Causality between Economic Policy Uncertainty and Real Housing Returns in Emerging Economies: A Cross-Sample Validation Approach

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ABSTRACT

This paper examines whether economic policy uncertainty Granger causes real housing returns in 8 emerging economies namely: Brazil, Chile, China, India, Ireland, Russia, South Africa and South Korea. Quarterly data were used for the analysis. Although, both in-sample and out-of-sample causal tests were conducted, the study focuses on the cross-sample validation (CSV) Granger causality approach which obviates the need to partition the data into an in-sample and out-of-sample periods. Results based on the CSV full sample period indicate no evidence of economic policy uncertainty Granger causing real housing returns except for Chile and China. However, there exists evidence of time varying causality in all the countries except India based on CSV rolling window results. The implications of these findings are drawn.

JEL CODES: C32, C53, G10, G17

Keywords: Economic policy uncertainty; housing returns; cross-sample validation causality; in-sample; post-sample; rolling window

INTRODUCTION

The 2007/2009 global economic and financial crisis had its root in the housing market with the subprime mortgage crisis. This has led to heightened interest in this market since the crisis given its susceptibility to shocks and its crucial role in the economy. Housing prices provides indication as to where the economy is heading to (Leamer, 2007; Aye et al., 2014). The aftermath of the global crisis has increased housing price volatility and economic uncertainty (Hirata, et al., 2013). Su et al. (2016) noted that attributing housing market instabilities to increased policy uncertainty is not uncommon. When there is uncertainty, policy authorities and investors are reluctant on the appropriate course of action. This may delay economic activity. Theoretically, uncertainty and the housing market should share a relationship. This is because economic policy uncertainty could delay investment decisions in the housing market due to its potential to reduce demand for capital, and hence housing returns as well as the irreversible nature of housing investments (Calcagnini and Saltari, 2000; Hirata et al. 2013; Burnside et al. forthcoming). Pastor and Veronesi (2013) also argue that increased political uncertainty can lead to rising cost of financing housing projects. Therefore, it is pertinent to empirically examine the causal link between economic uncertainty and housing returns. Since uncertainty is a latent variable that needs to be measured, this study uses the news-based measure of uncertainty, widely known as the economic policy uncertainty index (EPU) developed by Baker et al., (2016). Despite the availability of other measures of uncertainty, EPU has received wide acceptance in empirical applications (Redl, 2015; André et al., forthcoming), due to the fact that it is not model specific and has wide coverage beyond the US economy unlike many other uncertainty indicators.

A few studies have investigated the relationship between economic uncertainty and housing prices and/or volatilities. For instance, in a study by Sum and Brown (2012) based on a VAR model and monthly data covering 1985 to 2011, there is no support for a significant causal link

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between EPU and Real Estate Investment Trust returns in the United States. Using data from January 1999 to June 2013 and volatility impulse response functions (VIRFs) introduced by Hafner and Herwarz (2006) as well as variance causality test, Ajmi et al. (2014) find a two-way transmission channel between US-listed REITs conditional volatility and macroeconomic uncertainty proxied by two indices namely Economic Policy Uncertainty Index and the Equity Market Uncertainty Index.

Based on Dynamic Conditional Correlation Generalized Autoregessive Conditional Heteroskedastic (DCC-GARCH) model, Antonakakis et al. (2015) find that the correlation between EPU and housing market returns in US is negative consistently, but with varying magnitude over time peaking during the 2007/2009 financial crisis. Su et al. (2016) use a bootstrap rolling window causality developed by Balcilar et al. (2010) and find that EPU has no impact on housing returns in Germany but the latter has significant effects on EPU for a limited time period. Housing returns do not have significant effects on EPU in most time periods. The causal relationship between EPU and real house prices in Canada, France, Germany, Italy, Spain, UK, and US was examined by El Montasser et al. (2016) who employed quarterly data from 2001 to 2013 and a bootstrap panel VAR. Results show that a bi-directional causality exists for France and Spain, while unidirectional causality was found for the remaining countries. In a study by Antonanakis et al. (2016), they find a time-varying volatility spillover effect from EPU to real housing returns in US based on a VAR-based approach.

