Commercial Real Estate Market Structure and the Transaction Liquidity: A Social Network Analysis

Abstract

The study analyses the market network structure evolution of the selected commercial real estate (CRE) markets in the United Kingdom. While previous studies discuss investors' behaviours at an aggregate level but assuming investors make decisions independently, this paper investigates the transaction counterparties and their transaction networks, using Social Network Analysis (SNA) to explain the role changes of foreign investors, the evolution of transaction network structure, and the influences of the changes to market liquidity. Results from selected metro markets in 2001-2015 show that, the increasing number of foreign investors provide excess market demands but have not effectively improved the asset circulation. Only a certain number of foreign investors act as "core investors" and release the liquidity in the market. The UK CRE market structure follows an evolution process of "loose links – core-domain disassortative – integrated assortative" structure, and the structure is sensitive to the changes of market condition. VECM model suggests that the market structure formation has impacts on pricing efficiency. The results provide a new vision on analysing the influences of overseas investors, market liquidity and stability.

Keywords: Social Network Analysis, liquidity, market structure, investor composition, commercial real estate

JEL classifications: Z13, G14, G23, R33

1 Introduction

Commercial real estate (CRE) market is experiencing tremendous changes as a result of the global capital inflows. Growing numbers of international investors, including many from emerging markets, are reshaping the UK market after 2008 Global Financial Crisis (GFC). As in a private market, investors' decisions rely heavily on local knowledge and networks, in which foreign investors are assumed as less advantageous. The behaviours of foreign investors may rely much more on limited accessible market resource and exposure, potentially distinct from the local or incumbent investors. In previous sections, the study has discussed the different strategies of foreign investors on market entry, strategic alliance and property bidding prices.[1] The differences raise concerns about the market behaviours of foreign investors, and on a market level, the potential impacts of investors distribution on UK market depth and operation.

The inflow of global capital provides liquidity to local property markets but triggers higher volatilities in the market price. Lessons from the GFC suggests that the deepening investment links among financial institutions simultaneously increase market resilience and exaggerates the systemic risks (for example, Stiglitz, 2010; Mishkin, 2011). In real estate, the financialised natures of properties and the more complex ownerships among financial institutions become new conduits to transmit the systemic risks (Lizieri and Pain, 2014). Notwithstanding, existing studies provide few insights on how the transaction networks are formed in CRE market. Real estate assets tend to be more highly differentiate and illiquid comparing to those financial assets. The transaction mechanism of CRE market is an over-the-counter (OTC) market which depends on the information from broker, and more importantly, the connection and reputation of the ivestors. Foreign investors must also contend with the reality that their strategic decision making will be bounded by limits to the local market networks they can access. Their bounded rational behaviours hence add to complexity and risks in markets. The risk transmission process in that case is more complicated – some investors act in a more "crucial" position in the transmission process, and the transactions initiated by these investors could have larger impacts than the deals by others. This calls for an in-depth analysis of the connectivity between investors in the CRE market.

Hence, this study aims to explore:

1. The roles of foreign investors in UK real estate market networks, including how these vary within sub-markets and over time;

[1] See Zhang, Devaney and Nanda (2018) for the discussion on the strategic alliance choices of overseas investors in the host CRE market under the influence of peer investors.

2. The processes by which participants' networks form in the CRE market, and characteristics of these networks.

3. The impacts of network structure on market operation and market liquidity.

In the research of market structure in investment sector, studies in banking industry provide constructive insights. However, traditional banking competition studies that rooted in industrial economics framework quantify market power by the statistics based on market shares of participants (Bikker and Haaf, 2002; Fungacova, Solanko and Weill, 2014). Indicators such as Herfindahl-Hirschman Index and Lerner Index remain limited in commercial real estate market as a result of the heterogeneous asset features and investors' different investment strategies. Yet the traditional market-share-based methods fail to cover elements that are not revealed by financial information, such as investors' reputations, cultural background or the previous transaction experiences. These "soft elements" influence the investment decisions of market participants through their market network access (Minoiu and Reyes, 2013; Masso and Ruiz-Leon, 2017). Therefore, this research introduces Social Network Analysis (SNA) to help quantifying the clusters of market participants in different locations, and estimate the change of the market network structure through time. Centrality measurements are adopted to compare the positions of foreign investors in the transaction network with their UK counterparties in the market. Mapping network graphs of capital flow in the market accompanied with statistics about community structure demonstrate the evolution of the market structures in different locations. Further, the study employs vector error correction model (VECM) to analyse the relation between market structure and market liquidity.

The data sample is RCA CRE transaction records in London, Manchester, Midland and Northern England from 2001 to 2015. Empirical evidences show the integrating process of transaction networks in the 15-year period. Foreign investors improve the market liquidity by conducting more purchases with higher volumes comparing to UK investors. A few foreign investors become the core investors that facilitates the circulation of property assets, while other foreign investors are at the peripheral positions of the transaction networks or isolated from the main transaction clusters. The network formations vary among metros, but in general, the early stage of the markets is usually fragmental with loose links, then a few participants would become the core nodes and form a disassortative mixing. With the markets further develop, more investors become "core", the market power distributions become balanced i.e. no dominant investors in the network with tremendous more and larger transactions from others. The markets reflect integrated and less assortative structures. The disassortative structure is more efficient on information transmitting and pricing, but this structure also reflects the systemic importance of core participants in the markets.

Further results from VECM models find the market structure features can be used to explain the price-impact market liquidity but not transaction volume. Granger causality and impulse response results imply that, as the transactions with investors from the same countries reduce the searching and bargaining cost, high degree of same-country assortativity improve the market liquidity. Whereas the positive shock of degree assortativity, which implies core investors getting higher probabilities to connect with other core counterparties rather than the peripherals, impairs the market liquidity in the long run. The results reinforce the role of key investors on stabilising market pricing and facilitating market liquidity.

The study expects to contribute to existing studies in financial institutions and real estate in several aspects. As a novel method in social science, SNA receives wider attention in the finance literature especially after the GFC. A rising number of studies concentrate on interbank money markets and debt markets in order to understand the connection among institutions and contagion of systemic risks. This study contributes empirical evidence on the network study of OTC market with larger scales and highly heterogeneous products. Among the literature on real estate, discussions either focus on the micro-structure of the transaction, or on the aggregate level market performance, while studies about the components of real estate investors and market structure remain blank. This study shed lights on the meso-level market analysis on investor concentration and the influence on the market performance. Specifically, liquidity risk remains a major concern in CRE markets, with some of the existing studies discussing the causes, detection and price impacts in the real estate market (Devaney and Scofield, 2013; Ametefe, Devaney and Marcato, 2016, among others). The pioneer studies have not investigated in depth about how the concentration of market participants affect the market liquidity, whereas this study aims to enhance the discussion from the individual-level strategies to the meso-level market formation. A third contribution of the study is the analysis of foreign investors' impacts in CRE market. Existing studies argue that foreign investors improve the liquidity, while this study specifies the network formation channel through which foreign investor impact market liquidity. Results also captures the "role changes" of foreign investors in the market, thus contribute to the discussion on how foreign investors impact CRE market pricing and liquidity.

The following parts of this chapter review the previous literature and specify the gaps among existing market structure studies of financial institutions and real estate markets. The empirical analysis includes the comparisons between foreign investors and UK investors, evolution of market network formations, and the influence of market network structure to market liquidity. This chapter concludes and evaluate the implications and further directions in the final.

2 Literature Review: Applying SNA to CRE Liquidity

2.1 Market structure and network analysis

The discussions of financial market structure shed light on the connections of financial institutions, which inspire this study. The "traditional" market structure studies follow the "structural—(conduct)—performance" (SCP, or SP) framework, and discuss the firms' scales of economy as well as the market power distribution among the firms. The "concentration" in the framework means how much of the market share is occupied by those investors with large scales, and the concentration of incumbent investors potentially influences the product pricing and "squeezes out" the new entrants (Bergantino and Capozza, 2012; Fungacova *et al.*, 2014; Fu, Lin and Molyneux, 2014). Measurements for the "concentration" refer to the market power distribution. Indicators such as top-k concentration ratio, Herfindahl-Hirschman Index and Lerner Index are based on sizes or market shares of the financial institutions.[2]

This intuition generally applies to service sectors as the competition and collaboration behaviours focuses on the less differential services, like the competition in banking sector. Nevertheless, it is less convincing to proxy the market influences of participants if the assets or final product are highly heterogeneous. Namely, assets in CRE markets differ in types and geographical areas, thus asset scale does not necessarily indicate the influence of the investors in the market. Moreover, in over-the-counter markets, the decisions of investors largely depend on the accessible counterparties. Hence, information connectivity and the trusts among the counterparties become the crucial elements in these markets. A few studies have investigated the investment links among market counterparties and reveal the importance of social connections or reputations. Especially, some investors are "socially" influential to the market regardless of their scales, because they bridge gaps among investors, affecting the power distribution of investment markets (Anand and Galetovic, 2002; Guler and Guillen,2010).

Therefore, the following studies adopt ideas from institutional organisation to address more on these "social elements". SNA provides a visualised and quantifiable alternative for the question. SNA detects the links among participants in the markets and the positions of the participants in the networks. Baker (1984) investigates the different links of market counterparties in the US option market in late 1970s. As participants can only reach to limited number of counterparties in private markets, the "market is socially structured" based on the connections of participants. Larger markets have larger and more heterogeneous investor groups than smaller markets. Given the limited market access of participants, the competition is not efficient where larger market expects higher price turmoil.

Baker's argument, followed by the reassurance of subsequence studies, implies the benefit of highly-connected networks to market stability, whereas others raise concerns with the transmission of

[2] See Bikker and Haaf for a summary of the market power proxies.

idiosyncratic risk throughout the networks. Especially, the contagion of systemic risks in GFC has shocked the financial system worldwide. The complex ownerships of debts and derivatives among financial institutions reemphasises the importance of investigating the connection of financial markets. Studies such as Boss et al. (2004), Minoiu and Reyes (2013), Fricke and Lux (2015a) show the more intense links among investors in the market creates a "pool" of investors to absorb the downside risks thus improve the market resilience. However, if the downside loss is large enough that the pool of financial institutions fails to absorb, the excessive links also means wider contagion of the downside loss (Boss *et al.*, 2004; Nier *et al.*, 2007; Minoiu and Reyes, 2013; Alves *et al.*, 2013; Finger and Lux, 2017).[3]

The non-monotonic relations between investors' connections and market resilience require further investigation on the micro- and meso-scale properties of the networks. The connection preferences of the market participants and the community structure of the network have been discussed. On the one hand, Boss et al. find the Austrian banking system follows the power law and fits the scale-free structure. Masso and Ruiz-Leon (2017) found the "Matthew effect" exists among market participants, where the counterparties get greater chances to be connected due to the inequal distribution of existing social resources. Some counterparties have significantly more connections than others in the networks, the roles of counterparties in the network system hence differ in respective market structures. Fricke and Lux (2015b) found that the community structure of the overnight money market is disassortative[4], where smaller banks tend to trade with larger banks with strong reputations in the market. They argue that the disassortative structure reduces information searching costs, as a limited number of large banks can reach to other participants and facilitate the transaction. In this context, removing the highly connected nodes would severely affect the market stability.

Brede and de Vries (2009, cited by Fricke and Lux, 2015a) suggest the core-periphery structure as an accommodation between network efficiency and resilience. In core-periphery structure, there are limited number of core investors connected to other peripheral investors but also intensively link to each other, Investigations in syndicate issuance of Spanish government debts (Massó and Ruiz-León, 2017), national and global banking debt markets (Minoiu and Reyes, 2013; Craig and von Peter, 2014) and global trading market (Kali and Reyes, 2007; Schiavo *et al.*, 2013) all suggest the existence of "core-periphery structure" in the networks. Core participants connect with other cores as well as periphery groups, implying that the trading assets or resources would circulate more frequently among the cores or between core and periphery. Core participants are therefore more "important" in the system than the periphery participants. However, the persistence of the community structures varies, as Minoiu

[3] In the macroeconomic level, Minoiu and Reyes (2013), and Schiavo, Reyes and Fagiolo (2013) suggest the global financial and trading market become more integrated as the network evolves.

[4] (Dis)assortativity refers to the tendency that nodes share resembling features link with each other. See Section 5 for detailed explanations of network assortativity.

and Reyes find the core-peripheral relation is not stable throughout the 1978-2010 period, while Craig and von Peter (2014), and Fricke and Lux (2015a) find the core-peripheral structure of German and Italian interbank markets are quite stable in recent decades. In terms of market impacts, Minoiu and Reyes show that the unequal distribution of deal flow (thus weights of the links) is related to greater market vulnerability. Hence, the key players, rather than total number of participants, make greater impacts on global market stability. This also implies the different roles of market participants in the networks.

The nature of commercial real estate asset has become "financialised" as the capital from global institutional investors flow into the direct real estate market (Lizieri, 2009). Lizieri and Pain (2014) reemphasise the systematic risks influencing the market due to the complex ownerships and financing methods of real estate investors. They propose four channels that the systematic risk transmitting through office markets: occupation market (through leasing of financial companies), investment market (through property acquisition and the balance sheet effect if the property value is mark-to-market), supply market and real estate finance market. Activities of institutional investors cause the performance correlation among the property markets (Henneberry and Mouzakiz, 2012, Stevenson *et al.*, 2014), hence spread the systemic risks to a wider range. The transmission process of the information and the risks in the real estate market network, has not been investigate in depth. The real estate market shares a lot of similarities with over-the-counter markets of financial assets in terms of asset heterogeneity, information opaqueness etc. Moreover, as real estate market is segregated by geographical location and types, the segments are highly different. Investors in the market thus rely on the "reachable" networks when making the acquisition or disposal decisions. Hence, network analysis helps understand the connection and potential risk contagion routes of real estate market.

2.2 Real estate market liquidity

As it states in the introduction chapter, this study discusses the transaction liquidity of the UK CRE market under the influence of heterogeneous investors. Transaction or market liquidity is generally defined as the capacity of an asset in the market turning into cash without causing large deviation on price. Intuitively, some "stylish" evidences of a market that does not sustain sufficient liquidity is shown as low trading volumes, enlarging bid-ask spreads, long time-to-transactions etc. The identifications of market liquidity vary in different aspects, with measurements addressing on transaction cost, trading volume, price and return impacts. Studies including Bond *et al.* (2004) and Ametefe *et al.* (2016) summarise the identification in "tightness, depth, resilience, breadth and immediacy". Among the five dimensions, breadth of the market refers to the transaction volumes in the market. Market tightness and the immediacy of realising the transactions describe the transaction costs occurred when market participants enter in the market and source the proper asset or counterpart to trade; these include the explicit transaction costs in sorting and negotiating with counterparties, as well as the time costs in the sorting process. Market depth and market resilience refer to the capacity of market price "recover" to the equilibrium price from the abnormal bid-sell activities or unexpected turmoil, hence proxies on price-impact and return-base measurements capture this influence.

