Can bank-specific variables predict contagion effects?

Revised version: November 21, 2016

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Abstract

Assessing the systemic risk a bank poses to the system has become a central part in regulating its capital requirements (e.g. the buffer for global or domestic systemically important banks). As with conventional risk types, systemic risks need to be quantified. Currently global regulators propose a range of bank-specific indicators that measure size and interconnectedness to proxy systemic risk. In this study we gauge the capacity of such indicators to explain contagion losses triggered by realizations of sizeable idiosyncratic shocks. We study contagion impact through different channels, separating these effects into first-round, n^{th}-round, asset fire sale and mark-to-market losses. We evaluate the predictive power of models selected by best-subset selection and Lasso by applying 10-fold panel cross validation. We provide constructive proofs for the existence of clearing payment vectors and associated market equilibria for these contagion channels in a model of interlinked balance sheets. We provide algorithms that converge to the greatest market equilibrium in a finite number of steps. Our empirical results suggest that the Basel III indicator set performs well in comparison to alternative data sets of bank-specific indicators. We also find, however, that the proposed data sets without bank dummies do not perform well in capturing the relevance of the average network position for predicting contagion effects.

Keywords: systemic risk, financial stability, financial contagion.

Acknowledgements

We are grateful to T. Peltonen, P. Sarlin and participants of the 2015 RiskLab/BoF/ESRB Conference on Systemic Risk Analytics for their helpful helpful discussions and suggestions. We further thank two anonymous referees, Prof. J.D. Farmer and members of the Oxford Institute for New Economic Thinkting their comments and remarks.

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1. Motivation

A key topic in financial regulation is the negative externality that is not taken into account by banks in their risk level choice. Failing banks can become a large burden to the financial system, the government and ultimately the tax payer. Laeven and Valencia (2010) summarize the cost of banking crises between 1970 and 2006 as follows: (i) direct fiscal costs are around 10% of GDP, (ii) the increase in public debt is around 16% of GDP and (iii) output losses are on average 19.5% of GDP. Honohan and Klingebiel (2000) provide similar figures. Not surprisingly, regulators have responded and require large banks that would cause particularly high losses to the system to hold additional capital buffers in order to reduce their probability of failure.

The academic approach to quantifying systemic risk was shaped by contributions from Acharya et al. (2010), which was developed into SRisk (see Brownlees and Engle (2015)), and by Adrian and Brunnermeier (2016), who introduced the ΔCoVaR concept. In a nutshell, SRisk quantifies the capital shortfall of a bank given a strong market decline and ΔCoVaR estimates the value-at-risk (VaR) of the system as a whole when a particular bank faces distress, i.e. experiences a tail event.

However, while both concepts are used as part of a broader supervisory toolkit, supervisors employ simpler concepts when it comes to the quantification of capital add-ons on large institutions whose failure poses a risk to the whole system (see e.g. BIS (2012), BIS (2013), FED (2015), EBA (2014)). Why do practitioners choose a different path than academia?

There are several reasons. Most importantly, both SRisk and ΔCoVaR require that the bank is publicly listed. However, this is only true for 22% of banks in the US, 4% in the UK, 3% in France and as little as 1% in Germany.[3] Certainly, listed banks tend to be the larger institutions, but there are notable exceptions in many countries, e.g. large Landesbanken in Germany, or cooperative banks. This leads to a situation where supervisors cannot employ SRisk or ΔCoVaR for the whole banking system, which would however be necessary if they were to be connected to capital add-ons. Furthermore, time series are needed for reliable estimation of SRisk and ΔCoVaR[4], which may further reduce the sample in case of structural breaks like mergers.

Another major reason why supervisors have looked for approaches other than SRisk and ΔCoVaR is that the systemic capital add-on is designed for a different purpose. The problem with large, highly interconnected ('systemically important') banks is that they cause high losses to the system upon failure. FED (2015) refer to these losses as the systemic loss-given-default (LGD). However, requiring banks to hold more capital will mainly lower their probability of default (PD) and only to a lesser extent their LGD. Capital-add-ons for systemically important banks should thus target banks that exhibit a high systemic LGD, irrespective of their PD. In this manner, capital regulation can address the systemic expected loss

[3] See Table C.2 in the Appendix for an extended list of countries and the relevant sources. It seems that Asian countries are no exception, but we could not find a reliable source for the total number of banks per country for this area.

[4] For the purpose of estimating SRisk Brownlees and Engle (2015) use a GARCH-DCC model. ΔCoVaR estimations are based on quantile regressions.

(PD times LGD) from bank failures. Clearly, SRisk and ΔCoVaR do not aim at quantifying the systemic LGD. SRisk does only look at the capital shortfall of single institutions, conditional on systemic stress events, thus concentrating on the receiving end rather than the originators of systemic risk.[5] ΔCoVaR does not consider capital shortfalls or failures at all but only looks at changes in the tail of the loss distribution.

The above reasoning shows why regulators had to come up with their own quantification of the systemic LGD.[6] The approaches documented in (BIS (2012), BIS (2013), FED (2015), EBA (2014)) rely on a simple scorecard approach where a number of indicators are linearly combined to an overall score.

In this article we look into the question whether the indicators stipulated in these regulations do indeed provide a good proxy of the systemic LGD. Our dataset comprises a full interbank network observed each quarter for several years in Austria. We compute the systemic losses caused by the hypothetical failure of each individual bank in this full interbank network model — this can be thought of as the systemic LGD. Furthermore, we examine the more general question of whether it is possible to explain the systemic LGD by considering data at the level of individual banks only, i.e. without information on the complete network. Given that the full interbank network represents both rarely available and highly sensitive data, we can test only for the Austrian case.

The remainder of the paper is structured as follows: Section 2 discusses related literature to our work. Section 3 presents the model framework used for computing contagion losses. Section 4 gives an overview of the data set used for testing the regulatory scorecard approach. Section 5 lays out our econometric approach for performing the estimations. In section 6 we present and discuss the results of the estimations. Section 7 presents robustness checks, and section 8 concludes.

2. Related literature

Our work builds on a rich strand of literature on interbank contagion models. Much of the work on studying the relation between the structure of the interbank network and contagion was inspired by the seminal contribution of Allen and Gale (2000). Building on earlier work by Diamond and Dybvig (1983), they show that the potential amplification of idiosyncratic shocks through the interbank market depends on the network structure of that market. Another seminal, early contribution by Freixas et al. (2000) shows that for a given network structure, the extent of contagion heavily depends on the specific parameters of the model. Other early contributions focussing on systemic risk and contagion include Angelini et al. (1996), Rochet and Tirole (1996) and Suzuki (2002). Nier et al. (2007) confirm the existence of a relation between the connectivity of the interbank network and contagion and show that this relation is

[5] This difference in nature is also confirmed by regressing our measures of systemic contagion losses (see section 3) on SRisk and similar measures of systemic risk: the coefficient for SRISK is negative, indicating low systemic risk according to interbank contagion when SRrisk shows high level of systemic risk, and the explanatory power is very weak. Detailed results can be requested from the authors.

[6] Refer to Löffler and Raupach (2015) for further discussions on potential issues in the regulatory use of SRisk and ΔCoVaR.

in fact non-monotonous. Iori et al. (2006) report a similar result, namely that the relation between connectivity and and contagion becomes non-monotonous when heterogeneity among banks is introduced. This is again confirmed by Elliott et al. (2014), who study a linearized version of the Eisenberg and Noe (2001) model and also find a non-monotonic relation between connectivity and contagion. Note that in a non-connected system there is no danger of direct contagion. In a very dense network, interbank exposures are diversified and the likelihood of contagion is low. In lowly connected systems, however, the risk of contagion may be high. Leitner (2005), using a model with the possibility of bailouts, shows that interbank connectivity and the associated threat of contagion can also have positive effects, as it creates incentives for banks to provide mutual insurance. Drehmann and Tarashev (2013) develop measures to differentiate between the inward and the outward direction of systemic risk, as referred to in section 1. Gai and Kapadia (2010), using methods from complex network theory, find that financial networks show robust-yet-fragile features: the probability of contagion in general is low, but the effect of cascades can be widespread if they occur. Building on this work, Teteryatnikova (2014) shows that the commonly observed[7], 'tiered' structure of banking systems is less prone to contagion than other structures with positive degree correlations. Poledna et al. (2015) investigate the multi-layer structure of the interbank network using Mexican data. They find that the combination of systemic risk contributions across different layers (such as deposits, securitization, etc.) is super-additive. Bargigli et al. (2013) arrive at similar conclusions using Italian data.

There are several studies that assess the impact of Basel regulations, e.g. Angelini et al. (2011), Georg (2011) or Derviz (2013), but only few of them explicitly account for network effects. Thurner et al. (2003) study the effects of Basel II capital requirements under different network structures. They find that the impact of the regulatory parameter exhibits two plateaus, where small changes have very limited impact on financial stability, irrespective of the network structure. Krug et al. (2015) study the impact of micro- and macroprudential measures of Basel III regulations in an agent-based framework. They find that the contribution of combined regulatory measures to financial stability is super-additive. In their model the contribution of capital buffers for systemically important institutions to overall stability is low.

Our contagion model builds on the work of Eisenberg and Noe (2001), who show how to compute contagion results in the presence of cycles in the interbank network. This was further developed by Elsinger et al. (2006), who embed the model into a larger risk assessment framework covering different risk types.Elsinger (2009) introduces seniority structures and cross-holdings into the model of Eisenberg and Noe (2001). Rogers and Veraart (2013) show how to compute such a model with liquidation costs. Fischer (2014) develops a Merton (1974)-type valuation that is consistent with contractual relations including derivates. Barucca et al. (2016) show the consistency of these contagion models with the balance sheet identity in a comprehensive framework. They show that DebtRank, another popular contagion model developed by Battiston et al. (2012), is a linearized special case of the general contagion model.

Other contributions focus on the quantification of contagion. These include Furfine (2003), Upper and Worms (2004), Degryse and Nguyen (2007), Cont et al. (2013), and Caccioli et al. (2015). Upper (2011) provides a good overview of many of these approaches, Glasserman and Young (2015) give a more

[7]See for example Boss et al. (2004).

general overview. The endogeneity of market prices in our study is related to the model of Cifuentes et al. (2005), where banks engage in fire sales in order to meet regulatory leverage constraints. Other relevant contributions in this regard include Shin (2008), Adrian and Shin (2010), and Bluhm and Krahnen (2014). Halaj and Kok (2015) study price formation in a game-theoretic model of network evolution.

Performing a contagion analysis as we do in the present study requires complete information on the network of contractual linkages between financial institutions. Fortunately, this information is available in our data set, but this is often not the case. Hence, several statistical methods were developed to estimate the complete network from partially available data (such as the total sum of interbank assets and liabilities of each institution). In one of the early contributions, Elsinger et al. (2006) use a maximum entropy method to perform this estimation. Maximum entropy remains a popular general method for this purpose, however, given the typically sparse structure of financial networks, it may overestimate the actual number of links in some cases. Anand et al. (2015a) develop a minimum entropoy method aimed at better replicating the typically sparse structure of interbank markets. Several alternative approaches have been developed, including Drehmann and Tarashev (2013), Hałaj and Kok (2013) and Mastrandrea et al. (2014). Anand et al. (2015b) perform a quantitative comparison of these different methods using multiple data sets of financial networks of different types from different jurisdictions.

While our model of contagion builds on a network of contractual linkages, there exist also numerous approaches of identifying network connections and contagion effects based on statistical relationships, typically using observable market data such as stock prices. Billio et al. (2012) demonstrate the application of a range of common statistical methods to estimate such relationships, further contributions include Diebold and Yilmaz (2014) and Giudici and Parisi (2016). In a more recent strand, Graphical Models are employed to model dependency relationships between financial institutions. Denev (2015) provides a comprehensive introduction to the methodology and its application to Finance, applications to systemic risk include Ahelegbey and Giudici (2014) and Cerchiello and Giudici (2016). Giudici et al. (2016) develop a comprehensive approach to systemic risk, accounting for both direct exposures as well as statistical linkages.

