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* Views expressed are those of the authors and do not necessarily reflect official positions of De Nederlandsche Bank.

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# Price diffusion across international private commercial real estate markets

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**Abstract**

We explore spatio-temporal aspects of global commercial real estate price movements and consider two channels where prices may spill over between global cities: (i) through a dominant market and (ii) through "neighbouring" markets. Neighbouring, here, is defined as the degree of overlap in ownership. We document significant ripple effects from both channels in commercial real estate prices across 22 markets from 2005 to 2019. In particular, London is found to be the dominant market and price shocks significantly diffuse across other global cities in the short- to medium-run. Additionally, shocks from neighbouring markets are important in the short- to medium-run. In the long-run, macroeconomic factors play a much more critical role. The spillover effect through both channels is more predominant during the financial crisis. In fact, the dominant market channel is mostly driven by the financial crisis. By contrast, the neighbouring market channel is significant throughout the economic cycle.

*Keywords*: Commercial Real Estate, Prices, Spillovers, Spatial Dependence, Global Markets
*JEL classification*: R3, R12

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# 1 Introduction

When a market goes up or down, other markets tend to go up or down as well, at least to some extent, a phenomenon usually referred to as commonality. Studying commonality is important, since co-movement (or the lack thereof) between markets allows for diversification benefits. It is not particularly controversial to state that private real estate markets co-move within the same country or even internationally. See for example, MacGregor and Schwann (2003) for evidence of UK commercial real estate, Ang et al. (2013) for US commercial real estate, and Clark and Coggin (2009) for evidence of US housing. In fact, many models of private residential and commercial real estate price dynamics involve hierarchical modelling of returns based on the hierarchy of regions, thereby assuming commonality in regional developments in prices in housing or commercial real estate (Francke and De Vos, 2000; Francke and Vos, 2004; Francke and van de Minne, 2017).

Internationally, there may also be substantial co-movement between markets because of the financial connections through global capital markets and the emergence of the "World City Network" (Lizieri and Pain, 2014). However, international real estate portfolio diversification may benefit the real estate investor relatively strongly compared to stock and bond portfolios (Eichholtz, 1996). Van Dijk and Francke (2021) examine the co-movement in returns and market liquidity in US and international commercial real estate. The authors document substantial co-movement in both returns and market liquidity changes, but the co-movement in market liquidity is much stronger. Further, Stevenson et al. (2014) assess the degree of synchronization in cycles across twenty office markets, finding evidence of significant concordance across many markets. The concentration of investment also raises the possibility of a common flow of funds effects that may further reduce diversification opportunities. In related work, Zhu and Lizieri (2021) find that commonality in ownership significantly explains international co-movements in office market performance by constructing a network analysis based on "linked ownership" of properties. In other words, when more properties in different markets are owned by the same set of investors, markets tend to co-move more strongly and diversification benefits are lower. During the Global Financial Crisis (GFC) this mechanism is found to be stronger, a period in which investors needed diversification the most. Relatedly, co-movement in market liquidity and returns increases substantially during the GFC in securities markets (Karolyi et al., 2012) and commercial real estate (Van Dijk and Francke, 2021).

In practice, however, common regional movements do not have to occur at exactly the same point in time and the lead-lag structure may depend on spatial factors. Hence, there exists a spatial dependency with leads and lags between regions. This is particularly well-documented in price spillover, price diffusion, or ripple effects (we will use these terms interchangeably) literature for housing markets. For example, Tirtiroğlu (1992) finds that neighbouring localities influence price changes in a particular locality. Other examples include Meen (1999), Giussani and Hadjimatheou (1991) for the UK, Pollakowski and Ray (1997) for the US, and Stevenson (2004) for Ireland. In housing markets, the root of price diffusion may stem from the inefficiency of markets and imperfect information (Clapp et al., 1995). Similarly, Van Dijk et al. (2011) find that house prices in and around large cities in the Netherlands respond faster to informational shocks than other, more rural, regions. This, in effect, results in spatial and intertemporal spillovers between price changes of urban regions to rural regions. Likewise, Holly et al. (2011) find that shocks to house price changes in the dominant region (London) spillover to other parts of the UK. A possible reason considered by Holly et al. (2011) is that London is a significant major worldwide financial center by providing evidence that house price growth from New York City spills over to the UK, but only through London.

The literature on price diffusion in private commercial real estate markets is much sparser. Furthermore, the majority of the extant literature focuses on spatial dependency *within* regional markets. For example, Chegut et al. (2015) provide evidence for spatial dependence within the Hong Kong, London, New York City, Paris, and Tokyo office markets. Francke and Van de Minne (2020) argue that the predictive accuracy of pricing models improves strongly when taking spatial effects into account. Lee et al. (2018) provide evidence of significant lead-lag relationships between office property classes within Hong Kong. The literature looking at spillovers *between* regions is much more limited. Jackson et al. (2008) test for cointegration and Granger causality between the New York and London office markets. They find cointegration in the price but not the rent. They reason that investment behaviour contributes more to commonality than to underlying economic forces. Additionally, Shilling et al. (2017), provide evidence that commercial real estate return expectations from US core market spill over to return expectations in US non-core markets. We have found no literature that systematically documents price spillovers between a group of private commercial real estate markets.

Examining ripple effects between commercial real estate markets is important because it is useful to know which market is dominant and moves first. This allows for a better understanding of how economic shocks propagate through space and time, an important fact for policymakers and market watchers. Given the significant market size of commercial real estate, adjustments in commercial property prices are likely to affect developments in the real economy.[1] Furthermore, commercial real estate assets are extensively used as collateral for loans. As a result, the functioning of commercial property markets is crucial for risk managers to understand. However, even though commercial property market developments are historically relatively risky for balance sheets of financial institutions compared to for example housing, commercial real estate markets have attracted relatively less attention Ellis et al. (2010).

In this paper, we complement the literature by examining price return diffusion between 22 international commercial real estate markets. We use the commercial property price indices (CPPIs) and ownership data from Real Capital Analytics (RCA). We quantify the degree of price diffusion drawing on the method in Holly et al. (2011). We consider diffusion through two channels: (i) a dominant market channel and (ii) a "neighbouring" market channel based on the degree of overlap in ownership. We empirically find that London is the dominant market and document a significant propagation of price returns from this city to other cities in the short- to medium-run (channel i). On average across 22 cities, a significant positive response is found from the first to the eighth quarter after the shock. The response is the largest in the sixth quarter after the shock, amounting to 0.76%. We also empirically confirm significant price spillovers from neighbouring markets in the short- to medium-run (channel ii). Following Zhu and Lizieri (2021), we define neighbouring markets based on the degree

[1]NAREIT estimates that the 2018 total dollar value of the commercial real estate in the US was around 16 trillion USD, which was around half the size of US stock market capitalization. According to Ghent et al. (2019), in 2016, commercial real estate accounted for 0.8% of US GDP, as the third-largest asset class, following common stocks (1.65% GDP) and residential real estate (1.4% of GDP), but larger than T-bills (0.7% of GDP) and corporate debt (0.5% GDP). Globally, according to Savills, real estate is the world's most important asset class, with an estimated total value of 217 trillion USD at the end of 2016. Around 29 trillion USD was commercial real estate. By comparison, the size of the global bond market at the end of 2016 was 92.2 trillion USD, and global equity market capitalization was 70.1 trillion USD.

of overlap of investors between markets. On average, there is a significant positive response to the neighbouring market shocks from the first to the tenth quarter after that shock. In the third quarter, the response is highest, amounting to 0.78%.

Shocks from the dominant market and neighbouring markets both explain about 15% of the variance in prices in the short-run. General macroeconomic factors, such as interest rates, GDP, credit, and the exchange rate, play a much more critical role in the long-run as over 90% of the forecast error variance is explained by these factors. We further look at interactions between the real estate spillover variables and the real economy. In particular we find that real estate prices positively affect credit and GDP growth, amplifying the original shock.

We additionally allow for an asymmetric effect during the GFC and find that both channels are much more predominant in times of crisis. In fact, the significance of the dominant market channel over the full sample is mostly driven by the GFC. Conversely, and importantly, the neighbouring market channel is found to be significant in both crisis and tranquil times. On average, the share of forecasting variance of real estate price attributable to the shocks to London and neighbouring markets in the short-run rise to 35% and 21%, respectively. In the long-run, macroeconomic factors are still the most important driver.

The results are robust to inclusion of a global factor and alternative measures for the degree of interconnectedness. Additionally, we consider endogenous weight matrices and account for global co-movements in macroeconomic variables. Furthermore, the results of our impulse response functions are robust to alternative orderings and a re-sampling of (overrepresented) US cities.

The remainder of this paper is structured as follows. Section 2 outlines the methods underlying the price diffusion model and the construction of the weight matrices based on co-ownership. Section 2 additionally describes our data. Identification of the dominant market and the results of the price diffusion model are discussed in Section 3. Section 4 includes robustness checks. Finally, Section 5 concludes.

# 2 Methodology and Data

## 2.1 The price diffusion model

In this paper, we investigate how price shocks propagate from the dominant market (denoted by subscript 0 in the following equations) to the remaining cities using a diffusion model. $y_{i,t}$ denotes the log price of city $0...N$ in quarter $1...T$ in levels. The model of the dominant market is given by:

$$\begin{aligned}\Delta y_{0,t} = \phi_{0,s}(y_{0,t-1} - y^s_{0,t-1}) + \phi^X_0 \beta'_0(z_{0,t-1} - \iota_0 - \zeta_{0,t-1}) + a_0 + \\ \sum_{q=1}^{Q1} a_{0,q}\Delta y_{0,t-q} + \sum_{q=1}^{Q2} b_{0,q}\Delta y^S_{0,t-q} + \sum_{q=1}^{Q4} \lambda_{0,q}\Delta x_{0,t-q} + \varepsilon^y_{0,t},\end{aligned} \tag{1}$$

and for the remaining N regions are given by:

$$\begin{aligned}\Delta y_{i,t} = \phi_{i,s}(y_{i,t-1} - y^s_{i,t-1}) + \phi_{i,0}(y_{i,t-1} - y_{0,t-1}) + \phi^X_i \beta'_i(z_{i,t-1} - \iota_i - \zeta_{i,t-1}) + a_i + \\ \sum_{q=1}^{Q1} a_{i,q}\Delta y_{i,t-q} + \sum_{q=1}^{Q2} b_{i,q}\Delta y^S_{i,t-q} + \sum_{q=0}^{Q3} c_{i,q}\Delta y_{0,t-q} + \sum_{q=1}^{Q4} \lambda_{i,q}\Delta x_{i,t-q} + \varepsilon^y_{i,t},\end{aligned} \tag{2}$$

for $i = 1,...,N$.$y^s_{i,t}$ denotes the spatial variables for region $i$ defined by $y^s_{i,t} = \sum_{j=0}^N s_{i,j,t} y_{i,j,t}$ with $\sum_{j=0}^N s_{i,j,t} = 1$ , for $i = 0,1,2,...,N$ and $s_{i,j,t} \in (0,1)$. $s_{i,j,t}$ is the weight for the calculation of the average price of neighbouring markets. Equation (1) and (2) are allowed to be error correcting by estimating the long term trend. In principle, long-run relationships depend on the number of the cointegrating relationships that might exist amongst $y$ series across the $N+1$ markets. However, in order to avoid over-parametrization in the above specifications, Holly et al. (2011) suggest a relatively parsimonious specification. Here, the price in the dominant market is assumed to be cointegrated with the average price of the neighbouring markets ($y^s_{0,t-1}$), where the neighbouring market is defined as based on the overlap of property ownership. $\phi_{0,s}$ is the corresponding coefficient. For the remaining cities, prices are assumed to be cointegrated with the price in the dominant market ($y_{0,t-1}$) and the average price of its neighbourhood ($y^s_{i,t-1}$). $\phi_{i,0}$ and $\phi_{i,s}$ are the corresponding coefficients.

The impact of the dominant region to remaining regions occurs through contemporaneous and lagged changes in prices of the dominant market ($\sum_{k=0}^{K} b_{i,0}\Delta y_{0,t-k}$), but there is no contemporaneous local average price included in the equation for dominant markets. Additionally, the price dynamics are also influenced by the lagged price changes ($\sum_{q=1}^{Q1} a_{0,q}\Delta y_{0,t-q}$ in the leading market, and $\sum_{q=1}^{Q1} a_{i,q}\Delta y_{i,t-q}$ in the other cities). $a_{0,q}$ and $a_{i,q}$ are the corresponding coefficients. Moreover, the price dynamics are further affected by the price changes in the neighbouring markets ( $\sum_{q=1}^{Q2} b_{0,q}\Delta y_{0,t-q}^{S}$ as the leading market and $\sum_{q=1}^{Q2} b_{i,q}\Delta y_{i,t-q}^{S}$ as the remaining cities). $b_{i,q}$ and $b_{i,q}$ are the corresponding coefficients. Implicit in the above specification is that, conditional on the dominant regions' price changes, neighbouring regions' price changes, and lagged effects of the shocks, $\varepsilon_{i,t}^{y}$ are approximately independently distributed across i. Note that we aim to explicitly model any cross-sectional dependence through our spillover terms. The assumption that $\Delta y_{0,t}$ is weakly exogenous in the equation $\Delta y_{i,t}$ for $i = 1,...,N$ is tested using the procedure proposed by Wu (1973) and Holly et al. (2011).

Because macroeconomic conditions affect commercial real estate markets and vice versa, we also include country-level macroeconomic variables in $x_{i,t}$. We consider four variables for ($K = 4$): the interest rate, the credit to GDP ratio[2], GDP[3], and the exchange rate: $x_{i,t} = [ir_{i,t}; Credit_{i,t}; GDP_{i,t}; Exchange_{i,t}]$. In the short-run, the real estate price dynamics in the dominant market and remaining cities are influenced by the economic changes ($\sum_{q=1}^{Q4} \lambda_{0,q}\Delta x_{0,t-q}$, in the leading market and $\sum_{q=1}^{Q4} \lambda_{i,q}\Delta x_{i,t-q}$, in the remaining cities). $\lambda_{0,q}$ and $\lambda_{i,q}$ are the corresponding coefficients. The optimal lag length (i.e. Q1, Q2, Q3, and Q4) for each variable is tested using the Akaike information criterion (AIC).[4] In the long-run, the real estate price cointegrates with the macroeconomic conditions: $z_{i,t} = (y_{i,t}, x_{i,t})'$. $\phi_i^X$ is a 1 by $R_i$ vector of adjustment coefficients. $Ri$ is the number of cointegration ranks for city i. $\beta_i$ is a $K$ by $R_i$ matrix of coefficients for the cointegration relationship between real estate price and the $K$ macroeconomic variables for city $i$. Real estate prices in the dominant and other

[2] Instead of the credit to GDP ratio, we also used the log of credit amount and the lending premium to small to median business. The results regarding the spillover effects across international real estate markets are robust.

[3] Instead of GDP, we also used unemployment rate. The results regarding the spillover effects across international real estate markets are robust.

[4] Using other criteria, such as adjusted $R^2$, the Hannan–Quinn information criterion (HQC) or the Bayesian information criterion (BIC) generate robust results in terms of the spatial diffusion of real estate prices. The results based on other selection criteria are available per request.

markets adjust through $\phi_0^X \beta_0'$ and $\phi_i^X \beta_i'$, respectively.

We further accommodate a feedback effect from country-level real estate prices and country-level macroeconomic developments by estimating a Vector Error Correction model (VECM) for each country. The country-level real estate price is calculated as the average city-level price in the country.[5] The feedback effect of real estate markets on macroeconomic developments are modeled as follows:

$$\Delta x_{g,t} = \alpha_g + \kappa_g \eta_g'(z_{g,t-1} - \iota_g^x - \zeta_{g,t-1}^x) + \sum_{p=1}^{P} \varphi_{g,p} \Delta y_{g,t-p} + \sum_{p=1}^{P} \delta_{g,p} \Delta x_{g,t-p} + \varepsilon_{g,t}^x, \quad (3)$$

Note that we switch notation from $i$ to $g$, where subscript $g$ denotes countries with $g = 1, 2, .., N_c$, where $N_c$ is the number of countries. This is because we model endogenous feedback to macroeconomic developments at country-level $g$. The changes in the macroeconomic variables are affected by lagged macroeconomic variables ($\sum_{p=1}^{P1} \delta_{g,p} \Delta x_{g,t-p}$) and the lagged country-average real estate price ($\sum_{p=1}^{P} \varphi_{g,p} \Delta y_{g,t-p}$). $\delta_{g,p}$ and $\varphi_{g,p}$ are the corresponding coefficients. The optimal lag length for each variable ($P$) is again selected using the AIC. Furthermore, $z_{i,t}^g = (y_{i,t}^g, x_{i,t})'$. $\kappa_g$ is a vector of adjusted coefficients and $\eta_g$ is a $K \times R_g^X$ matrix of coefficients for the cointegration relationship between the $K$ macroeconomic variables and the real estate price for country $g$.

