A systematic and selective survey of literature on the analysis of interbank market networks

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Abstract

In this study, we conduct a selective and systematic review of the literature on interbank network analysis to highlight the key themes and issues discussed over the past seven years since the dawn of the global financial crises. The aftermath of the global financial crises of 2008 saw a rise in interest by both researchers and policy makers in interbank market networks. This has motivated several studies examining the linkages between banks via the interbank network and how these linkages affect the overall stability of the financial system. Our study finds very few empirical studies have been carried out although many theoretical studies have been conducted. This leads us to conclude with some promising research ideas that can be further investigated.

Keywords: literature review; interbank market; network analysis, core-periphery, actor oriented modelling, actor based modelling,

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1. Introduction

In this paper we conduct a systematic review of the literature on overnight interbank markets. We seek to extend the literature review by Green et al. (2016) which focused on the theoretical and empirical determinants of overnight lending rates, with examples from the US and European interbank markets. We note that the literature so far highlights four areas: 1) The evolution of overnight lending rate (an extension of market microstructure literature) and the price discovery process 2) The relationship between monetary policy and overnight lending rates 3) How interbank networks form a peer monitoring mechanism that mimics self-regulation, but which could also work as a channel for contagion and 4) The relationship between overnight rates and macro-prudential regulation. More recently there has been a shift in focus, with most papers investigating the formation of interbank networks and its effects on overnight lending rates.

Theoretically, the key factors that determine overnight interbank rates are: central bank operations, liquidity shocks to banks that must be settled by end of day, other interest rates and the operating costs of banks in the market (Green et al. 2016). Monetary policy and regulation affect the conditions under which banks trade which each other, as anticipations of change in policy would influence a bank's individual trading decision as well as its decision to supply or withhold liquidity. These anticipations of policy and cost changes produce an opportunistic behaviour which can influence the overnight lending rate with banks hoarding liquidity as observed by Brossard and Saroyan (2016) or change the conditions under which the banks trade as highlighted by Beaupin and Durre (2013) by measuring the changes in resiliency regimes.

The effects of network factors on overnight lending rates is a growing area of research. Green et al. (2016) suggest that relationships and network dynamics, influence the earlier highlighted four factors affecting overnight lending rates. The discussions around interbank networks have been largely concentrated on the formation of interbank lending relationships and the propagation of a contagion. These studies have been largely motivated by two dominant views on interbank networks. On one hand Allen and Gale (2000) define different network structures and postulates that interbank networks create a contagion channel which reduces the resilience of the market to liquidity shocks. On the other hand, Rochet and Tirole (1996), Furfine (2001) and Flannery (1996), promote a view that interbank networks exist to enable a peer review mechanism, which allows banks to quickly identify those with bad assets, and therefore produces a more efficient and resilient market with little need for intervention from central banks. The exact optimal structure of the interbank market and the argument that it serves as a channel of contagion or a channel for effective peer review mechanism, depends on the nature of the environment in which the network exists, with central bank intervention being optimal or sub-optimal depending of the nature of the shock to the market (Georg, 2013). The interbank network evolves over time with lending relationships established and dissolved in response to economic climate and individual bank needs. Banks create relationships with trusted trading partners with whom they deem to be creditworthy and do not pose an indirect source of risk (see Iori et al., 2015 and Finger & Lux , 2017). Estimating this evolution has been keenly debated by several researchers whom seek to establish a stylized approach to modelling interbank networks.

There has been much debate on the suitable model and architecture to estimate the evolution of interbank networks. Researchers have recently championed and shown the superiority of endogenous models over random networks or stationary approaches. Amongst

these deterministic or endogenous approaches, Veld and Lelyveld (2014) and Zhang et. al (2018) have provided convincing evidence of the superiority of a tiered or core-periphery interbank structure over other endogenous approaches such as the NSG approach. Other works by Xu et al. (2016) and Lui et al. (2017) have also lent credence to this approach by constructing a dynamic endogenous model that takes into consideration individual bank behaviour and characteristics. More recently, works by Craig et al. (2015) and Temizsoy et. al (2017) discuss how the position and the direction of the credit relationship between banks has an effect on the price a bank pays for liquidity. Craig et al.(2015) employs the use of the OLS regression analysis to confirm the presence of money centre banks and provide evidence of a correlation between the price paid for liquidity and the position of a bank relative to a money centre bank. While Temisvoy et al. (2017) provides evidence of a correlation between the price paid for liquidity and the centrality of the bank. Finger and Lux (2017) also examine how counterparty risk and indirect exposure significantly affect the establishment of lending relationships. Similar to Blasques et al. (2018), they provide a theory deduced by simulation which establishes a link between credit conditions and the formation of long-term credit relationships.

Although the effects of monetary policy and regulation on overnight lending rates are widely discussed, this paper will focus on the literature on interbank networks, its formation and its relationship with overnight lending rates. A systematic review of a survey of twenty articles published over the past seven years in leading academic journals, is carried out to identify the key themes within the literature and highlight areas for further investigation. In the review, we distinguish between theoretical work and empirical research, mainly because while the former offers important conceptual and theoretical modelling, the latter covers innovations in data structure as well novel techniques for estimation and testing. This paper provides a critical evaluation of the emerging empirical literature on the network formation and its effects on interbank overnight lending rates. The paper aims to examine the several dimensions within the established literature and bring to fore the most important issues on the effect of interbank networks on the determination of overnight lending rates. It will also identify promising research ideas for future research.

The remainder of the paper is structured as follows. In section 2, the methodology and approached is discussed. In section 3 a review of the discussions around interbank networks and its role as a source of financial contagion or financial resilience is conducted. In section 4, a critical evaluation of the weaknesses and strengths of applied network theory to interbank networks is discussed. In section 5, an analysis of the role relationships play in interbank networks is conducted while in section 6, a discussion on the empirical literature that investigate the impact of network properties on overnight lending rates is carried out. In section 7, we discuss the impact of the global financial crises on interbank networks. The final section contains concluding remarks and highlights key areas that require further research.

2. Methodology

A systematic approach was carried out to identify and select the literature on interbank network analysis. To begin a search through the following databases is conducted using keywords and phrases: ScienceDirect, EconLit and Google Scholar. The following key words were used: "Interbank Network", "Interbank Network Analysis", "Financial Contagion", "interbank contagion", however our primary search key phrase was "Interbank Network Analysis". The primary database used was ScienceDirect because it hosts all the journals published by Elsevier which is a publisher of most of the rated Finance and Economic journals. The primary key phrase was then used to query the EconLit database and Google Scholar engine. The other search phrases were then used on all three databases to identify any other studies not captured from our primary search.

Table 1.1 Table showing the article filtration process

Action	Resulting number of studies
Keyword Search	1500
Filter by date of publication (2011 to 2019)	900
Filter by journal ranking (3 star and above following ABS ranking guide)	40
Screening of Abstracts (Exclusion of studies not focused on overnight lending)	32
Introduction, Methodology, Findings categorization (Exclusion of studies on cross-border networks analysis)	28

Our primary search resulted in over 1,400 studies. These studies were first screened by date, starting from 2011 onwards reducing our sample size to over 900 studies (See Appendix Figure B1 for our search results of "Interbank Network Analysis" in the ScienceDirect database). The rationale behind this was to capture recent studies that occurred after the global financial crises. There is an observed increase in publications on "interbank network analysis" between 2008 and 2015 (see Figure 3). This suggests the the global financial crisis being an inflection point for research on network analysis as applied to interbank markets. This is also evident in our search results, in more than half of the 1,400 studies on interbank network analysis initially found, over half are found to be published between 2011 and 2018 (see Appendix Figure B2).