Several statistical methods were developed specifically to account for the fact that the main focus in systemic risk analysis lies on capital shortfalls and contagion effects under extreme scenarios (tail dependencies) rather than on unconditional relations. These undertakings gave rise to the aforementioned SRISK and ΔCoVaR, amongst many others: Acharya et al. (2010), Acharya et al. (2012), Brownlees and Engle (2015), Hautsch et al. (2015), Banulescu and Dumitrescu (2015), Adrian and Brunnermeier (2016), Betz et al. (2016). Several studies find that such indicators can act as early warning signals for financial crises, focusing on forecasts in time rather than on (intra-period) cross-sectional contagion: Minoiu et al. (2014) find that the connectivity of the global financial network has potential to act as an early warning indicator for systemic crises. Peltonen et al. (2015) build on the early-warning-model developed by Betz et al. (2014) and show that the inclusion of network indicators significantly improves forecast performance for crises of individual banks. Hautsch et al. (2014) focus on forecasting statistical systemic risk indicators directly rather than observable crises.

3. Computing contagion losses

3.1. Overview of contagion channels

In this section we briefly outline the basic framework for computing contagion losses. Full details are given in section 3.2. As a general setup, we assume that a bank is hit by an idiosyncratic shock that wipes out all of its assets. This corresponds to the realization of a high percentile-shock of the loss distribution of the bank, as assumed in the ΔCoVaR-methodology. There are numerous historical examples for such events, e.g. the failures of Herstatt, Barings Bank, Banker's Trust, Lehman Brothers, Northern Rock, Hypo Real Estate, to name some of the most famous. We then consider the impact on the financial system that occurs via the four different contagion channels described below. The mechanics of each of these channels is illustrated in Figure 1 for a small banking system of five banks.

The assumed exposure network exhibits a sparse core-periphery structure, as is typical for real-world banking networks (see for example Boss et al. (2004)): bank A has received a loan from bank B, who has received a loan from Bank C. There are two more peripheral banks, who have neither received nor granted any loans to any of the other banks in the system. All banks, however, are indirectly connected to each other through common asset holdings (overlapping portfolios). The structure can be seen from the graphs in Figure 1). Assuming that bank A is hit by an idiosyncratic shock and defaults, the different contagion channels will affect this system as follows:

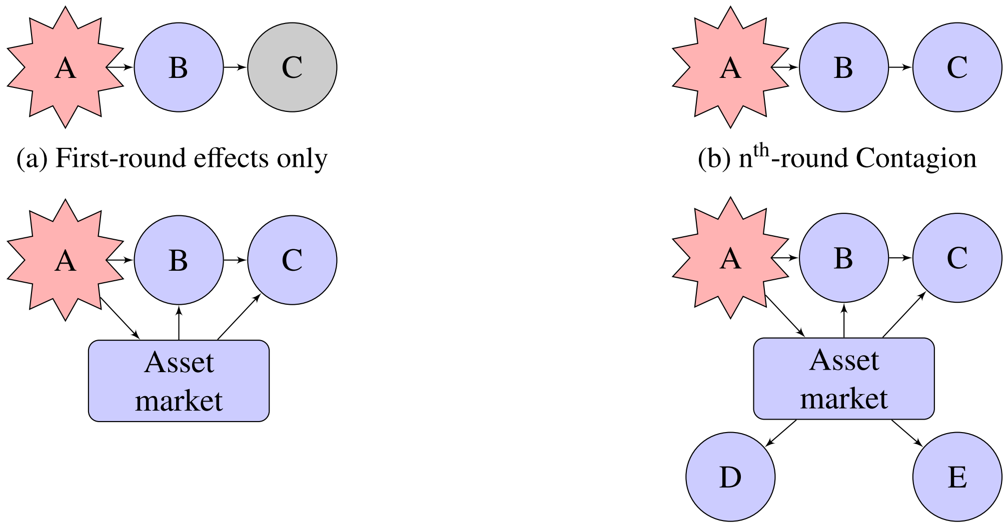
(a) **First-round effects** (Figure 1a): Only direct creditors of the bank are affected, in this example bank B. In reality Bank C would be affected through second-round effects if bank B defaulted due to the shock coming from A, but these higher-order effects are ignored when considering first-round losses (illustrated by the grey coloring of bank C in Figure 1a).

(b) **$\mathbf{n^{th}}$-round effects** (Figure 1b): The impact of the shock on the entire network of interbank loans is considered, i.e. also the losses of creditors of banks that are not directly exposed to the initially defaulting bank A, but who are creditors to banks that are pushed into default due to the initial shock (contagion spilling from bank B to C in this example). Banks with neither direct nor indirect exposures do not incur losses under this contagion channel.

(c) **Asset fire sale effects** (Figure 1c): Under this specification, losses that arise from the liquidation of defaulted banks are considered. Asset fire sale losses reduce the recovery value of loans towards defaulted banks, thereby increasing their creditors' losses. These losses are computed endogenously via a market adjustment process. Banks that are not at all exposed to defaulting banks are not affected by asset fire sale losses (in the absence of mark-to-market accounting). In the example depicted in Figure 1c bank C now suffers via an additional channel compared to case (b): the recovery on its exposure to B is now lower, as the fire sales by bank A and bank B push down their common assets' prices.

(d) **Mark-to-market effects** (Figure 1d): When banks hold common assets under a mark-to-market accounting regime, liquidation losses on firesold assets have to be recognized by all banks in the

Figure 1: Illustration of contagion channels



(a) First-round effects only

(b) n$^{\text{th}}$-round Contagion

(c) Asset Fire Sales

(d) Mark-To-Market Effects

system, even if they are not exposed to the interbank network at all (banks D and E in this example). Note that both, asset fire sales and mark-to-market effects, do also increase the losses for banks who are already affected by direct contagion losses.

3.2. Computation of shock impact

We employ a modified version of the framework developed in Siebenbrunner (2015) for computing contagion losses. The model is based on the underlying idea that one bank's interbank liabilities are another bank's interbank assets. The value of an interbank asset depends on the solvency of the borrower: if the obligor defaults, all lenders have to adjust the value of their claims, affecting their own solvency position. If the shock stemming from this impairment pushes another bank into default, then all of its creditors will have to adjust the value of their claims on this bank, potentially causing cascades of subsequent defaults.

Formally, consider a financial system composed of a set $\mathscr{N} = \{1, \dots, N-1\}$ of interlinked banks. The linkages among these banks are captured in the bilateral loan matrix $L \in \mathbb{R}_+^{N \times N}$, where $L_{i,j}$ represents the liabilities of firm i towards firm j. L includes an additional row and column for a sink node which captures liabilities outside the system (e.g. deposits by customers). This specification ensures that the total liabilities of bank i are given by the i-th entry of the vector of column sums of the liability matrix: $\bar{p}$, $\bar{p}_i = \sum_{j=1}^{n} L_{ij}$. Now consider the matrix $\Pi \in [0,1]^{n \times n}$ of relative liabilities, where each entry L_{ij} of L is divided by the total liabilities $\bar{p}_i$ of that bank:

$$\Pi_{ij} = \begin{cases} \frac{L_{ij}}{\bar{p}_i} & \text{if } \bar{p}_i > 0 \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

Banks hold two types of assets: external assets (these comprise all assets that are not interbank claims), denoted by the vector $e \in \mathbb{R}^N_+$, where e_i is the value of external asset holdings by bank i, and interbank assets. The value of interbank assets depends on the recovery rate of these claims: solvent debtor banks repay their liabilities in full, while insolvent banks split the remaining value of their assets minus any liquidation costs proportionally among their creditors. For a given payment vector $p \in \mathbb{R}^n_+$, the value of interbank assets is given by $\Pi' p \in \mathbb{R}^n_+$. Assuming that a bank $s \in \mathcal{N}$ is hit by an idiosyncratic shock, the payment vector for the different contagion channels is computed as follows. Note that the setup is similar to Siebenbrunner (2015), the main difference being that we set the repayments of the defaulted bank to 0, something that could not be realized using only a shock to external assets as specified therein.

(a) **First-round losses**

As described in Section 3.1, first-round losses consider only losses to direct creditors of the defaulted bank s. The payment vector first-round losses is thus simply given by setting $p_s = 0$ and letting all other banks repay their liabilities in full:

$$p_i^1 = \begin{cases} 0 & \text{if } i = s \\ \bar{p}_i & \text{otherwise} \end{cases} \tag{2}$$

(b) **n$^{\text{th}}$-round losses**

The recovery value of loan towards a defaulted bank will depend on the value of the remaining assets of this bank, which will be split proportionally among all creditors of the bank. These assets may include interbank assets, whose value will again depend on the solvency position of all obligors of the bank concerned. Hence, the equilibrium value of all interbank assets will depend on the solvency position of all banks in the system: claims on solvent banks are worth their full nominal value, all claims on defaulted banks are worth the fraction of remaining assets of that bank relative to its total liabilities (assuming equal seniority of all claims).

The idea described above was introduced and formalized as the **clearing payment vector** by Eisenberg and Noe (2001). Under the clearing payment vector, each solvent bank repays its liabilities in full and each defaulted bank repays the value of its external assets plus the value of its interbank claims under the clearing payment vector. Formally, we call a clearing payment vector a fixed point

$$p^{*,1}(\alpha) = \Phi_1(p^{*,1}(\alpha)) \tag{3}$$

of the following map:

$$\Phi_1(p)_i = \begin{cases} 0 & \text{if } i = s \\ \bar{p}_i & \text{if } i \neq s \wedge \bar{p}_i \leq e_i + (\Pi' p)_i \\ \alpha e_i + (\Pi' p)_i & \text{otherwise} \end{cases} \tag{4}$$

The intuition behind this map is as follows: the bank s who is affected by an idiosyncratic shock does not repay any of its obligations. Other banks repay their obligations in full if the value of their external assets plus the value of claims on other banks is greater than their total liabilities (i.e. if they are solvent). Insolvent banks repay the remaining value of their assets, i.e. their external assets plus the value of claims on other banks, when considering that each of its debtor banks may also be unable to repay its obligations in full. The α-parameter introduced in Φ_1 will only be used later for computing the effects of asset fire sales. We set $\alpha = 1$ and write $p^{*,1}(1) = p^{*,1}$ when considering n^{th}-round effects.

Note that this specification differs from the original specifications in Eisenberg and Noe (2001) and Siebenbrunner (2015) by accounting for the idiosyncratic shock to bank s. See Appendix A for a formal derivation of the clearing payment vector.

(c) **Asset fire sale losses**

The effects of asset fire sales (in the absence of mark-to-market accounting) are endogenized as a haircut on external assets of defaulted banks, captured by the α-parameter. The underlying idea is that, in case of default, companies are forced to sell their assets onto less than perfectly liquid markets, thus achieving below book-value liquidation prices. Liquidation prices are determined by equating demand and supply, where the supply function is given by the sum of external assets of banks that are defaulting under a given payment vector:

$$s(p) = \sum_{\{i \in \mathcal{N}\,:\, e_i + (\Pi' p)_i < \bar{p}_i\}} e_i \tag{5}$$

The inverse demand function (which gives the price, expressed as a percentage of the original book value) is assumed to take a linear form:

$$d^{-1}(s) = 1 - \kappa * \frac{s}{\sum_{i=1}^{n} e_i} \tag{6}$$

Where $\kappa \in [0, 1]$ is a slope parameter expressing the sensitivity of market prices to volume changes. This setup is, again, taken from Siebenbrunner (2015). The reason why we choose to adopt this setup over other settings (e.g. Cifuentes et al. (2005)) is that it allows for an appealing interpretation: when no one is willing to buy an asset, its liquidation price is equal to 0. In our setting, this would be the case when $\kappa = 1$ and all banks are in default. The κ-parameter can thus be interpreted as the share that the financial system under investigation represents in the overall market for firesold assets (buyers outside the system could be other financial investors not included in the sample, or foreign investors). The calibration of the κ-parameter is explained in section 3.3. The equilibrium price $\alpha^{*,1}$ is now defined to be the greatest fixed point of the map:

$$\Theta_1(\alpha) = d^{-1}(s(p^{*,1}(\alpha))) \tag{7}$$

Where $p^{*,1}(\alpha)$ is again a fixed point of the same map Φ_1 used in n^{th}-round contagion, but this time with a stressed α-parameter:

$$p^{*,1}(\alpha) = \Phi_1(p^{*,1}(\alpha)) \tag{8}$$

This gives the final payment vector $p^{*,1}$ for asset fire sales with the following properties:

$$p^{*,1} = p^{*,1}(\alpha^{*,1}) = \begin{cases} 0 & \text{if } i = s \\ \bar{p}_i & \text{if } i \neq s \wedge \bar{p}_i \leq e_i + (\Pi' p^{*,1})_i \\ \alpha^{*,1} e_i + (\Pi' p^{*,1})_i & \text{otherwise} \end{cases} \tag{9}$$

Next we show that the market equilibrium $\alpha^{*,1}$ exists and how it can be computed:

Theorem 1. *The sequence $\alpha^n, n \in \{0, 1, \dots\}$ defined as:*

$$\alpha^{n+1} = \Theta_1(\alpha^n) \tag{10}$$

and initialized with $\alpha^0 = 1$ converges to a limit satisfying $0 \leq \alpha^* = \Theta_1(\alpha^*) \leq 1$ in a finite number of steps. This limit is also the greatest fixed point of Θ_1.

