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Reneé van Eyden, University of Pretoria
Rangan Gupta, University of Pretoria
Christophe André, Organisation for Economic Co-operation and Development (OECD)
Xin Sheng, Anglia Ruskin University

香港城市大學
City University of Hong Kong
專業 創新 胸懷全球
Professional · Creative For The World
城大商學院
College of Business
CITY UNIVERSITY OF HONG KONG
Department of ECONOMICS & FINANCE

The Effect of Macroeconomic Uncertainty on Housing Returns and Volatility: Evidence from US State-Level Data[#]

Reneé van Eyden[*], Rangan Gupta[**], Christophe André[***] and Xin Sheng[****]

Abstract

In this chapter, we first estimate a dynamic factor model with time-varying loadings and stochastic volatility (DFM-TV-SV) using Bayesian methods to disentangle the national and local factors affecting real housing returns and volatility in the 50 US states and the District of Columbia. We then use panel data regressions with heterogeneous coefficients to relate the first and second-moment of the local factors to corresponding state-level uncertainty. The latter is estimated using the average forecast error variance of a range of regional variables and 248 national-level data series in a factor augmented forecasting regression with stochastic volatility in the regression residuals and the error term for the factor dynamics. We estimate uncertainty at a forecasting horizon of one to four quarters over the periods 1977Q2 to 2015Q3 and 1991Q1 to 2015Q3, depending on model specifications. We find that all but three states register a positive and significant spillover effect from macroeconomic uncertainty to house price stochastic volatility, with Hawaii and Michigan ranking highest in terms of spillover effects. The majority of the most severely impacted states are from the Midwest region, as well as a number of states in the Southern region, known to be lower income states. A negative impact of macroeconomic uncertainty on house price returns is recorded in some states, notably from the Midwest region. Our results have important implications for homeowners, mortgage lenders and investors.

Keywords: Uncertainty, Housing Returns and Volatility, Dynamic Factor Model, Panel Data Estimation, US State-Level Data

JEL Codes: C32, C33, D8, R31

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[*] Department of Economics, University of Pretoria, Private Bag X20, Hatfield 0028, South Africa; Email: renee.vaneyden@up.ac.za.

[**] Corresponding author. Department of Economics, University of Pretoria, Private Bag X20, Hatfield 0028, South Africa; Email: rangan.gupta@up.ac.za.

[***] Economics Department, Organisation for Economic Co-operation and Development (OECD), 75775 Paris, Cedex 16, France. Email: christophe.andre@oecd.org.

[****] Lord Ashcroft International Business School, Anglia Ruskin University, Chelmsford, CM1 1SQ, United Kingdom. Email: xin.sheng@anglia.ac.uk.

1. Introduction

A collapse in US house prices, following a prolonged boom, is associated with the global economic and financial crisis of 2007-2009 and the "Great Recession" (Leamer, 2007, 2015; Nyakabawo et al., 2015; Emirmahmutoglu et al., 2016). The period was also characterized by high levels of financial and macroeconomic volatility, after a sustained period of macroeconomic stability, known as the "Great Moderation" (Mumtaz, 2018; Mumtaz et al., 2018; Mumtaz and Musso, 2021). Understanding the role of uncertainty in driving housing market movements is of paramount importance in order to avoid a repeat of the catastrophic effects observed under the Great Recession, not only at the aggregate, but also at the individual state level. Moreover, predicting housing returns and volatility would assist investors in making timely portfolio allocation decisions (Nyakabawo et al., 2018; Gupta et al., 2020a; Segnon et al., 2020). Residential real estate has a major impact on household finances, as it represents about 84% of total household non-financial assets, 31% of total household net worth and 27% of household total assets (Financial Accounts of the US, Fourth Quarter, 2020).[1]

A growing number of studies, which we discuss in detail in the literature review segment of this chapter, have highlighted the role of uncertainty in predicting (primarily) US aggregate and regional housing returns and (to some extent) aggregate volatility (see for example, Antonakakis et al. (2015, 2016); André et al. (2017); Christou et al. (2017, 2019); Christidou and Fountas (2018); Aye et al. (2019); Nguyen Thanh et al. (2020); Strobel et al. (2020); Bouri et al. (forthcoming)). At the same time, some studies have indicated that heightened uncertainty can explain herding and comovement (i.e. synchronicity) of regional housing returns and volatility (Ngene et al., 2017; Gupta et al., 2021), and even decisions to buy or rent (Aye and Gupta, 2019).

Against this backdrop, the objective of our study is to add to the above line of research by providing a comprehensive analysis of the effect of state-level uncertainty on housing returns and volatility in the 50 US states and the District of Columbia, based on a panel data approach. State-level uncertainty is estimated using the average (n-period-ahead) forecast error variance of a range of regional variables derived from a factor augmented forecasting regression with stochastic volatility in the regression residuals and the error term for the factor dynamics. The estimation periods are 1977Q2 to 2015Q3 and 1991Q1 to 2015Q3, contingent on the usage of small (8) and large (21) numbers of state-level financial and macroeconomic variables, respectively, in the factor regressions, besides 248 aggregate country-level variables. Using a panel-based approach with heterogeneous responses of housing market movements to uncertainty, instead of a time series analysis involving each units considered separately, allows us to model the underlying interdependence as well as the heterogeneity across US states housing markets (see Gabauer et al. (2020), and Marfatia (2021) for detailed analyses). At this stage, we need to emphasize that given that the common or national component of housing returns and volatility tends

[1] The reader is referred to: https://www.federalreserve.gov/releases/z1/20210311/html/b101h.htm for further details.

to play an important role in driving the corresponding regional and/or state-level values (Del Negro and Otrok, 2007; Fairchild et al., 2015), analysing the effect of state-level uncertainty requires disentangling the national from the state or local level factors driving housing returns and volatility. Concentrating on the state-level component of housing returns and volatility after filtering out the national factor prevents us from underestimating the impact of state-level uncertainty. Note that the national common factor is understandably driven by aggregate-level US variables, i.e. shocks that are common to the entire economy. To estimate the factors driving house prices, we follow Gupta et al. (2020b) in using a dynamic factor model with time-varying loadings and stochastic volatility (DFM-TV-SV), estimated using Bayesian methods. The generalized DFM-TV-SV model does not only capture changing co-movements among house price returns in the 50 states and DC by allowing for their dependence on a common national factor to evolve over time, but also allows for stochastic volatility in the innovations to the processes followed by the national and the idiosyncratic (i.e. the state-level) components.