For China and India, Chow et al. (forthcoming) use linear and nonlinear panel and time series models. Results based on linear model show a unidirectional causality from EPU growth to housing returns in China but not India. The nonlinear Granger causality tests find mostly unidirectional causality from EPU to housing returns in both countries. When the two countries are taken as a panel, both panel linear and panel nonlinear tests reject the null of EPU not Granger causing housing returns. André et al. (forthcoming) use monthly data from 1953:1-2014:2 and a *k*-th order non-parametric Granger causality test. They split the whole sample into two equal parts of in-sample (1953:2-1983:8) and out-of-sample (1983:9-2014:1) periods. Their results show that EPU predicts both real housing returns and its volatility in the United States. For ten OECD countries: Canada, France, Germany, Italy, Japan, the Netherlands, South Korea, Spain, UK, and US, Christou et al. (forthcoming) use quarterly data from 2003 to 2014 with an out-of-sample period of 2008:Q2 to 2014:Q4 and panel VAR models. They evaluated the point and density forecasts at one-, two-, four-, and eight-quarters-ahead and find a predictive power of EPU for housing returns. Aye et al. (2017) employ a hazard model to investigate the spill-over effect of economic uncertainty on the housing market cycles in 12 OECD countries (Australia, Canada, Chile, France, Germany, Ireland, Italy, Japan, The Netherlands, Spain, Sweden, United Kingdom and United States) and find that while higher economic uncertainty significantly affects the probability of exiting housing market busts it has no significant effect on the probability of leaving booms and normal times.

Most of these studies barring André et al. (forthcoming) and Christou et al. (forthcoming) focus on in-sample predictability of economic uncertainty for the housing market. However, there is widespread evidence that in-sample predictive ability does not guarantee out-of-sample accuracy of forecasts (Rapach and Zhou, 2013). Ashley and Tsang (2014) confirmed that the in-sample estimation of causality can be a poor approach to out-of-sample forecasting. This study contributes to this line of research by examining the causal link between economic policy uncertainty and housing returns using the cross-sample validation (CSV) Granger causality approach which avoids the need to partition the data a priori into an in-sample and out-of-sample periods (Ashley and Tsang, 2014). Ashley and Tsang (2014) argued that the practice of a priori or arbitrarily partitioning of the data into in-sample period – used only for model specification/estimation- and out-of-sample period-used only for evaluating the model's forecast ability is not feasible with samples of modest length (T≤150) commonly seen in quarterly and sometimes monthly data sets. Thus, they proposed a cross sample validation (CSV) scheme whereby all of the available data is used at once in the testing procedure and every possible in-sample versus post-sample partitioning is examined. Thus, this preserves the power of in-sample testing. It also preserves most of the credibility of the out-of-sample testing by basing model forecast evaluation on data not used for estimating the particular model's coefficients. In this study, eight emerging market economies namely Brazil, Chile, China, India, Ireland, Russia, South Africa and South Korea are considred. Aside South Korea which was included in the panel in Christou et al. (forthcoming), and China and India in Chow et al. (forthcoming), the relationship has not been previously examined for the remaining countries to the best of my knowledge.

EMPIRICAL MODEL

This study employs the cross-sample validation (csv) test for Granger causality developed by Ashley and Tsang (2014). The model for y_t over the full (unrestricted) information set is given as

$$Y = X\beta^u + \varepsilon^u \tag{1}$$

where X is $T \times k$ vector of explanatory variables including the g putatively causative variables. The model for y_t over the restricted information set is given as:

$$Y = X^r \beta^r + \varepsilon^r \tag{2}$$

where the $T \times (k-g)$ array X^r is identical to X but omits the columns containing the data on the g putatively causative variables and where β^r omits the corresponding components. Additional explanatory variables may be included in X. In this study, only lagged values of real housing returns, y_t are included in X aside the lagged g putatively causative variable, economic policy uncertainty.

Assuming the sample of T observations is split into two parts: the first τ observations and the remaining $T-\tau$ observations. Letting the first τ observations be the "in-sample" period and the remaining $T-\tau$ observations be the "post-sample" period, for any given sample-split τ, the F_τ can be computed as

$$F_\tau \equiv \frac{\{RSS(\tau) - URSS(\tau)\}/g}{URSS(\tau)/(T-k)} \tag{3}$$

where $URSS_\tau$ and RSS_τ are an unrestricted and a restricted sum of T squared "out-of-sample" prediction errors respectively.[2] F_τ would be potentially useful in testing the null hypothesis that the coefficients on all g putatively Granger-causing explanatory variables are zero. However, F_τ depends on the (arbitrary) sample-split at period τ. To avoid this dependence on the sample-split choice, the Granger-causality inference can be based on every possible value of τ. This can be done by using a sample quantile of the observed values of F_τ over all of the feasible values of τ as the test statistic.