Proof: see Appendix B

(d) **Mark-to-market losses**

The equilibrium price under mark-to-market effects is defined in analogy to asset fire sales, as a fixed point $\alpha^{*,2}$ of the map:

$$\Theta_2(\alpha) = d^{-1}(s(p^{*,2}(\alpha))) \tag{11}$$

Where $p^{*,2}(\alpha)$ is again a fixed point of a new map Φ_2:

$$p^{*,2}(\alpha) = \Phi_2(p^{*,2}(\alpha)) \tag{12}$$

Where Φ_2 is more punitive than Φ_1 because the price drop affects even banks not exposed to defaulting banks:

$$\Phi_2(p)_i = \begin{cases} 0 & \text{if } i = s \\ \bar{p}_i & \text{if } i \neq s \wedge \bar{p}_i \leq \alpha e_i + (\Pi' p)_i \\ \alpha e_i + (\Pi' p)_i & \text{otherwise} \end{cases} \tag{13}$$

The proof of convergence for Θ_2 works in analogy to theorem 1.

3.3. Parameter calibration

As explained in section 3.2, the κ-parameter can be interpreted as the share that the financial system under investigation represents in the overall market for firesold assets. In the case of Austrian banking assets we argue that the relevant market consists mainly of major European banks. In order to calibrate this parameter we thus compare the assets of Austrian banks with the free leverage in excess of leverage targets of major European banks. The latter are identified as Significant Institutions (SIs) that fall under direct supervision of the European Central Bank within the Single Supervisory Mechanism EU (2013), excluding the Austrian SIs. By free leverage we denote the amount of assets that an institution could purchase using external funding before hitting the leverage target. This reasoning gives the following formula for κ:

$$\kappa = \frac{\sum_{i=1}^{N-1} Assets_i}{\sum_{i \in \text{external Buyers}} \max\left(\frac{Capital_i - Assets_i * \theta}{\theta}, 0\right)} \tag{14}$$

Free leverage was computed using leverage targets θ for both risk-weighted and total assets against corresponding capital items.[8] All calculations yielded values for κ close to 50%. We thus conclude that the Austrian banking system accounts for about 50% of the relevant market and set $\kappa = 0.5$ for our calculations.[9]

3.4. Computation of contagion losses

Contagion losses for any given contagion channel are computed conditional on an idiosyncratic shock to a single bank s, as defined above. The impact of bank s' default on the system is then given by the losses on interbank claims under the corresponding payment vector, as opposed to the original vector of nominal liabilities. These losses are summed over the entire banking system excluding the initially defaulted bank and the sink node. At any given point in time t, the losses caused by bank s are thus given by:

$$y_{s,t} = \vec{1}' S \Pi' (\bar{p}_t - p_t) \tag{15}$$

Where $p \in \{p^1, p^*, p^{*,1}(\alpha^{*,1}), p^{*,2}(\alpha^{*,2})\}$ for first-round, n$^{\text{th}}$-round, asset fire sales and mark-to-market effects, respectively. The matrix $S \in \{0, 1\}^{N \times N}$ removes bank s and the sink node from the computation:

$$S_{ij} = \begin{cases} 1 & \text{if } i = j \wedge i \neq s \wedge i < N \\ 0 & \text{otherwise} \end{cases} \tag{16}$$

[8] The exact leverage targets and capital items used used are confidential. Please contact the authors for further details.

[9] We investigate different values for κ as robustness checks in Section 7.

4. Data

The data used to construct the network of interbank liabilities are taken from the central credit registry, which covers all financial claims held by Austrian banks exceeding a reporting threshold of EUR 350k across asset classes on an obligor-basis. This data covers the same time span as the bank-specific indicators (see below) and has the same frequency. Thanks to unique identifiers we are able to identify interbank claims within the credit registry, which we combine with the regulatory reporting data to construct a large panel data set.

We now turn to describing the explanatory variables. These are bank-specific variables that cover a broad data set of balance sheet and profitability items, as well as regulatory capital and capital requirements. We also include network metrics, but we restrict our choice to variables that are observable at the level of a single bank, in line with our goal of determining whether bank-specific variables alone can act as a good proxy of contagion losses. We thus include the number of in-going and out-going links (degree centralities) in our data set. All these data are available on a quarterly basis for all domestically operating banks at the unconsolidated level. The observation horizon runs from the first quarter of 2008 to the first quarter of 2016, yielding $T = 33$ 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.

In order to assess whether the indicators proposed by Basel regulations — or any other set of bank-specific variables — can constitute a good set of proxies for contagion losses, we create different subsets of our data. We estimate separate models for (i) the full set of available data (referred to as the 'extended data set'), (ii) a restricted data set that includes only publicly available data (referred to as the 'publicly available data set') as well as (iii) data that are used under Basel regulations (referred to as 'Basel III data set'). There are different regulatory proposals for identifying global (BIS, 2013) and domestic (BIS, 2012) systemically important banks. We choose to work with the indicators stated in the EBA (2014) implementation of the BIS (2012) proposal for identifying domestic systemically important banks. There are several reasons for this choice: (i) There are no global systemically important banks present in our sample, so the domestic set seems more applicable. Moreover, (ii) we want to apply the analysis to the entire banking system, and several of the indicators for global institutions are not available for smaller and medium-sized banks, e.g. Level 3 assets. For the indicators listed by EBA (2014) we have no data gaps with the exception of the indicator "value of domestic payment transactions", which has to be dropped from further analysis. In consequence the number of indicators drops from 10 as recommended by EBA (2014) to 9 in our case. Compared with the indicator list for global systemically important banks by (BIS, 2013), there is a high degree of overlap with 8 of the 10 (9 in our case) indicators for domestic importance also being present in the set for global importance. The full overview of all variables, their treatment and their categorization is given in Table 1, summary statistics are provided in Table C.3 in the appendix.

We perform a series of panel unit root tests. First, we apply the test by Im and M. Pesaran (2003) that allows each panel unit i to have its own autocorrelation coefficient. As this test does not deliver robust results for all of our (unbalanced) time series, we also rely on the so-called meta panel unit root tests by

Choi (2001) that conducts the Phillips and Perron (1988) unit-root tests for each individual separately and then tests the p-values from these tests to produce an overall result.[10] The results, presented in Table C.4, show a mixed picture. For the explanatory variables, 71% of the tests reject the unit-root-hypothesis at the $p = 0.05$-level. Given that unit root tests usually require longer time series in order to draw meaningful conclusions, we make our final decision based on the following additional reasoning. First, consider the variables that show the strongest indication of a unit root across all tests: these are the Tier1-ratio, the Tier1-ratio for credit risk, and the leverage ratio. There was high pressure on banks from regulators to improve capitalization after the crisis, which may explain why the series seem to be integrated over our time horizon since 2008. From an economic point of view, however, capital ratios cannot grow indefinitely and should thus be expected to be stationary, at least once desired capital levels are reached. Based on these considerations, we thus reject the unit-root hypothesis for these variables. Similar reasoning applies for the other explanatory variables that appear to be integrated or show mixed results in the tests, as most of them are in fact ratios. Regarding the number of ingoing links, we again consider this figure as stationary in the long run. The number of links is always bounded by 0 and the number of banks in the system, and banks are not expected to increase or decrease their number of counterparties indefinitely.[11]

Regarding the dependent variables, 65% of the tests reject the unit-root hypothesis at $p = 0.05$. We consider the following reasoning to arrive at a final verdict on integration for these variables — note the following inequalities for contagion losses, as defined in section 3.4:

$$\vec{1}'S\Pi'(\bar{p} - p) \leq \vec{1}'M\Pi'(\bar{p} - p) \leq \vec{1}'M\Pi'\bar{p} \leq \vec{1}'M(\Pi'\bar{p} + e) = \sum_{i=1}^{N-1} TotalAssets_i \tag{17}$$

Where the matrix $M = \begin{cases} 1 & \text{if } i = j \wedge i < N \\ 0 & \text{otherwise} \end{cases}$ removes only the sink node from the computation.

Hence, total assets form an upper bound for the overall contagion losses. Most of the unit root tests reject the hypothesis that total assets have a unit root (see Table C.4). We can therefore reject the unit root hypothesis for contagion losses. This theoretical result is also in line with most of the unit root tests for contagion losses in Table C.4.

[10] We do not consider panel unit root tests that require strongly balanced panels since we do not want to exclude banks in order to achieve a balanced panel. Excluding time periods would be an even less desirable option.

[11] We further test if the time series of the number of banks in the system over the observation span is stationary. The standard Phillips–Perron unit root test rejects the hypothesis of a unit root at the $p = 0.05$-level.

Table 1: Description of variables

Dependent variables	Description	Unit		
First-round caused losses	Sum of losses caused by first-round contagion effects	No		
nth-round caused losses	Sum of losses caused by nth-round contagion effects	EUR		
Asset fire sales caused losses	Sum of losses caused under asset fire sales	EUR		
Mark-to-market caused losses	Sum of losses caused under mark-to-market effects	EUR		
Explanatory Variables	**Description**	**Unit**	**Basel III**	**Publicly available**
Total assets	Total assets	EUR	Yes	Yes
Private sector deposits	Deposits taken from domestic and foreign nonbanks (no public sector), all currencies	EUR	Yes	No
Private sector loans	Loans to foreign and domestic nonbanks (no public sector)	EUR	Yes	No
Face value of derivatives	Notional value of OTC derivatives	EUR	Yes	No
Cross border loans	Loans to foreign domiciled nonbanks and banks	EUR	Yes	No
Cross border deposits	Deposits from foreign domiciled nonbanks and banks	EUR	Yes	No
Bank deposits	Deposits taken from domestic and foreign banks, all currencies	EUR	Yes	Yes
Bank loans	Loans to domestic and foreign banks, all currencies	EUR	Yes	Yes
Securitized debt	Liabilities in the form of securitized debt obligations and transferable certificates	EUR	Yes	Yes
Loans to nonbanks	Loans to foreign and domestic nonbanks	EUR	No	Yes
Non-bank deposits	Deposits taken from domestic and foreign nonbanks (i.e. customers), all currencies	EUR	No	Yes
Net interest income	Net interest income	EUR	No	Yes
Interest rate nonbank loans	Average interest rate on nonbank loans	%	No	No
Interest rate bank loans	Average interest rate on bank loans	%	No	No
Interest rate nonbank deposits	Average interest rate on nonbank deposits	%	No	No
Interest rate bank deposits	Average interest rate on bank deposits	%	No	No
LLP	Specific loan loss provisions (loans to domestic and foreign nonbanks, all currencies), smoothed	EUR	No	Yes
Tier 1	Eligible tier 1 capital	EUR	No	Yes
RWA	Total risk-weighted assets	EUR	No	Yes
RWA for credit risk	Risk-weighted assets (credit risk only)	EUR	No	Yes
NFCI	Net fee and commission income (smoothed)	EUR	No	Yes
Interest bearing securities	Exchange-traded interest-bearing securities (held as assets) issued by domestic and foreign banks and non-banks, all currencies	EUR	No	Yes
Staff expenses	Staff expenses	EUR	No	Yes
Other operating expenses	Operating expenses other than staff expenses	EUR	No	Yes
Number of ingoing links	Number of bank deposits	count	No	No
Number of outgoing links	Number of bank loans	count	No	No

Source: OeNB. Regulatory reporting data and credit registry data.