The studies were then further screened according to journal ranking. Using the Association of Business Schools (ABS) journal ranking and the French National Centre for Scientific Research (CNRS) journal ranking, we select studies only published in three star journals and above to ensure only high quality publications are reviewed, given the rigorous referee process required to publish in these journals. We also filter for only journals published in English and this resulted in a shortlist of 40 papers which were further screened using their titles and abstracts. Studies which discussed cross-border interbank network analysis and studies that examined different loan terms were excluded, resulting in 28 papers which specifically examined interbank network analysis of the overnight lending segment of the market. These papers were then analysed by their abstract, introduction and conclusions to identify the key themes which are discussed in each section of this chapter and further split into theoretical (see Appendix Table A1) and empirical papers (see Appendix Table A2). Other

researchers may include working papers and official statements in their study, however this study is restricted to only academic research output published in leading academic journals. Reducing the journal rankings to accommodate more articles may affect the arguments within the themes presented in this paper, however, our aim is to capture the major themes surrounding the topic which is well covered within our sample. Further work may widen the scope of the sample within each theme to uncover any argument dimensions that has not been already captured.

3. Theoretical modelling of interbank networks

The discussion around the theoretical modelling of interbank networks has largely focused on robustness and how the network can form a channel of contagion. Allen and Gale (2000) define different network structures and postulates that complete networks are most resilient to financial shocks. There are two schools of thought that have largely driven this arguments. On one hand, Rochet and Tirole (1996) have argued that banks are better suited to monitor themselves and as thus would better evaluate counterparty risks and create and dissolve relationships accordingly. On the other hand, researchers promote the view that interbank markets are contagious where one bank with bad assets, effectively spreads these assets to other banks in the market thereby creating a net negative effect on the financial system. Thus requiring the intervention of central banks (see Allen et al. (2000), (2009), van Lelyveld I. (2006)). Given evidence of a tiered structure in most interbank markets and having identified that the magnitude of shocks and characteristics of banks at each node are more important in determining the robustness of a network to shocks, the view that banks are better suited to evaluate themselves is more profound.

Interbank networks have been found to have a tiered structure in the real world, with certain banks forming a core and other banks connected to it in a periphery manner (Craig and von Peter, 2014). The 'stylized fact' that interbank networks exhibit a core periphery structure (in't Veld and van Lelyveld, 2014), has motivated studies that examine the individual characteristics of the banks within the network and how these characteristics affect the resilience of the network to shocks. While evidence suggest that size and leverage are major characteristics of banks within the core of the network (Craig et al., 2014), the magnitude of the shock and characteristics of the banks at each node within the network is what ultimately determines the robustness of the network to financial shocks (Green et al., 2016). In light of this, many works have departed from the discussion of the optimal structure of an interbank market that can be robust enough to absorb financial shocks smoothly and have focused on the approach to modelling these networks. This has led to several which have been developed to approximate a network given available data (Liu et al., 2017).

The mechanism and approach to constructing interbank networks has spurred several theoretical articles. These articles either attempt to identify the most suitable approach that produces good estimates of loss propagation or establish what network configuration is more resilient to financial shocks. The models are either static or mathematical in nature. These models either employ optimization techniques that capture linkage formation at the network level (Anand et al., 2015) or they are dynamic in nature and employ simulation frameworks to model linkage formation based on individual bank decisions (Liu et al. 2017). These dynamic frameworks that are based on individual bank decisions are known as actor-based models (ABM). They offer researchers a level of flexibility to modelling financial networks as it enables the incorporation of social elements of interbank transactions.

Significant evidence have been provided to show the presence of relationships in interbank linkages and transactions (see Craig and Von Peter , 2014; Iori et al., 2015; Finger and Lux, 2017; Blasques et al., 2018; Kobayashi & Takaguchi, 2018). The ability of actor-based models (or dynamic models) to capture social dynamics, adaptive behaviours and information diffusion amongst agents provides an ideal platform to model endogenously formed networks (Liu at al., 2017). Models either take an endogenous approach to selecting trading counter-parties or a random approach. Most works that adopt an ABM model, follow an

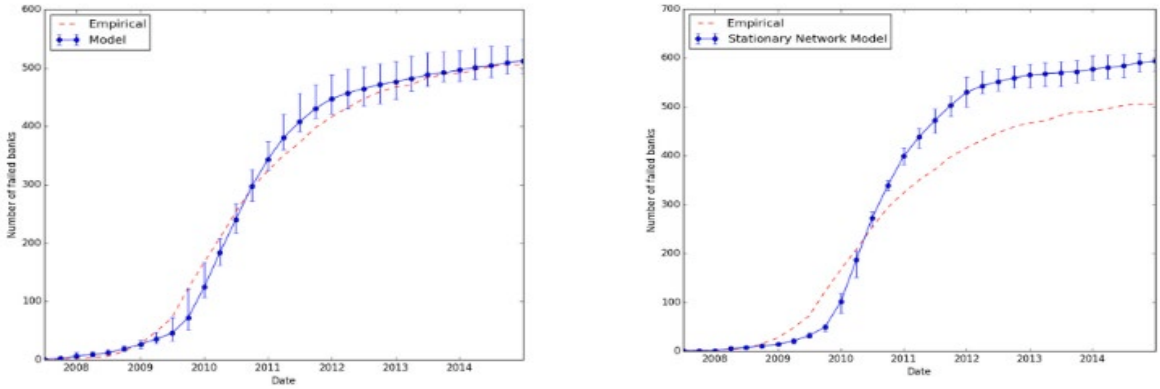
endogenous selection approach while static models typically follow a random selection approach.

Lenzu and Tedeschi (2012) develop an interbank market with credit relationships formed endogenously using a fitness mechanism based on individual bank performances. They then simulate the performance of the neighbouring banks to a particular bank to produce different network structures ranging from random networks to scale free networks. George (2013) examines the resilience of a random network and a money-centre network (which is similar to a scale free network) to financial shocks. The study however distinguishes between two market regimes of stability. A stable regime is where shocks can be contained and a fragile regime is where initial shocks can be transmitted through the network. Zhang et al. (2018), takes a different approach to evaluating the resilience of different network formations to financial shocks. Whereas, Lenzu and Tedeschi (2012) and George (2013) both adopt an endogenous approach to the formation of credit relationships and examine resilience the topological properties to financial shocks in their studies, Liu et al. (2017) and Zhang et al. (2018) develop two networks, one formed with endogenous selection of credit relationships and another with a random selection. They then examine their effects on estimating bank failures. The model developed by Lenzu and Tedeschi (2012) assume that interbank lending is backed by collateral which can be liquidated when a bank defaults, although this is plausible, this does not reflect the reality of transaction in the unsecured sub-segment of the overnight lending market. Simulation results provided by Lenzu and Tedeschi (2012), show that random networks are more resilient to financial shocks than scale free networks but George (2013) further explains that in times of stability, the method of network formation, be it random or endogenous, have little effect on financial stability in the face of a liquidity shock. However the study finds that in times of financial fragility, scale free networks are more resilient than random networks.