Theoretically, the effect of uncertainty on economic decisions, like consumption and investment, is generally explained by the real option theory (see for example, Bernanke (1983), Pindyck (1991), Dixit and Pindyck (1994), and more recently, Bloom (2009)), which suggests that decision-making is affected by uncertainty because it raises the option value of waiting. In other words, given that the costs associated with wrong investment decisions are very high, uncertainty makes investors and consumers of durable goods more cautious. As a result, economic agents postpone investment and consumption decisions to periods of lower uncertainty. Buying a dwelling is for many households the biggest single investment in their lifetime and hence has serious implications for their finances. Hence, uncertainty is bound to lower housing demand and prices. Moreover, as uncertainty is basically associated with second moment movements of macroeconomic and financial variables, the existence of significant spillover effects from the real and financial segments of the economy to the real estate sector (Gabauer and Gupta, 2020) is likely to raise the volatility of housing returns. In other words, we expect housing returns to decrease and their volatility to increase in episodes of heightened uncertainty.

To the best of our knowledge, this is the first study analyzing the effect of state-level uncertainty on corresponding real housing returns and volatility in the US. The remainder of the chapter is organized as follows: Section 2 presents a review of the literature that has thus far dealt with uncertainty and housing market movements in the US. Section 3 outlines the data and explains the econometric methodologies adopted in this chapter. Section 4 discusses the empirical results, and Section 5 concludes.

2. Literature review

To set the contribution of our analysis into perspective, we discuss below in a chronological order the existing literature that has related movements in housing returns and volatility in the US to uncertainty.

Antonakakis et al. (2015) investigate the co-movements between housing market returns and economic policy uncertainty (EPU) and find negative correlations throughout 1987 to 2014. These correlations are time-varying and tend to increase rapidly during high uncertainty times, specifically around US recessions. This implies that tail risks are significant, as also shown in André, et al. (2017).

Antonakakis et al. (2016), investigating dynamic spillovers between the housing market, stock market, and a news-based measure of EPU, find that US economic fluctuations are significantly impacted by the transmission of various types of shocks and that these spillovers vary considerably over time. They also find that the spillovers during the global financial crisis were exceptionally high from a historical perspective. Large spillovers run from EPU and stock and housing markets to inflation, industrial production and the federal funds rate in particular. The strong policy reaction to the crisis can be seen from the results.

André et al. (2017) find that EPU is useful for predicting future returns on housing-related investments, with EPU improving forecasts of the first and second moments (level and volatility) of real housing returns, both in-sample and out-of-sample. They also find that EPU not only has an indirect impact through the broader economy and financial markets, but also a direct impact on real housing returns and their volatility. André, et al. (2017) find evidence of non-linearity and structural breaks, and that large uncertainty shocks lead to disproportional falls in housing returns. This implies there are significant tail risks for investors during periods of high uncertainty.

Christou et al. (2017) investigate whether including EPU in the set of predictors can improve forecasting performance for real housing returns in 10 OECD countries, including the US. Their out-of-sample period is 2008Q2-2014Q4, with an in-sample period of 2003Q1-2008Q1. Using a combination of time series and panel data-based Vector Autoregressive (VAR) models (which account for heterogeneity, and static and dynamic interdependence), they find that EPU does improve forecasting performance, regardless of the model used. They also find that models pooling information (from panel data models, in particular the Bayesian variants which allow for parameter shrinkage) perform better than the time series autoregressive models.

Christidou and Fountas (2018) use bivariate Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models for each of the 48 US states in their sample to obtain proxies for house price uncertainty and housing investment (from house price index and housing permits, respectively) to investigate the effect of uncertainty on the housing market. They also use EPU as an alternative measure for uncertainty. They find that the effects are heterogeneous across states and that in most states uncertainty increases housing investment, while it decreases house price inflation.

Christou, et al. (2019) find time-varying impacts of uncertainty shocks on the US housing market, with longer-run uncertainties (two- to three-years-ahead-horizons) having a negative impact on the housing variables (sales, permits and starts). They use a time-varying factor augmented vector autoregression

(TVP-FAVAR) model, with quarterly data from 1963Q1 to 2014Q3 and control for economic activity, prices, and financial variables.

Aye et al. (2019) investigate economic uncertainty spillover effects on the duration of housing booms, busts, and normal times using quarterly data from 1985 to 2012 for 12 OECD countries in a discrete-time (hazard) model. They find that higher economic uncertainty significantly increases the probability of exiting housing market busts, while it does not significantly impact the probability of leaving booms and normal times. Thus, housing could serve as a possible hedge against uncertainty.

Strobel et al. (2020) show that macroeconomic uncertainty affects the housing market in two significant ways. First, controlling for a broad set of variables in fixed-effects regressions for US states, economy-wide uncertainty shocks, as developed by Jurado et al. (2015), adversely affect house prices but not the quantities that are traded. Second, when both uncertainty and local demand shocks are introduced, the effect of uncertainty on house prices, median sale prices, the share of houses selling for a loss and transactions dominates that of local labor demand shocks. The aforementioned effects are largest for the states that exhibit relatively high house price volatility, suggesting real options effects in the housing market during times of high uncertainty.

