

Cross-Country Evidence on the Causal Relationship between Policy Uncertainty and Housing Prices

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Abstract

In this paper, we examine the causal linkages between policy uncertainty and housing prices in a panel of seven advanced countries including Canada, France, Germany, Italy, Spain, the United Kingdom, and the United States. We implement a bootstrap panel causality test on quarterly data from 2001:Q1 to 2013:Q1, which allows us to circumvent the data limitation as observations are pooled across countries. The results provide evidence of a bi-directional causality between real housing prices and policy uncertainty, suggesting that high uncertainty related to future economic fundamentals and policies increases housing price volatility, which in turn may amplify financial and business cycles. The results also show bi-directional causality for France and Spain, but only unidirectional causality for the remaining countries. Specifically, unidirectional causality runs from policy uncertainty to real housing prices in Canada, Germany and Italy and from real housing prices to policy uncertainty in the U.K. and the U.S.

The past decade has witnessed ample housing cycles in many developed countries. Between 2001 and 2005, real housing prices increased on average at a quarterly rate of at least 1.5% in Canada, Italy, and the United States and 2% in France, Spain, and the United Kingdom. With the exception of Germany, which has seen real housing prices decline at an average rate close to 1% per quarter between 2001 and 2005, the increasing trend reversed after 2006, with housing prices falling sharply in Italy, Spain, the U.K. and the U.S. Housing market collapses have been at the epicenter of the global financial and economic crisis that started in 2007 and from which industrialized countries are pulling out with difficulty. The association between housing depressions and protracted recessions is well documented (Detken and Smets, 2004; ECB, 2005; Cecchetti, 2008; Claessens, Kose, and Terrones, 2008; Reinhard and Rogoff, 2009; IMF, 2011). There is also evidence of strong feedback effects between the housing sector and macroeconomic and financial variables (Iacoviello, 2000; Demary, 2010). These effects are particularly strong where expansions are characterized by buoyant residential investment and where sophisticated mortgage markets generate a strong link between housing prices and private consumption, notably through collateral effects (Catte, Girouard, Price, and André, 2004).

Beyond the lasting impact of the crisis on housing markets, balance sheets, and credit availability, the recovery seems to have been held back by uncertainty (Baker, Bloom,

and Davis, 2012; Bloom, Kose, and Terrones, 2013). Uncertainty shocks are also claimed to have played an important role in driving global housing price fluctuations (Hirata, Kose, Otrok, and Terrones, 2012). Hence it looks interesting to explore causal links between housing prices and economic uncertainty. Although such links can be inferred from economic theory, empirical evidence is scarce, as measuring economic uncertainty is fraught with difficulties. The Economic Policy Uncertainty (EPU) index developed by Baker, Bloom, and Davis (2012) provides an opportunity to test the relation between an important dimension of economic uncertainty and housing prices. The EPU index reflects fiscal, monetary, and regulatory policy uncertainty, which is bound to affect households' housing investment decisions and access to credit and thereby housing prices. Conversely, as housing market dynamics exert a large influence on financial and business cycle fluctuations, policymakers are likely to respond to housing price shocks (Simo-Kengne et al., 2013). As both the timing and content of policy and regulatory reactions is difficult to anticipate, volatile housing prices may increase EPU.

EPU can affect housing prices through a number of channels. Housing is both a consumption and an investment good and its demand can be derived from the utility function of households facing consumption and portfolio choices (Berkovec, 1989). As a consumption good, housing demand is bound to be reduced by uncertainty about future employment, income, and wealth, to which households tend to respond by increasing precautionary savings (Giavazzi and McMahon, 2012). Housing is often the largest single asset of a household and housing investment decisions may have a substantial impact on its long-term wealth and consumption levels. Therefore, households may postpone investments in time of uncertainty. Although the literature on the relation between uncertainty and investment generally focuses on investment by companies, it can at least partly be extended to households. Uncertainty increases the cost of finance (Pastor and Veronesi, 2011) and the risk of default (Gilchrist, Sim, and Zakrajsek, 2011). In the case of households, uncertainty increases mortgage costs through a higher risk premium. Uncertainty about employment and income raise the probability of default on the mortgage and foreclosure. When investment is irreversible, uncertainty increases the evaluation cost, as more information is required to establish the profitability of a project (Bernanke, 1983; Rodrik, 1991).