More recently, studies by Liu et al. (2017) and Zhang et al. (2018) have developed networks formed by endogenous selection models and compared them directly with networks formed by random selection models. Liu et al. (2017) develop a network from an ABM based on lending and borrowing preferences that are represented by financial ratios. The resulting network is then used to examine the propagation of losses through the U.S interbank market. Their study compares the results of the actor based model against results of a stationary network model and finds that the ABM produces better estimates of the cumulative number of default bank in the US financial system from 2007 to 2014, than a stationary network formation. The simulation results also provide evidence that the severity of default risk contagion is higher in network follow random selection than an endogenous selection method (see Fig. 1). Zhang et al. (2018) also examine differences in propagation of losses when the network follows a random selection approach than when it follows an endogenous one. They do this by varying a parameter of random selection probability under a stationary model and comparing it to results of varying an endogenous selection probability in an actor based model (see Fig 2). Their actor based model is based on lending and borrowing preferences of banks selecting a random pool of potential counterparties at every time step. This approach does not completely exploit the power of actor based models. The assumption that banks randomly select preferred counterparties does not effectively reflect the relationship lending dynamic that exists in interbank networks. This means that a bank can choose to dissolve a preferred relationship abruptly without any logical reason. The approach of Liu et al. (2017) where banks choose preferred trading partners based on the maintenance of certain internal ratios is more plausible. Banks establish relationship with

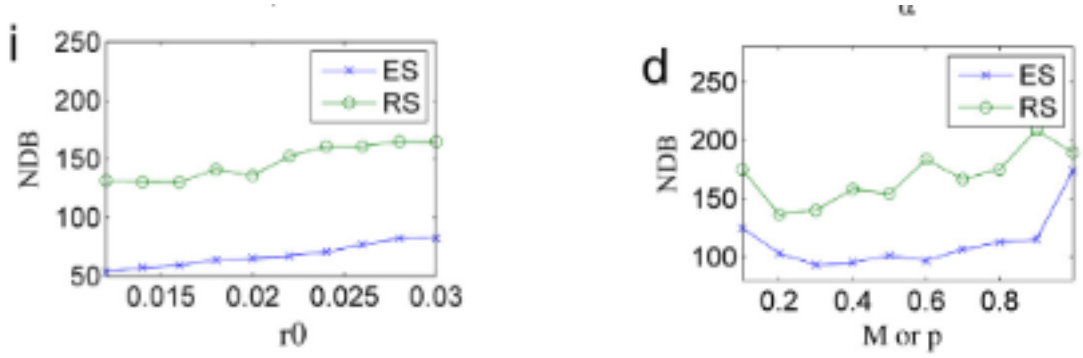
counterparties whom they perceive to not pose an indirect or direct source of risk (Finger and Lux, 2017) and are performance driven motivating them to adapt to market changes to achieve their overall performance objectives (Lui A. et al., 2017).

Fig. 1 Estimates of bank defaults (Liu et al., 2017, p.12)



(a) Endogenous Network Model (b) Stationary Network Model

Fig. 2 Sensitivity analysis of default risk contagion (Zhang et al., 2018, p.206)



(a) Central bank interest rates (r0) (b) Probability of Endogenous or random selection (M or p)

There is a difference in the effects of central bank operations on financial market contagion in endogenously formed networks and randomly formed ones. George (2013) finds that in a stable regime, central bank liquidity can help banks withstand shocks for a longer period and can lead to banks becoming more interconnected. Banks which could be otherwise insolvent are able to sustain themselves with interbank liquidity, thus leading to a more contagious regime. Zhan et al. (2018) provide evidence that the default risk contagion is more severe in random networks with an increasing central bank rate (see Fig. 2(b)) and in the face of severe fragility caused by a common shock to banks simultaneously, a recapitalization of banks is more effective than liquidity provision by central banks (George, 2013).

The ABM enables researchers to observe changes in network properties when calibrated to different time periods, therefore providing valuable information on bank behaviour. Liu et al. (2017) uses this to examine the US interbank market in the pre-crises and post crises periods. The study revealed that in the post-crises period, banks had fewer counterparty exposures and were more resilient to shocks arising from asset write-downs. The ABM also provides the opportunity to differentiate between aggregate network

properties and individual bank behaviour. The overestimation of defaults by randomly formed networks highlighted by Liu et al. (2017) may be due to its inherent control for bank specific behaviours and ultimate failure to capture unobserved bank characteristics which may have an effect on the decision to keep a bank afloat or let it default.

4. Critique of the application of network theory to interbank markets

The use of network analysis on interbank markets is premised on the assumption that banks are well poised to self-regulate themselves and as a result, the network organizes and re-organizes in response to individual bank assessments of other banks in the network. This is a view that has long been challenged by researchers.

Allen and Gale (2000) emphasizes the importance of market structure in examining interbank markets and argues that a 'complete' network where all banks are symmetrically connected to each other is more resilient to financial shocks than in an 'incomplete' network. Incomplete network structures are less resilient to financial shocks because the banks within the network do not possess hedging options to mitigate the risks it faces against existing exposure in the event of liquidity shocks in the market (Allen et al.., 2009). At the same time Allen et al. (2009) also shows that even in a 'complete' network, if shocks are large enough, the banks may be faced with the risk of the emergence of a contagion channel.

So far there hasn't been any empirical evidence of the existence of a complete network as defined by Allen et al., (2009) in real world interbank markets. Several researchers have shown that interbank networks exhibit a core-periphery structure where some banks are connected to a core bank which is in turn connected to other core banks (Craig and von Peter, 2014). This stylized fact means that real-world interbank markets are always incomplete and as thus, require the central bank to constantly intervene. If all must recourse to the central bank, it raises questions of the whole essence of studying interbank networks. Evidently from the 2008 global financial crises, interbank networks can freeze up to the extent where central banks have to begin to carry out 'unconventional' monetary operations to keep the financial system operating smoothly. This argument of the superintended role of central banks over the peer monitoring capabilities of banks themselves has been championed by several leading scholars over the years (see Allen et al., (2000) (2009) and val Lelyveld & Leidorp, (2006)).

Network analysis of interbank markets have not been able to comprehensively answer a critical question; If banks have an efficient peer monitoring role, then what is the optimal structure of the network for it to be resilient to financial shocks? Several studies have attempted to find this, but there hasn't been any evidence of a real world network configuration that is persistently resilient to financial shocks, rather the resilience of a financial network to shocks has been attributed to the characteristics of the banks within the network in relation to the shock the network experiences (Green et al., 2016). Most works employing network analytic methods have largely been theoretical in nature. With only few empirical studies being carried out, the real world application of network models may questionable.

5. The role of relationships in the interbank market

Relationships are important in interbank market lending, especially in the unsecured overnight segment where trust is important given its unsecured nature. Banks can establish relationships with other banks based on their perception of attractiveness (Iori et al., 2015), their assessment of the of the costs of mitigating uncertainties about counterparty risk (Blasques et al., 2018) or their assessment of the current state of the network if all relevant information on interbank transactions are available for their assessment (Finger and Lux, 2017).