Building on this work to a certain degree, Nguyen Thanh, et al. (2020) construct a new measure for uncertainty, specific to the real estate sector (REU). They show that REU accounts for twice as much variation in house prices and starts as aggregate US Macro Uncertainty (MU), as developed by Jurado et al. (2015). Using VAR and Granger-causality analyses, they find that REU affects house prices and starts, whereas MU only affects housing starts.

Finally, Bouri et al. (forthcoming), confirmed the findings of Christou et al. (2017) using a unique daily data set of US house prices. They use a *k*-th order nonparametric causality-in-quantiles test, as this allows them to control for misspecification due to nonlinearity and structural breaks, while testing predictability over the whole conditional distribution for returns and volatility, to show that EPU does predict daily housing returns and volatility (barring the extreme upper end of the respective conditional distributions). The results are robust to eight other popular measures of aggregate financial and macroeconomic uncertainty, as well as an alternative data set involving daily house prices of the ten major metropolitan statistical areas (MSAs), namely Boston, Chicago, Denver, Las Vegas, Los Angeles, Miami, New York, San Diego, San Francisco and Washington DC.

At this stage, we must also discuss the work by El Montasser et al. (2016). These authors examine the causal linkages between EPU and house prices in a panel of seven advanced countries including the US, based on a bootstrap panel causality test, which allows them to circumvent data limitations, as observations are pooled across countries. They find evidence of a bi-directional causality between real house prices and EPU, suggesting that high uncertainty related to future economic fundamentals and policies increases house price volatility, which in turn may amplify financial and business cycles. This finding is consistent with individual results for France and Spain, while contrasting with the unidirectional causality reported in the remaining countries. Particularly, support for a unidirectional causality running from EPU to real house prices is found in Canada, Germany and Italy, while a unidirectional causality running from real house prices to EPU prevails in the UK and the US. In other words, El Montasser et al. (2016), unlike the abovementioned papers, could not find evidence of predictability from uncertainty to real house prices in the US.

As can be seen from the discussion of the literature above, the analysis of effects of uncertainty on housing returns and volatility at the regional level is limited. Even if it exists to some extent, for instance in the case of Christidou and Fountas (2018), Strobel et al. (2020) and Bouri et al. (forthcoming), no attempt has been made to disentangle the national and local factors driving house price movements. In any event, Christidou and Fountas (2018) are more concerned with housing investment than house prices. Moreover, analyses have only been conducted using aggregate and not state-level measures of uncertainty. Our study provides novel information on the relationship between state-level housing returns and volatility, and corresponding uncertainty, which is undoubtedly useful to households, mortgage lenders and investors in making their respective buying, lending and investment decisions.

3. Data and methodologies

3.1 Data series used

We use the Federal Housing Finance Agency (FHFA)'s seasonally-adjusted house price indices for the 50 US states and DC to obtain our national and local factors from the Bayesian DFM-TV-SV for both housing returns and the corresponding stochastic volatility. The FHFA house price indices provide a broad measure of the movement of single-family house prices. They use weighted, repeat-sales data, i.e. they measure average price changes in repeat sales or refinancing on the same properties. This information is obtained by reviewing repeat mortgage transactions on single-family properties whose mortgages have been purchased or securitized by Fannie Mae or Freddie Mac since January 1975. In particular, we use the quarterly "All-Transactions Indexes".[2] To create a real version of house prices, we deflate the indices by the (seasonally-adjusted) US Consumer Price Index (CPI), derived from the FRED database of the Federal Reserve Bank of St. Louis. We use quarter-on-quarter (QoQ) changes in the real house price indices, as the DFM-TV-SV requires stationary data. The details of the model are discussed in the next sub-section.

Uncertainty is a latent variable, and hence implies measurement choices. In this regard, besides the various alternative metrics of aggregate uncertainty associated with financial markets (such as the implied-volatility indices (popularly called the VIX), realized volatility, idiosyncratic volatility of equity returns, corporate spreads), there are primarily three broad approaches to quantify uncertainty

[2] The data can be downloaded from: https://www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index.aspx.

(Gupta et al., 2018): (1) A news-based approach, whose main idea is to perform searches of major newspapers for terms related to economic and policy uncertainty, and then to use the results to construct uncertainty indices; (2) Deriving measures of uncertainty from stochastic-volatility estimates through various types of small and large-scale structural models related to macroeconomics and finance; and (3) Uncertainty obtained from disagreements among professional forecasters (dispersion of forecasts).

As far as our metric of state-level uncertainty is concerned, we rely on the second approach, whereby overall measures of state-level economic uncertainty (at forecasting horizons of 1 to 4 quarters) are derived from Mumtaz (2018), which thus far is the only publicly available data source on US state-level uncertainty.[3] Mumtaz (2018) obtains these measures by extending the data-rich environment used Jurado et al. (2015) to derive uncertainty indices for the overall US. It must be pointed out that, while the Jurado et al. (2015)-based measure of uncertainty is the average time-varying variance in the unpredictable component of the real and financial time-series, Mumtaz (2018) refines the estimates by filtering out the effects of idiosyncratic uncertainty and measurement error. Note that besides 248 aggregate US-level data series from the FRED-QD database, the state-level uncertainty measures covering 1977Q2 to 2015Q3 use 8 macroeconomic and financial data series,[4] while a broader estimate of uncertainty at the four horizons uses 21 variables[5] over the shorter period of 1991Q1 to 2015Q3. These periods constitute our short- and long-samples for the panel data analyses.

Technically speaking, state level uncertainty is derived using a factor-augmented econometric model. Let $W_{it,j}$ denote the jth data time series for state i. Uncertainty for $W_{it,j}$ is estimated using the n-period ahead forecast error variance of a factor augmented forecasting regression with stochastic volatility in the regression residuals and the error term for the factor dynamics. The measure thus depends on uncertainty in $W_{it,j}$ and the factors. State-level uncertainty u_{it} is defined as the average of the uncertainty measures for the $j = 1, 2, \ldots, J$ series for state i. We consider state-specific uncertainty measures for horizons one-, two-, three-, and four-quarter-ahead. W_{it} includes the 8 or 21 variables mentioned above. The factors in the forecasting regression F_{it} for state i are extracted using data for the remaining states and the US wide panel of 248 financial and macroeconomic data, i.e. the FRED-QD database.

