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Housing sector and economic policy uncertainty: A GMM panel VAR approach

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ABSTRACT

This study is aimed at examining the dynamic relationship between real housing prices (RHP) return and economic policy uncertainty (EPU) using a panel vector autoregressive (PVAR) approach and annual data for a panel of panel of 16 countries over the period 2004–2018. The study includes economic growth, short-term interest rate, and population as additional covariates. Empirical results show that a positive shock to EPU leads to a decrease in housing prices with EPU showing only a weak response to housing price shocks. This implies that EPU has a robust predictive power for the housing market, implying the need for evaluating the associated risks. The panel Granger causality tests indicate strong and robust Granger causality from the EPU to housing prices, but not *vice versa*. The causal links also indicate that the effect of the EPU on RHP is direct rather than indirect through other variables. Based on these outcomes, policy recommendations are made for real estate agents, portfolio managers, and policy makers.

1. Introduction

Housing sector has played a crucial role in societal progress and well-being across the globe. It forms one of the three basic needs of man that translate into better welfare for families, the community and the large world, especially when it is accessible (Cournède et al., 2019). The subprime mortgage crisis of 2007 that started in the United States (US) brought unprecedented interest in housing markets. This unexpected downturn of the subprime crisis led to heightened uncertainty in both the developed and developing economies. Following this development, the relationship between housing sector and economic policy uncertainty has attracted a significant attention from the policymakers, real estate agents, and portfolio managers in the housing market.

It is paramount to emphasize the importance of the dynamics of the housing market as it affects the macroeconomics trends and the business cycle. Housing prices affect household wealth accumulation, income, and the level of expenditure. This impact is often caused by the size of rents, variations in the house prices and/or interest rate associated with mortgage which exert a significant influence on the price level and aggregate demand. In addition, economic growth, investment in residential housing, and the living standard are influenced by the changes in housing prices.

Consequently, countries that experienced swift decreases in investment in residential housing, especially after the world economic

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and financial turbulence required additional time to recover from these shocks. More importantly, it takes time for such an economy to recover and reach the real per capita income level that existed before the crisis. Indeed, many economies did not yet recover from the global economic and financial crisis although it has been more a decade since the start of the crises in 2007. Although the US economy is at the epicenter of the worst global economic and financial crisis, the unexpected downturn had heightened the uncertainty in both developed and developing countries (Hirata et al., 2013). This reason accounts for why the housing sector has attracted attention much attention from policy makers, real estate agents, and portfolio managers.

Until now, several studies examined the relationship between housing market and business cycle (Aye et al., 2014; Balcilar et al., 2014; Case et al. 2005; Fehrle, 2019; Ghent & Owyang, 2010; Green, 1997; Iacoville and Neri, 2010; Kydland et al., 2016; Leamer, 2007, 2015; Lee & Song, 2015; Nyakabawo et al., 2015) while others consider the relationship between housing market and major macroeconomic variables (Cesa-Bianchi et al., 2015; Demary, 2010; Garriga et al., 2019; Goodhart & Hofmann, 2008; Gupta et al., 2019; Gupta & Hartley, 2013; Gustafsson et al., 2016; Kishor & Marfatia, 2017; Mohan et al., 2019; Panagiotidis & Printzis, 2016; Simo-Kengne et al., 2013). With regard to the relationship between housing price and the real gross domestic productRGDP, most studies confirm the existence of a correlation between housing prices and RGDP. Specifically, as shown by Kydland et al. (2016) and Leamer (2007, 2015), fluctuations in the housing market have a significant effect on the fluctuations in business cycle. Moreover, Aye et al. (2014) used rolling Granger causality to investigate the relationship between the housing and output growth considering the time of variation in the causal link for South Africa. The result shows that there is a unidirectional causality flowing from real housing price to output growth. In the case of the relationship between the housing market and macroeconomic variables, the position of the existing literature reveals that the housing market variables are associated with macroeconomic variables.[1]

Regarding the housing-macroeconomic variables nexus, Kishor and Marfatia (2017) find that housing prices are driven by income and interest rate in 15 Organization for Economic Co-operation and Development (OECD) countries. However, in the case of South Africa, Gupta and Hartley (2013) find that housing price can be used to forecast real gross domestic product (RGDP) growth and inflation. On the other hand, the study suggests that housing price has a major g indicative role on the South African economy. Also, Bernanke (2008) argues that “housing and housing finance played a central role in precipitating the current crises.” Similarly, Iacovillo (2010) confirm that during the Great Recession fluctuations in housing market reflects both in business cycle and macroeconomic fundamentals. Thus, it is important to consider factors that derive housing prices as well as what constitutes an appropriate housing price model to make reliable housing price predictions.

In the aftermath of the global financial and economic crisis in 2007, the volatility in both housing price and economic policy uncertainty significantly increased (Hirata et al., 2013). The return and volatility spillover effects of the global financial crises on the stock market and EPU have been documented by Balcilar et al. (2019), Li et al. (2016) and Balcilar et al. (2015). Given the importance of the relationship between the housing market and macroeconomic variables, there is a growing literature on showing the importance of the relationship between EPU and housing market (Aye et al., 2019; Christou and Fountas, 2018; Aye, 2018; Huang et al., 2018; André et al., 2017; Anoruo and Nwoye, 2017; Christou et al., 2017; El-Montasser et al., 2016; Antonakakis et al., 2016; André et al., 2015). For instance, Christidou and Fountas (2018) show that EPU tends to raise growth in housing investment and decrease housing price inflation in most of the US states. Additionally, Aye (2018) employs cross-sample validation Granger causality technique to analyze whether EPU causes real housing returns. The result indicates that EPU causes real housing returns in Chile and China among eight emerging economies. The study by Christou et al. (2017) also reports that EPU can be used to forecast real housing price returns for selected 11 OECD countries.

In other economic sectors such as tourism, economic, and environment, the EPU index has been increasingly employed, thus adding to the popular use of the index that was originally developed by Baker et al. (2016). Mainly, more attention has been given to examining between the investigation EPU and macroeconomic variables, with regards to their influence on the behavior of housing prices. The most important reason for these interests is the existence of a feedback mechanism between housing and macroeconomic variables. According to the housing price model, there seems to be no direct relationship between uncertainty and housing prices. This is because the housing pricing model is a function of some macroeconomic variables such as interest rate, unemployment, real income, population, etc. Intuitively, it can be deduced that uncertainty exhibit a significant influence on macroeconomic variables which in turn affects the housing price.

