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**Does Economic Policy Uncertainty Forecast Real Housing Returns in a Panel of OECD Countries? A Bayesian Approach**

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Does Economic Policy Uncertainty Forecast Real Housing Returns in a Panel of OECD Countries? A Bayesian Approach

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Abstract
This paper investigates whether the news-based measure of economic policy uncertainty (EPU) could help in forecasting the real housing returns in ten (Canada, France, Germany, Italy, Japan, The Netherlands, South Korea, Spain, United Kingdom, and United States of America) Organization for Economic Co-operation and Development (OECD) countries. We analyze the quarterly out-of-sample period of 2008:Q2-2014:Q4, given an in-sample period of 2003:Q1-2008:1Q1, using time series and panel data-based vector autoregressive models, with the latter allowing for heterogeneity, and static and dynamic interdependence. It is found that regardless of the forecasting model considered, EPU is useful for forecasting real housing returns. Our results show that, panel data models, especially the Bayesian variants which allow for parameter shrinkage, consistently beat time series autoregressive models suggesting the importance of pooling information when trying to forecast real housing returns.

JEL Codes: C33, C53, R31
Keywords: Real Housing Returns, Economic Policy Uncertainty, OECD Countries, Panel Vector Autoregressions

1. Introduction
The housing market meltdown associated with the subprime mortgage crisis of 2007 led to the worst global financial and economic crisis since the 1930s (André et al., (forthcoming)). This has resulted in a proliferation of research on the importance of the housing market in terms of the general economy in both advanced and developing/emerging countries (Cesa-Bianchi, 2013; Cesa-Bianchi et al., forthcoming). Ever since the crisis, global economies have been characterised by high housing price volatility, as well as unprecedented economic uncertainty

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(Hirata et al., 2013). Economic theory, as outlined and discussed in Hirata et al., (2013), Burnside et al., (forthcoming), suggests that uncertainty tends to hold demand for housing, thereby affecting housing returns. Furthermore, high uncertainty tends to increase housing price volatility and hence alter the risk-return properties of property investment (André et al., forthcoming). This, in turn, lead firms reduce (residential) investment, and delay their projects as they gather new information, because investment is often costly to reverse (Hirata et al., 2013). Hence, the question of how uncertainty impacts the housing market, and in particular housing prices, is highly relevant for would-be homeowners, financial institutions, policymakers, investors in property or related securities, such as mortgage-backed securities or equities in construction and real estate companies, and portfolio managers.

In addition, housing prices are believed to be a leading indicator of macroeconomic activity (Stock and Watson, 2003; Leamer 2007; Aye et al., 2014; Nyakabawo et al., 2015), with Balcilar et al., (2014), even providing evidence of the important role played by house price declines in causing the “Great Depression”. Given this, appropriate modeling of the housing market (prices or returns in particular), and predictors that drive housing prices, is of paramount importance. Since, accurate forecasting of house prices would also imply reliable prediction of where the real economy is headed. In this regard, a recent, but growing literature, has provided in-sample evidence, based on time series and panel data models, that various measures of economic uncertainty can actually predict movements of house prices or returns (and volatility) for the US and other OECD countries (Hirata et al., 2013; Antonakakis et al., 2015, forthcoming; André et al., forthcoming; El Montasser, forthcoming).\(^1\)