[3] The reader is referred to the computer codes to obtain the measures of uncertainty available at: https://sites.google.com/site/hmumtaz77/research-papers?authuser=0.

[4] The variables considered are: Total personal income divided by population and deflated by CPI; benefit income divided by population and deflated by CPI; dividend income divided by population and deflated by CPI; contributions for social insurance divided by population and deflated by CPI; other income divided by population and deflated by CPI; seasonally-adjusted employment; seasonally-adjusted unemployment rate; seasonally-adjusted house prices divided by CPI.

[5] The variables include: real personal income and its components (social insurance, dividends, benefits and other income), overall employment, unemployment rate, real house prices, i.e., the 8 variables above plus, non-performing loans and net assets of banks, leading indicator, coincident indicator, all employees in health and education, financial services, government, information, leisure and hospitality, manufacturing, non-farm, professional and business services, and other services.

3.2 Methodologies

In this sub-section, we outline the econometric methodologies associated with the DFM-TV-SV model used to obtain our state-level factors of housing returns and volatility, and the subsequent panel data estimation, whereby we relate these factors to the measures of uncertainty.

3.2.1 The DFM-TV-SV model

In this section, we present a generalized dynamic factor model (DFM) that is employed to decompose the real housing returns in each state into a common (or national) factor and an idiosyncratic (or state-specific) factor, following Gupta et al. (2020b). The DFM is often used to tease out the common movements among multiple time series, and has become a standard tool since the work by Stock and Watson (1989). We generalize the standard DFM with constant parameters to one that allows for time-varying loading parameters and stochastic volatility (DFM-TV-SV). As such, the generalized DFM-TV-SV captures important time-varying co-movements among multiple time series. Formally, our model specification closely follows Del Negro and Otrok (2008), and can be written as follows:

$$r_{i,t} = \beta_{i,t} \cdot f_t + e_{i,t} \quad (1)$$

Here, $r_{i,t}$ is the first-difference of the natural log of the real house price for state i at time t. f_t is the national factor that affects all house prices at time t, and $\beta_{i,t}$ is the time-varying loading parameter of this national factor in state i. $e_{i,t}$ is the idiosyncratic factor.

The common factor and the idiosyncratic factors are assumed to be independent from each other. Therefore, the variance decomposition of our model is given by:

$$Var\left(r_{i,t}\right) = \beta_{i,t}^2 \cdot Var(f_t) + Var(e_{i,t}) \quad (2)$$

Note that both the time-varying loading parameters and the stochastic volatility of the factors enables the factors to contribute to the total variations of each variable to vary over time.

Following the standard practice in this literature, we model the common factor f_t as a stationary

AR(p) process:

$$f_t = \phi_1^f f_{t-1} + \phi_2^f f_{t-2} + \dots + \phi_p^f f_{t-p} + \exp\left(h_t^f\right) \cdot \varepsilon_t^f \quad (3)$$

where $\varepsilon_t^f \sim i.i.d.\ N(0, \sigma_f^2)$. Therefore, the shock to the factor has a stochastic volatility, and its time-varying volatility is governed by $exp(h_t^f)$.

To keep the model parsimonious, we employ a driftless random walk process to capture the time variation of the volatility:

$$h_t^f = h_{t-1}^f + \sigma_f^h \cdot \xi_t^f, \quad \xi_t^f \sim i.i.d.\ N(0,1) \tag{4}$$

The factor loading $\beta_{i,t}$ varies over time, and is also assumed to follow a random walk process:

$$\beta_{i,t} = \beta_{i,t-1} + \sigma_i^\beta \cdot \eta_{i,t}, \quad \eta_{i,t} \sim i.i.d.\ N(0,1) \tag{5}$$

Here shocks to the loading parameters in different series are assumed to be orthogonal to each other.[6]

The idiosyncratic factor follows a stationary AR(q) process:

$$e_{i,t} = \phi_{(i,1)} e_{i,t-1} + \phi_{i,2} e_{i,t-2} + \cdots + \phi_{i,q} e_{i,t-q} + \exp\left(h_{i,t}\right) \cdot \varepsilon_{i,t} \tag{6}$$

where $\varepsilon_{i,t} \sim i.i.d.\ N(0,\sigma_i^2)$. The stochastic volatility of the idiosyncratic factor follows a random walk process:

$$h_{i,t} = h_{i,t-1} + \sigma_i^h \cdot \xi_{i,t}, \quad \xi_{i,t} \sim i.i.d.\ N(0,1) \tag{7}$$

Here we assume that the shocks to the stochastic volatility in different factors are independent from each other. This assumption simplifies the estimation algorithm.

As usual, some normalizations of the factor rotations are needed before the model can be identified and estimated. The loading parameters and the variance of the shock to the common factor are not separately identifiable. We choose to set $\sigma_f^2 = 1$ to achieve the identification. Following Del Negro and Otrok (2008), we also impose time-varying volatility all starting from zero, for the same identification purpose. We demean each series before the estimation since the means of factors are not separately identifiable. Finally, following works such as Neely and Rapach (2011) and Bhatt et al., (2017), we set $p = q = 2$ to keep the model parsimonious.

