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DYNAMIC RELATIONS BETWEEN HOUSING MARKETS, STOCK MARKETS, AND UNCERTAINTY IN GLOBAL CITIES: A TIME-FREQUENCY APPROACH

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Dynamic Relations Between Housing Markets, Stock Markets, and Uncertainty in Global Cities: A Time-Frequency Approach

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Abstract

This paper considers dynamic features of house prices in metropolises that are characterized by high degree of internationalization. Using the wavelet coherency procedure the degree of co-movement and causality between housing, stock markets and macroeconomic uncertainty are investigated. In addition, the existence of volatility spillover across housing markets is assessed in the time-frequency domain using a novel procedure that involves combining the wavelet decomposition with time varying parameter vector autoregression model. The results highlight that the clustering of global business in a limited number of metropolises that act as "global hubs" leaves local housing markets exposed to international shocks and volatility spillover. The empirical analysis suggests that the correlations between real estate and stock markets from one side, and real estates and uncertainty on the other side, intensify during the turmoil periods, but causality and co-movement relationships appear, predominately, in the medium-, long run period.

Keywords: Global Cities; Global Economic Policy Uncertainty Index; Wavelet-Time Varying Parameter Vector Autoregression.

JEL classification: G1; R3; C4; C32.

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1. Introduction

In the wake of globalization and financial liberalization the last decades have seen a large increase in cross-border investment in real estate. In this respect, a small, but growing literature supports the view that the globalization phenomena has paved the way for cross-border investment into real estate markets. Real estates have values both as a consumption good for their physical use and as investment assets. There is increasing evidence that, in some cities, the latter use has become more prominent since the turn of the millennium. For example, Favilukis et al. (2013) suggest that real estates in cities that are key financial and trade centres, constitutes a class of asset substitutes for low-yielding government bonds and it is one in which private-equity firms, investment trusts and individual investors tend to invest. Badarinza and Ramadora (2018) consider cross-border investment in the real estate market in London and find that foreign demand is an important part of the explanation for house price dynamics in London.[1] Lizieri (2009) mapped out the change in ownership in the city of London office market over the 1980s and 1990s in response to financial deregulation and the globalisation of financial markets and demonstrated that foreign owners were increasingly playing an important role (see also Lizieri and Kutsch, 2006).

From an investor point of view, the rationale of international asset diversification is that by diversifying globally investors should reduce the risk related to common underlying driving economic forces. Since housing market dynamics are closely correlated to the fundamentals of the local economy, international diversification should reduce correlations across assets and markets, thus inducing risk reduction benefits. Indeed, some empirical work seems to support this point. Goetzmann and Ibbotson (1990), for example, show that real estate can augment a portfolio by making the portfolio less sensitive to market swings (see also Anoruo et al. 2008; Apergis and Lambrinidis, 2011; Bahmani-Oskooee and Ghodsi, 2018). However, this literature may fail to consider one key element, namely that global real estate investment is mostly concentrated not only in a small number of countries, but also in a limited range of metropolitan areas within those countries.

Against this background, in this paper, we investigate the relationship between real estate prices, stock markets, and geopolitical risk in global cities. We are particularly interested in global cities that are also major financial centres. A global city (or world city) is defined as a city which is of primary importance to the global economic system (Sassen, 2003). The term "global city" has its origins in urban studies and relates to the idea that world globalisation is facilitated in strategic cities that are instrumental in supporting global trade operations. According to this literature, the process of globalisation has necessitated increasing integration and complexity of central organizational functions (see Sassen, 2003). In this respect, global cities provide specific knowledge for multinational enterprises to manage globalisation.

A small, but growing number of papers, share the view that the tendency for high-value services (professional, creative, financial) to cluster in a few metropolises around the globe has deeply affected local housing markets, for several reasons. First, these cities share many characteristic features in common attracting an internationally mobile and highly skilled labour force that in turn boosts demand for high-end residential property (see Canepa et al., 2020). Second, real estate markets in global metropolises attract inflows of foreign capital due to the

[1] To illustrate the scale of the phenomenon Badarinza and Ramadora (2018) use a property-level dataset for London and document that at least 85% of residential real estate purchases by foreigners in London occur through a corporation (a preferred vehicle over the period, for tax reasons) and are routed through off-shore special purpose vehicles registered in regions such as Gibraltar, Cyprus and Panama, with the effect that the ultimate source of the capital is essentially untraceable.

increasing financial market liberalisation (see, for example, Favilukis et al., 2017; Badarinza and Ramadorai, 2018). Third, many of these global cities are also key financial centres with a greater concentration of cross-border activity than domestic financial centres (see, for example, Stevenson et al., 2013). Yet, one issue this literature has hardly explored is how global risk factors affect local housing markets. In principle, the concentration of investments in a few cities around the world may create exposure to common patterns of volatility and increase the risk of contagion during periods of economic turmoil. As a result, an international investment strategy with a significant real estate exposure may fail to deliver diversification at the key moment when it is required.

Accordingly, in this paper, we are interested in answering three questions: First, are there co-movements and causality between housing markets in global cities and stock markets? Second, to what extent do major geopolitical events affect housing markets in global cities? Third, do housing markets in these cities move in a synchronized fashion?

Regarding the first point, despite the large amount of literature devoted to the relationship between stock markets and real estate markets, to the best of our knowledge, no empirical study is devoted specifically to the real estate market in global cities. Recent work by Canepa et al. (2020) suggest that strong demand pressure and inelastic supply leave these metropolises more exposed to bubbles in the housing market than the rest of the country (see also Alqaralleh and Canepa, 2020). The authors point out that in global cities the inertia of supply resulting from construction lags in combination with backwards-looking expectations generate more extreme asymmetric cycles (see also Capozza et al., 2004; Glaeser and Gyourko, 2018). In this paper, we argue that cross-border investments in global cities' real estate markets exacerbate the impact of shocks in turbulent periods. In the literature, a number of theoretical studies have shown that disturbances in housing markets can translate into much larger cyclical fluctuations in the real economy when financial imperfections are present (see for example Iacoviello, 2005; Davis and Heathcote, 2005). However, a comprehensive examination of this issue for global cities is still missing in the literature.

Accordingly, following the theoretical literature, this paper investigates if real estate is integrated with or is segmented from a related stock market. Market integration implies that a boom (bust) in one market is associated with a boom (bust) in the other market. In the case of market integration, the combined effect makes the economic system more prone to financial instability magnifying the amplitude of upswings and downswings. On the opposite, market segmentation implies a negative correlation, therefore, smoothing dangerous downturns and stabilizing investment allocations.

In the literature, researchers sought to answer the question of long-run co-movements by employing both linear and non-linear cointegration models (see Lizieri and Satchell, 1997; Apergis and Lambrinidis, 2011). The issue of lead-lag relationships has been tackled by applying Granger causality tests in vector autoregressive (VAR), vector error-correction (VEC), and threshold error-correction (TEC) models (Okunev et al., 2000; Sim and Chang, 2006; Su, 2011; Shirvani et al., 2012; Tsai et al., 2012). A possible limitation of these models is that they can only offer some insights into the time-domain aspect of the relationship.

In this paper, we use wavelet coherency and phase differences simultaneously to explore both the time-varying *and* the frequency-varying relationship between equity and real estate markets in global cities. Knowledge of the time- and frequency varying features of the relationship has profound implications for portfolio management and for policymakers since the former informs on how the magnitude of the estimated correlation changes over different phases of the business cycle, whereas the latter provides insights about the different nature of the relationship. In this respect, knowledge of short- versus medium, long-run relationships would allow investors better diversify portfolios and lower systematic risk. In turn, the joint effect of such portfolio strategies may affect overall wealth, consumption behaviours aggregate demand and employment (see for example Liow and Yang, 2005).

Coming to the impact of geopolitical risk, it is clear that the internationalisation of real estate markets entails a risk of global shock synchronization calling for a better appreciation of the geopolitical externalities and exteriorities of real estate. Geopolitical risk creates uncertainty and volatility in the housing market. Many theoretical papers support the view that uncertainty potentially affects investment, hiring, consumption, financing costs, asset prices, output growth and other economic outcomes as decision-makers hold off from making major commitments (see for example Gilchrist et al., 2014, and Pastor and Veronesi, 2013).

Although several studies investigate the link between uncertainty and real economic activity (see, for example, Bloom, 2009; Baker et al. 2014; Colombo at al. 2013), only few examine the impact of economic uncertainty on the housing market. For example, Sum and Brown (2012) examine the effect of uncertainty on the performance of the real estate returns in the U.S. and find that uncertainty does not affect housing market dynamics. Ajmi et al. (2014) show the existence of a two-way transmission channel be-tween U.S.-listed real estate market volatility and macroeconomic. Antonakakis et al. (2016) show that the correlation between macroeconomic uncertainty and real housing market returns is consistently negative, but with magnitude that varies greatly over time reaching its peak during the last financial crisis. El Montasser et al. (2020) consider the causal relationship between macroeconomic and real house prices in the U.S. and Europe and find bi-directional causality for France and Spain, but only unidirectional causality for the remaining countries (see also Choi, 2020; Demiralay and Kilincarslan, 2022)

In this work we build on this literature and investigate co-movements and causality between global economic policy uncertainty and the housing markets in some selected global cities using the widely used metric developed by Baker et al. (2016). The analysis is, once again, conducted using the wavelet coherency procedure since this methodology allows to investigate dynamic dependencies and interconnections between the housing markets and major geopolitical shocks. In particular, we are able to investigate if and how the correlation increases during major turmoil periods and how the relationship changes across frequencies (i.e. in the short, medium and long run).