\(^1\) See Babalos et al., (forthcoming) and Ajmi et al., (2015) for studies analysing the relationship between returns and volatility respectively, of Real Estate Investment Trusts (REITs) and economic uncertainty.
As indicated in the literature (see for example, Rapach and Zhou (2013)), in-sample evidence of predictability does not necessarily translate into the same for the out-of-sample horizon. In addition, Campbell (2008) suggests that the ultimate test of the predictive ability of variables and models are, in fact, in their out-of-sample forecasting performances. Given this, our paper, for the first time in the literature on economic uncertainty and house prices, aims to forecast real housing returns (real house price growth rates) based on information derived from a news-based measure of uncertainty, using a variety of time-series and panel data models. Specifically, for our purpose, we use quarterly data spanning the period of 2003:Q1-2014:Q4 for ten Organization of Organisation for Economic Co-operation and Development (OECD) countries (Canada, France, Germany, Italy, Japan, The Netherlands, South Korea, Spain, UK, and USA), with an out-of-sample period of 2008:Q2 to 2014:Q4, over which we evaluate point and density forecasts at one-, two-, four-, and eight-quarters-ahead. Note that, density forecasts are more informative than point forecasts, since the former presents a complete description of the uncertainty associated with a prediction and stands in contrast to a point forecast, which by itself contains no description of the associated uncertainty. Using an autoregressive model as benchmark, we evaluate the forecasting performances of a standard time series based VAR and variety of panel VAR models which allows for static and dynamic interdependencies across countries and cross-sectional heterogeneities using Bayesian methods. As indicated by Rapach et al., (2013), panel data regression tends to increase estimation efficiency relative to a time series approach, especially if the sample period is short, which happens to be the case with us using only 48 observations for each country. In addition, using a panel VAR approach, we are also able to control for interdependencies that exist across global economies in terms of both their housing markets (Cesa-Bianchi, 2013; Cesa-Bianchi et al., 2015) and economic uncertainties (Ajmi et al.,

At this stage, it is important to discuss a bit the measure of uncertainty we use here. Since uncertainty is unobservable, obtaining an appropriate measure for it is not straightforward. Two primary approaches that exist in this regard are: (i) The News-based approach of Brogaard and Detzel (2015), and Baker et al., (2015), whereby the authors perform month-by-month searches of newspapers for terms related to economic and policy uncertainty to construct their measure of economic policy uncertainty, and; (ii) Alternatively, Mumtaz and Zanetti (2013), Mumtaz and Surico (2013), Alessandri and Mumtaz (2014), Carriero et al., (2015), Mumtaz and Theodoridis (2015, forthcoming), Jurado et al., (2015), Ludvigson et al., (2015), Rossi and Sekhosyan (2015) and Mumtaz et al., (2016), and recover measures of uncertainty from stochastic volatility in the error structure of estimated structural VAR models.2 While there exists no clear-cut consensus in terms of which approach to use in constructing measures of uncertainty, the news-based measures of uncertainty, as developed by Baker et al., (2015), seems to have gained tremendous popularity in various applications in macroeconomics and finance.3 This is most likely due to the fact that data (not only for the US, but also other European and emerging economies) based on this approach is easily and freely available for use, and does not require any complicated estimation of a model to generate it in the first place. The remainder of the

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2 Though not as technical like the structural VAR based approaches, Bali et al., (2015) recovers a measure of uncertainty based on a weighted average of the dispersion of many macroeconomic variables.
paper is organized as follows: Section 2 presents the methodology, while Section 3 discusses the results and data, and finally, Section 4 concludes.

2. Econometric Methodology

In this paper we are interested in modeling several variables for each country using a Vector Autoregressive (VAR) model but also allow for linkages among countries. In such a setup, Panel VAR (PVAR) is the appropriate tool since it uncovers all sort of static and dynamic dependencies. Specifically, a PVAR model allows for (i) dynamic interdependencies (DI) which occur when one country’s variables affect another country’s lagged variables, (ii) static interdependencies (SI) which occur when the correlations between the VARs’ errors of two countries are non-zero, and (iii) cross-section heterogeneities (CSH) which occur when two countries have VARs with different coefficients. Furthermore, given the autoregressive structure of a PVAR endogeneity problems are solved. However, an unrestricted PVAR is heavily over-parameterized. For example, in a PVAR with P lags, N countries, each country with G variables, we have $P(NG)^2$ autoregressive coefficients, and $NG(NG + 1)/2$ parameters in the error covariance matrix. Consequently, the total number of possible restrictions on DIs, SIs and CSHs is also huge. Thus, the researcher is faced with an over-parameterized unrestricted model and a large number of potentially interesting restricted models. Recently, Koop and Korobilis (2016) develop methods which allow the researcher to select among all possible combinations of restricted PVARs and find a parsimonious PVAR which deals with the overparametrization problem. Following the contribution of Koop and Korobilis (2016), Korobilis (2016) define parametric and semiparametric Bayesian model selection priors carefully designed to incorporate restrictions in a PVAR framework. In the following subsection we briefly review the PVAR
analysis framework for a model with lag length of one (P=1) which is a reasonable assumption for financial variables in general, but more so due to the small-sample size in our case.