Even though the extant literature on the housing market and EPU is quite large, most of the studies focused only on the relationship between the housing market variables such as the real housing returns or real housing price (RHP) and economic policy uncertainty (EPU) (Antonakakis et al., 2016; Aye, 2018; Chow et al., 2017; Christou et al., 2017; El-Montasser et al., 2016) in a bivariate framework without considering the other important determinants of housing prices which is a common limitation of the previous studies. Moreover, the existing literature mostly focuses only on the relationship between the housing market variables and EPU. For instance, the study of Christou et al. (2017) investigates the relationship between EPU and real housing prices for selected 10 OECD countries without accounting for key macroeconomic variables such as interest rate, RGDP, etc. Similarly, El-Montasser et al. (2016) also examine also the EPU and housing price nexus using a panel of nine advance countries. Additionally, Chow et al. (2017) applied both panel linear and nonlinear Granger causality tests to examine the EPU growth and the real housing returns in China and India. Both test results show that there is a unidirectional Granger causality running from EPU to real housing prices. However, econometric models of housing prices should include macroeconomic activity such as a measure of income, real interest rate etc. to overcome the misspecification problem (Meen, 2002; Muellbauer & Murphy, 2008).

[1] For brevity, more literature on the housing price determinants, see Leung, C. (2004). Macroeconomics and housing: a review of the literature. Journal of Housing Economics, 13(4), 249–267.

Against this backdrop, this study investigates the dynamic relations among real housing prices (RHP) and EPU in a multivariate environment where short-term interest rate (IRATE), RGDP, and population (POP) do also enter into the model. There is potential threat associated with modelling RHP and EPU as observed by the previous literature. To circumvent such misspecification issues, like in the study of Antonakakis et al. (2016) which investigates the dynamic spillover among the housing market, EPU and stock market in the US using a time series model, but failed to account for other macroeconomic determinants. To this end, the present study extends the frontier of knowledge in the housing-EPU nexus by accounting for other key macroeconomic determinants that are relevant to housing market. Our study improves Chow et al. (2017) by including relevant covariates in the model by investigating the dynamic relations among the aforementioned variables for the selected 16 countries using a panel vector autoregressive (PVAR) model. . In the last two decades there has been a gradual but continuing increase in interdependencies across sectors, countries, and regions, which is framed by terms such “global economies”, “global interdependencies”, and “global transmission”. However, the subprime crises and global recession showed that there still exists considerable heterogeneity across sectors, countries, and regions. The dynamic panel data models offer great flexibility to capture both the cross-country interdependencies and heterogeneity. Therefore, by using PVAR model we employ also allows us to circumvent endogeneity problem together with the small sample size limitation when each country is analyzed individually.

In relative to the previous literature, our study obtains new and robust evidence from a large number of countries by taking into account both increasing dependency and also the existing heterogeneity across the countries. Our results indicate that housing market shows a significant negative and nonlinear response to economic policy uncertainty shocks. Similarly, economic policy uncertainty has a substantial negative effect on GDP growth. The negative effect of the EPU on housing market and economic activity is statistically significant for about six to eight quarters. We also find that economic policy uncertainty behaves quite independently from the housing prices, RGDP and interest rate. This finding is also supported by the Granger causality Wald tests. The robust Granger causality tests performed on lag orders one to three provide evidence that the EPU has a strong predictive content for the real housing prices, but the real housing prices do not help in predicting EPU. The results are found to be robust to alternative specifications. Finally, it is expected that the outcomes of this study will serve as policy instrument for all agents in the housing sector, especially in an era where the housing sector is plagued with high level of uncertainties.

The rest of this study is structured as follows: Section 2 presents data and methodology. Section 3 discusses the empirical results while section 4 concludes the paper.

2. Data and methodology

2.1. Data

The empirical model for this study has five variables, namely, RHP, EPU index, interest rate (IRATE), and population (POP) for panel of 16 countries (Australia, Canada, France, Germany, Greece, Hong Kong, Ireland, Italy, Japan, Netherlands, Russia, Singapore, Spain, Sweden, United Kingdom (UK), and US). This study uses a balanced quarterly panel data over the period 2004Q2 and 2018Q4. The choice of the period and countries is not only based on the availability of the data but also that these countries have implemented a series of housing policies which led to high fluctuations in the housing prices. The data for real housing prices are obtained from the OECD[2] and Bank of International Settlement (BIS) databases.[3] The data for annual RGDP in constant 2010 US dollars and population are retrieved from the World Bank Development Indicators (WDI) database and then converted to quarterly frequency data by using quadratic interpolation to be consistent with the quarterly data. Interest rate data is sourced from DataStream while the EPU data is obtained from Economic Policy Uncertainty database (Baker et al., 2016).[4] Baker et al. (2016) constructs the EPU indices by searching the lead newspaper of each country to find at least one term from three term sets. Under the first one, the newspaper contains uncertain, uncertainty or uncertainties. The second set includes economy or economics. The third set comprises policy related terms such as “monetary policy”, “central bank”, “legislation” and “deficit”. Notably, the EPU data originally has a monthly frequency. We convert the monthly EPU data to quarterly frequency by taking average over the three months within the quarter.[5] Table 1 provides the description and source of the data.

As a preliminary analysis, Levin et al. (2002) and Breitung (2000) panel unit root tests are conducted to determine the integration order of the variables. The results as reported in Appendix A reveal that with the exception of EPU and interest rate all other variables became stationary after taking their first differences. The evidence in favor of a unit root in the EPU series is weak. Hence, we used

[2] The countries include Australia, Canada, Germany, Greece, Ireland, Italy, Japan, Netherlands, Russia, Spain, Sweden, United Kingdom (UK) and US member of OECD. The rest of OECD countries could not be included into the panel due to the un availability of economic policy uncertainty Index data.

[3] Following Goodhart and Hofmann (2008) the housing prices are proxied by the residential property prices while the real residential property prices are obtained for Hong-Kong and Singapore from the BIS database.

[4] The EPU data is obtained from www.policyuncertainty.com.

[5] Following the study of Christou et al. (2017) and Balcilar, Gupta, and Pierdzioch (2016) data converted from monthly to quarterly for EPU to achieve a balance panel as well as robust estimation.

Table 1
Data description and source.