5. Econometric Approach

In this section we briefly outline our econometric approach. Our goal is to examine whether bank-specific indicators such as the Basel III indicators can predict contagion losses arising from different contagion channels, as described in section 3.

The multilevel structure of our data – around $N = 716$ banks are observed for $T = 33$ time periods – calls for an application of panel-data analysis. Usually panels are more informative than cross-sections, as unobserved characteristics of individuals can be taken into account. Furthermore, panels allow us to test whether individual histories and/or unobserved individual characteristics matter.

The results of these tests are given in Table C.5. First, we test for the importance of individual effects. This is done with the Breusch-Pagan Lagrangian multiplier test (Breusch and Pagan, 1980). The rejection of the Breusch-Pagan test indicates that individual effects are important. We also perform the test proposed by Honda (1985) as well as a standard F-test. Both of them compare the pooled model with the individual effects alternative[12]. The rejection of these tests again confirms the importance of individual effects. We proceed to the Hausman test (Hausman, 1978) to decide between fixed and random effects. The rejection of the Hausman test indicates that only the fixed effects model is consistent. As can be seen from Table C.5, all tests can be rejected with $p = 0.01$.

These test results show that a fixed-effects panel regression (or equivalently, least squares dummy variable regression, henceforth LSDV) is consistent for our data. In its general form, our static one-way regression with panel-specific effects reads as follows:

$$y_{i,t} = \beta' X_{i,t} + u_i + e_{i,t}, \quad i = 1, \cdots, N; \quad t = 1, \cdots, T, \tag{18}$$

Where $y_{i,t}$ denotes the contagion losses as defined in section 3. $X_{i,t}$ are the K explanatory variables, as described in section 4. e_{it} is the idiosyncratic error term, which we assume to be i.i.d.: $e_{i,t} \sim (0; \sigma_e^2)$. β represents the K regression coefficients, and u_i is the panel-specific, time-invariant fixed effect (with $\mathbb{E}_t[u_i] = u_i$, $\mathbb{E}_t[X_{i,t} \cdot u_i] \neq 0$).

Using three distinct data sets in our estimations, we need to account for the different sizes of these sets. Methods for choosing the best predictors from a data set include e.g. subset selection (forward- and backward-stepwise selection, best subset selection), shrinkage methods (e.g. LASSO, ridge regression) and Bayesian model averaging.[13] We apply best subset selection and Lasso shrinkage to compare and check the robustness of our results. For both methods we choose the best model size/shrinkage factor based on a 10-fold cross validation (CV). We then compare the 10-fold cross validation results (Lasso shrinkage and best subset selection) with the best subset selection model with size 9 (number of available Basel III indicators).

[12] We apply the routines implemented by Croissant and Millo (2008) to perform the tests.
[13] See Hastie et al. (2009) for a good overview of these methods.

To the best of our knowledge we are the first to apply 10-fold cross validation in the context of fixed effects panel models. Cross validation has been extensively used for cross sectional data but is less popular for time series models, as standard CV procedures break down since the validation and training samples are no longer independent (see Arlot and Celisse (2010) for more details). In order to address this problem we apply 10-fold CV over individuals (banks). This strategy allows us to identify the best model for predicting contagion losses for previously unseen banks, while avoiding time series related dependency issues. This procedure is also in line with the set-up of our analysis.

The best subset selection procedure (i) has the advantage of easy interpretation of the coefficients of a single, best-fitting model, (ii) allows for explicitly controlling the model size, (iii) allows exploiting the statistical relationship between fixed effects and least square dummy estimation (see below) and it (iv) allows to calculate standard errors and goodness of fit measures. The main issue with best subset selection for prediction is — of course — over-fitting. We thus perform cross validation to select the best model (size).

Best subset selection consists of an exhaustive search of the entire space of $2^K - 1$ models for K predictors. Given the exponential time-complexity of this task, we employ the leaps-and-bounds algorithm by Furnival and Wilson (1974) to perform the search.[14] Models are compared based on their predictive power in the LSDV-regression. Note that when comparing models of the same size k, as we do, the selection is insensitive to the goodness-of-fit measure used (e.g. R^2, AIC, BIC,...). We thus look for a model that optimizes the following problem for all $k \in \{1, \dots, K-1\}$:

$$\begin{aligned} \max \quad & R^2(X_k) = 1 - \frac{\sum_{i=1}^{NT}(\hat{y}_i - \sum_{i=1}^{k}\hat{\beta}_i X_k)^2}{\sum_{i=}^{NT}(y_i - \bar{y}_i)^2} \\ \text{s.t.} \quad & \hat{\beta} = (X_k^{'} X_k)^{-1} X_k^{'} y, \\ & X_k \subset X_K. \end{aligned} \tag{19}$$

The optimization problem in Eq. (19) is well defined by Weierstrass' extreme value theorem, as $R^2(X_k)$ is a continuous function and the set of all combinations of k variables out of the set of K variables is compact (the cardinality of the set is $\binom{K}{k}$). The key idea is that we do not search across different model sizes. All bank dummies are forced into the model in the LSDV-estimation, while the leaps and bounds algorithm searches for the best remaining predictors for a model of size k plus the number of bank dummies.

Lasso shrinkage (i) has advantages over other selection procedures in the case of more covariates than observations, (ii) it shows which covariates are the most important (i.e. their coefficients are shrunken to zero at last) and (iii) it has excellent prediction performance.[15]

Based on the econometric model in Eq. (18), we solve the following minimization problem in the Lasso procedure:

[14] We use the implementation of Thomas Lumley which is based on earlier work by Alan Miller.

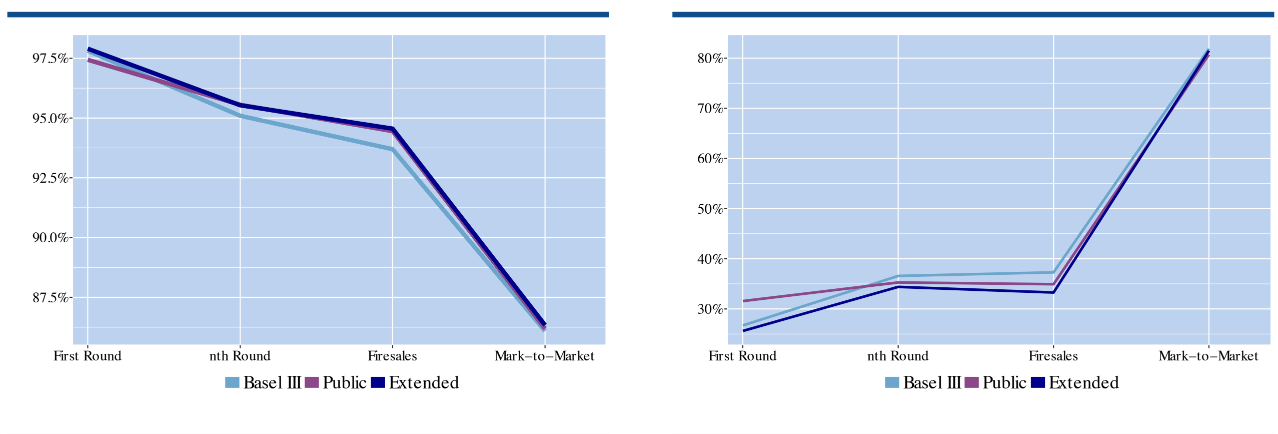
[15] See Hastie et al. (2009) ch. 3 for more details.

$$\hat{\beta}_L \quad \in \arg\min_b \quad \sum_{i=1}^{N} \sum_{t=1}^{T} \left(\ddot{y}_{i,t} - \sum_{j \in K} b_j \ddot{x}_{i,j,t} \right)^2 + \lambda \sum_{j=1}^{p} |b_j| \tag{20}$$

$\ddot{y}_{i,t}$ and $\ddot{x}_{i,j,t}$ refer to the within transformation of the respective variables to remove the fixed effect. Removing the fixed effect has the same effect as forcing the bank dummies into the regression (i.e. bank dummies are not shrunken). We then select the best Lasso model (λ) with respect to the average mean squared error that is calculated in the 10-fold cross validation. λ is referred to as the shrinkage parameter. The greater λ the bigger is the shrinkage effect on the coefficients b_j.

6. Results & Discussion

Figure 2: Fit of selected models



(a) LSDV R^2 of selected models

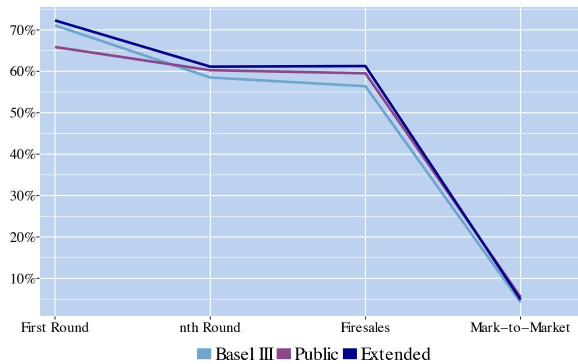
(b) Difference between LSDV and within R^2

Figure 2a plots the explained sum of squares of the least squares dummy variable estimation for different contagion channels. As can be seen from the chart, results are very similar across the models used for the different data sets (i.e. the models of size $k^* = 9$ plus bank dummy variables with the best fit, as selected by the LSDV-criterion, for the publicly available and extended data sets and the model for Basel III variables). The full results for these models are presented in Tables C.6, C.7, C.8, C.9, C.10, C.11, C.12, C.13, C.14, C.15, C.16 and C.17 in the appendix.

The first thing that draws attention is the high fit of all these models, ranging from around 98% for first-round losses to around 86% for mark-to-market losses. Note, however, that the R^2 depicted in Figure 2a shows the overall R^2 consisting of contributions from bank-specific variables, $X_{i,t}$, as well as the fixed effects, u_i. To isolate the contribution of bank-specific effects we conduct a de-meaned within estimation.[16] Figure 2b gives the difference in R^2 between the LSDV and the within estimation, and thus

[16]De-meaning instead of pooling is necessary to avoid an omitted variable bias.

Figure 3: Within R^2 for different models

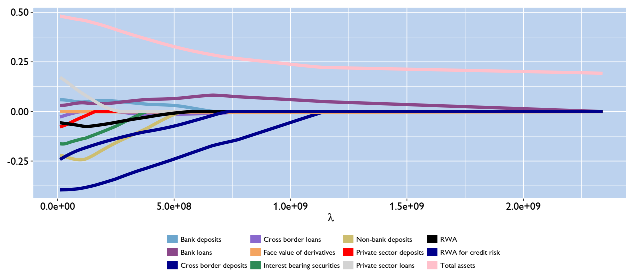


the contribution of the bank specific effects. As can be seen, the contribution of the bank-specific effect ranges from around $30pp$ to $81pp$, thus accounting for 31% to 94% of the explanatory power of the model. There is a marked difference between mark-to-market losses and the other contagion channels for this effect: while for the other channels (first-, n^{th}-round and asset fire sales), the average contribution of the fixed effect is around $60pp$ or 64% of explanatory power, this effect is much stronger for mark-to-market losses at around $83pp$ or 96%. The picture is very similar for the best subset CV models, with explanatory typically power falling by only around $5pp$ and markedly less in most cases. We take this as an indication that the predictive power of the models is of similar quality and exhibits the same overall patterns as the explanatory power. We interpret the substantial contribution of fixed effects as the importance of the average network position of the bank. This position cannot be proxied by other bank-specific variables in our set and it is crucial to explaining contagion losses. We conclude from these findings that: (i) bank-specific variables are able to provide a solid proxy for contagion losses, but (ii) network effects that cannot be captured by such variables are very important in terms of predictive power, especially for higher-order contagion channels.