As a result, the lack of liquidity in real estate market affect property price, portfolio risk management and market operation. Bond et al. (2005) adopt the model to test the market period risk in the UK commercial market; results suggest that the *ex ante* risk with market period risk into account is 1.5 times higher than the conventional statistical risk measurement. With the following study of Lin, Liu and Vandell (2007), the market period risk cannot be diversified away with increasing additional property assets. Marcato (2014) investigates the UK CRE market liquidity and the *ex ante* risk investor would face. Results indicate the *ex ante* risk premium on average reaches to 3% as a result of the illiquidity; with market period and sector differing, the premia range from 1.5%- 2% to 10%. Ling *et al.* (2016) discuss the relations among institutions' funding liquidities, market liquidity and the asset pricing of commercial properties, which both liquidities influencing the asset pricing, while the property asset price volatility also constrain the funding liquidity of investors.

Existing literature investigate the contributors of the market liquidity in the aspects of investor's objectives, transaction process and competitions, and the market mechanism. As Crockett (2008) summarises, a liquid market potentially attributes to 1) efficient market infrastructure that causes low transaction cost and narrow bid-ask spread; 2) adequate market participants that quickly adjust the movement in price; and 3) transparency in asset characteristics so that the change of underlying value would reflect on price. Vayanos and Wang (2011) (as cited by Ametefe *et al.*) attribute the reasons of market inefficiency in transactions and participation costs, imperfect competition, asymmetric information, funding constraint and search costs. Participations and the information access of investors affect participation costs, searching and the information circulating among the six attributes.

Direct real estate market is arguably one of the most typical illiquid markets of investment assets. Both the nature of the asset and the transaction mechanism contribute to the illiquidity of real estate. (Asset heterogeneity and information asymmetry). Real estate transaction in a private market is a "sequential searching and random matching" process (Cheng, Lin and Liu, 2013), sellers adjust their valuations after receiving the "noisy" bidding prices, thus delay the transaction process (Clayton et al., 2008). Meanwhile, market condition affects the realisation of transaction. Several studies indicate that the market condition affect the transaction realisation and seller's value of waiting. (Krainer, 2001; Novy-Max, 2007; Leung and Zhang, 2011; Clayton *et al.*) For example, in the down market when limited participants bid, seller tend to hold the asset and wait for the bidding above their reservation prices. The real-option value of waiting lead to the dry-up of market liquidity. Fisher *et al.* (2003) suggest the distributions of market participants during different market conditions vary i.e. fewer sellers participate in the market downturn, hence the realised transactions suffer the sample selection issue.

Further, Clayton et al. and Freybote and Seagraves (2018) suggest the overconfidence of investors also contribute to the market illiquidity. While Clayton et al. does not find significantly supports for the hypothesis on investors' sentiment, Freybote and Seagraves (2018) re-examine the impact of investors' overconfidence to market liquidity, with positive evidence capture, yet the effects of sentiment vary in different market states.

While above studies analyse the liquidity issue from the prospective of asset and individual transaction process, there is limited insight about the features of the market structure. Unlike that in equity market, the market mechanism of direct real estate still depends on agents and private connections. It is therefore uneasy to reach to a large proportion of market participants so that to find the matching buyers/sellers. Despite the total number of participants presented in the market, the connections among the counterparties are expected to be fragmental, and the price adjustment is comparatively slow. Studies has shown the constraints that seller need to bear with in a thinly traded real estate market. Meanwhile, the large size and heterogeneous features affect the value of property assets, which might not explicit show on the price. Investors need both the asset and market information a priori when making the investment decisions. Links among investors as transaction counterparties or partners of strategic alliance imply the circulation of the market information and the contagion of systemic risks. Thus, the network structure of real estate investors in the market – both investors composition and the linkage structure within participants – is supposed to be one of the important elements market resilience and liquidity.

Foreign investors are considered as the "liquidity contributors" for host markets in several studies and economic policies. Studies have established from the angles of corporate governance, financial liberalisation and market integration, yet the arguments along with empirical evidence on foreign investors enhancing market liquidity are mixed. In equity market, relevant studies concentrate on the discussions of foreign institutional ownership at the firm level and transaction liquidity of the stocks. Some "early stage" studies argue that, as many foreign investors are foreign institutions, who are possessed with sophisticated investment techniques, their entry helps improving the information disclosure of respective stocks (Stulz, 1999; Choe , Kho and Stulz, 1999; Grinblatt and Keloharju, 2000). Foreign investors are also hypotheses as "better informed" thus trade with higher sophistication but the empirical results are not overwhelmingly consistent. (Choe, Kho and Stulz, 2005; Bekaert, Harvey and Lumsdaine, 2002;) The stronger liquidity preference of foreign investors also motivates them to actively trade in the market. On a market level, the information disclosure and monitoring from large foreign investors help stabilising the stock market performance (Li et al., 2013). There is also argument that the foreign investors act as speculator hence provide liquidity to the market. (Hendershott, Jones, and Menkveld, 2010)

However, the active transaction behaviour and momentum chasing of foreign investors could fluctuate the market price and impair the transaction liquidity. Rhee and Wang (2009) found that in Indonesian stock market, though foreign institutions show preference to asset liquidity, the increase of foreign ownership in equity impede the liquidity, showing as the increase of bid-ask spreads, decrease in average depth and the rise in price sensitivity. While Rhee and Wang did not further investigate the potential reasons led to the bias, Ng et al. (2015) specify the liquidity preferences of foreign direct investors and foreign portfolio investors and examine the influence of those investors on transaction liquidity. Their findings reveal that foreign direct investors increase the degree of market asymmetry hence hinder the market liquidity, whereas foreign portfolio investors, as a group with limited control to the investment targets, are usually more active in transaction and help decrease the information asymmetry, hence their presence increases the stock liquidity.

What have been proved in equity market also applies to real estate market – arguably, the influence of foreign investors on the host market liquidity should be exaggerated under the private market mechanism. Liao et al. (2014) find the foreign investment, being active in central region of Singaporean housing market, not only affect the price of central area, but pass the shock to the non-central region where foreign investment is less active, and public housing market where foreign investment is prohibited. In commercial market, the investment activities of foreign investors compress the yield and boost the asset price (McAllister and Nanda, 2015, 2016). the increasing number of investors, if without the barriers of market access, is supposed to improve pricing competitions. In an efficient market, the market price should have quickly recovered from overshoot, and market price should have experienced less volatilities. However, the higher volatilities imply a less efficient market mechanism where investors are "clustered" due to their limited access of the market counterparties. Further, if the network structure of foreign investors fits the core-peripheral specification, the investors that is in the "core" positions are supposed to deal to both "peripheral" investors and other core investors, thus enhance liquidity to the market. Detecting the network structures of foreign investors and the different roles that investors play in the market therefore has strong implications to the liquidity of commercial real estate market.

This study aims to contribute to existing discussion on the determinants of real estate market liquidity from the micro-structure of the transaction market. While previous study either focus on individual transaction mechanism or the broad market evolvement, this study introduces SNA as a novel method proxying the connectivity among participants and examine the impacts of clustering to market liquidity. However, as transaction networks in private market, CRE market networks have a few features that differ from those of public markets or markets with comparatively homogeneous assets, hence the adoption of SNA measurements in this study need to consider the specific implications and limitations. For example, because transaction relations (the edges in the empirical study) are not necessarily dependent, the transaction relations are restricted in the one-step ego-alter distance i.e. transactions chain like A→B→C does not necessarily indicate the connection between A and C. The path concept would make sense with the property ownership information. Also, the highly heterogeneous asset attributes are "tailored" to the investment objectives of heterogeneous investors (Geltner et al. 2014), which, to a certain degree, restricts the counterparty choices of investors. The study will interpret the methodologies in detail in following Section 3 to Section 5.

3 Network Centralities of Foreign Investors and the UK Investors

3.1 Centrality measurements

In SNA, participants are nodes in the networks and their relations are defined as the edges that links the networks. A directed network includes the directions from senders to receivers in the edges, while an undirected network describes the relations when the orders of nodes on the two sides of the edge are indifferent. In the following network analysis, the study defines the transfer of property ownership as the network edges i.e. properties passing from sellers to buyers, thus statistics for directed networks are used. The strength of the links is evaluated by the number of transactions between each counterparty, as well as the capital amounts between each other (money-weighted).

3.1.1 Degree Centrality

There are several methods to evaluate the crucial position (centrality) of investors in the transaction networks. Degree level measures how many counterparties that one node has linked with. In a directed network, degree centrality specifies into in-degree level (edge "pointing-in") and out-degree level (edge "reaching-out"). A higher figure means a node has linked with more counterpart nodes. The average degree in the network is specified as

$$K_{in(out)} = {\sum_{i=1}^{n} \deg_{in(out)}(i)} \Big/ {N}$$

Where N denotes the number of all the nodes in the graph *G*, and $\sum_{i=1}^{n} \deg_{in(out)}(i)$ is the sum of the edges that point in (in-degree) from, or point out (out-degree) towards the nodes. In our directed network, the average in-degree and out-degree levels of the nodes of foreign and UK investors are different, but the average in- and out-degree levels of nodes for the full graph are the same; the average degree level for a network is also called degree density. To capture the divergence among the nodes, the degree standard deviations of the foreign and UK groups are derived.

3.1.2 Betweenness

Aside of the demand and supply of investment asset that investors provide to the market, the investors would improve market liquidity by facilitating the circulation of assets. Thus, betweenness centrality is introduced. Betweenness counts the number of shortest routes that a node has involved to link any two other nodes in the networks and compares it as a proportion of all the routes in the network. Although the links of the transaction networks do not necessarily indicate the real "flow" of property assets, they still proxy the potential connections that capital/asset could flow through. If one node stands in more of the "shortest route" in the transaction network, it potentially helps the capital and property assets circulating among more market participants. Mathematically, betweenness is denoted as

$$Betweenness(v) = \sum_{s \neq v \neq t} \frac{\rho_{s,t}(v)}{\rho_{s,t}}$$

In the specification, *v*, *s*, and *t* stand for any of the three different nodes in the graph *G*, and ρ stands for the number of shortest paths that between two of the nodes. This study computes the average betweenness of foreign and UK investor groups. If the average betweenness figure for foreign investor groups is higher, it would indicate that the foreign group potentially links more investors in the network. It may worth noticing that in the transaction network, the "path" in a series of nodes does not necessarily indicate the connectiveness from the two ends. Rather, it implies the investors with more buying and selling relations, and/or who conduct transactions with other investors with high "connectivity" could potentially transfer the assets to more counterparties.

3.1.3 Eigenvector centrality

Eigenvector centrality considers the position of a node by the centralities of its neighbours. Nodes are identified as crucial in the network if the linking nodes possess high centralities. Under this measurement, the centrality of investors does not essentially depend on the number or weight of the links, but the influence of transaction counterparties in the network. The eigenvector centrality (denoted as *x* as follow) specification of a node *v*, in graph *G* is

$$x_v = \frac{1}{\lambda} \sum_{t \in M(v)} x_t = \frac{1}{\lambda} \sum_{t \in G} a_{v,t} x_t$$

Where $M(v)$ stands for the neighbour nodes set, and *t* refers to each neighbouring node. **A** $=(a_{v,t})$ is the adjacency matrix of the graph G. λ is the eigenvalue of the below equation about the graph so that a non-zero eigenvector exists.

$$\boldsymbol{Ax} = \lambda \boldsymbol{x}$$

Eigenvector centrality provides good complement measurement to the degree centrality and betweenness. As a result of the low trading frequency and heterogeneous asset attributes, the transaction connections among investors depend both on limited accessible information and the asset attributes. As Geltner *et al.* (2014) explain it, the CRE market is segregated to certain degree where investors trade based on their investment scales and objectives. In certain time period, investors in CRE market may not show all their connections through the revealed transactions. However, private market transactions are assumed to rely heavily on organisational connection and trust. If an investor deals with several influential counterparties in the market (hence have high eigenvector centrality) in a period, it is assumed to be a trustful counterparty by the other influential participants in the network.[5] In the study of bank lending market, Cocco et al. (2009) found small banks or banks with local oriented business strategy only tend to transact with large and reputable counterparties as a result of their limited market

[5] Repeated transactions between counterparties are a better proxy of the trust. However, the number of repeated transaction relations would be too small to conduct network analysis, and the study admit this could be a limitation.

reputation and market access. In this sense, foreign investors that transact with only the crucial investors but with no lineages to other market participants are still not involved in the market in depth.

3.1.4 Empirical Results: comparisons of centralities

The first step is to compare the average trading number and volume between foreign investors and UK investors. This is proxied by average degree level in both unweighted mode and price-weighted mode (Figure 1 to Figure 4). On average, foreign counterparties have higher numbers and volumes of purchases than UK counterparties, suggesting the foreign investors have been more active on property acquisitions. Although in some of the exceptions such as Inner London, Nottingham, and the after-GFC periods in Leeds and Newcastle, the average acquisition numbers of foreign counterparties are slightly lower, the purchase volumes do not differ significantly. In Inner London market, the purchase volume of foreign counterparties surpasses the UK counterparties though the average unweighted average degree levels do not significantly differ, implying the foreign investors target on the more expensive assets. On the other hand, UK counterparties conduct higher numbers of disposals on average, but the average disposal volumes do not differ. In markets such as East Midland Other or Yorkshire/NE Other, the disposal volumes of foreign investors slightly exceed the UK counterparties.