Variable	Abbreviations	Transformation	Source
Real housing price	RHP	Growth	OECD, BIS
Real Gross domestic product	RGDP	Growth	WDI
Economic policy uncertainty	EPU	Growth	Baker et al. (2016) [a]
Population	POP	Growth	WDI
Short-term interest rate	IRATE	Level form	DataStream

[a] Source: The Economic Policy Uncertainty Index website (www.policyuncertainty.com).

year-on-year percentage growth rates of RHP, RGDP, POP and EPU[6] in the analysis.[7]

2.2. Methodology

This study investigates the dynamic and endogenous relations among RHP, RGDP, EPU and IRATE in selected countries over the period 2004Q2-2018Q4 by using PVAR model in the Generalized Method of Moments (GMM) framework. Sims (1980) proposes time series VAR models as an alternative to multivariate simultaneous equation models which built on macro-econometrics literature while panel version of VAR model is proposed by Hoaltz-Eakin et al. (1988) for multiple analysis techniques across fields. PVAR model is structured in an endogenous system, where all variables in the system are treated in an unrestricted manner. This is applicable where the outlined variables are strongly correlated with each other. Subsequently, relative to conventional time series modelling, PVAR model accommodates for cross-sectional dynamics heterogeneity, which provides more information about the sources of heterogeneity in the system. This kind of modelling technique helps in identifying the dynamic heterogeneity among the blocs of countries investigated. Finally, with the PVAR approach, it becomes easy to capture all time variations as regards to the coefficients as well as variance of the shocks. Given these features, it is imperative that the PVAR modelling is more suitable for our investigation.

Therefore, this study follows Abriago and Love (2016) who combine the conventional VAR models with panel data. Initially, k-variables are homogenous PVAR order of p with panel-specific effects defined in the following system of linear equation:

$$RHP_{it} = RHP_{it-1}A_1 + RHP_{it-2}A_2 + \ldots + HP_{it-p}A_p + X_{it}B + u_i + \varepsilon_{it} \quad (1)$$

where i denotes cross-sectional units (countries), t denotes time, RHP_{it} is a $(1 \times m)$ vector of the dependent variables, X_{it} is a $(1 \times n)$ vector of independent variables (covariates) including *EPU, IRATE* and *RGDP*. The $A_1,\ldots, A_p$ are $(m \times m)$ and B are $(n \times m)$ coefficient matrices. u_i captures country specific fixed effect while ε_{it} denotes idiosyncratic errors with the following assumptions: $E(\varepsilon_{it}) = 0,\ E(\varepsilon_{it}^{'}\varepsilon_{it}) = \sum$ and $E(\varepsilon_{it}^{'}\varepsilon_{is}) = 0$.

Abrigo and Love (2015)also confirm that the PVAR model based on equation (1) has cross-sectional heterogeneity and dynamic interdependency problems since u_i variables are related with the independent variables. Hence, Ordinary Least Square (OLS) technique cannot be appropriate due to biased coefficients (Nickell, 1981). To overcome this problem, GMM technique can be applied to estimate PVAR model (Arellano & Bond, 1991; Arellano & Bover, 1995; Blundell & Bond, 1998). Hoaltz-Eakin et al. (1988) confirm that the equation byequation method is consistent estimation of PVAR model. They also demonstrate that to estimate the model as a system of equations might lead to efficiency gains. Abrigo and Love (2015) assume that Z_{it} row vector includes the common set $L \geq kp + p$ instruments where $X_{it} \in Z_{it}$ and superscript numbers refer to number of equations in the system. Based on equation (1), Abriago and Love (2016) proposed the following transformed model:

$$\begin{aligned}
RHP_{it}^{*} &= \overline{RHP_{it}^{*}}A + \varepsilon_{it}^{*} \\
RHP_{it}^{*} &= \left[rhp_{it}^{1*}\ rhp_{it}^{2*} \ldots rhp_{it}^{k-1*}\ rhp_{it}^{k*}\right] \\
\overline{RHP_{it}^{*}} &= \left[RHP_{it-1}^{*}\quad RHP_{it-2}^{*} \ldots RHP_{it-p+1}^{*}\ RHP_{it-p}^{*}\ X_{it}^{*}\right] \\
\varepsilon_{it}^{*} &= \left[\varepsilon_{it}^{1*}\ \varepsilon_{it}^{2*}\ \ldots \varepsilon_{it}^{k-1*}\ \varepsilon_{it}^{k*}\right] \\
A^{'} &= \left[A_1^{'}\ A_2^{'} \ldots A_{p-1}^{'}\ A_p^{'}\ B^{'}\right]
\end{aligned} \quad (2)$$

Abriago and Love (2016), support that the PVAR model is invertible and has an infinite-order moving average (VMA) representation under the stability condition of the PVAR model. This characteristic of the stability helps us to interpret the estimated impulse-response functions (IRF) and forecast error variance decompositions (FEVD). The IRF (Φ_i) can be calculated by using infinite order VMA:

[6] The post-estimation results did not confirm the stability with the level form of EPU in the PVAR model. The stability is established when the year-on-year percentage growth rate of the EPU series is used.

[7] The year-on-year growth rate g for variable x of country i at time t is calculated as $g_{it} = (x_{it} - x_{it-4})/x_{it-4} \times 100$.

$$\Phi_i = \begin{cases} I_k,\ for\ i = 0 \\ \sum_{j=1}^{i} \Phi_{t-j} A_j\ ,\ for\ i = 1, 2 \end{cases} \tag{3}$$

where Φ_i represents the VMA parameters.

Also, h-step forecast error variance decomposition (FEVD) can be computed as:

$$RHP_{it+h} + E[RHP_{it+h}] = \sum_{i=0}^{h-1} \varepsilon_{i(t+h-i)} \Phi_i \tag{4}$$

where RHP_{it+h} represents the observed vector at period t + h while $E[RHP_{it+h}]$ represents the h-step ahead estimated vector at period t. Abriago and Love (2016) orthogonalize the innovations by using P matrix which is $P'P = \Sigma$ for IRF and FEVD techniques. The Cholesky decomposition of Σ depends on the ordering of selected variables in Σ since the first variable have simultaneous effect on the other variables (Sim, 1980).

This study uses the STATA statistical software programs advanced by Abriago and Love (2016) to run the PVAR fitted model. Abriago and Love (2016) advance the Helmert transformation to overcome the orthogonality problem.