Looking at housing prices from an asset pricing perspective sheds light on some of the channels through which EPU may affect housing prices. In this framework, the choice of investing in owner-occupied housing is driven by the user cost of housing. Equilibrium housing prices will tend to equal the discounted value of future rents, although adjustment may be slow, as arbitrage in housing markets is imperfect (Glaeser and Gyourko, 2007). Future rents are uncertain and homeownership is often seen as a hedge against the risk of rent increases (Sinai and Souleles, 2005). Nevertheless, uncertainty about rents is much smaller than uncertainty about the user cost of housing (Rosen, Rosen, and Holtz-Eakin, 1983).

Following Poterba (1984), the discount rate or user cost of housing can be written as follows:

$$uc = \delta + \gamma + (1 - \theta)(i + \mu) - \pi,$$

where δ is the depreciation rate of the dwelling, γ is the maintenance and repair costs as a fraction of the current value, θ is the marginal income tax rate, i is the nominal interest rate, μ is the property tax rate, and π is the expected nominal housing price inflation rate.¹

It is obvious that several parameters entering the user cost formula are affected by EPU. The expected nominal housing price inflation rate is influenced by uncertainty surrounding any determinant of housing prices, including income, taxation, interest rates, availability of credit, and housing market regulations. The tax parameters are also subject to fiscal policy uncertainty. In two countries of our sample, France and Spain, legislation regarding mortgage interest deductibility has been amended over recent years. There is evidence that uncertainty around the reform of mortgage interest deductibility in the Netherlands has led to a significant increase in precautionary saving (Mastrogiacomo, 2013). It is also likely to have contributed to the decline in housing transactions and prices. The deterioration of fiscal positions following the global economic crisis has increased the probability of property tax increases in many countries, especially in the eurozone.

Monetary policy uncertainty impacts both the expected real return from investing in housing and the mortgage interest rate. The interest rate risk varies across countries according to the prevalence of fixed or variable rate mortgages, which may increase the impact of monetary policy uncertainty on housing prices in the latter case. However, monetary policy uncertainty does not seem to have increased significantly in recent years, presumably because inflation and interest rates remained low (Baker, Bloom, and Davis, 2012).

So far, we have shown how uncertainty may restrain households from investing in housing. As for financial assets, risk and return in the U.S. housing market are positively correlated (Crone and Voith, 1996; Cannon, Miller, and Pandher, 2006). Hence, higher risks lead investors to demand higher returns. However, in a portfolio choice context, demand for housing depends not only on its own risk and return profile, but also on that of competing assets. One cannot rule out an increase in demand for housing as uncertainty increases, if demand for other classes of assets is more sensitive to uncertainty. In fact, housing is often seen as a relatively safe asset, especially in countries with a history of macroeconomic instability.

Most households are also constrained in their housing choices by the availability of credit. Uncertainty pushes lenders towards more caution in extending loans. EPU is particularly relevant here, as recent years have been marked by regulatory uncertainty in the financial sector. The recent financial crisis has seen the two major government-sponsored U.S. mortgage lenders, Fannie Mae and Freddie Mac, enter into receivership and has triggered a wide debate on the reform of mortgage finance (CBO, 2010). Major mortgage lenders also collapsed in the U.K. and continental Europe. The eurozone crisis, with links between sovereign and banking risks, is a lingering source of economic and policy uncertainty. Adding to high fiscal policy uncertainty, as implementing ambitious fiscal consolidation programs is politically challenging and their impact on growth is difficult to assess, uncertainty about reforms in the banking sector may reinforce the link between EPU and housing prices in the eurozone.

Against this backdrop, we investigate the housing price-policy uncertainty nexus across selected developed countries—Canada, France, Germany, Italy, Spain, the U.K., and the U.S.—based on data availability. These countries have recently been hit by internal and/or external shocks, such as the global financial crisis, the Great Recession and the euro crisis, with implications for their economic and financial systems, as well as their housing sectors. As there is considerable heterogeneity in domestic housing markets and national economic conditions, we implement a bootstrap panel Granger causality test developed by Emirmahmutoglu and Kose (2011), which accounts for both cross-country dependence and heterogeneity. The high level of integration of modern economies increases the likelihood of spillover effects across countries, and ignoring these econometric issues may lead to severe bias in the estimates (Pesaran, 2006). Moreover, this methodology has the advantage of limiting pretest bias, which is very common in the error correction model (ECM)-based causality analysis, as it requires pretesting for stationarity and cointegration. In the next section, we outline the essentials of the econometric methods used in this study. We then present the results and concluding remarks.