The issue of uncertainty and geopolitical risk leads us directly to the third point of our investigation. The intuition behind the research question of this paper is that the spatial clustering of global financial business in a small number of large cities, acting as coordinating centres for an interlinked international financial and trade system may leave the housing markets of these metropolises more exposed to synchronised shocks. In this respect, a small, but growing literature on the subject suggests that starting from the 1990s, real estate investment by private equity firms, real investment trusts, and institutional investors have increased business cycle synchronization in global cities (see, for example, Stevenson et al., 2013). Research in urban studies supports the view that globalisation has created a strong “agglomeration effect” attracting firms with employees performing knowledge-intensive work to locate near similar or closely related supplier firms. In this paper we are interested in testing the hypothesis that this agglomeration effect has left the real estate markets of these metropolises more exposed to synchronised global shocks. Moreover, we expect housing markets in cities that are also major financial centres to share the fluctuations in financial markets. This should induce common patterns of volatility and systemic risks of contagion during periods of financial turmoil. A wWell-established literature has supported evidence of a price-diffusion or ripple effect in the real estate markets (see Tsay, 2018; Cook and Watson, 2016; Taltavull et al. 2017). In this paper, we argue that spatial diffusion does not necessarily have to occur in contiguous geographical areas, but it may also affect discontinuous spatial territory with similar socio-economic conditions such as global cities. In this respect, a recent paper by Canepa et al. (2020) consider a number of global cities and show that housing market cycles tend to shore similar characteristic features. In addition, house prices in these metropolises are subject to strong exogenous shocks that make the stochastic processes highly nonlinear (see also Alqaralleh and Canepa, 2020).

In this study we build on Canepa et al. (2020) and investigate to what extent a shock to one global city affects the volatility of the housing market in fellow metropolises over different time scales. With this target in mind a novel procedure that allows to investigate the evolution of volatility spillover across different frequency bands is proposed. In particular, the suggested procedure is carried out in two steps. In the first stage the maximal overlap discrete wavelet transform is used to decompose the series of house price returns into components associated with different time scale resolutions. In the second step, the dynamic connectedness between implied volatility shocks is studied using a time varying parameter vector autoregression suggested in Antonakakis et al. (2020). The advantage of the suggested procedure, that we label as wavelet time-varying vector autogression (WTVP-VAR), is that it allows us to investigate how the structure of the volatility spillover varies over different time scales. Most previous studies focus on the relationship between real estate markets focusing on two-scale analysis, namely, short-run and long-run. However, the true dynamic structure of the relationship between real estate markets varies over different time scales and across cities.

The rest of the paper is organised as follows. Section 2 presents the dataset used in this work. Section 3 and 4 present the wavelet coherence analysis. Section 5 relates with the wavelet time-varying vector autogression procedure and presents the empirical results. Finally, Section 6 concludes the paper.

2. Data

The data used in this study consist of monthly house prices starting from January 1997 to August 2021 in seven global cities. The housing markets under consideration include the cities of New York, Los Angeles and San Francisco, Hong Kong, Tokyo, and London.

These metropolises rank at the top of the Global Power City Index (GPCI) world cities in the last ten years. The GPCI index provides a quantitative indicator of cities' global reach in terms of their "magnetism" or their comprehensive power to attract creative people and business enterprises from around the world. More precisely, the GPCI index ranks several metropolises according to the degree of international connectivity, density of financial and business services, the level of research and development, the degree of cultural interaction, the degree of liveability, the quality of the environment, the degree of accessibility, and other individual indicators. Most of the cities considered in the sample have in common the fact that they are: i) headquarters of several multinational corporations, ii) major financial or manufacturing centres, iii) important laboratories of new ideas and innovation hubs in business, economics, and culture, iv) host high-quality educational institutions, including renowned universities with international student attendance and world-class research facilities, v) feature a high degree of diversity in terms of language, culture, religion, and ideologies.

Note that many of these cities also rank at the top of the Global Financial Centres Index (GFCI) which is a ranking of the competitiveness of the world's leading financial centres.[2]

Table 1 reports the ranking of the metropolises under consideration according to the GPCI and the GFCI indexes between 2012 and 2021.[3]

Table 1: Ranking of global cities according to the Global Power City Index (GPCI) and the Global Financial Centres Index (GFCI).

City	GPCI	GFCI
Hong Kong	9	3
San Francisco	13	7
New York	2	1
Los Angeles	12	5
Vancouver	29	33
London	1	2
Tokyo	3	9

According to the GPCI measure, London was the most globally connected metropolis during the period under investigation, followed by New York. However, the latter city overtakes the former in terms of global financial competitiveness. East Asian cities also score highly according to the GPCI index and increased considerably in connectivity in the last twenty years. Hong Honk is the third most competitive financial centre according to the GFCI index. The two remaining American coastal cities are dominant financial centres, although Los Angeles increased its position as a major trade centre in the last twenty years.

The city of Vancouver is the only large urban area not included in the top-twenty, however, this metropolis is an example of a gateway city that has experienced a surge in demand for luxury housing, especially second homes (see, for example, Grigoryeva and Ley, 2019) and it scores highly in the UBS Global Real Estate Bubble Index.[4] For this reason, this city was included in the sample as an interesting case of real estate as an investment asset class.

As far as the stock market indexes are concerned, these are: the S&P500 Composite Index (S&P 500) for the United States, the S&P TSX Composite Index, (S&P/TSX) for Canada, the FTSE 100 Price Index (FTSE100) for the UK, the Nikkei 225 Stock Average Index (N225) for Japan and the Hang Seng index (HIS) for Hong Kong.

To account for policy-related economic uncertainty, we consider the Global Economic Policy Uncertainty Index (GEPU). The index is a GDP-weighted average of national EPU indices for 21 countries. Each national EPU index reflects the relative frequency of own-country newspaper articles that contain a trio of terms pertaining to the economy, policy, and uncertainty. In other words, each monthly national EPU index value is proportional to the share of own-country newspaper articles that discuss economic policy uncertainty in that month.

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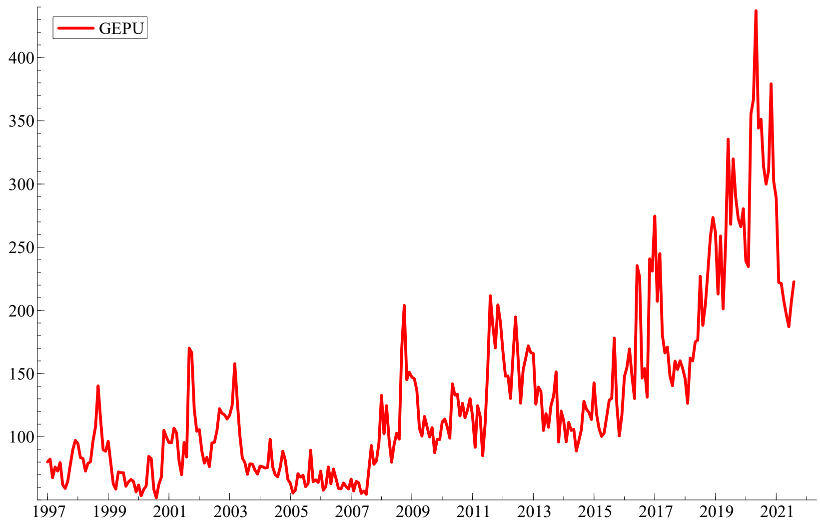
[2] The GFCI is a ranking of the competitiveness of financial centres based on over 29,000 financial centres assessments. The ranking is an aggregate of indices from five key areas: business environment, financial sector development, infrastructure factors, human capital, reputation, and other general factors.

[3] In many cases, the choice of metropolises was dictated by the availability of data. However, the final sample does include most of the top twenty metropolises in the GPCI index.

[4] The UBS Global Real Estate Index gauges the risk of a property bubble according to the pattern of indicators that account for the decoupling of local prices from local incomes and rents, or indications of excessive lending and construction activity.

As it appears from Figure 1, the GEPU index is able to capture many of the major events that increased uncertainty and geopolitical risk around the world over the period under consideration. the index rose sharply in reaction to the Asian financial crisis, the 9/11 terrorist attacks, the U.S.-led invasion of Iraq in 2003, the Global Financial Crisis in 2008-09, the European immigration crisis, concerns about the Chinese economy in late 2015, and the Brexit referendum in June 2016 in the United Kingdom. The index fluctuates consistently around high levels during the sovereign debt and banking crises in the Eurozone from mid-2011 to early 2013. This period also featured intense partisan battles over fiscal and healthcare policies in the United States, and a generational leadership transition in China. Finally, it reaches a pick during the COVID 19 pandemic outbreak. Overall, from Figure 1 it appears that the GEPU index seems to fluctuate across two different regimes: it was relatively low from 1997 to 2007, but it increases sharply starting from 2007 to reach a pick during the recent Covid 19 health crisis.

Figure 1. Global economic policy uncertainty index.



3. Dynamic Interaction Between Real Estate Price and Stock Markets

3.1 Methodology

The interdependence and causality between housing and stock market returns is investigated by using wavelet coherence approach, which is based on a continuous wavelet transform.

Wavelet is a technique that decomposes a time series into different short waves that start at a given point in time and end at a given later point in time. In other words, the wavelet approach is a non-parametric method that involves using small wave functions to approximate fluctuations in time series to extract information from a sequence of numerical measurements (signals). Broadly speaking, the wavelet methodology involves applying recursively a succession of low-pass and high-pass filters to the real estate and stock market series. This process allows separating the high-frequency components of the series from the low-frequency components (for more details see, for example, Benhmad, 2013).

Since the use of wavelets is a well-established methodology, in this section we only introduce the concepts and definitions useful for our purposes. For an excellent review of the theory and use of wavelets, see Percival and Walden (2000); Gençay *et al*. (2002).

For a given house price series $x(t)$ the continuous wavelet transform (CWT) acts as a band filter to the series $x(t)$ and is defined by the convolution

$$W_x(\tau, s) = \frac{1}{s}\sum_{t=1}^{T} x(t)\varphi^*\left(\frac{t-\tau}{s}\right), \qquad (1)$$

where the asterisk (*) denotes the complex conjugation, τ denotes the scale and s the position. The CWT of a given stock market series $y(t)$ can be defined likewise. In Eq. (1) wavelet $\psi(t)$ satisfy the condition

$$\psi(t) = \pi^{\frac{1}{4}} e^{iw_{0,t}} e^{\frac{-t^2}{2}},$$

where $e^{-t/2}$ ensure that the admissibility condition

$$0 \prec C_\varphi = \int_0^\infty \frac{|\psi(\omega)|^2}{\omega} d\omega \prec \infty,$$

and $\psi(\omega)$ is the Fourier transform of the mother wavelet $\psi(t)$. The cross wavelet transform for the stock market $y(t)$ is defined likewise.