Figure 1 Market average in-degree, unweighted

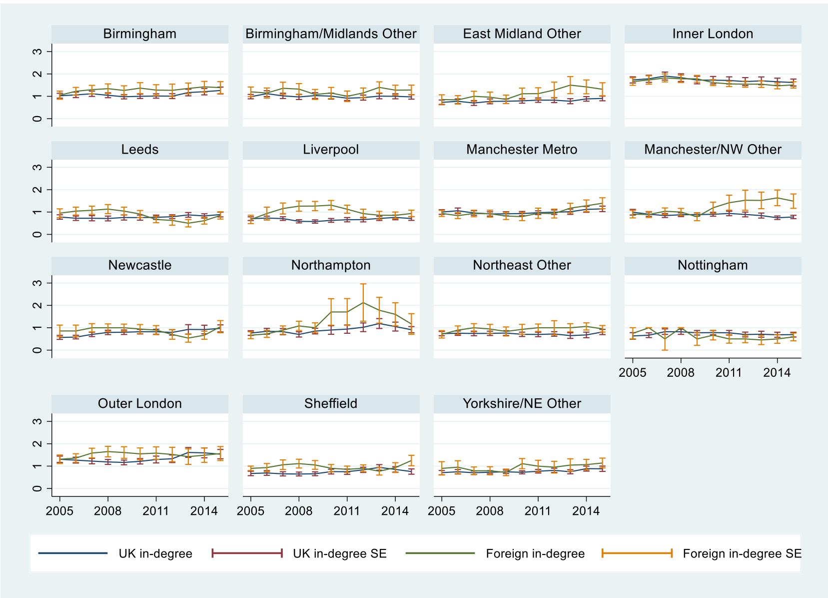
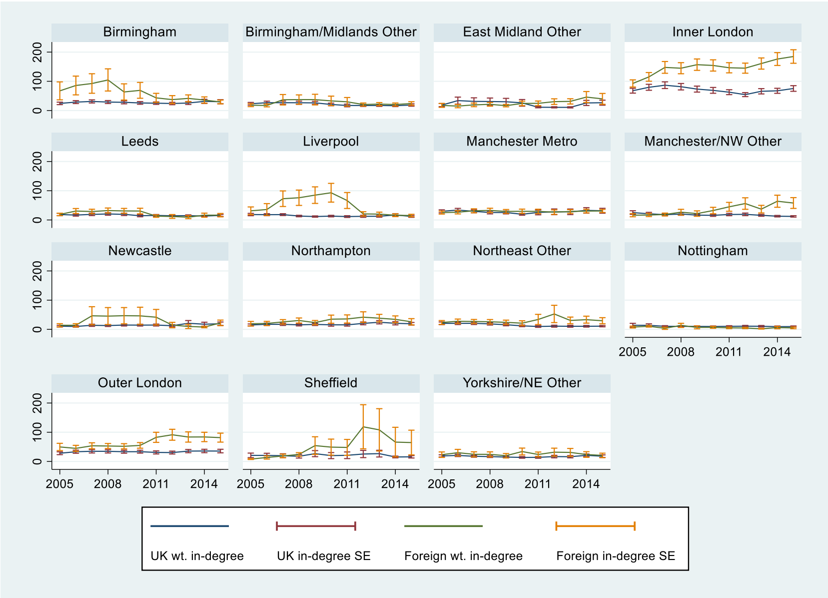


Figure 2 Market average in-degree, money-weighted



The purchase behaviour of foreign investors reveals a stronger cyclical trend than UK investors in a few metro markets. For example, the average purchase volume of foreign investors in the industrial sector keep increasing in Midlands region (Birmingham, Northampton, Birmingham/Midlands Other, and East Midlands Other), reflecting the growing popularity of the industrial sector. When the UK CRE market recovers from the GFC, capital flow into real estate sector and competitions become fierce, foreign investors that have higher risk/return requirement alternatively choose to expand into non-London markets. The entry of overseas investors might have indeed improved market liquidity by purchasing the assets while domestic investors sell the assets, but it is still unclear if foreign investors persistently improve the circulation of property assets in the market.

Figure 3 Market average out-degree, unweighted

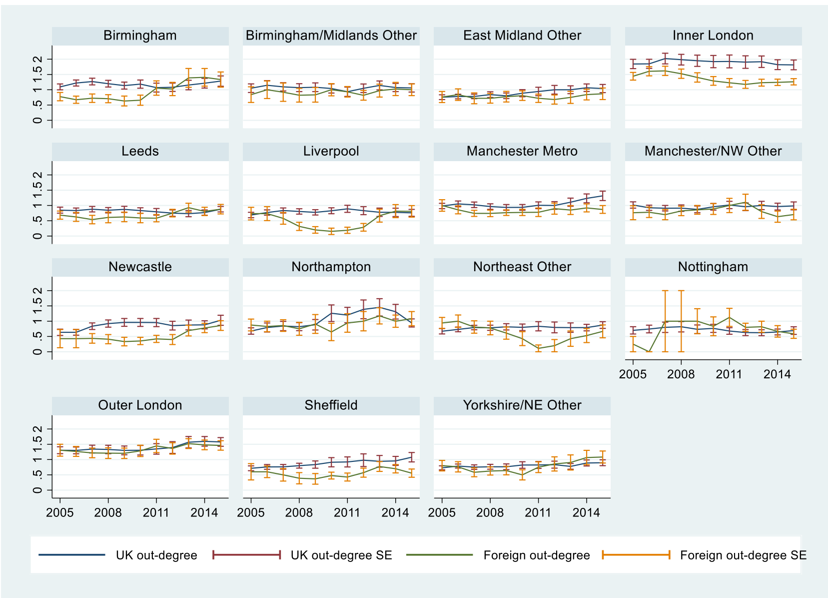
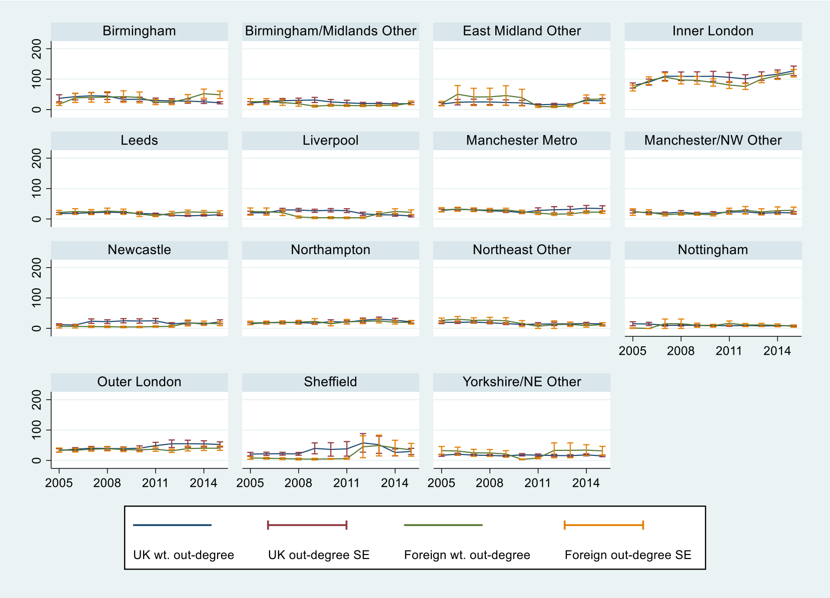


Figure 4 Market average out-degree, money-weighted



It is also worth noting that degree distributions within foreign groups are more highly dispersed than in the UK groups, as shown by the higher standard errors of the degree levels as well as the graph plots in the following section. While there are certain international institutions acting as key investors in the transaction networks, other foreign investors only link to the key investors but not connect with other counterparties.

Overall, foreign investors have contributed large amounts of purchases in CRE market, while UK investors conduct more disposals on average. The behaviours of foreign investors are more cyclical to certain extent. Higher dispersion on degree distribution of foreign investors imply the different investment strategies/market roles of foreign investors, which is also shown in following analysis on centralities and graph plots.

Figure 8 displays the betweenness centralities of foreign investors and UK investors. In markets such as Inner London, Birmingham, Liverpool, Newcastle and Sheffield, UK counterparties have higher betweenness centralities than foreign groups. The CRE market in central London is generally assumed to be most transparent and globalised, with a large amount of property assets circulating among all investors, hence one might expect the betweenness centralities of foreign and UK counterparties would be more similar. However, it seems throughout the sample period, UK counterparties consistently have higher centrality in the market despite that foreign group have higher acquisition volume.

The betweenness centrality also shows cyclical trends. In some markets that are not major cities, the figures of foreign investors exceed UK investors after the GFC but with higher standard errors. Especially, in office and industrial sectors, the average betweenness figures in Leeds, Northampton and

Sheffield surpass those of UK investors during the financial crisis time. In the market downturn, some active foreign investors potentially fix more gaps among market participants.

Nevertheless, the “central position” of foreign counterparties is shown by the eigenvector centralities, as seen in Figure 7. The average eigenvector centralities of foreign investors are higher than the UK counterparties in many metro markets. The leading positions or enlarging differences of foreign investors are even significant during and after GFC, whilst markets like Manchester Metro, Northampton and Nottingham are dominated by local investors. The higher average eigenvector centrality of foreign investors implies their preferential transaction behaviour to the key investors in the market, but the low (average) betweenness of foreign investors also suggest that a lot of foreign investors acquire properties but not dispose during the sample period. Their inactivity does not facilitate the market liquidity.

[Insert Figure 8 here]

[Insert Figure 9 here]

4 Transaction Network Evolutions

Network graphs and assortativity coefficients are presented to analyse the evolution of transaction networks, and the systemic importance of the market participants. The (comparative) scales of each transaction is reflected by the thickness of the edges. The following analysis derives the degree assortativity in order to detect if the transaction follow hierarchical distributions among the transaction counterparties. The other assortativity based on the nationality similarity is used to detect the trend if counterparties tend to transact with others from the same countries, so that to see if there is significant "same-country cluster" in the market.

4.1 Assortativity coefficient

In terms of the network structure, the study uses degree assortativity to measure the connectivity among nodes with the same feature in the network. Usually, the similarity refers to that of degree levels. Unlike the previous two statistics, assortativity is a meso-level instead of degree-level measurement. Assortativity coefficient is technically a Pearson's correlation coefficient. The assortativity coefficient ranges from -1 to 1. When the figure is positive, it implies that the nodes with same feature (degree level) tend to be connected, while if the figure is negative, it indicates the nodes with different degree levels tend to have links. When the figure equals to zero, it suggests that the nodes of the graphs link randomly, and the graph should show no clear pattern.

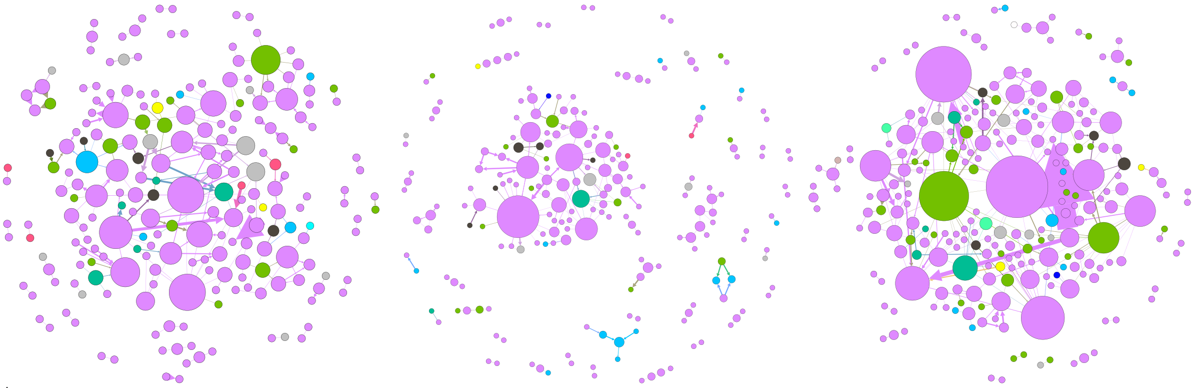
Intuitively, the positive degree assortativity in this transaction network implies that investors conducted more transactions tend to conduct deal with each other. Some studies explain this as the "power law", as economic agents possessed with more social resources tend to connect with each other. While if the coefficient in negative, it indicates that those node with fewer links tend to connect with those with more, and market are disassortative. In other words, there are investors that connect more nodes than others in the network ("star-structure"). The intuition matches the research in financial stability about "systemic important" participants (Boss et al. among others). Therefore, a negative assortativity figure in our network indicates that there are some crucial investors that have more transactions than others, and the market is more segmented in smaller groups. While a positive figure suggests the transactions are allocated evenly among investors.[6]

[6] However, the positive figure either indicates that the market is well connected where most of the investors form a well-connected cluster, or the investors link with separate counterparties where the whole market is fragmental. Therefore, the section combines graph plots with the assortative coefficients to show the community structures.

4.2 Empirical results: network graphs

Network graph figures exhibit the transaction networks of the market examined in this study. Time windows of the network graphs are 2001-2005, 2006-2010, and 2011-2015 respectively, which proxy the time prior to, during and after the GFC. The size of the nodes stands for the total number of deals one has involved (acquisition and disposal). The colours for the nationalities of the nodes (purple for UK investors). In Figure 5, the networks in Manchester metro has been brought in the context as an example. While the other transaction network graphs can be found in the appendices.

*Figure 5 Transaction network graph (Manchester as example)**



* Time windows of the graphs (left to right): 2001-05, 2006-10, 2011-15.

As one of the most transparent CRE market, London has concentrated a diverse group of investors in the investment market. In both inner-London and outer-London markets, foreign investors "scatter" in the networks with no clear "foreign cluster" captured from the initial glance. The giant nodes in the graphs indicate there exist a few participants as "core" —the majority of whom being UK investors—conducting significantly more transactions than other nodes. Specifically, in the post-GFC period of outer-London market, some of the foreign investors become the core investors and are positioned in more central places in the market. Moreover, if comparing the post-GFC graph with the two earlier-stage ones, one may notice the sizes of the nodes becomes less dispersed – in other words, as more investors conduct more deals each, the transaction distribution is less concentrated on specific investor(s), and the market should reveal (comparatively) fair pricing.

The less dispersed distribution is also found in Manchester and Birmingham markets. Among the major cities outside London, these two city metros have formed the integrated transaction networks. The foreign participants involve in the transactions throughout the 15-year window in these two markets, with a few foreign investors becoming "cores". The graphs show certain transactions that take place among foreign investors, or even within the investors from the same countries, but they merge into the main networks. Market network in Sheffield illustrates the forming process of transaction network. Initially being very sparse and heavily dominated by local investors, the market gradually forms small clusters, and eventually the participants assemble into one major cluster, with foreign investors bridging the connection gaps. It worth noting that a lot of the transactions in Sheffield market are conducted by a few core participants, thus the network shows the "star-structure", which is also revealed by the negative degree assortativity coefficient.

Meanwhile, the transaction networks in Leeds, Newcastle and Northampton form smaller-scale clusters but not integrated market networks, while markets such as Liverpool and Nottingham are fragmented throughout the select periods. "Foreign clusters" are easier to notice in these markets, such as the network plots in Liverpool and Northampton in 2011-2015 – it partly because of the transactions among the consortia, but it is still worth discussing the reason and implication that deals take place among counterparties from the same countries. Interestingly, in Northampton market, the key investors in the star-structure clusters during and after GFC are foreign investors. Transaction density is thin in the above market, hence the liquidity contributed by foreign investors becomes important.

In the markets outside the major cities, the West Midlands market show the integrated market cluster, while the East Midlands, Northeast and Yorkshire markets reflect the network formation process. Core investors include both UK investors and a few foreign investors. The negative nationality assortativity coefficient for the three market indicate the mixture of transaction counterparties in the transactions. On the other hand, the transaction network of Northwest market dissolved into smaller clusters, with a few dominant investors as the central counterparties. The dissolving process is also reflected by the dropping degree assortativity in the Northwest Market.