We estimate this DFM-TV-SV model using the Monte Carlo Markov Chain (MCMC) Bayesian estimation method. Specifically, we employ the well-established Gibbs-Sampling algorithm by breaking the model into several blocks and sampling sequentially from posterior conditional densities. The idea of the Gibbs-Sampling algorithm is that when the algorithm converges after the initial burn-in draws, these random draws from the conditional densities altogether constitute a good approximation of the underlying joint densities. Applying the law of large numbers, the numerical integration can be easily performed to obtain the marginal densities of the parameters and the state variables of interest. Most blocks in the model are linear and Gaussian, and as a result the standard algorithms in Kim and Nelson (1999) are readily applicable. The stochastic volatility introduces a non-Gaussian feature into the model. We apply the procedure proposed in Kim et al. (1998) that utilizes a mixture of normal densities to approximate the underlying non-Gaussian distribution in order to simulate the stochastic volatility. This procedure has been widely used in the literature (e.g. Stock and Watson (2007) and

[6] It is straightforward to see that potential co-movements in the factor loadings across all series can be captured by the common factor volatility. This was pointed out by Del Negro and Otrok (2008).

Primiceri (2005)). For further details on the Gibbs-Sampling estimation algorithm, the reader is referred to Gupta et al. (2020b).

3.2.2 *The panel data model*

3.2.2.1 Model specification

Given the evidence of US state heterogeneity (Mumtaz et al., 2018) we consider a panel estimator that will appropriately address heterogeneity concerns, while allowing for cross-sectional dependence. Fixed- and random-effects models incorporate panel-specific heterogeneity by including a set of nuisance parameters that essentially provide each panel with its own constant term. However, all panels share common slope parameters, which is undesirable in the current context. Random-coefficients models (Swamy, 1970) are more general in that they allow each panel to have its own vector of slopes randomly drawn from a distribution common to all panels. Implementation of the estimator ensures best linear unbiased predictors of the panel-specific draws from said distribution (Poi, 2003).

Consider a random-coefficients model of the form:

$$y_i = X_i\beta_i + \epsilon_i \tag{8}$$

where $i = 1 \ldots 51$ denotes the 50 US states and DC, y_i is a $T_i \times 1$ vector of median value of the state-level real house price returns factor and stochastic volatility observations (i.e., either *fmed* or *svmed* respectively) for the ith panel (derived from the DFM-TV-SV), X_i is a $T_i \times 1$ vector of uncertainty measures according to the Mumtaz (2018) or Jurado et al. (2015) methods, for the 1 to 4-period forecasting horizons (*u1*, *u2*, *u3*, and *u4*). β_i is a parameter specific to panel i, measuring the impact of uncertainty on the relevant real house price returns factor or stochastic volatility. The error term vector ϵ_i is distributed with mean zero and variance $\sigma_{ii}I$.

3.2.2.2 Random-coefficients (RC) estimator

The useful contribution of Swamy's (1970) RC estimator is that cross-section specific slope parameters can be estimated, an improvement over fixed-effects or random-effects models, which only allow for cross-section specific intercept parameters. In the case of RC, each panel specific β_i is related to an underlying common parameter vector β:

$$\beta_i = \beta + v_i \tag{9}$$

where $E\{v_i\} = 0, E\{v_i v_i'\} = \Sigma, E\{v_i v_j'\} = 0$ for $j \neq i$, and $E\{v_i \epsilon_j'\} = 0$ for all i and j. We may combine equations (8) and (9) to get:

$$y_i = X_i(\beta + v_i) + \epsilon_i$$

$$= X_i\beta + u_i$$

with $u_i \equiv X_i v_i + \epsilon_i$. Furthermore,

$$E\{u_i u_i'\} = E\{(X_i v_i + \epsilon_i)(X_i v_i + \epsilon_i)'\}$$

$$= X_i \Sigma X_i' + \sigma_{ii} I$$

$$\equiv \Pi_i$$

We can stack the P panels,

$$y = X\beta + u \tag{10}$$

where

$$\Pi \equiv E\{u_i u_i'\} = \begin{bmatrix} \Pi_1 & 0 & \cdots & 0 \\ 0 & \Pi_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \Pi_P \end{bmatrix}$$

Estimating the parameters in equation (9) is a standard problem, which can be solved with generalised least squares (GLS),

$$\hat{\beta} = (X'\Pi^{-1}X)^{-1}X'\Pi^{-1}y$$

$$= \left(\sum_i X_i'\Pi_i^{-1}X_i\right)^{-1}\sum_i X_i'\Pi_i^{-1}y_i$$

$$= \sum_i W_i b_i \tag{11}$$

with W_i the GLS weight and $b_i = (X_i'X_i)^{-1}X_i'y$. The resulting $\hat{\beta}$ for the overall (national) result is therefore a weighted average of the state-specific OLS estimates. For more detail on GLS weight and $\hat{\beta}$ variance specification, refer to Poi (2003).

In order to obtain the state-specific $\widehat{\beta_i}$ vectors, Judge et al., (1985) suggest that if attention is restricted to the class of estimators $\{\beta_i^*\}$ for which $E\{\beta_i^* | \beta_i\} = \beta_i$, then the state-specific OLS estimator b_i is appropriate. Following Green's (1997) suggested method to obtain the variance of $\widehat{\beta_i}$, it follows that $\hat{\beta}$ is both consistent and efficient; and although inefficient, b_i is also a consistent estimator of β.

Poi (2003) also suggests a test to determine whether the panel-specific β_is are significantly different from one another. The null hypothesis is stated as:

$$H_0\colon \beta_1 = \beta_2 = \cdots = \beta_P \tag{12}$$

and the test statistic is defined as:

$$T \equiv \sum_{t=1}^{P}\left(b_i - \beta^\dagger\right)'\left\{\hat{\sigma}_{ii}^{-1}(X_i X_i)\right\}\left(b_i - \beta^\dagger\right) \tag{13}$$

where

$$\beta^{\dagger} = \left\{\sum_{t=1}^{P} \hat{\sigma}_{ii}^{-1}(X_i X_i)\right\}^{-1} \sum_{t=1}^{P} \hat{\sigma}_{ii}^{-1}(X_i X_i) b_i.$$

The test statistic T is distributed as χ^2 with $k(P-1)$ degrees of freedom.