Methodology

Emirmahmutoglu and Kose (2011) propose a causality test in heterogeneous mixed panels based on the meta-analysis of Fisher (1932). They extended the lag-augmented VAR (LA-VAR) approach by Toda and Yamamoto (1995), who use the level VAR model with extra $dmax$ lags to test Granger causality between variables in heterogeneous mixed panels. Consider a level VAR model with $k_i + d$ max_{*i*} lags in heterogeneous mixed panels:

$$x_{i,t} = \mu_i^x + \sum_{j=1}^{k_i+d \max_i} A_{11,ij} x_{i,t-j} + \sum_{j=1}^{k_i+d \max_i} A_{12,ij} y_{i,t-j} + u_{i,t}^x, \tag{1}$$

$$y_{i,t} = \mu_i^y + \sum_{j=1}^{k_i+d \max_i} A_{21,ij} x_{i,t-j} + \sum_{j=1}^{k_i+d \max_i} A_{22,ij} y_{i,t-j} + u_{i,t}^y, \tag{2}$$

where $i(i = 1, \dots, N)$ denotes individual cross-sectional units and $t(t = 1, \dots, T)$ denotes time periods. μ_i^x and μ_i^y are two vectors of fixed effects, $u_{i,t}^x$ and $u_{i,t}^y$ are column vectors of error terms, k_i is the lag structure, which is assumed to be known and may differ across cross-sectional units, and $dmax_i$ is the maximal order of integration in the system for each i . Following the bootstrap procedure of Emirmahmutoglu and Kose (2011), testing causality from x to y is summarized as follows:

1. Determine the maximal order $dmax_i$ of integration of variables in the system for each cross-section unit based on the augmented dickey fuller (ADF) unit root test and select the lag orders k_i s via information criteria (AIC or SBC) by estimating the regression (2) using the OLS method.
2. Re-estimate equation (2) using the $dmax_i$ and k_i under the non-causality hypothesis:

$$\hat{u}_{i,t}^y = y_{i,t} - \hat{\mu}_i^y + \sum_{j=1}^{k_i+d \max_i} \hat{A}_{21,ij} x_{i,t-j} + \sum_{j=1}^{k_i+d \max_i} \hat{A}_{22,ij} y_{i,t-j}. \tag{3}$$

3. Residuals are centered using Stine’s (1987) suggestion, i.e.,

$$\tilde{u}_t = \hat{u}_t - (T - k - l - 2)^{-1} \sum_{t=k+l+2}^T \hat{u}_t, \tag{4}$$

where $\hat{u}_t = (\hat{u}_{1t}, \hat{u}_{2t}, \dots, \hat{u}_{Nt})'$, $k = \max(k_i)$, and $l = \max(d \max_i)$. Next, we develop the $[\tilde{u}_{i,t}]_{N \times T}$ from these residuals. We randomly select a full column with replacement from the matrix at a time to preserve the cross-covariance structure of the errors. We denote the bootstrap residuals as \tilde{u}_i^* where $(t = 1, \dots, T)$.

4. A bootstrap sample of y is generated under the null hypothesis, i.e.,

$$y_{i,t}^* = \hat{\mu}_i^y + \sum_{j=1}^{k_i+d \max_i} \hat{A}_{21,ij} x_{i,t-j} + \sum_{j=1}^{k_i+d \max_i} \hat{A}_{22,ij} y_{i,t-j}^* + \tilde{u}_{i,t}^*. \tag{5}$$

where $\hat{\mu}_i^y$, \hat{A}_{21} and \hat{A}_{22} are the estimations from step 3.

5. For each individual, Wald statistics are calculated to test for the non-causality null hypothesis by substituting $y_{i,t}^*$ for $y_{i,t}$ and estimating equation (2) without imposing any parameter restrictions.

6. Using individual p -values (p_i) that correspond to the Wald statistic of the i^{th} individual cross-section, the Fisher test statistic (λ) is obtained as follows:

$$\lambda = -2 \sum_{i=1}^N \ln(p_i) \quad i = 1, \dots, N. \tag{6}$$

7. The bootstrap empirical distribution of the Fisher test statistics are generated by repeating steps 3 to 5 times and specifying the bootstrap critical values by selecting the appropriate percentiles of these sampling distributions.

Using simulation studies, Emirmahmutoglu and Kose (2011) demonstrate that the performance of the LA-VAR approach under both heterogeneity and cross-section dependence seem to be satisfactory for the finite sample of T and N .