In summary, the regression model incorporates three levels of error correcting towards (1) the dominant market, (2) neighbouring markets, and (3) national economic conditions. Under the assumption of weak exogeneity of the contemporaneous changes in the dominant market $\Delta y_{0,t}$, Equation (1), (2) and (3) can be estimated using OLS.

## 2.2 Weight matrix

We base the weights $s_{i,j}$ in weight matrix $S_n$ on the proportion of properties between the cities that are held by the same investors. As shown in Andonov et al. (2015), private, institutional, and listed real estate investors, such as occupational pension funds, insurance companies, and sovereign wealth funds, increasingly hold global real estate portfolios by acquiring private real estate directly or through fund structures. As a result, the commonality in the property investors can lead to linkages between

[5] We use equal weights per city: $y_{g,t} = \frac{1}{Ncity} \sum_{i=1}^{Ncity} y_{i,g,t}$, where $g$ denotes the country.

commercial real estate markets. One channel comes from the risk that portfolio holders in the market where the crisis initiates face collateral write-downs or have issues refinancing in that market. As a consequence, they may undertake actions to liquidate their investments in other markets forcing down asset prices in other markets as well. Moreover, given information spillovers, investors and agents will be more aware of the difficulties in other markets and mark prices accordingly. Opposite effects will occur with positive market shocks, although we suggest that downside risk effects are likely to dominate the linkage between markets. Zhu and Lizieri (2021) show that a weight matrix based on overlapped ownership best captures the spatial linkages between cities using spatial panel models. When overlap in ownership is included, other traditional measures of the interconnectedness between real estate markets, such as geographic distance, openness, similarity, the legal system, currency unit and even the overlap between occupiers located in the cities, become insignificant. Hence, this paper uses the overlap in property ownership to construct the weights.[6] In general, the weight from city $i$ to city $j$ is defined as the proportion of the properties located in city $i$ that are owned by investors with stakes in city $j$:

$$w_{i,j,t} = \frac{1}{L_t} \sum_{h=1}^{L_t} q_{i.l,j,h,t}, \tag{4}$$

with $l = 1,2,...L_t$ and $L_t$ is the total number of properties in city $i$. $j = 1,2,...H_t$ and $H_t$ is the total number of properties in city $j$ in period $t$. $w_{i,j,t}$ measures the dependence of city $i$ on city $j$. In other words, it shows the potential influence of city $j$ on city $i$. $q_{l,i,h,j,t}$ is a dummy variable with a value of 1 if property $l$ in city $i$ and property $h$ in city $j$ owned by the same investors at time $t$, and 0 otherwise:

$$q_{l,i,h,j,t} = \begin{cases} 1, & \text{if property } l \text{ in city } i \text{ and property } h \text{ in city } j \text{ owned by the same investor} \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

[6] We include traditional measures with instrumented weights for interconnectedness as a robustness check.

A complete index would require a full ownership census for all the cities being assessed, which is not currently available. Instead, following Zhu and Lizieri (2020), patterns of linked ownership are derived using individual transactions data in a wide range of global markets.[7]

## 2.3 Generalized impulse response with "structural shocks"

In order to examine price diffusion over time and across regions by taking into account all model dynamics, we calculate impulse response functions (IRFs). We illustrate the response of the real estate price in each of the cities to (1) a one standard deviation shock to their own market, (2) a one standard deviation shock to the London real estate price, and (3) a one standard deviation shock to each neighbouring market where the weighting is based on overlapping ownership. We also examine the endogenous relationship between the real estate price variables and macroeconomic conditions. We additionally calculate the forecast error variance decomposition (FEVD) to assess the economic significance.

Due to the large scale of variables across cities and countries, it is infeasible to estimate the effects of all shocks on all markets. Therefore, we run a generalized impulse response analysis. To identify "structural shocks", we adapt the strategy from Dees et al. (2007) to our purpose. Since we focus on the spillover of real estate prices, we include real estate prices in the first "block" of the model.[8] The remaining block contains the macroeconomic variables. As long as the contemporaneous correlations of these shocks are left unrestricted, the outcome of our price spillover results will be invariant to the ordering of the rest of the variables in the system (Dees et al., 2007). Within the real estate price block, we apply a Cholesky decomposition on the real estate price error terms. We set the dominant market as first market in the system. For the remaining cities, we use the trading volume as the Cholesky ordering. This implies that a larger market is more likely to influence smaller markets and is less likely to be influenced by the other markets. For more details on the generalized impulse response functions with "structural shocks", see Appendix A. We will consider

[7] Details regarding how to calculate the overlap ratio in terms of the commercial property ownership can be found in Zhu and Lizieri (2021).

[8] This can be seen in parallel to Dees et al. (2007) where the US variables are included in the first block and where the goal is to identify a US monetary policy shock.

alternative orderings as robustness check in Section 4.

## 2.4 Data

We use commercial property price indices of 22 commercial real estate markets from RCA (RCA CPPIs) over the period from 2007Q2 to 2020Q1. These are generally large global markets for which RCA publishes price indices. Figure 1 displays the log price index of ten large international markets. From early 2007, many cities' price indices dropped rapidly, then rebounded after reaching a through between 2010 and 2011. Table 6 in Appendix B shows the results of Dickey-Fuller Tests for the log of price in each market. Most series follow an I(1) process.[9]

[Place Figure 1 about here]
[Place Figure 2 about here]

For the weight matrix, we use transaction-level data to construct weights across cities. On average, 16.2% of properties are owned by investors who also have investments in other cities—San Francisco and Seattle exhibit the highest overlap ratio, amounting to 81.2%. Figure 2 visualizes the degree of centrality for the 22 cities. New York has the highest level of overlap, followed by Los Angeles and San Francisco. An average of 33.7%, 29.8% and 29.2% of the properties in one of the other 22 cities are owned by investors who also have an investment in New York, Los Angeles and San Francisco, respectively. It should be noted that the ranking of the centrality will be influenced by the constitution of the samples. In our sample, nearly half of the cities are US cities. Since domestic cities in the US are more likely to have a higher overlap in property ownership, US cities are ranked higher in this case. Additionally, RCA has higher capture rates for US cities compared to cities in other countries. However, the constitution of the sample will only affect the ranking. The diffusion results will not be affected, since the diffusion model depends on the overlap between each pair of cities. Furthermore, our robustness checks will show results based on other measures for interconnectedness where this should not be an issue. We will also run a robustness test where we will re-sample 6 US cities randomly in order to address the overrepresentation of US cities.

[9] Price index returns of Atlanta are not found to be stationary, the results are robust to leaving out Atlanta.

We collect country-level long term interest rates from the Oxford Economics database [10] Exchange rates are measured as national currency per Special Drawing Right (SDR) with data from the IMF database. Credit to GDP ratios are taken from the BIS database and GDP is from the OECD database. Table 1 includes summary statistics of our main variables.

[Place Table 1 about here]

# 3 Results

## 3.1 Identifying the leading market

We start with the pairwise analysis of the cointegration characteristics.[11] As expected, according to the RCA data, New York, London, and Tokyo are the three markets with the highest transaction volume in each continent. Furthermore, conventional wisdom suggests that these cities are the most important global markets. Therefore, we consider each of these three cities as the potential dominant market. First, we calculate the trace statistics to identify whether cointegration exists between each of the three dominant markets and other cities. As is customary in cointegration analysis, the null hypothesis is that the price in the dominant market is not cointegrated with the other markets. As shown in Table 2, for New York, this null hypothesis is rejected at least at the 10% significance level with all other cities (for at least one cointgrating vector). In London, a significant cointgrating relationship is identified with all but Houston. For Tokyo, a cointgrating relationship is found with all but three cities. Overall, this suggests that all three cities show a long-run relationship with most other cities.

[10] Instead of long term interest rate, we alternatively included the short-term interest rate. The results regarding the spillover effect are robust. However, short-term interest rates have a weaker explanatory power in commercial real estate prices than long term interest rates as might be expected given long holding periods and the duration of real estate investments.

[11] In this paper, we follow Holly et al. (2011) and test the cointegration relationship pairwise. Alternatively, the cointegration can be tested jointly, which would involve a setting of a VAR based on all of the 22 real estate market price series and then test for cointegration across all possible cities. Holly et al. (2011) argue that too many regions may reduce the reliability of the cointegration test, as this approach is likely to be statistically reliable only if the number of regions under consideration is relatively small, around 4–6 and the time series data available sufficiently long (120-150 quarters) – not the case here.

[Place Table 2 about here]

To identify the dominant market effect, we further estimate the error correction coefficient for each market pair involving New York, London and Tokyo. Table 3 reports the coefficients and their significance. Panel A is for New York and other markets, Panel B for London and other markets and Panel C for Tokyo and other markets. In each panel, the estimates for the New York, London and Tokyo equations are presented in the left columns. The right columns are for the other regions. In order for a market to be "dominant", the coefficient on the other market error correction term needs to be insignificant in the dominant market equation and the coefficient of the dominant market error correction terms needs to be significant in the other market equation.

As shown in Panel A, the error correction term is significant in the equation for the other market, but insignificant for the New York equation in ten cities. This implies that the market dynamics in New York forces the price in the other ten cities, but not vice versa. Regarding the London market, its market dynamics are significantly driving prices (and not vice versa) in 15 cities. Particularly, we can see that real estate prices in New York and Tokyo are also forced by the London market (the right column of Panel B in Table 3), but the London real estate price is not forced by the real estate price dynamics in New York and Tokyo (see the left column of Panel B in Table 3). Regarding Tokyo, as shown in Panel C, the price dynamics of the Tokyo real estate market are not solely forcing price dynamics in any of the other cities. The fact that London price dynamics are forcing in 15 other cities and not vice versa suggests that London is the dominant market. Therefore, in the following estimations, we choose London as the dominant city.

[Place Table 3 about here]

The cointegration of real estate market price with the macroeconomic conditions for each city is also tested using Johansen statistics, with the specification of unrestricted intercept and restricted trend. The number of ranks at the 5% significance level for each city is reported in Table 4. As we can see from Table 4, except for Boston, the real estate market is long term adjusted by the included macroeconomic conditions.

[Place Table 4 about here]

## 3.2 Estimates of the price diffusion model

Table 5 summarizes the regression results from Equations (1) and (2). It should be noted that examining individual coefficients in the models presented may be potentially misleading because of the various layers of dynamics (e.g. own lagged effects, contemporaneous, short- and long-run effects of dominant and neighbouring markets, feedback effects with macroeconomic variables etc.). Nevertheless, we will provide a short interpretation of some stylised facts from the analysis. The results that take all layers of model dynamics into account are shown by calculating the impulse response functions in Section 3.3.

The value of the error correction coefficient $\phi_{i,0}$ implies the correcting process to the price in London and $\phi_{i,s}$ represents the convergence to prices in their local neighbours.[12] Of the 22 cities, five markets (Munich, Atlanta, Singapore, Seattle and Washington DC) have a significant error correction coefficient to the price in London, indicating the convergence of the price relationship in these cities and London. All significant error correction coefficients are negative, indicating convergence to the leading market. Regarding convergence to local neighbours, our results show a significant long term convergence of real estate price to their neighbours in seven out of 22 cities (Paris, Stockholm, London, Seoul, LA Metro, Miami, and New York).

The short term dynamics and spatial effects are captured by the coefficient of domestic lagged effect, the lagged effects of the local neighbouring markets and the lagged and contemporaneous effect from London. The optimal number of lags, decided by AIC, is reported in column 8, 9 and 10, as Q1, Q2 and Q3 respectively. A significant impact of the lagged price in local neighbouring markets is found in 11 cities. We find a significant lagged impact of changes in London prices in nine cities and a significant contemporaneous impact of London prices in three cities. The Wu-Hausman statistic is used to test our prior assumption that the price change in London is weakly exogenous to the evolution of the real estate market in other regions. The test results are reported in the last column. The null hypothesis cannot be rejected in 19 out of the 21 cities (excluding London). This confirms that price changes in London are indeed weakly exogenous and reinforces the leading market status of London.

[12] Please note again that "neighbouring" or "local" here is defined by a high score on our connectivity matrix not by geographical proximity. In our robustness tests, the geographic proximity is also considered.

[Place Table 5 about here]

## 3.3 Spillover effects and interaction with the real economy

The ripple effects are measured by the response of real estate prices to a one standard deviation shock in the London real estate market (channel i) and neighbouring markets (channel ii). Figure 3 illustrates the cumulative responses to a (positive) London shock (the channel i spillover).[13] The solid line is the response and dotted lines display the 90% bootstrapped confidence bounds for each market. In addition to the responses for individual markets, we also calculate the average response and corresponding confidence bounds across the 22 cities ($\overline{IRF}$). These concern weighted averages, where the weights are based on office market transaction volume.[14]

As shown in Figure 3, on average across 22 cities, a significant positive response is found from the first to the eighth quarter after the shock. The response is the largest in the sixth quarter after the shock, amounting to 0.76%. Moreover, we find significant individual responses in 19 out of the 22 cities. In London and Singapore, the responses exceed 1.5%.

In Amsterdam, however, the response is significantly negative. A negative response could be explained by capital switching, where investors switch capital from one city to another. Amsterdam is sometimes regarded as an alternative market that could benefit from extra investments in the aftermath of Brexit.[15] Indeed, this story would be consistent with our results. We, however, also note that Brexit happened at the end of our sample period and feel the evidence is too thin to conclude that capital switching is in fact the reason for the negative response. Alternatively, this could be caused by the rather odd behaviour of the Amsterdam market in the aftermath of the GFC. The Amsterdam CRE market fell early, in 2007 and only started recovering in late

[13] Please note that all responses are symmetric. The response for London indicates a shock in the own market.

[14] The average IRF is: $\overline{IRF} = \sum_{i=1}^{22} v_i IRF_i$, where $IPF_i$ is the response in city $i$, and $v_i$ is the percentage of trading volume in city $i$ to total trading volume. The confidence interval is calculated based on the standard errors of the weighted average responses: $SD(\overline{IRF}) = \sqrt{\sum_{i=1}^{22} v_i^2 var(IRF_i) + \sum_{i=1}^{22} \sum_{j=i+1}^{22} 2 v_i v_j cov(IRF_i, IRF_j)}$. Here, $var(IPF_i)$ is the variance of responses in city $i$, $cov(IPF_i, IPF_j)$ is the covariance between the responses in city $i$ and $j$.

[15] Anecdotally, Reuters reported in February 2021 reported that over 200 firms had relocated to the Netherlands in the aftermath of the 2016 EU referendum vote.

2013, whereas many other markets showed recovery well before that. This prolonged period of price decrease could be reflected in the negative response.[16]

[Place Figure 3 about here]

Figure 4 displays the responses to a one standard deviation increase in real estate price in neighbouring markets (channel ii spillover). On average, there is a significant positive response to the neighbouring market shocks from the first to the tenth quarter after that shock. In the third quarter, the response is highest, amounting to 0.78%. Moreover, significant positive responses are found in 15 of the 22 cities. Again, Amsterdam shows a negative response in the long-run (after more than two years), most likely because of similar issues as discussed before.

[Place Figure 4 about here]

Figure 5 shows the interaction between commercial real estate markets and the real economy. In Panel A, we see that the real estate price responds significantly negatively to an interest rate shock from the fourth to the twelfth quarter after the shock, amounting to -3.2% after three years. As expected, the effect of GDP on commercial real estate pricing is significantly positive in the first three years after the shock. Exchange rate shocks have a small positive effect in the short-run (during the first four quarters). The effect of credit on prices also is positive, but only marginally significant.

In the model, we also take feedback effects from the commercial real estate market to the real economy into account. We observe some significant feedback effects. In particular, we find that GDP and credit growth respond positively to shocks in commercial real estate prices. Not only do domestic shocks affect the domestic real economy, but ripple effects from the London real estate market and neighbouring markets significantly spill over to GDP of the "home" country. Even though the responses are significant, we note that they are economically small. The largest effect is found from a domestic real estate shock after four quarters: A positive one standard deviation shock in domestic pricing results in about 0.015% growth in GDP. Note that these findings provide evidence for an amplification effect between real estate prices and

[16]Dropping the Amsterdam market from the sample yields robust results.

the real economy. To illustrate this, consider the example of a negative commercial real estate price shock. This results in a decrease in credit and GDP, which further dampens commercial real estate prices. We additionally find that interest rates respond positively to shocks in commercial real estate prices. This most likely reflects the behaviour of central banks as a response to the GFC. After the collapse of the economy that was paired with negative price shocks in commercial real estate globally, central banks generally lowered interest rates. Note that —as opposed to the interaction with GDP and credit growth— this does not amplify a shock. Consider again a negative price shock. This results in a decrease in interest rates, which in turn increases prices, other things equal.