In the next section we present the empirical results for the datasets discussed in section 3.1.

4. Empirical results

We start by analyzing the univariate properties of the housing factor series, as well pairwise correlations present in the dataset, for both the longer Muntaz uncertainty dataset (1977Q2 – 2015Q3) based on 8 underlying economic and financial series, and the shorter dataset (1991Q1 – 2015Q3) based on 21 series.

4.1 Unit root test results

We apply three unit root tests to the house price factor series and uncertainty measures, namely Levin, Lin and Chu (LLC) (2002), Im, Pesaran, Shin (IPS) (2003), and Pesaran (CIPS) (2007). The unit root tests differ in that LLC assumes a common unit root process across the different cross-sections, while IPS assumes a cross-sectional specific unit root process, which is better suited to account for state heterogeneity. CIPS accounts for cross-sectional dependence in addition to cross-section heterogeneity, thereby also allowing for potential spillover effects between cross-sections. Results are presented in Table 1. In all instances, a maximum lag of 8 is allowed in the augmentation of the test regression. All unit root tests confirm that both house price factors and uncertainty are stationary, I(0) processes, rejecting the null of a unit root in all instances.

Table 1: Unit root test results

Uncertainty dataset: Mumtaz (2018), 1977Q2 – 2015Q3			
	LLC	IPS	CIPS
fmed	Adj t* =-4.13*** p=0.0000	W-t-bar = -12.68*** p=0.0000	CIPS = -3.190*** Crit 10% -2.01; 5% -2.06; 1% -2.14
svmed	Adj t* =-2.83*** p=0.0023	W-t-bar = -7.22*** p=0.0000	CIPS = -2.019* Crit 10% -2.01; 5% -2.06; 1% -2.14
u1	Adj t* =-12.26*** p=0.0000	W-t-bar = -18.54*** p=0.0000	CIPS = -4.431*** Crit 10% -2.01; 5% -2.06; 1% -2.14
u2	Adj t* =-8.91*** p=0.0000	W-t-bar = -16.02*** p=0.0000	CIPS = -4.058*** Crit 10% -2.01; 5% -2.06; 1% -2.14
u3	Adj t* =-5.73*** p=0.0000	W-t-bar = -13.92*** p=0.0000	CIPS = -3.720*** Crit 10% -2.01; 5% -2.06; 1% -2.14
u4	Adj t* =-5.73*** p=0.0000	W-t-bar = -13.75*** p=0.0000	CIPS = -3.411*** Crit 10% -2.01; 5% -2.06; 1% -2.14
Uncertainty dataset: Mumtaz (2018), 1991Q1 – 2015Q3			
	LLC	IPS	CIPS
fmed	Adj t* =-2.61 p=0.0046	W-t-bar = -8.28*** p=0.0000	CIPS = -3.543*** Crit 10% -2.01; 5% -2.06; 1% -2.14
svmed	Adj t* =-4.50*** p=0.0020	W-t-bar = -1.98** p=0.0240	CIPS = -2.081** Crit 10% -2.01; 5% -2.06; 1% -2.14
u1	Adj t* =-15.82*** p=0.0000	W-t-bar = -22.39*** p=0.0000	CIPS = -4.760*** Crit 10% -2.01; 5% -2.06; 1% -2.14

u2	Adj t* =-13.97*** *p*=0.0000	W-t-bar = -20.65*** *p*=0.0000	CIPS = -4.524*** Crit 10% -2.01; 5% -2.06; 1% -2.14
u3	Adj t* =-12.97*** *p*=0.0000	W-t-bar = -20.511*** *p*=0.0000	CIPS = -4.116*** Crit 10% -2.01; 5% -2.06; 1% -2.14
u4	Adj t* =-11.06*** *p*=0.0000	W-t-bar = -18.24*** *p*=0.0000	CIPS = -3.695*** Crit 10% -2.01; 5% -2.06; 1% -2.14

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.2 *Pairwise correlation analysis*

The overall correlation results are presented in Table 2, with correlation coefficients supplemented by *p*-values. There is a clear indication of a positive and statistically significant correlation between uncertainty and the house price stochastic volatility measure. The correlation between increased volatility and housing returns is negative as expected in the longer sample, but there is no statistically significant overall correlation between uncertainty and housing returns. In subsequent analysis, the case for individual states will be explored.

Table 2: Pairwise correlation coefficients

Uncertainty dataset: Mumtaz (2018), 1977Q2 – 2015Q3						
	fmed	*svmed*	*u1*	*u2*	*u3*	*u4*
fmed	1.0000					
svmed	-0.0830*** 0.0000	1.0000				
u1	-0.0056 0.6189	0.0243** 0.0312	1.0000			
u2	-0.0060 0.5958	0.0237** 0.0357	0.9995*** 0.0000	1.0000		
u3	-0.0056 0.6211	0.0218* 0.0531	0.9989*** 0.0000	0.9998*** 0.0000	1.0000	
u4	-0.0052 0.6436	0.0219* 0.0524	0.9981*** 0.0000	0.9992*** 0.0000	0.9998*** 0.0000	1.0000
Uncertainty dataset: Mumtaz (2018), 1991Q1 – 2015Q3						
	fmed	*svmed*	*u1*	*u2*	*u3*	*u4*
fmed	1.0000					
svmed	0.0077 0.5858	1.0000				
u1	-0.0046 0.7476	0.1205** 0.0000	1.0000			
u2	-0.0042 0.7694	0.1221*** 0.0000	0.9996*** 0.0000	1.0000		
u3	-0.0046 0.7470	0.1247*** 0.0000	0.9996*** 0.0000	0.9997*** 0.0000	1.0000	
u4	-0.0048 0.7376	0.1227*** 0.0000	0.9995*** 0.0000	0.9995*** 0.0000	0.9998*** 0.0000	1.0000

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.3 *Regression analysis*

The random-coefficient (Swamy 1970; Poi, 2003) estimator is used to obtain an overall combined (national) result for the impact of uncertainty on housing returns and the stochastic volatility measure. The result for the longer Muntaz (2018) dataset is reported in Table 3, while the state-specific results are presented in Tables 4 to 7, which display the coefficient β_i in equation (8). Results for the shorter sample are included in Tables A1 to A5 in the Appendix. The overall results for the Jurado et al. (2015) dataset are presented in Table A6 in the Appendix.

