Do interbank markets price systemic risk?

Draft version (preliminary results), February 18, 2018

Christoph Siebenbrunner[1], Michael Sigmund[2]

Abstract

An important motivation for financial regulation is the premise that the externality imposed by bank failures on the financial system is not reflected in market pricing. In this study we empirically assess this premise by studying whether systemic contagion losses are reflected in bilateral prices charged on interbank markets. We study this question within a simultaneous equation model in order to account for the endogeneity induced by the simultaneous determination of interbank lending and deposit rates. We use a rich data set on the Austrian interbank market with over 16.000 observations and control i.a. for bilateral credit risk, funding needs and relationship lending. Our inference suggests that systemic contagion losses are not adequately reflected in interbank prices – if anything, higher contagiousness confers an advantage to a bank on the interbank market. We consider this socially undesirable and a case for the regulation of systemic risk.

Keywords: financial stability; financial regulation.

1. Introduction: Systemic risk and financial regulation

Not only since the Lehman Brothers crisis it has been understood that in financial systems there is an inherent risk that originally idiosyncratic shocks or crises can spread through entire systems. Iori et al. (2006) refer to this risk as "systemic risk". In many cases, the materialization of "systemic risk" can lead to "systemic failure" because markets, policy makers and/or individuals do not correctly anticipate the system risk or its consequences. Systemic risk thus poses a significant risk to financial stability, defined by ECB (2009) as *"a condition in which the financial system - comprising of financial intermediaries, markets and market infrastructures - is capable of withstanding shocks and the unraveling of financial imbalances, thereby mitigating the likelihood of disruptions in the financial intermediation process which*

Email addresses: `christoph.siebenbrunner@maths.ox.ac.uk` (Christoph Siebenbrunner), `michael.sigmund@oenb.at` (Michael Sigmund)

[1]University of Oxford, Mathematical Institute and Institute for New Economic Thinking

[2]Oesterreichische Nationalbank (OeNB), Otto-Wagner-Platz 3, A-1090 Vienna, Austria. The views expressed in this paper are those of the authors and do not necessarily reflect those of the Eurosystem or the OeNB.

are severe enough to significantly impair the allocation of savings to profitable investment opportunities".

Safeguarding financial stability is a key "raison d'être" for financial regulation. By imposing rules designed to limit damage to the economy and the recourse to public funds during financial crises, regulators are trying to address an externality created by interconnectedness in the financial system and the systemic risk that it induces. They are thereby assuming that this externality has not already been internalized by banks in their pricing of risks in those interconnections, which to a great extent are transactions on the interbank market. While the financial crisis of 2008 provides ample anecdotal evidence that systemic risk may indeed not be internalized by banks, our goal in this study is to undertake a quantitative assessment of this question.

In order to address this question, we need to incorporate both a quantitative approach to measuring systemic risk, as well as a model of price formation on interbank markets. There exists a rich literature on the quantification of systemic risk, understood as the risk of contagion, i.e. the cascading spread of initially idiosyncratic shocks, in line with the literature (de Bandt and Hartmann, 2000; IMF, 2010). Seminal early contributions date back to Allen and Gale (2000) and Eisenberg and Noe (2001), and even further back to Rochet and Tirole (1996). Methodologically, at least two major strands of approaches can be identified in the literature. The first strand could be seen as more statistical in nature and focuses on extreme movements of prices and conditional forecasts thereof. Major contributions in this strand include Brownlees and Engle (2015) and Adrian and Brunnermeier (2016), better known by their acronyms SRisk and CoVaR. The second major strand adopts a balance-sheet-based view of each institution in the financial system and models the risk stemming from writedowns on bilateral exposures. This approach was pioneered by the aforementioned Eisenberg and Noe (2001) and has been further developed by a variety of authors, most notably Elsinger et al. (2006), Battiston et al. (2012) and Barucca et al. (2016). In deciding between these two approaches to measuring systemic risk, we follow Siebenbrunner et al. (2017) who argue that the balance-sheet-based approaches provide a better basis for financial regulation, as they provide a better estimate of the "*systemic loss given default*" (FED, 2015) of individual institutions and can be performed for all institutions, regardless of whether they are publicly listed or not.

The literature on the industrial organization of the interbank market is less rich in comparison. The most popular approach looks at banks as "passive dealers" between providers and users of funds (Ho and Saunders, 1981; Klein, 1971). Banks maximize their spreads on loans and deposits. In these models there exists a "money market" (interbank market) where banks can demand or supply their net funding gap (loans-deposits) at a common rate. However, Siebenbrunner and Sigmund (2017) (directly) and Elyasiani et al. (1995) (indirectly) provide strong theoretical and empirical evidence for Austria and Italy that loan and deposit rates on interbank markets differ in fact. Elyasiani et al. (1995) show that the "portfolio separation" hypothesis (Sealey, 1985) does not hold, i.e. it is costly for banks to change their interbank market portfolio. Even more directly, Siebenbrunner and Sigmund (2017) show that (i) deposit and loan rates differ even after controlling for multiple factors, (ii) different banks also pay and demand different rates beyond what is explained by credit risk and (iii) the interbank market is more than a liquidity pool, i.e. banks use it to grow their balance sheet.