Iori et al. (2015) assumes first that if a bank lends may times to another bank in a previous time period then it is likely to keep doing so in the future unless external conditions change. They assume that banks can anticipate their future liquidity needs and as thus, allocate a certain number of transactions that they execute in the interbank market within a period of time. The number of transactions that a bank is allocated to execute in a time period is arbitrarily set and transactions are divided into borrower aggressor and lender aggressor transactions following the outcome of a random binary variable. In lender aggressor transaction, an order to borrow is assumed to be placed by a randomly selected Bank B_i, following a probability function given the total number of transactions Bank B_i has left to carry out in the time frame (see equation (1)).

$$p_b(B_i, t) \propto B_i^{b,la}(t). \tag{1}$$

After the selection of a borrower, a lender Bank B_j is selected randomly following a probability function. The function uses the given the total number of transactions left for Bank B_j to carry out in the time frame, the total number of transactions in which B_j lent money to $B_i$over previous time windows (regardless of the type of transaction (borrower aggressor or lender aggressor)) and a parameter w, which indicates the level of attractiveness of a borrower (in this case B_i) (see equation (2)).

$$p_l\left(B_j, t \middle| B_i\right) \propto B_j^{l,la}(t)[w + N_{B_j \to B_i}(t)] \tag{2}$$

This parameter is assumed to be equal for all banks and is what captures the dynamics at the beginning of the simulation exercise. Once a lending bank is selected, the resulting probability that a transaction occurs between the selected borrowing and lending bank is given by equation (3).

$$p\left(B_j \to B_i, t\right) = p_b(B_i, t) p_l\left(B_j, t \middle| B_i\right)$$

$$= \frac{B_i^{b,la}(t)}{\sum_{k=1}^{n} B_k^{b,la}(t)} \cdot \frac{B_j^{l,la}(t)[w + N_{B_j \to B_i}(t)]}{\sum_{q=1}^{n} B_q^{l,la}(t)[w + N_{B_q \to B_i}(t)]} \tag{3}$$

In borrower aggressor transactions, the lending bank B_j is first selected (following equation (4)) and then the borrowing bank is selected following the probability function described for the lender in the lender aggressor transaction. The key difference is, the lender can reject to trade with the selected borrower given the attractiveness parameter w and the

number of previous transactions carried out with the borrowing bank, B_i, therefore the probability that Bank B_j lends to B_i is given by equation (5).

$$p_l(B_j, t) \propto B_j^{l,ba}(t). \tag{4}$$

$$p_b(B_i, t|B_j) \propto B_i^{b,ba}(t)[w + N_{B_j \to B_i}(t)] \tag{5}$$

If a borrower is rejected, another borrower is selected until a counterparty is accepted by the lending bank B_j and the probability that a transaction occurs between the selected lending bank and the accepted borrowing bank is given by equation (6).

$$p(B_j \to B_i, t) = p_l(B_j, t) p_b(B_i, t|B_j)$$

$$= \frac{B_j^{l,ba}(t)}{\sum_{q=1}^{n} B_q^{l,ba}(t)} \cdot \frac{B_i^{b,ba}(t)[w + N_{B_j \to B_i}(t)]}{\sum_{m=1}^{n} B_m^{b,ba}(t)[w + N_{B_j \to B_m}(t)]} \tag{6}$$

The assumption that banks can anticipate their future liquidity needs is a strong one. Although there are new macro-prudential standards requiring banks to conduct more comprehensive tests to anticipate liquidity needs, the practicality of banks accurately forecasting their liquidity needs is difficult. However, this assumption can be further relaxed, modelled and estimated, to create a comprehensive model that incorporates both bank's liquidity needs and trading approach.

A different approach is proposed by Finger and Lux (2017) as they assume that all banks have full knowledge of the network at any point in time, including all actors, relations and covariates. The model builds on two functions that determine the decision of a bank, a rate function and an objective function. The rate function, expresses how often a bank (be it a lender or a borrower), on average, is willing to change its position in the network. When a bank is activated by the rate function, the objective function is then used to indicate the preference of the bank and determine its action. The objective function captures the satisfaction of a bank to maintain of dissolve existing credit relationships given the current state of the network. This approach makes actors act with a myopic view. By only considering the maximization of their short term utility given the network status without considering the actions of other actors or the future ramifications of their actions. Also, having full knowledge of the state of the network in order for a bank to make trading decisions has its limitations. With most interbank transactions done over the counter, it is difficult for an actor to measure the state of the network. Blasques et al. (2018) in contrast to Iori et al. (2015) and Finger and Lux (2017), develop a model where banks trade in the interbank market with an objective to maximize discounted profits by choosing which banks to approach to negotiate interest rates (Using a Nash Bargaining approach) and setting monitoring expenditures to mitigate uncertainty about counterparty risk. There is a limitation to this approach however, as the estimation of the cost of monitoring is practically difficult to quantify.

Kobayashi & Takaguchi (2018) propose a new measure to quantify the strength of relationships in the interbank market. They identify a 'significant tie' between banks as a measure of the strength of relationship and as thus, two banks connected by a significant tie are said to be engaging in relationship lending. A significant tie is identified when banks with small activity levels are observed to have traded multiple times in several time periods. To

determine the activity levels of banks, a maximum likelihood estimation is carried out over several time periods. The probability that two banks trade with each other in a time period is assumed to follow a binominal distribution following a baseline fitness model. Deviations from this binominal distribution indicates presence of relationship lending. The underlying idea behind their approach is similar to that of Iori et al. (2015) in the fact that they both assume that if banks have traded before they are more likely to continue to trade thereby forming a relationship as long as there are no external factors that affect the conditions under which they trade. The difference however, is that Kobayashi and Takaguchi (2018), also take into consideration the activity levels of the banks which have a history of repeated trades with each other. This provides powerful insights, by distinguishing banks that are lending dependent or borrowing dependent and provides explanations for the rise of relationship dependent banks in the dawn of the global financial crises.

6. Empirical relationship between network properties and overnight lending rates

Empirical literature on network analysis have either examined the effect of relationship measures on the price paid for liquidity (Temisvoy et al., 2015), the effect of the position of a bank in the network on price (Temisvoy et al., 2017) or a joint effect of relationship and centrality measures on the price of liquidity (Craig et al., 2015). Most works that examine the position of a bank in the interbank network employ the use of centrality measures to assess and identify the importance of institutions within the network (Leon et al., 2018). One approach to measure centrality is the use of local metrics such as the number of links (both incoming and outgoing) and the strength of those links. Another is the betweenness centrality measure, which involves the use of metrics that indicate the extent to which a node lies within the paths between other nodes. Local metrics however fail to measure the centrality of the nodes connected to a particular node (Leon et al., 2018). This is particularly worrisome in interbank networks that are typically hierarchal in nature and exhibit a core-periphery structure (Craig & von Peter, 2014). Implicitly local measures may identify a central institution that is connected to other peripheral institutions but not necessarily an institution that forms part of the core nodes of the network.

Using centrality measures, researchers have attempted to examine the effects of relationships indirectly (Craig et al., 2015) or indirectly (Temisvoy et al., 2015) on the price paid for liquidity. Given individual bank level data on primary auction bids, Craig et al. (2015) attempt to examine the effects of relationship and centrality measures on bank bidding behaviour. The underlying assumption is that banks that do not benefit from relationships in the interbank market will turn to the primary market to meet their liquidity needs and as thus bid more aggressively (Craig et al., 2015). Using borrowing concentration measures (i.e the diversity of an individual banks borrowings) as a proxy to measure the degree of relationship lending, a panel regression with control variables for individual bank characteristics is constructed to examine the relationship between these measures and the bidding price of banks at the primary auction.

The results suggest that banks with more concentration on borrowing (proxy for relationship) in the interbank market bid more aggressively at primary market auctions. While banks that have more diversified borrowing counterparties pay less for liquidity from the central bank. The study focuses on state owned German banks, thus assuming an implicit government guarantee for the banks used in the study. The study also downplays the role that bank health (or the riskiness of a bank) can play in determining the bidding behaviour of a bank in the primary auctions. Using concentration of borrowers as a proxy to measure relationship might not truly reflect the presence of relationship lending. Banks may trade repeatedly but may be borrowing dependent or lending dependent on the counterparty with whom they trade (Kobayashi & Takaguchi, 2018). This may explain why banks with lower diversified borrowing structures may turn aggressively to the primary market for their liquidity needs.