The weighted overall slope coefficient for the relationship between uncertainty at all horizons and the housing returns factor for all 50 states and the District of Columbia combined is negative as expected, and marginally significant ($p < 0.10$) for horizons 2, 3 and 4. A statistically significant relationship exists between macroeconomic uncertainty and the stochastic volatility measure at all horizons ($p < 0.01$), with a larger impact at longer horizons. The test statistic $T \sim \chi^2$ for the null hypothesis of parameter constancy ($H_0: \beta_1 = \beta_2 = \cdots = \beta_P$) is rejected at the 1 per cent significance level, supporting the notion of state heterogeneity.

Table 3: Estimation results for overall uncertainty impact, 1977Q2-2015Q3 (Horizons 1 to 4)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent: Housing returns factor (*fmed*)				Dependent: Stochastic volatility (*svmed*)			
u1	-0.331				1.741***			
	(-1.04)				(7.59)			
u2		-0.406*				1.870***		
		(-1.75)				(6.71)		
u3			-0.486*				2.229***	
			(-1.83)				(6.15)	
u4				-0.557*				2.541***
				(-1.72)				(5.61)
_cons	0.082	0.133	0.161	0.192	-0.766***	-1.098***	-1.577***	-2.043***
	(0.30)	(0.43)	(0.54)	(0.44)	(-4.27)	(-3.57)	(-4.36)	(-4.58)
Obs	7854	7854	7854	7854	7854	7854	7854	7854
Groups	51	51	51	51	51	51	51	51
Chi²(100)	22143***	22539***	23085***	23739***	214.83***	202.31***	198.40***	191.06***

t statistics in parentheses
t statistics based on standard errors that are robust to group (bootstrap) heteroscedasticity.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Chi² is a test for parameter constancy.

When analyzing state-specific results, it is evident that all states register a positive relationship between macroeconomic uncertainty and the stochastic volatility measure. With the exception of 3 states, the recorded impact is also statistically significant at the 1 per cent level. It is therefore evident that macroeconomic uncertainty also exacerbates uncertainty/volatility in the housing market virtually across all states. Hawaii ranks highest in terms of uncertainty spillover effect, followed by the state of Michigan.

The negative impact of increased uncertainty on the housing returns factor is markedly less severe, with only between 12 and 14 states recording a statistically significant negative impact, across the different horizons. Wyoming ranks at the top of the list with the largest negative impact.

An interesting observation is that 6 out of the top 12 states experiencing a positive spillover between macroeconomic uncertainty and house price stochastic volatility are from the Great Lakes/Midwest region, namely Michigan, Indiana, Ohio, Wisconsin, Illinois and Minnesota. Of the states in this region, Michigan, Illinois, Iowa, Wisconsin and Indiana also recorded a negative and significant relationship between uncertainty and housing returns. This result is also visually evident from the spatial depiction in Figures 1 and 2.

From Figure 2, it can be observed that apart from the Midwest, the Southern states, most notably Arkansas, Mississippi, Tennessee, North Carolina, South Carolina and Florida and the Southwestern states of Texas, Arizona and Nevada, together with Oregon on the West coast, are all recording large and significant positive links between macroeconomic uncertainty and housing market volatility.

Apart from the Midwestern states mentioned above, other states that registered a significant negative link between macroeconomic uncertainty and housing returns include Wyoming, Oregon and Nevada.

When considering the shorter sample period from 1991Q1 onwards, and using the broader measure of uncertainty, we note that all states in the West, with the exception of Washington, are also affected by large spillover effects from macroeconomic uncertainty to house price volatility, especially at 3- and 4-quarter horizons. In addition, states in the Midwest and Southeastern regions are persistent in recording large spillover effects (refer to Tables A1 to A4 and Figures A1 and A2 in the Appendix). For the macroeconomic uncertainty measure constructed by Jurado et al. (2015), the causal link between macroeconomic uncertainty and housing market is less pronounced. Whereas, the negative relationship between macroeconomic uncertainty and house price returns is confirmed, the earlier positive and significant relationship between macroeconomic uncertainty and the stochastic volatility measure does not find support (refer to Table A6 in the Appendix).

Overall, there is a marked correspondence between the results obtained in this analysis and that of Mumtaz et al. (2018) (refer to Fig. 1 and Fig. 4). Mumtaz et al. (2018) find that, in the regions mentioned above, the magnitude of the decline in income is largest, while these are also the states with a larger share of manufacturing and construction industries. Hence, uncertainty shocks seem to have the greatest impact on income and house prices broadly in the same states. A number of factors could explain this parallel. First, regions with a large manufacturing sector, like those of the Great Lakes/Midwest region, are vulnerable to external shocks. A fall in activity can result in sizeable job losses, with a clear impact on demand for dwellings. Second, house prices affect consumption through wealth and collateral effects. Mian, Rao and Sufi (2013), investigating the impact of the US subprime crisis on consumption, find that areas with poorer and more levered households have a significantly higher marginal propensity to consume out of housing wealth. Higher uncertainty will lead indebted households to increase precautionary savings. Furthermore, low-income households may face more difficulties in accessing credit, as lenders may tighten credit conditions, because both collateral values and household income become more uncertain. This will in turn depress consumption and income. A fall in housing transactions is also likely to impact the consumption of durable goods, which is often closely related to house purchases. Third, a reduction in consumption following house price falls disproportionately hits employment in the non-tradable sector, which depends on local demand. Mian and Sufi (2014) find that this mechanism played a significant role in the decline in US employment between 2007 and 2009. Finally, as uncertainty affects both house prices and residential investment, states with a large construction sector are likely to suffer most from high uncertainty.