### 2.1 The PVAR framework

Let \( y_{it} \) a vector of \( G \) dependent variables for country \( i \) at time \( t, i = 1,2,\ldots,N, \) \( t = 1,2,\ldots,T. \) In this paper \( y_{it} = (HOUSE,UNC)' \), where \( UNC_{it} \) and \( HOUSE_{it} \) stand for the logarithm of uncertainty index and the real housing returns for country \( i \) at time \( t, \) respectively. The PVAR equation of country \( i \) is written as:

\[
y_{it} = A_{i1}y_{1,t-1} + \cdots + A_{ii}y_{i,t-1} + \cdots + A_{iN}y_{N,t-1} + u_{it}, \tag{1}
\]

Where \( A_{ij} \) are \( G \times G \) matrices for each \( i, j = 1,2,\ldots,N, \) and \( u_{it} \sim N(0, \Sigma_{ii}) \) with \( G \times G \) covariance matrices \( \Sigma_{ii}. \)

The unrestricted PVAR model is defined as:

\[
Y_t = AY_{t-1} + U_t, \tag{2}
\]

where \( Y_t = (y'_{1t}, \ldots, y'_{Nt})' \) is a \( NG \times 1 \) vector of endogenous variables, \( U_t \sim (0, \Sigma) \) with \( \Sigma \) a full \( NG \times NG \) matrix. It is assumed that \( \text{cov}(u_{it}, u_{jt}) = \Sigma_{ij} \neq 0, \) where \( \Sigma_{ij} \) denotes the covariance matrix between the errors of country \( i \) and country \( j. \)

Within the unrestricted PVAR in equation (2), Koop and Korobilis (2016) define three categories of restrictions. First, \( N(N-1) \) dynamic interdependency (DI) restrictions can be defined by imposing \( A_{ij} = 0 \) for \( i, j = 1,2,\ldots,N \) and \( \neq j, \) implying no DIs from country \( j \) to country \( i. \)

Second, we can construct \( N(N-1)/2 \) static interdependency (SI) restrictions by setting \( \Sigma_{ij} = 0 \) for \( i, j = 1,2,\ldots,N \) and \( \neq j, \) implying no SIs between country \( i \) and country \( j. \) Third,
cross section heterogeneity (CSH) restrictions can be defined. By imposing $A_{it} = A_{jj}$ for $i, j = 1, 2, \ldots, N$ and $i \neq j$ we impose homogeneity between two countries, i and j.

The authors developed a stochastic search algorithm, the Stochastic Search Specification Selection (SSSS) algorithm, which explicitly tests all possible $2^{N(N-1)}$ DI restrictions and all possible $2^{N(N-1)/2}$ CSH restrictions. It is clear that the SSSS algorithm takes into account the panel structure of the model in equation (2).

Korobilis (2016) following the contribution of Koop and Korobilis (2016), proposed two model selection priors designed to incorporate panel restrictions within the PVAR framework. The author stress out the importance of being agnostic about which restrictions apply to a specific PVAR model, and the necessity of building priors which allow the examination of the existence (or absence) of certain dependencies and homogeneities across countries. Furthermore, Korobilis (2016) argues that the SSSS prior suffers from two serious shortcomings. First, this prior cannot account for the fact that only some elements of a coefficients matrix could be equal to zero. Second, the SSSS prior allows the DI and CSH restrictions to hold only approximately. Motivated by this fact, Korobilis (2016) proposed two priors that does not have these shortcomings, the Bayesian Factor Clustering and Selection (BFCS) prior and the Bayesian Mixture Shrinkage (BMixS) prior. In this study we employ the BFCS and BMixS priors of Korobilis (2016), as well as the SSSS prior of Koop and Korobilis (2016).