[Place Figure 5 about here]

We further show the FEVD of commercial real estate prices in the 22 markets based on the full model in Figure 6. We illustrate the average percentage variance explained by different shocks (Figure 6a) and the percentage explained variance to shocks to the leading market (channel i, Figure 6b) and neighbouring markets (channel ii, Figure 6c) four quarters and twelve quarters after the shock. As shown in Figure 6a, in the short-run, shocks to the own market explain the largest proportion of the variance in most markets. On average, across the 22 cities, a one standard deviation shock from the London market and from the neighbouring markets each explains around 15% of the forecast variance of the real estate price in the sixth quarter after the shock. There is heterogeneity in the explanatory variance of both spillover channels. As shown in Figure 6b, in London, Singapore, Seattle, Los Angeles, and Washington DC, shocks to the leading market explain over 20% of price forecasting variance in the fourth quarter after the shock. In Los Angeles and Seattle, over 20% of price forecasting variance is attributable to the shocks in neighbouring markets in the short term.

[Place Figure 6 about here]

In the long-run (after 12 quarters) the picture reverses. On average, the idiosyncratic shocks from the domestic market, shocks from London and neighbouring markets all three individually explain only 5% of variance. Instead, macroeconomic fundamentals become much more important in explaining prices in the long-run. On average, for the 22 cities, over 90% of the variance in prices can be explained by these factors. Of these factors, shocks to interest rates and credit are found to be the most important (42% and 31% of the total variance, respectively). Shocks to GDP and exchange rate each explain around 10% of forecasting error variance in the long-run.

### 3.4 Asymmetry in times of crisis

Because global co-movements generally become larger in times of crisis (Van Dijk and Francke, 2021), we suspect that spillover effects may also change. In order to capture an asymmetric effect during the crisis period, we add a crisis dummy variable ($I_t$) and interactions with the spillover variables into the system.[17] An F-test confirms that adding crisis dummy variables significantly improves the model fit compared the baseline model (Equations (1) and (2)) at the 1% level. In this section, we will focus on the IRFs; the regression coefficients are available upon request.

The responses during the tranquil and crisis period are illustrated in Figure 7. The red lines represent the responses in the crisis period and the black lines are for the tranquil period. Panel (a) shows the responses to a shock in the leading market (channel i) and Panel (b) reports the responses to one standard deviation shocks in the neighbouring markets (channel ii). The model becomes more cumbersome to estimate due to a smaller effective sample size for the crisis and tranquil periods. This is indicated by the relatively large error bounds, which make the graphs more difficult to interpret visually.

Comparing the average responses across the 22 cities in tranquil and crisis times, we observe that the responses are significantly higher in crisis times compared to tranquil times from the first to the eighth quarter.[18] More specifically, the leading market effect is only found to be significant in times of crisis for that two year period. Even with the relatively wide confidence bounds, we find positive responses in 19 out of the 22 markets. In 14 out of 22 cities, the responses to a London shock increase significantly

[17]We add the following terms to Equation (1): $\phi^I_{0,s}(y_{0,t-1} - y^s_{0,t-1})I_t$ and $\sum_{q=1}^{Q2} b^I_{0,q}\Delta y^S_{0,t-q}I_t$. To Equation (2) we add: $\phi^I_{i,s}(y_{i,t-1} - y^s_{i,t-1})I_t$, $\phi^I_{i,0}(y_{i,t-1} - y_{0,t-1})I_t$, $\sum_{q=1}^{Q2} b^I_{i,q}\Delta y^S_{i,t-q}I_t$, and $\sum_{q=0}^{Q3} c^I_{i,q}\Delta y_{0,t-q}I_t$. $I_t$ is a dummy variable with the value of one during the period from 2008Q1 to 2011Q1 and zero otherwise. $\phi^I_{i,0}$ and $c^I_{i,q}$ capture the change in the ripple effect from the dominant market during the crisis period. $\phi^I_{0,s}$, $b^I_{0,q}$, $\phi^I_{i,0}$ and $b^I_{i,q}$ capture the change in the influence of the neighbouring markets.

[18]A significant difference is defined when the lower bound of the 90% confidence interval for the responses in the crisis period does not overlap the upper bound of the 90% confidence interval for the responses in the tranquil period.

during the crisis period. In tranquil times, the effect is not significant on average. For individual cities, only seven out of the 22 markets respond significantly positively to the shocks in London real estate market. We also observe more (individual) negative responses during tranquil times, perhaps reflecting capital switching occurring in these times (see also the earlier discussion on this topic in Section 3.3.)

However, unlike the dominant market effect, significant responses to the shocks in the neighbouring markets occur at an aggregate level and also in many of the individual 22 markets, even during the tranquil period. On average, during the crisis and the tranquil period, a significant response to the neighbouring market shocks lasts for around eighteen months. However, the magnitude of the response grows during the crisis period. The increase in the average response is statistically significant between the third and the eighth quarter after the shock. At a city-level, significant increases are found in six out of the 22 cities.

[Place Figure 7 about here]

If we compare Figure 6 to Figure 8, we observe that spillovers are much more pronounced in times of crisis.[19] The contribution of the first channel, the leading market effect, increases to 35% of price forecasting error variance in the fifth quarter after the shock (compared to a maximum of 15% for the full sample). The contribution of the second channel, the neighbouring market effect, also rises to 21% of forecasting variance in the third quarter after the shock (compared to 15% for the full sample). This confirms the asymmetric response in the crisis and tranquil periods, most notably for the leading market effect. In the fourth quarter after the shock, the price forecasting error variance explained by the shocks to the leading market exceeds 20% in 13 out of the 20 cities, and in ten cities, the contribution by the shocks to neighbouring market exceeds 20%. In the short term, in Paris, Stockholm, Sydney, Boston, and Washington DC, the real estate price is largely influenced by the leading market shock. In San Francisco, the price is dominated by the neighbouring market effect, while in Seattle, Houston, New York and New York, prices are influenced by both. Figure 8 further shows that the variance of commercial real estate prices in the long-run is still dominated by macroeconomic factors.

[19] We only show the FEVD for the crisis sample to conserve space, results available upon request.

[Place Figure 8 about here]

In general, this section shows that both the leading market effect (channel i) and neighbouring market effect (channel ii) become more predominant in times of crisis. In fact, the dominant market effect found in the previous section mostly stems from the GFC. The neighbouring market effect, by contrast exists during all parts of the real estate cycle.

# 4 Robustness checks

## 4.1 Global market factor

Concerns may arise that the ripple effect from the dominant market is in fact capturing co-movement in the global markets and not necessarily a London spillover effect. Therefore, we follow Pesaran (2006) by adding a transaction volume weighted average price index into the system as a measure of the commonality in global markets. Hence, the model of the dominant market is given by:

$$\Delta y_{0,t} = \phi_{0,s}(y_{0,t-1} - y^{s}_{0,t-1}) + \phi_0^X \beta_0^{'}(z_{0,t-1} - \iota_0 - \zeta_{0,t-1}) + \bar{\phi}_{0,s}(y_{0,t-1} - \bar{y}_{t-1}) + a_0 + \sum_{q=1}^{Q1} a_{0,q}\Delta y_{0,t-q} + \sum_{q=1}^{Q2} b_{0,q}\Delta y^{S}_{0,t-q} + \sum_{q=1}^{Q4} \lambda_{0,q}\Delta x_{0,t-q} + \sum_{q=1}^{Q5} \vartheta_{0,q}\Delta \bar{y}_{t-q} + \varepsilon^{y}_{0,t}. \tag{6}$$

For the remaining N regions are given by

$$\begin{aligned}\Delta y_{i,t} = {} & \phi_{i,s}(y_{i,t-1} - y^{s}_{i,t-1}) + \phi_{i,0}(y_{i,t-1} - y_{0,t-1}) + \phi_i^X \beta_i^{'}(z_{i,t-1} - \iota_i - \zeta_{i,t-1}) + \\ & \bar{\phi}_{i,s}(y_{i,t-1} - \bar{y}_{t-1}) + a_i + \sum_{q=1}^{Q1} a_{i,q}\Delta y_{i,t-q} + \sum_{q=1}^{Q2} b_{i,q}\Delta y^{S}_{i,t-q} + \sum_{q=0}^{Q3} c_{i,q}\Delta y_{0,t-q} + \\ & \sum_{q=1}^{Q4} \lambda_{i,q}\Delta x_{g,t-q} + \sum_{q=1}^{Q5} \vartheta_{i,q}\Delta \bar{y}_{t-q} + \varepsilon^{y}_{i,t},\end{aligned} \tag{7}$$

for $i = 1, ..., N$. $\bar{y}_t$ is the transaction volume weighted average price of all $N+1$ cities,

$\bar{y}_t = \sum_{i=1}^{N} vol_{i,t} y_{i,t}$ , and $vol_{i,t}$ is the share of transaction volume of total global volume in city $i$ period $t$. $\bar{\phi}_0$ and $\bar{\phi}_i$ capture the adjustment to the global movements in prices, and $\vartheta_{0,q}$ and $\vartheta_{i,q}$ measure the short term co-movement with the global market. Comparing the response to the leading market and to neighbouring markets based on the model without the average price (Equation 2) and in the model with the average price (Equation 7) should test whether the ripple effect and short term co-movement are driven by global commonality in real estate markets. In estimating the response to the London real estate shock and to the neighbouring market shock, $\bar{y}_{t-q}$ is treated as an exogenous global factor. Hence, the coefficients for global factors, including $\bar{\phi}_{0,s}$, $\vartheta_{0,q}$, $\bar{\phi}_{i,s}$ and $\vartheta_{i,q}$, are not used in the calculation of the response to real estate shocks in London and neighbouring markets. However, note that the spillover effects are estimated *ceteris paribus* on this global market factor.

Figure 9 illustrates the response to the shocks in the London market (Panel a) and the shock to neighbouring markets (Panel b). It is based on the average response across the 22 cities. Red lines represent the responses when the average price of the 22 cities is included. Black lines represent the responses without it, as in our baseline model. When the commonality in the global real estate market is controlled for, there are only marginal changes in the two effects of the two spillover channels. Regarding the responses in individual cities, there is no significant difference in the responses to the London market shock and neighbouring market shocks in all 22 cities.[20] This indicates that adding the global effect does not markedly change the magnitude of the two spillover channels.

[Place Figure 9 about here]

## 4.2 Alternative measures for interconnectedness

Further concerns could arise due to the use of the overlap in property ownership as the measure of the connectivity between real estate markets. In the baseline model, neighbouring markets are defined as markets with a high overlap in ownership. However, previous literature has documented other measures of connectivity, such as geographic

[20] The individual responses of this and further robustness checks are omitted to conserve space, these are available upon request.

distance, the overlap in the location of advanced producer service (APS) firms[21], and being in the same country or currency zone. Therefore, in this robustness check, we add alternative matrices into the system as an additional definition of neighbouring markets. Hence, the resultant model of the dominant market becomes:

$$\begin{aligned}\Delta y_{0,t} = \phi_{0,s}(y_{0,t-1} - y^s_{0,t-1}) + \phi_0^X \beta_0^{'}(z_{0,t-1} - \iota_0 - \zeta_{i,t-1}) + \phi_0^*(y_{0,t-1} - y^*_{t-1}) + a_0 + \\ \sum_{q=1}^{Q1} a_{0,q}\Delta y_{0,t-q} + \sum_{q=1}^{Q2} b_{0,q}\Delta y^S_{0,t-q} + \sum_{q=1}^{Q4} \lambda_{0,q}\Delta x_{0,t-q} + \sum_{q=1}^{Q5} \vartheta_{0,q}\Delta y^*_{t-q} + \varepsilon^y_{0,t}.\end{aligned} \tag{8}$$

For the remaining N regions the model is given by:

$$\begin{aligned}\Delta y_{i,t} = \phi_{i,s}(y_{i,t-1} - y^s_{i,t-1}) + \phi_{i,0}(y_{i,t-1} - y_{0,t-1}) + \phi_i^X \beta_i^{'}(z_{i,t-1} - \iota_i - \zeta_{i,t-1}) + \\ \phi_i^*(y_{i,t-1} - y^*_{t-1}) + a_i + \sum_{q=1}^{Q1} a_{i,q}\Delta y_{i,t-q} + \sum_{q=1}^{Q2} b_{i,q}\Delta y^S_{i,t-q} + \sum_{q=0}^{Q3} c_{i,q}\Delta y_{0,t-q} + \\ \sum_{q=1}^{Q4} \lambda_{i,q}\Delta x_{g,t-q} + \sum_{q=1}^{Q5} \vartheta_{i,q}\Delta y^*_{t-q} + \varepsilon^y_{i,t},\end{aligned} \tag{9}$$

for $i = 1,...,N$. $y^*_t$ is the average price of neighbouring cities based on the alternative definition of connectivity, $y^*_{i,t} = \sum_{j=0}^N s^*_{i,j} y_{j,t}$ with $\sum_{j=0}^N s^*_{i,j} = 1$, for $i = 0,1,2,...,N$ and $s^*_{i,j} \geq 0$. $\phi_0^*$ and $\phi_i^*$ quantify the influence from the alternative neighbouring markets in the long term while $\vartheta_{0,q}$ and $\vartheta_{i,q}$ are for the short term co-movement. We then calculate the response with only one matrix (based on equation 1 and 2) and the response based on two matrices (Equation 8 and 9).

Figure 10 compares the response to shocks to the neighbouring markets based on Equations (1) and (2) (in black lines) and the response based on Equations (8) and (9) (in red lines). Panel (A) adds geographic distance between cities. Panel (B) adds the overlap in the location of APS firms. Panel (C) adds the matrix based on whether the two cities are in the same currency area. Panel (D) adds the matrix based on whether

[21] The Globalization and World Cities ranking (GaWC) define connectivity between cities using the location of 100 leading firms in accounting, banking, financial, advertisement and other firms. The weight matrix can be constructed by the proportion of same APS firms between pairs of cities. The commonality in global firms also reflects the financial and economic interconnectedness between cities.

the two cities are in the same country. If we compare the average response before and after adding the second weight matrices, the differences are marginal.

Overall, the responses are robust when the alternative matrix is included, confirming that the alternative definitions do not add much additional information to our connectivity measure. It should be noted that we are not claiming that the overlap in the property ownership is the *only* channel that leads to the short-term co-movement with the other cities. As shown in Zhu and Lizieri (2021), a higher common property ownership tends to happen between geographically close cities, cities in the same country or in the same currency zone, or with a higher proportion of same APS firms. This may result in a positive correlation between the ownership matrix and the alternative matrix. Our results simply indicate that the ownership matrix adequately captures connectivity between the commercial real estate markets, which might essentially be caused by geographic closeness or similarity in the APS firms etc. and, in turn, this has implications for price dynamics.