3. Empirical results

Panel A of Table 1 presents the key descriptive statistics for the overall sample. As can be seen from the table, population growth is the lowest average while the EPU growth is the highest per quarter. Specifically, the end of 2009 witnessed the least change in EPU for Australia. The highest EPU growth is observed in Canada at the beginning of 2008. For housing prices, the lowest growth occurred in the first quarter of 2011 and the highest growth occurred in the last quarter of 2011 in Russia. Expectedly, EPU growth is more volatile and population growth is less volatile than the other selected variables. Under the normal distribution, skewness value should be around zero and kurtosis value should be around three. Hence, the distribution of all series is positively skewed with excess kurtosis (i.e. leptokurtic).

Panel B of Table 2 shows the Pearson correlation coefficient estimates. The correlation coefficient is found negative between housing price growth and EPU growth. However, other variables are positively correlated with housing price change which concur with the theoretical expectation.

The lag order selection is crucial to proceed with PVAR model. Given the weak evidence in favor of a unit root in the interest rate series, our benchmark model includes year-on-year growth rates of RHP, RGDP, and EPU and the level of the interest rate (IRATE). We perform the identification using the benchmark model.[8] Table 3 provides that the overall coefficient determination (CD), Hansen J-statistic of over-identifying restrictions and three information criteria suggested by Andrews and Lu (2001). Andrews and Lu (2001) propose a moment selection criterion for the GMM estimation and modify the well-known Akaike, Bayesian, and Hannan-Quinn information criteria, which are called, MAIC, MBIC, and MQIC respectively. These modified information criteria include bonus terms that reward using more moment conditions for a given number of parameters and less parameters for a given number of moment conditions. Table 3 shows that the null hypothesis that over-identified restrictions are valid cannot be rejected at 5% significance when lag order is 3. Also, MAIC has the smallest value for the lag order of 3. Hence, the rest of the analysis is based on a PVAR model of order 3.[9]

IRFs are used to examine the dynamic interrelationship among the selected variables in VAR models. Fig. 1 provides the IRF plots with the 95% confidence bands, which are estimated by using Monte Carlo simulations with 1000 repetitions and Gaussian approximation. Expectedly the impact of economic policy uncertainty on real housing prices is significantly negative between the second and eighth horizon after which it turns insignificant relation. It means that a positive shock to EPU growth leads to a decrease in the housing price return. This can be explained by both the demand and supply sides. According to the demand side, the household might delay home-buying decisions due to an increased uncertainty about their future income. Further, uncertainty about the demand for housing can cause investors and firms to postpone their investment as a result of the increased cost of finance and the risk of default, and thereby reducing supply. The combination of both side effects leads to a decrease in housing returns due to the nature of irreversible investment in housing. This aligns with the findings of Su et al. (2019), Aye (2018), Burnside et al. (2016), Hirata et al. (2013), Givanzi and Mochan (2012), Cunningham (2006) and Berkovec (1989). With respect to the IRF of EPU growth on IRATE show that the positive shock to EPU growth leads to decrease in IRATE just at the fifth horizon. The impact of this shock turns into insignificant for the other horizons. The consequence of this insignificant impact might be explained by the action of Central Bank (CB). Because, the CB is able to adjust the short-term interest rate through open-market operations to predetermined level regarding to their policy objectives. Moreover, the Central Bank implement the interest rates of wholesale short-term securities across the banking sector, thus affecting the market interest rates in a short-term (Moore, 1988). Also, the results of the IRF show that RGDP growth reacts negatively

[8] We estimate two other specification for robustness check. The same optimal lag order is also selected for these additional specifications.

[9] Before estimating IRFs and FEVDs, we check the stability condition of the estimated PVAR model. The stability condition requires that all roots of the companion matrix must lie inside the unit circle. The estimates confirm that the estimated PVAR model is stable since all the roots lie inside the unit circle.

Table 2
Descriptive statistics and Pearson correlation coefficients.

Panel A: Descriptive Statistics						
	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
RHP	2.0286	8.1061	−28.7906	55.5858	0.7098	8.2450
RGDP	2.0663	3.4338	−9.6220	27.6151	1.1073	12.9432
EPU	11.4988	45.8125	−62.0387	312.6817	1.7015	8.4777
POP	0.6798	0.7949	−1.9700	5.6683	1.7112	10.2985
IRATE	2.4715	2.7361	−0.7767	21.1433	1.6205	8.1590
Panel B: Correlation coefficient estimates						
	RHP	RGDP	EPU	POP	IRATE	
RHP	1.0000					
RGDP	0.5879*	1.0000				
EPU	−0.0373	0.0272	1.0000			
POP	0.2668*	0.9362*	0.0850*	1.0000		
IRATE	0.0972*	−0.1854*	0.1167*	0.1934*	1.0000	

Note: * denotes significance at 1% level.

Table 3
Lag order selection criteria.

Lag	CD	*J*-statistic	*p*-value of *J*-statistic	MBIC	MAIC	MQIC
1	0.9982	169.4603	1.78E-11	−257.0619*	41.4603	−73.3277
2	0.9986	82.9052	0.0013	−236.9864	−13.0948	−99.1858*
3	0.9964	43.8611	0.0789	−169.4000	−20.1389*	−77.5329
4	0.9992	12.7088	0.6939	−93.9218	−19.2912	−47.9822

Note: The asterisk * denotes the selected optimal lag order.

to a shock to EPU growth. This relation is consistent with the theoretical expectation of Bloom (2009), Dixit et al. (1994) and Bernanke (1983). It has been argued that EPU may influence the decision-making process of managers in terms of investing and hiring of an organization. It is paramount for an organization to pass through higher levels of EPU to forecast future sales which will dictate whether to improve or slow down production activities in order to maximize business objectives. This process leads to decrease economic activity (Balcilar, Gupta, & Segnon, 2016; Jones & Olson, 2013).