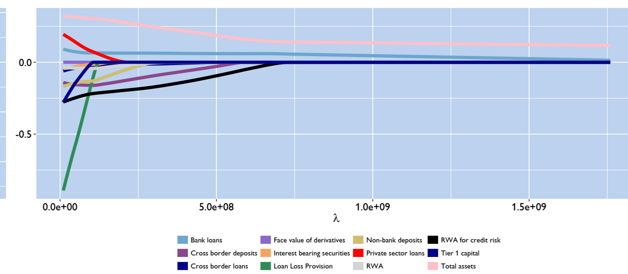
Looking at the difference in performance across different data sets, we see that the extended data set strictly dominates the other two data sets for all contagion channels. Given that both the publicly available as well as the Basel III data set are true subsets of the extended set, their explanatory power acts as a lower bound for that of the extended data set. While performing slightly worse on some contagion channels, the explanatory power of the Basel III data set typically falls within a range of $5pp$ of that of the other data sets. This holds both when including (Figure 2a) and when excluding (Figure 3) the contribution of fixed effects. We therefore conclude that the Basel III data set is an efficient selection of bank-specific variables to capture systemic risk effects (keeping in mind the general above mentioned limitations regarding bank-specific variables).

Looking at the differences between contagion channels, we see that the explanatory power in the LSDV estimation declines monotonously across the increasing complexity of contagion channels from first-round to n^{th}-round to fire sales to mark-to-market losses. Note that contagion affects banks who are increasingly further away from the defaulted bank (in a network-topological sense) as one moves from first-round to mark-to-market losses. The drop in explanatory power thus shows that these effects become increasingly harder to predict from data relating only to the initially defaulted bank. Looking at the results of the within estimation, one can see that the models for the mark-to-market channel have almost zero explanatory power without the contribution of the fixed effects.We infer that it is not possible to produce models with meaningful predictive power for the mark-to-market channel from bank-specific data alone.

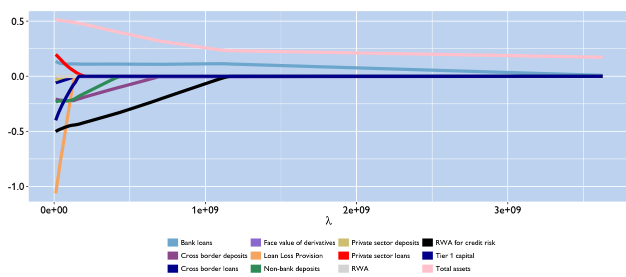
Figure 4: Lasso Shrinkage of Selected Models (extended data set)



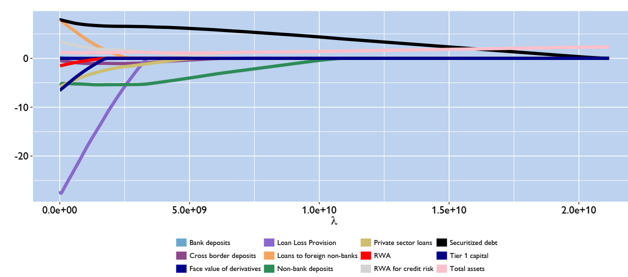
(a) First round caused losses



(b) n$^{\text{th}}$-round caused losses



(c) Firesales caused losses



(d) Mark-to-market caused losses

We now turn our attention to the contributions of individual variables (Figure 4 shows the Lasso shrinkage of the twelve most important selected variables[17], Tables C.6 to C.17 show the estimation results of the selected models). For all contagion channels except mark-to-market losses — where we already noted the poor predictive power of the models — we can see that total assets are the most prominent variable. They are selected and highly significant in all data sets both by best-subset selection and by CV best-subset selection. They are also selected in all Lasso CV models. Furthermore, the Lasso shrinkage shows that total assets are the most important variable, being the last variable to be shrunk in all contagion channels except mark-to-market losses. Total assets consistently carry a positive sign, meaning that higher total assets imply higher caused losses. This finding is in line with regulations for global and domestic systemically relevant banks (BIS (2013), EBA (2014), FED (2015)), where a general size criterion is given the highest weight.

[17]We only present the shrinkage of the twelve most important variables (instead of 26) to improve readability. The full set of Lasso results with 15,000 values of different λ (shrinkage parameter) are available from the authors upon request. See Eq. (20) for more details.

The contributions of other variables are less stable: for first-round losses, we find that liabilities other than bank deposits tend to be important variables with negative signs, whereas bank deposits and other assets tend to be important variables with positive signs. The importance of non bank deposits and other liabilities follows naturally from the definition of first-round (caused) losses. The negative sign for liabilities like cross-border deposits shows that the impact of a default on the national banking system is reduced when foreign investors have to share a portion of the losses. The positive sign for bank loans and the negative sign for risk-weighted assets indicate that banks who are more/less active on the interbank market cause higher/lower contagion losses (keeping in mind that interbank assets typically carry low risk weights as opposed to other types of lending. e.g. retail lending). The picture is similar for n^{th}-round and asset fire sale losses, but the coefficients of the models tend to be shrunk much sooner, indicating that they contribute less to explaining the outcome. This is in line with the lower explanatory power of these models, as noted above.

We also note that the number of ingoing and the number of outgoing links are not selected in any of the CV models where they are available (i.e. the Extended data set). We conclude that these network characteristics are too simple to explain contagion losses and that one should consider contagion output rather than simple network measures when assessing systemic risk. When a regulator has access to the information on network measures, usually the full information on the interbank network and balance sheets will be available as well. Computing contagion output is thus only a matter of additional methodological and computational effort. Thanks to recent methodological contributions by various authors, there exist comprehensive frameworks that allow computing contagion losses, as shown in this study.

7. Robustness checks

The robustness of the results has been assessed by performing the estimations with lower and higher values for $\kappa = 0.4$ and $\kappa = 0.6$ instead of $\kappa = 0.5$ for the benchmark model. Different values of κ change the contagion impact for asset fire sales and mark-to-market losses.

Table C.18 and C.19 summarize the estimation results for asset fire sales and mark-to-market losses. We only compare the best subset selection results with model size of 9 variables.[18] The results appear robust for all three data sets: in the Basel III data set, all signs remain the same, variables carry same signs, similar coefficients and similar significance levels. For the set of publicly available data, it can be noted that the selection algorithm chooses the same set of variables. The results for these variables are also in line with the benchmark model. For the extended data set, the algorithm selects cross boarder loans instead of securitized debt for $\kappa = 0.4$, which improves the fit for this model. The other variables are in line with the benchmark model. For the $\kappa = 0.6$ specification, the same variables as for the benchmark model are selected, and the results for the variables are in line with the benchmark model. The explanatory power for the models of the robustness checks are in line with the benchmark model, so the important finding of the high contribution of the fixed effect is robust to variations in the κ parameter

[18] Further tables for best subset selection with CV and Lasso CV are available from the authors upon request.

for the fire sale models. Regarding the mark-to-market estimations, the results are more different. There are more differences between the sets of variables selected for the publicly available and for the extended data sets as compared to the benchmark model. For all data sets, coefficients are not always the same and significance levels are generally lower. We combine this finding with the fact that all model fits with mark-to-market data are very low and conclude that it is difficult to estimate robust models for mark-to-market effects from bank-specific data alone.

8. Conclusion

The purpose of this study was to assess whether the systemic risk indicators proposed in the Basel III regulations are able to capture network contagion effects. We have examined this question by computing contagion losses for different contagion channels and estimating the impact using bank-specific data.

Contagion losses are computed for four different channels: first-round, n^{th}-round, asset fire sales and mark-to-market effects. These effects are separated using novel extensions of the Eisenberg and Noe (2001)-framework. The existence and construction of clearing payment vectors for n^{th}-round and asset fire sale effects follows directly from Rogers and Veraart (2013). We endogenize liquidation losses using a market demand function for firesold assets, as pioneered by Cifuentes et al. (2005). We separate the impact of asset fire sales and mark-to-market accounting, as introduced in Siebenbrunner (2015). We show the existence of market equilibria for both channels and provide an algorithm for computing the greatest market equilibrium in a finite number of steps. Losses stemming from idiosyncratic bank defaults are computed for all contagion channels and then aggregated over the system to give the total impact of a default on the system.

We then estimate these contagion losses using 9 out of the 10 systemic risk indicators proposed in the EBA (2014) implementation of BIS (2012) recommendations (referred to as the Basel III data set). Results for this data set are then compared against two different models, one consisting of publicly available data only, the other containing an extended data set of bank-specific indicators that include all Basel III and publicly available data. In order to test the predictive power of the selected models, we apply cross validation on all selected best subset models across different sizes and (in order to test the robustness of the best variable selection) Lasso shrinkage with cross validation. We perform a within and a least square dummy variable regression to get an unbiased contribution of the bank-specific fixed effect, which we interpret as the average contribution of a bank's network position to its systemic risk contribution. Results show that this fixed effect account for about 30% of explanatory power for most contagion channels.

Regarding the mark-to-market channel, the estimations do not yield models with satisfying explanatory power, indicating that these effects are more driven by features of the interbank network than by bank-specific characteristics. Comparing the different data sets, we find that the models using Basel III indicators produce similar as the models for the other data sets. We interpret this finding as an indication that the Basel III indicators represent a good choice of bank-specific variables. We also find that the explanatory power decreases as one moves to contagion channels that affect increasingly larger parts of the network, indicating that bank-specific indicators are less able to explain such systemic effects. We also find that measures of degree centrality do not have significant explanatory power for contagion impact. We thus advocate the use of more sophisticated contagion models rather than simple network measures such as degree centralities whenever network data are available. We reach this conclusions based on our dataset that comprises a full interbank network of Austrian banks and therefore encourage researchers to test these findings on data from other countries.

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Appendix A. Existence and construction of the clearing payment vector

The existence of the clearing payment vector as defined above follows directly from Rogers and Veraart (2013), who show that there exists a largest clearing payment vector for the following map:

$$\Phi(p)_i = \begin{cases} \bar{p}_i & \text{if } \bar{p}_i \leq e_i + (\Pi' p)_i \\ \alpha e_i + (\Pi' p)_i & \text{otherwise} \end{cases} \tag{A.1}$$

Note that we omit the liquidation costs for interbank assets from the original specification from Rogers and Veraart (2013). This is necessary to avoid inconsistencies with regards to the assumption of limited liability, as shown in Siebenbrunner (2015). The proof of existence for the largest clearing payment vector is completely analogous to Rogers and Veraart (2013) by considering the sequence p^n defined as below and initialized with $p^0 = \bar{p}$:

$$p^{n+1} = P\Phi(p^n) \tag{A.2}$$

Where the matrix P is defined as: $P = \begin{cases} 1 & \text{if } i = j \wedge i \neq s \\ 0 & \text{otherwise} \end{cases}$. Note that $P\Phi = \Phi_1$.

The convergence of the sequence p^n to the greatest clearing payment vector follows from:

Proof. i Note that Φ_1 is monotone (i.e. if $\tilde{p} \leq p$ then $\Phi_1(\tilde{p}) \leq P\Phi(p)$), monotone from above, bounded above by $\bar{p}$ and that all p^n are non-negative. All of these follow from the definition of Φ in Eq. (4). A more extensive derivation is equivalent to Rogers and Veraart (2013).

ii Let $P = \{p^n\}_{i=1}^n$ be the set of clearing payment vectors. Note that $(P, \leq)$ is a directed set because of the monotonicity of $\Phi_1(p)$. It is also a complete lattice since $\Phi_1 : [\vec{0}, \bar{p}] \rightarrow [\vec{0}, \bar{p}]$, as discussed in (i).

iii Note that for any $Q \subset P$ it holds that $\sup Q = p^j$ where j is the lowest index of ps in Q. Note that Q is a directed set because of the monotonicity of Φ_1. Note that $\Phi_1(p^j) = p^{j+1}$. Let $\bar{Q} = Q \backslash p^j$. Note that for all $p^k \in \bar{Q}$: $\Phi_1(p^k) = p^{k+1}$. Note that $\forall p^k \in \bar{Q}$: $\Phi_1(p^k) \leq p^{j+1}$. Hence, we have established Scott-continuity of Φ_1.

iv From (ii) and (iii) it follows that p^* is the greatest fixed point of Φ_1 by applying Kleene's fixed point theorem.

□

Note the equivalence of these results with the results of Rogers and Veraart (2013) for Φ. We chose to establish the proof differently, using Kleene's theorem, for the sake of brevity and alignment with the new proof in Appendix B. The convergence of the sequence after a finite number of steps follows analogously, from the fact that the system comprises a finite number of banks.