[Place Figure 10 about here]

## 4.3 Endogenous weight matrix

When economic or financial variables are used to define the weights, such as bilateral trade or linked ownership matrix, endogeneity issue may arise due to the correlation between $s_{i,j,t}$ and $y_{i,t}$. In other words, the assumption of "exogenous weights" may be violated, especially for economic or financial weights. As investors may strategically select which cities to invest, real estate market performance and the ownership overlap ratio could be endogenously related. For instance, opportunistic funds may be attracted by cities with higher investment yields, such as cities in some emerging countries, but other risk-averse investors may be interested in well-developed real estate markets, such as London. As a result, different types of investors may cluster in some cities due to the real estate market performance of these cities. This bilateral relationship may result in endogeneity and lead to biased results. We follow Kelejian and Piras (2014) and use instruments ($D_{i,j,t}$) to estimate the weights. The instruments include geographic distance, being in the same country, cultural distance, being in the same legal system, being in the same currency unit and the overlap ratio of international firms:

$$s_{i,j,t} = \tau + \varpi ln(D_{i,j,t}) + \varsigma D_t^{year} + e_{i,j,t}. \tag{10}$$

We follow the argument of Kelejian and Piras (2014) and assume that these instruments should be (largely) exogenous to the performance of the real estate market. We first regress the ratio of properties owned by the same investors between each pair of cities on these instrumental variables (stage one regression). The results for the first stage regression are presented in Table 8 in Appendix B. All instruments are significant with an expected sign. An F-test for the relevance of the instruments is also significant at the 1%-level[22]. In the second stage regression, we run the regression again with the estimated weights ($\widehat{s_{i,j,t}}$). In other words, instead of $y^s_{i,t}$, we have $\widehat{y^s_{i,t}}$ in Equation (1) and Equation (2), where $\widehat{y^s_{i,t}} = \sum_{j=0}^{N} \widehat{s_{i,j,t}} y_{i,j,t}$:

$$\begin{aligned} \Delta y_{0,t} = {} & \phi_{0,s}(y_{0,t-1} - \widehat{y^s_{0,t-1}}) + \phi_0^X \beta_0^{'}(z_{0,t-1} - \iota_0 - \zeta_{i,t-1}) + a_0 + \\ & \sum_{q=1}^{Q1} a_{0,q} \Delta y_{0,t-q} + \sum_{q=1}^{Q2} b_{0,q} \Delta \widehat{y^S_{0,t-q}} + \sum_{q=1}^{Q4} \lambda_{0,q} \Delta x_{0,t-q} + \varepsilon^y_{0,t}. \end{aligned} \tag{11}$$

For the remaining N regions the model is given by:

$$\begin{aligned} \Delta y_{i,t} = {} & \phi_{i,s}(y_{i,t-1} - \widehat{y^s_{i,t-1}}) + \phi_{i,0}(y_{i,t-1} - y_{0,t-1}) + \phi_i^X \beta_i^{'}(z_{i,t-1} - \iota_i - \zeta_{i,t-1}) + \\ & a_i + \sum_{q=1}^{Q1} a_{i,q} \Delta y_{i,t-q} + \sum_{q=1}^{Q2} b_{i,q} \Delta \widehat{y^S_{i,t-q}} + \sum_{q=0}^{Q3} c_{i,q} \Delta y_{0,t-q} + \sum_{q=1}^{Q4} \lambda_{i,q} \Delta x_{g,t-q} + \varepsilon^y_{i,t}, \end{aligned} \tag{12}$$

We then, once again, calculate the IRFs to examine both spillover channels (the leading market effect and the neighbouring market effect). We also bootstrap the

[22] Ideally, we should also test the exogeneity of these instruments. The standard method is Sargan–Hansen test. However, as is the case in this paper, data often have a different dimension in the first and second stage. Hence, we are not able to perform the Sargan-Hansen test here. An exogeneity test for instrumented weights in the spatial econometric models could be a topic for future research. Additionally, we also carefully select instruments that should be exogenous to city office market performance, such as variables based on the geographic location of the city and variables based on the overall economy of the cities.

confidence interval by bootstrapping both the residual from stage one and stage two. Figure 11 illustrates the average response across the 22 cities. The response from the baseline model is shown in black. The response based on the instrumented weights is shown in red. As shown in 11, the results are robust. The differences between the responses are very marginal and insignificant.

[Place Figure 11 about here]

## 4.4 Correlation in global economies

In Equation (3), we do not consider co-movement in global economies. In practice, monetary policy and economic growth are very likely to be correlated across countries. Therefore, as a robustness check, we apply a "Global VAR model" and consider co-movement in the economic variables across countries. We follow previous literature (see e.g.,Pesaran et al. (2004), Chudik and Pesaran (2016) and many others) and use bilateral trade as the linkages between countries. Equation (3) becomes:

$$\Delta x_{g,t} = \alpha_g + \kappa_g \ddot{\eta}_g'(\ddot{z}_{g,t-1} - \iota_g^x - \zeta_g^x(t-1)) + \sum_{p=1}^{P^1} \varphi_{g,p}\Delta y_{g,t-p} + \sum_{p=1}^{P^1} \delta_{g,p}\Delta x_{g,t-p} + \sum_{p=0}^{P^2} \delta_{g,p}^W \Delta x_{g,t-p}^W + \varepsilon_{g,t}^x, \tag{13}$$

where $x_{g,t-p}^W$ denotes the spatial variables for country $g$. It is defined by $x_{g,t}^W = \sum_{h=1}^{Nc} w_{g,h,t} x_{h,t}$ for $g,h = 1,2,\ldots,Nc$. and $w_{g,h,t} > 0$. $w_{g,h,t}$ is the weight for the importance of country $h$ for country $g$'s economy. It is based on the trade between the two countries as a proportion of the total trade of country $g$ with all other countries:

$$w_{g,h,t} = \sum \frac{Export_{g,h,t} + Export_{h,g,t}}{\sum_g Export_{g,g,t} + \sum_h Export_{h,h,t}}, \tag{14}$$

where $Export_{g,h,t}$ is the export of country $g$ to country $h$ at period t. $w_{g,h,t}$ is standardized to between zero and one. Moreover, $\ddot{z}_{g,t-1} = \begin{bmatrix} x_{g,t-1} & x_{g,t-1}^W & y_{g,t-1} \end{bmatrix}$. $\kappa_g$ is a vector of adjusted coefficients. $\ddot{\eta}_g$ is a $(2K+1) \times R_g^X$ matrix of coefficients for the cointegration relationship. $\eta_g'$ can be partitioned as:

$$\eta_g' = \begin{bmatrix} \eta_g' \\ \eta_{wg}^{W\prime} \\ \eta_g^{Y\prime} \end{bmatrix}. \tag{15}$$

Following Dees et al. (2007), $x_{g,t}^W$ are treated as weakly exogenous, which implies that $x_{g,t}^W$ is long-run forcing $x_{g,t}$. The IRFs will be based on Equations (1), (2) and (13).

The responses to the leading market and neighbouring market shocks are shown in Figure 12. Again, the black lines show the responses based on the baseline model and the red lines show the response after the co-movement across global economic variables are included in the system. The Figure 12 shows that the responses to the London shock becomes slightly more persistent. This difference, as the difference of the neighbouring market channel, is insignificant.

[Place Figure 12 about here]

## 4.5 Alternative orderings in the identification of structural shocks

In our baseline model, the ordering of the markets in the first block (i.e. the "real estate block") of the model is based on commercial real estate trading volume of the individual cities. Here, we consider an alternative ordering based on the centrality of the market. Centrality is defined as the weighted in-degree centrality of the linked ownership weight matrix. This implies that more connected cities are less likely to be contemporaneously influenced by the other markets and are more likely to influence other markets. The results are displayed in Figure 13a. Again, London is ordered as the first and the remaining cities are ordered based on their centrality. The black lines denote the response based on the baseline model, and the red lines show the responses using this ordering. As shown in Figure 13a, the results are, once again, robust.

There could also be concerns that there are contemporaneous correlations between the shocks in real estate prices and macroeconomic variables. To address this issue, we define an alternative first "block" of variables. In this alternative first block we include the UK macroeconomic variables and the London real estate price. The considered ordering is: interest rate, credit to GDP ratio, exchange rate, real estate price, and the GDP. The spillover results remain robust (Figure 13b).

[Place Figure 13 about here]

Next, we further consider different assumptions on the contemporaneous correlation of the variables in the system. More specifically, we create "blocks" of all real estate and macroeconomic variables per country. Thus, matrix $\mathbf{P_0}$ is now set as one block for each country. Country blocks are then ordered according to GDP. This assumption implies that countries with a larger economic size are less likely to be influenced by other countries. Note that this basically assumes no contemporaneous cross-country correlation between the macroeconomic variables. For countries with more than one included real estate market, they are ordered by city-level office trading within this country block. The variables within each country block are ordered as follows: interest rate, credit, exchange rate, real estate price, and GDP. The responses based on this ordering are illustrated by red lines in Figure 14. The black lines illustrate the response based on our baseline model. As shown in Figure 14, the responses are qualitatively robust by this alternative ordering. As expected, when the simultaneous cross-country correlation in the macroeconomic variables is restricted to zero, the responses to the real estate shock in London and in foreign real estate markets slightly drop. However, except for the GDP response to the real estate shocks in neighbouring markets, the difference in the responses are all insignificant.

[Place Figure 14 about here]

## 4.6 Re-sampling the Cities

In our sample, 11 out of the 22 cities are US cities. To address the issue that US cities may be overrepresented in our main sample, we perform a robustness test by randomly dropping 6 US cities for 100 iterations. Then, each time, our sample includes 16 cities with 11 non-US cities and 5 US cities. Figure 15 reports the impulse response to the leading market shock and neighbouring market shocks. The black and red lines illustrates the responses based on a sample including all 22 and 16 cities, respectively. As shown in Figure 15, the responses of real estate prices in other cities to the London real estate market shock remain robust. The estimated average response of based on 22 cities is within the confidence interval of that based on 16 cities. Regarding the response to the shocks from neighbouring markets, the response decreases when some US cities are dropped from the sample. However, the responses remain statistically significant and are economically comparable. Hence our results do not seem too seriously affected by the uneven distribution of the cities from different countries.

[Place Figure 15 about here]

# 5 Conclusion

This paper provides empirical evidence on the international propagation of property price shocks across 22 markets between 2005 and 2019. We identify two price diffusion channels: (i) a dominant market channel and (ii) a "neighbouring" market channel based on the degree of overlap in ownership. The empirical results suggest that, among the 22 studied markets, London is the dominant market. We document significant propagation of price shocks from London to the other markets in the short term. Besides the first channel, we additionally show empirical evidence for the second channel in the short-run. We further find empirical evidence that real estate price spill over to the real economy. Particularly, we find a positive feedback loop between real estate spillovers, GDP and credit, resulting in an amplifying mechanism. The spillover channels explain a noticeable proportion of forecasting error variance in the short-run. In the long-run, macroeconomic factors, such as interest rates, GDP, credit ratios, and the exchange rate, play a much more critical role.

We further explore a potential asymmetry in the effect of the two channels during crisis and tranquil times. We show that both channels become much larger in times of crisis. This holds most notably for the dominant market channel, which is even found to be insignificant for many markets during non-crisis times. Hence, this suggests that the significance of this channel over the full sample mostly stems for the GFC. The neighbouring market channel is found to be significant during all parts of the sample. Note that this finding has implications for financial stability: Especially in times of crisis —when risks are the greatest— global spillovers in commercial real estate markets are more likely to occur.

Our results imply that commercial real estate prices are globally interlinked through at least two channels: a dominant markets and a neighbouring market channel. Moreover, macroeconomic fundamentals such as GDP, interest rates, credit, and exchange rates affect and are affected by commercial real estate price movements. Therefore, global real estate movements can potentially affect local real estate movements and the local real economy. These are risks that could potentially affect global financial stability and should therefore be monitored properly.

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# Tables

Table 1: Summary statistics

| | Mean | Std Deviation | Max | Min | 75% | 50% | 25% |
|---|---|---|---|---|---|---|---|
| **City Level Data** | | | | | | | |
| Log of Price | 4.675 | 0.335 | 5.804 | 3.897 | 4.849 | 4.63 | 4.451 |
| Ownership Overlap Ratio | 0.164 | 0.152 | 0.812 | 0.002 | 0.223 | 0.106 | 0.054 |
| **Country Level Data** | | | | | | | |
| Long-term rate | 3.51% | 1.38% | 6.55% | 0.56% | 4.55% | 3.59% | 2.49% |
| GDP (Million USD) | 795 | 1188 | 5036 | 60 | 785 | 344 | 129 |
| Credit to GDP ratio | 194.56 | 40.22 | 324.00 | 110.10 | 206.30 | 183.70 | 168.70 |
| Exchange Rate (per SDR currency unit) | 167.76 | 476.85 | 2113.88 | 0.76 | 11.78 | 1.78 | 1.19 |

Table 2: Results of trace cointegration tests with unrestricted intercepts and restricted trend coefficients in bivariate VAR (1) models of New York, London, and Tokyo

| | Panel A: New York | | Panel B: London | | Panel C: Tokyo | |
|---|---|---|---|---|---|---|
| | H0: $r=0$ vs H1: $r \geq 1$ | H0: $r \leq 1$ vs H1: $r=2$ | H0: $r=0$ vs H1: $r \geq 1$ | H0: $r \leq 1$ vs H1: $r=2$ | H0: $r=0$ vs H1: $r \geq 1$ | H0: $r \leq 1$ vs H1: $r=2$ |
| Paris | 36.4*** | 13.3** | 34.4*** | 12.7** | 23.2 | 10.4 |
| Munich | 35.4*** | 12.8** | 36.1*** | 17*** | 28.2** | 11.1* |
| Amsterdam | 34.7*** | 9.87 | 46.7*** | 8.88 | 24* | 10.4 |
| Stockholm | 39.4*** | 10.3 | 36.5*** | 9.74 | 31.7*** | 13.8** |
| London | 27.7** | 7.14 | - | - | 24* | 8.48 |
| Melbourne | 25.5* | 5.48 | 32.8*** | 7.51 | 17.2 | 6.37 |
| Sydney | 24.8* | 7.58 | 30.1** | 13.4** | 15.5 | 5.85 |
| Hong Kong | 40.1*** | 12.2* | 26.8** | 7.35 | 34.1*** | 9.91 |
| Tokyo | 30.3** | 8.99 | 24* | 8.48 | - | - |
| Singapore | 46.4*** | 18.4*** | 27.1** | 10.2 | 32.9*** | 11.3* |
| Seoul | 43.8*** | 5.47 | 31.9*** | 9.47 | 24.2* | 6.31 |
| Atlanta | 33.2*** | 10.3 | 30.4** | 8.34 | 28.9** | 11.2* |
| Boston | 31.6*** | 4.14 | 32.1*** | 8.13 | 26.7** | 10.7* |
| Chicago | 36.1*** | 11.6* | 32.7*** | 10.5 | 30.8** | 8.6 |
| Dallas | 29.4** | 7.68 | 24.7* | 6.91 | 24.7* | 7.95 |
| Houston | 24.5* | 5.38 | 23.3 | 7.36 | 23.8* | 10.6 |
| Los Angeles | 40.2*** | 15.6** | 24.3* | 7.4 | 25.2* | 8.14 |
| Miami | 44.4*** | 14.2** | 36.1*** | 13.1** | 44.6*** | 17.4*** |
| New York | - | - | 27.7** | 7.14 | 30.3** | 8.99 |
| San Francisco | 39.3*** | 13.2** | 33*** | 14.4** | 23.9* | 7.13 |
| Seattle | 40.8*** | 14.9** | 34.3*** | 11.2* | 33.7*** | 8.97 |
| Washington | 46.2*** | 19.1*** | 30.7** | 9.33 | 36.5*** | 9.95 |

Notes: the trace statistics reported are based on the bivariate VAR (1) specification of return series of London, New York and other markets, with intercepts and restricted trend coefficients. The trace statistic is the cointegration test statistic of Johansen. ***, ** and , *, denote significance at the 1%, 5%, and 10% levels, respectively.

