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# TIME-FREQUENCY CONNECTEDNESS ACROSS HOUSING MARKETS, STOCK MARKET AND UNCERTAINTY: A WAVELET-TIME VARYING PARAMETER VECTOR AUTOREGRESSION

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# Time-frequency connectedness across housing markets, stock market and uncertainty:

## A Wavelet-Time Varying Parameter Vector Autoregression


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**Abstract**

In this study the time-frequency uncertainty and connectedness across housing markets, stock market are investigated through wavelet coherence analysis based on a continuous wavelet transform. Moreover, another interesting question about whether the risk in housing market would be spilled-over from one region to another is answered using a novel model whose strength lies in combining wavelet analysis with Time Varying Parameter Vector Auto-regression (W-TVP-VAR). Our analysis reveals evidence of long-run interdependence that intensified during the crisis period across short, medium, and long investment horizons. Moreover, the findings suggest a role for volatility spillover in the housing market from one region to another. The results of the latter connectedness in the network indicate that the housing market in one region is dominated by housing prices in another region.



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

**JEL classification:** G1; R3; C4


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## 1. Introduction

The subprime mortgage market meltdown and the global financial crisis (GFC) in 2007 has strengthened recognition that more attention needs to be paid to the interdependence between housing prices, uncertainty, and stock market returns. Based on an observation from the last crisis, the contraction in output during the latest recession was combined with an unprecedented fall in the national indices of housing prices and sharp drop in the stock market (e.g., Bahmani-Oskooee and Ghodsi, 2018).

There is every reason to expect that analogous effects from the housing market exert upon uncertainty and stock markets. Theoretically, potential collateral channels could be generating a link between the housing market and stock markets (e.g., Chaney et al., 2012; Deng et al., 2017). Indeed, investing in the real estate market may affect not only the housing market, but also how corporations evaluate the real estate they already hold, and, hence, could affect stock market prices. At the same time, the housing markets are dominated by unsophisticated households and often arbitrage is prohibitively costly, which results in a more volatile market, even more prone to bubbles than stock markets are (Scherbina and Schlusche, 2014; Iacoviello, 2005).

Additionally, the exceptional policy (in terms of interventions to buttress the financial system and monetary policy) in response to the crises has intensified the challenge of isolating sources of macroeconomic volatility, because the housing market, economic uncertainty, and the financial sector are so closely intertwined (Antonakakis et al., 2016). This fact has raised the spectre that the developments in the housing market are not simply a rejection of macroeconomic activity but may be among the driving forces of business cycles.

Historically, abundant attempts have been made to analyse the interdependence between housing prices, uncertainty, and stock market returns. Numerous studies have provided important information on the segmentation between the housing markets and the stock market (for example, Miles, 2013; Liow and Yang, 2005; Miles et al., 1990; Liu et al., 1990), the contagion effect (Chan et al., 2011; Antonakakis and Floros, 2016, and references cited therein) and cointegration between the two markets (Lizieri and Satchell, 1997; Liow and Yang, 2005; Apergis and Lambrinidis, 2011). Conversely, some studies (e.g., Quan and Titman, 1999; Liow et al., 2005; Ansari, 2006) have found no evidence of long-run relationships among the property stock markets. Among other studies (see also Liow and Yang, 2005), Apergis and Lambrinidis (2011) suggest the absence of gains for portfolio holders that include assets in both those portfolios.

In the wake of the recent financial crisis, there is a growing literature seeking to account for the economic uncertainty in the housing market and linking it to asset prices (Bloom 2009; Baker et al., 2014; Jurado et al., 2015). One study by Gupta and Majumdar (2015) highlights the fact that fluctuations in housing prices play a vital role in predicting the ‘business cycle’ in real sectors of the economy, because they reflect a large portion of overall economic wealth (also, Balcilar et al., 2014; Davis and Heathcote, 2005).

A growing body of literature recognises the exorbitant housing-price appreciation and links it to the spillover (ripple) effects of spillovers across markets. Writers stress that the high housing prices apparently deviating from economic fundamentals indicate risks that originated in the subprime segment of the mortgage market and exerted a negative impact on housing market; there they were amplified and subsequently spread to the stock market and other sectors of the economy (see, e.g., Gerardi et al, 2015; Damianov and Elsayed, 2018).

In view of all the above, one may readily suppose the existence of the spillover effects across housing prices, uncertainty, and stock market returns for longer time periods. Four questions that need to be asked, however, are (i) whether the lead-lag between the housing prices and stock market returns changes in intensity and direction differently over dissimilar time scales? (ii) how do housing prices interact with global economic shocks and uncertainty events? (iii) how different are these lead-lag relationships in different geographic areas? (iv) is there a risk that the effects on a housing market will spill over from one region to another?

In addressing these questions, this study contributes to the literature in several ways; First, this paper considers the issue of modelling the lead-lag relationship from a series of housing markets to the stock market return by analysing different frequency components so as to examine this relation over different time intervals, thus capturing the possible changes in the relationship. Second, we extend the existing research, focused on the linkages between housing prices and global economic uncertainty, by providing dynamic transmission in the frequency domain to identify specific time periods where the lead-lag relations are more intense and determine if such intensifications coincide with new policy issues and different institutional settings in an economy. Third, this paper exploits the heterogeneity in a regional housing market to estimate the extent to which the shock in a given market is a global city spills over to another market in a "global city" (see p.4, below). These contributions are briefly presented in turn below.

With regard to the first two points, the paper asks whether the housing and stock markets are integrated or segmented? If they are integrated, investors can reduce risk through diversification by holding both kinds of assets in the same portfolio. In fact, the integration of the stock and housing markets does not offer investors the benefit (i.e., risk reduction) associated with diversification in the same portfolio. What does reduce risk for investors through diversification, however, is segmentation between the two markets. The evidence for this relationship will be more relevant if the exposure association over different investment time horizons is incorporated, since the time varying trend of housing prices and stock market returns provides important information on the risk profile of a portfolio over varying horizons. Importantly, the present study also investigates how far these spillovers intensify during crisis periods. In fact, spillovers stronger than in normal times may explain the depth of particular recessions, such as the Great Recession, and the difficulty for the economy of getting back to a path of steady growth.

Statistically speaking, this paper argues that the lead-lag relationship between housing prices and stock market returns on the one hand and between housing market and uncertainty on the other might change not only in certain market events but also in different (low vs high) frequencies. To test the above, we implement wavelet coherence to evaluate the evolution of the correlations in time as well as for different frequencies and, thus, distinguish between different types of lead-lag over different investment horizons.

Turning to the third contribution, a sizable literature about contagion effect in housing explains how housing markets in different geographic areas become correlated (Del Negro and Otrok, 2007; Fu, 2007; Meen, 1996). The seminal work of Shiller (2005) mentioned that psychological contagion may sometimes have led to an irrational exuberance that could have a spatial dimension. Bailey et al., (2016) show that recent house price experiences within an individual's geographically distant social network can directly affect this individual's expectations and housing market behavior in her local market. Recently, DeFusco et al. (2018) provided evidence of the likelihood that a housing market boom will significantly increase if a nearby neighbor's booms. it is, therefore, intuitive to understand the co-movement of housing prices in "global cities".