2.2 PVAR priors

2.2.1 Stochastic Search Specification Selection (SSSS) prior
The SSSS algorithm of Koop and Korobilis (2016) is based on the Stochastic Search Variable Selection (SSVS) hierarchical prior (see George and McCulloch (1993); George et al (2008)). Within the SSSS prior the DI restrictions can be expressed as:

\[
\text{vec}(A_{ij}) \sim (1 - \gamma_{ij}^{DL}) N(0, \tau_1^2 \times I) + \gamma_{ij}^{DL} N(0, \tau_2^2 \times I),
\]

(3)

\[
\gamma_{ij}^{DL} \sim \text{Bernoulli}(\pi^{DL}), \ \forall \ i \neq j,
\]

(4)

where \(\tau_1^2\) is “small” and \(\tau_2^2\) is “large” so that, if \(\gamma_{ij}^{DL} = 0\), \(A_{ij}\) is shrunk to be near zero, and if \(\gamma_{ij}^{DL} = 1\), a relatively noninformative prior is used. According to the SSSS prior the CSH restrictions are:

\[
\text{vec}(A_{ij}) \sim (1 - \gamma_{ij}^{CSH}) N(0, \xi_1^2 \times I) + \gamma_{ij}^{CSH} N(0, \xi_2^2 \times I),
\]

(5)

\[
\gamma_{ij}^{CSH} \sim \text{Bernoulli}(\pi^{CSH}), \ \forall \ i \neq j,
\]

(6)

where \(\xi_1^2\) is “small” and \(\xi_2^2\) is “large” so that, if \(\gamma_{ij}^{CSH} = 0\), \(A_{ij}\) is shrunk to be near zero, and if \(\gamma_{ij}^{CSH} = 1\), a relatively noninformative prior is used.

### 2.2.2 Bayesian Factor Clustering and Selection (BFCS) prior

In order to present the priors introduced by Korobilis (2016) let us first rewrite the PVAR model in the following form:

\[
Y_t = Z_t \alpha + U_t,
\]

(7)
where \( Z_t = I_{NG} \otimes y_{t-1} \), \( \alpha = \text{vec}(A') \) is a \((NG^2 \times 1)\) vector of all PVAR coefficients. The BFCS prior is based on the approach of Canova and Ciccarelli (2009) who restrict the coefficients to depend on a low dimensional vector of latent factors. Such structure can be represented as:

\[
\alpha = \Xi \theta + \varepsilon, \quad (8)
\]

Where \( \Xi \) is a \((NG^2 \times s)\) matrix of loadings, \( \theta \) is an \( s \times 1 \) low dimensional vector of factors with \( s \ll NG^2 \), and \( \varepsilon \sim N(0, \Sigma \otimes \sigma^2 I) \). However, the prior of Canova and Ciccaralli (2009) is restrictive since it assumes that a single coefficient \( \alpha_k \) is always clustered with some other non-zero coefficient \( \alpha_l \). Korobilis (2016) proposed a modification which overcomes this restrictive assumption. The author refers to the resulting prior as the Bayesian Factor Clustering Selection (BFCS) prior, which is of the following form:

\[
\alpha_k \sim (1 - \gamma_k) \delta_0(\alpha) + \gamma_k \Delta_k, \quad (9)
\]

\[
\Delta \sim N(\Xi \theta, \Sigma \otimes \sigma^2 I), \quad (10)
\]

\[
\theta \sim N(0, \Sigma), \quad (11)
\]

\[
\gamma_k \sim \text{Bernoulli}(\pi), \quad (12)
\]

where \( \delta_0 \) is the Dirac delta. Note that in this framework the coefficient \( \alpha_k \) has prior a point mass at zero with probability \((1 - \pi)\).

### 2.2.3 Bayesian Factor Clustering and Selection (BMixS) prior

The BFCS prior is based on the ideas from Dunson et al. (2008) for using infinite mixtures, by means of Dirichlet process priors, in order to generalize spike and slab priors and at the same
time allow for clustering of similar coefficients. However, Korobilis (2016) argue that the specification of Dunson et al. (2008) is not flexible since for example, it does not allow us to obtain enough information about common prior locations for homogeneous coefficients. Korobilis (2016) propose the Bayesian Mixture Shrinkage (BMixS) prior which can achieve more complex patterns of parameters clustering:

\[ \alpha_k \sim N(\mu_k, \tau_k^2), \]  
\[ \mu_k, \tau_k^{-2} \sim \pi \delta_0(\alpha) \times \delta_1(\tau^{-2}) + (1 - \pi)F, \]  
\[ F \sim DP(\theta F_0), \]  
\[ F_0 \sim N(0, \lambda) \times Gamma\left(\frac{1}{2}, \frac{1}{2}\right), \]  
\[ \pi \sim Beta(1, \varphi), \]  

Where \( DP(\theta F_0) \) is a Dirichlet process with base measure \( F_0 \).

