c) fail to reject the hypothesis of uncorrelatedness. The time-variation in the network effects therefore does remove some of the autocorrelation introduced by the NE model.

Table 6: Residual tests

We refer to footnote 15 on page 19 on the distinction between 'clean' and 'dirty' residuals. The p-values presented are averages and cannot be used directly for hypothesis testing.

(a) Average correlations of residuals and squared residuals

		Residuals			Squared residuals		
NE	Country	Baseline	Dirty	Clean	Baseline	Dirty	Clean
	BE,NL	0.310	0.287	0.103	0.177	0.162	0.106
	ES	0.304	0.287	0.122	0.188	0.173	0.131
	FR	0.356	0.339	0.161	0.209	0.194	0.124
	AT,DE	0.256	0.236	0.081	0.140	0.129	0.098
	IT	0.354	0.339	0.160	0.208	0.192	0.123
	All banks	0.306	0.288	0.118	0.177	0.163	0.114
DNE	Country	Baseline	Dirty	Clean	Baseline	Dirty	Clean
	BE,NL	0.310	0.275	0.100	0.177	0.183	0.102
	ES	0.304	0.279	0.130	0.188	0.204	0.125
	FR	0.356	0.325	0.161	0.209	0.221	0.120
	AT,DE	0.256	0.223	0.076	0.140	0.150	0.098
	IT	0.354	0.331	0.163	0.208	0.228	0.120
	All banks	0.306	0.276	0.117	0.177	0.189	0.111

(b) Ljung-Box test for residual autocorrelation

		Test statistic			p-value		
NE	Country	Baseline	Dirty	Clean	Baseline	Dirty	Clean
	BE,NL	0.402	1.970	12.231	0.613	0.171	0.013
	ES	0.813	6.910	22.566	0.612	0.015	0.000
	FR	0.002	0.787	4.298	0.964	0.566	0.265
	AT,DE	1.122	2.277	6.760	0.517	0.261	0.089
	IT	0.267	2.268	6.081	0.607	0.233	0.095
	All banks	0.614	2.792	10.088	0.645	0.252	0.092
DNE	Country	Baseline	Dirty	Clean	Baseline	Dirty	Clean
	BE,NL	0.402	0.385	6.148	0.613	0.627	0.049
	ES	0.813	1.562	7.370	0.612	0.394	0.009
	FR	0.002	0.174	1.475	0.964	0.787	0.360
	AT,DE	1.122	1.221	4.329	0.517	0.480	0.135
	IT	0.267	0.213	2.012	0.607	0.666	0.192
	All banks	0.614	0.803	4.378	0.645	0.572	0.145

(c) ARCH-LM test for residual heteroskedasticty

		Test statistic			p-value		
NE	Country	Baseline	Dirty	Clean	Baseline	Dirty	Clean
	BE,NL	36.086	37.160	33.495	0.000	0.001	0.003
	ES	17.953	17.773	29.013	0.006	0.022	0.003
	FR	3.717	2.838	2.911	0.242	0.291	0.297
	AT,DE	21.877	21.070	19.562	0.188	0.193	0.247
	IT	40.229	42.161	36.704	0.000	0.000	0.000
	All banks	22.948	22.957	23.124	0.105	0.118	0.134
DNE	Country	Baseline	Dirty	Clean	Baseline	Dirty	Clean
	BE,NL	36.086	35.887	32.742	0.000	0.000	0.002
	ES	17.953	17.685	19.469	0.006	0.003	0.057
	FR	3.717	6.171	3.143	0.242	0.214	0.347
	AT,DE	21.877	21.549	18.787	0.188	0.184	0.289
	IT	40.229	37.036	28.540	0.000	0.000	0.000
	All banks	22.948	22.769	19.934	0.105	0.098	0.166

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