For any housing return series, $x(t)$ and its counterpart stock market returns $y(t)$, the cross-wavelet spectrum is defined as

$$W_{xy}(\tau, s) = W_x(\tau, s)W_y^*(\tau, s). \qquad (2)$$

The cross wavelet power spectrum gives a measure of the localized covariance between $x(t)$ and $y(t)$. Therefore, the cross wavelet distribution is given as

$$\frac{|W_x(s)W_y(s)|}{\sigma_x\sigma_y}.$$

The wavelet coherence between two-time series is a localized correlation coefficient in the time-frequency space, which closely resembles that of a traditional correlation coefficient but it allows for a three dimensional analysis which simultaneously considers the time and the frequency components, as well as the strength of the correlation between the time series component (see Pal and Mitra, 2019; Sharif et al., 2020; Choi, 2020).

Following and Torrence and Webster (1999) the wavelet capturing the co-movement between two time series then can be obtained as

$$R^2(\tau, s) = \frac{\left|s\left(\frac{1}{s}W_{xy}(\tau,s)\right)\right|^2}{s\left(\left(\frac{1}{s}|W_x(\tau,s)|^2\right)s\left(\frac{1}{s}|W_y(\tau,s)|^2\right)\right)}, \qquad (3)$$

A possibly drawback of Eq. (3) is that $0 \le R^2(\tau, s) \le 1$, therefore this expression does not allow to distinguish between positive and negative co-movements, we thus implement the analysis by using the phase difference to extract information on the sign of the correlation in addition to the lead-lag relationship.

Following Bloomfield et al. (2004), the phase difference from the phase angle of the cross-wavelet transform is defined as

$$\rho_{xy}(\tau, s) = \tan^{-1}\left[\frac{Im\left[\left|s\left(\frac{1}{s}W_{xy}(\tau,s)\right)\right|^2\right]}{Re\left[s\left(\left(\frac{1}{s}|W_x(\tau,s)|^2\right)\right)s\left(\left(\frac{1}{s}|W_y(\tau,s)|^2\right)\right)\right]}\right] \; ; \rho_{xy} \in [-\pi, \pi], \qquad (4)$$

where $Im[\cdot]$ and $Re[\cdot]$ are the imaginary and real parts respectively of the smoothed power spectrum. The phase difference, $\rho_{xy}(\tau, s)$, indicates the co-movements and causality relationships between real estate prices and stock markets at different time scales. If the two series are in phase and the phase difference is between 0 and $\pi/2$, it means that stock market leads the related real estate market (i.e. x_t positive co-move with y_t and x_t leads y_t). Similarly, if the phase difference is between 0 and $-\pi/2$, then real estate prices lead the related stock market.

3.2 Empirical Results

To identify causality and phase differences between the real estate and stock market returns, the wavelet coherency given in Eq. (3) was estimated for each pair of the housing market index and its stock market counterpart is estimated and plotted, as shown in Figure 2-8. The horizontal axis denotes the time component while the vertical axis represents the frequency component. Frequency, plotted on the logarithmic scale, is converted into time units (months) to facilitate the interpretation and the range is from the lowest of 2 months to the highest of 64 months. We define time scales between 2-8 months, 9-32, and above 32, as short, medium and long-run periods, respectively. The wavelet squared coherency power is represented by colours, with deep red indicating the highest power (1.0) and deep blue the lowest power (0). The area within the white contours indicates power at the 5% significance level (i.e. the wavelet squared coherency is statistically significant within such delimited area). Furthermore, the phase differences given in Eq. (4) are indicated by black arrows on the wavelet coherence plots. For example, → and ← indicate that housing prices and stock returns are in phase (positively correlated) or out of phase (negatively correlated), respectively. The lead-lag relationships are detected by an inclined arrow. Arrows pointing ↗ and ↙ indicate that housing prices are led by stock returns, whereas arrows pointing to the left, ↘ and ↖, indicate that stock returns are leding housing market, therefore the latter are lagging the former.

Looking at Figure 2, a visual assessment of the red colour of the wavelet coherency plot reveals that the Asian financial crisis in 1997 had an impact on the housing market in New York over the short-, medium periods. Similarly, we observe patches of high correlation in the medium-run period between 2001 and 2003, when the 9/11 terroristic attach and the Iraq war occurred. High coherency levels between stock and real estate markets are also observed after 2006 mostly in the medium-, long- run periods in the wake of the credit crunch period. This correlation remains strong also during the Covid 19 health crisis. Considering now the phase differences, the lead-lag relationships between the two markets appear to change both over time and across frequencies. From Figure 2, it appears that, in New York City, the housing market was leading the S&P 500 returns (i.e. arrow pointing ↗ (↙)) around 2001-2003, 2008-2012 and 2016- 2018 in the 4-month band (i.e. short run period). This picture changed in the medium run when the housing market returns were lagging those of the S&P 500. Interestingly, the series were in phase during 2020 -2021 (i.e. the time of the COVID-19 pandemic).

As regards San Francisco (shown in Figure 3), the wave coherence shows similar results. Looking at the short run period, the phase difference arrows are pointing down around 2003, 2018, and 2020, indicating that the housing market was lagging the stock returns. In the 16 month band (i.e. medium-run period) the housing market was leading the stock market around 2000, but it lagged the S&P index around 2006. This implies that the shocks to housing market in this city were due more to financial instability that followed the subprime market in other regions than the real estate sector itself. By contrast, in the long-run, stock and housing markets move mostly in phase, meaning that in the long run co-movement between the two markets are mainly related to the macroeconomic fundamentals. From Figure 4, it appears that the dynamic behaviour of the two markets is not too different from Los Angeles with the two markets mostly moving in phase in the long run.

Turning to Vancouver, from Figure 5, there is clear evidence of medium-, long-run interdependence, at low frequency, between the two markets. To be specific, the slope of the arrows around 2005 and 2008- 2012 indicate that housing prices were lagging those of stock returns in the 8-16 and 16-32 month bands, while the housing returns were leading those of stock returns around 1999-2000. A cyclical effect can be identified in the 32-64 month band around 2006 -2011.

For the case of Hong Kong (shown in Figure 6), the correlation between the two markets is high in the medium-, long run, but is greater during well-known turmoil periods, such as the Asian financial crisis in 1997, the 9/11 terroristic attach, and the Iraq war, the subprime crisis, and during the Covid19 pandemic. More precisely, the direction of the arrows shows that the positive relationship between housing prices and stock markets in the medium- and long-run around 2000, 2003 and 2008-2018 was one in which housing prices were leading. However, a negative relationship was also found in the 32-64 month band around 1997-2000, where housing prices lagged stock returns, whereas a cyclical effect around the latter period was found in the 16-32 month band.

Two similar cases, the cities of Tokyo and London, are shown in Figures 7 and 8. Looking at Figure 7, the arrows point to the left and upward for short-run scales indicating a negative relationship between the two series during 2005-2012 with the housing markets lagging the stock markets. Similarly, in the long-run scales around 1999-2001 and 2008-2011, we find a negative relationship. The picture does not change when we consider the case of the London housing market with the FTSE100 return.

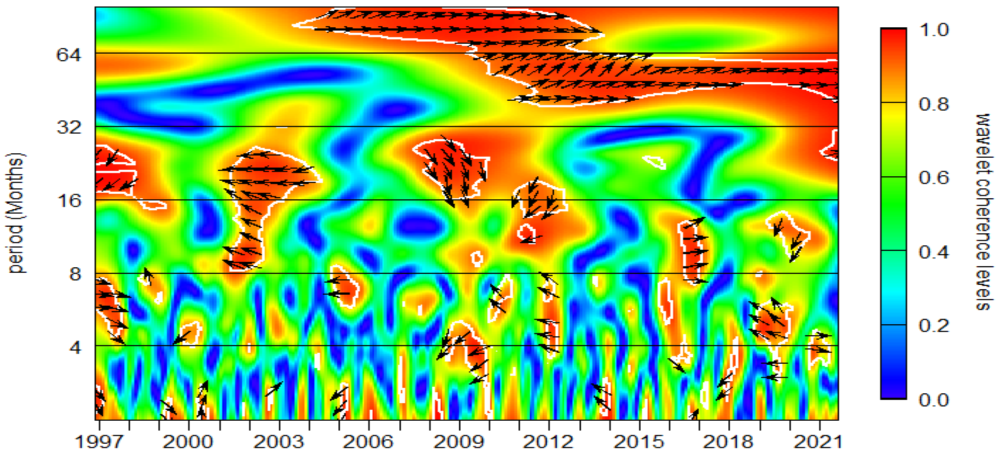


Figure 2 : Cross wavelet transform between New-York housing market and SP500 index.

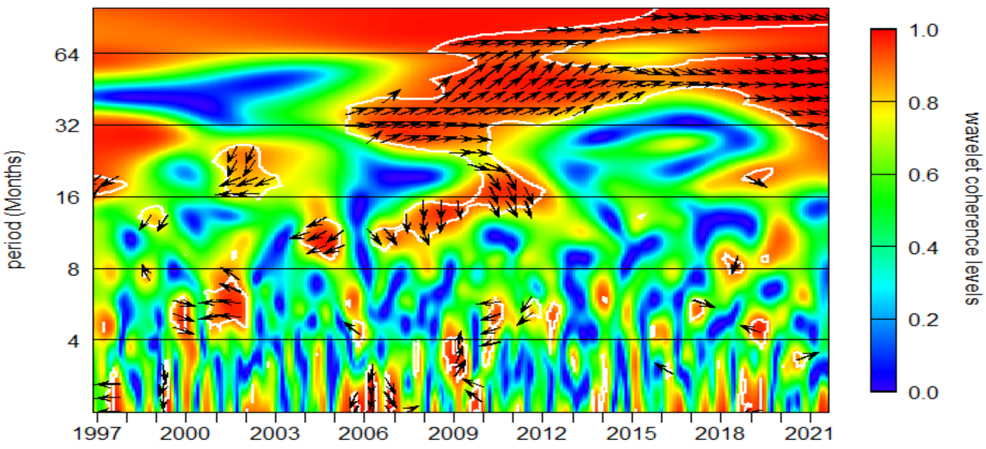


Figure 3: Cross wavelet transform between Los Angeles housing market and SP500 index.