The IRF plots in Fig. 1 also reveal that the dynamic impact of real housing prices on economic policy uncertainty is statistically insignificant over the whole horizon considered. The result is in line with the findings of Chow et al. (2017), who report that there is no panel nonlinear and linear Granger causality running from real housing returns to EPU changes for the case of China and India. However, the result is in contrast with the findings of El-Montasser et al. (2016) and Su et al. (2016) for the US and UK. This conflict perhaps depends on the specific set of countries in the panel. Also, the interest rate response is insignificant to shocks in real housing prices. This finding might be linked to central bank policy rules such as the Taylor rule. According to the Taylor rule, there is no direct feedback effect from asset prices to the policy interest rate. Asset prices may only indirectly impact interest rate through its effects on output and inflation and for this to occur, wealth and income effects of asset price variations must be significant. This result confirms the conclusion reached by Singh and Pattanaik (2002). Lastly, RGDP responses positively and significantly for one to five quarters to real housing prices with a quite nonlinear pattern. In other words, rising housing prices causes an increase in economic growth. This perhaps due to collateral and wealth effects of housing price changes on consumption (Miller et al., 2011). If households consider their property as wealth and adjust their spending decisions according to net wealth, changes in housing prices may affect their consumption. More so, based on the permanent income hypothesis unexpected increases in housing prices lead to increasing homeowner' expected lifetime wealth and they will tend to increase their consumption. Thereby, housing equity may trigger a wealth effect. The results concur with the existing literature such as Antonakakis and Floros (2016), Nyakabawo (2015), Aye et al. (2014), Demary (2010).

It is worthy of mentioning here that in order to explain the exogenous shock the outlined variables by the aid of FEVD of the fitted model over the specified horizon. By doing so, the FEVD helps us to determine the relative importance of each exogenous shock on the variables in the PVAR model.

We also present FEVDs of the benchmark model for 16 quarters to shed some light on the magnitude of dynamic interactions. FEVDs helps us to determine the relative importance of each shock on the variables in the PVAR model. Table 3 provides the FEVDs of the benchmark specification with four varibles. As can be seen from Table 4, 16 percent of variation in real housing prices is explained by RGDP and five percent can be explained by EPU for a four-year horizon. However, the contribution of interest rates shocks to real housing is small and almost constant over time. This result shows that RGDP has a relatively greater influence on real housing prices both in the short term and long term. On the other hand, the FEVDs of EPU shows that interest rate, real housing prices and RGDP has a negligee effect on the variations of EPU with 1.65, 0.97 and 0.52 percent contribution, respectively, in 16 quarters horizon. About 97 percent of the variation in EPU is accounted by other factors, implying EPU behaves quite independently.

In order to discover the dynamic transmission mechanism through which the EPU effects housing prices we perform Granger

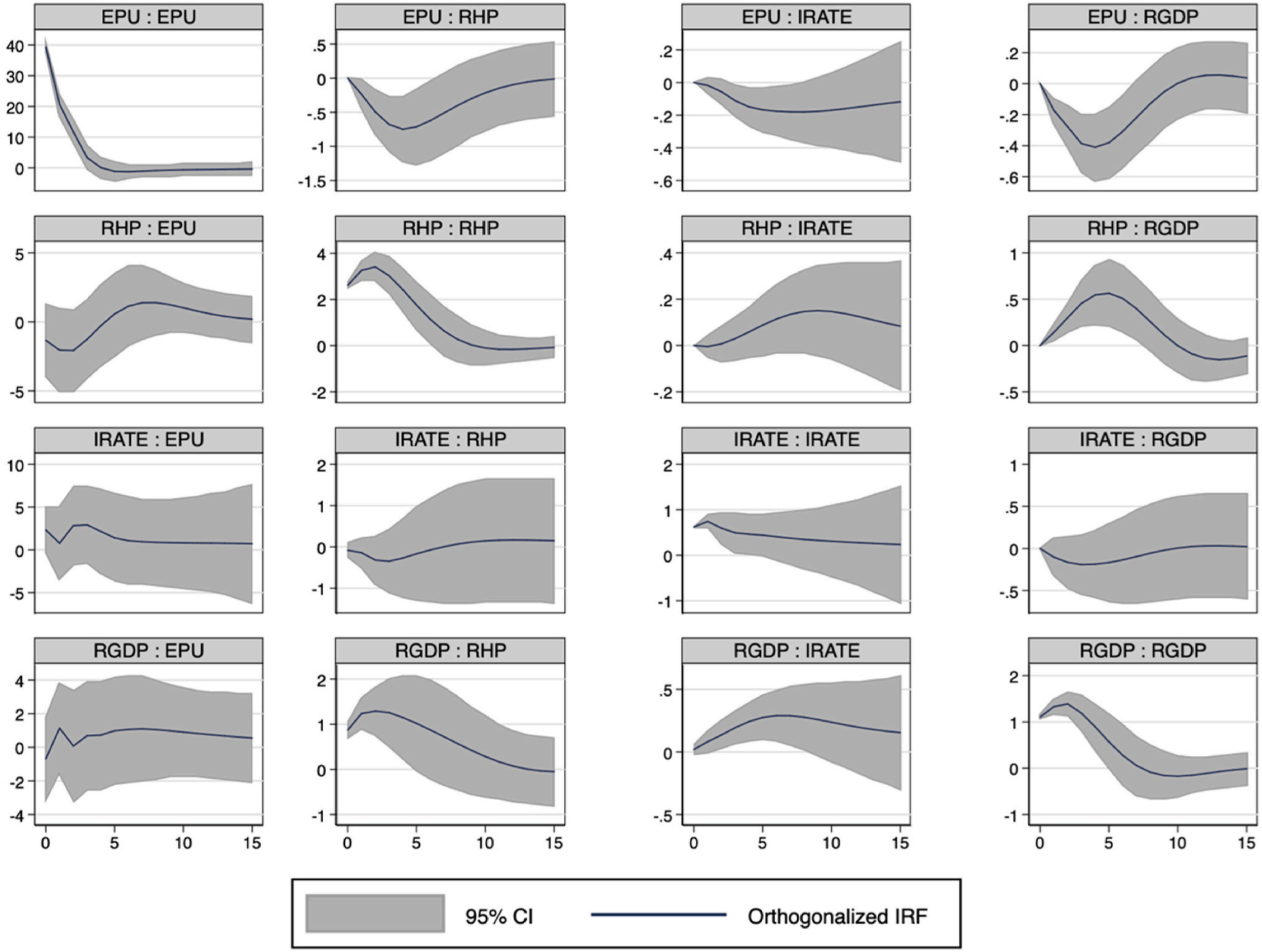

Fig. 1. Impulse response estimates for the benchmark model.
Note: The benchmark model is estimated of RHP, RGDP and EPU and IRATE. The optimal lag order is 3.