Preliminary Data Analysis

We use quarterly data over the period from 2001:1 to 2013:1 in order to capture a causality relation between real housing prices and the EPU index for Canada, France, Germany, Italy, Spain, the U.K., and the U.S. Monthly EPU indexes for the seven countries are drawn from the EPU index website² and converted to quarterly frequency. To evaluate policy-related economic uncertainty in the five largest European countries (Germany, the U.K., France, Italy, and Spain), Baker, Bloom, and Davis (2012) construct an index based on two components: the news coverage and the divergence in individual predictions regarding economic variables by professional forecasters. The news coverage consists of the number of news articles from the two top newspapers from each of the five countries containing the terms uncertain or uncertainty, economic or economy, as well as policy-relevant terms. A similar procedure is applied to compute the Canadian EPU, with the only difference being that the first component relies on five Canadian newspapers besides the Canadian Newswire. Different from all other countries, the construction of the EPU index for the U.S. takes into account the number of tax code provisions set to expire in

future years as the third component. The second component consists of economic forecasters' disagreements, while news coverage includes ten large newspapers. For all countries, the index is computed by first normalizing each component by its standard deviation and the final index is the weighted average value of the different components. For further details on the construction of the EPU for the countries we evaluate, please refer to the Appendix. The seasonally-adjusted housing price data are obtained from the Federal Housing Finance Agency (FHFA) for the U.S., Department of Finance for Canada, Deutsche Bundesbank for Germany, Institut National de la Statistique et des Etudes Economiques (INSEE) for France, Nomisma for Italy, Department for Communities and the Local Government for the U.K., and Banco de Espana for Spain. The private consumption deflator from the national account statistics is used to obtain real housing prices.

As indicated earlier, one important issue in a panel causality analysis is to take into account possible cross-sectional dependence across countries. This is because a high degree of economic and financial integration makes a country sensitive to economic shocks in other countries. Cross-country dependence may therefore play an important role in detecting causal linkages between policy uncertainty and housing prices.

The second issue to decide before carrying out a causality test is to find out whether the slope coefficients should be treated as homogenous or heterogeneous to impose causality restrictions on the estimated parameters. As pointed out by Granger (2003) and Breitung (2005), imposing the joint restriction of homogeneity for the panel is a strong hypothesis. Given the above considerations, before we conduct tests for causality, we start with testing for cross-sectional dependence and then test slope homogeneity across countries. Then, we decide which panel causality method should be employed to appropriately determine the direction of causality between housing prices and policy uncertainty in a panel of developed countries.

Cross-sectional Dependence

To test for cross-sectional dependence, the Lagrange multiplier (LM) test of Breusch and Pagan (1980) has been extensively used in empirical studies. The procedure to compute the LM requires the estimation of the following panel data model:

$$y_{it} = \alpha_i + \beta_i' x_{it} + u_{it} \quad \text{for } i = 1, 2, \dots, N; t = 1, 2, \dots, T, \quad (7)$$

where i is the cross-section dimension, t is the time dimension, x_{it} is $k \times 1$ vector of explanatory variables, and α_i and β_i are respectively the individual intercepts and slope coefficients that are allowed to vary across countries. In the LM test, the null hypothesis of no cross-sectional dependence— $H_0: Cov(u_{it}, u_{jt}) = 0$ for all t and $i \neq j$ —is tested against the alternative hypothesis of cross-sectional dependence $H_1: Cov(u_{it}, u_{jt}) \neq 0$, for at least one pair of $i \neq j$. In order to test the null hypothesis, Breusch and Pagan (1980) developed the cross-sectional dependence (CD) LM test as:

$$LM = T \sum_{i=1}^{N-1} \sum_{j=i+1}^N \hat{\rho}_{ij}^2, \quad (8)$$

where $\hat{\rho}_{ij}$ is the sample estimate of the pair-wise correlation of the residuals from ordinary least squares (OLS) estimation of equation (1) for each i . Under the null hypothesis, the LM statistic has asymptotic chi-square distribution with $N(N - 1)/2$ degrees of freedom. It is important to note that the LM test is valid for N relatively small and T sufficiently large.

However, the CD test is subject to decreasing power in certain situations where the population average pair-wise correlations are zero, although the underlying individual population pair-wise correlations are non-zero (Pesaran, Ullah, and Yamagata, 2008). Furthermore, in stationary dynamic panel data models, the CD test fails to reject the null hypothesis when the factor loadings have zero mean in the cross-sectional dimension. In order to deal with these problems, Pesaran, Ullah, and Yamagata (2008) propose a bias-adjusted test, which is a modified version of the LM test by using the exact mean and variance of the LM statistic. The bias-adjusted LM test is:

$$LM_{adj} = \sqrt{\left(\frac{2T}{N(N - 1)}\right)} \sum_{i=1}^{N-1} \sum_{j=i+1}^N \hat{\rho}_{ij} \frac{(T - k)\hat{\rho}_{ij}^2 - \mu_{Tij}}{\sqrt{\nu_{Tij}^2}}, \tag{9}$$

where μ_{Tij} and ν_{Tij}^2 are respectively the exact mean and variance of $(T - k)\hat{\rho}_{ij}^2$, which are provided in Pesaran, Ullah, and Yamagata (2008). Under the null hypothesis with first $T \rightarrow \infty$ and then $N \rightarrow \infty$, the LM_{adj} test is asymptotically distributed as standard normal.