The remainder of the paper is structured as follows: Section 2 gives an overview of the data sets used for calculating the contagion losses and testing the hypothesis if banks price contagion losses. Section 3 presents the theoretical models adopted for measuring systemic risk and modeling price formation on interbank markets. In section 4 we present our strategy for estimating and identifying different versions of the models developed in the previous version, which correspond to competing hypotheses about whether banks internalize systemic contagion effects in interbank market prices or not. In section section 5 we present the results of these estimations and infer an answer to the question in the title. Section 6 concludes.

2. Data

Our data set consists of two data sources. Balance sheet, income statement and regulatory capital requirements data are collected from the regulatory reporting system. The network data on banks' bilateral interbank assets and liabilities are taken from the central credit register.

2.1. Balance sheet, Income Statement and Report on Compliance with Regulatory Standards

All these data are available on a quarterly basis for all domestically operating banks at the unconsolidated level. The observation horizon runs from the second quarter of 2008 to the first quarter of 2016, yielding $T = 32$ time periods. Taking into account all institutions that have held a banking license at some point during the observation horizon, but excluding special purpose banks and affiliates of foreign banks, we arrive at a sample of $N = 716$ banks.

Our endogenous variables, bank deposit and loan rates are calculated on the basis of balance sheet and income statement data. These rates are calculated by dividing the total interest expenses (income) from the income statement by the average volume outstanding in each period.

Total assets, non-bank loans and deposits are taken from the balance sheet data. Total assets control for size effects and might also be a proxy for market power at least on the interbank market. Non-bank loans minus non-bank deposit divided by total assets is defined as the funding gap that has to be closed by operations on the interbank market.

Risk weighted assets are taken from the report on compliance with regulatory standards. Dividing them by total assets gives us the risk weighted asset ratio (RWA). With the RWA we proxy the creditworthiness of the average borrower. A higher RWA is associated with a riskier portfolio. Banks should therefore require higher loan rates to compensate for their riskier assets.

To prevent outliers from distorting the empirical analysis, we follow Gunter et al. (2013); Sigmund et al. (2017) and apply a two-stage cleaning algorithm to the variables used. First, we eliminate outliers across banks for each time period. An observation is considered an outlier if it is too far from the median (more than four times the distance between the median and the 2.5% or 97.5% quantile). In a second stage, we eliminate outliers across time for each bank. Here, the threshold distance is defined as 12 times the distance between the median and the 10% or 90% quantile. Such parameters ensure that the number of removed observations remains limited and the resulting distributions exhibit a reasonable shape when judged from a qualitative perspective. This procedure leaves eliminates only 0.77% of observations that are considered as reporting errors, and leaves us with around 16,600 observations.

2.2. *Credit Register Data*

The data source for the network of interbank liabilities and loans is the central credit register, which covers all financial claims held by Austrian banks exceeding a reporting threshold of EUR 350k across asset classes on an obligor-basis. In particular, we are able to identify all interbank loans and liabilities for each bank vis-à-vis all other banks.

In this setting, we are able to capture the lending and funding share of each bank in its sector. Relationship lending, defined as the existence of deep bilateral lending relations with significant coverage across time and/or product categories, is a well-documented phenomenon (Memmel et al., 2007; Bräuning and Fecht, 2017).

The credit registry also contains data on bilaterally assigned credit quality ratings of banks. Siebenbrunner et al. (2017) summarize how this information is converted to a "consensus" probability of default for each bank using the approaches developed by Eisl et al. (2013) and Hornik et al. (2008).

Following Siebenbrunner and Sigmund (2017), we include the average collateral ratio of interbank loans and deposits in the respective equations. Collateral values are taken as the maximum of the values used in the bank's internal risk management system and the values recognized by applicable regulations[3]. Values are capped at the exposure amount at the counterparty level, to avoid counting the same collateral for different counterparties in the aggregation.

3. Theoretical Model

Our analysis is based on a combination of two different theoretical models. Our model of how banks set interbank deposit and loan rates is based on Siebenbrunner and Sigmund (2017). The theoretical model of contagion losses is based on Siebenbrunner et al. (2017). The foundation for both models is a stylized balance sheet representation of each bank in the system, illustrated in Figure 1.

We consider a system of $N-1$ banks and define their balance sheets through the N-dimensional vectors listed in table 1 (the N^{th} entry corresponds to a sink node, which is included for technical reasons and will be explained in the following).