Appendix B. Proof of Theorem 1

Proof. When $\alpha^1 = \alpha^0 = 1$ convergence is trivial. This is the case when the defaulted bank has no liabilities, implying $p_s^* = \bar{p}_s = 0$ or when the bank has no external assets, i.e. $e_s = 0$. For all other cases consider the following:

i Θ_1 is bounded above by 1. This follows from the fact that $\forall i\colon e_i \geq 0$, hence $\forall p\colon s(p) \geq 0$. If we consider that $\kappa \in [0, 1]$, it follows that that $\forall p\colon d^{-1}(s(p)) \leq 1$.

ii $p^{*,1}(\alpha)$ is monotone in α, i.e. if $\tilde{\alpha} \leq \alpha$ then $p^{*,1}(\tilde{\alpha}) \leq p^{*,1}(\alpha)$. This follows from the definition of Φ_1 and the fact that $\alpha \in [0, 1]$.

iii Θ_1 is monotone, i.e. if $\tilde{\alpha} \leq \alpha$ then $\Theta_1(\tilde{\alpha}) \leq \Theta_1(\alpha)$. To see this, note that (ii) implies $s(p^{*,1}(\tilde{\alpha})) \geq s(p^{*,1}(\alpha))$ and thus $d^{-1}(s(p^{*,1}(\tilde{\alpha}))) \leq d^{-1}(s(p^{*,1}(\alpha)))$.

iv From (i), (iii) and the fact that $\alpha^0 = 1$ it follows that the sequence α^n is monotonously decreasing, i.e. $\forall n\colon \alpha^{n+1} \leq \alpha^n$.

v Θ_1 is bounded below by 0. This follows from the fact that $\forall p\colon s(p) \leq \sum_{i=1}^n e_i$. If we consider that $\kappa \in [0, 1]$ it follows that that $\forall p\colon d^{-1}(s(p)) \geq 0$.

vi Consider the set $A = \{\alpha^i\}_{i=0}^\infty$. It follows from (iv) that $(A, \leq)$ is a partially ordered set. It is also a complete lattice since $\Theta_1\colon [0, 1] \to [0, 1]$, as shown in (i) and (v).

vii Note that for any $S \subset A$ it holds that $\sup S = \alpha^j$ where j is the lowest index of αs in S. Note that S is a directed set by (iv). Note that $\Theta_1(\alpha^j) = \alpha^{j+1}$. Let $\bar{S} = S \setminus \alpha^j$. Note that for all $\alpha^k \in \bar{S}: \Theta_1(\alpha^k) = \alpha^{k+1}$. Note that $\forall \alpha^k \in \bar{S}: \Theta_1(\alpha^k) \leq \alpha^{j+1}$. Hence, we have established Scott-continuity of Θ_1.

viii (*Existence of a limit*) From (iv) and (v) it follows that there exists a monotone limit $\alpha^* = \lim_{n\to\infty} \alpha^n$.

ix (*Convergence to the greatest fixed point*) From (vi) and (vii) it follows that the limit derived in (viii) is the greatest fixed point of Θ_1 by applying Kleene's fixed point theorem.

x Consider the set $D(\alpha) = \{i\colon p^{*,1}(\alpha)_i < \bar{p}_i\}$, i.e. the set of banks that are in default under the payment vector for a given α. Note that for $\tilde{\alpha} \leq \alpha$ it holds that $D(\tilde{\alpha}) \supseteq D(\alpha)$.

xi From (iv) and (x) it follows that the cardinality of $D(\alpha^n)$ increases monotonously, i.e. $D(\alpha^{n+1}) \supseteq D(\alpha^n)$.

xii Note that $\forall\alpha\colon D(\alpha) \subseteq \mathscr{N}$ because the sink node cannot be in default by construction, hence the cardinality of D is bounded above by $N - 1$.

xiii (*Convergence after finite number of steps*) Note that $D(\alpha^{n+1}) = D(\alpha^n)$ implies that $s(p^{*,1}(\alpha^{n+1})) = s(p^{*,1}(\alpha^n))$ and thus $d^{-1}(s(p^{*,1}(\alpha^{n+1}))) = d^{-1}(s(p^{*,1}(\alpha^n))) = \alpha^{n+1}$.

□

Note that the fixed point of Θ_1 is not necessarily unique. This is not an issue in our setting as the adjustment process stops when no new banks enter into default, hence lower fixed points than $\alpha*, 1$ are never reached.

Appendix C. Tables

Table C.2: Share of listed banks in different countries

Country	Number of listed banks	Total number of banks	Percentage of banks listed
Austria	5	690	0.7%
Belgium	4	101	4.0%
Bulgaria	5	28	17.9%
Cyprus	3	65	4.6%
Czech Republic	1	59	1.7%
Denmark	23	115	20.0%
Finland	2	287	0.7%
France	19	581	3.3%
Germany	15	1,779	0.8%
Greece	7	46	15.2%
Hungary	1	145	0.7%
Ireland	2	430	0.5%
Italy	19	658	2.9%
Luxembourg	1	147	0.7%
Malta	4	29	13.8%
Netherlands	5	213	2.3%
Poland	16	674	2.4%
Portugal	3	149	2.0%
Slovakia	5	29	17.2%
Slovenia	2	24	8.3%
Spain	8	268	3.0%
Sweden	5	160	3.1%
Switzerland	27	282	9.6%
Turkey	17	52	32.7%
United Kingdom	15	360	4.2%
United States	1,179	5,381	21.9%
Total	**1,396**	**12,752**	**10.9%**

Sources:
Number of listed banks: Datastream (primary quotes of major securities, actively traded as of 22/12/2015).
Number of total banks: FED St.Louis (US), www.theBanks.eu (all other countries); most recent data available as of 22/12/2015.

Table C.3: Summary statistics of included variables

Var.Name	Min.	1st Qu.	Median	Mean	3rd Qu.	Max	Data C.	StD
Total assets	4.15	68.59	148.50	1242.00	338.30	157200.00	0.95	7261.19
Net interest income	-48.18	0.31	0.67	3.08	1.41	361.50	0.94	15.28
LR on bank loans	-0.01	0.0024	0.0041	0.0047	0.0062	0.08	0.93	0.00
LR on non bank loans	-0.02	0.0069	0.0083	0.0092	0.0106	0.24	0.95	0.00
DR on bank deposits	-0.05	0.0009	0.0017	0.0029	0.0031	1.00	0.92	0.01
DR on non bank deposits	-0.01	0.0014	0.0025	0.0032	0.0037	0.06	0.95	0.00
Loan Loss Provision	0.00	2.90	6.38	37.77	14.41	5193.00	0.94	231.17
Tier 1 capital	0.00	6.12	13.23	91.26	28.94	14150.00	0.93	666.62
RWA	0.00	35.96	83.14	648.60	187.40	83850.00	0.95	3911.01
RWA for credit risk	0.00	32.21	73.69	581.50	168.50	78130.00	0.95	3514.58
NFCI	-13.87	0.10	0.24	1.29	0.59	214.20	0.95	6.86
Bank loans	0.00	16.59	30.01	346.30	64.33	56000.00	0.95	2639.03
Loans to foreign non-banks	0.00	0.40	1.62	155.00	8.53	21200.00	0.92	1170.93
Interest bearing securities	0.00	1.92	7.87	157.80	28.35	17090.00	0.95	959.50
Bank deposits	0.00	2.99	10.60	361.60	38.28	56700.00	0.95	2798.00
Non-bank deposits	0.00	53.94	112.60	483.30	245.70	53340.00	0.95	2314.12
Securitized debt	0.00	0.00	0.00	246.80	0.00	31720.00	0.95	1859.65
Staff expenses	0.00	0.20	0.44	2.15	1.04	1013.00	0.95	14.50
Other operating expenses	0.00	0.12	0.25	1.34	0.55	210.60	0.95	7.68
Number of ingoing links	0.00	1.00	1.00	4.59	1.00	390.00	0.93	23.34
Number of outgoing links	0.00	1.00	3.00	4.83	5.00	129.00	0.93	10.04
Private sector deposits	0.00	54.23	113.50	484.30	246.80	54010.00	0.95	2340.72
Private sector loans	0.00	34.44	82.26	593.10	194.30	73110.00	0.95	3262.45
Face value of derivatives	0.00	0.00	0.00	3520.00	7.75	1231000.00	0.95	37999.11
Cross border deposits	0.00	0.98	2.92	190.40	11.17	43500.00	0.95	1516.06
Cross border loans	0.00	0.88	4.14	365.60	17.37	67200.00	0.95	3000.08
First round caused losses	0.00	1.96	9.20	250.50	34.02	43810.00	0.93	1635.26
n^{th}-round caused losses	0.00	0.00	0.00	0.12	0.00	35.93	0.93	1.00
Asset fire sales caused losses	0.00	0.00	0.00	0.15	0.00	40.59	0.93	1.37
Mark-to-market caused losses	0.00	0.00	0.00	6.97	0.00	452.40	0.93	51.02

Source: OeNB. Regulatory reporting data and credit registry data.
This table shows the summary statistics of the included variables. To improve readability all variables with unit EUR (see Table 1) are expressed in Mio EUR.
Data C. refers to data coverage. 0.95 means that 95% of all data are available for the observation span 2008Q1 to 2016Q1.

Table C.4: p-values of unit root tests

Variable	IPS Unit Root	DF: Inverse chi-squared (1390)	DF: Inverse Normal	DF: Inverse logit	DF: Modified inv. chi-squared	PP: Inverse chi-squared (1390)	PP: Inverse Normal	PP: Inverse logit	PP: Modified inv. chi-squared
First round	n.a.	0.00	0.00	0.06	0.00	0.00	0.00	0.00	0.00
n^{th}-round	n.a.	1.00	0.00	0.02	1.00	1.00	0.00	0.00	1.00
Asset fire sales	n.a.	1.00	0.00	0.01	1.00	1.00	0.00	0.00	1.00
Mark-to-market	n.a.	0.88	0.00	0.00	0.89	0.00	0.00	0.00	0.00
Total assets	0.94	0.00	1.00	1.00	0.00	0.00	0.00	0.09	0.00
Net interest income	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
LR on bank loans	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
LR on non bank loans	n.a.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
DR on bank deposits	n.a.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
DR on non bank deposits	n.a.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Loan Loss Provision	n.a.	0.00	0.71	0.90	0.00	0.41	1.00	1.00	0.40
Tier 1 capital	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
RWA	0.13	0.04	0.99	1.00	0.04	0.00	0.00	0.00	0.00
RWA for credit risk	0.01	0.00	0.85	0.98	0.00	0.00	0.00	0.00	0.00
NFCI	n.a.	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Bank loans	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Loans to foreign non-banks	n.a.	0.09	1.00	1.00	0.09	0.00	0.00	0.06	0.00
Interest bearing securities	n.a.	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00
Bank deposits	0.00	0.00	0.46	0.93	0.00	0.00	0.00	0.00	0.00
Non-bank deposits	0.18	0.00	0.29	0.85	0.00	0.00	0.00	0.00	0.00
Securitized debt	n.a.	1.00	0.00	0.12	1.00	1.00	0.00	0.00	1.00
Staff expenses	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Other operating expenses	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Number of ingoing links	n.a.	1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00
Number of outgoing links	n.a.	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
Private sector deposits	0.99	0.00	1.00	1.00	0.00	0.00	0.83	0.99	0.00
Private sector loans	1.00	1.00	1.00	1.00	1.00	0.86	1.00	1.00	0.86
Face value of derivatives	n.a.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Cross border deposits	n.a.	0.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00
Cross border loans	n.a.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

This table shows the p-values of three types of unit root tests. IPS refers to the Im-Pesaran-Shin test. DF refers to Dickey-Fuller type tests. PP refers to Phillips Peron type tests. See section 4 for more details.