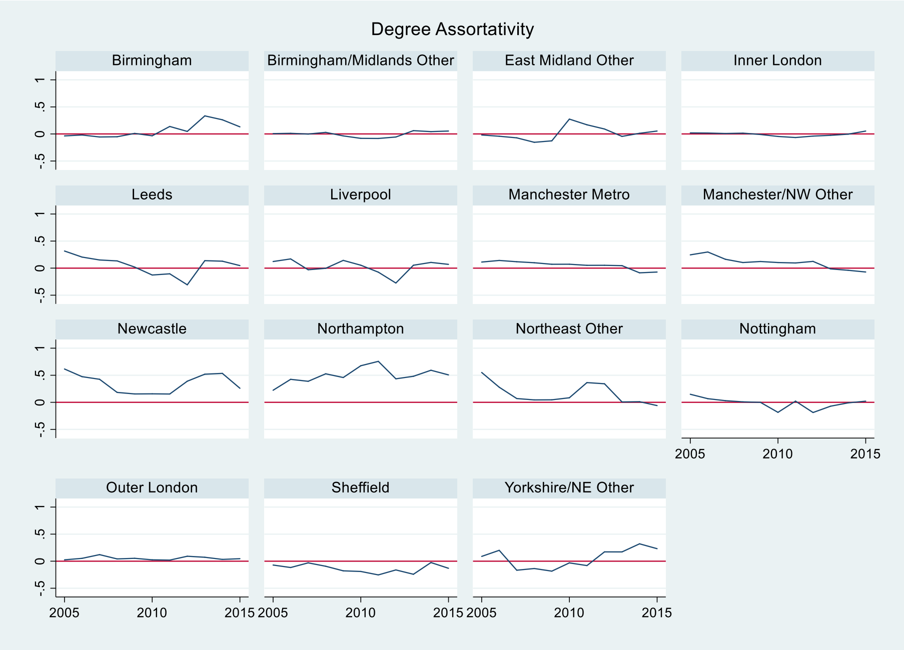
4.3 Empirical results: assortativity coefficients

Figure 6 and Figure 7 exhibit the assortativity coefficients based on the similarity among the nodes in degree level and nationalities. Though more of the previous literature suggests that the networks in the financial markets are degree-assortative or have core-periphery structures, in Figure 4, quite a few networks in this sample shows a disassortative status or becomes less assortative during the financial crisis period. It can also be found in the network plots that some of the "hubs" become dominant participants in the market in these periods. This indicates the existence of dominant market participants releasing market liquidity during the time. The study also adopts the core-periphery identification process by Borgatti and Everett (2000) to the networks[7], but it seems the transaction links among core investors are scarce, the networks in the sample do not form a typical "core-periphery" structure.

Meanwhile, when detecting the assortativity based on the nationality of the counterparties, markets such as Birmingham, Liverpool, Leeds and Northeast reveal positive relations during and after GFC. No clear pattern in degree assortativity nor nationality assortativity is found in London markets.

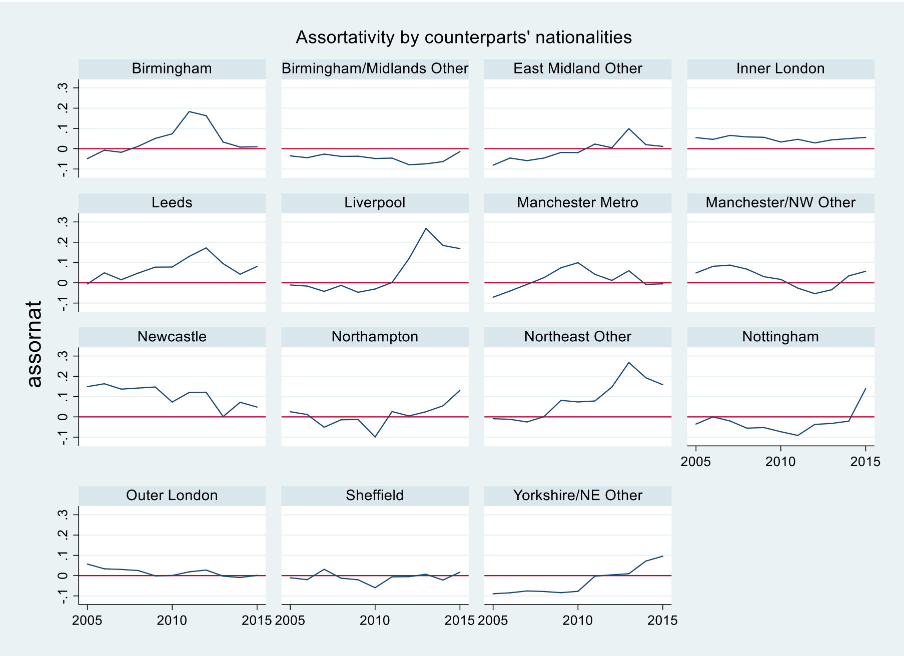
[7] The process is conducted with UCINET.

Figure 6 Degree assortativity



The graph set exhibits the assortativity coefficients in the selected markets. A positive figure indicates the investors in the market tend to transact with the one share same attributes, which in this case are the total degree level and nationality.

Figure 7 Nationality Assortativity



5 Market Structure and Market Liquidity

After analysing the market structure evolution in the network graphs, the empirical tests in this step investigate the influences of market structure and the entry of foreign investor group to transaction liquidity. As previous studies such as Clayton et al. (2008) and Ling et al. (2016) discuss the dynamics of price impact, return and transaction volume in an endogenous system, this study adopts vector error correction model (VECM) for the panel dataset.

5.1 Key variables and hypotheses

The endogenous system of the model includes variables for market structure and market liquidity. The model also introduces exogeneous variables to control underlying economic condition on the market level.

Market degree density and degree assortativity are employed as general market structure measurements. As introduced in Sector 4, a higher degree density indicates more frequent transactions taken places among counterparties in the given period – a stable high level in the long-term indicate the abundant market liquidity. A positive degree assortativity implies the higher probability that investors conducting similar number of deals would be counterparties of each other. This could imply that the market structure follows the "power-law", where core investors with more connections also tend to connect each other; but when the markets have thin transaction number without dominant investors, the proxy is still positive – in this case the degree density variable capture the thin-trading condition.

To examine the impact of foreign entrants' presence in the market, the study adopts the nationality assortativity from Section 4, as well as the proportion of foreign investors in the whole investor group. If foreign investors improve the market liquidity as early-stage literature suggest, the increase in foreign investors' proportion is expected to give a rise of transaction volume and make an impact on pricing competition. However, the access of market counterparties brings interesting discussions to the pricing efficiency. From the network resilience aspect, limited market access for investors (i.e. investors only deal with the counterparties from their own countries) restricts the market pricing competitions, thus the market is exposed to biased agreed prices within the market clusters. While from the network efficiency aspect, the connections within the counterparties from the same countries (including UK investors) should reduce the frictions in the transaction process thus improve the liquidity.

In terms of market liquidity, Amihud (2002) measurement and the transaction volume of the selected markets are employed to proxy the market resilience and market breadth respectively. Following Marcato (2014) and Freybote and Seagraves (2018), this study derives the AMH in the below form:

$$AMH_{i,t} = \frac{\sum |Total\ Return_{i,t,m}|}{Vol_{i,t}}$$

Where i and t are for the respective metro market and year, m for the specific property. $\Sigma|Total\ Return_{i,t,m}|$ is the total return value of a market in absolute term from MSCI Key Centres annual data; the city/town-level data is aggregated to match the metro categories in RCA. $Vol_{i,t}$ is the transaction volume sum-up from individual deal records in RCA. Amihud ratio is a proxy for "market inefficiency". When market liquidity is drying out, the thin trading volume and high required return result in a higher ratio. Because the market structure proxies are based on all the transactions taken place in the past 5 years, the study adopt both market liquidity proxies in the single year, as well as 5-year rolling average and the total transaction volume in the 5 years.

The estimations also include control variables at metro-market level. The two variables controlling economic fundamental are the local employment rate of 16-64 populations, and the gross disposable household income (GDHI) of the market.[8] Market transaction volume and GDHI have adjusted the inflation effect. To avoid multicollinearity, both GDHI and employment rate are converted into growth rate form. Moreover, assuming the time trend would be captured by the economic fundamental variables, the model should also control the cross-market difference. Nevertheless, as the panel data sample is comparatively small, adding the market fixed effects restrict the degree of freedom and violate the stationary of residual, with only the coefficients of the inner- and outer-London fixed effect being significant. Instead, the models use an indicator variable to control the different between the markets in London and the metros in non-London area.

Descriptive are presented in Table 1. No significant correlation is detected among the endogenous and exogeneous variables.

5.2 Model specification

Unit root tests in Table 2 indicate that, some of the variables in the system, such as the 5-year rolling Amihud ratio, nationality assortativity and transaction volume, give inconsistent stationary test results at the level, but all of the variables can reject the non-stationary hypotheses at 1st-order difference. This indicates a VECM model specification would be a preferred choice than unrestricted vector autoregressive (VAR) model. Brunnermeier and Peterson (2009) and Ling et al. (2016) address on the importance of detecting the long-term vs short-term effect of market price impact and volatility, in which VECM model can capture the long-term cointegration and short-run adjustment. Further, Johanson cointegration test in Table 3 indicates there is one cointegration term in the system. The time lags of the endogenous system (lag 3) as well as those of exogeneous variables are based on the

[8] The two variables for metro-level are derived from the NUTS3-leve data. Both variables are from ONS.

information criteria and the stationary of residual lag structure. To sum up, the VECM model is specified as

$$\Delta Y_{i,t} = \alpha_i + \Pi Y_{i,t-1} + \sum_{p=1}^{3} \Theta^{*} \Delta Y_{t-p} + \gamma X_{i,t-q} + \epsilon_{i,t}$$

Where Y is the vector containing the endogenous variables in the system, including Amihud ratio (AMH or AMH_5Y), transaction volume (VOL or VOL_5Y), degree density (DDIN), counterparties' degree assortativity (ASSOR), counterparties' nationality assortativity (ASSORNAT) and the proportion of foreign investors in the active investor group (FORPROP). $\Pi Y_{i,t-1}$ is the error correction term including an intercept but no trend.[9] X in the equation refers to the exogeneous control variables GDHI growth rate (GDHIR), employment rate (EMPRR) and the indicator variable of London market (LONDON).

5.3 Empirical results: influence of market structure to market liquidity

Table 4 (with single-year AMH and VOL) and Table 6 (with 5Y-rolling AMH and VOL) present the estimation of the VECM results. The upper half of the tables give the result of long-term cointegration, while the lower half show the short-term adjustments of each variables. Among all the columns, the columns with AMH and VOL as dependent variables display the co-movement of market structure variables with market liquidities.

In the estimations where AMH acts as dependent variables, coefficients of cointegration terms are both significant, indicating the existence of long-term equilibrium of the endogenous system, while the long-run equilibria for transaction volume are not significant. In the estimation with single-year liquidity proxies, nationality assortativity shows a positive and significant results, which means the increase of nationality assortativity would give a rise to the error term. In the short-run adjustments, the market structures proxies except FORPROP show significant results in different time lags.

In the estimation with single-year liquidity proxies, ASSOR and ASSORNAT have significant impacts to the error term in the long run. In the short-run adjustments, the difference of ASSOR, ASSORNAT and DDIN all show significant adjustment effects on lag 2, and the difference of FORPROP are significant on lag 1 and lag 3. But the adjustment effects of the market structure variables to transaction volume are not significant. Aside of market liquidity, the cointegration term is also significant when DDIN and FORPROP are as the dependent variables in the long run, but the short-run adjustment in this specification does not show significant evidence.

[9] The study also tried the specification including linear trend in error correction term, but the estimation results do not deviate significantly.

As VECM estimation results do not indicate the causality among variables, a number of post-estimation tests are employed to investigate the relations within the endogenous system. This includes Granger causality test, impulse response and variance decomposition. Granger causality tests the strength of using explanatory variable to predict the dependent variable against dependent variable predicts itself. When estimating the model with single-year data, Granger causality test (Table 5) shows the change of Amihud measurement is Granger-caused by nationality assortativity as well as the joint effect of all the endogenous variables, while the individual effect of other endogenous variables do not show significant causality. No significant Granger causality is detected when transaction volume is the dependent variable.

Impulse response and variance decomposition further test the short-term vs long-term fluctuations of dependent variables under the impact of explanatory variable. Impulse response quantifies the standard deviation of price impact (Amihud ratio) and trading volume with one standard deviation "shock" as a result of the change of market structure. While variance decomposition shows that how much proportion of the of dependent variables variance can be explained by that of explanatory variables. In the results with single-year market liquidity proxies in Figure 11, most of the shocks dissolve after 10 years/periods time. For the response of Amihud ratio, the positive shocks from degree density and degree assortativity decrease the Amihud ratio (hence improve the liquidity) in the starting periods, but the shocks adjust and in turn increase the Amihud ratio afterwards; in the long run, the shock from degree density dissolves while the shock from degree assortativity deviate the Amihud ratio by a steady deviation of 0.02. The exogeneous shock from foreign investors' proportion does not deviate Amihud ratio either, but the shock of the nationality assortativity gives a steady negative impact to Amihud ratio, which persist to the long-term equilibrium. The impact of an increase of trading volume does not clearly affect the Amihud ratio. Variance decomposition of Amihud in Figure 11 shows consistent effects, as the propotion explained by nationality assortativity gradually increases from the short run to the long run and reach to over 60%, while the degree assortativity explains less than 10% of the variance in the long run.

On the other hand, the responses of trading volume to the market structure elements are not very clear. Only the nationality assortativity triggers a persist negative effect to trading volume, while the clearly distinguished responses come from the shocks of trading volume and Amihud ratio. In the variance decomposition results, over 80% of the variance of trading volume is explained by itself while the rest is explained by Amihud ratio. Therefore, no significant evidence is detected for market structure change affect trading volume.

The impulse responses and variance decompositions of 5-year rolling Amihud ratio (Figure 13) reveal slightly different pictures. Shock of degree density gives Amihud ratio a negative deviation of around -0.03 in the beginning four years. After adjustment, the long-term impact of degree density shock becomes -0.01. The shock of degree assortativity does not show clear effect to the Amihud ratio in the beginning 4 years, but the impact rises to over 0.02 standard deviation afterwards. Meanwhile, the impact of the increasing proportion of foreign investors (as a positive shock) increases Amihud ratio, with the long-term impact over 0.02 standard deviation. Whereas the shock from nationality assortativity leads to a negative standard deviation of Amihud ratio, with the long-term impact at -0.02. The shock of trading volume increases Amihud ratio with 5-year period, but the shock response gradually vanishes in the long term.

Variance decomposition of 5-year rolling Amihud ratio (Figure 14) indicates that more of the market structure features help explain the variance. Proportion of the foreign investors contribute explaining over 20% of the variance from the 4th year, while nationality assortativity and degree density contribute to 20% and 10% each. It seems degree assortativity does not help explain the variance after the 5th year, but its contribution gradually increases to over 20% and overpass the previous two features.

As for the reactions of trading volume, except degree density and trading volume itself, most of the endogenous variables have rather faint impact to trading volume. In this system, the trading volume also explain most of its own variances comparing to the contribution from other variables.

To summarise the findings between market structure and liquidity, evidence shows the impacts of specific market structure features on price-impact Amihud ratio but not on trading volume. Among the market structure features, nationality assortativity has significant impact on Amihud ratio, which the negative shock implies the cluster within investors from the same country improve the market pricing efficiency. Results from the 5-year rolling effect also suggest higher degree density (thus more intensive transactions in the market) enhance the market pricing efficiency. Degree assortativity, as a proxy of the "power law distribution" does not show effect in the short run, but the assortative structure deviates the market pricing efficiency in the long run. It also worth noting that, the increase proportion of foreign investors does not help boost the transaction volume nor improve the pricing efficiency; rather, the positive shock on the proportion of foreign investors hinder the pricing efficiency.