[3]Latest version: REGULATION (EU) No 575/2013. See: http://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX:32013R0575

Table 1: Primary variable definitions

q_L	Interbank loans
q_D	Interbank deposits
a	External loans and other non-interbank assets
d	External deposits and other non-interbank liabilities
e	Equity

Note that equity is a residual quantity, whose definition captures the **balance sheet identity** in our model:

$$e = q_L + a - q_D - d \tag{1}$$

Further note that there exists a link between the vectors of interbank assets and interbank liabilities, as every bank's interbank loan is another bank's interbank deposit. In order to formalize this link we first consider the matrix $L \in \mathbb{R}_+^{N \times N}$ of bilateral interbank exposures, where $L_{i,j}$ represents the liabilities of bank i towards bank j. The N-th column of L records all the external liabilities, such that $L_{i,N} = d_i$ and $\sum_{j=1}^{N-1} L_{i,j} = q_D^i$ for all $i \in 1 \dots N-1$. This allows to define the **total liabilities** $\bar{l} = d + q_D = \sum_{j=1}^{N} L_{i,j}$ as the row sum of the liability matrix. The sink node is assumed not to have any liabilities, so $L_{N,j} = 0 \; \forall \; j \in 1 \dots N$. We then define the relative liability matrix

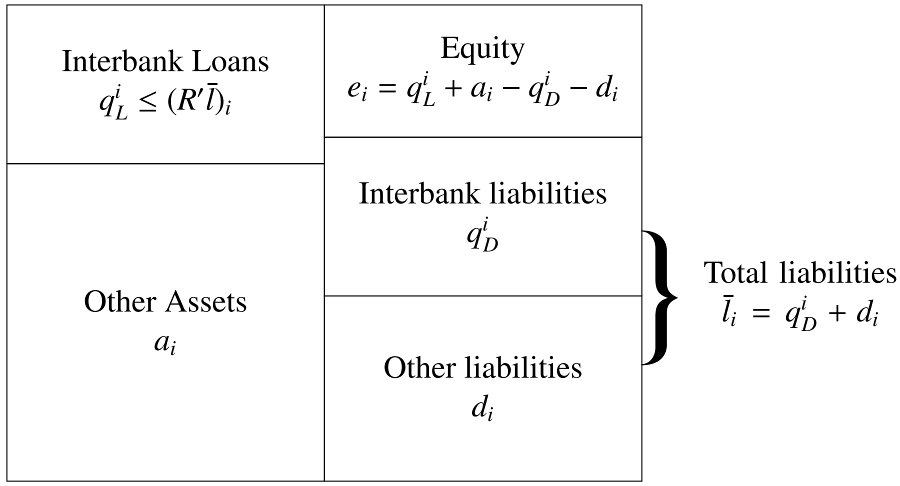
$$R_{i,j} = \begin{cases} \frac{L_{i,j}}{\bar{l}_i} & \text{if } \bar{l}_i > 0 \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

whose (i, j)-th entry gives the share that bank's j claim on bank i represents as a fraction of i's liabilities. Following Eisenberg and Noe (2001) we assume equal seniority of all liabilities, which allows defining a relation between interbank assets and liabilities:

$$q_L \leq R'\bar{l} \tag{3}$$

Where $a \in \mathbb{R}^N \leq b \in \mathbb{R}^N \Leftrightarrow a_i \leq b_i \; \forall \; i \in [1 \dots N]$. Note that setting interbank assets q_L equal to $R'\bar{l}$ would imply that all banks always repay their liabilities in full, i.e. that there are no defaults in the system and that credit and/or systemic risk would be absent. It is the task of the contagion model to compute losses on interbank assets, which will be explained in Section 3.1.

Figure 1: Stylized balance sheet of a bank i



3.1. Systemic losses under different contagion channels

As discussed before, the recovery value of interbank assets may be reduced in the case of defaults. We account for this by writing their value as $R'l$, where $l \leq \bar{l}$ remains to be determined by the contagion models described below. We can thus rewrite the balance sheet identity as:

$$e = R'l + a - \bar{l} \tag{4}$$

Following Siebenbrunner et al. (2017), we will assume an idiosyncratic shock to a single bank $s \in 1 \ldots N-1$ and compute the equilibrium value of interbank assets under four different contagion channels. The first channel, denoted **First-Round contagion**, consists of simply setting the repayment of the shocked bank to zero:

$$l_i^{\text{First-Round}} = \begin{cases} 0 & \text{if } i = s \\ \bar{l}_i & \text{otherwise} \end{cases} \tag{5}$$

The second channel, denoted **n$^{\text{th}}$-round contagion**, computes equilibrium values based on the notion that every bank in the system can distribute at most the value of its total assets among its creditors. Losses are thus computed for direct creditors of the shocked bank, as well as for their creditors and so on, until equilibrium is reached.[4] Equilibrium payments are computed as a fixed point of the map:

[4]This idea was introduced by Eisenberg and Noe (2001), the map presented here with an idiosyncratic shock is taken from Siebenbrunner et al. (2017)

$$l_i^{\text{n}^{\text{th}}\text{-round}} = \begin{cases} 0 & \text{if } i = s \\ \bar{l}_i & \text{if } i \neq s \wedge \bar{l}_i \leq a_i + (R' l^{\text{n}^{\text{th}}\text{-round}})_i \\ a_i + (R' l^{\text{n}^{\text{th}}\text{-round}})_i & \text{otherwise} \end{cases} \tag{6}$$