Attempting a more direct approach to measuring the impact of relationship lending on overnight rates, Temisvoy et al. (2015) carry out a panel regression analysing bank pair trades to determine the influence of relationship on the price paid for liquidity. They measure price by the spread paid for the trade to the volume weighted average price in a month. Dividing the transaction pairs into subsets of ‘lender as aggressor’ and ‘borrower as

aggressor', they calculate a lender preference index (LPI) and a borrower preference index (BPI) for each transaction pair (similar to the theoretical constructs of relationship measures of Iori et al. (2015)) and examine the effects of these indices on the price spread. The underlying hypothesis is that banks moved to a relationship driven approach to trading with the advent of the financial crises to avoid the extra cost of for intelligence on their counterparty's credit profile. Hence, the study examines the trades in three time periods, pre-crises (2006-2007), during crises (2007-2008) and post crises (2008-2009).

Their results show a positive and significant effect of LPI on the spread and a negative and significant effect of BPI on the spread in the Lender as Aggressor sub sample for all three time periods. The results from the Borrower as Aggressor sub-sample however show only a significant effect of the LPI variable on the spread only during and after the crises. The inconsistency with the results from the Borrower as Aggressor sub-sample may be attributable to the fact that when lenders quote, the decision for borrowers to accept a quote may be driven more by prices than relationships (Temisvoy et al., 2015). The results are in contrast with the findings of Craig et al. (2015), which is based on a measure of relationship that attempts to quantify the presence of relationship lending on an aggregate level for a single bank rather than on a transactional level. Also the study examines the bidding pattern of banks in the primary auction, banks may choose to go to the primary auction for other reasons that may be unobserved. The findings of Temisvoy et al. (2015) provides empirical evidence of the presence of relationship lending in the interbank market and further highlights how relationship lending can influence the overnight lending rate.

Other than examining relationship lending dynamics, studies have also attempted to construct empirical models that capture the relationship between the position of a bank in the interbank market and the price paid for liquidity using local and global measures of centrality. Craig et al. (2015) adopts a global measure of connectivity that captures the connectivity of a bank to other centrally connected banks to measure centrality and study its effects on bidding behaviour. Their results provide evidence that banks that are more interconnected (i.e higher levels of centrality) bid higher at primary auctions perhaps due to the systemic risk surrounding them (Craig et al., 2015).

Looking more directly at transactional level in the interbank secondary market, Temisvoy et al. (2017) examines pair transactions to measure how the position of a bank affects the price it pays for liquidity from other financial institutions in the market. They construct different measures of centrality, distinguish between local centrality measures (InDegree, OutDegree) and global centrality measures (InBetweeness and OutBetweeness). The study also introduces alternative measures such as Katz, PageRank and Sinkrank, which differ by the way in which the centrality measure is calculated for each node. While Katz measures the distance between nodes by unrestricted walks of any length rather than paths or geodesics as is the case with betweenness, PageRank assigns a fraction of the source nodes centrality to each connected neighbour and SinkRank uses harmonic distance to calculate the distance between two nodes (Temisvoy et al., 2017).

Empirical evidence suggests that more interconnected borrowers benefit from lower rates in comparison to the market. Using both global measure of betweenness & eigenvector measures and local measures of indegree & outdegree, borrowers who have high Inbetween and OutBetween (or indegree and outdegree) figures benefit from lower spreads in the market (Temisvoy et al., 2017). Although both global and local measures provide similar findings, global measures provide more insights into the systematic importance of a node to the whole network. Evidence from Temisvoy et al. (2017) shows that borrowers whose

lenders are important borrowers as well, become important borrowers, likewise lenders whose borrowers are important lenders, become important lenders. These centrally connected important borrowers and lenders are 'too-connected-to-fail' and pose a systematic risk to the network (Temisvoy et al., 2017).

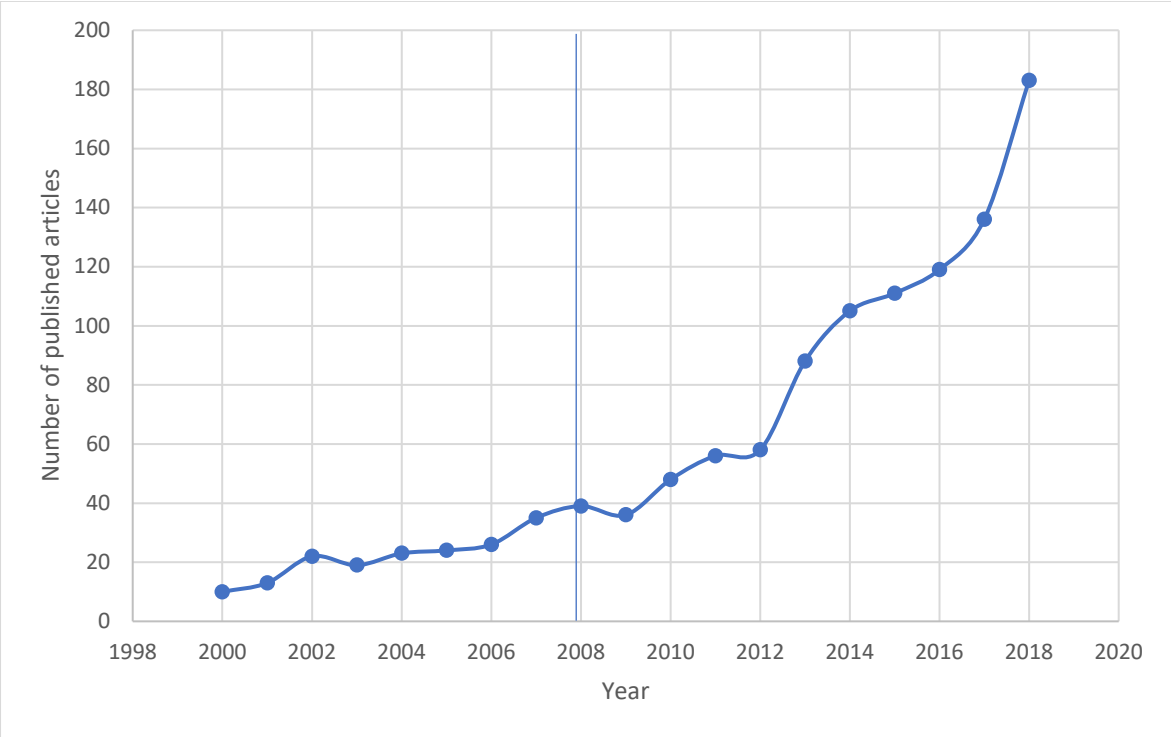
In the Colombian interbank market, Leon et al. (2018) calculates a liquidity spreading index (LSI) for each financial institution participating in the interbank market. The index is constructed using a Hypertext Induced Topic Search (HITS) algorithm which estimates the authority or hub centrality of a node using a modified version of the eigen vector centrality approach. Two major differences between the HITS approach and other eigenvector approaches is that weakly connected nodes are not stochastically or arbitrarily adjusted (as is the case with PageRank and Katz centrality) and the HITS algorithm is specifically designed for directed networks where the adjacency matric may not be directed (Leon et al., 2018). Using a random effect probit regression model to examine the determinants of intermediary and highly connected banks (institutions with high LSI), it is observed that that size, leverage and lending concentration are all significant determinants (Leon et al., 2018). However, given that a probit model is adopted, causality cannot be necessarily inferred although the findings are in line with previous research carried out by Craig and von Peter (2014) where they found size as a major characteristic of banks in the core of interbank networks.