Letting $\hat{Q}_v(x_1 \ldots x_m)$ denote the v^{th} sample quantile of the distribution from which the observations $x_1 \ldots x_m$ are drawn, these sample order statistics can be expressed as:

$$\hat{Q}_v(F_{k+1} \ldots F_{T-k-1}) \tag{4}$$

where τ must lie in the interval $[k+1, T-k-1]$ so that both $\hat{\beta}^u_\tau$, the estimator of β^u in Equation (1) using only the first τ observations, and $\hat{\beta}^u_{-\tau}$, the estimator of β^u in Equation (1) using only the last $T-\tau$ observations are computable.

Granger-causality tests based on $\hat{Q}_v$ are appropriately called "cross-sample validation' tests because they are based on applying the model coefficients estimated on one portion of the data to predicting the other portion of the data. Consequently, $\hat{Q}_{0.50}$, the sample median of $F_{k+1} \ldots F_{T-k-1}$ is denoted as the "$CSV50$" statistic. Analogously, $\hat{Q}_{0.75}$, the sample third-quartile of $F_{k+1} \ldots F_{T-k-1}$ is denoted as the "$CSV75$" statistic, and so forth for the other values of v. These sample order statistics, by construction, do not depend on τ. Granger causality inferences based on $\hat{Q}_v$ are usually obtained using bootstrap methods as this ensures that the sizes of the CSV tests are reasonably accurate, even for the modest sample lengths.

DATA

The data consists of two variables: real housing prices and economic policy uncertainty (EPU) for 8 emerging countries namely Brazil, Chile, China, India, Ireland, Russia, South Africa and South Korea. Following Cesa-Bianchi et al. (2015), the housing prices data are obtained from the OECD house price database, the BIS (Bank of International Settlement) property price dataset and the Federal Reserve of Dallas international house price database. The real house prices were obtained by deflating the nominal house prices with a country-specific consumer price index. The economic policy uncertainty indices were obtained from www.policyuncertainty.com. Month-by-month searches of leading newspapers in each country, for terms pertaining to uncertainty, the economy and policy was performed by Baker et al. (2016). The original source documents the EPU data on monthly frequency. To be consistent with the real housing price data which are quarterly, the EPU data are converted into their quarterly frequency in this study by taking averages over three-months comprising a

[2] More technical details can be found in Ashley and Tsang (2014).

quarter. Preliminary analysis indicates that both EPU and housing prices have unit roots.[3] Since the Granger causality tests performed here requires the series to be stationary, the variables are used in their log first difference form. Table 1 reports key statistics for the log-difference of real house price and economic policy uncertainty for each country. The starting and ending dates are determined by data availability. Real house price returns is highest in India (1.68% per quarter) and lowest, in fact negative in South Korea (-0.27% per quarter). The housing market in Chile and Russia are more volatile than the rest of the economies while that of China is the least volatile. Based on the Jarque-Bera test, the real housing returns in China, Ireland and South Africa are normally distributed while the rest are not. For EPU, the highest growth is witnessed in Brazil (2.27% per quarter) while the least growth is witnessed in India (0.05%). The EPU growth series appear to be normally distributed in almost all the countries.

Table 1: Descriptive Statistics

Real housing returns						
Country	Sample period	Mean (%)	Std Dev(%)	Skewness	Kurtosis	Jarque-Bera test (P-value)
Brazil	2001Q1-2016Q2	0.831	2.897	-0.762	3.008	0.052
Chile	1993Q1-2015Q3	0.842	7.407	1.272	9.349	0.000
China	1999Q1-2016Q2	0.526	1.349	-0.497	3.392	0.194
India	2003Q1-2016Q2	1.682	3.772	-0.641	7.834	0.000
Ireland	1985Q1-2016Q2	0.760	2.770	-0.208	2.721	0.521
Russia	2001Q1-2016Q2	0.820	5.858	-2.014	14.398	0.000
South Africa	1985Q1-2016Q5	0.314	2.648	0.046	3.700	0.270
South Korea	1990Q1-2016Q3	-0.270	1.991	-0.669	6.052	0.000