Note that under n$^{\text{th}}$-round contagion it is assumed that there are no liquidation losses on assets in the resolution process of a bank. This assumption is relaxed under the **fire sales contagion** channel, where an endogenous recovery rate $r \in [0, 1]$ is computed through a fire sales model, giving the equilibrium value of interbank assets (Siebenbrunner et al., 2017):

$$l_i^{\text{Fire Sales}}(r) = \begin{cases} 0 & \text{if } i = s \\ \bar{l}_i & \text{if } i \neq s \wedge \bar{l}_i \leq a_i + (R' l^{\text{Fire Sales}})_i \\ r a_i + (R' l^{\text{Fire Sales}})_i & \text{otherwise} \end{cases} \tag{7}$$

The equilibrium recovery value $r^{\text{Fire Sales}}$ is computed as the greatest fixed point of the tâtonnement process

$$r^{\text{Fire Sales}} = \delta^{-1}(s(l^{\text{Fire Sales}}(r^{\text{Fire Sales}}))) \tag{8}$$

for the supply function

$$s(l) = \sum_{\{i \in \mathcal{N} \,:\, a_i + (R' l)_i < \bar{l}_i\}} a_i \tag{9}$$

and the inverse demand function

$$\delta^{-1}(s) = 1 - \kappa * \frac{s}{\sum_{i=1}^{N} a_i}, \tag{10}$$

where κ is a sensitivity parameter calibrated here as $\kappa = 0.5$ using the procedure explained in Siebenbrunner et al. (2017).

Note that the fire sale channel generally incurs higher losses than n$^{\text{th}}$-round contagion as the losses for creditors are increased through the liquidation losses. An even more punitive specification assumes that all banks hold a common asset under a **mark-to-market** accounting regime and thus have to account for the losses induced by the liquidation regardless of their exposure through the interbank network. This leads to the more punitive equilibrium value for interbank assets (Siebenbrunner et al., 2017)

$$l_i^{\text{MtM}}(r) = \begin{cases} 0 & \text{if } i = s \\ \bar{l}_i & \text{if } i \neq s \wedge \bar{l}_i \leq ra_i + (R' l^{\text{MtM}})_i \\ ra_i + (R' l^{\text{MtM}})_i & \text{otherwise} \end{cases} \tag{11}$$

with the equilibrium recovery value r^{MtM} given by the greatest fixed point of the tâtonnement process:

$$r^{\text{MtM}} = \delta^{-1}(s(l^{\text{MtM}}(r^{\text{MtM}}))) \tag{12}$$

Existence and convergence results for equilibrium values are presented in Siebenbrunner et al. (2017).

We use the equilibrium values of interbank assets $l^{\text{First-Round}}$, $l^{\text{n}^{\text{th}}\text{-round}}$, $l^{\text{Fire Sales}}$ and l^{MtM} to compute systemic losses under these contagion channels. We define a matrix $C \in \mathbf{R}^{N \times N}$ of contagion losses, where C_{ij} are the losses caused to bank j by a default of bank i. The s^{th} column for $s < N$ of this matrix for First-Round contagion losses is then given by the vector:

$$c^{\text{First-Round}}(s) = S R'(\bar{l} - l^{\text{First-Round}}), \tag{13}$$

where the matrix $S \in \{0, 1\}^{N \times N}$ ensures that losses caused by a bank to itself and to the sink node are not included in the matrix $C^{\text{First-Round}} = \left(c^{\text{First-Round}}(1), \ldots, c^{\text{First-Round}}(N-1), \mathbf{0}^N\right)$, where $\mathbf{0}^N$ denotes an N-dimensional vector of 0's:

$$S_{ij} = \begin{cases} 1 & \text{if } i = j \wedge i \neq s \wedge i < N \\ 0 & \text{otherwise} \end{cases} \tag{14}$$

Contagion losses caused through the systemic contagion channels are defined analogously:

$$c^{\text{n}^{\text{th}}\text{-round}}(s) = S R'(\bar{l} - l^{\text{n}^{\text{th}}\text{-round}}) \tag{15a}$$
$$c^{\text{Fire Sales}}(s) = S R'(\bar{l} - l^{\text{Fire Sales}}) \tag{15b}$$
$$c^{\text{MtM}}(s) = S R'(\bar{l} - l^{\text{MtM}}) \tag{15c}$$

Note that first-round losses relate only to bilateral credit risk and do not contain systemic contagion effects yet. In order to clearly separate bilateral credit risk from systemic risk, we will subtract the bilateral part of the losses from the losses under n$^{\text{th}}$-round, fire sales and mark-to-market contagion, in oder to obtain the purely systemic losses in the estimations. We also consider the losses caused by a particular bank in the estimations, taken as the rows of C (see section 4).