The position of bank within the network have clear empirical implications on the price it pays for liquidity. Banks that particularly lend to other centrally located banks typically pay more for liquidity (Craig et al., 2015) while borrowers who are more centrally located pay a lower price for liquidity (Temisvoy et al., 2017). These findings suggest that institutions whom are typically brokers or intermediaries, do not benefit by obtaining lower cost of funding as they are viewed as systematically risky, while rather, institutions who are more centralized borrowers (or borrow from a diverse selection of lenders) are 'too-interconnected' to fail and as thus, systematically important.

7. Impact of the global financial crises on interbank markets

Following the aftermath of the 2008 global financial crises (GFC), the importance of interbank markets to policy makers and researchers become more pronounced. This is evident from a surge in academic literature on interbank networks since the GFC, as observed in figure 3 below. The global financial crises not only impacted interest in studying interbank networks but also impacted the networks themselves. In the literature that examines interbank relationships and interbank network evolution, several studies have examined the behaviour of banks in the network before the crises, during the crises and after the crises.

Fig. 3 Chart showing number of articles published in journals listed on ScienceDirect journal database on 'interbank network analysis' from 2000 to 2018



The crises, prompted central banks to intervene aggressively by injecting liquidity into the financial system. The aftermath of the crises saw even more unconventional monetary policies being adopted, such quantitative easing in Europe, which led to a decline in overnight lending rates and build-up of excess reserves held at central banks (Green et al., 2016). The resulting effect of the GFC on the interbank market from a network perspective has been studied. However, if these effects are a result of network response to monetary policy or just a result of individual bank risk assessments, is not explicitly clear from the literature.

Affinito and Pollozo (2017) estimate a fixed effects panel regression model to first identify if and in what direction the network topology of the interbank market (measured by eigenvector centrality) changed during major GFC events. Using a similar method, Temisvoy et al. (2015) examine the impact of relationship lending measures on interbank spreads in three time periods: pre-crises (2006-2007), during crises (2007-2008) and post crises (2008-2009).

Empirical results provide evidence of a negative and statistically significant impact of the global financial crises on average bank interconnectedness (Affinito and Pollozo, 2017) as

well as an increase in the preference of banks to trade with established counterparties (Temisvoy et al., 2015). Results also suggest a recovery of average interconnectedness with the announcement and subsequent implementation of post-crises monetary policies by the European central bank, primarily the 3-year Long Term Refinancing Operations and the Outright Monetary transactions (OMT) (Affinito and Pollozo, 2017).

However, not all institutions reacted (in terms of connectivity) to GFC events in the same way. Empirical evidence suggests that there are some varying effects of the GFC events on banks with different levels of initial connectivity prior to the event. More connected banks for example became more interconnected after the sovereign debt crises of August 2011 while less initially connected banks became even more disconnected (Affinito and Pollozo, 2017). There is also a larger effect of the GFC on lender preference after the crises than on borrower preference (Temisvoy et al., 2015).

The reduction in average centrality might be reflective of an increased avoidance of indirect counterparty risk as banks do not want to be indirectly exposed to risky counterparties through intermediaries. Results from simulations conducted by Finger and Lux (2017) provide evidence of a decreasing network density after the onset of the global financial crises in line with a recorded decrease in average centrality as observed by Affinito and Pollozo (2017). The reduction could also be attributable to a lack of incentive for banks to lend to each other in the uncollateralised overnight market, with central bank rates being brought to near zero figures (Green et al., 2016). Whichever the case may be, the global financial crises caused a shift in interbank markets with banks trading less with each other and holding more reserves at the central bank. Most of the studies have concentrated largely on European markets where the GFC saw the birth of ‘unconventional’ monetary policy operations which were first used in Japan in the late 90’s. A clear disentanglement of the effects of monetary policy and bank perception of counterparty risk on decreased interbank network connectivity is yet to be uncovered.

8. Conclusion

The application of network theory to interbank market analysis has provided several insights and contribution to the analysis of interbank market activity. There is widely documented evidence of a relationship factor influencing the price paid for liquidity by market participants. Network measures have been developed and applied in in several ways in the literature. Commonly used measures are the Lender Preference Index (LPI) and Borrowers Preference Index (BPI) which are calculated using either local or global measures of centrality (InDegree, OutDegree or InBetweness, OutBetweeness).

The structure of the market has also been widely discussed, with considerable evidence suggesting that real-world networks exhibit a tiered structure with peripheral banks being connected to an interconnected network of core banks. The formation of these connections has been shown to be more dependent on individual bank decisions that are endogenous in nature. However, the optimal set of rules used by banks in forming relationships is an interesting dimension that has not been widely discussed.

Most studies have been theoretical in nature, as they primarily focused on the formation mechanism of network simulation. Very few empirical studies have been carried out. These empirical studies have mainly focused on network centrality measures and their effects on overnight lending rates. Future research can build on these papers to apply these network measures in the wider literature. These measures van be used to improve systematic banking risk measures such as the Z-Score and S-score. Given that Z-score is used to proxy individual bank fragility, the introduction of local network centrality measures can provide a more insightful measure. This can be estimated using mixed data sampling regression models. There could be interesting insights into how a bank's perception of risk influences its trading activity in the market.

The effects of the network position of a failing bank when examining the contagion effect and propagation of losses when the system is perturbed with financial shocks is an interesting dimension for further research. Given that Banks can be systematically important borrowers or important lenders depending on their position within the network (Temisvoy et al., 2017) and the resilience of the system to financial shocks is dependent on the affected bank and magnitude of the shock (Green et al., 2016), the contagion effects when a financial shocks affects a bank can be dependent of on the network position of the bank other than the size and other factors earlier highlighted in the literature.

Conventionally, interbank markets have been studied from a horizontal perspective, looking at banks trading liquidity between each other. However with the existence of banking groups with cross-border operations, a three dimensional perspective can be adopted, where the role of banking groups in the interbank market can be extensively explored. This could potentially yield interesting results as to the effects of the existence of relationships with foreign parent counterparties on the trading behaviour of banks in a local interbank market.

Although these research dimensions may yield very interesting findings and contributions, there is one major constraint: Given the proprietary nature of the data required to carry out these studies, the extensiveness of available data may limit the results obtained.

APPENDICES

Appendix Table A1: Summary of selected theoretical literature on network analysis of interbank markets

Author	Main Idea	Model Used	Data Source	Major Findings
Krause & Giasante (2012)	The paper seeks to examine the spread of contagion through the interbank network connections when there is an exogenous shock to the market	Theoretical Paper	Simulative method	The paper finds that the contagion spread of shocks between banks in the network is heavily dependent on the network structure. The size of the bank that is first affected by the initial shock is the largest determinant of the trigger of a contagion.
Lenzu & Tedeschi (2012)	The paper seeks to evaluate what network structure (configuration) is more robust to financial shocks	Theoretical Paper	Simulative method	Their results suggest that random networks are more resilient than scale free ones. The key difference between their papers and others is that, the affected bank is only removed from the network if it cannot raise liquidity in the interbank network to cope with the shock
Georg C. (2013)	The paper seeks to examine an optimal structure of the interbank market that is less prone to systematic risk. It also examines the effectiveness of central bank interventions and compares two different sources of systematic instability	Theoretical Paper	Simulative method	The network structure only has an impact on financial stability in times of distress. Random network models tend to overestimate contagion effects than small world networks. The paper also shows that central