3. Data and Empirical Results

3.1 Data

Our analysis comprises of two variables, namely, the real housing returns and the EPU. We look at ten OECD countries (Canada (CA), France (FR), Germany (DE), Italy (IT), Japan (JP), The Netherlands (NL), South Korea (KR), Spain (ES), UK (GB), and USA (US)) over the quarterly period of 2003:Q1-2014:Q4, with the start and end date being purely driven by data availability of the EPU variable. Real housing returns is defined as the first-difference of the natural log of real house price index. The data on real house price index are obtained from the macroeconomic indicators database of the OECD. Note that, OECD derives the real house price index by
dividing the nominal house price index with the private consumption deflator. The data on the EPU indices for the ten OECD countries are obtained from www.policyuncertainty.com, and is based on the work of Baker et al., (2015). The authors construct indices for major economies of the world by quantifying month-by-month searches for newspaper coverage on terms related to policy-related economic uncertainty. For inclusion in the index, the articles must contain all of the three terms of economy, policy and uncertainty simultaneously. The data on EPU is originally monthly, but is converted into quarterly values, to match the frequency of the house price, by taking averages over three months constituting a quarter. The EPU index is transformed into its natural logarithmic form. As can be seen from the summary statistics reported in Table A1 in the Appendix, Canada (France) has the highest average real housing returns (EPU), and Netherlands (Netherlands) has the lowest average housing returns (EPU). Spain (UK) has the highest standard deviation for the housing returns (EPU), Germany (Italy) has the lowest corresponding values of the standard deviation for the real housing returns (EPU). Further, housing returns are non-normal for Japan, Netherlands, UK and US (at 10 percent), while for the EPU normality cannot be rejected for any of the ten countries.

3.2 Empirical Results

We now turn our attention to the main focus of the paper, i.e., the out-of-sample forecasting of real housing returns. To conduct the exercise, we split the total sample period into an in-sample period of 2003:Q1-2008:Q1, and an out-of-sample period of 2008:Q2-2014:Q4. The split is to ensure that the out-of-sample period covers the period of the financial crisis and thereafter. We use five forecasting models: The PVAR model with BFCS, BMixS and SSSS priors described in the previous section, an unrestricted PVAR model estimated by OLS (using Minnesota prior) and
a single country VAR model. Forecasting models are evaluated against a standard autoregressive (AR) model, which we treat as the benchmark. Note that, the models are estimated recursively over the out-of-sample period. For the BFCS prior we specify $\pi$ following Canova and Ciccarelli (2013), and we set $\xi = 4$, $\pi = 0.5$, as in Korobilis (2016). Furthermore, for the BMixS prior, following Korobilis (2016), we set: $\lambda = 4$, $\varphi = 1$.

To compare the out-of-sample forecasting ability, this study focuses on the root mean-squared forecast error (RMSFE) and the average predictive likelihood (APL). The forecasting results have been presented in Tables 1 and 2. Forecasts are generated for horizons $h = 1, 2, 4, 8$.

Table 1 reports the forecasting results with respect to the RMSFE metric for forecasting horizons $h=1,2,4,8$. First row of each panel reports the MSFE of the AR benchmark model, while rows 2 to 6 of each panel refer to the relative RMFEs (R-RMSFEs), i.e. the ratios of MSFEs to the MSFE of the AR benchmark model. We find that in most cases all PVAR models improve the out-of-sample forecasting performance over the AR model.

Specifically, in the one-step ahead forecasting case (Panel A, Table 1) all PVAR models outperform the AR benchmark model while single country VAR model seems to “beat” the benchmark model only in four countries. The BFCS-PVAR model demonstrates best forecasting performance in six countries (Canada, France, Germany, Italy, the Netherlands and Spain), while the PVAR-BMixS performs as well or better than the PVAR-BFCS in three countries (Germany, Japan and the US). Our results suggest best forecasting ability of the PVAR-SSSS model only in two countries, Korea and the UK.