Table 4
Forecast error variance decomposition.

h	RHP	RGDP	EPU	IRATE
RHP equation				
4	0.8540	0.1234	0.0170	0.0056
8	0.8030	0.1504	0.0407	0.0059
12	0.7905	0.1576	0.0451	0.0068
16	0.7891	0.1572	0.0452	0.0084
EPU equation				
4	0.0055	0.0010	0.9830	0.0104
8	0.0071	0.0027	0.9758	0.0143
12	0.0094	0.0044	0.9707	0.0155
16	0.0097	0.0052	0.9686	0.0165
RGDP equation				
4	0.0454	0.9801	0.0367	0.0107
8	0.1380	0.7720	0.0730	0.0170
12	0.1441	0.7652	0.0737	0.0170
16	0.1500	0.7590	0.0739	0.0172
IRATE equation				
4	0.0005	0.0390	0.0097	0.9507
8	0.0155	0.1311	0.8074	0.0461
12	0.0351	0.1680	0.0675	0.7295
16	0.0414	0.1771	0.0766	0.0766

Note: The table presents the forecast error variance decomposition of the benchmark model, which is estimated with year-on-year growth rates of RHP, RGDP and EPU and levels of the interest rate. The optimal lag order is 3. denotes horizons in quarters.

Table 5
Granger causality tests.

Benchmark Model				–	Alternative specification			
Hypothesis					**Hypothesis**			
IRATE ⇏ DRGDP	6.796***	1.070	1.298		DIRATE ⇏ DRGDP	0.802	0.505	5.071
DRHP ⇏ DRGDP	2.255	11.168***	13.549***		DRHP ⇏ DRGDP	3.547*	11.777***	14.177***
DEPU ⇏ DRGDP	19.736***	17.14***	19.335***		DEPU ⇏ DRGDP	34.901***	23.662***	26.65***
DRGDP ⇏ IRATE	6.835***	6.098**	6.443*		DRGDP ⇏ DIRATE	0.251	5.276**	9.417**
DRHP ⇏ IRATE	0.044	0.245	0.382		DRHP ⇏ DIRATE	4.102**	5.676*	5.610
DEPU ⇏ IRATE	0.610	3.398	4.798		DEPU ⇏ DIRATE	0.410	12.319***	13.099***
DRGDP ⇏ DRHP	0.052	0.633	6.75*		DRGDP ⇏ DRHP	0.052	0.546	6.279**
IRATE ⇏ DRHP	3.924**	0.833	3.967		DIRATE ⇏ DRHP	0.723	0.312	2.197
DEPU ⇏ DRHP	8.705***	7.84**	10.627**		DEPU ⇏ DRHP	14.089***	6.145**	6.027
DRGDP ⇏ DEPU	0.945	1.826	2.611		DRGDP ⇏ DEPU	1.484	2.002	2.167
IRATE ⇏ DEPU	0.983	1.164	3.206		DIRATE ⇏ DEPU	1.874	3.724	5.319
DRHP ⇏ DEPU	0.294	1.556	1.982		DRHP ⇏ DEPU	0.640	2.029	2.935
Extended specification								
Hypothesis					**Hypothesis**			
DRGDP ⇏ DPOP	7.409***	10.021***	11.824***		DPOP ⇏ DRHP	0.360	0.893	0.381
IRATE ⇏ DPOP	0.001	4.427	8.375**		DRGDP ⇏ DRHP	0.030	0.561	5.919
DRHP ⇏ DPOP	2.687	4.599	5.865		IRATE ⇏ DRHP	4.028**	0.768	3.663
DEPU ⇏ DPOP	0.124	1.443	9.009**		DEPU ⇏ DRHP	9.041***	7.855**	10.773**
DPOP ⇏ DRGDP	0.223	0.000	0.207		DPOP ⇏ DEPU	0.120	6.288**	9.166**
IRATE ⇏ DRGDP	5.645**	0.918	1.352		DRGDP ⇏ DEPU	0.904	1.902	2.508
DRHP ⇏ DRGDP	2.255	11.577***	13.846***		IRATE ⇏ DEPU	0.641	0.934	3.047
DEPU ⇏ DRGDP	20.55***	17.393***	19.85***		DRHP ⇏ DEPU	0.296	1.895	2.329
DPOP ⇏ IRATE	0.363	3.113	4.879					
DRGDP ⇏ IRATE	8.002***	6.798**	6.928*					
DRHP ⇏ IRATE	0.043	0.099	0.450					
DEPU ⇏ IRATE	0.924	4.895*	6.168					

Note: The granger causality tests are performed on benchmark, alternative and extended specifications. The table reports the Granger causality Wald tests for each equation of the underlying panel VAR model estimated by the GMM. In addition to optimal lag order 3, the tests are also reported for lag orders 1 and 2 for robustness.