				bank interventions are effective in the short run, but can create a contagious regime in the long-run. When the instabilities is caused by common shocks, recapitalization is more effective than liquidity provision
Memmel & Sachs (2013)	The paper seeks to establish an indicator of financial contagion in the interbank market and examine what its determinants are	Theoretical Paper (Data from 'German Credit Register' and 'BAKIS')	Simulative method (then calibrated to data on German banks)	The paper find that a single indicator can be produced to compare the distribution of bank failures over time. The paper then goes further to find that there are four determinants of this indicator: 1) Bank's capital Ratio 2) the share of interbank assets to total assets 3) The 'loss given default' 4) Network entropy (the degree of equality in the distribution of interbank exposures)
Lee S.H. (2013)	The paper examines liquidity risk and aims to propose a method for calculating systematic liquidity risk	Theoretical Paper	Simulative method	The paper presents a framework to measure systematic liquidity shortages by capturing both direct shortages in one bank and indirect shortages due to a knock on effect because of interbank linkages. The paper also finds that a core-periphery network with a deficit money centre bank

				gives rise to high levels of systematic liquidity shortage
Ladley D. (2013)	The paper seeks to examine the conditions under which interbank lending promotes stability or a channel of contagion	Theoretic Paper	Simulative method	The paper finds that there is no single network structure that limits contagion (or maximizes stability) from a financial shock, however they find that more connectivity reduces the cost of deposit insurance
Veld & Leyveld (2014)	The paper seeks to examine an appropriate model that best fits the structure of interbank markets and examine the key characteristics of the core banks in the core-periphery model	Deterministic (Core periphery model)	Prudential reports of Dutch banks	The paper finds that core-periphery models have a better empirical fit than static models and nested graph models. They also introduce new methods of comparing models, using a combination of error score evaluation and monte-carlo simulations. The individual characteristics of the banks that form the core are not uniform (there are mostly large banks but medium and small sized banks are also present). Also they

				tended to have lower capital buffers
Craig & von Peter (2014)	The paper seeks to provide evidence of a tiering of interbank networks as a result of the heterogeneity of banks in the network	Theoretic Paper	Simulative	The paper provides evidence of a core periphery structure not as a result of randomization but of behavioural reasons. The paper provides evidence of bank characteristics such as size are strongly correlated to money centre banks
Iori et. al (2015)	The paper seeks to introduce a proxy for trust in modelling interbank networks.	Theoretical Paper/Empirical Paper (Data from e-MID')	Simulative method (then calibrated to e-MID)	The paper finds that preferential trading patterns produced by the model are close to those observed in real world data thus suggesting the presence of trust in network formation
Cohen-Cole et al. (2015)	The paper seeks to examine the link between propagation of financial risks and individual bank incentives on a network	Theoretic Paper	Simulative	The paper presents a measure of systematic risk in the market and links bank behaviour to network structure. The paper highlights the dividends of a dynamic modelling technique

Hatzopoulos et al. (2015)	The paper seeks to examine the presence of preferential trading in interbank networks	Theoretic Paper	Simulative	The paper finds evidence of preferential trading on the E-MID platform. They find that, the average volume of transactions by preferential trading links was larger than the average volume of other transactions before, during and after the crises. However they find that the average price in preferential links was higher than the average price of other links during the crises
Lux T. (2015)	The paper seeks to examine the emergence of a core-periphery structure in the interbank market using a dynamic model	Theoretical Paper	Simulative	The paper find that constructing a dynamic model where there is heterogeneity of bank size and decision mechanism that produces preferential trading, a core periphery structure emerge. The big sized mostly form the core money centres.
Anand et al. (2015)	The paper seeks to establish an alternative method of estimating counterparty exposure using a static model	Theoretical Paper	Simulative	The paper presents a minimum density approach where the most probable links are loaded with the largest exposure in line with the total lending and borrowing of each bank. They find that this method tends to

				overestimate contagion in a stress testing context while a maximum entropy approach underestimates it.
Halaj & Kok (2015)	The paper seeks to examine the impact of changes in regulation and policies on an endogenously formed interbank network structure	Theoretical Paper	Simulative	The paper find that macroprudential policies make a significant effect on network formation which ultimately affects the contagion risk to adverse shocks
Xu et. al (2016)	The paper aims to build a dynamic model that captures the evolution of network architecture over time.	Theoretical Paper	Simulative method	The paper finds that network structure evolves over time but network properties remain unchanged. They also find that an increase in lending risk preference, causes the average shortest path length to become shorter. Decreasing the fluctuation in bank investment yield and deposits reduces the chances of bank failure
Erol & Ordonez (2017)	This paper explores the impact of regulation on interbank network interconnectedness	Theoretical Paper	Mathematical models	The paper finds that tightening liquidity requirements beyond a threshold can cause a reduction in interconnectedness, or a dissolution of credit relationships which in turn increases systematic risk by

				inducing an asset fire sale contagion
Finger & Lux (2017)	The paper seeks to investigate the motivation behind establishing lending relationships in the network	Stochastic Actor Oriented Model	e-MID	The paper finds that counterparty risk and indirect exposures are two main factors that affect the establishment of lending relationships. It also reveals that past lending relationships also plays a role
Lui et. al (2017)	This paper seeks to use an alternative approach to interbank network modelling by adopting an approach that takes into consideration, individual bank decisions	Agent Based Model	FFIEC (Federal Financial Institutions Examination Council Reports for Conditions and Income)	The paper finds that the endogenously formed model (the ABM) creates a better measure of the interbank linkages that produces better estimates of loss propagation through the network
Zhang et. al (2018)	The paper seeks to evaluate the difference in assessing default risk contagion in two network architectures: An endogenous selection model and a random selection model	Theoretical Paper	Simulative method	The paper finds that the endogenous selection model produces default risk contagion that is less severe than random selection models. They attribute this to the fact that endogenously formed models produce money-centre structures, which enables borrowers to borrow from more

				liquid banks with lower interest rates
Blasques et al. (2018)	The paper seeks to analyse the role of credit uncertainty and peer monitoring in the overnight interbank lending network by developing a dynamic network model (the model incorporates indirect interference using network statistics)	Theoretical Paper	Simulative method (then calibrated to Dutch banks)	The paper finds that banks formation of long-term credit relationships is associated with positive credit conditions. An increase or shock in credit risk uncertainty diminishes lending activity. A widening of central bank corridor causes an indirect multiplier effect of increased trading activity triggered by an increase in monitoring and search activity amongst banks
Brandi et al. (2018)	The paper seeks to examine financial contagion arising from liquidity shocks by adopting a different approach borrowed from epidemiology, treating liquidity shocks as an epidemic (they call this model an EDB model (epidemic-Distressed-Removed))	Theoretical Paper	Simulative method (then calibrated to e-MID)	The paper finds that network topology is important when examining liquidity shocks to the market. There was a disappearance of hub banks and preferential lending during the GFC. Weak initial liquidity shocks can cause severe losses in the system. Banks who are heavily dependent on the market for liquidity provision (in terms of number of borrowers not