3.2. A Model of Interbank Interest Rates

We follow Siebenbrunner and Sigmund (2017) and introduce the following interbank market model. They assume that loan and deposit markets vis-à-vis the real economy, i.e. corporate and household sectors, and for loans and deposits within the banking sector are cleared in sequence. Their model starts after the loan market for the real economy has cleared and looks at the clearing of the interbank market. We denote by p_L^i and p_D^i the respective prices of interbank loans and deposits and assume that banks optimize their profits from interbank lending and deposit activities:

$$\max \Pi = p_L^i * q_L^i - p_D^i * q_D^i \tag{16}$$

Subject to a balance sheet condition:

$$a_i + q_L^i = d_i + e_i + q_D^i \tag{17}$$

Siebenbrunner and Sigmund (2017) assume that banks choose optimal prices, instead of quantities, as the structure of the interbank market suggests that loan size and deposit size can be easily changed. Their strategy is supported by Bluhm et al. (2016) who confirm the "Interbank exposure accumulation" hypothesis, as in the majority of interbank books, consisting of borrowing and lending positions, grow over time by accumulating gross interbank exposures vis-à-vis counterparties rather than netting exposures. In other words, the administrative costs of interbank loans/deposits are clearly not proportional to its size.

Siebenbrunner and Sigmund (2017) set up the following Lagrangian optimization problem with local Bertrand oligopolistic demand functions for horizontally differentiated interbank deposit and loans:

$$\max_{p_L^i, p_D^i} \Pi_C = p_L^i * q_L^i\left(p_L^i\right) - p_D^i * q_D^i\left(p_D^i\right) - \lambda\left(d_i + e_i + q_D^i\left(p_D^i\right) - a_i - q_L^i\left(p_L^i\right)\right) \tag{18a}$$

$$q_D^i = \alpha_D^i + \alpha_D X_D^i + b_D p_D^i - \gamma_D p_D^{-i} \tag{18b}$$

$$q_L^i = \alpha_L^i + \alpha_L X_L^i - b_L p_L^i + \gamma_L p_L^{-i} \tag{18c}$$

Where p_L^{-i} and p_D^{-i} are aggregates of the prices of all competitors, X^i is a vector of control variables that shift the local demand and supply functions and α_D^i, α_L^i, α_D, α_L, b_D, b_L, γ_D and γ_L are scalar sensitivity parameters.

Siebenbrunner and Sigmund (2017) show that the game defined by 18 has a Nash equilibrium that allows every bank to satisfy its balance sheet constraint. The solution can be written as a structural equation system for interbank loan and deposit prices:

$$p_L^i = \frac{1}{b_L}\left(\overbrace{a_i - d_i - e_i}^{\text{Funding gap}} + \overbrace{\alpha_L^i - \lambda b_D}^{\text{Fixed effect}} + \overbrace{\alpha_L X_L^i + \gamma_L p_L^{-i}}^{\text{Exogenous drivers}} + \overbrace{b_D p_D^i}^{\text{Interaction term}}\right) \tag{19a}$$

$$p_D^i = \frac{1}{b_D}\left(\overbrace{a_i - d_i - e_i}^{\text{Funding gap}} - \overbrace{\alpha_D^i - \lambda b_L}^{\text{Fixed effect}} - \overbrace{\alpha_D X_D^i + \gamma_D p_D^{-i}}^{\text{Exogenous drivers}} + \overbrace{b_L p_L^i}^{\text{Interaction term}}\right) \tag{19b}$$

Note that this solution implies a **simultaneity** of interbank lending and deposit rates. Siebenbrunner and Sigmund (2017) provide strong evidence that this simultaneity is indeed present in the empirical data.

4. Inference strategy

We aim to assess the impact of contagion losses, computed as described in Section 3.1 on interbank lending and deposit rates. We account for the simultaneity of these two prices explained in Section 3.2 by estimating a simultaneous equation system. Our identification strategy, inspired by Siebenbrunner and Sigmund (2017), consists of the instrument mapping for the exogenous drivers X_L and X_D for the loan and deposit rate equation summarized in Table 2.

We estimate different models which correspond to different hypotheses about the inclusion of systemic risk in interbank prices: In the first model specification, we consider only First-Round losses, both received losses in the loan rate equation and caused losses in the deposit rate equation. Note that First-Round losses correspond to exposure, and together with the PD and collateral ratio, we include the main components of the expected loss. This model specification thus accounts for bilateral credit risk, but does not include any aspects of systemic contagion losses. We compare this to three other models, which include not only first-round losses but also the additional losses incurred under each of the three systemic contagion channels outlined in Section 3.1: n^{th}-round, Firesales and Mark-To-Market contagion.

Our inference is based both on a statistical assessment of the quality of each model as well as an economic interpretation of signs and coefficients of the estimated parameters, in particular those for systemic contagion losses. Under the hypothesis that banks accounted for systemic risk in their pricing on interbank markets we would expect the models with systemic contagion losses to show better correspondence with the data than the First-Round model. Furthermore, the signs and coefficients of systemic contagion losses would be statistically significant and economically meaningful, i.e. showing a positive relation between losses caused or received and prices charged on deposits or loans, respectively.