Aside of the impact from market structure variables to market liquidity, some of the causalities or "prediction relations" have been capture by the post estimation tests. Granger causality, impulse response and variance decomposition all suggest the significant effect of nationality assortativity towards degree assortativity, but the stronger degree assortativity dissolve the same-country clustering though the causality effect is not statistically significant. There are also a few relations among the market structure attributes reflected by impulse response, but this section does not explain in detail, as the impulse results from the two regressions are not consistent, and causality effects are not statistically significant.

6 Discussions of Empirical Results

To summarise the empirical results, this section analyses the role of foreign investors by comparing the average centralities between UK investors and foreign investors, and by investigating the evolution of transaction networks in different metro markets. The different results from the degree centrality, betweenness centrality and eigenvector centrality have interesting implications. Foreign investors conduct more purchases with higher volume on average, the average betweenness centralities are lower than those figures of UK group. Although foreign investors improve the market liquidity by providing the investment demand in the investment market, the UK investor group has more central position in the transaction networks and facilitate the asset circulations in the market in the sample time period. Nonetheless, a few international investors act as "core investors" in the markets and contribute to the market liquidity. Further, the comparison on eigenvector centrality suggest the foreign investors tend to conduct transactions with the highly influential counterparties in the network i.e. the market counterparties with higher degrees themselves or the counterparties that have connections with the high-degree ones.

Given the thin trading volume in commercial market, some other centrality measurements such as the local clustering coefficient do not effectively apply to the transaction network in the sample; this in turn reveals the market counterparties are loosely connected with "structural holes" in the transaction network. Instead, a few systemic important counterparties have been recognised as the core nodes that potentially influence the market transactions. The disassortative network structure with a few core investors reduces the cost of peripheral investors and improves the pricing efficiency.

In terms of the network formations, while some of the markets like London, Birmingham and Manchester already have integrated markets throughout the sample period, some other cities/regions have shown the integration process in the 15-year time window, with Northwest market showing the opposite network "dissolving" process. Degree assortativity in many markets show a "dip" during the GFC, either become less "assortative" or even "disassortative". This implies the liquidity dry-up during the market downturn; however, what worth discussing is the liquidity providing from certain foreign investors during the market downturn. "Foreign clusters" are captured in some non-London markets, which, aside of the network constraints, might also matter with the assets being transact and the investment strategy of the participants.

It is inevitable that the connections in the transaction network are restricted by the heterogeneous assets that market counterparties are possessed with. The institutional investors with international background generally look for the investment asset with large scales are premium investment characters. However, the changing trend that the international institutions become "core investors" extends what Lizieri and Pain (2014) suggest on the role of international investors in the global capital flow network.

Moreover, from a regulatory purpose, policy maker also needs to be aware the systemic importance of the investors to CRE market stability. As the activities of dominant investors in the CRE markets is crucial to market liquidity and pricing, their acquisitions and disposals would be affected by their investment objectives and financial soundness. The SNA analysis helps policy makers to track the stability of the market, and systemic importance of certain investors. It remains a challenge to design proper guidance/regulation, and beyond the focus of this paper, which hopefully will be address by proceeding studies.

Modelling the relations between market structure attributes and market liquidity provide more insights. The impact from an increasing proportion of foreign investors in the market is limited to market pricing efficiency, comparing to other market structure indices. Rather, the power distributions implied by the assortativity ratios in the market are influential to the pricing efficiency. A market structure following the “power law” (reflected by the positive degree assortativity) hinder the market liquidity, as market participants are limited within the counterparties with same level of connections. In the short run, the degree-assortative but fragmented structure forms small transaction clusters, keeping the market efficient within small segments. This coincides Baker’s (1984) proposition on small-but-efficient market network. However, in the long term, as individual investors’ reach can hardly cover the full market, this segregated structure potentially hinders the price-impact liquidity.

The investor clusters with the counterparties from the same countries improve the pricing efficiency, which consists to the hypothesis that counterparties from the same countries act as the “bridges” in the investment market, and the transactions with these counterparties reduce the property searching costs and potentially bargaining costs, hence improve the liquidity.

However, the entry of foreign investors, reflected by the exogeneous shock of the proportion of foreign investors in total investor group, does not show significant influence towards the increase of transaction volume or improve the price-impact liquidity. Instead, foreign investors “flooding” into the market distorts the pricing efficiency – as it implies in the analysis of the centrality statistics, when foreign investors buy-and-hold without considering the liquidity benefit of the asset.

Previous research in the transaction community structure draw mixed conclusion on the financial market structure formation. Boss et al. found the degree assortative therefore a hierarchical distribution following “power law” in the interbank market. While Fricke and Lux (2015b) found the degree-disassortative mixing in the bank lending market i.e. small banks tend to lend to large and reputable banks. Many studies confirm the existence of a core-periphery structure in financial markets. Participants can transaction with more of other counterparties indirectly without reaching to the specific ones, but via a few core counterparties in the network because of their wider connections to both other core counterparts as well as peripheral ones. In our analysis on the network graphs, although most of the markets show the existence of the core nodes, the links among the cores are comparatively sparse, hence the CRE market seems to be a more disassortative mixed market than a typical core-periphery market. More in-depth investigations on transaction mechanism as well as market participants between CRE market and other investment asset markets are required in order to explain the market structure formations.

Regarding the market price impact, more intensive transaction and an assortative structure improve the market liquidity in the short term; however, in the long run, if investors can only access limited counterparties with the same connections but not the full market, the assortative structure with an intensive transaction amount would potentially hinder the market liquidity.

Comparing to the assortative structure, the disassortative structure are more vulnerable, as the shock or absence of the core investors would change the market formation. This, in turn, indicate the importance of essential supervision and cultivation of the crucial investors in the market. In CRE market specifically, the entry of foreign investors gradually changes the “eco-system” of the whole market, and a few international investors have become the “core nodes” in the transaction network. As a result, their actions are expected to influence the market transactions.

7 Conclusions

This study contributes a new vision to the rising discussion of foreign investors in host real estate market with SNA methods on meso-level of the market. In the selected submarkets in England throughout the 15-year time window, this study compares the centrality states of foreign investors with the UK investors and how the roles of foreign investors change over time. Results from multiple centralities indicate that, the overseas investors provide investment demands in the market and improve the market liquidity in most of the market; the trend is especially clear after the financial crisis period. Nevertheless, as shown by the high average eigenvector centrality but low betweenness centrality figures, a lot of foreign investors are usually the buyers of the influential market participants in the network, rather than the participants that sustain the market transactions. In this sense, the "liquidity-providing" role of foreign investors that proposed by previous literature need to be more carefully defined.

However, the role among foreign investors are diverse within foreign investor group, and the roles (reflected by the position in the network) of investors change over time. There are a few reputable real estate firms and institutional investors with international backgrounds act in investment market while the other investors are identified as "typical" foreign entrants. With the active foreign investors entering into the host markets, quite a few submarkets reflect a balancing distribution on market transactions among the participants, and the hub investors are not rigidly limited within UK groups. Therefore, the results suggest specifying the market status of participants when evaluating the impact of overseas capital.

In terms of the market structure formation, the study investigates the market power distributions and country-base clustering in the selected market. Results show the power distribution exists in many market networks, while during the GFC a limited number of investors are the "liquidity providers", reflecting that the transaction network is vulnerable under the change of the capital market changes. There is also a rising trend that market participants tend to transact with their home peers. VECM results provide the evidence that CRE market structure features affect the market liquidity, as the accomplished results with Amihud ratio implies that a more integrated market would stabilise the market price dispersion, while a strong cluster within home peers would aggravate the market price dispersion.

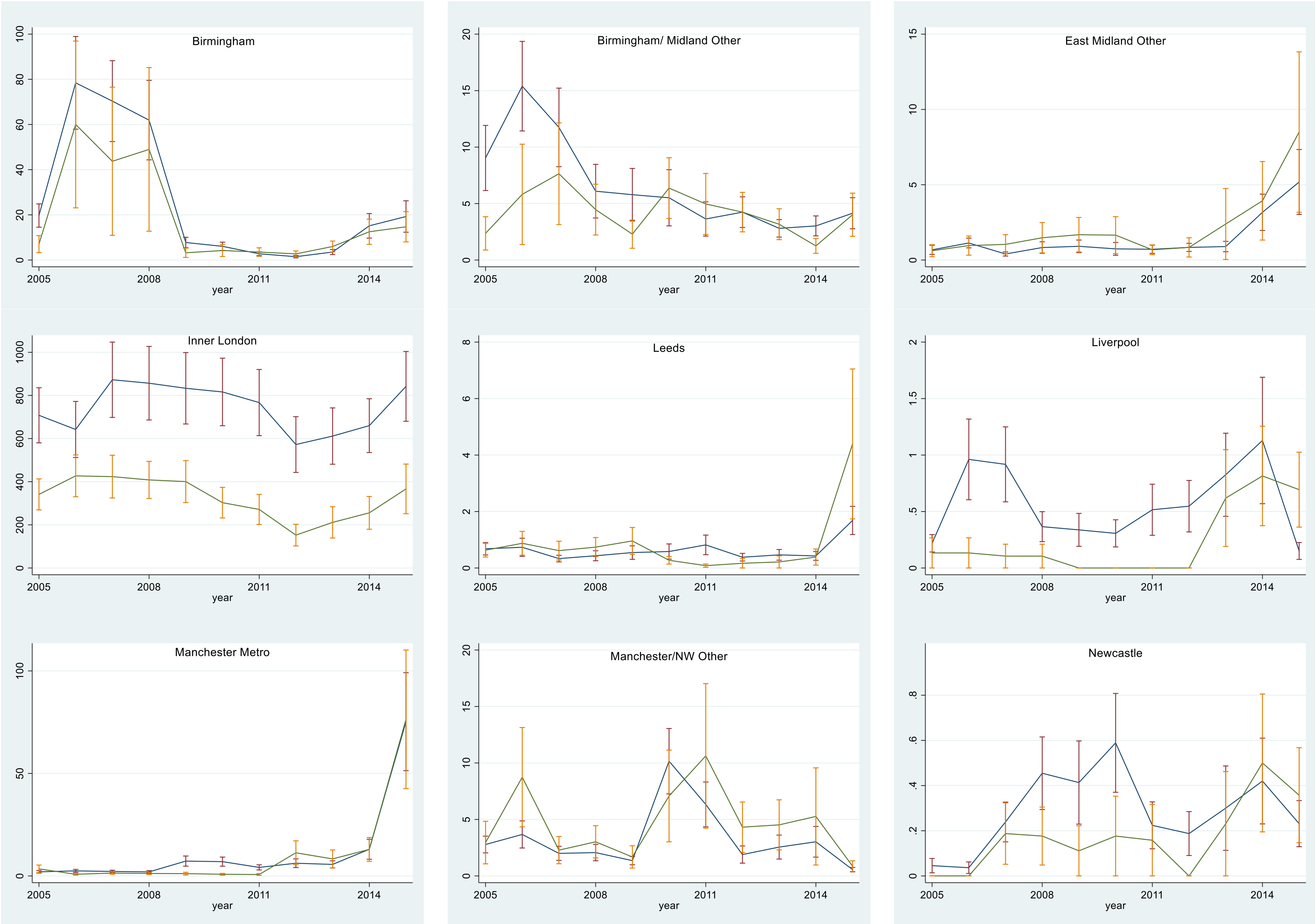
The analysis of CRE transaction network have multiple implications. While the common vision describes the foreign capital in the CRE investment market as a newly rising group after GFC, the study suggests as the market status of investors vary, it is very important to break down the "foreign group" and discuss the different impacts towards the markets. The study enhances the idea about the role of financial investors in the real estate market with the interpretation from market structure. Specifically, there exists the "systemic important" market participants who facilitate the circulation of the property assets or release the liquidity when market liquidity dry out. Behaviours of the systemic important investors are expected to have stronger influence towards the market pricing, liquidity thus guarantee the market stability.

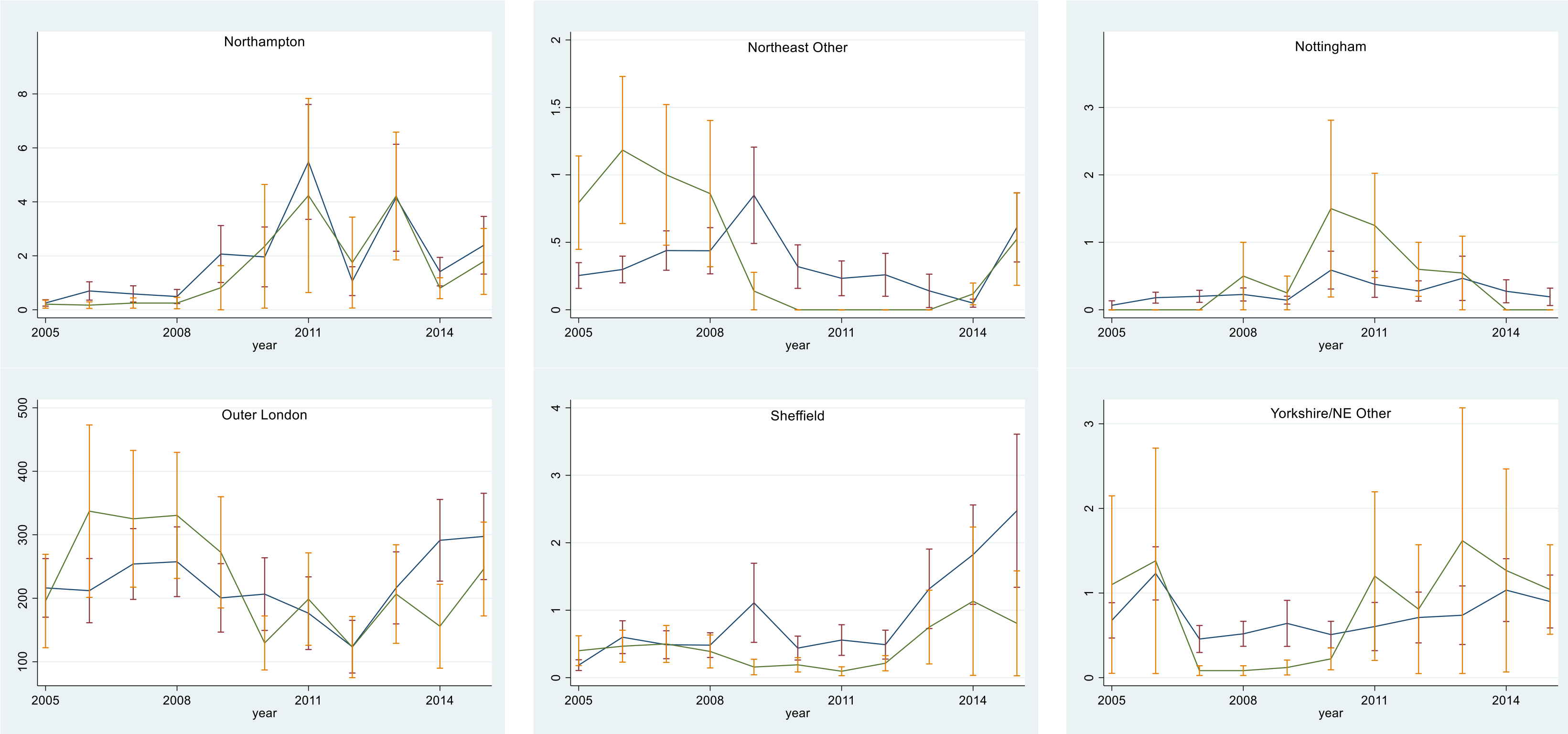
While previous discussions on CRE transaction liquidity from the market-searching mechanism (Clayton et al., 2008) and investor sentiment (Freybote and Seagraves, 2018), this study shed light on the investors' interconnectivity influencing the transaction liquidity. Moreover, the market formation reflects different stages of the CRE market evolution under the impacts of international capital flow, which further implies the potential development of the CRE market structure.