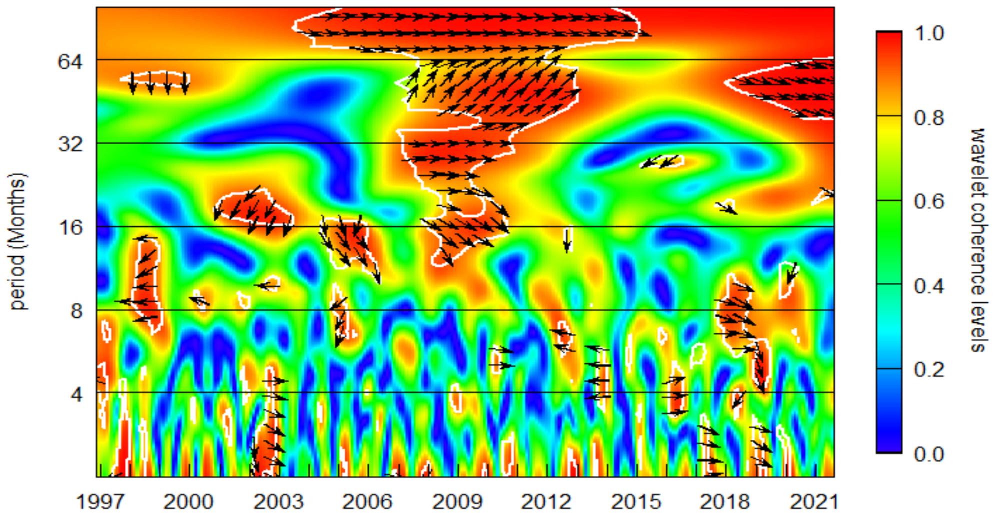


Figure 4 Cross wavelet transform between San Francesco housing market and SP500 index.

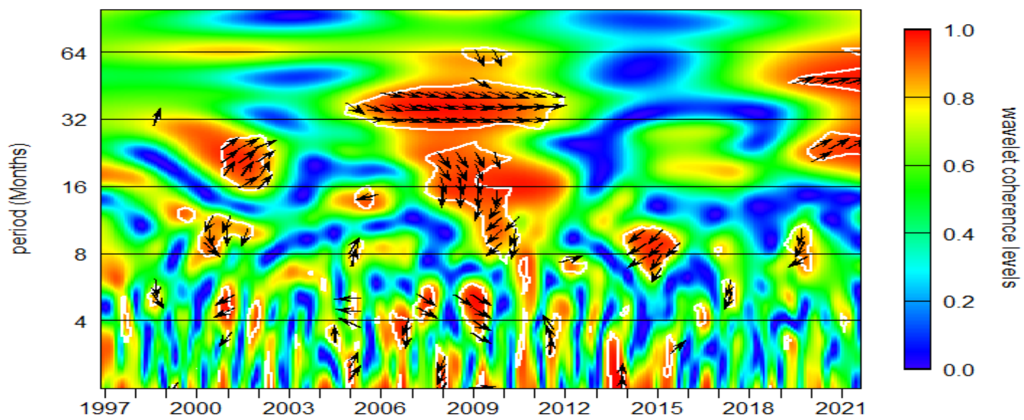


Figure 5 Cross wavelet transform between Vancouver housing market and GSPTSE index.

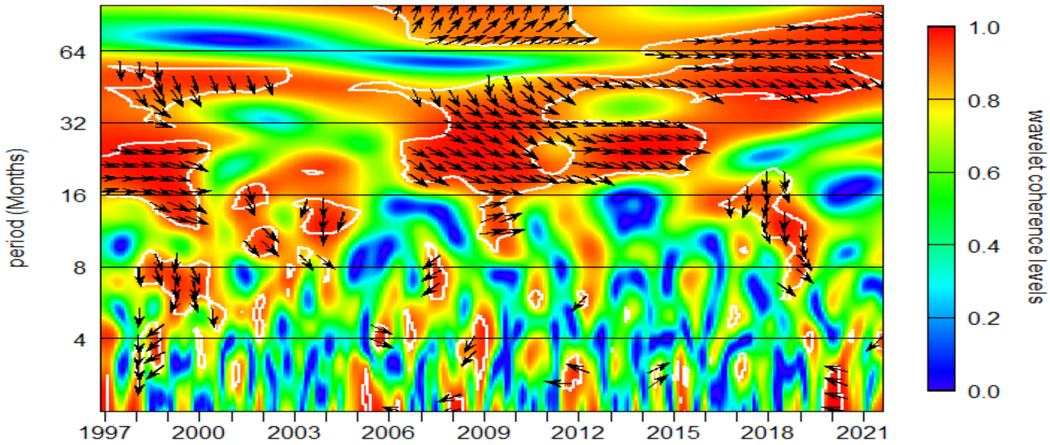


Figure 6. Cross wavelet transform between Hong Kong housing market and HSI index.

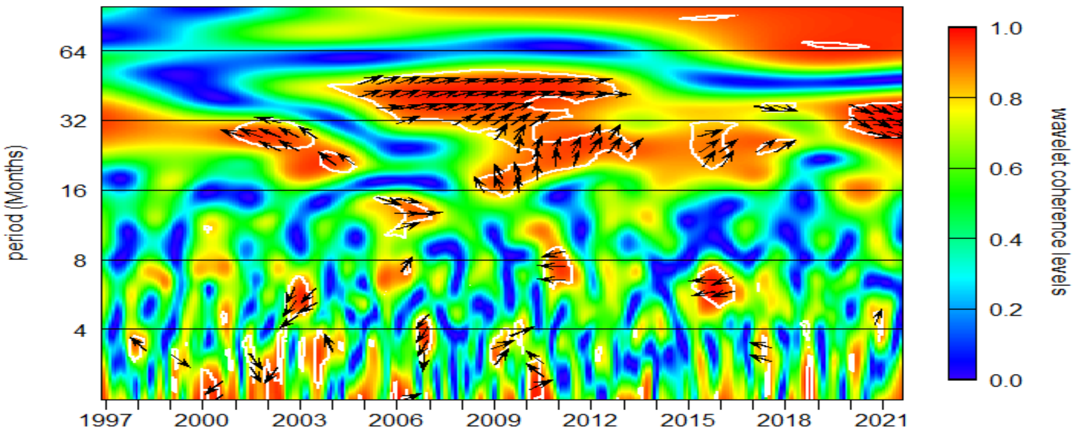


Figure 7. Cross wavelet transform between Tokyo housing market and N225 index.

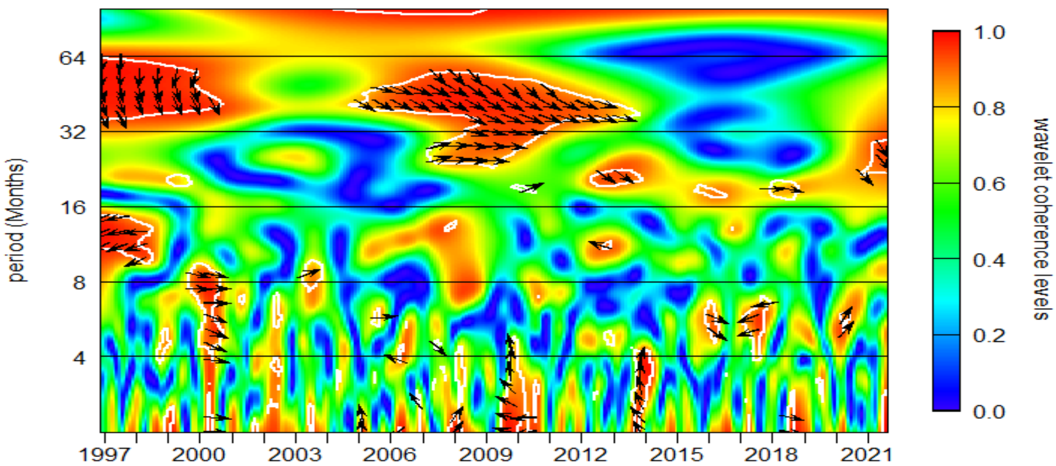


Figure 8 Cross wavelet transform between London housing market and FSTE100 index.

To summarize the results, looking at Figures 2-8, it appears that the correlations between real estate and stock markets are mostly significant over the medium and long run periods, as indicated by the deep red colour in the time scales 9-64 months. It is of interest to note that there is a close match between the ranking of global cities in Table 1 and the magnitude of the correlation shown in Figures 2-8. Honk Hong and New York, that score highly in Table 1, also show the highest level of coherency between the two markets. On the other side, the city of Vancouver, which is relatively low in the ranking in Table 1, shows the lowest coherency levels in Figure 4. The correlation is however not constant over time, but it increases especially over the long-run period following major economic shocks. In particular, a significantly high degree of co-movement can be identified between 2007 and 2013 over medium-run and long-run scales. Some evidence of weaker, but still significant coherence above the 16-month frequency cycle was also observed in the period 2005-2008 (U.S. subprime crisis) and between 2010-2011 (European debt crisis). Moreover, significant coherences over the long-term time frequency bands are observed during the COVID-19 period, compared to the pre-COVID-19 pandemic.

4. Dynamic Relations Between Housing Markets and Geopolitical Risk

In Section 3 we show that stock market dynamics share important links with real estate prices, however, the direction of co-movements and causality are time-varying and strongly scale-dependent. Having looked at the dynamics of stock market returns, a natural follow up question is: to what extent does stock market volatility affect the housing market in global cities? The issue of stock market volatility is closely related to uncertainty. In the related literature stock market volatility has often been used to investigate the link between economic uncertainty and macroeconomic fluctuations. For example, in his seminal paper Bloom (2009) used a structural model to show that shocks to macroeconomic uncertainty, as proxied by innovation in stock market volatility, generate large swings in aggregate output and employment. The author explains that uncertainty shocks generate short sharp recessions and recoveries by inducing firms to hold back their investments and hiring decisions. In the medium term, the increased volatility from the shocks induces an overshoot in output, employment, and productivity. One can expect stock market volatility to affect the housing market returns in a similar way as it affects the other macroeconomic and financial variables. A possible drawback of using stock market volatility as a proxy for uncertainty is that it only accounts for major economic and political shocks indirectly and may not be able to capture the persistence of these shocks. Accordingly, in this paper the GEPU index suggested by Baker et al. (2016) is used rather than other indexes such as implied volatility index.