On the extensive margin, this study asks whether such spatial spillovers were an important contributing factor in the spread of the housing shocks across housing markets of the "global cities". In fact, research into urban studies strengthens the view that internationalization in the financial and service sectors has created "global cities" (see, for example, Canepa et al., 2020). These cities are "global hubs" which are instrumental in supporting the operation of the global financial and trade systems. Consequently, we ask whether the shock in in a given global cities market is materially influenced by whether a shock has recently been felt in another global cities market.

From the econometrics point of view, this study argues that the shock in a given global cities market will spill over to another global cities market. As explained more fully below, the dynamic connectedness of volatility shocks is used as a source of variation in the data to identify this type of extensive margin spillover effect. The baseline specification is performed in two steps. The first stage uses wavelet analysis to decompose the series of house prices returns into components associated with different scale resolutions. In the second step, the dynamic connectedness between implied volatility shocks is studied, using a TimeVarying Parameter Vector Autoregression (TVP-VAR) which was developed by Antonakakis and Gabauer (2017) to generate the spillover effects. The main benefits of doing so are that we do not have to choose the window size, we are not losing observations, we have no outlier problem and our parameters are not too volatile or too flattened out. In other words, using these tests permits us to evaluate the evolution of exuberance and spillovers and thereby lets us examine the effectiveness of the argument that exuberance leads to spillovers over different investment horizons.

The rest of the paper is organized in four sections. Section 2 describes the methodologies employed. Section 3 discusses the empirical evidence. Section 4 concludes the paper.

## 2. Econometric modelling framework

### *2.1. The Wavelet Coherence Analysis*

The interdependence and causality between housing prices and stock market return on the one hand and between housing market and uncertainty on the other are investigated through wavelet coherence analysis based on a continuous wavelet transform. This analysis can shed more light on such interdependence and draw inferences in a time-frequency frame. Following the literature (e.g. Pal and Mitra, 2019; Sharif et al., 2020; Choi, 2020), for any housing price time series, $x(t)$ and its counterpart stock market return $y(t)$, the cross-wavelet transform is given by

$$W_{xy}(\tau, s) = W_x(\tau, s)W_y^*(\tau, s), \quad (1)$$

where the continuous wavelet transform a time series x(t) (with the translation parameter controlling the wavelet location in time $(\tau)$, and $(s)$ is the scaling factor that determines the length of the wavelet) is given as

$$W.(\tau, s) = \int_{-\infty}^{\infty} x(t)\tilde{\psi}_{\tau,s}^*(t)\, dt\,, \quad (2)$$

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

$$R^2(\tau, s) = \frac{\left|S\left(\frac{1}{s}W_{xy}(\tau,s)\right)\right|^2}{S\left(\left(\frac{1}{s}|W_x(\tau,s)|^2\right)\right)S\left(\left(\frac{1}{s}\left|W_y(\tau,s)\right|^2\right)\right)}; \quad 0 \le R^2(\tau, s) \le 1, \quad (3)$$

Following Bloomfield et al. (2004), to capture the two possible co-movements: positive and negative, the phase difference from the phase angle of the cross-wavelet transform is defined as

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

where $Im[\cdot]$ and $Re[\cdot]$ are the imaginary and real parts respectively of the smoothed cross-wavelet transform,. The $\rho_{xy}(\tau, s)$ demonstrates the dependence and causality relationships between two series depending on the level of phase difference $\rho_{xy}(\tau, s)$. This phase is indicated by black arrows on the wavelet coherence plots. The arrows point to the right (left) when time series are in-phase (out of phase) or are positively (negatively) correlated. An upward pointing arrow means that the first time series leads the second, whereas an arrow pointing down indicates that the second time series leads the first.

### *2.2. The Wavelet-Time Varying Parameter Vector Autoregression (W-TVP-VAR) Procedure*

The proposed W-TVP-VAR can be carried out in two steps. In the first step a discrete wavelet transform (DWT) is applied to the housing price indexes to decompose the series into high-frequency and low-frequency components. In the second step, the filtered series thus obtained 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 (Antonakakis and Gabauer, 2017).

To save space, the first step involving *The Wavelet Series Expansion* is not discussed here, but interested readers may refer to Alqaralleh and Canepa, 2021 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

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

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

where $y_t$ and $z_t = [y_{t-1}, \dots, y_{t-p}]'$ represent $N \times 1$ and $P \times 1$ dimensional vectors, respectively. $\beta_t$ is an $N \times \mathrm{Np}$ dimensional time-varying coefficient matrix and $\epsilon_t$ 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 $\upsilon_t$ 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 $L = [I_N, \dots, 0_p]'$ 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, and$F_{t-1}$ 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:

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

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

$$C_{t}^{g}(K) = \frac{\sum_{i,j=1,i\neq j}^{N}\widetilde{\Phi}^{g}{}_{ij,t}\,(K)}{N} * 100 \qquad (13)$$

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

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

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

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

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

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

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:

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

Under Equation (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 $j$.

## 3. Empirical Application

### 3.1. Data and Sample Selection

The data under consideration are related, first, to the monthly residential property prices index for seven large metropolitan areas, namely, San Francisco, New York, Los Angeles, Tokyo, London, Hong Kong and Vancouver; and second, to its stock market indexes counterpart. In particular, we consider 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)[4]. The data were collected from Bloomberg for all metropolitan areas over the period from January 1997 to August 2021. Stock returns are calculated as the difference between the logarithms of the price index.

With regard to the sample selection, the cities on the list were selected on the basis of the Global Financial Centres Index (GFCI)[5] as a representative sample of metropolitan areas that are major financial centres according to the market-based system where securities markets share the centre stage with banks in getting society's savings to firms, exerting corporate control and easing risk management. Moreover, for different reasons, all the metropolises in the sample feature an inelastic housing supply and excess demand.

### 3.2. *Dynamic wavelet correlation*

In this section, we begin by briefly indicating the nature of the interdependence and causality between housing prices and the stock market return. As discussed in Section 2.2, this wavelet coherence provides a measure of the time series variance at each time and on each scale (frequency). The horizontal axis denotes the time component while the vertical axis represents the frequency component, from short-term variations due to shocks occurring at a time scale from $2^2 = 4$ months up to long-term variations at a time scale of $2^6 = 64$ months. Furthermore, the phase differences are indicated by black arrows on the wavelet coherence plots. The white contours indicate regions with significance at the five percent level. The range of power is from red (high power) to blue (low power).

#### a) *Dynamic correlation between Housing markets and Stock markets return*

To identify causality and phase differences between the house prices index and stock market return, the wavelet coherence for each pair in the housing prices index and its stock market counterpart is estimated and plotted, as shown in Figure 1-7. To ease the interpretation, arrows indicate the phase differences between the considered series. For example, → and ← indicate that housing prices and stock returns are both in phase or both out of phase, respectively. ↗ and ↙ indicate that housing prices are

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[4] See https://www.policyuncertainty.com/global_monthly.html
[5] More details can be found on https://www.longfinance.net/media/documents/GFCI_30_Report_2021.09.24_v1.0.pdf

leading those of stock returns, while ↘ and ↖ indicate that housing prices are lagging those of stock returns.