Slope Homogeneity

A second issue in a panel data analysis is to decide whether or not the slope coefficients are homogenous. The most usual way to test the null hypothesis of slope homogeneity, $H_0: \beta_i = \beta$ for all i , against the hypothesis of heterogeneity, $H_1: \beta_i \neq \beta_j$ for a non-zero fraction of pair-wise slopes for $i \neq j$, is to apply the standard F-test. The F-test is valid for cases where the cross-sectional dimension (N) is relatively small and the time dimension (T) of the panel is large; the explanatory variables are strictly exogenous; and the error variances are homoscedastic. By relaxing the homoscedasticity assumption in the F-test, Swamy (1970) developed the slope homogeneity test on the dispersion of individual slope estimates from a suitable pooled estimator. However, both the F-test and Swamy’s test require panel data models where N [7, the number of countries] is small relative to T [52, the number of observations for each country]. Pesaran and Yamagata (2008) proposed a standardized version of Swamy’s test (the so-called $\tilde{\Delta}$ test) for testing slope homogeneity in large panels. The $\tilde{\Delta}$ test is valid as $(N, T) \rightarrow \infty$ without any restrictions on the relative expansion rates of N and T when the error terms are normally distributed. In the $\tilde{\Delta}$ test approach, the first step is to compute the following modified version of the Swamy’s test:

$$\tilde{S} = \sum_{i=1}^N (\hat{\beta}_i - \tilde{\beta}_{WFE})' \frac{x_i' M_\tau x_i}{\tilde{\sigma}_i^2} (\hat{\beta}_i - \tilde{\beta}_{WFE}), \tag{10}$$

where $\hat{\beta}_i$ is the pooled OLS estimator, $\tilde{\beta}_{WFE}$ is the weighted fixed effect pooled estimator, M_τ is an identity matrix, the $\tilde{\sigma}_i^2$ is the estimator of σ_i^2 .³ Then the standardized dispersion statistic is developed as:

**Exhibit 1. Cross-sectional Dependence and Homogeneous Tests
(Policy Uncertainty and Real Housing Prices)**

Variable	Result
CD_{BP}	93.771***
CD_{LM}	11.229***
CD	4.925***
LM_{adj}	38.221***
$\tilde{\Delta}$	10.577***
$\tilde{\Delta}_{adj}$	0.226
Swamy Shat	61.829***

Note:

* Significant at the 0.1 level.

** Significant at the 0.05 level.

*** Significant at the 0.01 level.

$$\tilde{\Delta} = \sqrt{N} \left(\frac{N^{-1}\tilde{S} - k}{\sqrt{2k}} \right), \quad (11)$$

Under the null hypothesis with the condition of $(N, T) \rightarrow \infty$ so long as $\sqrt{N}/T \rightarrow \infty$ and the error terms are normally distributed, the $\tilde{\Delta}$ test has asymptotic standard normal distribution. The small sample properties of the $\tilde{\Delta}$ test can be improved under the normally distributed errors by using the following bias-adjusted version:

$$\tilde{\Delta}_{adj} = \sqrt{N} \left(\frac{N^{-1}\tilde{S} - E(\tilde{z}_{it})}{\sqrt{\text{var}(\tilde{z}_{it})}} \right), \quad (12)$$

where the mean $E(\tilde{z}_{it}) = k$ and the variance $\text{var}(\tilde{z}_{it}) = 2k(T - k - 1)/T + 1$.

As expected, results of cross-sectional dependence and homogeneous tests (Exhibit 1) lead to strong rejections of the no cross-sectional dependence and homogeneity hypotheses, hence providing the rationale for using Emirmahmutoglu and Kose (2011) panel causality, which addresses these econometric issues.

Results

First, we test the presence of unit roots using the augmented Dickey-Fuller (ADF) test for the levels, first differences, and second differences to fix the maximum order of integration in the VAR systems ($dmax$). The ADF test results are reported in Exhibit 2. In as a consequence of the ADF test, the maximum order of integration in the VAR system is determined as 2 for all countries under investigation (Exhibit 3).