To answer the question above, once again, we consider the possible lead-lag relationships between the time series in the time frequency space described above. The wavelet methodology is particularly suitable for our application since it is a non-parametric approach which allows us to examine the short-, medium-, and long-run relationship of interest in the case of nonlinear stochastic processes without loss of information. Another important feature of interest is that the wavelet coherence is robust to endogeneity, this is particularly useful feature since any parametric model would suffer from the reverse causality problem (see, for example, Jurado et al. 2015; Demiralay and Kilincarslan, 2022).

The wavelet coherency results are reported in Figures 9-15. An inspection of these figures shows several patches of high coherence level between the housing markets and the uncertainty index over different time scales.

In particular, for the city of New York, during the Asian financial crisis period the direction of the phase arrows in the short-run scale band (Figure 9) is turned down-left, indicating that the correlation between them is negative, with the uncertainty index driving the housing market. The impact of the terroristic attach on 9/11, and the U.S. led war in Iraq (between 2001-2003) also show an estimated negative correlation with the uncertainty index leading the housing market in the short- medium time scale. On the opposite, during the global financial crisis and COVID-19 pandemic, the arrows points ↗ and ↙ over the short-term time frequency bands, indicating that the correlation between the two series is positive with the housing market leading the uncertainty index.

Looking at Figure 8, it appears that major geopolitical events have an impact on the medium-, long- run periods. This is particularly true for the subprime crisis and the COVID 19 pandemic where strong negative correlation is observed between the real estate market and the uncertainty index. On the other side, the housing market led the uncertainty index during the subprime market crises when the housing market collapsed.

Looking now at Figure 10 and 11, the pictures for San Francisco and Los Angeles are not very different, in the sense that high levels of wavelet coherency are detected during periods of major political and economic turbulence. Figure 12 displays the dynamic correlations for the London housing market with the uncertainty index. It is interesting to note a positive relationship, with the housing market leding the uncertainty index during both global financial crisis and Brexit referendum (2016-2018) at the short run frequency scale. This positive correlation was also observed in the medium run period (i.e. at the frequency band of 8-16 months) around 1998-2003. The picture changed in the long run period, where the housing market lagged the uncertainty index around 1998-2002.

Coming to Vancouver, it is clear that the strong economic fundamentals and solid financial sector enjoyed by the Canadian economy have generated a perception of relatively low risk associated with housing market developments since, from Figures 13, there is little evidence of causality and co-movement between the real estate market and the GEPU index apart from 2001-2003 during the 9/11 terroristic attach and the Iraq invasion, the global financial crisis, and the Covid 19 pandemic.

Considering now the city of Tokyo, from Figures 13-14, it appears that the correlations increase during periods of major economic turmoil, with the high coherency levels mostly confined to the medium-, long run periods for both cities. In particular, we can see signs of the economic stagnation in Japan caused by the asset price bubble's collapse in late 1991 and lasted until 2003. Also, we notice that the correlations are greater during the global financial crisis in 2008, the Tōhoku Earthquake and Tsunami and Fukushima Nuclear Disaster in 2011, and with the COVID-19 pandemic.

Finally, looking at the Hong Kong case, we notice a positive correlation during the financial crisis period in the short-, medium period. In the long run period, the correlation is mostly negative with the housing markets leading the uncertainty index.

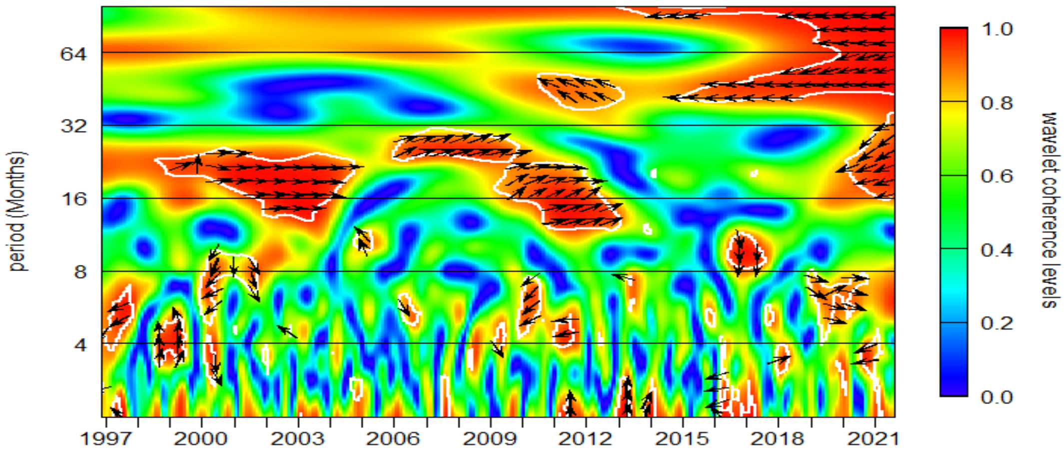


Figure 9. Cross wavelet transform between New-York housing market and GEPU Index.

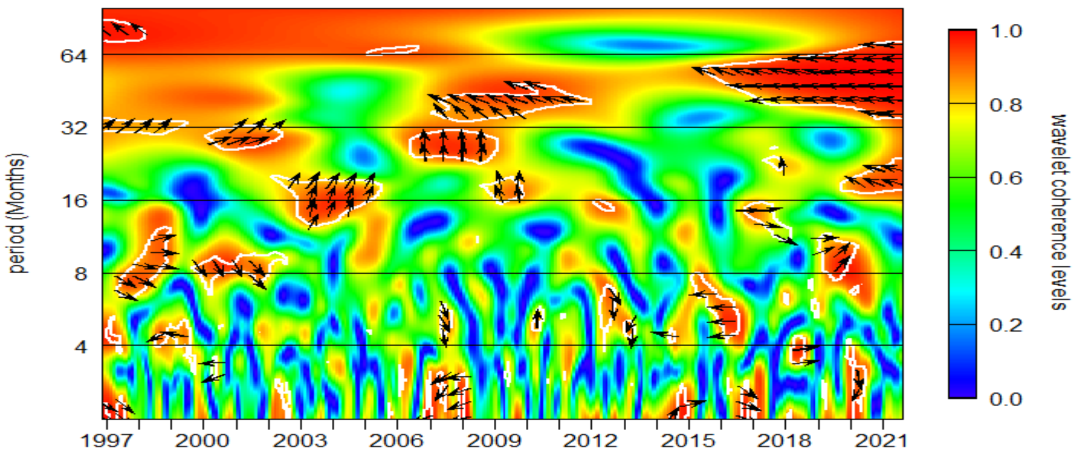


Figure 10. Cross wavelet transform between San Francesco housing market and GEPU Index.

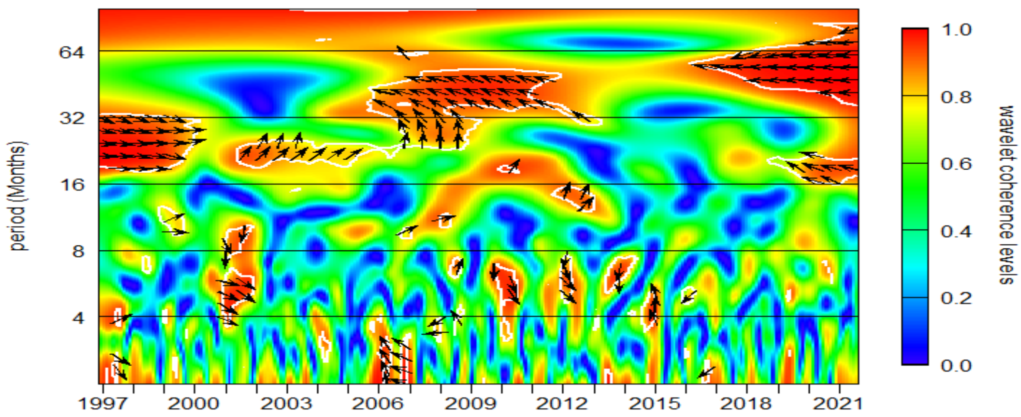


Figure 11. Cross wavelet transform between Los Angeles housing market and GEPU Index.

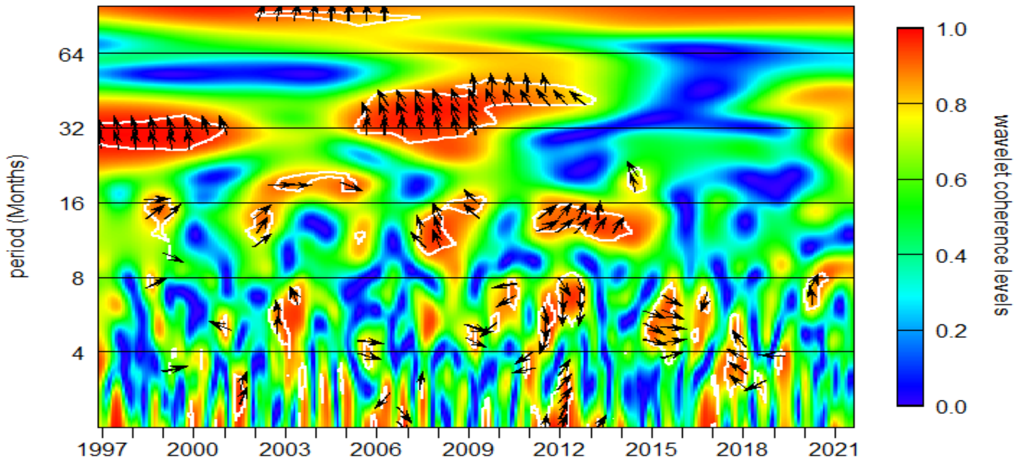


Figure 12. Cross wavelet transform between London housing market and GEPU Index.