In the case of two-step ahead forecasting results reported in Panel B of Table 1, the picture is similar; all PVAR models outperform the AR benchmark model, while single country VAR model seems to “beat” the benchmark model only in four countries. However, in this case the
pest performing model is the PVAR-BMixS model which demonstrates the best forecasting ability in five countries (Italy, Japan, Korea, Spain and the UK). The PVAR-OLS model seems to perform as good as the PVAR-BMixS model in Italy, Korea and Spain. The BFCS-PVAR model shows best forecasting accuracy in France, Germany and the Netherlands. Lastly, the PVAR-SSSS model performs best only in two countries, Korea and the UK.

In the case of four-step ahead forecasting case (Panel C, Table 1) all PVAR models outperform the AR benchmark model, except for the PVAR-SSSS model which fails to “beat” the benchmark in the case of Canada. The single country VAR model performs relatively better than in the previous cases; it seems to outperform the benchmark model in five countries. The PVAR-BFCS and the PVAR-BMixS models perform best in four (Canada, Italy, Korea, Spain) and three (France, Japan, Netherlands) countries, respectively. PVAR-OLS performs as good as PVAR-BMixS in the case of Japan. The PVAR-SSSS model demonstrates best forecasting ability for Germany, the UK and the US.

Lastly, in the case of 8-quarters-ahead forecast results reported in Panel D of Table 1, all PVAR models continue to demonstrate better forecasting ability relative to the AR benchmark model, while single country VAR model “beats” the benchmark in six countries. The PVAR-BMixS demonstrates the best forecasting accuracy in five countries (Italy, Japan, Korea, the UK and the US), while PVAR-OLS performs equally well in Japan, the UK and the US. The PVAR-BFCS model shows best forecasting accuracy in Canada, France and the Netherlands. Our results suggest that the PVAR-SSSS model performs equally well as the PVAR-BMixS model in the case of the UK while it outperforms all the other competing models in Germany and Spain.

Furthermore we evaluate and compare the predictive accuracy of real housing returns forecasts from the candidate models using the APL metric. Table 2 reports the forecasting results with
respect to the APL metric for forecasting horizons h=1,2,4,8. First row of each panel reports the APL values of the AR benchmark model, while rows 2 to 6 of each panel refer to the relative APLs (R-APLs), i.e. the ratios of APLs of competing forecasting models to the APL of the AR benchmark model. R-APL values greater than unity indicate better forecasting performance relative to the AR benchmark.

In the one-step ahead forecasting case (Panel A, Table 2) all PVAR models outperform the AR benchmark model while single country VAR model seems to “beat” the benchmark model only in two countries. The BFCS-PVAR model demonstrates best forecasting performance in seven countries (France, Germany, Korea, the Netherlands, Spain, the UK and the US), while the PVAR-BMixS performs best in three countries (Canada, Italy and Japan).

In the case of two-step ahead forecasting results reported in Panel B of Table 2, all R-APL values for the PVAR models are greater than unity indicating that they always “beat” the AR benchmark in respect to the APL metric. Single country VAR model seems to outperform the benchmark model only in the case of Japan. In the case of two quarters ahead forecasts, the best forecasting model is the PVAR-BFCS model since it performs better than all the competing models in six countries, namely France, Germany, Italy, the Netherlands, Spain and the US, while the PVAR-BMixS performs best in Canada, Japan, and the UK, while it performs and as good as the PVAR-BFCS in the case of France. Surprisingly, the PVAR-OLS model performs similarly well as the two previous models in France, Japan and the UK, while it demonstrates the best forecasting accuracy in the case of Korea.

In the case of four-step ahead forecasting case (Panel C, Table 2) all PVAR models outperform the AR benchmark model, except for the PVAR-BFCS and PVAR-SSSS models which fail to “beat” the benchmark in the case of Korea. The single country VAR model seems to outperform
the benchmark model in three countries (Germany, Japan and the Netherlands). In the case of four quarters ahead forecasts the PVAR-BMixS model demonstrates the best forecasting accuracy in all countries.