In order to account for the simultaneity of loan and deposit rates explained in Section 3.2 we estimate the following system using two-stage (2SLS) and three-stage least squares (3SLS):

Table 2: Mapping of variables to equations

Variable description and abbrevation		**Deposit Rate**	**Loan Rate**
Loan rate	LR	✓	
Deposit rate	DR		✓
Total assets	TA	✓	✓
Funding share from the same sector (relationship proxy)	F-Sec	✓	
Lending share to the same sector (relationship proxy)	L-Sec		✓
EURIBOR (instrument for aggregate borrowing rate)	STI	✓	
10y government bond yield	LTI		✓
Probability of default	PD	✓	
Average loan risk weight	RW		✓
Funding gap	FG	✓	✓
Average collateral ratio of interbank deposits	COL_Owing	✓	
Average collateral ratio of interbank loans	COL_Holding		✓
Losses caused[a]		✓	
Losses received			✓

[a]Losses Caused/Received stands as a placeholder for either only First-Round or First-Round plus either n$^{\text{th}}$-round, Firesales or Mark-To-Market contagion losses. We include these losses computed as described in Section 3.1 and normalize them by the total assets of the bank concerned to bring them to scale with the other variables and avoid ill-conditioning of the regressor matrix.

$$Y_{i,t} = \alpha_i + BX_{i,t} + \epsilon_{i,t}, \tag{20}$$

where

$$Y_{i,t} = \begin{pmatrix} \text{Deposit Rate}_{i,t,1} \\ \text{Loan Rate}_{i,t,2} \end{pmatrix}, B^{\intercal} = \begin{pmatrix} \alpha_1 & \alpha_2 \\ 0 & \beta_{2,1} \\ \beta_{1,2} & 0 \\ \beta_{1,3} & \beta_{2,3} \\ \beta_{1,4} & 0 \\ 0 & \beta_{2,5} \\ \beta_{1,6} & 0 \\ 0 & \beta_{2,7} \\ \beta_{1,8} & 0 \\ 0 & \beta_{2,8} \\ \beta_{1,9} & \beta_{2,9} \\ \beta_{1,10} & 0 \\ 0 & \beta_{2,11} \\ \beta_{1,12} & 0 \\ 0 & \beta_{2,13} \end{pmatrix}, X_{i,t} = \begin{pmatrix} \mathbf{I} \\ \text{LR} \\ \text{DR} \\ \ln(\text{TA}) \\ \text{F-Sec} \\ \text{L-Sec} \\ \text{STI} \\ \text{LTI} \\ \text{PD} \\ \text{RW} \\ \text{FG} \\ \text{COL\_Owing} \\ \text{COL\_Holding} \\ [\text{Losses\_Caused}] \\ [\text{Losses\_Received}] \end{pmatrix} \tag{21}$$

Table 3: Models for deposit rate equation

ID	First-Round	n^{th}-round	Firesales	Mark-to-Market
LR	-0.0812 ***	-0.0827 ***	-0.0840 ***	-0.0799 ***
TA	-0.1082 ***	-0.1069 ***	-0.1159 ***	-0.1055 ***
FG	-0.0022 ***	-0.0027 ***	-0.0021 ***	-0.0022 ***
FS	6e-04 **	5e-04 *	0.0009 ***	6e-04 **
STI	0.4772 ***	0.4784 ***	0.4780 ***	0.4765 ***
PD	-0.0215 *	-0.0184	-0.0454 ***	-0.0211 *
COL	-0.0787 *	-0.0559	-0.0606	-0.0808 **
FR caused	0.4144 ***	0.567 ***	0.3863 ***	0.4212 ***
NR caused		-0.751 ***		
FS caused			0.3046 *	
MtM caused				-0.0026 **
Hansen	8.941	11.1758	52.2896	16.1329
McElroy	0.7879	0.7876	0.7875	0.7886

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Results of 3SLS estimation procedure.

5. Results

Before we move to discussing inference from our models, we first report the results of several statistical tests to assess the adequacy of the chosen estimation procedure. Table C.8 reports the results of these tests for each model in the Tables 3 and 4. Overall, they confirm the selected estimation approach. Most importantly, the Durbin-Hausman-Wu test clarifies that the interbank loan and deposit rates are truly endogenous.[5] The rejection of the null hypothesis confirms the endogeneity of the interbank rates. As for any instrumental variable estimator, we test the quality of instruments (F-Test)[6] and the exogeneity of the instruments.[7] The J-Test does not reject the null hypothesis that the instruments are exogenous. Finally, the system overidentification test is used to test the null hypothesis of 3SLS versus the alternative of 2SLS (Wooldridge, 2002). The test suggests a preference for 3SLS over 2SLS, except for the Firesales model.

The first thing to note about our results is that they confirm that loan and deposit rates are determined simultaneously on the interbank market, as observed by Siebenbrunner and Sigmund (2017). We add further stability to their results, as adding the different contagion channels does not alter the sign, magnitude or the significance of the other coefficients.

The main contribution of our paper lies in the comparison of the First-Round model with the models

[5] See Nakamura and Nakamura (1981) for details.
[6] See Stock et al. (2002)
[7] See Bhargava (1991) for details.