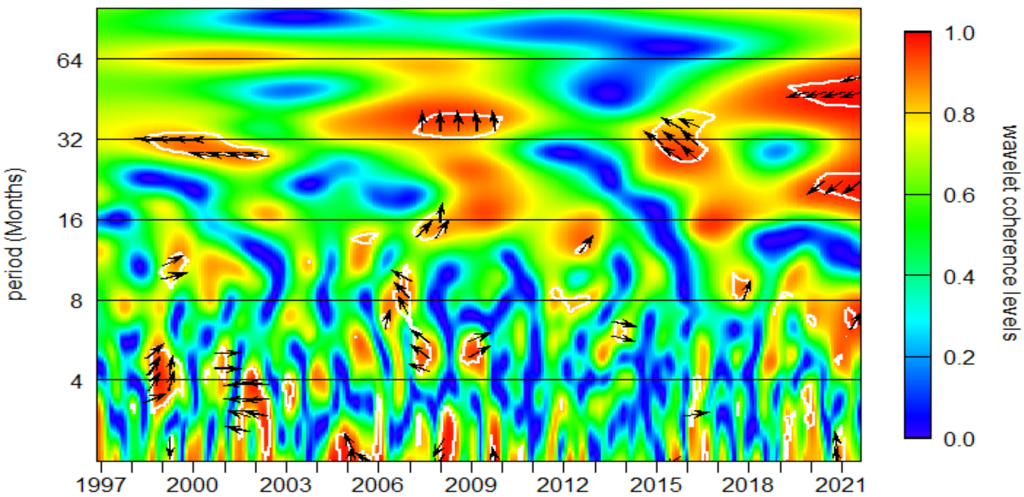


Figure 13. Cross wavelet transform between Vancouver housing market and GEPU Index.

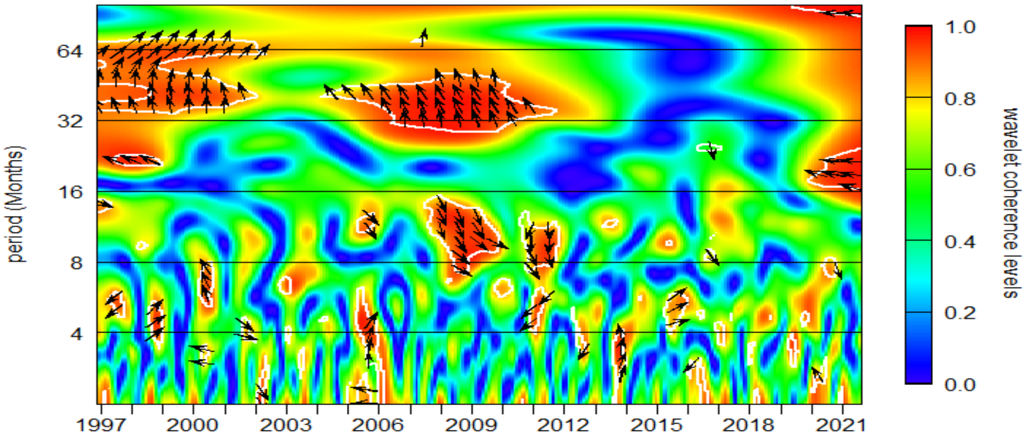


Figure 14. Cross wavelet transform between Tokyo housing market and GEPU Index.

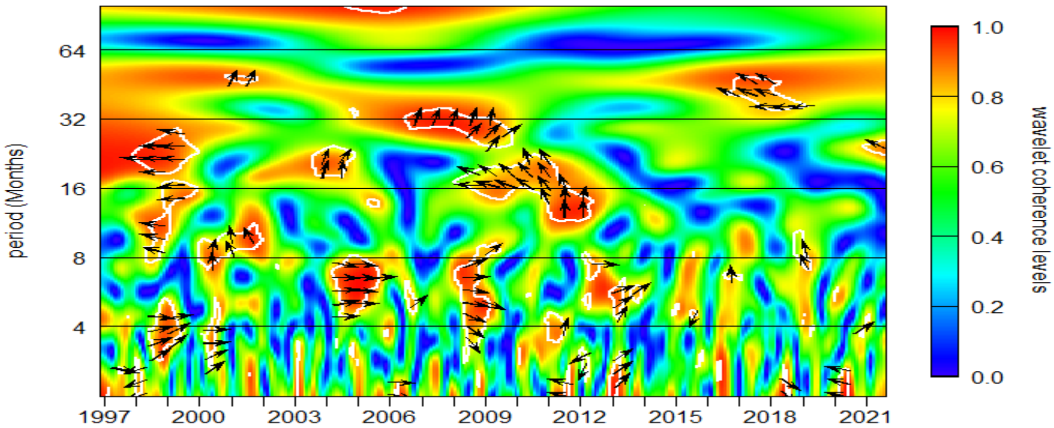


Figure 15. Cross wavelet transform between Hong-Kong housing market and GEPU Index.

To summarize, our results show that major economic and political shocks like the Asian Financial Crisis in 1997, 9/11 terroristic attacks, the U.S.-led invasion of Iraq in 2003, the Global Financial Crisis in 2008-2009, and the Covid 19 pandemic that started in 2019, deeply affected house price dynamic in the global cities under consideration. Obviously, shocks such as the Brexit referendum in 2016, have a greater impact on the domestic real estate market than international markets. However, uncertainty appears to increase dramatically after major economic and political shocks and this has strong repercussion on local housing markets. From Figures 8-15, it is clear that major uncertainty shocks spread through the housing market of the metropolises under consideration, indeed evidence of the deep red areas is found in correspondence of major uncertainty shocks. The sign of the correlation and the nature of the causal relation change over time since these are related to the nature of the shock, with housing markets leading the uncertainty index in some periods (e.g. the subprime mortgage crises in 2005) and the other way around in cases of major geopolitical turmoil (i.e. the 9/11 terroristic attach in New York). Although uncertainty shocks have important effects on domestic real estate markets, contagion effect across global cities can clearly be noticed, especially in the medium-, long-periods. In this respect, the estimated signs mostly support the prediction of the real option models (see, for example, Bernanke, 1983) were a negative correlation between uncertainty and investments in the real estate. Our results, are in line with Antonakakis et al. (2015) who found that the correlation between EPU and real housing market returns is mostly negative (see also El Montasser et al., 2016; Ajmi et al., 2014; Christou et al, 2017).

5. Time Frequency Connectedness Across Real Estate Markets

The analysis in the previous sections provides several insights into the interdependence structure between the housing and stock markets on the one hand and the housing markets and uncertainty on the other. In particular, the wavelet coherence analysis reveals that: *i*) the lead-lag relationships between the housing prices and stock market returns changed in intensity and direction in dissimilar time scales, *ii*) housing market dynamics are closely related to global uncertainty events. However, housing markets can also induce considerable political and economic uncertainty, this was particularly during the sovereign debt crisis period.

To develop a full picture of the interdependence structure, a further interesting question could be asked: could the risk in the housing market spillover from one city to another? Also, what is the direction of volatility spillover and how long does it take for the shock to propagate across the housing market network? Finally, to what extent a city is a shock transmitter (receiver) within the global city network in the short-, medium-, long run periods? To address these questions, we employ the WTVP-VAR procedure described below.

5.1. Methodology

The proposed WTVP-VAR can be carried out in two steps. In the first step the maximal overlap discrete wavelet transform (MODWT) is applied to the housing price indexes to decompose the series into high-frequency and low-frequency components. In the second step, the obtained filtered series are used as input variables to analyse correlations between stock markets using the TVP-VAR model. The benefit of the TVP-VAR approach is that it lifts the burden of the often arbitrarily chosen rolling-window-size, which may lead to very erratic or flattened parameters, and the loss of valuable observations. Moreover, this approach can also be adopted to examine dynamic connectedness at lower frequencies and with limited time-series data (see Antonakakis et al. 2016; Antonakakis et al. 2020).

The first step involves using the maximal overlap discrete wavelet transform to decompose the house price series. To save space the details of the procedure are not discussed here, interested readers are referred to Alqaralleh and Canepa (2022) and the references therein.

The second step of the suggested procedure involves using the filtered series obtained from the j-level multi-resolution decomposition to estimate the TVP-VAR model in the time-frequency framework.

The TVP-VAR approach can be written as

$$y_t = \beta_t z_{t-1} + \epsilon_t \;;\; \epsilon_t | \, F_{t-1} \sim N(0, S_t), \tag{5}$$

$$vec(\beta_t) = vec(\beta_{t-1}) + \upsilon_t, \;\; \upsilon_t | F_{t-1} \sim N(0, R_t), \tag{6}$$

where y_t and $z_t = [y_{t-1}, \dots, y_{t-p}]'$ represent $N \times 1$ and $P \times 1$ dimensional vectors, respectively. β_t is an $N \times$ Np dimensional time-varying coefficient matrix and ϵ_t is an $N \times 1$ dimensional error disturbance vector with an

$N \times N$ time-varying variance-covariance matrix S_t, $vec(\beta_t)$ and υ_t are $\mathrm{N}^2\mathrm{p} \times 1$ dimensional vectors and R_t is an $\mathrm{N}^2\mathrm{p} \times \mathrm{N}^2 p$ dimensional matrix.

The VAR system is then transformed to its vector moving average (VMA) representation to calculate the generalized impulse response functions (GIRF) and generalized forecast error variance decomposition (GFEVD) (Koop et al., 1996; Pesaran and Shin, 1998) as follows:

$$y_t = \sum_{j=0}^{\infty} L' W_t^j L \epsilon_{t-j} \;, \tag{7}$$

$$y_t = \sum_{j=0}^{\infty} A_{it} \epsilon_{t-j} \,, \tag{8}$$

where $L = \left[I_N , \ldots, 0_p\right]'$ is an $Np \times N$ dimensional matrix, $W = [\beta_t;\, I_{N(p-1)}, 0_{N(p-1)\times N}\,]$ is an $Np \times Np$ dimensional matrix, and A_{it} is an $N \times N$ dimensional matrix.