Figure 1-7 indicates causality and phase differences between the housing prices and its counterpart stock return. Broadly speaking, a significantly high degree of co-movement can be identified as the series demonstrates high power between 2007 and 2013 over medium-run and long-run scales (at a time scale ≥ 16 months). Some evidence of weaker, but still significant coherence above the 16-month frequency cycle was also observed from 2004 to 2008 (US subprime crisis) and from 2010 to 2011 (European debt crisis). Moreover, significant and huge coherences over the long-term time frequency bands are observed during the COVID-19 period, compared to the pre-COVID-19 pandemic. At all other times and frequencies variability was low. These findings support the interdependence effect during the global financial crisis and the European sovereign debt crisis.

The causality and phase differences were reported using black arrows on the wavelet coherence plots. We found evidence of varying dependence across time-frequency domains. The case of New York, Figure 1, shows the house prices leading the S&P 500 returns as arrow points ↗ (↙) around 2002-2003, 2008 - 2012 and 2016- 2018 in the 4-month band. This picture changed in the medium-run scale (up to 32 months) where the arrows signified that New York housing prices were lagging the S&P 500 returns. The most interesting aspect is that both series were in phase during 2020 -2021 (the time of the COVID-19 pandemic).

As regards San Francisco (shown in Figure 2), the arrow point ↘ around 2003, 2018 and 2020 signified that housing prices were lagging those of stock returns in the 4-month band. In the higher month bands (8 – 16 months), the housing prices were leading the S&P 500 around 2000, while they lagged S&P around 2006.  Phase differences were also identified between the 8- and the 16-months' bands around 1998 where both housing prices and stock returns were out of phase, with the arrow pointing ←. During the COVID-19 pandemic, the housing markets lagged the stock return.

A significant dependence can be seen in Figure 3 between Los Angeles and S&P 500 in which the housing market lagged the stock market return around 2000-2001 and 2005 in the 4-month band, when the arrow pointed ↘ (↖). Both series demonstrated high power in the 2000-2014 period over medium-run and long-run scales in which the housing prices were leading the return. As with New York, both series were in phase (a cyclical effect) during 2020 -2021.

Turning to the evidence from Vancouver with S&P/TSX (Figure 4), there was clear evidence of medium- and long-run interdependence (at low frequency) between the considered series. To be specific, the arrows around 2005 and 2008- 2012 signified that housing prices were lagging those of stock returns in the 8-16 and 16-32 month bands, while the housing prices were leading those of stock returns around 1999 – 2000. A cyclical effect can be also identified in the 32-64 month band around 2006 -2011.

The case of Hong Kong (shown in Figure 5) showed 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 in the lead. However, a negative relationship was also found in the 32-64 month band around 1997-2000, and housing prices lagged stock returns, whereas a cyclical effect around the latter period was found in the 16 – 32 month band.

Two similar cases, Tokyo and London, are shown in Figures 6 and 7. Arrows point to the left and upward for short-run scales in the phase analysis between Tokyo and the N225 return, showing the negative relationship between the two series during 2005-2012 with the housing markets as the lagging ones. 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.

Overall, the results of the continuous wavelet show that the relationship between housing markets and stock returns dynamically changes across time and frequency. Moreover, this relationship is intensified by the onset of financial turmoil, and consequently, the reduced short-run effectiveness of diversification benefits from combining the real estate market and stock market during crisis periods.

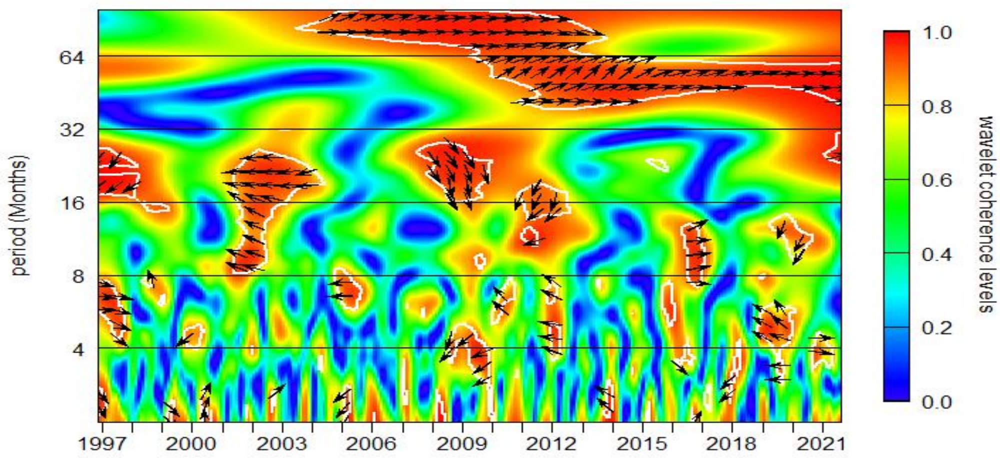


Figure 1 : Cross wavelet transform between New-York housing market and SP500.

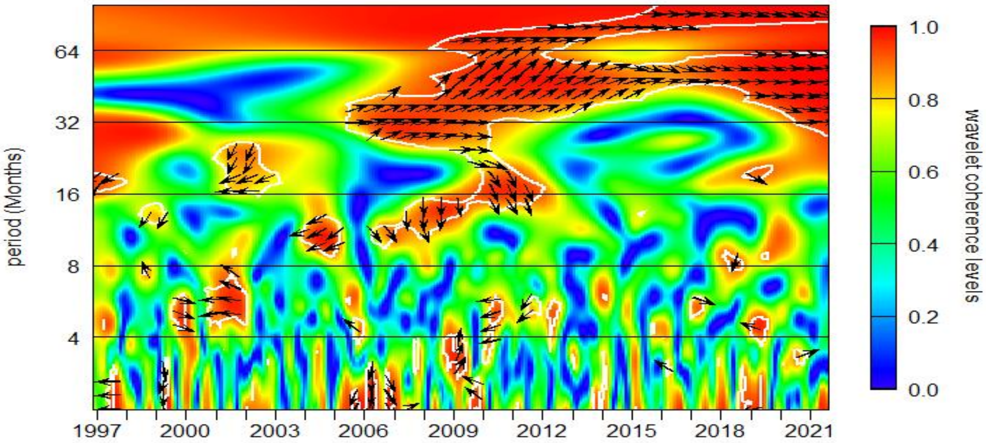


Figure 2: Cross wavelet transform between Los Angeles housing market and SP500.