Next, we use the LA-VAR approach in a mixed panel to test the causality relations between the housing price and uncertainty indexes for each country. The results in Exhibit 4 suggest a bi-directional causality for France and Spain, unidirectional causality running from housing prices to uncertainty for the U.K. and the U.S., and unidirectional

Exhibit 2. Unit Root (ADF) Results

Country	Housing Prices						Uncertainty Index					
	Constant			Constant and Trend			Constant			Constant and Trend		
	Level	1 st Diff	2 nd Diff	Level	1 st Diff	2 nd Diff	Level	1 st Diff	2 nd Diff	Level	1 st Diff	2 nd Diff
Canada	0.648	0.125	0.000	0.528	0.234	0.004	0.467	0.000	—	0.454	0.051	—
France	0.161	0.353	0.025	0.293	0.061 ^c	—	0.521	0.000	—	0.508	0.000	—
Germany	0.942	0.999	0.000	1.000	0.780	0.000	0.443	0.016	—	0.282	0.062	—
Italy	0.539	0.887	0.011	0.985	0.125	0.068	0.865	0.064	—	0.945	0.025	—
Spain	0.021	—	—	0.195	0.668	0.814	0.175	0.101	0.001	0.429	0.174	0.013
U.K.	0.346	0.193	0.002	0.800	0.224	0.010	0.905	0.000	—	0.730	0.539	0.000
U.S.	0.200	0.416	0.000	0.375	0.790	0.000	0.280	0.000	—	0.204	0.000	—

Exhibit 3. Maximum Order of Integration ($dmax_i$) in the VAR Systems

Country	Housing Prices	Uncertainty Index	$dmax_i$
	$I(d)$	$I(d)$	
Canada	2	1	2
France	2	1	2
Germany	2	1	2
Italy	2	2	2
Spain	0	2	2
U.K.	2	1	2
U.S.	2	1	2

Exhibit 4. Panel Causality Test Results

Country	k_i	Uncertainty Index	Housing Prices	Uncertainty Index	Housing Prices
		W_i	p_i	W_i	p_i
Canada	3	17.328	0.001	1.928	0.587
France	5	11.437	0.043	10.155	0.071
Germany	2	4.750	0.093	1.154	0.562
Italy	4	16.681	0.002	5.235	0.264
Spain	5	9.663	0.085	12.166	0.033
U.K.	2	0.700	0.705	9.225	0.010
U.S.	3	2.419	0.490	7.320	0.062
Calculated			44.747 (1%)		37.149 (1%)
Fisher Test		45.106	31.376 (5%)	31.795	28.807 (5%)
Statistic (λ)			26.910 (10%)		25.504 (10%)

Notes: Lag orders k_i are selected by minimizing the Akaike information criterion. W_i and p_i indicate the individual Wald statistics and individual p -values, respectively.

causality from uncertainty to housing prices for Canada, Germany, and Italy. Although one could not a priori rule out two-way causality between EPU and housing prices in any country in the sample, these results are plausible given cross-country differences in the structure of housing and mortgage markets, housing market developments over the estimation period, and policy responses to the global financial and economic crisis. EPU impacts housing prices in all eurozone countries. This was expected, as uncertainty is largely related to fiscal policy, which affects household disposable income, and to the robustness of banks, which are the main players in mortgage finance in these countries. Interestingly, the causality between EPU and housing prices is weaker in Germany than in the other eurozone countries, which is in line with the greater fiscal and financial stability of the country. In the U.K. and the U.S., mortgage institutions suffered severely

from the financial crisis. However, even though the supply of mortgages tightened, prompt government intervention may have reduced uncertainty in the mortgage market. In particular, the Bank of England created facilities for banks to obtain funding for mortgages and the Federal Reserve bought huge quantities of mortgage-backed securities. The strong impact of EPU on housing prices in Canada may be related to concerns about the sustainability of the housing expansion, as housing prices and household debt continued to increase after the global financial crisis (Cheung, 2014). Such concerns and the uncertainty about measures the authorities may take to cool the housing market could have contributed to the slowdown in housing prices towards the end of the period.