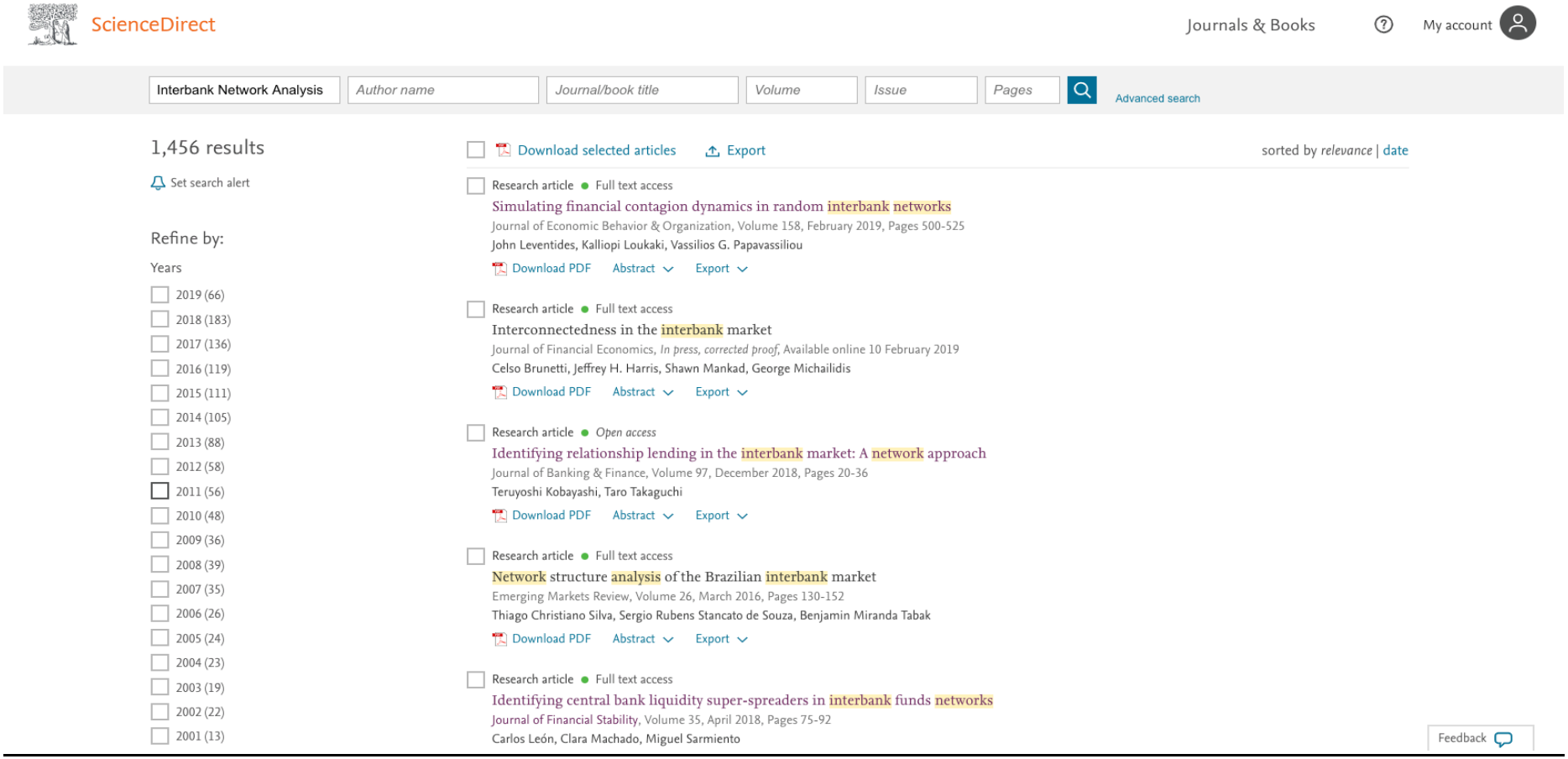
				volume) are more affected by liquidity shocks
Kobayashi & Takaguchi (2018)	The paper seeks to address measures of relationship lending	Modified Fitness Model	e-MID (Italy)	Using a new proposed measure of measuring relationship lending, identified relationship lenders affect the price of liquidity paid by borrowers as borrowers are still willing to pay higher rates for liquidity from banks with which they have a significant tie
Leventides et. al (2019)	The paper investigates how heterogeneity, bank balance sheet composition and network structure affect the spread of contagion in interbank networks	Theoretical Paper	Simulative method	The paper finds that heterogeneity helps in bringing stability in the face of a financial shock (diversity in size is good). Interconnectedness impacts network resilience (highly interconnected networks are more resilient to shocks). Highly leveraged banks are more exposed to default risk in the face of shocks

Appendix Table A2: Summary of selected empirical literature on network analysis of interbank markets

Author	Main Idea	Model Used	Data Source	Major Findings
Craig et. al (2015)	How the position of a bank within the network affects the price it pays for liquidity	OLS Regression	Deutsche Bundesbank	The presence of money centre banks within the network who act as intermediaries for liquidity. The price paid for liquidity depends on if a bank is lender to or a borrower from a money centre bank
Temisvoy et. al (2015)	The paper seeks to explore the impact of relationship lending on interbank rates and volumes. The paper introduces a measure of relationship lending	Regression Model	e-MID	The paper finds that measures of relationship lending affects the price paid or charged for liquidity. Relationship lending became more important in determining overnight rates after the GFC crises. Relationship lending can be linked to financial stability
Temizsoy et. al (2017)	How the position of a bank within a network affects the price paid for or received for liquidity	Fixed Effects Regression model	e-MID (Italy)	Banks that are centrally located in a network come with higher borrowing and lending costs
Affinito & Pozzolo (2017)	The paper seeks to examine the impact of the GFC and other major financial events on the network formation and connectivity	Fixed Effects Panel Regression model	Bank of Italy prudential supervisory reports	Events and policy announcement have effects on the network. They can reduce or increase interconnectedness within the network

Leon et al. (2018)	The paper investigates the structure of the Colombian interbank market and examines the role of core-periphery banks that re-distribute central bank liquidity (They are identified as 'super-spreaders'). The paper also examines the determinants of these 'super-spreaders'	Random effects Probit regression model	Colombian Central Bank	The paper confirms evidence of super-spreaders in the Colombian interbank market thus confirming a hierarchal structure similar to the 'core-periphery' structure. The paper also find that the probability of being a super-spreader is determined by size, leverage and lending concentration

Appendix Figure B1: Search results of "Interbank Network Analysis" in ScienceDirect database



Appendix Figure B2: Restricted Primary search to between 2011-2019

ScienceDirect

Journals & Books | My account

Interbank Network Analysis | Author name | Journal/book title | Volume | Issue | Pages | Advanced search

922 results

Set search alert

Refine by:

Years

- 2019 (66)
- 2018 (183)
- 2017 (136)
- 2016 (119)
- 2015 (111)
- 2014 (105)
- 2013 (88)
- 2012 (58)
- 2011 (56)
- 2010 (48)
- 2009 (36)
- 2008 (39)
- 2007 (35)
- 2006 (26)
- 2005 (24)
- 2004 (23)
- 2003 (19)
- 2002 (22)
- 2001 (13)

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Simulating financial contagion dynamics in random interbank networks
Journal of Economic Behavior & Organization, Volume 158, February 2019, Pages 500-525
John Leventides, Kalliopi Loukaki, Vassilios G. Papavassiliou
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Journal of Financial Economics, *In press, corrected proof*, Available online 10 February 2019
Celso Brunetti, Jeffrey H. Harris, Shawn Mankad, George Michailidis
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Journal of Banking & Finance, Volume 97, December 2018, Pages 20-36
Teruyoshi Kobayashi, Taro Takaguchi
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Network structure analysis of the Brazilian interbank market
Emerging Markets Review, Volume 26, March 2016, Pages 130-152
Thiago Christiano Silva, Sergio Rubens Stancato de Souza, Benjamin Miranda Tabak
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Identifying central bank liquidity super-spreaders in interbank funds networks
Journal of Financial Stability, Volume 35, April 2018, Pages 75-92
Carlos León, Clara Machado, Miguel Sarmiento

Feedback

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