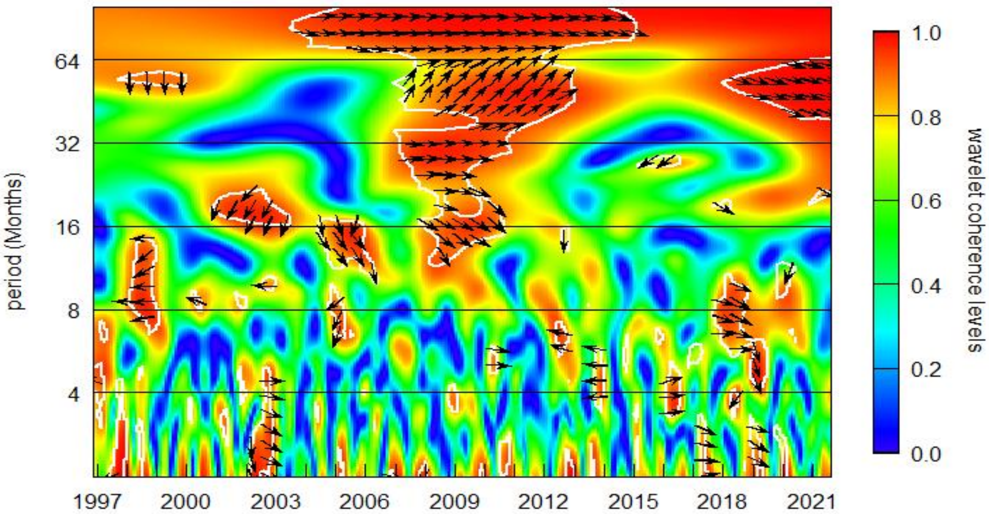


Figure 3 Cross wavelet transform between San Francesco housing market and SP500.

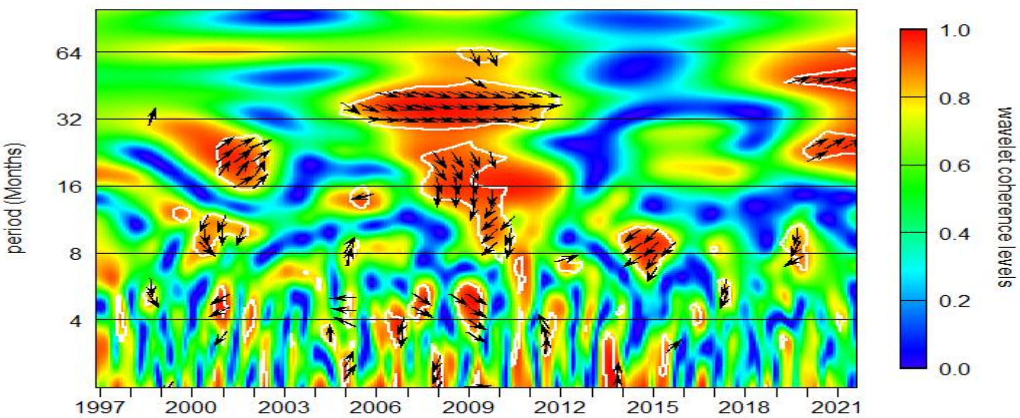


Figure 4 Cross wavelet transform between Vancouver housing market and GSPTSE.

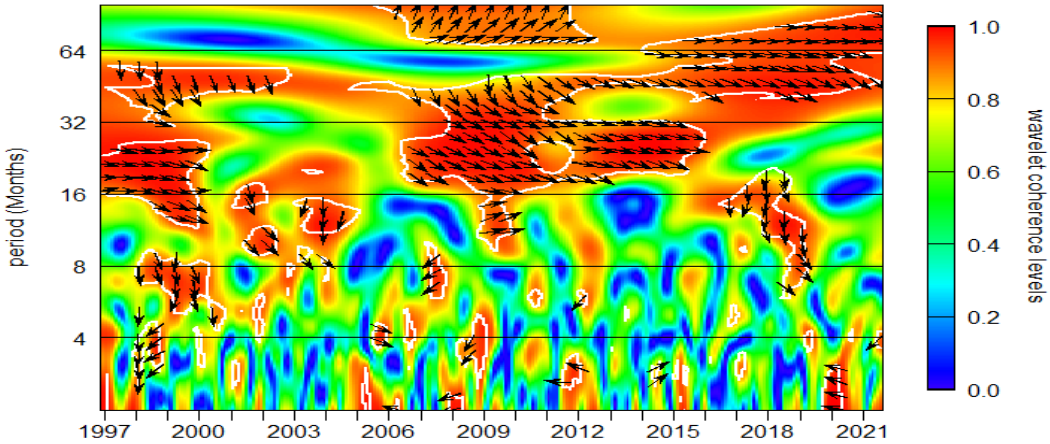

Figure 5 Cross wavelet transform between Hong Kong housing market and HSI.

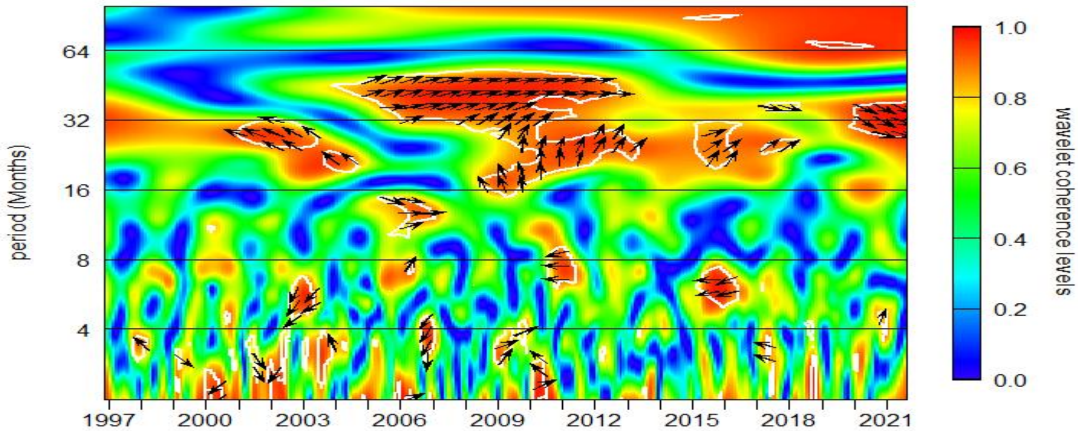

Figure 6 Cross wavelet transform between Tokyo housing market and N225.

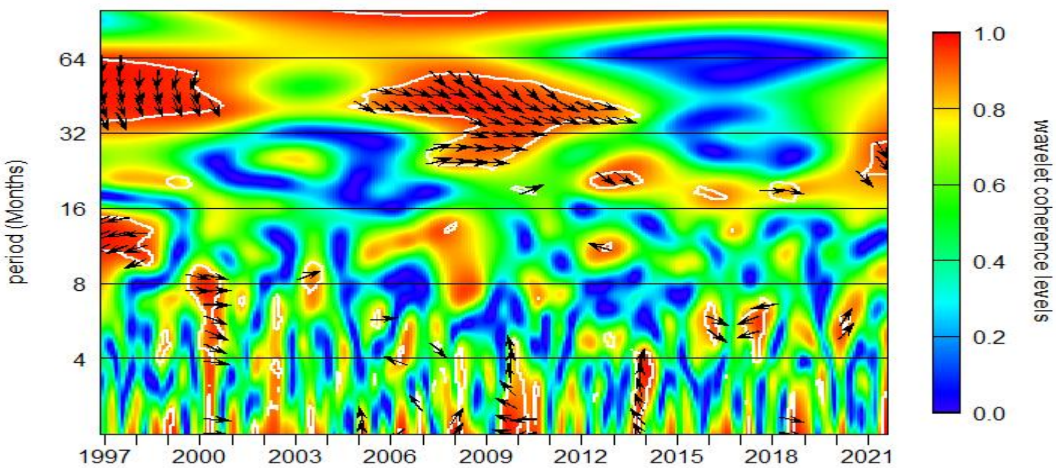

Figure 7 Cross wavelet transform between London housing market and FSTE100.