The GIRFs represent the reactions of all variables following a shock in variable i. Due to the absence of a structural model, the differences between a J-step-ahead forecast are computed, once for where variable i is shocked and a second time where variable i is not shocked. This difference is considered to be owing to a shock in variable i, which is consequently computed by

$$GIRF_t\left(K, \delta_{j,t}, F_{t-1}\right) = E(y_{t+K} \,|\epsilon_{j,t} = \delta_{j,t}, F_{t-1}) - E(Y_{t+K} |\, F_{t-1}), \tag{9}$$

$$\psi_{j,t}^{g}(K) = \frac{A_{K,t} S_t \epsilon_{j,t}}{\sqrt{S_{jj,t}}} \frac{\delta_{j,t}}{\sqrt{S_{jj,t}}}, \qquad \delta_{j,t} = \sqrt{S_{jj,t}}\,, \tag{10}$$

$$\psi_{j,t}^{g}(K) = \frac{A_{K,t} S_t \epsilon_{j,t}}{\sqrt{S_{jj,t}}}, \tag{11}$$

where $\psi_{j,t}^{g}$ represents the GIRFs of variable j and K represents the forecast horizon, $\delta_{j,t}$ the selection vector with one on the jth position and zero otherwise, andF_{t-1} the information set until $t-1$. Afterwards, the variance share that one variable has on others (known as the GFEVD) can be computed as follows:

$$\tilde{\Phi}^{g}{}_{ij,t}(K) = \frac{\sum_{t=1}^{K-1} \psi_{j,t}^{2,g}}{\sum_{j=1}^{N} \sum_{t=1}^{K-1} \psi_{j,t}^{2,g}}. \;\; \sum_{j=1}^{N} \tilde{\Phi}^{g}{}_{ij,t}(K) = 1 \;\; and \;\; \sum_{j=1}^{N} \mathrm{N}^{g}{}_{ij,t}(K) = N \tag{12}$$

Based on Equation (12), one can explore how a housing market in one city spills over to other city under investigation through the total connectedness index, which can be constructed as

$$C_t^{g}(K) = \frac{\sum_{i,j=1, i\neq j}^{N} \tilde{\Phi}^{g}{}_{ij,t}(K)}{N} * 100. \tag{13}$$

More interesting is to analyse the directional connectedness. The method under consideration considers three aspects of this direction:

First, total directional connectedness *to others,* given as

$$C_{i\to j,t}^{g}(K) = \frac{\sum_{i,j=1, i\neq j}^{N} \tilde{\Phi}^{g}{}_{ij,t}(K)}{\sum_{j=1}^{N} \tilde{\Phi}^{g}{}_{ji,t}(K)} * 100. \tag{14}$$

Second, total directional connectedness *from others,* given as

$$C_{i\leftarrow j,t}^{g}(K) = \frac{\sum_{i,j=1, i\neq j}^{N} \tilde{\Phi}^{g}{}_{ij,t}(K)}{\sum_{j=1}^{N} \tilde{\Phi}^{g}{}_{ij,t}(K)} * 100. \tag{15}$$

Last, Eq. (15) may be subtracted from Equation (14) to obtain the *net* total directional connectedness as follows:

$$C_{i,t}^{g}(K) = C_{i\to j,t}^{g}(K) - C_{i\leftarrow j,t}^{g}(K). \tag{16}$$

It is worth noting that Equation (16) illustrates the influence which house prices in city i have on the analysed network. Thus, a positive value of Equation (16) means that house prices in city i influence the network more than the network influences them, while a negative value means that house prices in a city i are driven by the network.

Finally, the bidirectional relationships are further examined by computing the net pairwise directional connectedness (NPDC) as follows:

$$NPDC_{ij}(K) = \widetilde{\Phi}^{g}{}_{ij,t}\,(K) - \widetilde{\Phi}^{g}{}_{ji,t}\,(K). \quad (17)$$

Under Eq. (17), a positive value of NPDC implies that house prices in city j are dominated by house prices in city i, while a negative value of NPDC implies that house prices in city i are dominated by house prices in city j.

5.2. Empirical Results

The results of the network connectedness contained many notable features. In the short run (time scales D_1) as shown in Panel A of Table 2, the spillover index is 49.32%, which means that around half of the volatility forecast error variance comes from the spillover in housing prices, and the other half of the co-movement is caused by purely domestic factors. Moreover, the volatility of each housing market is largely influenced by other markets in other global cities, almost all of which fluctuate from 30% to 90%. The results also highlight the housing market in London as a major recipient of volatility from other real estate markets (33.67%), followed by San Francisco (36.56%), and Tokyo (11.11%), whereas Hong Kong and New York are the major transmitter of volatility with net directional volatility spillovers of 28.54% and 25.76% respectively.

The picture changes when we consider time scales D_2 and D_3 (4-16 months). Panel B and C of Table 2 reveal that only around one-third of the volatility forecast error variance comes from housing market spillover, while the remainder of the co-movement is caused by other factors. What is interesting about the data in this table is that Los Angeles became the major recipient of volatility (39.31%), followed by London (26.52%), and San Francisco (21.08%). In contrast to the results in Table 2-A, the main diagonal in Tables 2-B and 2-C highlights that the own-effects range from 47.86% to 94.43% and are greater than other own-effects indices shown in Table 2-A but the own-connectedness is small compared with the total spillover effect of other housing prices indices.

In time scales D_4 and D_5 (16-64 months), the differences in volatility spillover begin to show. It is apparent from Tables 2-D and 2-E that the total connectedness indexes are around 80% and 60%, respectively, suggesting that the housing market in these global cites became highly prone to risk spillover. The highest contribution to this connectedness came from Hong Kong, whereas San Francisco was the major receiver. Tokyo and London followed, taking second and third places respectively for the entire sample under consideration. What is interesting in Table 2-D is that the own-effect was less than 15% (except for Hong Kong), whereas, in Table 2-E this effect ranged from 27.29% to 67.43%.

Looking at the net pairwise directional connectedness (NPDC) from Table 2 it appears that it is positively estimated in all cases, suggesting that the housing market in one region is dominated by housing prices in another region.

Table 2. The network connectedness in the housing market.

	Hong Kong	*San Francisco*	*New York*	*Los Angeles*	*Vancouver*	*London*	*Tokyo*	***FROM***
				Panel A: D1 (Horizon: 0-4 Months) ***TCI = 49.32***				
Hong Kong	93.66	0.12	0.46	0.44	0.39	2.91	2.01	6.34
San Francisco	1.77	29.95	26.19	12.74	25.54	2.48	1.33	70.05
New York	1.21	13.28	31.3	20.58	29.67	2.6	1.36	68.7
Los Angeles	1.06	2.49	26.99	41.71	24.53	2.02	1.2	58.29
Vancouver	2.22	13.1	29.53	20.85	30.19	2.91	1.19	69.81
London	10.92	4.05	9.63	7.37	9.75	52.23	6.06	47.77
Tokyo	17.71	0.45	1.66	1.75	1.53	1.16	75.74	24.26
TO others	**34.89**	**33.49**	**94.46**	**63.73**	**91.41**	**14.1**	**13.15**	**345.22**
NET	**28.54**	**-36.56**	**25.76**	**5.44**	**21.6**	**-33.67**	**-11.11**	
NPDC	0	5	2	3	1	6	4	
				Panel B: D2 (Horizon: 4-8 Months) ***TCI = 27.71***				
Hong Kong	94.43	0.42	0.66	0.19	0.69	0.66	2.96	5.57
San Francisco	5.9	71.47	9.3	1.97	4.95	2.94	3.48	28.53
New York	2.9	0.28	78.08	6.4	9.02	0.8	2.52	21.92
Los Angeles	6.06	3.54	31.19	47.86	5.13	3.34	2.89	52.14
Vancouver	11.33	0.7	9.69	0.97	69.14	2.61	5.55	30.86
London	4.32	2.1	16	3.1	8.4	62.66	3.42	37.34
Tokyo	12.32	0.41	1.2	0.2	2.97	0.48	82.42	17.58
TO others	**42.84**	**7.45**	**68.02**	**12.84**	**31.16**	**10.83**	**20.82**	**193.95**
NET	**37.26**	**-21.08**	**46.1**	**-39.31**	**0.3**	**-26.52**	**3.24**	
NPDC	0	5	2	6	3	4	1	
				Panel C: D3 (Horizon: 8-16 Months) ***TCI = 33.42***				
Hong Kong	88.78	2.28	0.61	2.17	1.19	2.53	2.43	11.22
San Francisco	5.4	72.65	3.63	2.19	4.5	9.34	2.29	27.35
New York	9.39	12.06	47.27	6.41	11.18	8.85	4.85	52.73
Los Angeles	5.53	11.91	4.9	54.2	7.61	6.75	9.1	45.8
Vancouver	5.72	15.44	3.27	8.94	54.7	4.3	7.63	45.3
London	8.28	9.91	2.29	4.86	2.96	66.96	4.73	33.04
Tokyo	7.08	2.74	1.16	2.84	1.01	3.67	81.5	18.5
TO others	**41.39**	**54.35**	**15.87**	**27.42**	**28.45**	**35.44**	**31.03**	**233.95**
NET	**30.17**	**27**	**-36.87**	**-18.38**	**-16.85**	**2.4**	**12.53**	
NPDC	0	1	6	4	5	3	2	

Results are based on a W-TVP-VAR model with a lag length of order one (BIC) and a 100-step-ahead generalized forecast error variance decomposition. Short-, medium and long term is referred to as the obtained series from the j-level multi-resolution decomposition ($j = 5$ in our case).

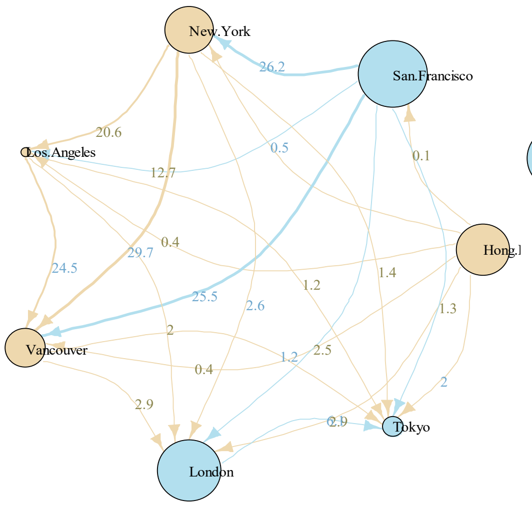
Table 2 (Continue). The network connectedness in the housing market.