Economic policy uncertainty growth						
Country	Sample period	Mean(%)	Std Dev(%)	Skewness	Kurtosis	Jarque-Bera test (P-value)
Brazil	2001Q1-2016Q2	2.269	35.369	0.063	2.580	0.783
Chile	1993Q1-2015Q3	1.514	24.744	-0.172	2.746	0.711
China	1999Q1-2016Q2	1.578	36.854	0.604	3.634	0.069
India	2003Q1-2016Q2	0.045	29.729	0.390	3.528	0.375
Ireland	1985Q1-2016Q2	0.961	33.080	0.249	3.239	0.452
Russia	2001Q1-2016Q2	1.475	34.825	0.085	2.832	0.929
South Africa	1985Q1-2016Q5	1.451	90.020	0.309	4.141	0.012
South Korea	1990Q1-2016Q3	0.288	36.720	0.149	2.772	0.733

RESULTS

The results for the usual in-sample F test, the standard post-sample MSE-F and CSV tests are presented in Table 2. The p-values of each test for the null hypothesis that economic policy uncertainty does not granger cause real housing returns are reported for each of the eight emerging countries. For the cross-validation test, only the third quartile or CSV75 test p-values are reported as this is consistent with suggestions by Ashley and Tsang (2014) that this should

[3] These results are available from the author upon request.

be used in empirical applications given their power over the class of CSV tests. In all cases the p-values were obtained via bootstrapping with M = 10,000 simulations. As determined by the SIC lag length criteria, two lags of real housing returns were included on as explanatory variable for South Africa and Ireland while one lag was included for the remaining countries. Looking at the in-sample test, it is observed that the null hypothesis can be rejected only for China at 5% level of significance. For the rest of the countries, EPU growth does not Granger cause housing returns. Moving to the CSV75 test, the null hypothesis is rejected at 5% for Chile and China only. While the CSV test supports the in-sample tests for China, and the rest of the countries, there is mixed evidence for Chile. The rejection p-values for the standard MSE-F tests are reported for post-sample periods of lengths 5 and 10 quarters. The null hypothesis is rejected for India, Russia and South Africa for the 5 quarter-ahead while it is not rejected for 10 periods in any of the countries. Given the shortness of the sample data, the results of the standard post-sample MSE-F test should be interpreted with caution.

Aside the results based on the full sample, this paper also presents the results from the rolling window cross-sample validation test with the rolling window size set to 20. These are presented for the various countries in Figures 1 to 8. These figures graph the bootstrapped p-values for the CSV57 test as a function of the forecast windows; the horizontal line represents a p-value of 0.10 (10% significance level). Figure 1 presents the CSV75 p-values for the null hypothesis that EPU growth does not Granger cause real housing returns in Brazil. The null hypothesis is rejected for Brazil in 2013Q3 only. This means that EPU has a very limited predictive power for housing returns in Brazil. In Figure 2, the null hypothesis is rejected for Chile during 2002Q4 – 2003Q3, 2007Q1, 2008Q4, 2009Q2 – 2011Q4 sub-periods. These periods fall much within the recent global crisis and appear to connote that Chile's housing market must have been seriously affected by high economic uncertainty during and after the crisis. For China as represented in Figure 3, EPU has significant causality for real housing returns in 2005Q1-2005Q2, 2005Q4 and 2011Q4 – 2015Q3. In Figure 4, the results show that there is clearly no causal relationship between EPU and real housing returns in India. In Ireland as depicted in Figure 5, there seems to be some significant causal relationship between EPU and real housing returns at different periods but these do not seem to span for long. Specifically, there is evidence of EPU causing real housing return in the following periods: 1995Q4, 2002Q2-2002Q4, 2003Q1, 2010Q3 and 2014Q3-2014Q4. In Figure 6, the results show that during 2010Q3-2010Q4 and 2012Q4, EPU has a predictive power for real housing returns in Russia. Results based on Figure 7 shows that in South Africa, EPU has basically no predictive power for the housing market as its significance is felt only in 1991Q4. Finally for South Korea, there is evidence of predictive power of EPU for real housing returns during 2000Q2-2000Q4, 2001Q2-2001Q3, 2002Q1, 2002Q3, 2004Q2-2004Q3, 2005Q2, 2009Q4-2010Q1 periods.