*b) Dynamic correlation between Housing markets and uncertainty*

As far as crisis periods are concerned, the existing research was extended in the present paper to focus on the linkages between housing prices and global economic uncertainty, and provide dynamic transmission in the frequency domain to identify specific time periods where the lead-lag relations were more intense and determine if such intensified relations coincided with new policy issues and different institutional settings in an economy.

The results of correlation between the housing markets index and uncertainty can be compared in Figures 8-14. Closer inspection of these figures shows that many small islands represent a high degree of co-movement between the housing market prices and uncertainty over different time horizons.

Particularly the direction of the arrows for the New York and uncertainty pairs (Figure 8) around 2000 is turned down-left, indicating that the correlation between them is negative, with the uncertainty conditions driving the housing market. While during GFC and COVID-19, the arrows points ↗ and ↙ over the short-term time frequency bands, indicating that the correlation between the two series is positive where the housing market lead the uncertainty index. Over the medium- and long-term time frequency bands a cyclical effect around the 2000-2005 period is found in the 16 – 32 months' band. Whereas a countercyclical effect can be noted between them between the frequency bands of 16 – 32 months during the COVID-19 pandemic.

The case of San Francisco is presented in Figure 9. The direction of the arrows (down-right/ up-right) in the medium-run around 2000- 2012 signifying a positive correlation between the two series, where the housing market leads the uncertainty. The same picture can be seen during the COCID-19 pandemic but at the frequency bands of 4 months. However, a countercyclical effect is noted during the pandemic between the frequency bands of 16 – 32 and 32-64 months.

In contrast to San Francisco, the case of Los Angeles (shown in Figure 10) indicate a negative correlation, where the housing market in this city lags the uncertainty. In specific, the direction of the arrows (down-left/ up-left) indicate a s significant correlation during both US subprime crisis (2006-2008) and the European debt crisis (2010 to 2012).

Figure 11 displays the dynamic correlation in the case of the London housing market with the uncertainty index. It is interesting to note a positive relationship in which the housing market led the uncertainty during both GFC and Brexit (2016-2018) at the frequency band of 4 months. this positive correlation was also observed at the frequency band of 8-16 months around 1998-2003. The picture changed in the long term, when the housing market lagged the uncertainty index around 1998-2002.

With regard to Vancouver and Tokyo, a notable point in Figures 12 and 13 is that they were not correlated for most of the period. To be specific, the housing markets lagged the uncertainty at the short- and medium-run frequency around 2003 and in the period 2008-2012. A positive correlation was identified over the long run during the COVID-19 pandemic in Vancouver. By contrast, in the case of Tokyo the housing market around 1998-2003 led the uncertainty in the long term.

Looking at the direction of the arrows reveals a positive and statistically significant correlation for Hong Kong (see Figure 14). This suggests that the housing market led the uncertainty around 2000 in the 4-month band. This positive correlation can also, be seen in the 8–16-month band around 2008-2014. By contrast, the housing market lagging the uncertainty around the European debt crisis and the COVID-19 at a 4 months' band.

Together these results provide important insights into the intense lead-lag relations between each pair of variables, particularly during crises, such as the GFC (2006-2008), European debt crisis (2011-2013), Brexit (2016) and the recent health crisis (2020).

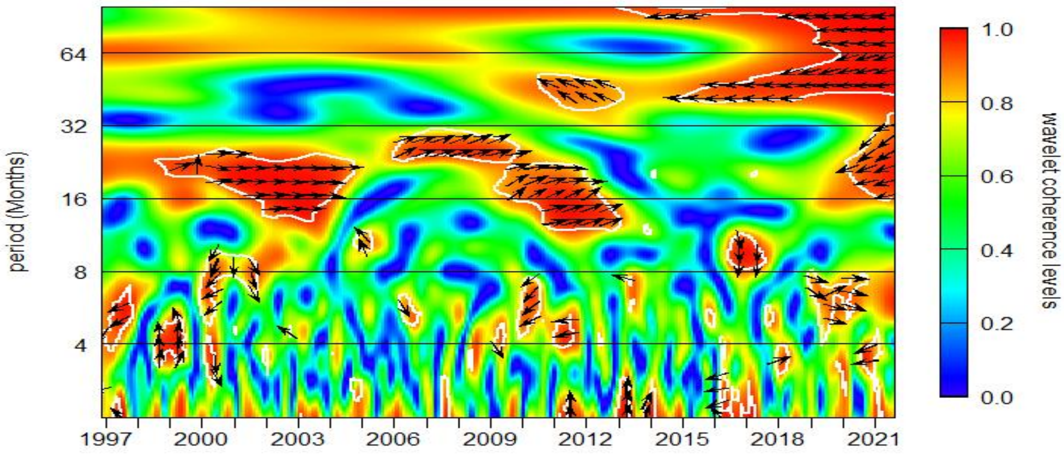


Figure 8 Cross wavelet transform between New-York housing market and Uncertainty.

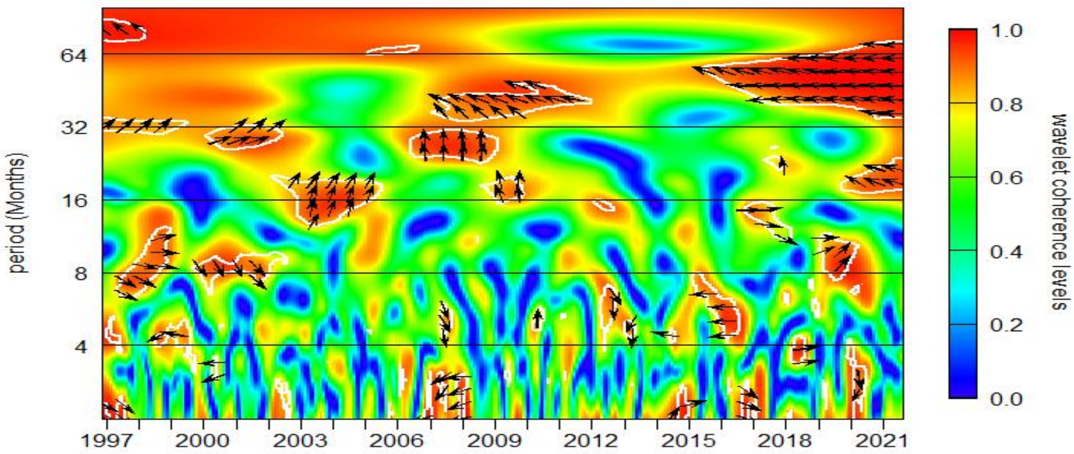


Figure 9 Cross wavelet transform between San Francesco housing market and Uncertainty.