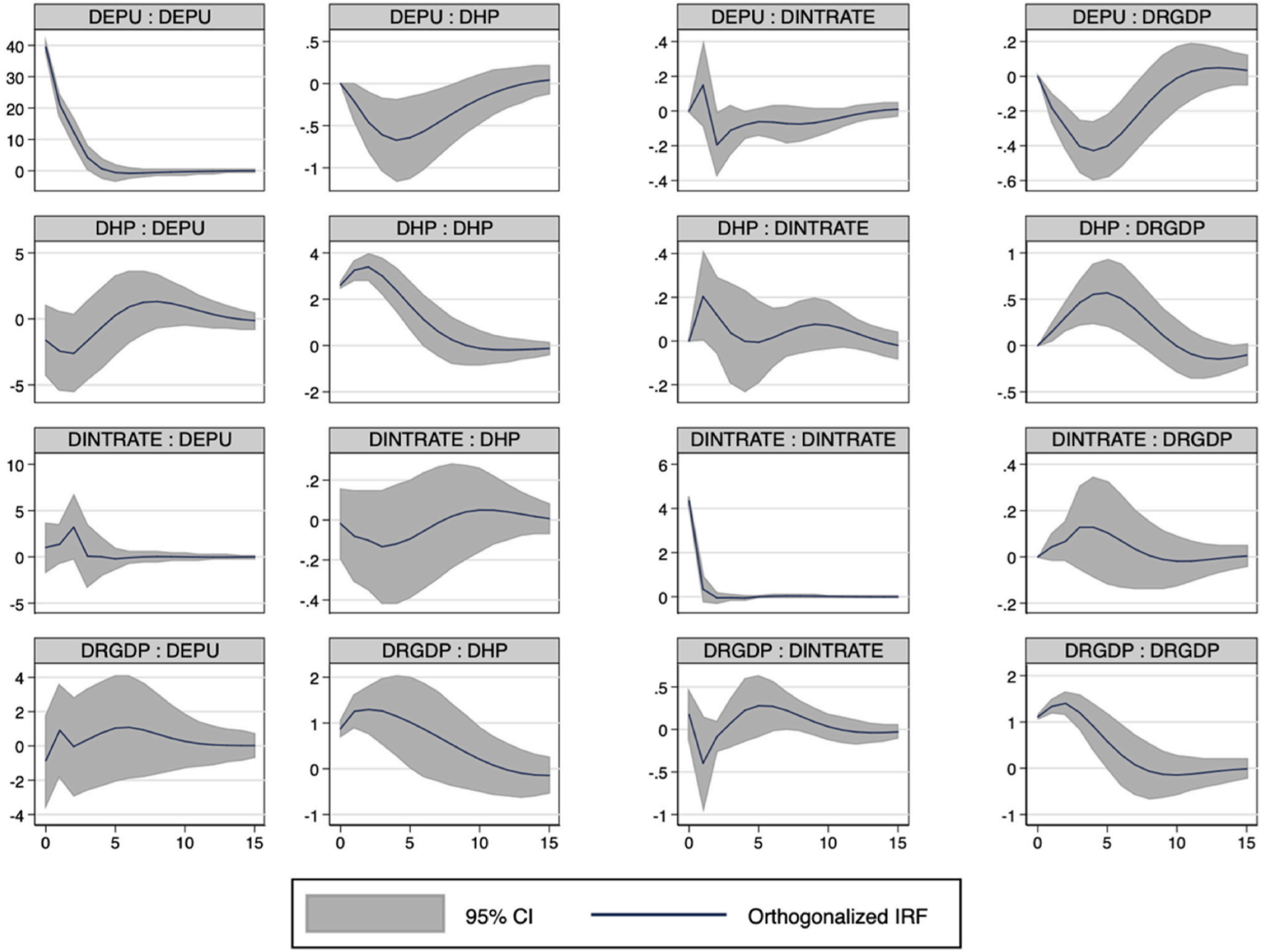

Fig. 2. Impulse response estimates for the alternative specification.

Note: The alternative specification is estimated with growth rates of RHP, RGDP, EPU and IRATE. The optimal lag order is 3.

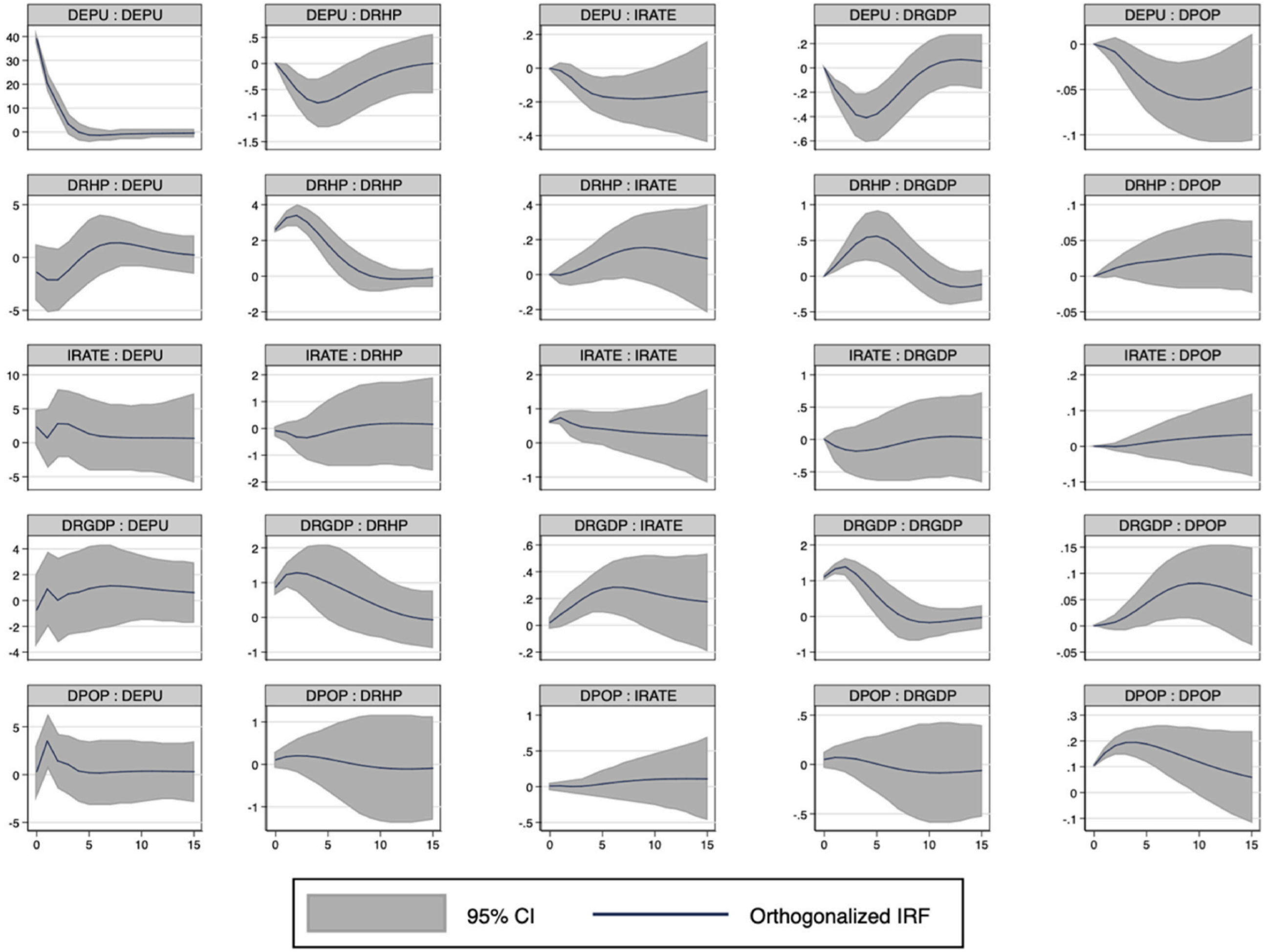

Fig. 3. Impulse response estimates for the extended specification.
Note: The extended specification adds growth rates of the population to the benchmark model. The optimal lag order is 3.