Table 2: In- Sample and Post-Sample Granger Causality test

Country	Brazil	Chile	China	India	Ireland	Russia	South Africa	South Korea
Sample Length	60	90	68	52	123	60	124	105
In-Sample F Test	0.323	0.303	**0.016**	0.209	0.972	0.259	0.129	0.151
CSV 75 ($\hat{Q}_{0.75}$) Test	0.467	**0.037**	**0.035**	0.177	0.544	0.319	0.113	0.163
Post-Sample MSE-F Tests:								
5 periods	0.182	0.974	0.971	**0.012**	0.692	**0.078**	**0.086**	0.992
10 periods	0.221	0.989	0.956	0.549	0.498	0.611	0.142	0.993

Note: These are p- values for rejecting the null hypothesis that EPU growth does not Granger cause real housing returns. Values in bold signify that the null hypothesis is rejected.

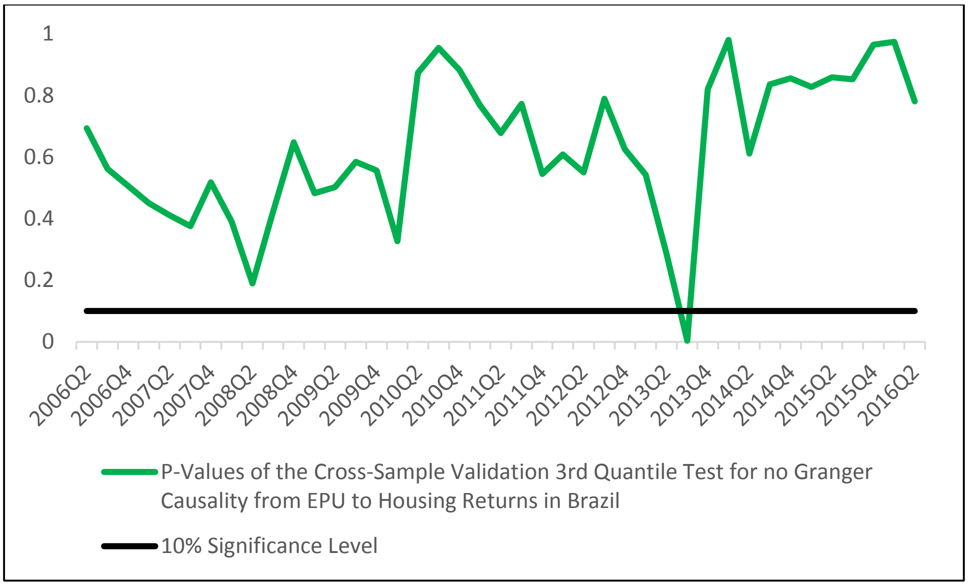

Figure 1: The Cross-Sample Validation Granger Causality Test for Different Rolling Windows for Brazil

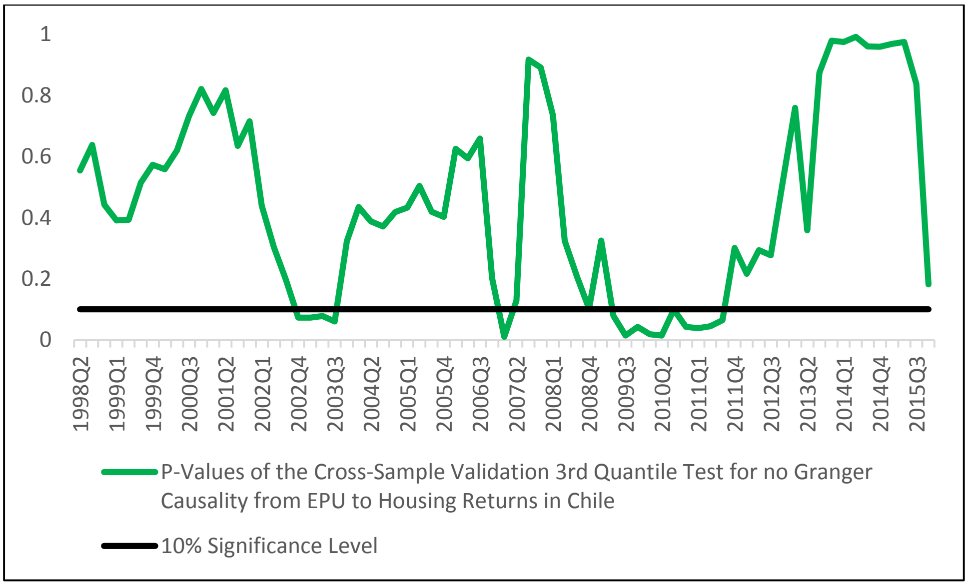

Figure 2: The Cross-Sample Validation Granger Causality Test for Different Rolling Windows for Chile