	Hong Kong	*San Francisco*	*New York*	*Los Angeles*	*Vancouver*	*London*	*Tokyo*	***FROM***
				Panel D: D4 (Horizon: 16- 32 Months) ***TCI = 80***				
Hong Kong	64.59	2.14	6.85	6.86	6.83	7.82	4.9	35.41
San Francisco	27.87	3.89	15.72	15.73	15.65	10.9	10.24	96.11
New York	26.02	2.64	16.3	16.33	16.24	11.66	10.81	83.7
Los Angeles	26.99	2.67	15.92	15.93	15.86	11.85	10.78	84.07
Vancouver	29.29	2.82	15.13	15.13	15.06	11.99	10.58	84.94
London	26.37	3.99	15.15	15.15	15.06	13.57	10.71	86.43
Tokyo	30.15	2.92	14.75	14.74	14.65	12.13	10.66	89.34
TO others	**166.69**	**17.18**	**83.51**	**83.94**	**84.3**	**66.35**	**58.02**	**559.99**
NET	**131.28**	**-78.93**	**-0.19**	**-0.13**	**-0.64**	**-20.08**	**-31.32**	
NPDC	0	6	3	2	1	4	5	
				Panel E: D5 (Horizon 32 - 64 Months) ***TCI =60.02***				
Hong Kong	67.6	3.87	2.91	3.03	4.01	6.89	11.69	32.4
San Francisco	4.69	32.9	5.69	27.69	3.96	14.32	10.74	67.1
New York	1.7	4.7	45.76	4.16	33.7	4.37	5.6	54.24
Los Angeles	4.09	24.37	14.02	35.16	8.4	6.91	7.06	64.84
Vancouver	1.87	6.06	30.43	5.04	42.64	5.58	8.38	57.36
London	8.56	16.87	4.64	12.36	4.63	28.51	24.42	71.49
Tokyo	9.54	13.82	7.13	11.44	11.99	18.79	27.29	72.71
TO others	**30.46**	**69.7**	**64.83**	**63.72**	**66.69**	**56.86**	**67.89**	**420.15**
NET	**-1.94**	**2.61**	**10.59**	**-1.13**	**9.32**	**-14.64**	**-4.82**	
NPDC	3	3	1	3	2	5	4	

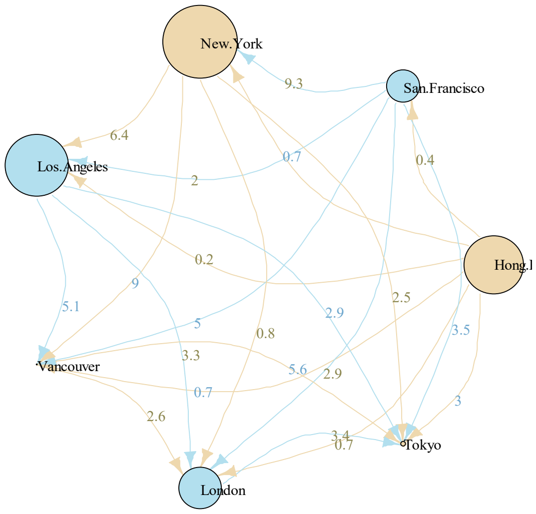
Results are based on a W-TVP-VAR model with a lag length of order one (BIC) and a 100-step-ahead generalized forecast error variance decomposition. Short-, medium and long term is referred to as the obtained series from the j-level multi-resolution decomposition ($j = 5$ in our case).

Finally, the connectedness is presented by using the network graph, which illustrates the degree of total connectedness among the housing prices in the considered global financial cities with each time scale. The node size and colour represent the magnitude of each series to the total system connectedness and origin of this connectedness (see Figure 16).

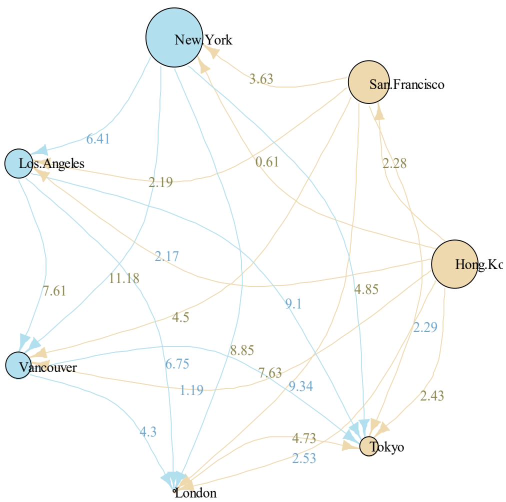
The network representation: 0



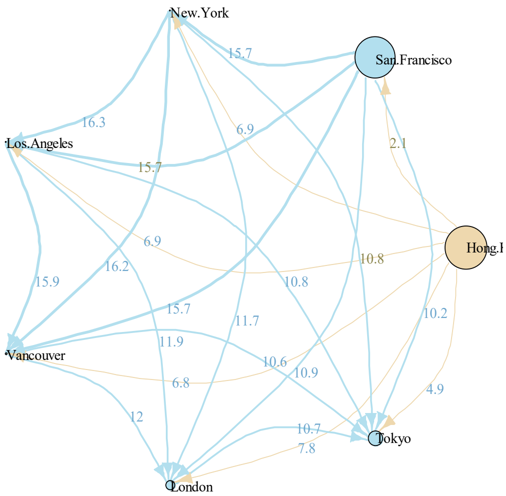
The network representation: 4



The network representation: 8 -1



The network representation: 16



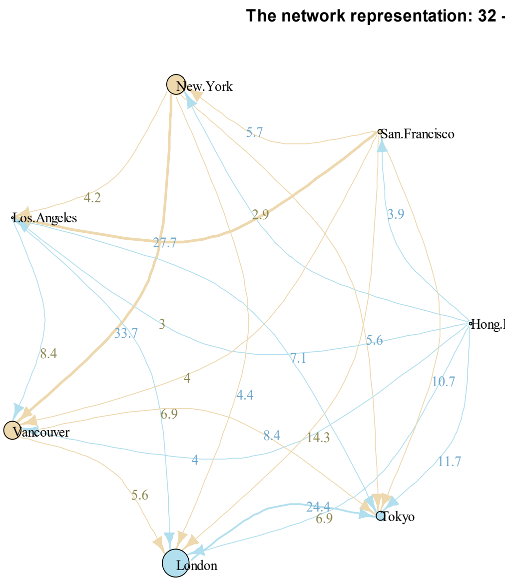


Figure 16: The degree of pairwise weighted directional connectedness of the system. Colours on the borders show the origination of the connectedness. The yellow (blue) colour points toward the contribution (receiver) of spillovers from a particular market to the other market in the whole system. The edge size of each figure indicates the magnitude of total directional connectedness. And the link size corresponds to the degree of risk send to all other markets or receive from all other markets.

6. Conclusion

In this study we consider a number of cities that score highly in global ranking indexes and investigate the links between real estate markets, stock markets and uncertainty in the time and frequency domains by using wavelet analysis. The wavelets are treated as a "lens" that enable the researcher to explore the relationships that would otherwise be unobservable. In particular, we start our investigation by using wavelet coherency and phase differences to assess how the co-movement and causality between real estate markets and stock markets change over time and across frequencies. In this way we are able to observe how short-, medium-, and long run relationships between the two markets evolve over time. The starting point of our work is that global trade and financial activity are mostly concentrated in a relatively small number of cities that have a pivotal role in coordinating and controlling the international flows of capital, goods, and workers. The fact that these cities share many characteristic features in common leave local housing markets exposed to international shocks. Since most of the global cities under consideration are also key financial service centres, we also investigate the dynamic relationships between real estate and stock markets.

Having analysed the links between stock and real estate markets, in the second step of our investigation, the wavelet coherency analysis is replicated to examine the dynamic relationships between geopolitical risk and housing markets. The underlying idea is that although stock market volatility and uncertainty are closely related, the impact of the latter may better be observed by using a news-based measure of uncertainty such as the one suggested in Baker et al. (2016). In addition, uncertainty is a latent variable, notoriously difficult to measure and estimate in parametric models due to endogeneity and non-linearity problems (see, for example, Balcilar et al., 2021). In this respect, the non-parametric approach used in this paper is particularly suitable to the problem at hand since it is robust to non-linearity and reverse causality issues.

In the third step of our investigation we consider the issue of volatility spillover among the global city networks. With this target in mind, building on Antonakakis et al. (2016), we propose a novel procedure to investigate the occurrence of volatility spillover across the real estate markets of the metropolises under consideration. The main novelty of our model lies in combining the wavelet analysis with the time varying parameter VAR estimation proposed in Antonakakis et al. (2016) (see also Diebold and Yilmaz, 2012). In other words, the decomposed series obtained from the wavelet spectrum analysis is used to estimate the generalised impulse response function and the generalized forecast error variance decomposition developed by Koop et al. (1996) (see also Peseran and Shin, 1998).

The main findings of this paper can be summarized as follows. First, significant correlation is found between real estate markets and stock markets. However, the magnitude of the correlation is not constant overtime since, in most cases, it increases as the time scale increases. In particular, we find that the correlation between real estate and stock markets is mostly positive in the long run, with the housing markets mostly leading the stock markets. Moreover, this relationship intensified particularly during turmoil periods. In this respect, we find that stock markets are a good proxy for uncertainty since patches of high wavelet coherency mimics, over time, the behaviour of the uncertainty index. Second, our results show that major economic and political shocks like the Asian Financial Crisis in 1997, 9/11 terroristic attacks, the U.S.-led invasion of Iraq in 2003, the Global Financial Crisis in 2005-2009, and the Covid 19 pandemic that started in 2019, deeply affected house price dynamic in the global cities under consideration. The sign of the correlation and the nature of the causal relation change over time since these are related to the nature of the shocks, with the housing market leading the uncertainty index in some periods (e.g. the subprime mortgage crises in 2005) and the other way around in cases of major geopolitical turmoil (e.g. the 9/11 terroristic attach in New York). Third, the clustering of global business in a limited number of metropolises that act as "global hub" leaves local housing markets exposed to international shocks since significant volatility spillover is found across the sample of global cities under consideration. In addition, it is found that metropolises that are key global financial centres also acts as major transmitter and receiver of volatility, this is particularly true for the medium-, long time scales.

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