Table C.5: Pooled vs. Individual effects models and Fixed vs. random effects models

Dependent variable	Data set	Kappa	Breusch-Pagan	p-value	Honda	p-value	F-test	p-value	Hausman	p-value
First round (BS 9)	Basel III	0.5	206,672.27	0.00	454.61	0.00	86.01	0.00	1,210.21	0.00
First round (BS CV)	Basel III	0.5	153,999.31	0.00	392.43	0.00	75.20	0.00	1,319.63	0.00
n^{th} round (BS 9)	Basel III	0.5	72,761.89	0.00	269.74	0.00	38.89	0.00	1,267.89	0.00
n^{th} round (BS CV)	Basel III	0.5	72,126.46	0.00	268.56	0.00	35.41	0.00	3,973.79	0.00
Asset fire sales (BS 9)	Basel III	0.5	91,591.57	0.00	302.64	0.00	27.54	0.00	1,087.00	0.00
Asset fire sales (BS CV)	Basel III	0.5	32,960.51	0.00	181.55	0.00	19.74	0.00	3,190.52	0.00
MtM (BS 9)	Basel III	0.5	247,543.30	0.00	497.54	0.00	69.73	0.00	51.65	0.00
MtM (BS CV)	Basel III	0.5	154,240.62	0.00	392.73	0.00	55.39	0.00	609.92	0.00
First round (BS 9)	Public	0.5	426,105.39	0.00	652.77	0.00	108.68	0.00	784.83	0.00
First round (BS CV)	Public	0.5	339,145.93	0.00	582.36	0.00	110.55	0.00	11,623.68	0.00
n^{th} round (BS 9)	Public	0.5	121,943.01	0.00	349.20	0.00	39.30	0.00	2,035.32	0.00
n^{th} round (BS CV)	Public	0.5	102,912.30	0.00	320.80	0.00	37.08	0.00	2,899.49	0.00
Asset fire sales (BS 9)	Public	0.5	144,074.96	0.00	379.57	0.00	40.56	0.00	845.66	0.00
Asset fire sales (BS CV)	Public	0.5	58,590.69	0.00	242.06	0.00	26.77	0.00	1,940.15	0.00
MtM (BS 9)	Public	0.5	259,257.20	0.00	509.17	0.00	71.40	0.00	249.76	0.00
MtM (BS CV)	Public	0.5	253,108.50	0.00	503.10	0.00	59.53	0.00	414.50	0.00
First round (BS 9)	Extended	0.5	403,659.74	0.00	635.34	0.00	158.55	0.00	311.02	0.00
First round (BS CV)	Extended	0.5	377,751.17	0.00	614.61	0.00	95.50	0.00	151.49	0.00
n^{th} round (BS 9)	Extended	0.5	157,907.81	0.00	397.38	0.00	62.35	0.00	4,127.71	0.00
n^{th} round (BS CV)	Extended	0.5	167,725.21	0.00	409.54	0.00	51.23	0.00	1,043.47	0.00
Asset fire sales (BS 9)	Extended	0.5	123,689.24	0.00	351.69	0.00	33.54	0.00	795.81	0.00
Asset fire sales (BS CV)	Extended	0.5	84,579.06	0.00	290.82	0.00	31.61	0.00	3,408.82	0.00
MtM (BS 9)	Extended	0.5	259,257.20	0.00	509.17	0.00	71.40	0.00	249.76	0.00
MtM (BS CV)	Extended	0.5	259,275.27	0.00	509.19	0.00	57.70	0.00	493.57	0.00

This table shows two group of tests. Tests that show the importance of individual effects and in the last two columns the Hausman test to decide between the random effects and the fixed effects model.
These tests are carried out for all model with different dependent variables (first round, n^{th}-round, asset fire sales and mark-to-market), different data sets (Basel III, publicly available and extended) and for both models that are chosen with best subset selection (BS 9, model with 9 variables and BS CV, model with the lowest average mean squared prediction error in the 10-fold cross validation)
The Breusch-Pagan Lagrange multiplier test rejects the null hypothesis that the variance of the unobserved fixed effects is zero. The Honda test is a one-sided refinement of the Breusch-Pagan test and also rejects the same null hypothesis. The standard F-test reject the the OLS model as its null hypothesis. Finally, the Hausman test rejects the null hypothesis that both fixed and random effects models are consistent. So the fixed effects model is preferred.

Table C.6: Basel III Models for first round caused losses

	Basel III Size	Best Subset CV	Lasso CV
Total assets	0.5365***	0.5614***	0.5253
	(0.0037)	(0.0031)	
Private sector deposits	−0.5638***	−0.4552***	−0.3109
	(0.0092)	(0.0082)	
Private sector loans	0.2739***		0.0097
	(0.0097)		
Face value of derivatives	−0.0040***	−0.0048***	−0.0050
	(0.0002)	(0.0002)	
Cross border deposits	−0.4127***	−0.6025***	−0.3588
	(0.0079)	(0.0056)	
Cross border loans	−0.1745***		−0.1425
	(0.0054)		
Bank deposits	−0.0856***		0.0000
	(0.0060)		
Bank loans	0.1800***	0.0950***	0.0371
	(0.0061)	(0.0032)	
Securitized debt	−0.2266***	−0.2485***	−0.0922
	(0.0055)	(0.0056)	
within R^2	0.7110	0.6897	
LSDV R^2	0.9781	0.9765	
between R^2	0.9640	0.9490	

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table C.7: Extended Models for first round caused losses

	Basel III Size	Best Subset CV	Lasso CV
Total assets	0.6030***	0.5711***	0.4652
	(0.0035)	(0.0032)	
Tier 1 capital	−0.6251***		−0.0564
	(0.0148)		
RWA for credit risk	−0.3113***		−0.1993
	(0.0056)		
Loans to foreign non-banks	0.0711***		0.0000
	(0.0088)		
Interest bearing securities	−0.3483***		−0.1457
	(0.0078)		
Other operating expenses	−45.9236***	−55.3787***	0.0000
	(1.3302)	(1.1321)	
Number of ingoing links	9152.4194***		0.0000
	(420.6308)		
Private sector deposits	−0.3250***	−0.3753***	−0.0414
	(0.0080)	(0.0079)	
Cross border deposits	−0.4864***	−0.5361***	−0.3907
	(0.0052)	(0.0047)	
RWA		−0.3651***	−0.0685
		(0.0052)	
Private sector loans		0.2950***	0.1113
		(0.0080)	
Net interest income			0.0000
LR on bank loans			0.0000
LR on non bank loans			0.0000
DR on bank deposits			0.0000
DR on non bank deposits			0.0000
Loan Loss Provision			−0.2811
NFCI			0.0000
Bank loans			0.0416
Bank deposits			0.0494
Non-bank deposits			−0.2424
Securitized debt			0.0000
Staff expenses			0.0000
Number of outgoing links			0.0000
Face value of derivatives			−0.0015
Cross border loans			−0.0047
within R^2	0.7371	0.7396	
LSDV R^2	0.9812	0.9803	
between R^2	0.9490	0.8787	

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table C.8: Publicly available Models for first round caused losses

	Basel III Size	Best Subset CV	Lasso CV
Total assets	0.4565***	0.4779***	0.3524
	(0.0037)	(0.0032)	
Loan Loss Provision	−1.0058***	−1.3751***	0.0000
	(0.0342)	(0.0345)	
Tier 1 capital	−0.3813***		0.0000
	(0.0162)		
RWA for credit risk	−0.4011***	−0.4336***	−0.1797
	(0.0067)	(0.0066)	
NFCI	−41.9585***	−38.0874***	0.0000
	(1.5057)	(1.5325)	
Bank loans	−0.0302***		0.0103
	(0.0034)		
Interest bearing securities	−0.6521***	−0.3479***	−0.2146
	(0.0093)	(0.0070)	
Non-bank deposits	−0.2799***	−0.2316***	−0.1940
	(0.0084)	(0.0084)	
Securitized debt	0.3250***		0.0016
	(0.0075)		
Net interest income			0.0000
RWA			−0.0286
Loans to foreign non-banks			0.0000
Bank deposits			0.0000
Staff expenses			0.0000
Other operating expenses			0.0000
within R^2	0.6519	0.6162	
LSDV R^2	0.9740	0.9709	
between R^2	0.9172	0.8905	

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table C.9: Basel III Model for nth-round caused losses

	Basel III Size	Best Subset CV	Lasso CV
Total assets	0.3485***	0.2980***	0.1912
	(0.0034)	(0.0031)	
Private sector deposits	−0.4040***	−0.4388***	0.0000
	(0.0085)	(0.0084)	
Private sector loans	0.2528***	0.3257***	0.0000
	(0.0089)	(0.0086)	
Face value of derivatives	−0.0031***		−0.0038
	(0.0002)		
Cross border deposits	−0.1447***		0.0000
	(0.0073)		
Cross border loans	−0.1942***	−0.2804***	0.0000
	(0.0050)	(0.0036)	
Bank deposits	−0.1329***	−0.1759***	0.0000
	(0.0055)	(0.0051)	
Bank loans	0.1868***	0.2042***	0.0000
	(0.0056)	(0.0052)	
Securitized debt	−0.0860***		0.0000
	(0.0051)		
within R^2	0.5851	0.5630	
LSDV R^2	0.9509	0.9483	
between R^2	0.9618	0.9546	

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table C.10: Extended Models for nth-round caused losses

	Basel III Size	Best Subset CV	Lasso CV
Total assets	0.4494***	0.4316***	0.2996
	(0.0030)	(0.0027)	
Loan Loss Provision	−0.8523***		0.0000
	(0.0281)		
Tier 1 capital	−0.3506***		0.0000
	(0.0129)		
RWA for credit risk	−0.3544***	−0.3356***	−0.2126
	(0.0053)	(0.0051)	
NFCI	−14.9072***		0.0000
	(1.3499)		
Loans to foreign non-banks	−0.0158		0.0000
	(0.0084)		
Interest bearing securities	−0.1960***		−0.0112
	(0.0073)		
Other operating expenses	−18.2466***	−36.1491***	0.0000
	(1.2599)	(1.0441)	
Cross border deposits	−0.2795***	−0.3464***	−0.1560
	(0.0048)	(0.0044)	
Net interest income			0.0000
LR on bank loans			0.0000
LR on non bank loans			0.0000
DR on bank deposits			0.0000
DR on non bank deposits			0.0000
RWA			−0.0407
Bank loans			0.0650
Bank deposits			0.0000
Non-bank deposits			−0.1165
Securitized debt			0.0000
Staff expenses			0.0000
Number of ingoing links			0.0000
Number of outgoing links			0.0000
Private sector deposits			0.0000
Private sector loans			0.0542
Face value of derivatives			−0.0007
Cross border loans			−0.0208
within R^2	0.6155	0.5977	
LSDV R^2	0.9582	0.9524	
between R^2	0.9262	0.9001	

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table C.11: Publicly available Models for nth-round caused losses

	Basel III Size	Best Subset CV	Lasso CV
Total assets	0.3418^{***}	0.3279^{***}	0.2729
	(0.0030)	(0.0025)	
Net interest income	-17.0605^{***}		0.0000
	(0.5563)		
Loan Loss Provision	-1.1411^{***}	-1.1544^{***}	0.0000
	(0.0279)	(0.0280)	
Tier 1 capital	-0.1260^{***}		0.0000
	(0.0130)		
RWA for credit risk	-0.3781^{***}	-0.3983^{***}	−0.1588
	(0.0056)	(0.0055)	
NFCI	-17.0403^{***}		0.0000
	(1.2649)		
Interest bearing securities	-0.1825^{***}		−0.0740
	(0.0063)		
Bank deposits	0.0215^{***}		0.0000
	(0.0024)		
Non-bank deposits	-0.1288^{***}	-0.1987^{***}	−0.1136
	(0.0069)	(0.0069)	
RWA			−0.0714
Bank loans			0.0043
Loans to foreign non-banks			0.0000
Securitized debt			0.0009
Staff expenses			0.0000
Other operating expenses			0.0000
within R^2	0.5801	0.5286	
LSDV R^2	0.9530	0.9458	
between R^2	0.9554	0.9335	

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table C.12: Basel III Models for asset fire sales caused losses

	Basel III Size	Best Subset CV	Lasso CV
Total assets	0.5155***	0.4801***	0.2327
	(0.0052)	(0.0040)	
Private sector deposits	−0.5496***	−0.4170***	0.0000
	(0.0130)	(0.0116)	
Private sector loans	0.2169***		0.0000
	(0.0137)		
Face value of derivatives	−0.0068***	−0.0077***	−0.0030
	(0.0002)	(0.0002)	
Cross border deposits	−0.1990***	−0.3835***	0.0000
	(0.0111)	(0.0075)	
Cross border loans	−0.2108***		0.0000
	(0.0076)		
Bank deposits	−0.1531***		0.0000
	(0.0085)		
Bank loans	0.2682***	0.0703***	0.0000
	(0.0086)	(0.0036)	
Securitized debt	−0.1594***		0.0000
	(0.0078)		
within R^2	0.5640	0.5311	
LSDV R^2	0.9370	0.9322	
between R^2	0.9723	0.9344	