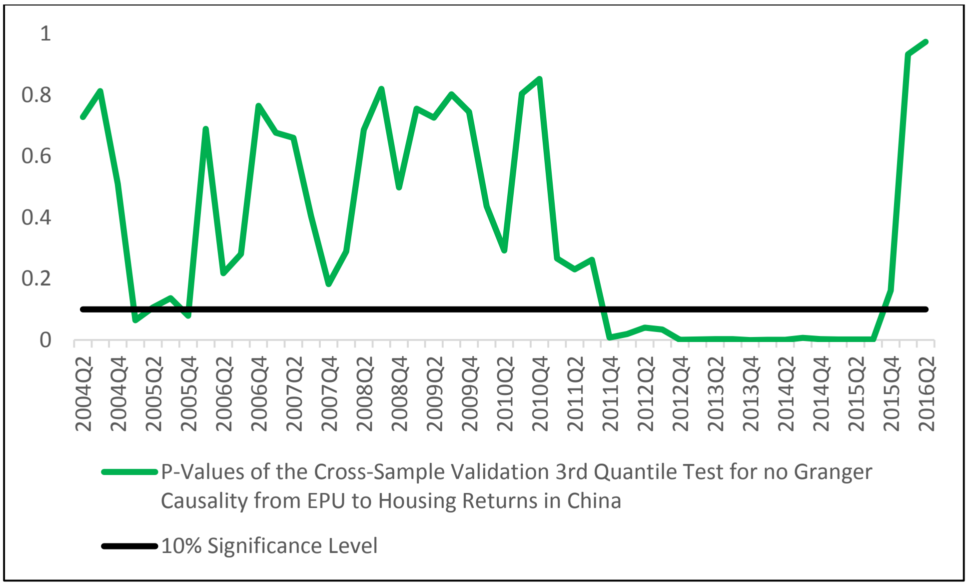

Figure 3: The Cross-Sample Validation Granger Causality Test for Different Rolling Windows for China

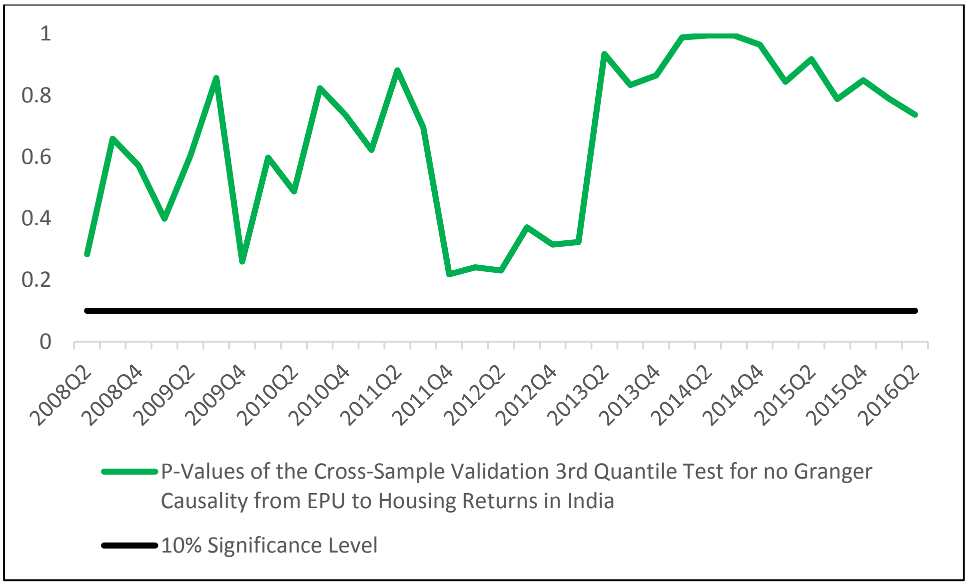

Figure 4: The Cross-Sample Validation Granger Causality Test for Different Rolling Windows for India