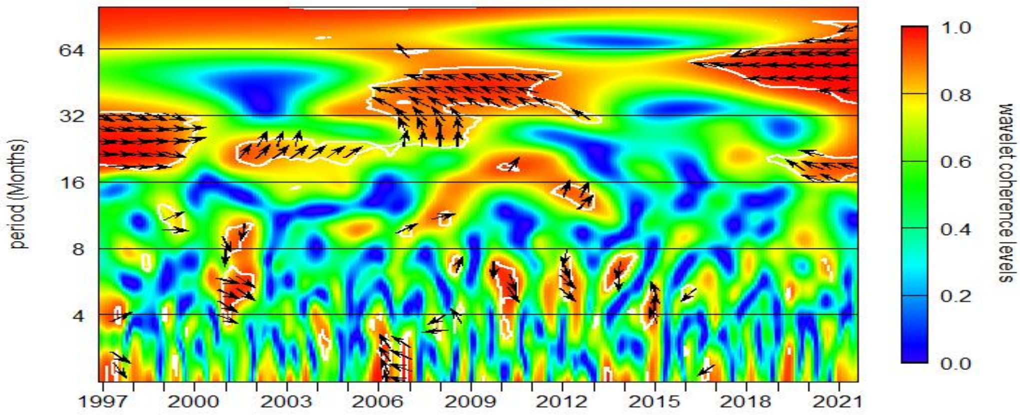


*Figure 10 Cross wavelet transform between Los Angeles housing market and Uncertainty.*

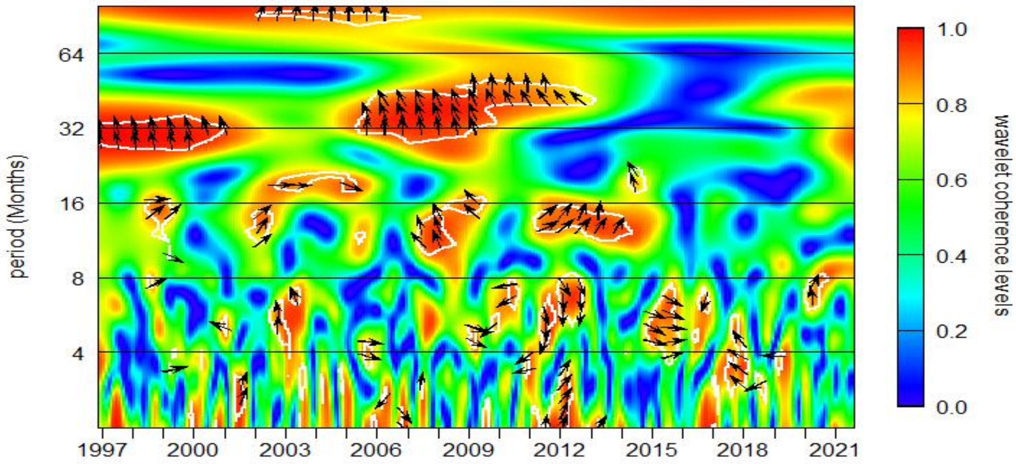


*Figure 11 Cross wavelet transform between London housing market and Uncertainty.*

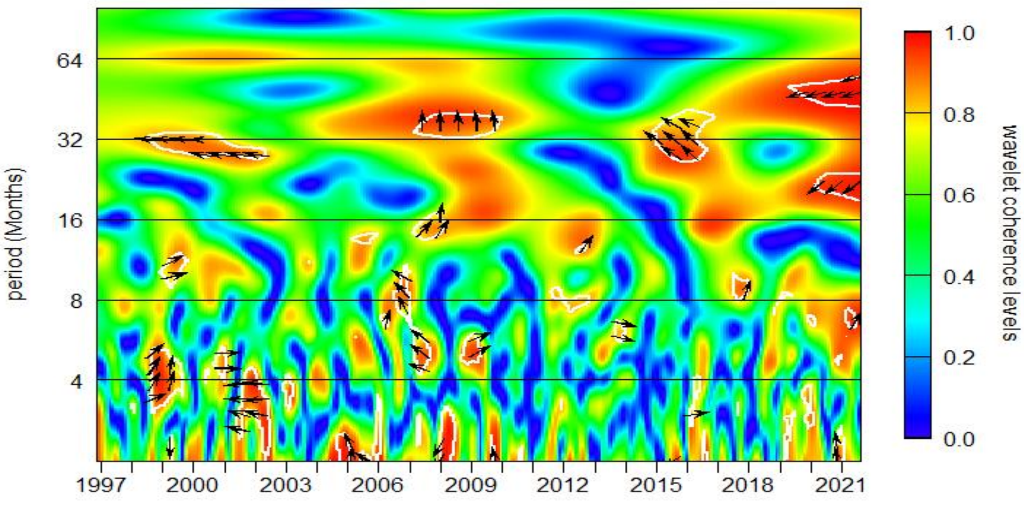


*Figure 12 Cross wavelet transform between Vancouver housing market and Uncertainty.*

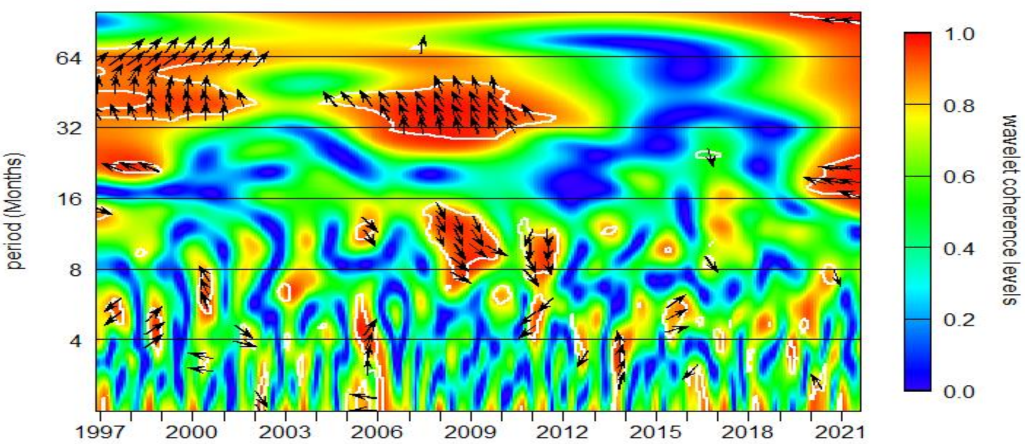


*Figure 13 Cross wavelet transform between Tokyo housing market and Uncertainty.*