As expected, the causality running from real housing prices to policy uncertainty is significant in most of the countries where housing has played an important role in macroeconomic developments over the sample period. Canada is an exception, perhaps because continued housing price increases after the global financial crisis, strong economic fundamentals, and a solid financial sector generated a perception of relatively low risk associated with housing market developments. The last economic cycle in Spain was largely driven by the housing market. The collapse of the housing bubble has had sizeable effects on employment, wealth, income, public finances, and financial stability. As a result, uncertainty has risen significantly. In the U.K. and the U.S., spillovers from housing to the wider economy are traditionally strong and tend to prompt policy responses (Leamer, 2007; Muellbauer and Murphy, 2008). To a lesser extent, this is also true in France, where there is evidence that housing prices have a significant impact on residential investment and consumption (Chauvin and Damette, 2010; André, Gupta, and Kanda, 2012). Contrary to other countries in the sample, Germany has not experienced large housing price increases in the 2000s. Furthermore, housing prices tend to have little impact on the German economy, in particular because of their weak link with private consumption (Catte, Girouard, Price, and André, 2004). The latest housing cycle has also been milder in Italy than in most other OECD countries. As in Germany, the link between housing prices and private consumption is weak (Catte, Girouard, Price, and André, 2004). Thus, it is hardly surprising that housing prices are not found to have had a significant effect on EPU in these countries.

Because of the potential small sample bias, inference based on individual countries should be taken with caution. This motivates our decision to rely on panel results to confirm the significance of the causality relations between EPU and housing price, which are found in the majority of individual cases. As pointed out Emirmahmutoglu and Kose (2011), in case of cross-sectional dependence in mixed panels, the bootstrap method allows generating the exact figure of the empirical distribution of the Fisher test of causality. The bootstrap distribution of Fisher test statistics derived from 1,000 replications indicates for the sample of countries under investigation the following critical values: 44.7, 31.4, and 26.9 at the 1%, 5%, and 10% significance levels, respectively, for causality running from the uncertainty index to housing prices, and 37.1, 28.8, and 25.5 at the 1%, 5%, and 10% significance levels, respectively, for testing causality running from housing prices to the uncertainty index. In both cases, the Fisher statistics appear to be greater than their corresponding bootstrap critical values at the 5% level of significance, indicating a bi-directional causality between the real housing price and uncertainty index

across the selected countries. This implies that increasing uncertainty exerts a significant impact on housing price volatility and vice versa.

Conclusion

In this paper, we examine the causal relation between EPU and real housing prices in advanced economies over the past decade. The results indicate a bi-directional causality between the two variables in France and Spain, a unidirectional causality running from policy uncertainty to real housing prices in Canada, Germany, and Italy and reverse causality for the U.S. and the U.K. As results for individual countries may be affected by a small sample bias, a bootstrap panel causality approach is used to obtain more robust results. While we provide evidence of bi-directional causality between the EPU index and housing prices and plausible explanations for cross-country differences, further research should try to quantify the impact of variations in uncertainty and housing prices on each other and to further investigate the contribution of the different economic mechanisms at play. To be more specific, given the difficulty in analyzing causality beyond a bivariate system (Lutkepohl, 1993; Eichler, 2007; Doan and Todd, 2010; Dufour and Taamouti, 2010), future research should revisit the question of the relation between housing prices and EPU using an impulse response analysis in a panel vector autoregressive model, with additional variables that affect both the housing market and policy uncertainty. The impulse response analysis would not only help decipher the direction of the effect, but also its persistence.

Appendix

Economic Policy Uncertainty (EPU) Index Construction

Baker, Bloom, and Davis (2013) construct the monthly EPU index mainly by using two underlying components: (1) the news coverage about policy-related economic uncertainty and (2) economic forecasters' disagreement. However, in the case of the U.S., we use the federal tax code provisions set to expire in coming years as an additional component. In the following discussion, we summarize Baker, Bloom, and Davis' (2013) approach to constructing each underlying component, as well as the overall EPU index for the U.S., Canada, France, Germany, Italy, Spain, and the U.K.

News Coverage about Policy-related Economic Uncertainty (all countries)

The news coverage component is an index of search results of a given country's top newspapers (done using the native language of the paper in question) for terms related to economic and policy uncertainty. Exhibit A.1 illustrates the structuring of the first component in the case of the U.S., Canada, and Europe.

Exhibit A.1 Structure of the News Coverage Component

Country	Newspapers	Terms Searched
U.S.	<i>USA Today, Miami Herald, Chicago Tribune, The Washington Post, Los Angeles Times, The Boston Globe, San Francisco Chronicle, The Dallas Morning News, The New York Times, and The Wall Street Journal</i>	uncertainty, uncertain, economic, economy, congress, legislation, white house, regulation, federal reserve, deficit
Canada	<i>The Gazette, The Vancouver Sun, The Toronto Star, The Ottawa Citizen, The Globe and Mail</i>	policy, tax, spending, regulation, central bank, budget, deficit
Europe	Two papers from Germany, the U.K., France, Italy and Spain: <i>El Pais, El Mundo, Corriere della Sera, La Repubblica, Le Monde, Le Figaro, the Financial Times, The Times, Handelsblatt, Faz</i>	policy, tax, spending, regulation, central bank, budget, deficit

Baker, Bloom, and Davis (2013) deal with fluctuating volumes of news articles for a given newspaper by dividing the raw counts of policy uncertainty articles by the total number of news articles in the paper. The authors normalize each newspaper’s series to one standard deviation for periods prior to 2011 (2010 for the U.S.) and aggregate each paper’s series and normalize the series to an average value of 100 prior to 2011 (2010 for the U.S.).