Table 4: Models for loan rate equation

ID	First-Round	n^{th}-round	Firesales	Mark-to-Market
DR	1.2176 ***	1.2132 ***	1.2300 ***	1.2173 ***
TA	0.2221 ***	0.2323 ***	0.2296 ***	0.2226 ***
FG	-0.0031 ***	-0.0029 ***	-0.0042 ***	-0.0031 ***
RW	0.0116 ***	0.0113 ***	0.0141 ***	0.0115 ***
LS	-0.0022 ***	-0.0022 ***	-0.0018 ***	-0.0021 ***
LTI	0.2138 ***	0.2165 ***	0.2032 ***	0.2141 ***
COL	-0.115	-0.0965	-0.0619	-0.1136
FR received	0.5688 ***	0.5954 ***	0.3607 ***	0.5676 ***
NR received		-1410.705 ***		
FS received			-997.2972 ***	
MtM received				-2.0165
Hansen	8.941	11.1758	52.2896	16.1329
McElroy	0.7879	0.7876	0.7875	0.7886

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Results of 3SLS estimation procedure.

including the different systemic contagion losses. As noted before, these models constitute competing hypotheses about the inclusion of systemic contagion effects in interbank prices. We first note that the First-Round model, corresponding to the view that banks do not include systemic effects in their pricing, shows solid explanatory power with a McElroy R^2 value of around 0.79. Furthermore, most coefficients are significant or highly significant and show an economically meaningful sign.

Comparing the First-Round model to the models of systemic contagion losses, we first note that the coefficients and significance of the control variables largely do not change. The explanatory power is largely unaffected as well. However, the results of the Hansen overidentification test show that these models add endogeneity to the model when compared to the First-Round model. If we were to select models based on this assessment alone, we would thus reject the view that systemic losses are considered in interbank prices. If we take a closer look and inspect the coefficients of contagion losses, we observe that all contagion channels have negative signs and are almost all highly significant in both equation (Mark-to-Market losses are less significant and in particular not significant for the loan rate equation). As discussed before, the socially desired behaviour for banks would be to penalize higher systemic contagion losses with higher rates charged on the interbank market. Our results suggest that – if anything – the opposite is the case and that banks that cause higher contagion losses actually enjoy a premium on the interbank market. While this phenomenon might be explicable through market power, it is certainly not socially desirable and thus constitutes a case for the regulation of systemic risk.

Before we conclude we would like to draw the attention to the importance of accounting for the simultaneity of interbank lending and deposit rates in the inference. In Tables B.6 and B.7 in the appendix we report the results of a fixed-effect, equation-by-equation estimation of the same system as described in Section 4. This specification is identical to the one described above except that the aforementioned endogeneity is not accounted for. As can be seen in Table B.6, the coefficients of n^{th}-round and Firesales contagion losses are still highly significant in this specification and of comparable magnitude, their sign however is different. The endogeneity in this case causes the coefficient to be biased by over 200% when compared to the unbiased estimate. More importantly, it risks leading to a seriously flawed inference, as the biased coefficient estimates would correspond to a socially desirable pricing of systemic contagion effects.

6. Conclusion

In this paper we employ a granular balance-sheet based model of interbank markets to assess whether systemic contagion losses are considered in interbank pricing. We compute systemic contagion losses under three different channels, n^{th}-round, Firesales and Mark-to-Market contagion, and compare them to First-Round contagion losses, which relate only to bilateral credit risk. We wish to assess whether systemic contagion losses are capable of explaining interbank prices once bilateral credit risk as well as a number of other factors are controlled for.

Our inference is based on a simultaneous equation model which accounts for the simultaneous determination of interbank lending and deposit rates. This simultaneity can be explained theoretically through a model of profit maximization on interbank markets under horizontally differentiated Bertrand competition. We also show that accounting for this simultaneity is essential, as the endogeneity bias in this case risks leading to seriously flawed inference. Looking at the estimation results we first observe that the model without systemic contagion losses has higher correspondence with the data as measured by the Hansen overidentification statistic. Looking at the coefficients of systemic contagion losses we observe that higher contagiousness actually confers a premium to a bank on the interbank market that is highly significant in most cases. While this could be explained through market power, it is highly socially undesirable as it sets incentives for banks to increase their systemic contagiousness in order to gain a better market position.

Overall, our results suggest that systemic contagion effects are not appropriately priced on interbank markets – if anything, they have positive effects for the bank concerned. We consider this highly undesirable from a social perspective and thus view it as a case for regulation of systemic risk.

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Appendix A. Data Coverage and Summary Statistics