Table 3: Error correction coefficients in cointegration bivariate VAR (1) of prices in New York, London, and Tokyo.

| | Panel A: New York | | Panel B: London | | Panel C: Tokyo | |
|---|---|---|---|---|---|---|
| | ECT New York | ECT Other | ECT London | ECT Other | ECT Tokyo | ECT Other |
| | $p_{0,t}$ | $p_{i,t}$ | $p_{0,t}$ | $p_{i,t}$ | $p_{0,t}$ | $p_{i,t}$ |
| Paris | -0.026 | -0.050*** | -0.009 | -0.044*** | -0.080*** | 0.031* |
| Munich | 0.001 | -0.036** | 0.002 | -0.045*** | -0.027 | 0.015 |
| Amsterdam | 0.014 | -0.036*** | 0.006 | -0.026*** | 0.025* | -0.056*** |
| Stockholm | -0.070*** | -0.026 | -0.042 | -0.044*** | -0.068*** | 0.038*** |
| London | -0.062** | -0.026 | - | - | -0.041*** | 0.019 |
| Melbourne | -0.032 | -0.001 | -0.012 | -0.061 | -0.041*** | 0.045*** |
| Sydney | -0.010 | -0.007 | 0.010 | -0.006 | -0.025*** | 0.014 |
| Hong Kong | -0.050*** | 0.006 | -0.040*** | -0.024 | -0.026*** | 0.000 |
| Tokyo | 0.035* | -0.060*** | 0.019 | -0.041*** | - | - |
| Singapore | -0.083*** | 0.060*** | -0.048*** | -0.002 | -0.037*** | 0.016 |
| Seoul | -0.023 | -0.031*** | 0.017 | -0.031*** | -0.067*** | -0.012 |
| Atlanta | 0.047*** | -0.045*** | 0.047** | -0.058*** | -0.018 | -0.022 |
| Boston | 0.028 | -0.109*** | 0.008 | -0.090*** | -0.086*** | 0.021 |
| Chicago | 0.017 | -0.057*** | 0.009 | -0.043*** | -0.080* | 0.014 |
| Dallas | 0.026 | -0.063* | -0.008 | -0.037* | -0.083*** | 0.020 |
| Houston | 0.000 | 0.002 | -0.007 | -0.007 | -0.055*** | 0.023* |
| Los Angeles | 0.022 | -0.090* | 0.018 | -0.119*** | -0.059*** | 0.047 |
| Miami | 0.055* | -0.193*** | -0.018 | -0.102*** | -0.044* | -0.006 |
| New York | - | - | -0.026 | -0.062** | -0.060*** | 0.035* |
| San Francisco | -0.008 | -0.008 | -0.002 | -0.028* | -0.022*** | -0.003 |
| Seattle | 0.055 | -0.135*** | 0.030 | -0.109*** | -0.075*** | 0.031 |
| Washington | 0.025 | -0.110*** | 0.029 | -0.074*** | -0.091*** | 0.044* |

Notes: Columns "ECT New York", "ECT London", and "ECT Tokyo" show the coefficients of the error correction term of the other specified markets in the dominant market equations: $\hat{\phi}_{0,i}$ in $\Delta p_{0,t} = \phi_{0,i}(p_{0,t-1} - p_{i,t-1}) + \sum_{k=1}^{1} a_{0,i,k}\Delta p_{0,t-l} + \sum_{k=1}^{1} b_{0,i,k}\Delta p_{0,t-l} + \varepsilon_{0it}$. The columns "ECT Other" show the estimates of the error correction term of the specified dominant markets in the other markets equations: $\hat{\phi}_{i,0}$ in $\Delta p_{i,t} = \phi_{i,0}(p_{i,t-1} - p_{0,t-1}) + \sum_{k=1}^{1} a_{0,i,k}\Delta p_{0,t-l} + \sum_{k=1}^{1} b_{0,i,k}\Delta p_{0,t-l} + \varepsilon_{0it}$. Intercepts are included in all regressions. ***,** and , *, denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Cointegration ranks of commercial real estate prices and macroeconomic factors.

| City | Rank | City | Rank |
|---|---|---|---|
| Paris | 3 | Atlanta | 1 |
| Munich | 1 | Boston | 0 |
| Amsterdam | 2 | Chicago | 1 |
| Stockholm | 3 | Dallas | 2 |
| London | 1 | Houston | 1 |
| Melbourne | 4 | Los Angeles | 1 |
| Sydney | 2 | Miami | 1 |
| Hong Kong | 1 | New York | 1 |
| Tokyo | 3 | San Francisco | 2 |
| Singapore | 4 | Seattle | 2 |
| Seoul | 2 | Washington | 2 |

Table 5: Estimation results of price diffusion equation with London as a dominant market.

| | $EC1_{Neighb}$ $\hat{\phi}_{is}$ | $EC2_{LDN}$ $\hat{\phi}_{i0}$ | Own Lag $\sum_{q=1}^{Q1} a_{iq}$ | Neighb Lag $\sum_{q=1}^{Q2} b_{iq}$ | LDN Lag $\sum_{q=1}^{Q3} c_{iq}$ | LDN Cont. $c_{i0}$ | Q1 | Q2 | Q3 | Wu |
|---|---|---|---|---|---|---|---|---|---|---|
| Paris | -0.125** | 0 | 0.476*** | -0.065*** | - | 0.207*** | 1 | 1 | 0 | -0.282** |
| | (-2.500) | (0.001) | (8.819) | (-5.198) | - | (2.815) | | | | |
| Munich | 0.077 | -0.090** | 0.584*** | -0.341*** | - | 0.061 | 1 | 1 | 0 | -0.188 |
| | (1.236) | (-2.105) | (8.314) | (-4.588) | - | (0.914) | | | | |
| Amsterdam | -0.086 | 0.102 | 0.626*** | 0.327*** | - | 0.025 | 1 | 1 | 0 | -0.147 |
| | (-1.232) | (1.614) | (8.555) | (3.231) | - | (0.278) | | | | |
| Stockholm | -0.189** | -0.007 | 0.729*** | -0.098*** | - | -0.079 | 1 | 1 | 0 | -0.0576 |
| | (-1.962) | (-0.166) | (8.557) | (-4.826) | - | (-0.728) | | | | |
| London | -0.067* | - | 0.830*** | 0.599*** | - | - | 1 | 1 | 1 | |
| | (-1.773) | - | (12.292) | (4.111) | - | - | | | | |
| Melbourne | -0.069 | -0.064 | 0.699*** | 0.454** | - | -0.173 | 1 | 1 | 0 | -0.029 |
| | (-0.728) | (-0.824) | (7.062) | (2.250) | - | (-1.115) | | | | |
| Sydney | 0.038 | -0.059 | 0.511*** | 0.116*** | - | 0.117 | 1 | 1 | 0 | 0.0849 |
| | (0.621) | (-0.989) | (7.752) | (3.764) | - | (1.138) | | | | |
| Hong Kong | -0.061 | 0.025 | 0.586*** | - | - | 0.28 | 1 | 0 | 0 | 0.357 |
| | (-1.466) | (0.414) | (7.656) | - | - | (1.567) | | | | |
| Tokyo | -0.012 | -0.004 | 0.473*** | 0.277*** | - | 0.151 | 1 | 1 | 0 | -0.033 |
| | (-0.193) | (-0.074) | (6.161) | (2.884) | - | (1.393) | | | | |
| Singapore | 0.04 | -0.109** | 0.540*** | -0.227*** | - | 0.318** | 1 | 1 | 0 | -0.105 |
| | (0.800) | (-2.029) | (7.641) | (-3.265) | - | (2.451) | | | | |
| Seoul | -0.082** | -0.015 | - | - | - | 0.062 | 0 | 0 | 0 | 0.0162 |
| | (-2.500) | (-1.088) | - | - | - | (0.869) | | | | |
| Atlanta | 0.033 | -0.073** | 0.553*** | - | -0.045*** | 0.115 | 1 | 0 | 1 | 0.214 |
| | (0.976) | (-2.464) | (8.479) | - | (-7.495) | (1.064) | | | | |
| Boston | -0.069 | -0.055 | 0.613*** | - | 0.007*** | 0.065 | 1 | 0 | 1 | -0.126 |
| | (-0.835) | (-1.106) | (9.027) | - | (4.629) | (0.373) | | | | |
| Chicago | 0.042 | -0.046 | 0.515*** | - | -0.255*** | 0.247** | 1 | 0 | 1 | -0.046 |
| | (0.997) | (-1.497) | (8.975) | - | (-7.918) | (2.362) | | | | |
| Dallas | -0.028 | -0.014 | 0.524*** | - | -0.035*** | 0.103 | 1 | 0 | 1 | 0.674** |
| | (-0.432) | (-0.417) | (7.401) | - | (-6.374) | (0.673) | | | | |
| Houston | 0.004 | -0.002 | 0.603*** | 0.065*** | 0.034*** | 0.026 | 1 | 1 | 1 | -0.0309 |
| | (0.137) | (-0.081) | (8.625) | (7.080) | (12.725) | (0.392) | | | | |
| LA Metro | -0.223** | -0.049 | 0.445*** | - | 0.135*** | -0.003 | 1 | 0 | 1 | -0.0667 |
| | (-2.270) | (-1.241) | (8.541) | - | (6.400) | (-0.018) | | | | |
| Miami | -0.152** | -0.027 | 0.548*** | -0.011*** | - | 0.014 | 1 | 1 | 0 | -0.276 |
| | (-2.066) | (-0.746) | (7.931) | (-4.581) | - | (0.157) | | | | |
| NYC | -0.085* | -0.03 | 0.576*** | 0.224*** | 0.143*** | 0.091 | 1 | 1 | 1 | -0.351 |
| | (-1.748) | (-0.810) | (7.431) | (4.885) | (7.503) | (0.713) | | | | |
| SF Metro | 0.021 | -0.05 | 0.605*** | - | -0.002*** | -0.037 | 1 | 0 | 1 | 0.195 |
| | (0.734) | (-1.328) | (11.008) | - | (-7.308) | (-0.283) | | | | |
| Seattle | -0.09 | -0.065** | 0.299*** | - | - | 0.042 | 1 | 0 | 0 | -0.00949 |
| | (-1.429) | (-2.490) | (9.356) | - | - | (0.501) | | | | |
| DC Metro | 0.01 | -0.096*** | - | - | 0.073*** | 0.061 | 0 | 0 | 1 | 0.0264 |
| | (0.133) | (-3.444) | - | - | (9.210) | (0.474) | | | | |

Notes: This table reports estimates based on Equations (1) and (2). Abbreviations: EC = Error-correction, Neighb. = neighbouring, LDN = London, Cont. = contemporaneous. $EC_{Neighb}$, $EC_{LDN}$, Own Lag, Neighb. Lag, LDN Lag, and LDN Cont. relate to $\phi_{is}$, $\phi_{i0}$, $\sum_{q=1}^{Q1} = a_{iq}$, $\sum_{q=1}^{Q2} = b_{iq}$, $\sum_{q=1}^{Q3} = c_{iq}$, $c_{i0}$, respectively. T-statistics are shown between parenthesis. The standard deviation for lagged variables are calculated using delta methods. ***,** and , *, denote significance at the 1%, 5%, and 10% levels, respectively. Wu is the t-statistic for testing H0: $\varphi_i = 0$ in the Equation (2) augmented with $\varphi_i \hat{\varepsilon}_{0t}$, where $\hat{\varepsilon}_{0t}$ is the residual from the London price equation. In selecting the lag orders, Q1, Q2 and Q3 are set based on AIC criteria, with a maximum lag of 1. The coefficients regarding the short-term impact of the four macroeconomic variables is not reported. Complete results are available upon request.

# Figures

Figure 1: Log of price in the 10 largest commercial real estate markets.

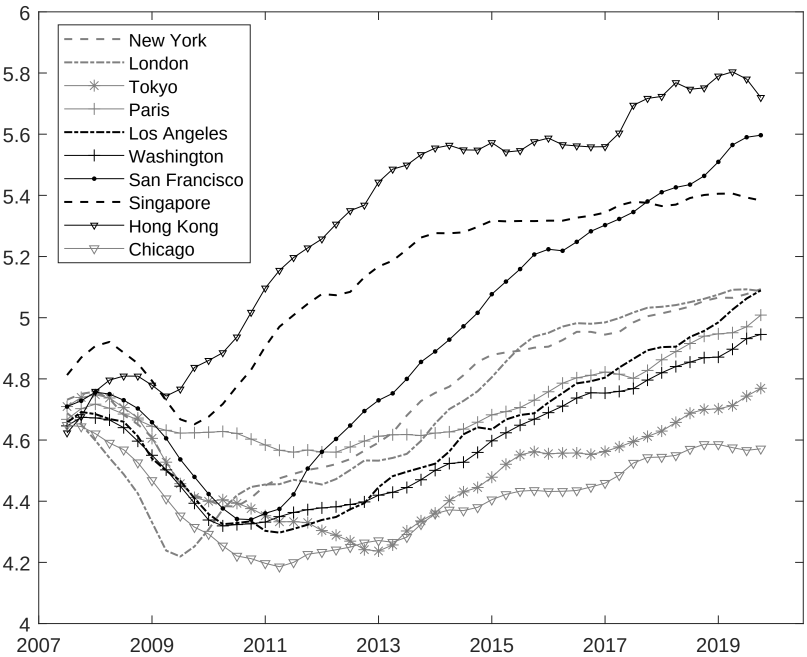
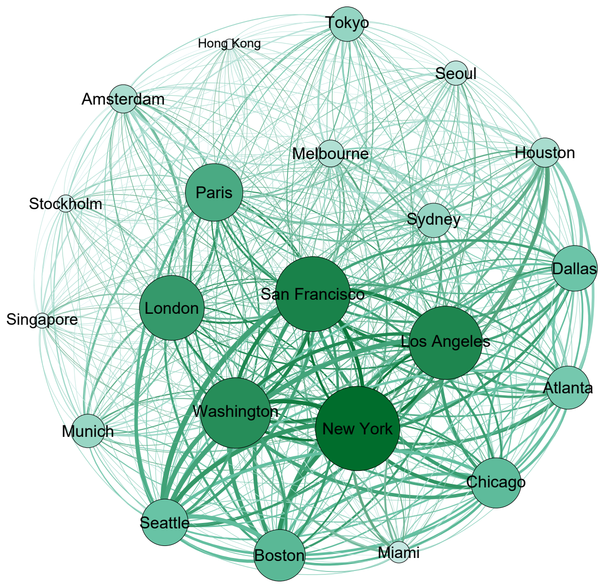


Figure 2: Degree of centrality based on common ownership across real estate markets.




This figure visualises average common real estate ownership across 22 cities. The size and the colour of the circle for each city show the weighted in-degree of the centrality of each city. The darkness of the green colour implies the degree of the overlap.

Figure 3: Response of 22 real estate markets to a one standard deviation shock in the London market.

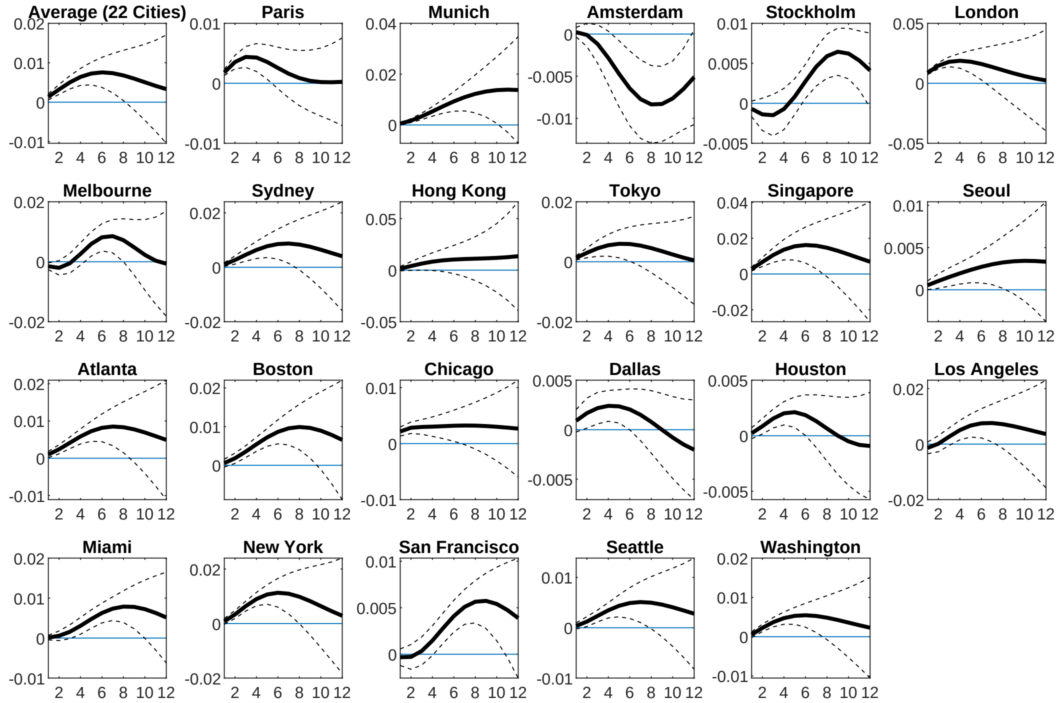



Figure 4: Response of 22 real estate markets to a one standard deviation shock in "neighbouring" markets.