As an incipient study on the investment market structure, further studies could enhance and further extend this topic in several directions. When discussing the market network formation, broker is the important contributor assisting the formation of transaction network. Unlike the "market-makers" in public market, the brokers in direct market help with asset information sorting, but do not take property asset in stock themselves. There exists a multilevel network structure with investors set up the connection via brokers' community. With previous literature suggest that the broker potentially have influences to transaction prices, it would be important to investigate the interaction among investors' network, broker's network and the market performance.

Tables and Graphs

Figure 8 Betweenness centralities





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year
Nottingham
0
1
2
3
2005
2008
2011
2014
year
Outer London
100
200
300
400
500
2005
2008
2011
2014
year
Sheffield
0
1
2
3
4
2005
2008
2011
2014
year
Yorkshire/NE Other
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1
2
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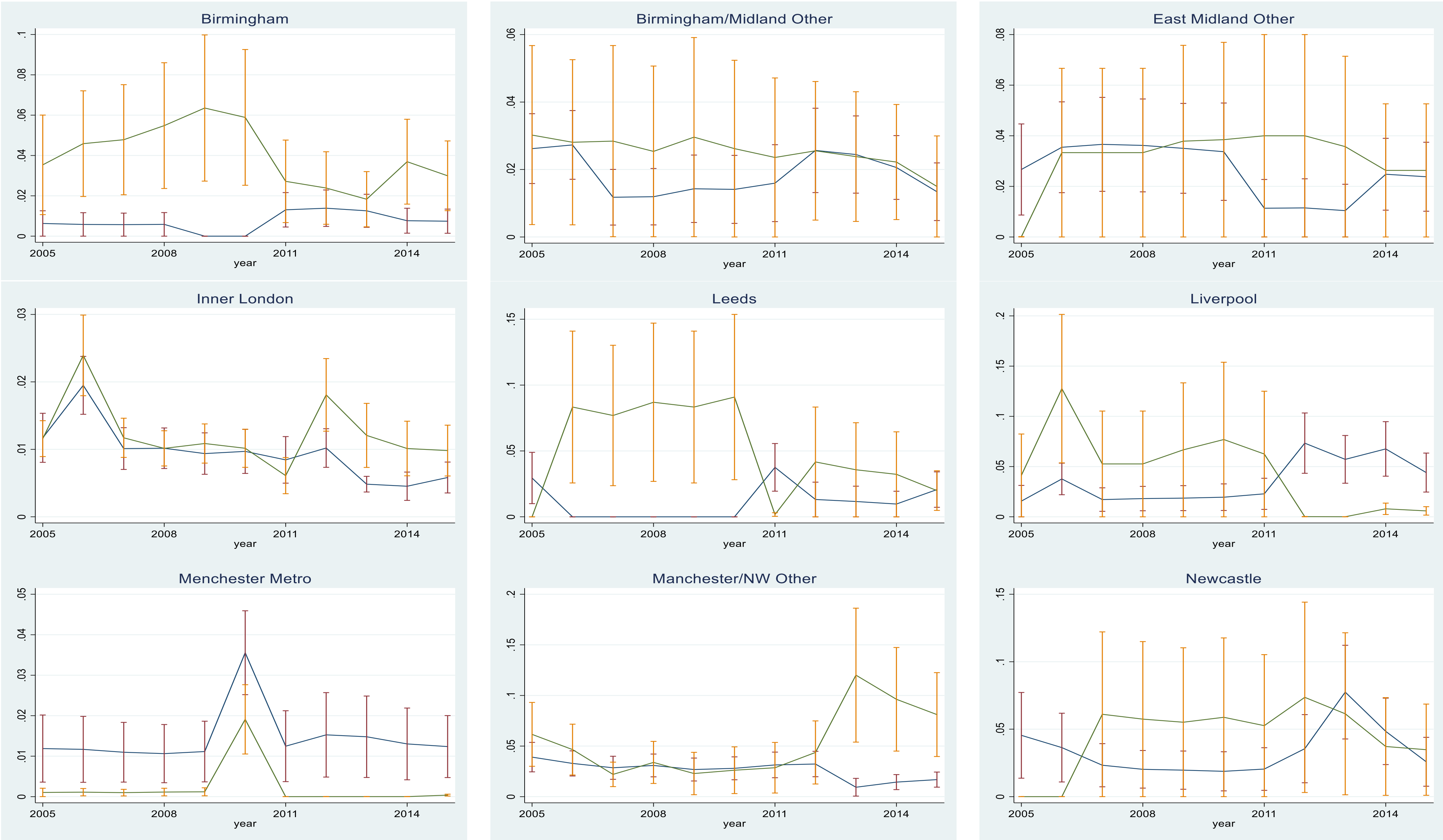
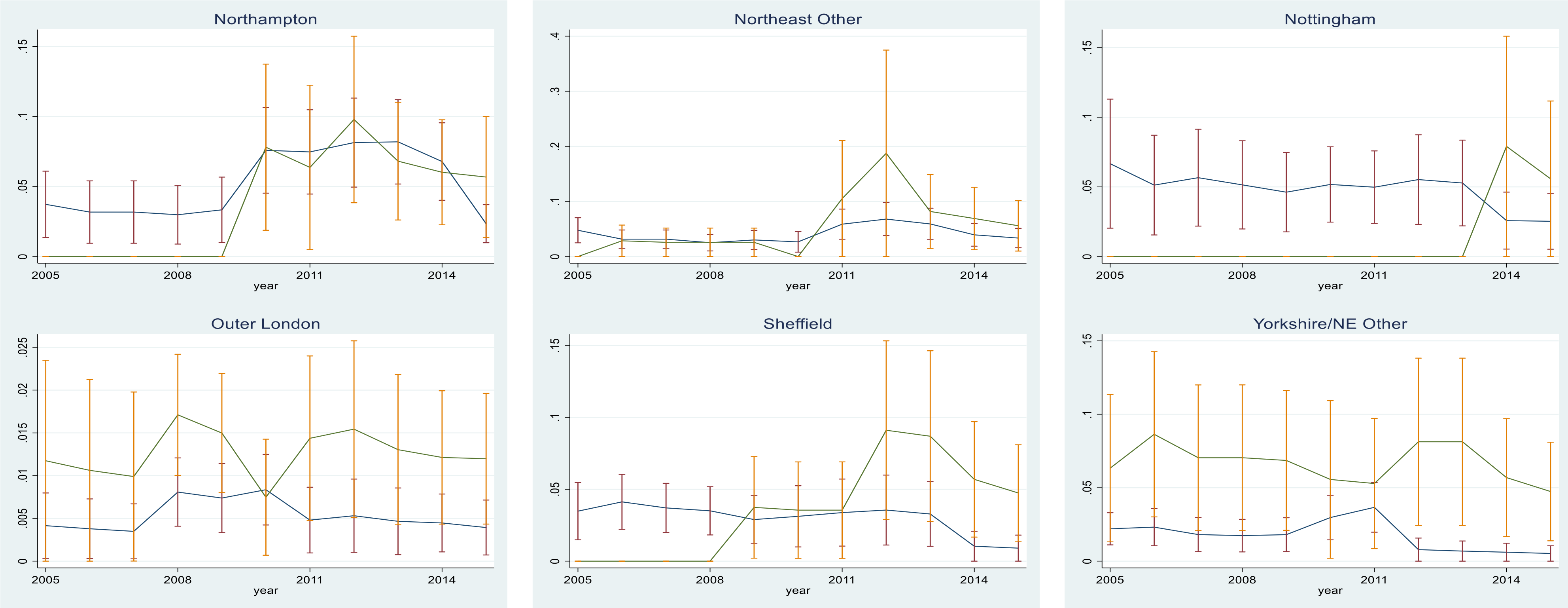
2005
2008
2011
2014
year

Figure 9 Eigenvector Centralities




Northampton
Northeast Other
Nottingham
Outer London
Sheffield
Yorkshire/NE Other
0
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2014
year

Table 1 Descriptive Statistics

						Correlations									
	Obs.	Mean	Std. Dev.	Max.	Min	AMH	AMH_5Y	ASSOR	ASSORNAT	EMPRR	FORPROP	GDHIR	VOL	VOL_5Y	DD
AMH	225	0.45	0.56	5.28	0.00	1									
AMH_5Y	165	0.45	0.38	2.66	0.02	0.649***	1								
ASSOR	165	0.08	0.19	0.76	-0.32	-0.041	-0.073	1							
ASSORNAT	165	0.02	0.07	0.27	-0.10	-0.194**	-0.235***	0.160**	1						
EMPRR	165	0.00	0.02	0.09	-0.11	-0.047	-0.130	0.088	0.069	1					
FORPROP	165	0.22	0.07	0.44	0.04	-0.136	-0.335***	-0.002	0.134	0.208**	1				
GDHIR	210	0.01	0.03	0.08	-0.05	-0.133	-0.108	0.022	0.111	0.127	0.321***	1			
VOL	225	1495.44	3228.05	19946.31	20.05	0.037	-0.041	-0.130	0.070	0.151	0.671***	0.324***	1		
VOL_5Y	165	7529.14	15132.38	78926.90	583.12	0.098	-0.018	-0.147	0.080	0.118	0.692***	0.272***	0.936***	1	
DD	165	0.01	0.00	0.02	0.00	0.107	0.391***	0.360***	-0.037	0.000	-0.389***	-0.157**	-0.456***	-0.487***	1

Table 2 Unit Root Tests

		Level			*1st Difference*		
		with intercepts	with intercepts and trends	none	with intercepts	with intercepts and trends	none
AMH	*ADF*	46.32**	62.28***	45.81**	130.93***	88.18***	205.19***
	PP	125.38***	164.22***	73.27***	302.29***	275.72***	313.41***
AMH_5Y	*ADF*	9.11	17.26	60.55***	45.37**	48.11**	68.77***
	PP	17.40	49.74**	78.09***	140.64***	124.51***	155.72***
ASSOR	*ADF*	32.10	22.42	65.52***	44.71**	33.52	94.99***
	PP	47.26**	29.20	72.19***	118.58***	108.60***	187.38***
ASSORNAT	*ADF*	21.01	26.92	47.16**	59.88***	57.42***	92.51***
	PP	31.13	34.89	59.49***	104.58***	99.97***	158.38***
EMPRR	*ADF*	31.55	27.08	76.59***	64.11***	44.96**	132.02***
	PP	56.93***	61.38***	119.97***	155.32***	151.90***	227.79***
FORPROP	*ADF*	15.97	19.78	6.89	45.89**	40.36	81.00***
	PP	19.92	48.48**	6.09	131.89***	130.23***	156.03***
GDHIR	*ADF*	70.90***	39.24	135.26***	144.32***	113.01***	234.32***
	PP	135.55***	93.40***	200.58***	265.47***	257.10***	313.27***
VOL	*ADF*	57.70***	37.06	20.74	93.44***	56.45***	166.40***
	PP	73.80***	56.03***	31.63	209.08***	152.80***	255.43***
VOL_5Y	*ADF*	54.0***	19.88	19.20	32.85	17.36	83.79***
	PP	23.49	14.69	8.36	51.33**	43.35	110.82***
DD	*ADF*	35.17	23.75	25.01	38.71	21.23	81.12***

PP	22.63	15.61	46.13**	58.58***	39.15	114.26***

Table 3 Johansen Cointegration Test Summary

Data Trend: Test Type	None No Intercept No Trend	None Intercept No Trend	Linear Intercept No Trend	Linear Intercept Trend	Quadratic Intercept Trend
With single-year liquidity					
Trace	2	2	1	1	1
Max-Eig	2	1	1	1	1
With 5Y-rolling liquidity					
Trace	2	1	1	1	1
Max-Eig	1	1	1	1	1

Table 4 VECM Estimation (single-year liquidity)