Lastly, in the case of 8-quarters-ahead forecast results reported in Panel D of Table 1, the picture is different; PVAR models fail to beat the AR benchmark in certain cases. Specifically, PVAR-BFCS model performs worse than the benchmark in Canada, Germany and Korea. PVAR-BMixS and PVAR-SSSS also fail to beat the benchmark in the case of Korea. The benchmark AR model beats all the competing models in the case of Korea. On the other hand, single country VAR model seems to perform better than the benchmark only in the case of Germany. The PVAR-BMixS demonstrates the best forecasting accuracy in five countries (Canada, Italy, Japan, the Netherlands and the US), while PVAR-OLS performs equally well in the cases of the Netherlands, and the US, while it outperforms all the other models in the case of Germany. The PVAR-BFCS model performs equally well as the PVAR-BMixS and PVAR-OLS models in the case of the US. Lastly, The PVAR-SSSS models demonstrate best forecasting performance in the cases of France and the UK.

Table 1: Forecast evaluation results relative to the AR benchmark model

<table>
<thead>
<tr>
<th></th>
<th>CA</th>
<th>FR</th>
<th>DE</th>
<th>IT</th>
<th>JP</th>
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<th>NL</th>
<th>ES</th>
<th>GB</th>
<th>US</th>
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<tbody>
<tr>
<td><strong>Panel A: One quarter ahead forecast</strong></td>
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<tr>
<td>AR</td>
<td>1.26</td>
<td>0.68</td>
<td>0.82</td>
<td>0.71</td>
<td>1.57</td>
<td>0.68</td>
<td>1.53</td>
<td>1.57</td>
<td>1.40</td>
<td>1.02</td>
</tr>
<tr>
<td>VAR</td>
<td>0.94</td>
<td>1.02</td>
<td>0.91</td>
<td>1.09</td>
<td>1.02</td>
<td>0.92</td>
<td>0.98</td>
<td>1.04</td>
<td>1.02</td>
<td>1.06</td>
</tr>
<tr>
<td>PVAR-OLS</td>
<td>0.33</td>
<td>0.64</td>
<td>0.48</td>
<td>0.47</td>
<td>0.22</td>
<td>0.46</td>
<td>0.31</td>
<td>0.24</td>
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<tr>
<td>PVAR-BFCS</td>
<td><strong>0.29</strong></td>
<td><strong>0.43</strong></td>
<td><strong>0.45</strong></td>
<td><strong>0.40</strong></td>
<td>0.30</td>
<td>0.58</td>
<td><strong>0.23</strong></td>
<td><strong>0.17</strong></td>
<td>0.29</td>
<td>0.30</td>
</tr>
<tr>
<td>PVAR-BMixS</td>
<td>0.31</td>
<td>0.63</td>
<td><strong>0.45</strong></td>
<td>0.47</td>
<td><strong>0.18</strong></td>
<td>0.47</td>
<td>0.32</td>
<td>0.21</td>
<td>0.26</td>
<td><strong>0.23</strong></td>
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<tr>
<td>PVAR-SSSS</td>
<td>0.66</td>
<td>3.17</td>
<td>0.71</td>
<td>1.21</td>
<td>0.86</td>
<td><strong>0.26</strong></td>
<td>0.58</td>
<td>0.25</td>
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<tr>
<td><strong>Panel B: Two quarters ahead forecast</strong></td>
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### Panel C: Four quarters ahead forecast

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**Notes:** First row of each panel reports the RMSE of the AR benchmark model (AR). All other figures are relative RMSFE (R-RMSFE), i.e., ratios of MSFEs to the MSFE of the AR benchmark model. A R-RMSFE below unity indicates that the forecasting model over-performs the benchmark forecasting model according to the MSFE metric. BFCS and BMixS stand for the Bayesian Factor Clustering and Selection and Bayesian Mixture Shrinkage priors of Korobilis (2016) respectively. SSSS stands for the Stochastic Search Specification Selection prior of Koop and Korobilis (2016). PVAR-OLS and VAR stand for the panel and single-country VAR models, respectively. For all models we use one lag. When entries are compared column-wise, bold entries indicate best forecasting model for each country.