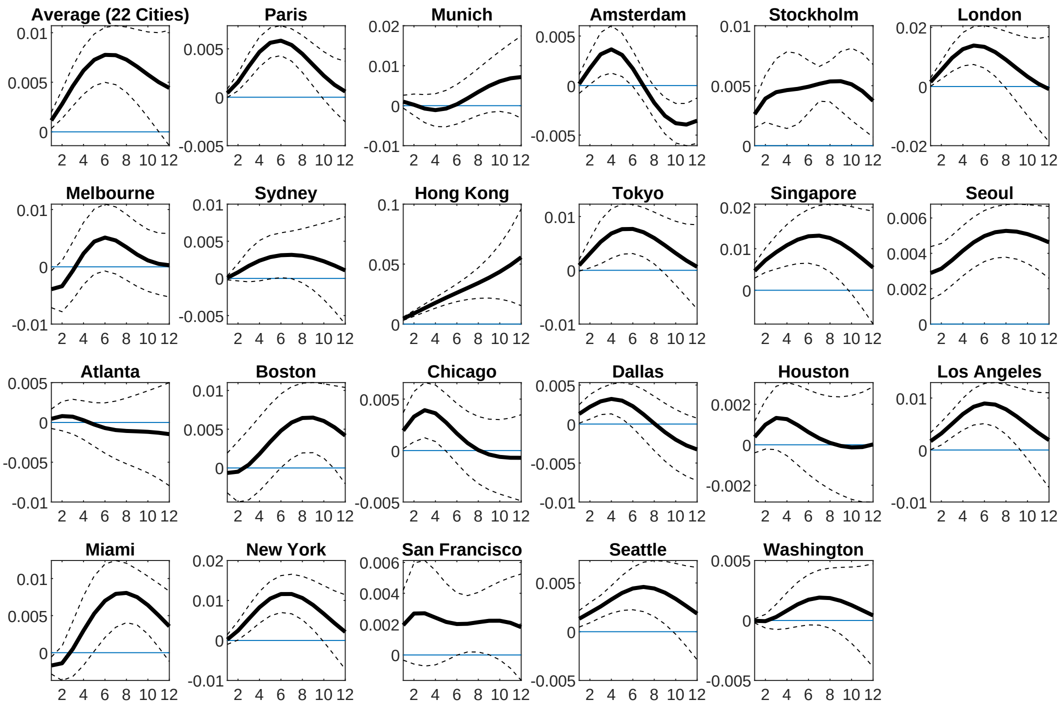
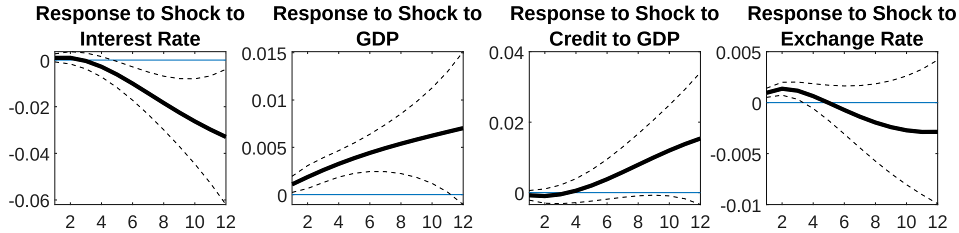
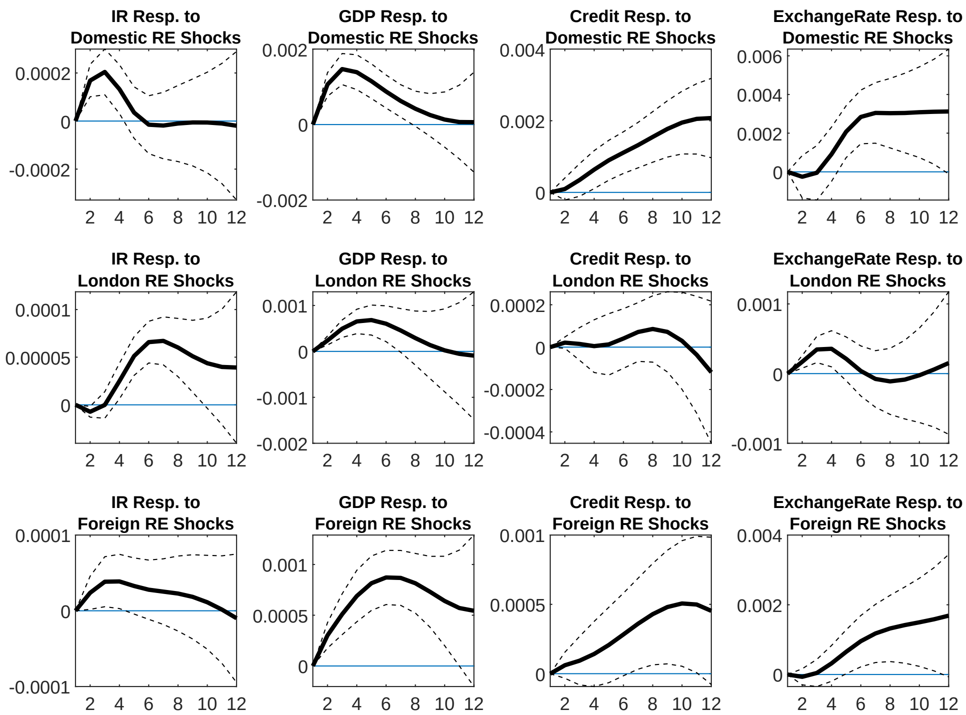


Figure 5: Average response of 22 global real estate markets to macroeconomic shocks and average response of 11 countries to real estate shocks during the crisis and tranquil periods.

(a) Panel A: Response of real estate prices to macroeconomic shocks



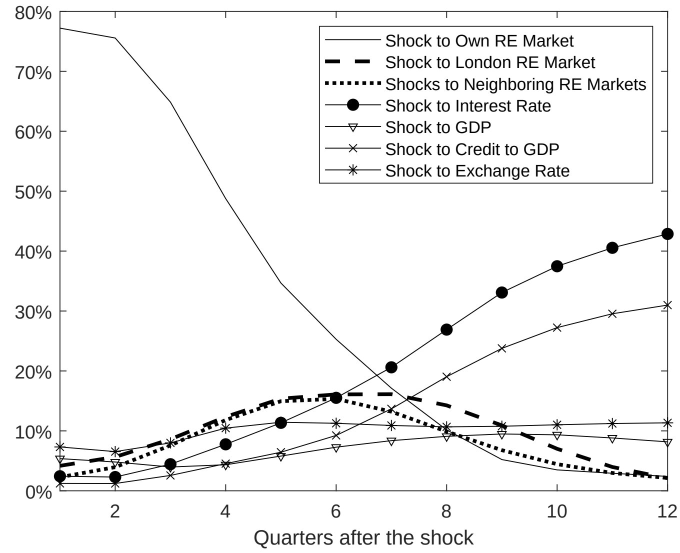

(b) Panel B: Response of macroeconomic variables to real estate shocks



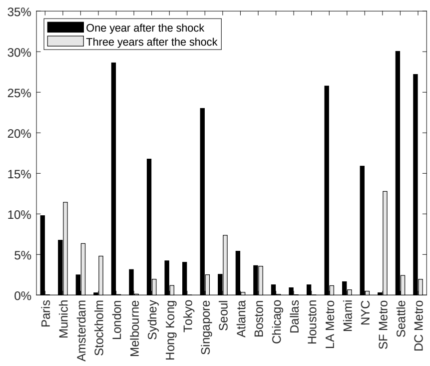

This graph compares the responses of real estate prices to shocks to interest rate, GDP, credit to GDP ratio and exchange rate (Panel A) and the response of interest rate, GDP, credit to GDP ratio and exchange rate to domestic real estate, London real estate and foreign real estate shocks (Panel B). The solid line denotes the response and the dotted line denotes the upper and lower bound of 90% confidence interval.

Figure 6: Percentage of the variance of commercial real estate prices explained by shocks.

(a) Average percentage explained variance across 22 cities




(b) Shocks to leading market




(c) Shocks to neighbouring markets

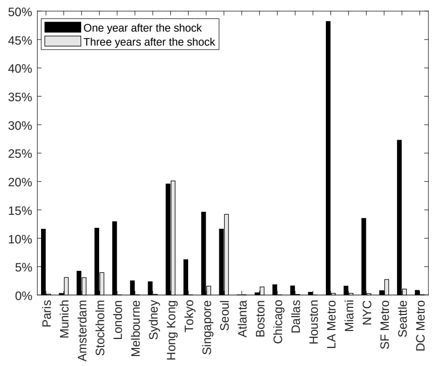
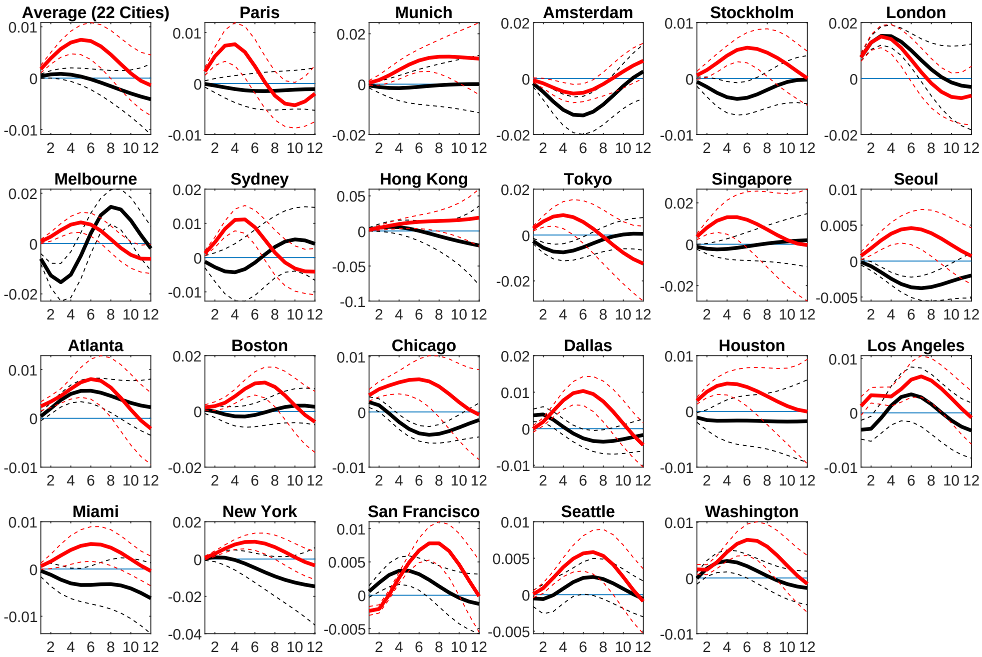
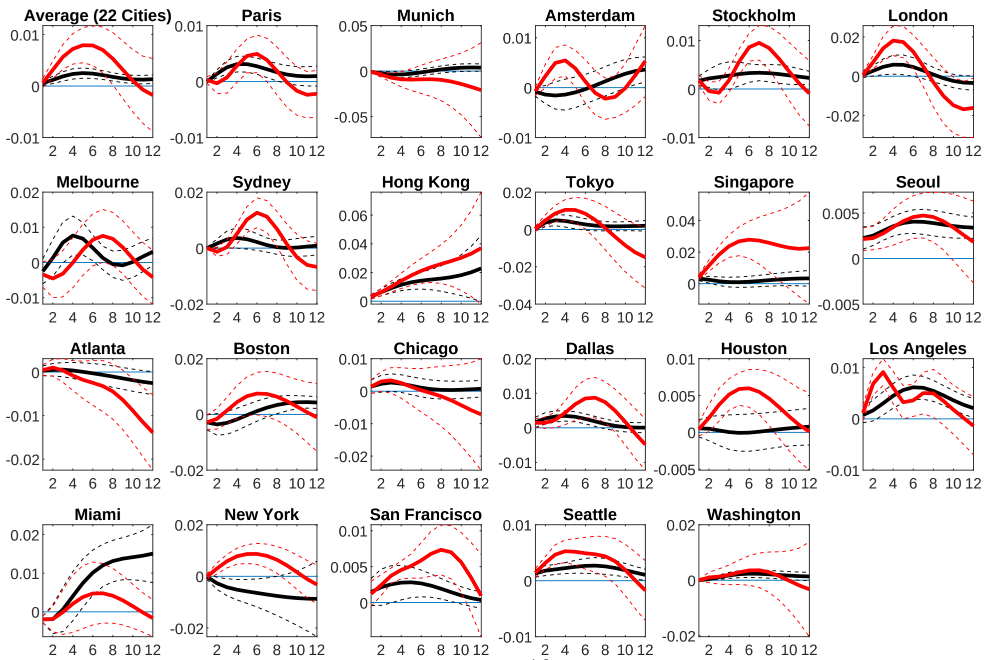


Figure 7: Response of 22 global real estate markets to a one standard deviation shock in London and neighbouring markets.

(a) Response to Shock in London




(b) Response to Shock in Neighbouring Markets

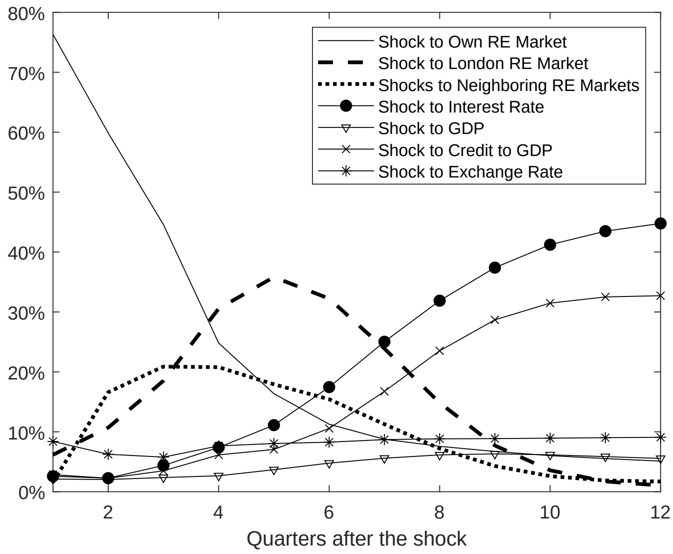




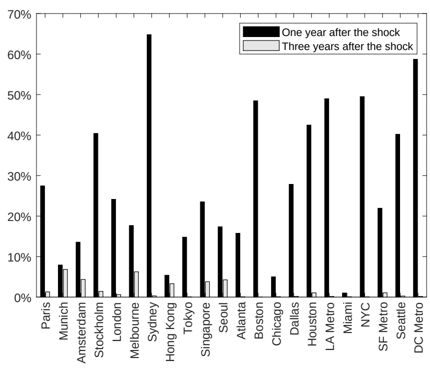

Red lines represent the responses to shocks to London (Panel a) and the neighbouring markets (Panel a) during the crisis period. Black lines represent the responses to shocks to London (Panel a) and the neighbouring markets (Panel b) in tranquil time. The solid line denotes the response and the dotted line denotes the upper and lower bound of 90% confidence interval.

Figure 8: Percentage of the variance of commercial real estate prices explained by shocks in times of crisis.

(a) Average percentage explained variance across 22 cities




(b) Shocks to leading market




(c) Shocks to neighbouring markets

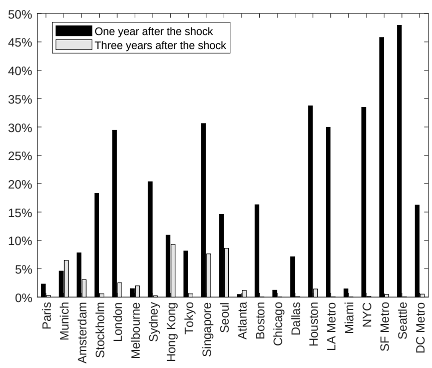
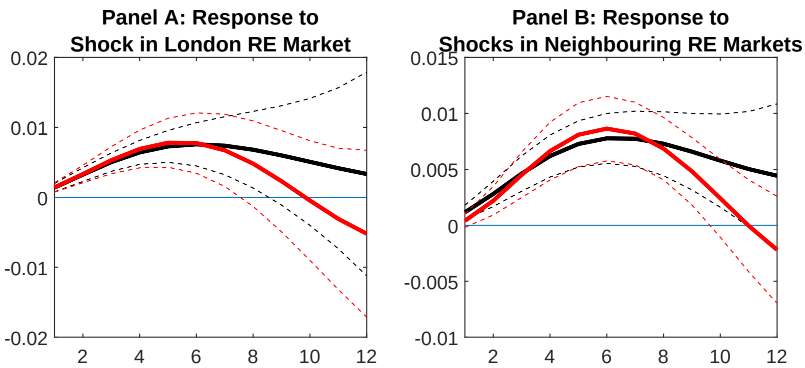
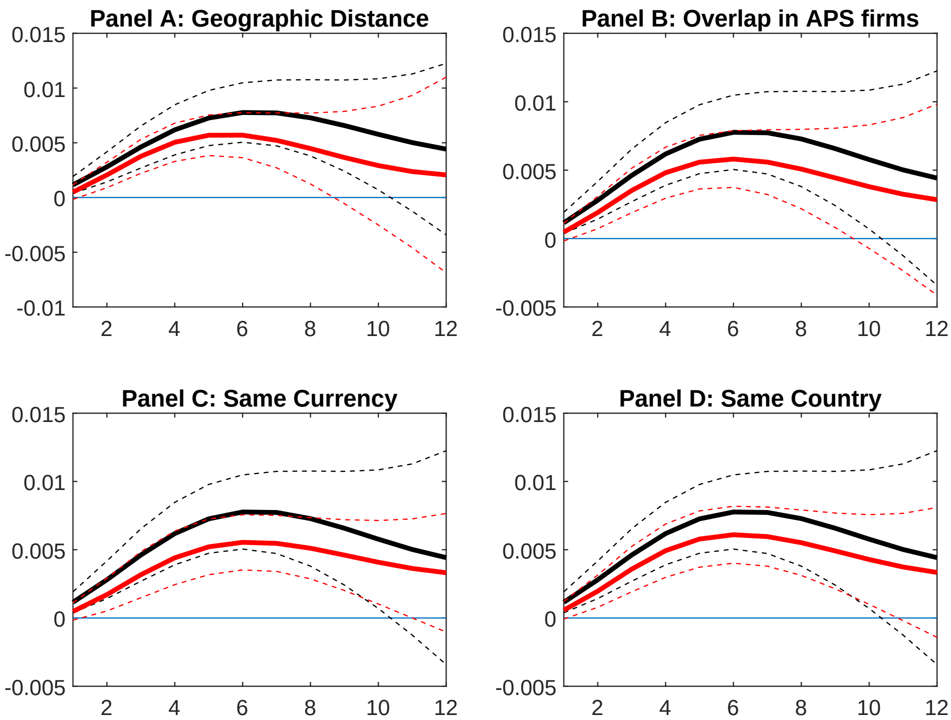


Figure 9: Average response of 22 global real estate markets to a one standard deviation shock in London and neighbouring markets with a global market factor.