Coint. Eq.	C	ASSOR(-1)	ASSORNAT(-1)	DDIN(-1)	FORPROP(-1)	VOLREAL(-1)
	-0.411	-0.002	1.240***	-8.909	0.345	0.000
		[-0.01]	[2.83]	[-0.96]	[0.53]	[-0.64]
EC	D(AMH)	D(ASSOR)	D(ASSORNAT)	D(DDIN)	D(FORPROP)	D(VOLREAL)
CointEq1	-0.764***	-0.058	-0.018	0.000	0.019	74.890
	[-8.068]	[-0.927]	[-0.693]	[-0.434]	[1.438]	[0.405]
D(AMH(-1))	-0.088	0.027	0.011	0.000	-0.019	-93.448
	[-1.048]	[0.485]	[0.457]	[-0.432]	[-1.611]	[-0.567]
D(AMH(-2))	0.013	-0.008	-0.008	0.001	-0.013	-87.963
	[0.156]	[-0.149]	[-0.367]	[1.148]	[-1.104]	[-0.545]
D(AMH(-3))	0.055	0.019	0.004	0.000	0.001	22.372
	[0.942]	[0.484]	[0.223]	[0.387]	[0.122]	[0.196]
D(ASSOR(-1))	0.010	-0.271***	-0.012	0.001	-0.022	86.735
	[0.06]	[-2.453]	[-0.250]	[1.118]	[-0.930]	[0.267]
D(ASSOR(-2))	-0.277	-0.087	-0.027	0.000	0.007	99.178
	[-1.666]	[-0.785]	[-0.595]	[0.357]	[0.303]	[0.305]
D(ASSOR(-3))	0.170	-0.213**	-0.015	0.000	0.025	-268.005
	[0.94]	[-1.778]	[-0.309]	[-0.323]	[0.962]	[-0.761]
D(ASSORNAT(-1))	-0.310	0.160	0.004	0.003	0.030	773.998
	[-0.685]	[0.534]	[0.031]	[1.147]	[0.462]	[0.877]
D(ASSORNAT(-2))	-0.149	0.816***	-0.209	-0.004	0.017	-572.699
	[-0.317]	[2.612]	[-1.601]	[-1.449]	[0.256]	[-0.624]
D(ASSORNAT(-3))	1.776***	0.319	0.152	-0.005	-0.065	362.607
	[3.048]	[0.825]	[0.940]	[-1.349]	[-0.788]	[0.319]
D(DDIN(-1))	-36.262**	10.387	4.144	0.291**	1.017	5756.832
	[-1.98]	[0.854]	[0.816]	[2.447]	[0.392]	[0.161]
D(DDIN(-2))	24.804	2.121	-3.560	-0.160*	2.364	-5321.795
	[1.187]	[0.153]	[-0.615]	[-1.177]	[0.799]	[-0.131]
D(DDIN(-3))	9.721	-14.882	2.080	-0.125	-2.274	28723.980
	[0.487]	[-1.124]	[0.376]	[-0.965]	[-0.805]	[0.738]
D(FORPROP(-1))	1.115	-0.014	-0.248	-0.012**	-0.211*	-379.089
	[1.344]	[-0.025]	[-1.075]	[-2.264]	[-1.796]	[-0.234]
D(FORPROP(-2))	0.420	0.186	-0.270	0.000	0.019	713.618
	[0.492]	[0.327]	[-1.141]	[-0.025]	[0.155]	[0.428]
D(FORPROP(-3))	0.501	0.528	0.013	0.004	0.062	-554.772
	[0.554]	[0.879]	[0.050]	[0.713]	[0.486]	[-0.315]
D(VOLREAL(-1))	0.000	0.000	0.000	0.000	0.000	-0.108*
	[1.89]	[0.044]	[-0.013]	[-0.594]	[0.511]	[-1.783]
D(VOLREAL(-2))	0.000	0.000	0.000	0.000	0.000	-0.124**
	[-0.345]	[0.767]	[0.240]	[0.747]	[-0.176]	[-2.036]
D(VOLREAL(-3))	0.000	0.000	0.000	0.000	0.000	-0.069
	[-0.345]	[1.072]	[-0.168]	[0.150]	[0.004]	[-1.065]
C	-0.157***	-0.010	0.013*	0.000	0.012***	15.216
	[-6.416]	[-0.598]	[1.932]	[0.530]	[3.460]	[0.319]
LONDON =1	0.181***	0.028	-0.011	0.000	-0.007	163.147
	[3.026]	[0.696]	[-0.661]	[0.672]	[-0.793]	[1.400]
EMPRR(-1)	-1.113	-0.626	0.332	-0.009	0.26*	141.897
	[-1.162]	[-0.983]	[1.249]	[-1.506]	[1.918]	[0.076]
GDHIR(-1)	3.139***	-0.131	-0.088	-0.015***	0.081	1532.440
	[3.489]	[-0.22]	[-0.353]	[-2.559]	[0.638]	[0.873]
Adj. R-squared	0.808	0.064	-0.068	0.240	-0.045	-0.065
F-statistic	20.856	1.321	0.697	2.490	0.797	0.712
Akaike AIC	-0.280	-1.099	-2.846	-10.354	-4.190	14.872

Table 5 Granger Causality (single-year liquidity)

	D(AMH)	D(ASSOR)	D(ASSORNAT)	D(DDIN)	D(FORPROP)	D(VOLREAL)
D(AMH)		1.896	2.113	5.603	3.854	1.055
D(ASSOR)	5.251		0.389	1.414	1.904	0.901
D(ASSORNAT)	10.722**	8.216**		6.581*	0.994	1.198
D(DDIN)	5.443	2.742	0.83		1.815	0.546
D(FORPROP)	2.467	0.811	2.106	5.317		0.511
D(VOLREAL)	4.145	1.518	0.103	1.034	0.318	
All	38.91***	16.606	7.384	24.854*	10.778	4.244

Figure 10 Impulse Response, single-year liquidity data

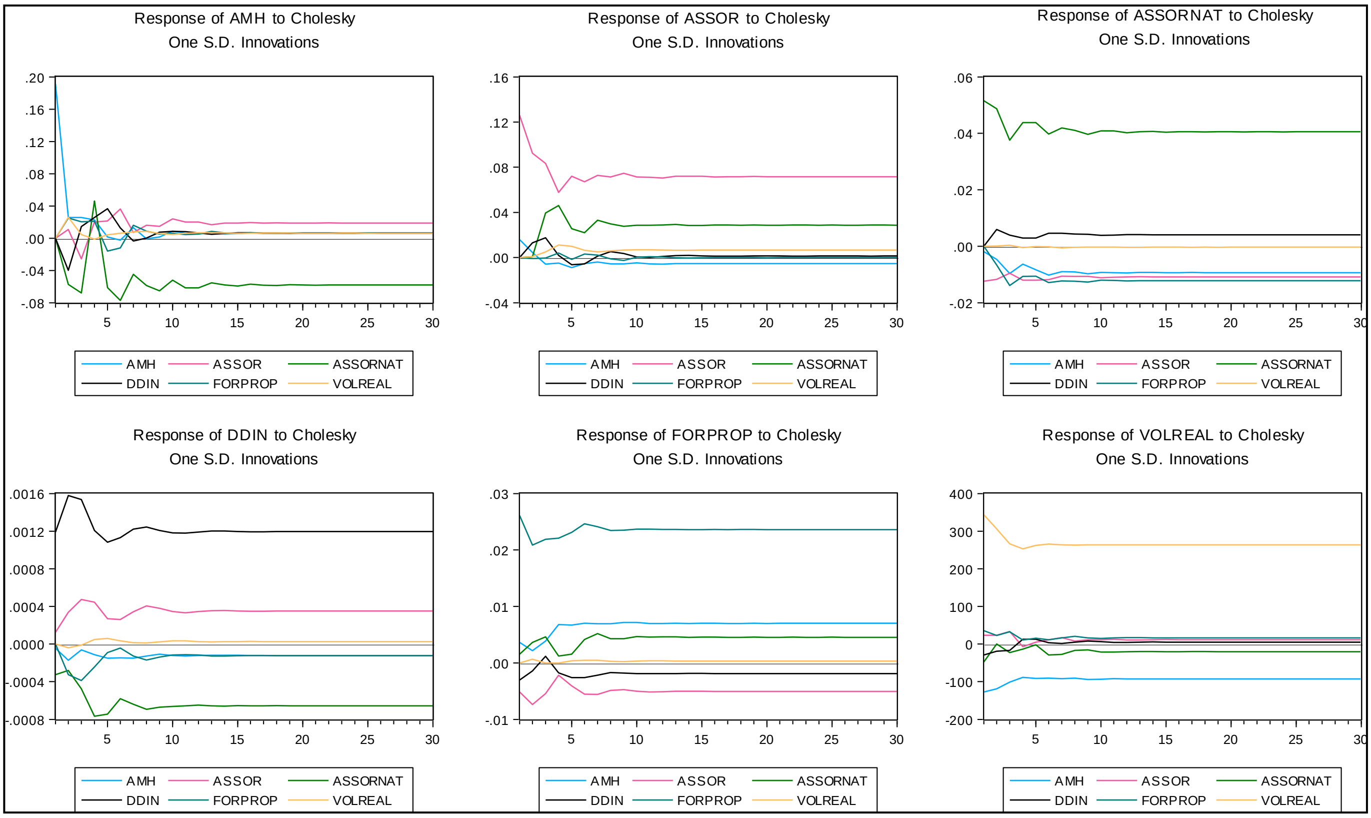


Figure 11 Variance decomposition, single-year liquidity data

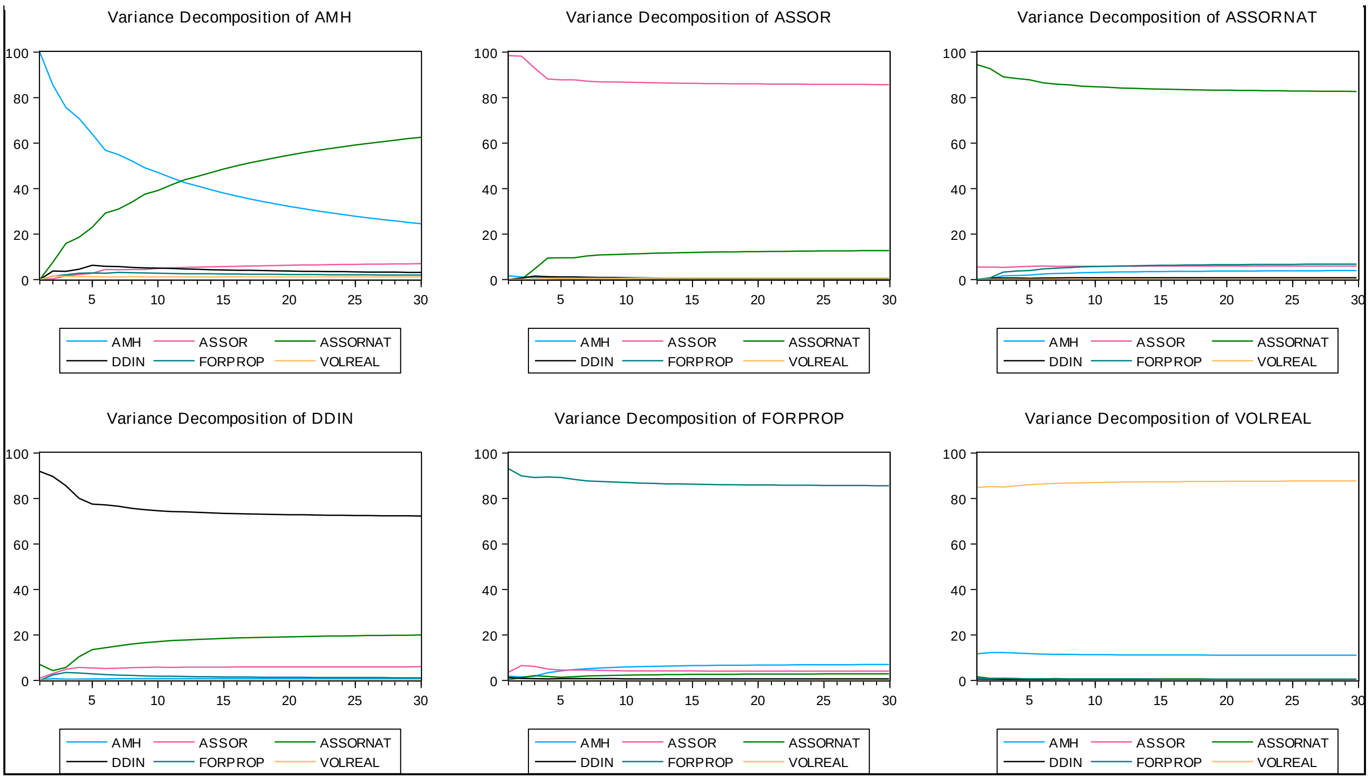


Table 6 VECM Estimation (5Y-rolling liquidity)

Coint.	C	ASSOR(-1)	ASSORNAT(-1)	DDIN(-1)	FORPROP(-1)	VOL_5YREAL(-1)
	-0.330	-0.409**	1.014**	10.727	-0.800	0.000
		[-2.252]	[2.285]	[0.958]	[-1.238]	[-0.330]
EC	D(AMH)	D(ASSOR)	D(ASSORNAT)	D(DDIN)	D(FORPROP)	D(VOLREAL)
CointEq1	-0.317***	0.004	-0.002	-0.001**	0.017*	226.210
	[-11.672]	[0.076]	[-0.122]	[-1.990]	[1.685]	[1.042]
D(AMH(-1))	-0.172***	-0.084	-0.022	0.001	-0.039	855.027
	[-2.635]	[-0.723]	[-0.454]	[1.086]	[-1.620]	[1.643]
D(AMH(-2))	0.152*	-0.132	-0.073	0.003**	-0.029	-867.983
	[1.966]	[-0.954]	[-1.261]	[2.518]	[-1.020]	[-1.404]
D(AMH(-3))	0.073	0.126	0.026	-0.001	-0.013	-263.105
	[0.961]	[0.925]	[0.451]	[-1.072]	[-0.453]	[-0.431]
D(ASSOR(-1))	-0.079	-0.263**	-0.016	0.001	-0.024	450.913
	[-1.231]	[-2.287]	[-0.332]	[0.984]	[-0.998]	[0.878]
D(ASSOR(-2))	-0.135**	-0.111	-0.040	0.001	0.001	-7.058
	[-2.098]	[-0.971]	[-0.826]	[0.871]	[0.033]	[-0.014]
D(ASSOR(-3))	-0.010	-0.225*	-0.026	0.000	0.014	-57.554
	[-0.139]	[-1.788]	[-0.503]	[-0.031]	[0.547]	[-0.103]
D(ASSORNAT(-1))	0.196	0.174	-0.009	0.003	0.034	249.432
	[1.192]	[0.589]	[-0.073]	[1.146]	[0.556]	[0.190]
D(ASSORNAT(-2))	-0.521***	0.956***	-0.147	-0.006**	0.030	859.529
	[-2.888]	[2.959]	[-1.093]	[-2.095]	[0.448]	[0.597]
D(ASSORNAT(-3))	0.264	0.287	0.163	-0.007*	-0.051	-510.061
	[1.197]	[0.730]	[0.995]	[-1.946]	[-0.629]	[-0.291]
D(DDIN(-1))	-10.330	18.810	7.147	0.182	4.077	23498.110
	[-1.457]	[1.483]	[1.351]	[1.525]	[1.566]	[0.415]
D(DDIN(-2))	-17.896**	8.029	0.272	-0.283*	1.965	50971.510
	[-2.073]	[0.520]	[0.042]	[-1.943]	[0.620]	[0.740]
D(DDIN(-3))	-3.980	-18.199	1.476	-0.076	-0.983	8519.173
	[-0.489]	[-1.250]	[0.243]	[-0.554]	[-0.329]	[0.131]
D(FORPROP(-1))	0.565*	-0.071	-0.272	-0.009*	-0.246**	-1116.539
	[1.845]	[-0.129]	[-1.190]	[-1.671]	[-2.189]	[-0.457]
D(FORPROP(-2))	0.089	0.162	-0.282	0.002	-0.007	1279.111
	[0.279]	[0.284]	[-1.188]	[0.286]	[-0.061]	[0.504]
D(FORPROP(-3))	0.771**	0.369	-0.050	0.007	0.012	-563.596
	[2.191]	[0.586]	[-0.190]	[1.140]	[0.094]	[-0.201]
D(VOL_5YREAL(-1))	0.000**	0.000	0.000	0.000	0.000	0.351***
	[2.119]	[0.151]	[0.128]	[0.321]	[-0.358]	[4.110]
D(VOL_5YREAL(-2))	0.000	0.000	0.000	0.000	0.000	-0.056
	[0.590]	[-0.053]	[0.073]	[0.818]	[-0.370]	[-0.651]
D(VOL_5YREAL(-3))	0.000	0.000	0.000	0.000	0.000	-0.518***
	[0.974]	[-0.421]	[0.137]	[-0.842]	[0.221]	[-6.448]
C	-0.063***	-0.016	0.009	0.000	0.007*	-37.606
	[-5.626]	[-0.812]	[1.046]	[1.240]	[1.810]	[-0.418]
LONDON =1	0.030	0.013	-0.009	0.000	0.000	-144.049
	[1.279]	[0.325]	[-0.526]	[0.073]	[0.018]	[-0.781]
EMPRR(-1)	-0.628	-0.115	0.431	-0.017**	0.279*	88.637
	[-1.575]	[-0.161]	[1.451]	[-2.497]	[1.908]	[0.028]
EMPRR(-2)	-1.601***	0.266	0.040	-0.008	0.045	4575.557
	[-3.991]	[0.371]	[0.132]	[-1.220]	[0.304]	[1.430]
GDHIR(-1)	-0.748**	-0.068	-0.137	-0.012**	0.059	8411.496***
	[-2.395]	[-0.121]	[-0.586]	[-2.347]	[0.514]	[3.375]
Adj. R-squared	0.666	0.047	-0.085	0.280	0.014	0.572
F-statistic	10.002	1.222	0.644	2.762	1.065	7.054
Akaike AIC	-2.237	-1.074	-2.823	-10.403	-4.242	15.732