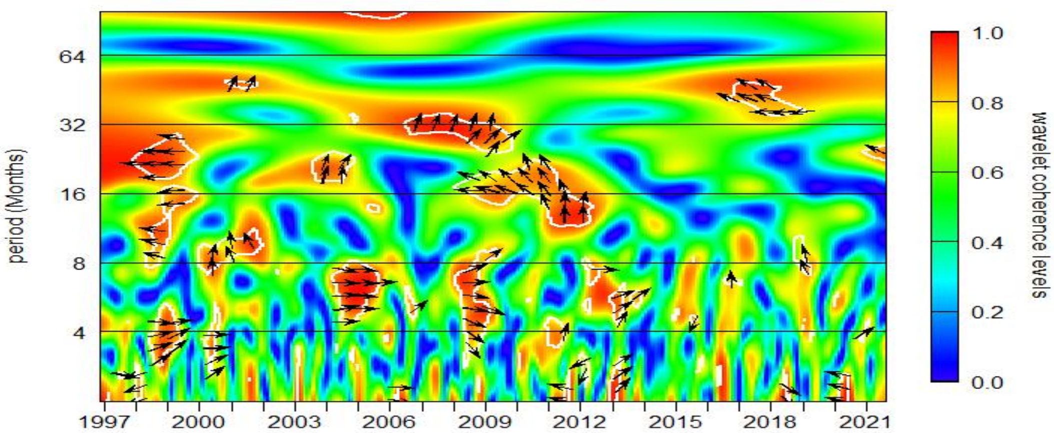


*Figure 14 Cross wavelet transform between Hong-Kong housing market and Uncertainty.*

### 3.3. *Risk of spillover in housing market prices*

The analysis in the previous sections provided several insights into the interdependence structure between the housing market and stock market on the one hand and the housing market and uncertainty on the other. In particular, the analysis in Sections 3.2.a and 3.2.b allowed the investigators to hypothesise that, first, the lead-lag relationships between the housing prices and stock market returns changed differently in intensity and direction in dissimilar time scales. Second, housing prices were predicted to interact with global uncertainty events, where the housing market plays the main role in leading the uncertainty, particularly during a crisis.

To develop a full picture of this interdependence structure, a further interesting question could be asked: could the risk in the housing market spill over from one region to another?

To address this question, we estimated the TVP-VAR model in the time-frequency framework. 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 1, 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 prices index is largely influenced by other housing prices in other global cities, almost all of which fluctuate from 30% to 90%. The results also highlight London as a major recipient of volatility from other housing markets (33.67%), followed by San Francisco (36.56%), and Tokyo (11.11%), whereas Hong Kong and New York are the major transmitter of this volatility with net directional volatility spillovers of 28.54% and 25.76% respectively.

The picture changes when we consider time scales $D_2\ and\ D_3$. Panel B and C of Table 1 reveal that only around one-third of the volatility forecast error variance comes from housing prices 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 the short run, the main diagonal in Tables 1-B and 1-C highlights that the own-effects range from 47.86% to 94.43% and are greater than other own-effects indices shown in Table 1-A but the own-connectedness is small compared with the total spillover effect of other housing prices indices.

In time scales $D_4$ and $D_5$, the differences in volatility spillover begin to show. It is apparent from Tables 1-D and 1-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, while 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 D is that the own-effect was less than 15% (except for Hong Kong), whereas, in Table 1-E this effect ranged from 27.29% to 67.43%.

Interestingly, the net pairwise directional connectedness (NPDC) in Table 1 is positively estimated in all cases, suggesting that the housing market in one region is dominated by housing prices in another region.

**Table 1 The network connectedness in the housing market**

| | *Hong Kong* | *San Francisco* | *New York* | *Los Angeles* | *Vancouver* | *London* | *Tokyo* | *FROM* |
|---|---|---|---|---|---|---|---|---|
| | | | | *D1 (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** |
| *Inc. own* | 128.54 | 63.44 | 125.76 | 105.44 | 121.6 | 66.33 | 88.89 | |
| ***NET*** | **28.54** | **-36.56** | **25.76** | **5.44** | **21.6** | **-33.67** | **-11.11** | |
| *NPDC* | 0 | 5 | 2 | 3 | 1 | 6 | 4 | |
| | | | | *D2 (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** |
| *Inc. own* | 137.26 | 78.92 | 146.1 | 60.69 | 100.3 | 73.48 | 103.24 | |
| ***NET*** | **37.26** | **-21.08** | **46.1** | **-39.31** | **0.3** | **-26.52** | **3.24** | |
| *NPDC* | 0 | 5 | 2 | 6 | 3 | 4 | 1 | |
| | | | | *D3 (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** |
| *Inc. own* | 130.17 | 127 | 63.13 | 81.62 | 83.15 | 102.4 | 112.53 | |
| ***NET*** | **30.17** | **27** | **-36.87** | **-18.38** | **-16.85** | **2.4** | **12.53** | |
| *NPDC* | 0 | 1 | 6 | 4 | 5 | 3 | 2 | |
| | | | | *D4 (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** |
| *Inc. own* | 231.28 | 21.07 | 99.81 | 99.87 | 99.36 | 79.92 | 68.68 | |
| ***NET*** | **131.28** | **-78.93** | **-0.19** | **-0.13** | **-0.64** | **-20.08** | **-31.32** | |
| *NPDC* | 0 | 6 | 3 | 2 | 1 | 4 | 5 | |
| | | | *D5 (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** |
| *Inc. own* | 98.06 | 102.61 | 110.59 | 98.87 | 109.32 | 85.36 | 95.18 | |
| ***NET*** | **-1.94** | **2.61** | **10.59** | **-1.13** | **9.32** | **-14.64** | **-4.82** | |
| *NPDC* | 3 | 3 | 1 | 3 | 2 | 5 | 4 | |

Finally, this connectedness is presented through 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 Figures 15 –19).

In these figures, blue (yellow) nodes illustrate net transmitters (receivers) of shocks. Vertices are weighted by averaged net pairwise directional connectedness measures. The size of nodes represents weighted average net total directional connectedness.