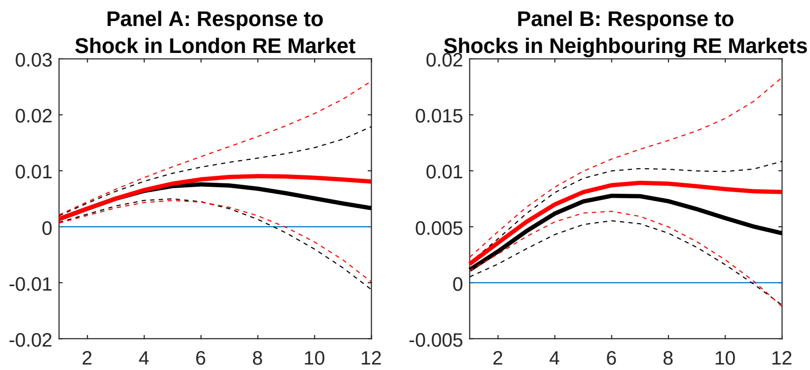

This graph compares the response with and without the control for the commonality in the global real estate markets. Red lines represent the responses to shocks to London (Panel A) and the neighbouring markets (Panel B) when the average of the price of 22 cities are included (Equation 6, 7, and 3). Black lines represent the responses to shocks to London (Panel A) and the neighbouring markets (Panel B) without the average of the price of 22 cities (Equation 1, 2, and 3). The solid line denotes the response and the dotted line denotes the upper and lower bound of 90% confidence interval.

Figure 10: Average response of 22 global real estate markets to a one standard deviation shock in the neighbouring markets with additional weight matrices.



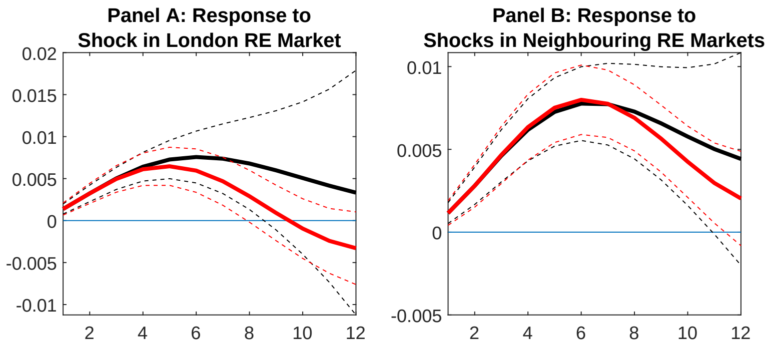

This graph compares the response when an alternative matrix is added into the system in addition to overlapping in property ownership. Panel A adds geographic distance between cities. Panel B adds the overlap in the location of advanced service firms. Panel C adds the matrix based on whether the two cities have the same currency. Panel D adds the matrix based on whether the two cities are in the same country. Red lines represent the responses to shocks to the neighbouring markets based on two weight matrices (Equation 8, 9, and 3). Black lines represent the responses to shocks to neighbouring markets without the additional weight matrix (Equation 1, 2 and 3). The solid line denotes the response and dotted line denotes the upper and lower bound of 90% confidence interval.

Figure 11: Average response of 22 global real estate markets to a one standard deviation shock in London and neighbouring markets with instrumented weights.




This graph compares the response with observed and instrumented weights. Red lines represent the responses to shocks to London (Panel A) and the neighbouring markets (Panel B) using the instrumented overlap ownership matrix (Equation 11, 12 and 3. Black lines represent the responses to shocks to London (Panel A) and the neighbouring markets (Panel B) in the baseline model (Equation 1, 2 and , 3). The solid line denotes the response and the dotted line denotes the upper and lower bound of 90% confidence interval.

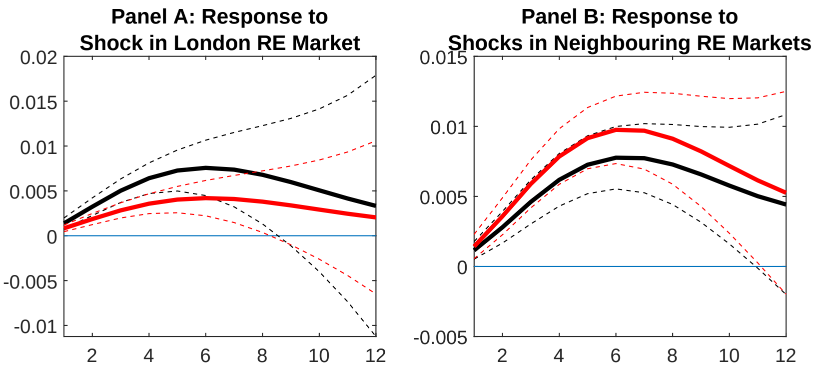
Figure 12: Average response of 11 global real estate markets to a one standard deviation shock in London and neighbouring markets accounting for cross-county co-movements.



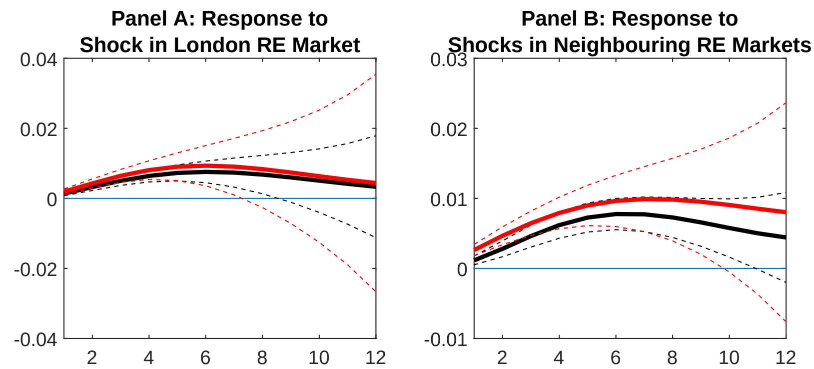

This graph compares the response with and without the control for co-movement of global economies. Red lines represent the responses to shocks to London (Panel A) and the neighbouring markets (Panel B) with a "Global VAR model" for macroeconomic variables (Equation 1, 2 and , 13) . Black lines represent the responses to shocks to London (Panel A) and the neighbouring markets (Panel B) in the baseline model (Equation 1, 2 and 3). The solid line denotes the response and the dotted line denotes the upper and lower bound of 90% confidence interval.

Figure 13: Average response of 22 global real estate markets to a one standard deviation shock in London and neighbouring markets based on alternative orderings.

(a) Ordered by connectivity



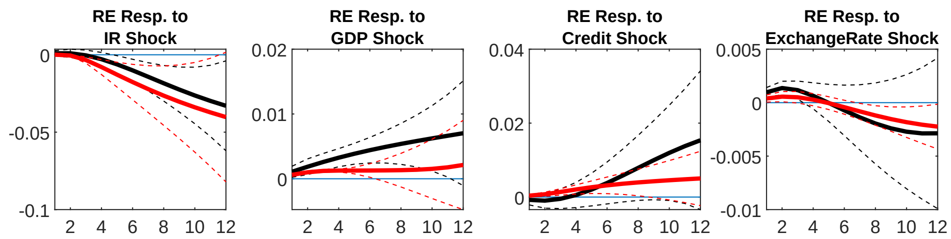

(b) Ordered by interest rate, credit to GDP, exchange rate, real estate price, GDP in the UK country



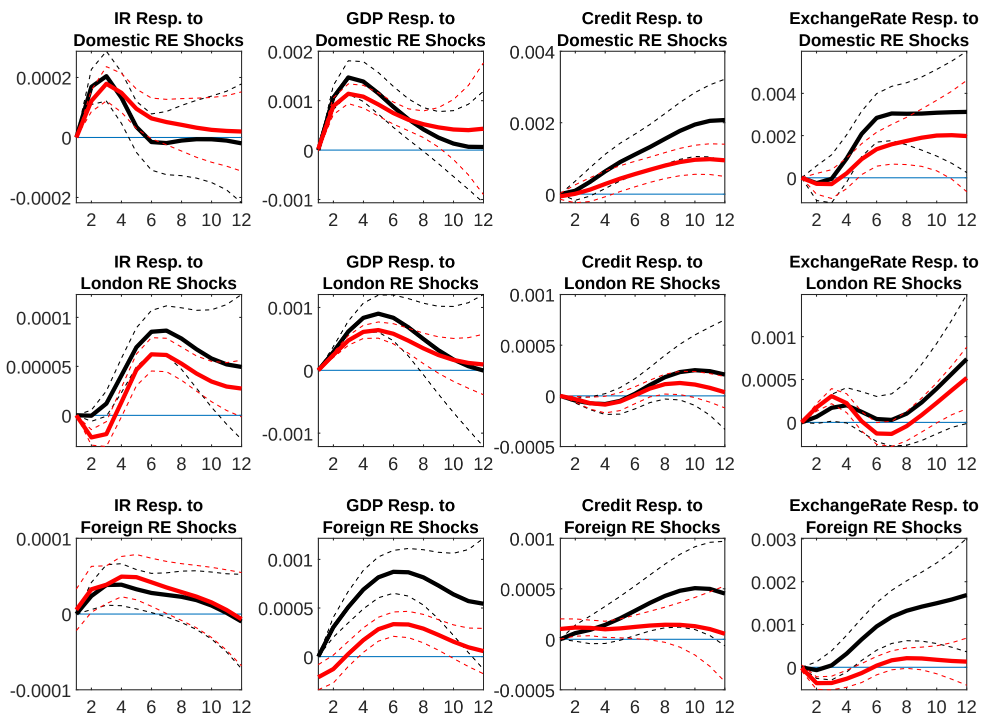

This graph compares the response with alternatively ordering in the identification of 'structural shocks'. Red lines represent the responses to shocks to London (Panel A) and the neighbouring markets (Panel B) based on alternative orderings of the variables. Black lines represent the responses to shocks to London (Panel A) and the neighbouring markets (Panel B) in the baseline model. The solid line denotes the response and the dotted line denotes the upper and lower bound of 90% confidence interval.

Figure 14: Average response of 22 global real estate markets to economic shocks and average response of 11 countries to real estate shocks with alternative orderings.

(a) Panel A: Response of real estate prices to macroeconomic Shocks

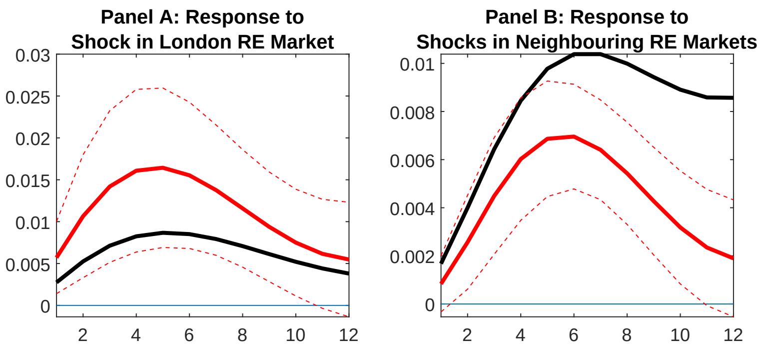



(b) Panel B: Response of macroeconomic variables to real estate Shocks




This graph compares the responses of real estate prices to shocks to interest rate, GDP, credit to GDP ratio and exchange rate (Panel A) and the response of interest rate, GDP, credit to GDP ratio and exchange rate to domestic real estate, London real estate and foreign real estate shocks (Panel B). Red lines represent the responses to the alternative ordering of the variables (country block). Black lines represent the responses based baseline model. The solid line denotes the response and the dotted line denotes the upper and lower bound of 90% confidence interval.

Figure 15: Average response of 11 global real estate markets to a one standard deviation shock in London and neighbouring markets when randomly excluding 6 US cities.




This graph compares the response with randomly re-sampled samples. Red lines represent the responses to shocks to London (Panel A) and the neighbouring markets (Panel B) of 11 Non-US cities after randomly dropping six US cities. Black lines represent the responses to shocks to London (Panel A) and the neighbouring markets (Panel B) of the 11 non-US cities based on the sample with 22 cities. The solid line denotes the response and the dotted line denotes the upper and lower bound of 90% confidence interval.

# A Generalized impulse response functions and "structural shocks"

The impulse response functions and variance decomposition are based on a system of equations for real estate price ($y_t$) and macro-economic variables ($x_t$). We reorganize (1), (2) and (3) as:

$$\begin{pmatrix} \Delta y_t \\ \Delta x_t \end{pmatrix} = \begin{pmatrix} \mathrm{H}_{11} + \mathrm{H}^s_{11} S_N & \mathrm{H}_{12} \\ \mathrm{H}_{21} & \mathrm{H}_{22} \end{pmatrix} \begin{pmatrix} y_{t-1} \\ x_{t-1} \end{pmatrix} + \begin{pmatrix} a^y \\ a^x \end{pmatrix} + \\ \sum_{q=1}^{Q} \begin{pmatrix} A_{11q} + B^s_{11,q} S_N & A_{12q} \\ A_{21q} & A_{22q} \end{pmatrix} \begin{pmatrix} \Delta y_{t-q} \\ \Delta x_{t-q} \end{pmatrix} + \begin{pmatrix} C_{11} & 0 \\ 0 & 0 \end{pmatrix} \begin{pmatrix} \Delta y_t \\ \Delta x_t \end{pmatrix} + \begin{pmatrix} \varepsilon^y_t \\ \varepsilon^x_t \end{pmatrix} \tag{16}$$

where $y_t = (y_{0,t}, y_{1,t}, \ldots, y_{N,t})'$, $x_t = (X_{1,1,t}, X_{2,1,t}, \ldots, X_{Nc,1,t}, X_{1,2,t}, X_{2,2,t}, \ldots, X_{Nc,2,t}, \ldots X_{Nc,K,t})'$, $a^y = (a_0, a_1, \ldots, a_N)'$, and $a^x = \left(a^x_{1,1}, a^x_{2,1}, \ldots a^x_{Nc,1}, a^x_{1,2}, a^x_{2,2}, \ldots a^x_{Nc,2}, \ldots, a^x_{Nc,K}\right)'$, $\varepsilon^y_t = (\varepsilon_0, \varepsilon_1, \ldots, \varepsilon_N)'$ and $\varepsilon^x_t = \left(\varepsilon^x_{1,1}, \varepsilon^x_{2,1}, \ldots \varepsilon^x_{Nc,1}, \varepsilon^x_{1,2}, \varepsilon^x_{2,2}, \ldots \varepsilon^x_{Nc,2}, \ldots, \varepsilon^x_{Nc,K}\right)'$
. All coefficients are defined as in section 2. $\mathrm{H}_{11}$ is a $N+1$ by $N+1$ matrix, and $N+1$ is the total number of real estate markets, as:

$$\mathrm{H}_{11} = \begin{pmatrix} \phi_{0s} + \phi^X_{0,0} & 0 & \cdots & 0 \\ -\phi_{10} & \phi_{1s} + \phi_{10} + \phi^X_{0,1} \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots \\ -\phi_{N-1,0} & 0 & \cdots \phi_{N-1,s} + \phi_{N-1,0} + \phi^X_{0,N-1} & 0 \\ -\phi_{N0} & 0 & \cdots & \phi_{Ns} + \phi_{N0} + \phi^X_{0,N} \end{pmatrix}. \tag{17}$$

$$\mathrm{H}_{12} = \begin{pmatrix} \phi^X_{0,1} \beta^{X\prime}_{0,1} \otimes \mathbf{I}^{1\times Nc}_0 \\ \phi^X_{1,1} \beta^{X\prime}_{1,1} \otimes \mathbf{I}^{1\times Nc}_1 \\ \vdots \\ \phi^X_{N,1} \beta^{X\prime}_{N,1} \otimes \mathbf{I}^{1\times Nc}_N \end{pmatrix}, \tag{18}$$

where $\mathbf{I}_i^{1\times Nc}$ is a 1 by $Nc$ vector and $I_{i,g}^{1\times Nc} = 1$ if city $i$ belongs to county $g$, and zero otherwise.