Table A.5: Summary statistics of included variables

Var.Name	Min.	1st Qu.	Median	Mean	3rd Qu.	Max	NAs	Variance
LR on bank loans	-2.45	0.90	1.57	1.76	2.34	5.67	2594.00	1.39
DR on bank deposits	-1.64	0.31	0.61	0.73	0.99	2.97	4753.00	0.41
Log total assets	5.71	11.12	11.90	12.12	12.74	18.87	1911.00	2.11
Funding gap	-274.25	-24.20	-13.04	-13.35	-1.23	110.43	2576.00	492.87
Funding Share Sector	0.00	100.00	100.00	82.69	100.00	100.00	2208.00	1312.75
Short-term interest rate	-0.19	0.20	0.67	0.99	1.15	4.98	0.00	1.72
Consensus PD	0.00	0.04	0.06	0.10	0.08	11.12	5119.00	0.08
Coll Ratio Owing	0.00	0.00	0.00	0.02	0.00	1.00	2208.00	0.01
RWA	0.00	48.58	57.16	56.10	65.77	185.22	1945.00	280.92
Lending Share Sector	0.00	91.96	97.89	87.82	100.00	100.00	2208.00	670.78
Long-term interest rate	0.45	1.78	2.71	2.57	3.63	4.58	0.00	1.49
Coll Ratio Holding	0.00	0.00	0.00	0.02	0.00	1.00	2208.00	0.01
First round caused loss ratio	0.00	0.02	0.06	0.10	0.13	0.95	1745.00	0.01
First round received loss ratio	0.00	0.15	0.24	0.25	0.35	1.00	1745.00	0.02
nth-round caused loss ratio	0.00	0.00	0.00	0.01	0.00	0.76	1745.00	0.00
nth-round received loss ratio	0.00	0.00	0.00	0.00	0.00	0.00	1745.00	0.00
Firesales caused loss ratio	0.00	0.00	0.00	0.01	0.00	0.99	1745.00	0.00
Firesales received loss ratio	0.00	0.00	0.00	0.00	0.00	0.00	1745.00	0.00
mark-to-market caused loss ratio	0.00	0.00	0.00	0.40	0.00	167.29	1745.00	19.96
mark-to-market received loss ratio	0.00	0.00	0.00	0.00	0.00	0.19	1745.00	0.00

Appendix B. Fixed Effects Equation-by-equation Estimation

In this section we reestimate with the fixed effects equation-by-equation procedure. In particular we show how the simultaneity bias changes the RHS deposit/loan rate coefficient.

Table B.6: Deposit rate equation with FE-OLS

ID	First-Round	n^{th}-round	Firesales	Mark-to-Market
LR	0.0742 ***	0.0761 ***	0.0758 ***	0.0742 ***
TA	-0.0443	-0.0446	-0.0493 *	-0.0446
FG	-0.0021 ***	-0.0016 ***	-0.0016 ***	-0.0021 ***
FS	9e-04 ***	0.0011 ***	0.0011 ***	9e-04 ***
STI	0.367 ***	0.3659 ***	0.3658 ***	0.367 ***
PD	-0.0203	-0.0229	-0.0227	-0.0204
COL	-0.0601	-0.0799 *	-0.0823 *	-0.0596
FR caused	0.2329 ***	0.0734	0.0867	0.2313 ***
NR caused		0.7759 ***		
FS caused			0.6652 ***	
MtM caused				5e-04
DR_R2	0.6565	0.6568	0.6568	0.6565

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Results of fixed effects equation-by-equation estimation procedure.

Table B.7: Loan rate equation with FE-OLS

ID	First-Round	n^{th}-round	Firesales	Mark-to-Market
DR	0.5177 ***	0.5171 ***	0.5174 ***	0.5175 ***
TA	0.1044 **	0.118 ***	0.1191 ***	0.1051 **
FG	-0.0046 ***	-0.0044 ***	-0.0044 ***	-0.0046 ***
RW	0.0103 ***	0.0101 ***	0.0101 ***	0.0103 ***
LS	-0.0016 ***	-0.0016 ***	-0.0016 ***	-0.0016 ***
LTI	0.3871 ***	0.389 ***	0.3892 ***	0.3872 ***
COL	-0.5066 ***	-0.4937 ***	-0.4872 ***	-0.5023 ***
FR received	0.2295 ***	0.2536 ***	0.2511 ***	0.2317 ***
NR received		-1605.477 ***		
FS received			-1069.487 ***	
MtM received				-2.6632
LR_R2	0.7263	0.7268	0.7268	0.7263

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Results of fixed effects equation-by-equation estimation procedure.

Appendix C. Specification Tests

The next table shows the specification tests for the results shown in Table 3 and Table 4. We check for the quality of instruments (F-test) and the exogeneity of instruments (J-test and Lagrange multiplier test). We test the endogeneity of the RHS endogenous variables (Durbin-Hausman-Wu test). We check whether 3SLS is preferred to 2SLS (System overidentification test).

Table C.8: Test Statistic for estimation results in Section 5

	F-Stat.	p value	J-test stat.	p-value	LMF test stat.	p-value	Hausman.Endo	p value	Hansen	p-value
FR: DR	130.46	0.00	0.11	0.93	16.06	0.00	10.56	0.00	8.94	0.35
FR: LR	310.66	0.00	0.02	1.00	2.37	0.67	-57.33	0.00		
Direct: DR	130.30	0.00	0.11	0.96	13.31	0.02	10.35	0.00	11.18	0.34
Direct: LR	310.01	0.00	0.12	0.95	14.36	0.01	-56.99	0.00		
FS	130.33	0.00	0.11	0.96	13.10	0.02	10.46	0.00	52.29	0.00
FS: LR	310.00	0.00	0.10	0.97	11.54	0.04	-56.98	0.00		
MtM: DR	130.26	0.00	0.11	0.95	13.64	0.02	10.52	0.00	16.13	0.10
MtM: LR	310.26	0.00	0.03	1.00	3.63	0.60	-57.34	0.00		