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

Table C.13: Extended Models for asset fire sales caused losses

	Basel III Size	Best Subset CV	Lasso CV
Total assets	0.6218^{***}	0.5153^{***}	0.5230
	(0.0050)	(0.0037)	
Loan Loss Provision	-0.9477^{***}	-1.5744^{***}	−1.0654
	(0.0424)	(0.0436)	
Tier 1 capital	-0.4658^{***}		−0.4381
	(0.0191)		
RWA for credit risk	-0.5533^{***}	-0.6262^{***}	−0.5238
	(0.0081)	(0.0080)	
NFCI	-22.0063^{***}	-41.1485^{***}	−2.2894
	(1.9688)	(1.8662)	
Bank loans	0.0317^{***}		0.1478
	(0.0045)		
Loans to foreign non-banks	0.0215		0.1097
	(0.0126)		
Other operating expenses	-44.8772^{***}	-25.0520^{***}	−30.3862
	(1.8519)	(1.7413)	
Cross border deposits	-0.3841^{***}		−0.2108
	(0.0070)		
Net interest income			8.1899
LR on bank loans			0.0000
LR on non bank loans			0.0000
DR on bank deposits			0.0000
DR on non bank deposits			0.0000
RWA			0.0164
Interest bearing securities			0.0318
Bank deposits			−0.0508
Non-bank deposits			−0.2349
Securitized debt			−0.0597
Staff expenses			3.7822
Number of ingoing links			0.0000
Number of outgoing links			0.0000
Private sector deposits			−0.0439
Private sector loans			0.2098
Face value of derivatives			−0.0018
Cross border loans			−0.0700
within R^2	0.6117	0.5532	
LSDV R^2	0.9475	0.9367	
between R^2	0.9669	0.9242	

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table C.14: Publicly available Models for asset fire sales caused losses

	Basel III Size	Best Subset CV	Lasso CV
Total assets	0.5178***	0.5127***	0.4271
	(0.0042)	(0.0037)	
Loan Loss Provision	−0.9940***	−1.3159***	0.0000
	(0.0440)	(0.0427)	
Tier 1 capital	−0.5354***		0.0000
	(0.0191)		
RWA for credit risk	−0.5622***	−0.6628***	−0.4033
	(0.0080)	(0.0080)	
NFCI	−41.8255***		0.0000
	(1.8219)		
Interest bearing securities	−0.4523***		−0.1121
	(0.0112)		
Non-bank deposits	−0.2274***		−0.2177
	(0.0102)		
Securitized debt	0.2768***		0.0492
	(0.0082)		
Other operating expenses	−11.6291***	−31.5913***	0.0000
	(1.8378)	(1.7582)	
Net interest income			0.0000
RWA			−0.0501
Bank loans			0.0598
Loans to foreign non-banks			0.0000
Bank deposits			0.0000
Staff expenses			0.0000
within R^2	0.5945	0.5418	
LSDV R^2	0.9444	0.9349	
between R^2	0.9712	0.9094	

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table C.15: Basel III Models for mark-to-market caused losses

	Basel III Size	Best Subset CV	Lasso CV
Total assets	5.1744***	4.3813***	2.7625
	(0.2888)	(0.1820)	
Private sector deposits	−5.0418***		0.0000
	(0.7244)		
Private sector loans	−5.3212***		0.0000
	(0.7630)		
Face value of derivatives	−0.0324*		0.0000
	(0.0134)		
Cross border deposits	−5.0913***	−3.6563***	0.0000
	(0.6217)	(0.3820)	
Cross border loans	2.4636***		0.0000
	(0.4262)		
Bank deposits	−0.3376		0.0000
	(0.4734)		
Bank loans	−1.1155*		0.0000
	(0.4815)		
Securitized debt	1.7501***		0.0000
	(0.4364)		
within R^2	0.0420	0.0325	
LSDV R^2	0.8609	0.8603	
between R^2	0.8402	0.5958	

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table C.16: Extended Models for mark-to-market caused losses

	Basel III Size	Best Subset CV	Lasso CV
Loan Loss Provision	-23.8163^{***}	-32.4542^{***}	0.0000
	(2.6051)	(2.1732)	
Tier 1 capital	-1.9495		0.0000
	(1.1338)		
RWA	-7.7921^{***}		0.0000
	(1.0937)		
RWA for credit risk	9.6446^{***}		0.0000
	(1.1510)		
NFCI	-643.5561^{***}		0.0000
	(120.1842)		
Loans to foreign non-banks	7.4153^{***}		0.0000
	(0.9417)		
Securitized debt	9.4237^{***}		3.6423
	(0.5080)		
Other operating expenses	-1160.0154^{***}		0.0000
	(114.5010)		
Private sector loans	-5.7988^{***}		0.0000
	(0.7863)		
Total assets		2.5709^{***}	1.5540
		(0.1321)	
Net interest income			0.0000
LR on bank loans			0.0000
LR on non bank loans			0.0000
DR on bank deposits			0.0000
DR on non bank deposits			0.0000
Bank loans			0.0000
Interest bearing securities			0.0000
Bank deposits			0.0000
Non-bank deposits			0.0000
Staff expenses			0.0000
Number of ingoing links			0.0000
Number of outgoing links			0.0000
Private sector deposits			0.0000
Face value of derivatives			0.0043
Cross border deposits			0.0000
Cross border loans			0.0000
within R^2	0.0536	0.0373	
LSDV R^2	0.8625	0.8601	
between R^2	0.7050	0.5844	

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table C.17: Publicly available Models for mark-to-market caused losses

	Basel III Size	Best Subset CV	Lasso CV
Net interest income	-329.8432^{***}		0.0000
	(53.8463)		
Loan Loss Provision	-20.7173^{***}	-32.4542^{***}	0.0000
	(2.6242)	(2.1732)	
RWA	-8.2229^{***}		0.0000
	(1.0778)		
RWA for credit risk	9.5955^{***}		0.0000
	(1.1367)		
NFCI	-631.9773^{***}		0.0000
	(114.5604)		
Loans to foreign non-banks	6.0518^{***}		0.0000
	(0.8254)		
Non-bank deposits	-4.5543^{***}		0.0000
	(0.6628)		
Securitized debt	8.1622^{***}		2.1425
	(0.5015)		
Other operating expenses	-1047.4271^{***}		0.0000
	(113.8635)		
Total assets		2.5709^{***}	1.9368
		(0.1321)	
Tier 1 capital			0.0000
Bank loans			0.0000
Interest bearing securities			0.0000
Bank deposits			0.0000
Staff expenses			0.0000
within R^2	0.0546	0.0373	
LSDV R^2	0.8619	0.8601	
between R^2	0.7138	0.5844	

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table C.18: Robustness Checks: Model for asset fire sales caused losses

	Basel III kappa 0.4	Basel III kappa 0.6	Public kappa 0.4	Public kappa 0.6	Extended kappa 0.4	Extended kappa 0.6
Total assets	0.4785***	0.5573***	0.4748***	0.5649***	0.6175***	0.6744***
	(0.0047)	(0.0057)	(0.0040)	(0.0046)	(0.0040)	(0.0055)
Private sector deposits	−0.5120***	−0.5908***				
	(0.0117)	(0.0144)				
Private sector loans	0.2267***	0.1983***				
	(0.0123)	(0.0152)				
Face value of derivatives	−0.0059***	−0.0080***				
	(0.0002)	(0.0003)				
Cross border deposits	−0.1847***	−0.2231***			−0.3279***	−0.4023***
	(0.0100)	(0.0124)			(0.0064)	(0.0077)
Cross border loans	−0.2117***	−0.2023***				
	(0.0069)	(0.0085)				
Bank deposits	−0.1484***	−0.1557***	0.0081*			
	(0.0076)	(0.0094)	(0.0034)			
Bank loans	0.2498***	0.2841***				0.0393***
	(0.0078)	(0.0096)				(0.0049)
Securitized debt	−0.1432***	−0.1744***	0.2514***	0.2896***		
	(0.0070)	(0.0087)	(0.0078)	(0.0090)		
Loan Loss Provision			−1.0337***	−1.0401***	−0.9120***	−0.9827***
			(0.0379)	(0.0485)	(0.0379)	(0.0468)
Tier 1 capital			−0.4858***	−0.5755***	−0.5295***	−0.5136***
			(0.0177)	(0.0210)	(0.0174)	(0.0211)
RWA for credit risk			−0.5098***	−0.6228***	−0.5109***	−0.6137***
			(0.0073)	(0.0088)	(0.0071)	(0.0089)
NFCI			−38.3384***	−47.0356***	−29.8664***	−26.6123***
			(1.6698)	(2.0086)	(1.8210)	(2.1726)
Interest bearing securities			−0.4508***	−0.4495***	−0.2088***	
			(0.0101)	(0.0123)	(0.0098)	
Non-bank deposits			−0.2221***	−0.2427***		
			(0.0092)	(0.0112)		
Other operating expenses				−16.9478***	−32.4699***	−51.3330***
				(2.0262)	(1.6997)	(2.0437)
Loans to foreign non-banks					0.0021	0.0268
					(0.0113)	(0.0139)
within R^2	0.5771	0.5498	0.6005	0.5875	0.6259	0.6060
LSDV R^2	0.9419	0.9312	0.9481	0.9401	0.9522	0.9434
between R^2	0.9729	0.9709	0.9692	0.9712	0.9458	0.9688

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table C.19: Robustness Checks: Model for mark-to-market sum caused losses

	Basel III kappa 0.4	Basel III kappa 0.6	Public kappa 0.4	Public kappa 0.6	Extended kappa 0.4	Extended kappa 0.6
Total assets	4.2232***	5.3323***	1.7986***	2.8544***	1.8061***	3.6220***
	(0.1448)	(0.4755)	(0.1354)	(0.4133)	(0.1437)	(0.4092)
Private sector deposits	0.0167	−1.0508				
	(0.3632)	(1.1927)				
Private sector loans	−0.2445	−3.2410**				
	(0.3826)	(1.2563)				
Face value of derivatives	0.0368***	−0.0079				
	(0.0067)	(0.0220)				
Cross border deposits	−2.3469***	−5.4532***				
	(0.3117)	(1.0236)				
Cross border loans	−0.4147	0.9704			−2.5981***	−3.3348***
	(0.2137)	(0.7017)			(0.1564)	(0.5829)
Bank deposits	−0.0813	1.5174	0.6372**		1.6694***	
	(0.2373)	(0.7794)	(0.1968)		(0.2066)	
Bank loans	−0.1416	−1.5162	−0.7598***		−0.9048***	
	(0.2414)	(0.7928)	(0.2110)		(0.2145)	
Securitized debt	1.7740***	−0.9411	2.8880***			
	(0.2188)	(0.7185)	(0.2123)			
Loan Loss Provision			−21.4570***	−32.7984***	−24.7129***	−44.1976***
			(1.1833)	(4.2048)	(1.2496)	(4.0859)
Tier 1 capital			5.8000***	5.0698**		
			(0.5530)	(1.9165)		
RWA			−5.0213***	−10.6517***		−8.2350***
			(0.5438)	(1.8815)		(1.8111)
RWA for credit risk			8.9481***	10.2281***	5.4670***	7.8610***
			(0.5636)	(1.9337)	(0.2402)	(1.8665)
NFCI			−1063.7493***	−1253.6256***	−895.1605***	−1056.3192***
			(54.3243)	(178.7914)	(52.6922)	(174.1498)
Net interest income				−173.4305*		
				(80.9010)		
Interest bearing securities				5.1431***		6.0347***
				(0.9185)		(0.9096)
Other operating expenses				−590.5983**		−614.9703***
				(179.9122)		(171.4666)
Non-bank deposits					1.7661***	
					(0.3062)	
Number of ingoing links					371711.0815***	
					(15612.7228)	
Number of outgoing links						1818774.9316***
						(107417.2429)
within R^2	0.1620	0.0130	0.1940	0.0176	0.2170	0.0312
LSDV R^2	0.9067	0.8329	0.9085	0.8348	0.9113	0.8356
between R^2	0.8688	0.8316	0.7924	0.7630	0.7986	0.7349

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$