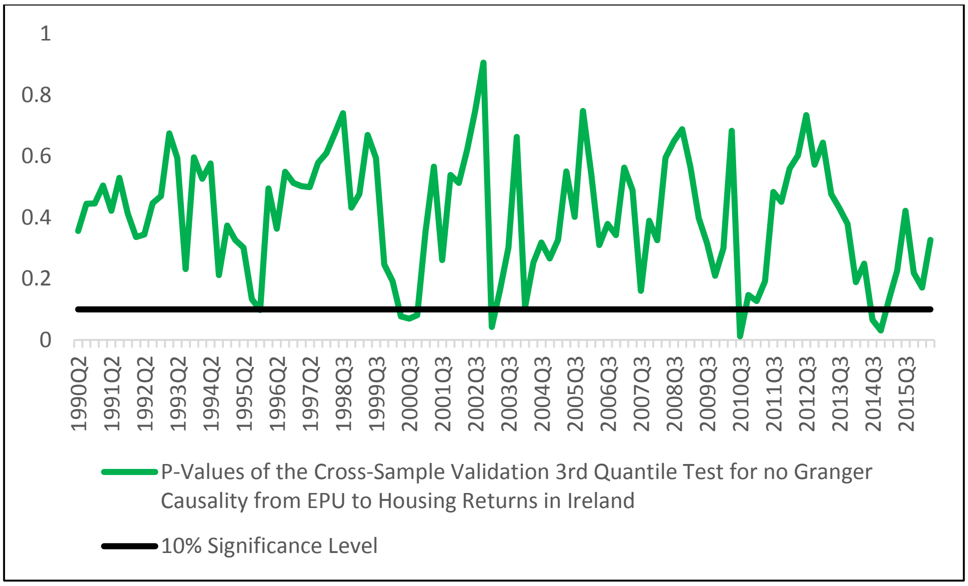

Figure 5: The Cross-Sample Validation Granger Causality Test for Different Rolling Windows for Ireland

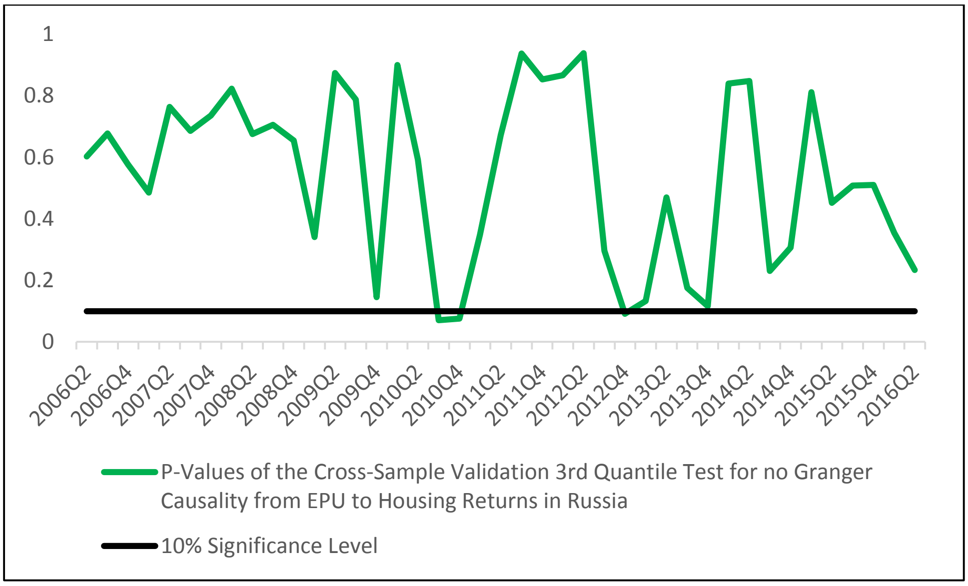

Figure 6: The Cross-Sample Validation Granger Causality Test for Different Rolling Windows for Russia