### Table 2: Predictive Likelihood results relative to the AR benchmark model

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| Panel B: Two quarters ahead forecast |
| AR            | 0.28   | 0.23   | 0.35   | 0.38   | 0.15   | 0.47   | 0.25   | 0.14   | 0.19   | 0.17   |
| VAR           | 0.93   | 0.96   | 1.09   | 0.90   | 2.07   | 0.92   | 1.00   | 1.00   | 0.90   | 1.00   |
| PVAR-OLS      | 2.11   | 2.65   | 1.80   | 1.82   | 5.33   | 1.58   | 2.16   | 3.93   | 3.26   | 5.71   |
| PVAR-BFCS     | 2.00   | 2.65   | 2.29   | 2.29   | 2.96   | 1.36   | 3.00   | 7.36   | 2.90   | 6.00   |
| PVAR-BMixS    | 2.18   | 2.65   | 1.80   | 1.76   | 5.33   | 1.34   | 2.28   | 4.14   | 3.26   | 5.29   |
| PVAR-SSSS     | 1.93   | 2.57   | 1.63   | 1.61   | 4.60   | 1.09   | 2.04   | 3.57   | 3.05   | 4.77   |

Panel C: Four quarters ahead forecast
4. Conclusions

Theory suggests that uncertainty is likely to affect house prices through its effect on both households and investors, who tend to delay their decision to participate in the housing market. Some in-sample evidence in this regard tends to suggest that uncertainty Granger causes housing returns. The forecasting literature suggests that in-sample evidence of predictability does not necessarily translate into the same for the out-of-sample horizon, and also that the ultimate test of the predictive ability of variables and models are, in fact, in their out-of-sample forecasting performances. Given this, we analyse whether real housing returns can be forecasted by a news-based measure of uncertainty, using a variety of time-series and panel data models over a quarterly period of 2003:Q1-2014:Q4 for ten OECD countries (Canada, France, Germany, Italy, Japan, The Netherlands, South Korea, Spain, UK, and USA).

Panel D: Eight quarters ahead forecast

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Notes: First row of each panel reports the Average Predictive Likelihood (APL) of the AR benchmark model (AR). All other figures are relative APLs (R-APLs), i.e., ratios of APLs to the APL of the AR benchmark model. A R-APL value greater than unity indicates that the forecasting model out-performs the benchmark forecasting model according to the PL metric. BFCS and BMixS stand for the Bayesian Factor Clustering and Selection and Bayesian Mixture Shrinkage priors of Korobilis (2016) respectively. SSSS stands for the Stochastic Search Specification Selection prior of Koop and Korobilis (2016). PVAR-OLS and VAR stand for the panel and single-country VAR models, respectively. For all models we use one lag. When entries are compared column-wise, bold entries indicate best forecasting model for each country.
Over an out-of-sample period of 2008:Q1 to 2014:Q4, over which we evaluate both point and density forecasts at one-, two-, four-, and eight-quarters-ahead, we observe the following: (i) Single country VAR models improve forecasting accuracy over the AR benchmark in certain countries indicating that EPU helps forecasting real housing returns. (ii) With respect to the RMSFE metric, PVAR models, especially the Bayesian variants which incorporates parameter shrinkage to prevent overparameterization, always outperform the benchmark and the single country VAR models at all forecasting horizons, suggesting that utilizing international information leads to significant out-of-sample forecast gains. (iii) According to the predictive likelihood metric, PVAR models always outperform the benchmark and the single country VAR models at short-term forecasting horizons (one and two quarters ahead). However, this evidence seems to get weaker as the forecasting horizon increases. Specifically, when forecasting four and eight quarters-ahead the AR benchmark forecasting model performs better than a PVAR model in two and six cases (out of forty cases), respectively.

As part of future research, the current paper can be extended into at least two directions: First, we can check for the robustness of our results by estimating large Bayesian time-varying parameter panel vector autoregressions as in Koop and Korobilis (2016), which in turn, will allow us to control for possible nonlinearity in the relationship between housing returns and economic uncertainty, as pointed out by André et al., (forthcoming). And second, it would be interesting to also look at the role uncertainty plays in forecasting house prices of developing and/or emerging markets.
References


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Note: Std. Dev.: stands for standard deviation; Probability corresponds to the Jarque-Bera test which tests the null hypothesis of normality.