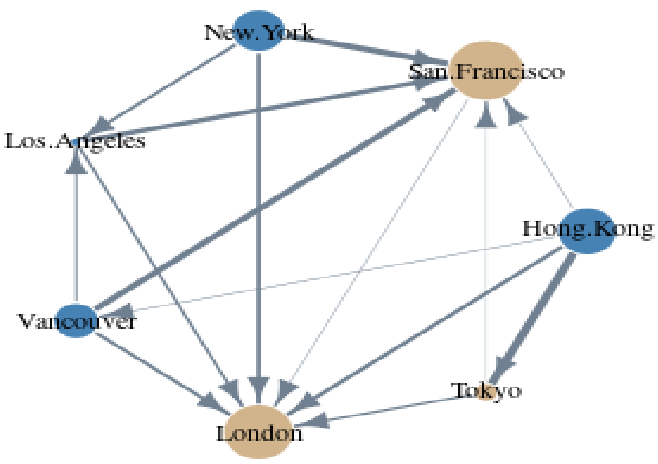


*Figure 15 The network graph for short term (0-4 Months)*

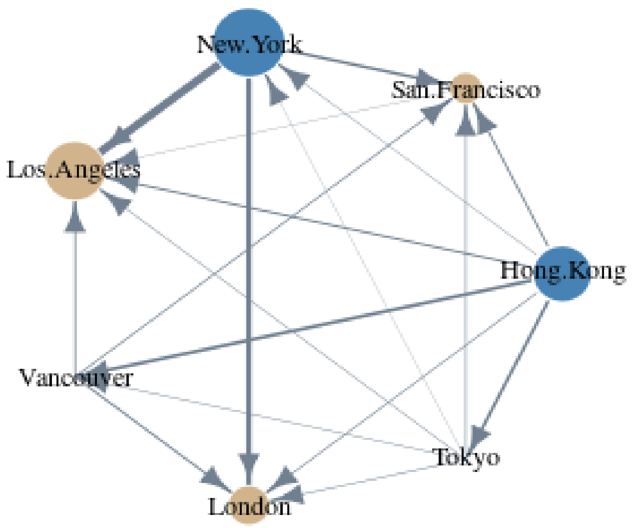


*Figure 16 The network graph for short term (4- 8 Months)*

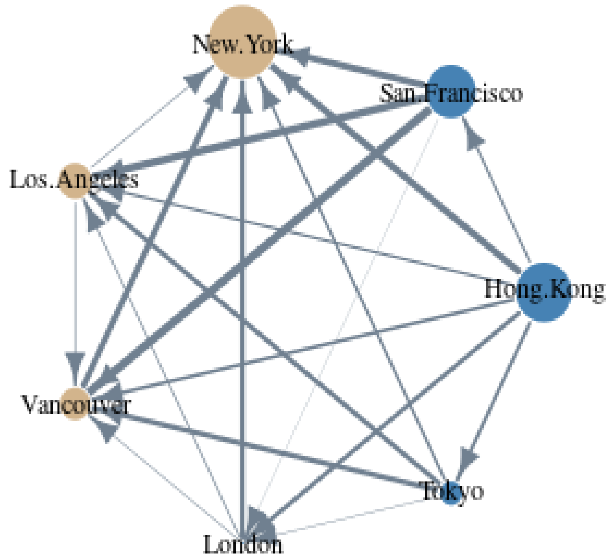


*Figure 17 The network graph for Medium term (8-16 Months)*

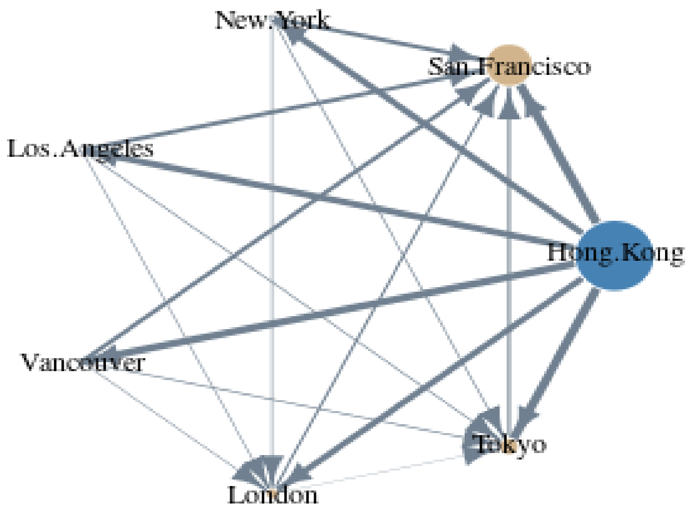


*Figure 18 The network graph for Medium term (16 - 32 Months)*

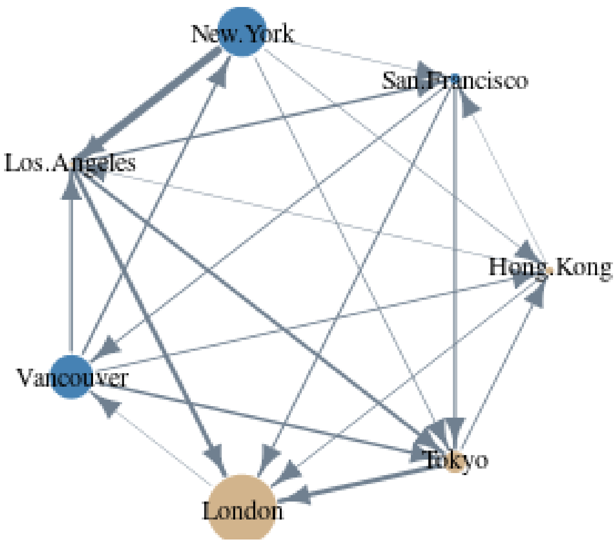

*Figure 19 The network graph for Long term (32 - 64 Months)*

## 4. Conclusion

In this study a novel procedure to investigate the occurrence of cross market linkages is proposed. The main novelty of our model lies in combining wavelet analysis with Time Varying Parameter Vector Auto-regression (W-TVP-VAR). In other words, the decomposed series obtained from the wavelet spectrum analysis is used to estimate a Time Varying Parameter Vector Auto-regression. The two interesting features of the W-TVP-VAR procedure are: *i*) its ability to expose relationships between housing market prices, stock market returns and uncertainty in the time-frequency domain, allowing a simultaneous assessment of relationships between the series at different frequencies and the evolution of these links over time; and *ii*) its capacity to provide an alternative representation of the association structure of certain stochastic processes on a scale-by-scale basis.

To investigate cross-market linkages we estimate the regular "interdependence", i.e. that forms of change at lower frequencies are associated with interdependence, which relates to the spillover of shocks resulting from the normal dependence between markets and refers to the dependence that exists in the global financial cities due to their trade links and geographical position.

The estimation results reveal, first, evidence of long-run interdependence between housing markets and stock returns. Further, this interdependence dynamically changes across time and frequency. Moreover, this relationship is intensified by the onset of financial turmoil. The second finding is that there is a dynamic transmission between housing prices and global economic uncertainty in the time-frequency domain wherever the lead-lag relations are more intense, particularly during crises, such as the GFC (2006-2008), European debt crisis (2011-2013), Brexit (2016) and the recent health crisis (2020). Taken together, these findings suggest a role for volatility spillover in housing markets from one region to another. The results of the latter connectedness between networks indicate that the housing market in one region is dominated by housing prices in another region.

These findings have significant implications for understanding the interdependence between housing prices, uncertainty, and stock market returns, since they show that, despite the policy measures that were put in place after the financial crisis of 2005-2009, more has to done to mitigate the impact of shocks on financial markets. The Covid-19 pandemic is the first health crisis to have had the potential to trigger effects as devastating as those seen during the global financial crisis, which was arguably the first truly major global crisis since the Great Depression of 1929-32. The sub-prime financial crisis had its origin in the United States in a relatively small segment of the lending market, but it rapidly spread across virtually every country in the world.

In this respect, the lesson to be learned from such experience is that evidence of long- and short-run cross-market linkages constitutes a wake-up call to governments to devise policies to mitigate interdependence.

Academic scholars may also benefit from the contribution of this study to the literature on interdependence between housing prices, uncertainty, and stock market returns. Future researchers may assess these interdependences; it may lead them to consider, (i) whether the probability of a boom starting in a given global cities market is materially influenced by the recent start of a boom the in another global cities market; (ii) the diversified impact of the real estate market in developed and emerging markets; (iii) different methodologies and fresh econometric tools. Furthermore, with a more diverse data set they could investigate the connectivity between these indexes.

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