causality tests on all estimated equations. The Granger causality is tested using a Wald statistic calculated by imposing the relevant zero restrictions on the GMM estimates. In addition to optimal lag order of three, we report Granger causality tests for lag orders one and two for robustness. In Table 5 we report the Granger causality Wald test results for all model specifications. The Wald tests reject the null hypothesis that the EPU does not Granger cause real housing prices for all models at 1% significance level with one exception, which occurs in alternative model specification and lag order three. Indeed, the support for Granger causality from the EPU to real housing prices is the one of the two robust result in Table 5. The second robust support for the Granger causality is found for the case of causality from the EPU to RGDP series. Indeed, the null of no Granger causality from the EPU to the RGDP is rejected for all cases. There is also quite strong evidence to support the Granger causality from the housing price series to the RGDP series. Thus, the EPU has the highest predictive power for the housing price series. Moreover, the predictive power of the EPU for the housing price series is stronger than its predictive power for the RGDP series. Additionally, the RGDP does have only weak predictive power for the real housing prices. Thus, the causality from the EPU series to real housing prices is rather direct than indirect through its effect on other variables. The EPU also Granger causes GDP both directly and indirectly via its effect on the real housing prices. This last result occurs since real housing prices have predictive power for the GDP.

3.1. Robustness check

As a robustness check of our findings, we estimate two additional models. In the first model, the interest rate is considered as nonstationary and an alternative model (benchmark model) with all variable in year-on-year growth rates is estimated. We do this since the evidence in favor of the stationarity of the interest rate is weak. Following the study of Jäger and Schmidt (2017), Chow et al. (2016) and Bian and Gete (2015), we also estimate an extended model by adding the year-on-year growth rate of the population variable to the benchmark model. Since the population is the slowest moving variable it takes the first place in the ordering of the variables. Optimum lag order is selected by using the MAIC which is 3 for both additional models we estimate. Before comparing the results of IRF estimations, the stability of the two models needs to be established. All the roots of the companion matrix are within the unit circle for both of the additional model specifications, which establishes the stability of the two estimated models. The IRF results of the alternative model is presented in Fig. 2 and while Fig. 3 presents the IRF estimates of the extended model. The IRF results in Figs. 2 and 3 are qualitatively quite similar to IRFs obtained from the benchmark model. Thus, our results are robust to the integration order of the interest rate variable and inclusion of the population variable. The Granger causality test results reported in Table 4 are also robust to model specification.

4. Conclusion

In 2007, the global financial and economic crisis that was triggered by a subprime mortgage crisis had not happened without leaving some adverse traces. This sudden slump or depression has exacerbated uncertainties in the developed and developing economies. Thereafter, the relationship between housing sector and economic policy uncertainty have attracted a lot of attention in the existing housing market literature. However, a common limitation of this literature is that many of these studies focused only on the relationship between the housing market variables and EPU without considering other crucial determinants of the housing market. By addressing the gap in the literature, the present study offers new insight into the dynamic relationships between housing price return and the EPU growth. In doing this, the economic growth and the short-term interest rate were incorporated in the model both as additional variables to circumvent for omitted variable bias approach. To achieve this aim, the study conducted PVAR technique which allow the consideration of endogeneity problem while also overcoming the small sample size limitations.

The empirical results of IRF show that the positive shock to EPU growth leads to decrease in the housing price return. From the investors' point of view, heightened uncertainty regarding economic policy translates into weak investment in the housing sector. Consequently, the weak housing investment is observed to cause adverse effect on economic growth since the housing sector (a leading sector for economic growth) reportedly shown strong resilience. Similarly, evidence from the FEVD results indicate that housing has a relatively greater impact on economic growth in both the short- and long term. However; the dynamic impact of housing price return on EPU growth is statistically insignificant over the sample period. This is also confirmed by the FEVD results which shows that the housing price return have very weak effect in explaining the changes in EPU growth. Regarding the policy framework, this finding reveals that EPU has more power to explain the changes in itself. Moreover, the Granger causality tests show that the EPU is a strong predictor for both the real housing prices and RGDP. Regarding the policy framework, our results imply that EPU has significant effect on both the housing market and economic activity at large. Moreover, the EPU is quite independent from the observables such as the housing prices, RGDP and interest rate. Hence, policymakers, real estate agents, and portfolio managers in the housing market should consider economic policy uncertainty as a significant signaling variable. Although the current does not provide country-specific inference, the panel result further presents monetary policy caution to countries such as the United States and other major world economies that were significantly affected following the mortgage crisis vis-à-vis global financial crisis.

Thus, future study could replicate the current case from the country-specific perspectives in order to provide additional information that demonstrated the panel relationship between the EPU and RHP. Future studies can explore the theme while considering asymmetry and other demographic variables like political regimes, democracy using disaggregated data.

Author statement

This is to certify that there is no conflict of interest with respect to any authors of this paper listed below.

Appendix A. Panel unit root test results

	Level							
	LLC[a]	*p*-value	LLC[b]	*p*-value	Breitung[a]	*p*-value	Breitung[b]	*p*-value
RHP	0.1066	0.5424	−1.5149	0.0649	6.2879	1.0000	−1.4377	0.0753
RGDP	0.8117	0.7915	0.1065	0.5424	14.1721	1.0000	3.3329	0.9996
EPU	−6.4649***	0.0000	−11.8875***	0.0000	−1.5404[aaa]	0.0617	−3.5731***	0.0002
IRATE	−2.5349	0.0056	−4.1998	0.0000	−4.2641	0.0000	−4.0019	0.0000
POP	−2.3466	0.0095	−1.5345	0.0625	19.3565	1.0000	14.8193	1.0000
	Year-on-year growth rates							
RHP	−6.4883***	0.0000	−1.8717******	0.0306	−3.7815***	0.0001	−2.8394***	0.0023
RGDP	−6.4837***	0.0000	−4.0390***	0.0000	−8.1637***	0.0000	−6.6777***	0.0000
EPU	−14.7040***	0.0000	−9.5227***	0.0000	−9.8733***	0.0000	−5.2475***	0.0000
IRATE	−13.6062***	0.0000	−13.8041***	0.0000	−4.0327***	0.0000	−3.4122***	0.0003
POP	−3.0931***	0.0010	−2.5736***	0.0000	−2.5736***	0.0000	−1.9918******	0.0232

Notes: [a] refers to unit root test model with constant and [b] refers to unit root test model with constant and trend. *, ** and *** indicate significance at 10%, 5% and 1% level, respectively.

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