$$\mathrm{H}_{21} = \begin{pmatrix} \kappa_{1,1}\eta_{1,1}^{Y\prime} \bigotimes \mathbf{I}_1^{1\times(N+1)} \\ \vdots \\ \kappa_{Nc,1}\eta_{Nc,1}^{Y\prime} \bigotimes \mathbf{I}_{Nc}^{1\times(N+1)} \\ \kappa_{1,2}\eta_{1,2}^{Y\prime} \bigotimes \mathbf{I}_1^{1\times(N+1)} \\ \vdots \\ \kappa_{Nc,K}\eta_{Nc,K}^{Y\prime} \bigotimes \mathbf{I}_{Nc}^{1\times(N+1)} \end{pmatrix}, \tag{19}$$

where $\mathbf{I}_g^{1\times(N+1)}$ is a 1 by $N+1$ vector and $I_{g,i}^{1\times N+1} = 1/L_g$ if city $i$ belongs to county $g$, and zero otherwise.$L_g$ is the total number of markets in the sample in country g.

$$\mathrm{H}_{22} = \begin{pmatrix} \kappa_{1,1}\eta_{1,1}^{X\prime} \bigotimes (\mathbf{1}^K \bigotimes \mathbf{I}_1^{Nc}) \\ \kappa_{2,1}\eta_{2,1}^{X\prime} \bigotimes (\mathbf{1}^K \bigotimes \mathbf{I}_2^{Nc}) \\ \vdots \\ \kappa_{Nc,1}\eta_{Nc,1}^{X\prime} \bigotimes (\mathbf{1}^K \bigotimes \mathbf{I}_{Nc}^{Nc}) \\ \kappa_{1,2}\eta_{1,2}^{X\prime} \bigotimes (\mathbf{1}^K \bigotimes \mathbf{I}_1^{Nc}) \\ \vdots \\ \kappa_{Nc,2}\eta_{Nc,2}^{X\prime} \bigotimes (\mathbf{1}^K \bigotimes \mathbf{I}_{Nc}^{Nc}) \\ \vdots \\ \kappa_{Nc,K}\eta_{Nc,K}^{X\prime} \bigotimes (\mathbf{1}^K \bigotimes \mathbf{I}_{Nc}^{Nc}) \end{pmatrix}, \tag{20}$$

where $\mathbf{1}^K$ is a 1 by $K$ vector with all values as one. $\mathbf{I}_g^{Nc}$ is a 1 by $Nc$ vector with value of one for the $g^{th}$ element and zero otherwise.

$$\mathrm{H}_{11}^{\mathrm{s}} = \begin{pmatrix} -\phi_{0s} & 0 & \dots & 0 \\ 0 & -\phi_{1s} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & -\phi_{Ns} \end{pmatrix} \tag{21}$$

$S_N$ is a N by N matrix with zeros on the diagonal and non-zeros off-diagonal. $S_N$ is defined in Section 2.2.

$$\mathrm{A}_{11\mathrm{q}} = \begin{pmatrix} a_{0q} & 0 & \dots & 0 \\ c_{1q} & a_{1q} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ c_{Nq} & 0 & \cdots & a_{N,q} \end{pmatrix}, \tag{22}$$

$$\mathrm{A}_{12\mathrm{q}} = \begin{pmatrix} \lambda_{0,1,q} & 0 & \cdots & 0 & \dots & \lambda_{0,K,q} & 0 & \cdots & 0 \\ 0 & \lambda_{1,1,q} & \cdots & 0 & \dots & 0 & \lambda_{1,K,q} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \lambda_{N,1,q} & \dots & 0 & 0 & \cdots & \lambda_{N,K,q} \end{pmatrix} \tag{23}$$

$$A_{21q} = \begin{pmatrix} \delta_{1,1q} & 0 & \dots & 0 \\ 0 & \delta_{2,1} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \delta_{Nc,1,q} \\ \vdots & \vdots & \ddots & \vdots \\ \delta_{1,K,q} & 0 & \dots & 0 \\ 0 & \delta_{2,K,q} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \delta_{Nc,K,q} \end{pmatrix} \tag{24}$$

$$B^{s}_{11q} = \begin{pmatrix} b_{0q} & 0 & \dots & 0 \\ 0 & b_1 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & b_{N,q} \end{pmatrix} \tag{25}$$

$$C_{11} = \begin{pmatrix} 0 & 0 & \dots & 0 \\ c_{1,0} & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ c_{N,0} & 0 & \cdots & 0 \end{pmatrix} \tag{26}$$

If we set:

$$z_t = \begin{pmatrix} y_t \\ x_t \end{pmatrix}, \tag{27}$$

$$\mathbf{H_0} = \begin{pmatrix} \mathrm{H}_{11} + \mathrm{H}^{\mathrm{s}}_{11} S_N & \mathrm{H}_{12} \\ \mathrm{H}_{21} & \mathrm{H}_{22} \end{pmatrix}, \tag{28}$$

$$a = \begin{pmatrix} a^y \\ a^x \end{pmatrix}, \tag{29}$$

$$\mathbf{A_q} = \begin{pmatrix} A_{11q} + B^S_{11,q} S_N & A_{12q} \\ A_{21q} & A_{22q} \end{pmatrix}, \tag{30}$$

$$\mathbf{C_0} = \begin{pmatrix} C_{11} & 0 \\ 0 & 0 \end{pmatrix}, \tag{31}$$

$$\varepsilon_t = \begin{pmatrix} \varepsilon^y_t \\ \varepsilon^x_t \end{pmatrix}, \tag{32}$$

we obtain:

$$\Delta z_t = \mathbf{H_0} z_{t-1} + a + \sum_{q=1}^{Q} \mathbf{A_q} \Delta z_{t-q} + \mathbf{C_0} \Delta z_t + \varepsilon_t. \tag{33}$$

Equation (33) can be rearranged as:

$$\begin{aligned}\Delta z_t &= \left(\mathbf{I}_{N+1+K\times Nc} - \mathbf{C_0}\right)^{-1}\mathbf{H_0} z_{t-1} + \left(\mathbf{I}_{N+1+K\times Nc} - \mathbf{C_0}\right)^{-1} a + \\ &\left(\mathbf{I}_{N+1+K\times Nc} - \mathbf{C_0}\right)^{-1}\sum_{q=1}^{Q}\mathbf{A_q}\Delta z_{t-q} + \left(\mathbf{I}_{N+1+K\times Nc} - \mathbf{C_0}\right)^{-1}\varepsilon_t.\end{aligned} \tag{34}$$

Setting $\Omega = \left(\mathbf{I}_{N+1+K\times Nc} - \mathbf{C_0}\right)^{-1}$, we first write (34) as a vector autoregressive (VAR) process:

$$z_t = \Omega a + \sum_{q=1}^{Q+1}\Xi_q z_{t-q} + \Omega\varepsilon_t, \tag{35}$$

where $\Xi_q$ captures the spatial and temporal dependence of variable $z$. $\Xi_q$ is affected by the spatial patterns in the price returns and macroeconomic variables, since we have set the lagged effects and the error correction terms to match certain spatial patters as identified as $S_N$. The above VAR model is used for the impulse response analysis. Under the assumption that price shocks in the dominant market are weakly exogenous to price shocks in other markets, the variance covariance matrix is defined as $\Sigma = \begin{pmatrix}\Sigma_{11} & \Sigma_{12}\\ \Sigma_{21} & \Sigma_{22}\end{pmatrix}$, with

$$\Sigma_{11} = \begin{pmatrix} \sigma_{00}^y & 0 & \cdots & 0 & 0 \\ 0 & \sigma_{11}^y & \cdots & \sigma_{1,N-1}^y & \sigma_{1,N}^y \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & \sigma_{N-1,1}^y & \cdots & \sigma_{N-1,N-1}^y & \sigma_{N-1,N-1}^y \\ 0 & \sigma_{N,1}^y & \cdots & \sigma_{N,N-1}^y & \sigma_{N,N}^y \end{pmatrix}. \tag{36}$$

The generalized impulse response function is then defined as:

$$IRF_{i,k}(h) = \frac{\Xi_h\Omega\Sigma e_i}{\sqrt{\sigma_{ii}}}, \tag{37}$$

with $\mathrm{k} = 0,1,2,..\mathrm{K}$, and for $h = 0,1,2\ldots,T$. We then follow Dees et al. (2007)

to identify the "structural shocks" under the generalized impulse response function framework. Equation 35 is pre-multiplied by $\mathbf{P_0}$. So:

$$\mathbf{P_0} z_t = \mathbf{P_0} \Omega a + \mathbf{P_0} \sum_{q=1}^{Q+1} \Xi_q z_{t-q} + \mathbf{P_0} \Omega \varepsilon_t, \tag{38}$$

where $u_{0,t} = \mathbf{P_0} \Omega \varepsilon_{0,t}$ are the structural shocks. The identification conditions are defined as: $\mathbf{P_0}$ as a lower triangular matrix, $Cov(\varepsilon_{0,t}) = \Sigma_{\varepsilon 0} = \mathbf{Q_0}'\mathbf{Q_0}$, and $Cov(u_{0,t}) = \Sigma_{u_{0,t}} = \mathbf{P_0}\Omega\Sigma_{\varepsilon_{0,t}}\Omega'\mathbf{P_0}'$, where $\mathbf{Q_0}$ is the upper Choleskey factor of $\Sigma_{\varepsilon_{0,t}}$. Hence, $\mathbf{P_0}\Omega\Sigma_{\varepsilon 0}\Omega'\mathbf{P_0}\prime =$ $\mathbf{P_0}\Omega\mathbf{Q_0}'\mathbf{Q_0}\Omega'\mathbf{P_0}' = \Sigma_{u_{0,t}}$, and $\mathbf{P_0}\Omega\Omega'\mathbf{Q_0}' = \Sigma_{u_{0,t}}^{1/2}$, which is a diagonal matrix. Consider the system with all equations:

$$\mathbf{P_G^0} = \begin{pmatrix} \mathbf{P_0} & 0 & \cdots & 0 \\ 0 & \mathbf{I} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \mathbf{I} \end{pmatrix}, \mathbf{P_G^0} z_t = \mathbf{P_G^0} \Omega a + \mathbf{P_G^0} \Sigma_{q=1}^{Q+1} \Xi_q z_{t-q} + \mathbf{P_G^0} \Omega \varepsilon_t, \tag{39}$$

According to Dees et al. (2007), under the orthogonalization scheme, $\Sigma_{\varepsilon_t}$ in Equation 39 is specified as $V(\varepsilon_{0t}) = \mathbf{I}$ and:

$$Cov(u_{j,t}, \varepsilon_{0t}) = \mathbf{P_G^0} \Omega \Sigma_{\varepsilon_{0j}}, for j = 1, 2, ..., N + (N_c - 1)K. \tag{40}$$

Under this specification, as shown by Dees et al. (2007), we have $\mathbf{P_0}\Omega = (\mathbf{Q_0'})^{-1}$ and $(\mathbf{P_G^0}\Omega)^{-1}$. The latter is a block diagonal matrix with $\mathbf{Q_0}$ on its first block and identify matrices on the remaining blocks. In this way, we identify the "structural shocks" from the London real estate markets and from neighboring markets to the markets included in the system.

# B Extra Tables

Table 6: Dickey-Fuller test for the commercial real estate price variables.

| | Log Price | ΔLog Price | | Log Price | Δ Log Price |
|---|---|---|---|---|---|
| Paris | 0.0005 | -0.2639*** | Atlanta | 0.0002 | -0.0787 |
| Munich | 0.0007 | -0.1615** | Boston | 0.0004 | -0.3422*** |
| Amsterdam | 0.0000 | -0.1497** | Chicago | 0.0002 | -0.1957*** |
| Stockholm | 0.0006 | -0.1755** | Dallas | 0.0004 | -0.2687*** |
| London | 0.0006 | -0.2152*** | Houston | 0.0001 | -0.2153*** |
| Melbourne | 0.0011 | -0.4283*** | Los Angeles | 0.0006 | -0.2156** |
| Sydney | 0.0009 | -0.2099** | Miami | 0.0006 | -0.1927** |
| Hong Kong | 0.0010 | -0.3808*** | New York | 0.0004 | -0.2002*** |
| Tokyo | 0.0001 | -0.1927*** | San Francisco | 0.0004 | -0.1229* |
| Singapore | 0.0003 | -0.2348*** | Seattle | 0.0002 | -0.1660** |
| Seoul | 0.0007 | -0.2157*** | Washington | 0.0002 | -0.1341* |

Notes: This table report the Dicky-Fuller tests for the level of the time series and the differenced time series without a deterministic part. H0 is non-stationarity. ***, ** and * signifies that the test rejects the null at the 1%, 5% and 10% level, respectively.

Table 7: Dickey-Fuller test for the macroeconomic variables.

| | Log GDP | Δ Log GDP | Interest Rate | Δ Interest Rate | Credit/GDP | ΔCredit/GDP | Exch. Rate | ΔExch. Rate |
|---|---|---|---|---|---|---|---|---|
| Australia | 0.001 | -0.139 | -0.005 | -1.111*** | 0.000 | -0.291** | -0.003 | -0.903*** |
| France | 0.000 | -0.321** | 0.000 | -1.216*** | 0.001 | -0.238** | -0.009 | -0.862*** |
| Germany | 0.000 | -0.551*** | -0.008 | -1.104*** | 0.000 | -0.663*** | -0.009 | -0.862*** |
| Hong Kong, China | 0.000 | -0.532*** | 0.012 | -1.170*** | 0.002 | -0.703*** | 0.000 | -0.961*** |
| Japan | 0.000 | -0.775*** | 0.012 | -0.709*** | 0.000 | -0.558*** | 0.000 | -0.861*** |
| Netherlands | 0.000 | -0.540*** | -0.002** | -0.082 | 0.000 | -0.319** | -0.009 | -0.862*** |
| Singapore | 0.001 | -0.575*** | 0.007 | -1.370*** | 0.001 | -0.469*** | -0.006** | -0.762*** |
| South Korea | 0.001 | -0.359*** | 0.000 | -1.097*** | 0.000 | -0.287*** | 0.000 | -0.808*** |
| Sweden | 0.000 | -0.407*** | -0.003 | -1.188*** | 0.001 | -0.590*** | 0.001 | -0.817*** |
| United Kingdom | 0.000 | -0.267** | -0.004 | -1.069*** | -0.001 | -0.869*** | -0.066* | -0.811*** |
| United States | 0.000 | -0.302** | -0.011 | -0.939*** | 0.000 | -0.764*** | -0.003 | -0.864*** |

Notes: This table report the Dicky-Fuller tests for the level of the time series and the differenced time series without a deterministic part. H0 is non-stationarity. ***, ** and * signifies that the test rejects the null at the 1%, 5% and 10% level, respectively.

Table 8: First stage regression for instrumented regression.

| | Overlap in Ownership |
|---|---|
| Const. | 0.1848*** |
| | (0.0388) |
| Geographic distance | -0.0253*** |
| | (0.0029) |
| Same Country | 0.0175* |
| | (0.009) |
| Same Currency | 0.1805*** |
| | (0.0101) |
| Same Legal System | 0.0081* |
| | (0.0045) |
| Overlap in APS Firms | 0.0302*** |
| | (0.004) |
| Year Dummies | Yes |
| No of Obs. | 4620 |
| Adjusted R2 | 0.4345 |
| F test | 694.52*** |

Notes: This table report first stage regression for the instrumented weights based on Equation (10). The dependent variable is the overlap ratio. Standard errors are shown between parenthesis. ***, ** and * signifies that the test rejects the null at the 1%, 5% and 10% level, respectively.

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