Economic Forecaster Disagreement (all countries)

The economic forecaster disagreement component of the EPU index is a proxy for uncertainty. Essentially, we use professional forecasters’ projections of inflation (as measured by the Consumer Price Index) as well as government spending or budget balance (see Exhibit A.2). Given the fact that monetary and fiscal policies affect these variables, the period-specific spread (measured by the interquartile range) in the forecasts of each variable captures the uncertainty in monetary and fiscal policies (Baker, Bloom, and Davis, 2013).

Exhibit A.2 Structure of the Economic Forecaster Disagreement Component

Country	Variables	Source	Time Horizon
U.S.	Quarterly forecasts of inflation (CPI-based), purchase of goods and services by state, local as well as federal government	Federal Reserve Bank of Philadelphia	Four quarters-ahead
Canada	Monthly forecasts of consumer prices and federal government budget balance	Consensus Economics	Twelve months-ahead
Europe	Monthly forecasts of consumer prices and federal government budget balance	Consensus Economics	Twelve months-ahead

In the U.S. case, Baker, Bloom, and Davis (2013) divide the interquartile range of four-quarter-ahead projections of the federal and state/local government purchases by the median four-quarter-ahead forecast and multiply the resulting numbers by a five-year backward-looking moving average for the ratio of nominal (federal or state) purchases to nominal gross domestic product (GDP). Next, the authors keep constant the values of the forecast disagreement measures within each quarter. Lastly, they aggregate the two indices—weighted by their normal sizes—to obtain one federal or state index. Given the lag in the release of data, they set each quarter's data forward one month. For Canada and the European countries, they consider the monthly raw interquartile range of the budget balance's forecasts for 12 months ahead and divide it by the respective country's current annual GDP. Given the mechanically decreasing variance in projections of both inflation and government balance as the following calendar year nears, they rid the data from monthly fixed effects.

Tax Code Expiration Data (only in the U.S. case)

Baker *et al.* (2013) obtain the tax code expiration data from the Congressional Budget Office (CBO) reports which have information on planned termination of federal tax code provisions in the corresponding calendar year and each of the upcoming ten years. According to the authors, the fact that Congress usually postpones temporary tax measure at the last minute makes them a source of uncertainty for businesses and households. Baker *et al.* (2013) compute the total yearly dollar amount of expirations up to years in the future. The authors also weight the data for January of each year using a formula that corresponds to a yearly discount rate of 100%. Thereafter, Baker *et al.* (2013) aggregate the discounted number of tax code expirations to arrive at an index value for each January which they keep constant throughout the calendar year.

Constructing the Overall Policy-related Economic Uncertainty Index (all countries)

Baker, Bloom, and Davis (2013) normalize each component by its standard deviation prior to January 2011 (January 2012 for the U.S. case). Next, they determine the weighted average value of component indices as follows:

- **For the U.S.:** They use weights of $\frac{1}{2}$ on the news coverage component index and $\frac{1}{6}$ on each of the tax expirations index, CPI forecast disagreement measure, and the federal/state purchase disagreement measure.
- **For Canada:** They use weights of $\frac{1}{2}$ on the news coverage component index and $\frac{1}{4}$ on each (inflation and government balance) forecast disagreement measure. They use an equal weight of $\frac{1}{2}$ for all components for periods with no budget balance forecasts. They then standardize the mean to 100 before 2011.
- **For Europe:** They use weights of $\frac{1}{2}$ on the news coverage component index and $\frac{1}{4}$ on each (inflation and government balance) forecast disagreement measure. However, for Spain, given the absence of budget balance data, equal weights of $\frac{1}{2}$ are assigned to the new coverage index and the CPI dispersion measure. After normalizing each

country's index by its standard deviation, they then combine each individual country index to obtain the final index whose mean is standardized to 100 before 2011.

Endnotes

- ¹ The formula relates to the U.S. case where mortgage interest and property tax are deductible from taxable income. If this is not the case, the formula boils down to $uc = \delta + \gamma + i + \mu - \pi$.
- ² <http://www.policyuncertainty.com>.
- ³ In order to save space, we refer to Pesaran and Yamagata (2008) for the details of estimators and for Swamy's test.

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