Table 7 Granger Causality Test (5Y-rolling liquidity)

	D(AMH)	D(ASSOR)	D(ASSORNAT)	D(DDIN)	D(FORPROP)	D(VOL_5YREAL)
D(AMH)		2.415	2.112	9.16**	3.802	4.769
D(ASSOR)	5.281		0.762	1.492	1.358	0.83
D(ASSORNAT)	10.373**	10.15**		11.816***	0.934	0.445
D(DDIN)	8.494**	5.406	1.966		3.865	0.933
D(FORPROP)	9.898**	0.378	2.467	3.746		0.718
D(VOL_5YREAL)	9.088**	0.348	0.073	1.763	0.54	
All	45.993***	16.622	6.362	27.407**	10.165	6.798

Figure 13 Impulse response, 5Y rolling market performance

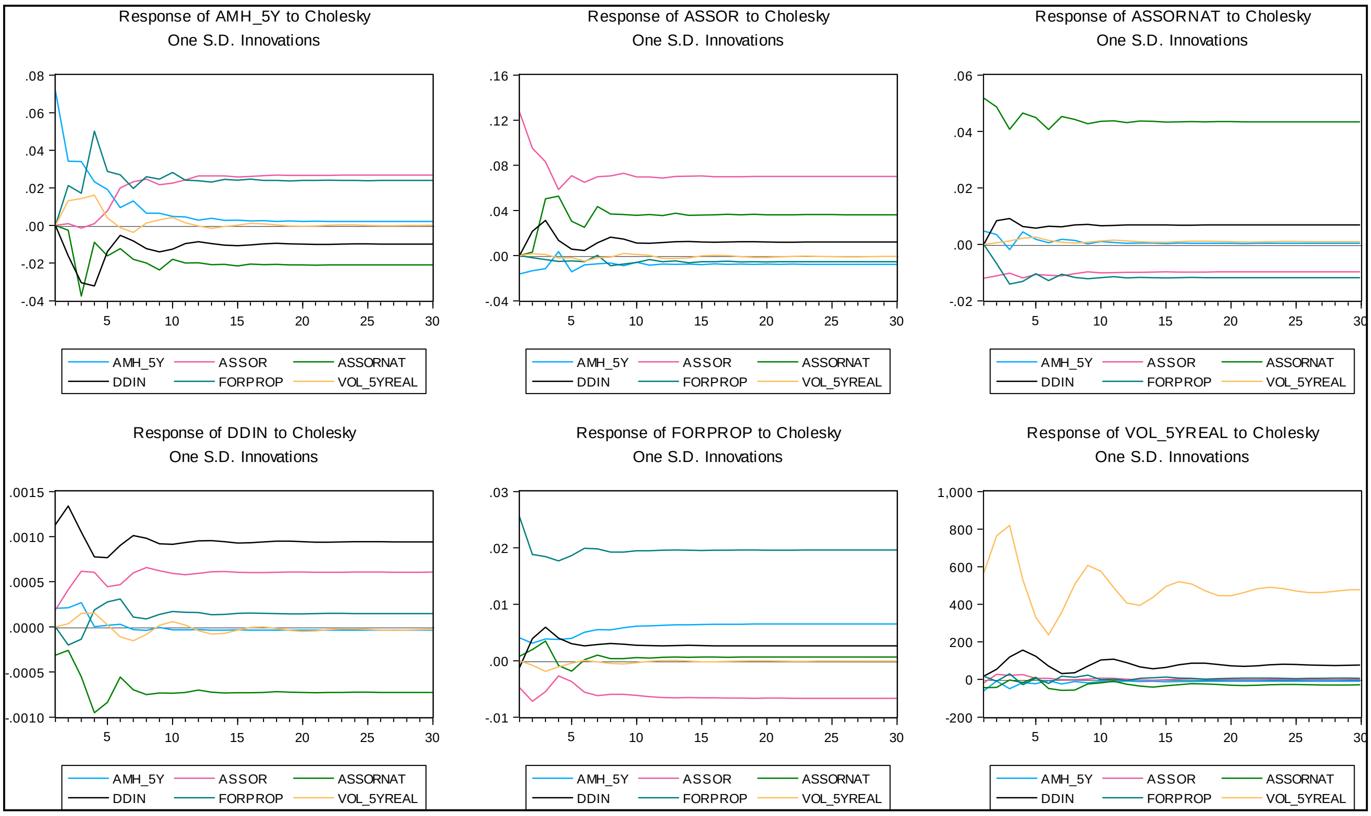
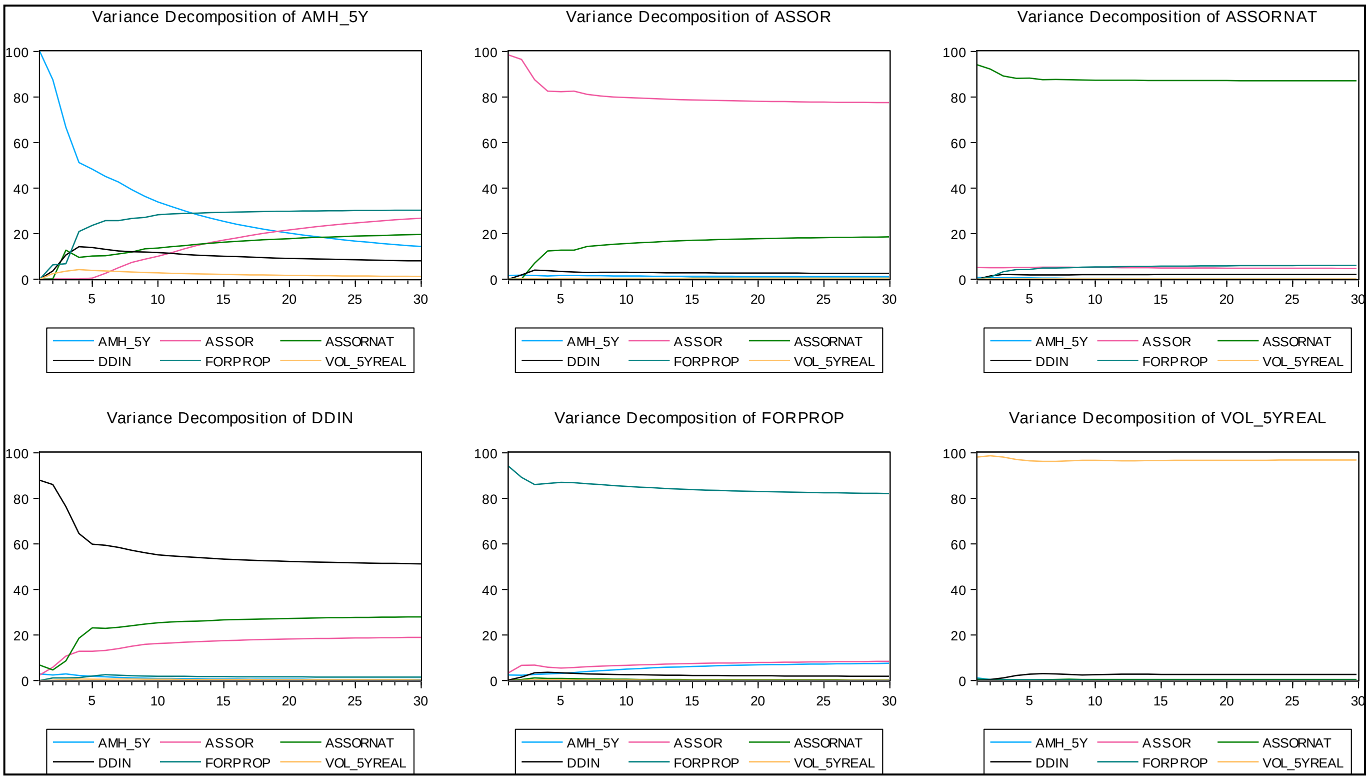


Figure 14 Variance decomposition, 5Y rolling market liquidity



References

Alves, I., Ferrari, S., Franchini, P., Heam, J.-C., Jurca, P., Langfield, S., et al. (2013) 'The structure and resilience of the European interbank market (No. 3)'. European Systemic Risk Board.

Ametefe, F., Devaney, S., & Marcato, G. (2016). Liquidity: A review of dimensions, causes, measures, and empirical applications in real estate markets. *Journal of Real Estate Literature*, 24(1), 1-29.

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets*, 5(1), 31-56.

Anand, B. N., & Galetovic, A. (2006). Relationships, competition and the structure of investment banking markets. *The Journal of Industrial Economics*, 54(2), 151-199.

Baker, W. E. (1984). The social structure of a national securities market. *American Journal of Sociology*, 89(4), 775-811.

Bekaert, G., Harvey, C. R., & Lumsdaine, R. L. (2002). Dating the integration of world equity markets. *Journal of Financial Economics*, 65(2), 203-247.

Bergantino, A. S., & Capozza, C. (2012). The effect of bank concentration on entrepreneurship in Central and Eastern European Transition Countries. *SSRN*.

Bikker, J. A., & Haaf, K. (2002). Measures of competition and concentration in the banking industry: a review of the literature. *Economic & Financial Modelling*, 9(2), 53-98.

Boss, M., Elsinger, H., Summer, M., & Thurner, S. (2004). Network topology of the interbank market. *Quantitative Finance*, 4(6), 677-684.

Choe, H., Kho, B.-C., & Stulz, R. M. (1999). Do foreign investors destabilize stock markets? The Korean experience in 1997. *Journal of Financial Economics*, 54(2), 227-264.

Choe, H., Kho, B.-C., & Stulz, R. M. (2005). Do domestic investors have an edge? The trading experience of foreign investors in Korea. *The Review of Financial Studies* 18(3), 795-829.

Clayton, J., MacKinnon, G., & Peng, L. (2008). Time variation of liquidity in the private real estate market: An empirical investigation. *Journal of Real Estate Research*, 30(2), 125-160.

Cocco, J. F., Gomes, F. J., & Martins, N. C. (2009). Lending relationships in the interbank market. *Journal of Financial Intermediation*, 18(1), 24-48.

Craig, B., & von Peter, G. (2014). Interbank tiering and money center banks. *Journal of Financial Intermediation*, 23(3), 322-347.

Devaney, S., & Scofield, D. (2013). Broker use and the cost of liquidity in commercial real estate investment. *Journal of European Real Estate Research*, 6(3), 279-302.

Finger, K., & Lux, T. (2017). Network formation in the interbank money market: An application of the actor-oriented model. *Social Networks*, 48, 237-249.

Freybote, J., & Seagraves, P. (2018). The Impact of Investor Sentiment on Commercial Real Estate Market Liquidity. *Journal of Real Estate Research*, 40(4), 597-627.

Fricke, D., & Lux, T. (2015a). Core–periphery structure in the overnight money market: evidence from the e-mid trading platform. *Computational Economics*, 45(3), 359-395.

Fricke, D., & Lux, T. (2015b). On the distribution of links in the interbank network: evidence from the e-MID overnight money market. *Empirical Economics*, 49(4), 1463-1495.

Fu, X. M., Lin, Y. R., & Molyneux, P. (2014). Bank competition and financial stability in Asia Pacific. *Journal of Banking & Finance*, 38, 64-77.

Fungáčová, Z., Solanko, L., & Weill, L. (2014). Does competition influence the bank lending channel in the euro area? *Journal of Banking & Finance*, 49, 356-366.

Grinblatt, M., & Keloharju, M. (2000). The investment behavior and performance of various investor types: a study of Finland's unique data set. *Journal of financial economics*, 55(1), 43-67.
Guler, I., & Guillen, M. F. (2010). Home country networks and foreign expansion: Evidence from the venture capital industry. *Academy of Management Journal*, 53(2), 390-410.
Hendershott, T., Jones, C. M., & Menkveld, A. (2011). Does algorithmic trading improve liquidity? *The Journal of Finance*, 66(1), 1-33.
Henneberry, J., & Mouzakis, F. (2014). Familiarity and the determination of yields for regional office property investments in the UK. *Regional Studies*, 48(3), 530-546.
Kali, R., & Reyes, J. (2007). The architecture of globalization: a network approach to international economic integration. *Journal of International Business Studies*, 38(4), 595-620.
Lizieri, C., & Pain, K. (2014). International office investment in global cities: the production of financial space and systemic risk. *Regional Studies*, 48(3), 439-455.
Massó, M., & Ruiz-León, A. A. (2017). The configuration of a status based model of economic actors: The case of Spanish government debt market. *Social Networks*, 48, 23-35.
Minoiu, C., & Reyes, J. A. (2013). A network analysis of global banking: 1978–2010. *Journal of Financial Stability*, 9(2), 168-184.
Mishkin, F. S. (2011). Over the cliff: From the subprime to the global financial crisis. *Journal of Economic Perspectives*, 25(1), 49-70.
Ng, L., Wu, F., Yu, J., & Zhang, B. (2015). Foreign investor heterogeneity and stock liquidity around the world. *Review of Finance*, 20(5), 1867-1910.
Nier, E., Yang, J., Yorulmazer, T., & Alentorn, A. (2007). Network models and financial stability. *Journal of Economic Dynamics Control*, 31(6), 2033-2060.
Novy-Marx, R. (2007). An equilibrium model of investment under uncertainty. *The review of financial studies*, 20(5), 1461-1502.
Rhee, S. G., & Wang, J. (2009). Foreign institutional ownership and stock market liquidity: Evidence from Indonesia. *Journal of Banking & Finance*, 33(7), pp.1312-1324.
Schiavo, S., Reyes, J., & Fagiolo, G. (2010). International trade and financial integration: a weighted network analysis. *Quantitative Finance*, 10(4), 389-399.
Stevenson, S., Akimov, A., Hutson, E., & Krystalogianni, A. (2014). Concordance in global office market cycles. *Regional Studies*, 48(3), 456-470.
Stiglitz, J. E. (2010). Risk and global economic architecture: Why full financial integration may be undesirable. *American Economic Review*, 100(2), 388-92.
Stulz, R. M. (1999). Golbalization, corporate finance, and the cost of capital. *Journal of applied corporate finance*, 12(3), 8-25.