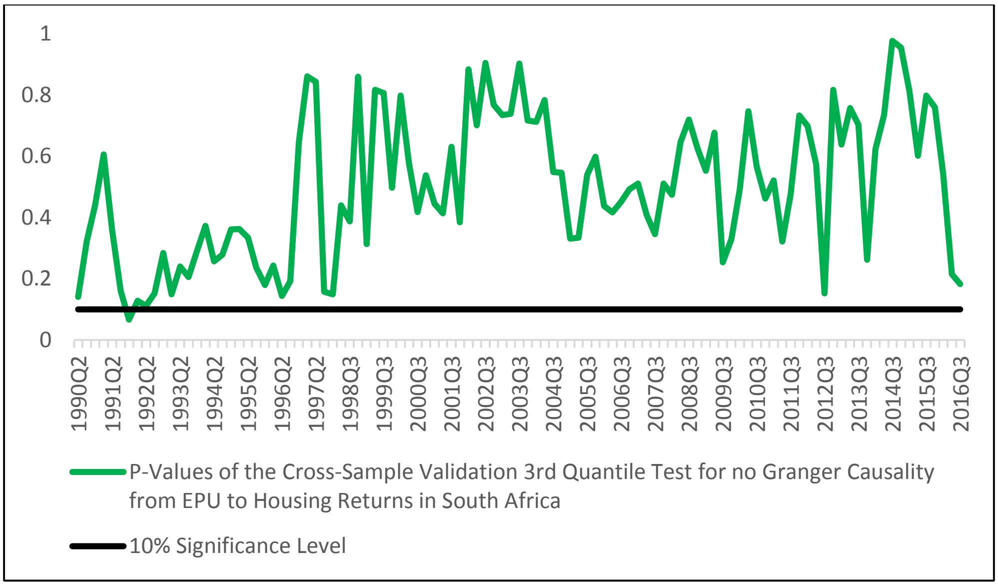

Figure 7: The Cross-Sample Validation Granger Causality Test for Different Rolling Windows for South Africa

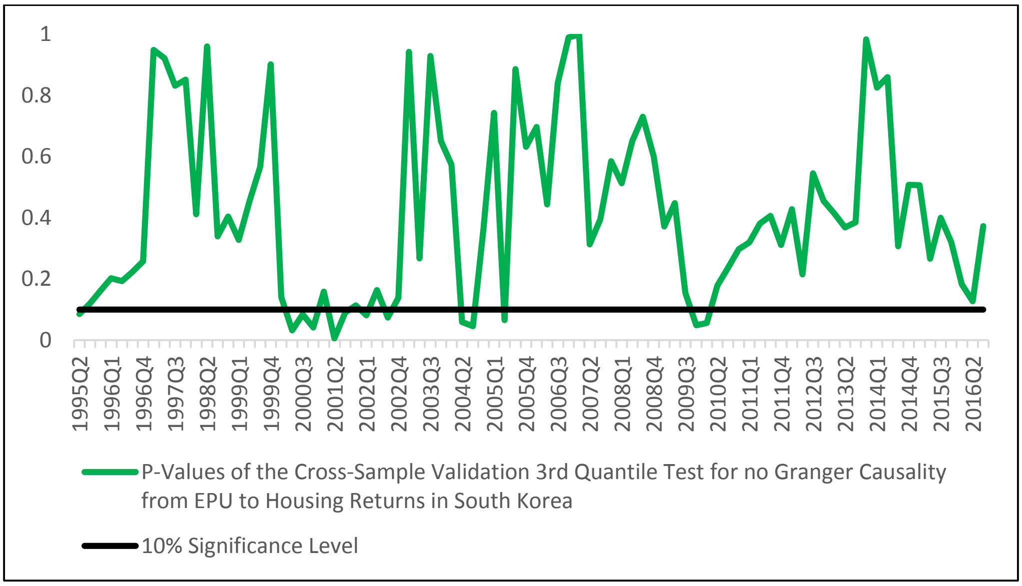

Figure 8: The Cross-Sample Validation Granger Causality Test for Different Rolling Windows for South Korea

CONCLUSION

This study investigates the causal relationship between economic policy uncertainty and real housing returns for 8 emerging markets using the cross-sample validation causality (CSV) test. These are Brazil, Chile, China, India, Ireland, Russia, South Africa and South Korea. Results show that economic policy uncertainty growth has predictive ability for Chile and China based on the full sample CSV test. However, with the rolling window CSV test, all countries barring India indicate evidence of EPU Granger causing real housing returns. This finding has important implications. From a policy perspective, this results show that high economic policy uncertainty can weaken the impact of economic policies and hence calls for the respective policy makers to consciously seek for strategies for reducing uncertainty in these economies. The need for timely policy initiatives cannot be overstressed. Appropriate balance between fiscal adjustment and policy measures should be sought to reduce vulnerabilities. From investors' perspective, heightened uncertainty may weigh on confidence, thereby restraining household and business spending. High policy uncertainty affects returns from real estate investment. This may lead to delayed business decisions such as delaying business expansion plans, putting off investment decisions which may stall company growth and considerations to invest offshore in perhaps more stable business environments. It also has implications for portfolio repositioning as every rational investor would want to reduce his/her holdings in unsafe stocks. Since heightened uncertainty about policy direction leads to weak investment growth in the housing sector, this will consequently affect economic growth given that housing has been shown to be a leading indicator. From academic perspective, the CSV test is more feasible and provides more credibility than post-sample testing when the sample data is scarce since the tests does not depend on the decision on in-sample/post-sample split.

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