Table 4: Estimation results for state-specific uncertainty coefficient, 1977Q2-2015Q3 (Horizon 1)

Housing returns factor (*fmed*)					Stochastic volatility (*svmed*)				
State		Coeff	SE	p-value	State		Coeff	SE	p-value
WY	Wyoming	-4.27***	0.75	0.0000	HI	Hawaii	9.27***	0.58	0.0000
NH	New Hampshire	-3.90***	1.21	0.0010	MI	Michigan	5.54***	0.66	0.0000
OR	Oregon	-3.10***	1.05	0.0030	ND	North Dakota	3.28***	0.41	0.0000
HI	Hawaii	-2.83**	1.19	0.0180	IN	Indiana	3.06***	0.25	0.0000
IL	Illinois	-2.57***	0.70	0.0000	NC	North Carolina	3.00***	0.24	0.0000
MI	Michigan	-2.47***	0.95	0.0090	OR	Oregon	2.84***	0.42	0.0000
NV	Nevada	-2.37*	1.22	0.0520	AR	Arkansas	2.58***	0.33	0.0000
DC	Distr. of Columbia	-1.96*	1.19	0.1000	OH	Ohio	2.50***	0.25	0.0000
IA	Iowa	-1.79***	0.48	0.0000	WI	Wisconsin	2.43***	0.21	0.0000
WI	Wisconsin	-1.00**	0.45	0.0250	IL	Illinois	2.42***	0.27	0.0000
DE	Delaware	-1.00***	0.37	0.0070	MS	Mississippi	2.34***	0.25	0.0000
KY	Kentucky	-0.81***	0.28	0.0040	TN	Tennessee	2.28***	0.30	0.0000
AK	Alaska	0.15	1.12	0.8960	MN	Minnesota	2.18***	0.43	0.0000
AL	Alabama	-0.43	0.26	0.1010	MO	Missouri	2.05***	0.22	0.0000
AR	Arkansas	0.61	0.95	0.5200	WV	West Virginia	2.05***	0.51	0.0000
AZ	Arizona	1.76	1.13	0.1190	TX	Texas	2.03***	0.29	0.0000
CA	California	0.92	1.17	0.4330	CT	Connecticut	1.98***	0.31	0.0000
CT	Connecticut	1.40	1.21	0.2470	FL	Florida	1.84***	0.17	0.0000
FL	Florida	-0.19	0.94	0.8430	AZ	Arizona	1.78***	0.25	0.0000
GA	Georgia	0.46	0.67	0.4910	GA	Georgia	1.74***	0.24	0.0000
ID	Idaho	-0.24	0.80	0.7630	SC	South Carolina	1.73***	0.19	0.0000
IN	Indiana	-0.74	0.61	0.2240	VA	Virginia	1.68***	0.19	0.0000
KS	Kansas	-0.58	0.59	0.3240	RI	Rhode Island	1.61***	0.24	0.0000
MA	Massachusetts	1.93	1.18	0.1010	NV	Nevada	1.55***	0.38	0.0000
MD	Maryland	0.41	1.13	0.7190	PA	Pennsylvania	1.55***	0.17	0.0000
ME	Maine	0.19	1.19	0.8740	WA	Washington	1.50***	0.37	0.0000
MN	Minnesota	0.00	0.64	0.9990	KY	Kentucky	1.37***	0.10	0.0000
MO	Missouri	-0.49	0.58	0.3940	SD	South Dakota	1.35***	0.14	0.0000
MS	Mississippi	-0.39	0.89	0.6590	NM	New Mexico	1.32***	0.17	0.0000
MT	Montana	-0.41	0.83	0.6250	MA	Massachusetts	1.26***	0.14	0.0000
NC	North Carolina	-0.39	0.49	0.4290	OK	Oklahoma	1.26***	0.09	0.0000
ND	North Dakota	-0.31	1.16	0.7910	NJ	New Jersey	1.24***	0.19	0.0000
NE	Nebraska	0.20	0.59	0.7390	IA	Iowa	1.13***	0.15	0.0000
NJ	New Jersey	-0.85	1.12	0.4500	NE	Nebraska	1.06***	0.18	0.0000
NY	New York	-0.15	0.65	0.8160	ME	Maine	1.04***	0.35	0.0030
OH	Ohio	-0.33	0.58	0.5720	WY	Wyoming	1.02***	0.10	0.0000
RI	Rhode Island	-1.61	1.21	0.1820	NY	New York	1.01***	0.08	0.0000
SC	South Carolina	0.19	0.72	0.7890	MT	Montana	0.92***	0.08	0.0000
SD	South Dakota	-1.04	0.71	0.1440	CO	Colorado	0.92***	0.18	0.0000
TN	Tennessee	-0.66	0.77	0.3930	UT	Utah	0.86***	0.16	0.0000
UT	Utah	0.28	1.06	0.7910	MD	Maryland	0.83***	0.17	0.0000
VT	Vermont	-0.60	0.87	0.4950	AL	Alabama	0.82***	0.05	0.0000
WA	Washington	1.20	1.07	0.2640	DE	Delaware	0.76***	0.15	0.0000
WV	West Virginia	-1.16	1.02	0.2570	LA	Louisiana	0.74**	0.31	0.0170
VA	Virginia	1.23**	0.55	0.0250	KS	Kansas	0.67**	0.30	0.0270
NM	New Mexico	1.28**	0.58	0.0260	CA	California	0.67***	0.08	0.0000
OK	Oklahoma	1.31**	0.61	0.0320	DC	Distr. of Columbia	0.24***	0.03	0.0000
PA	Pennsylvania	1.38*	0.74	0.0630	VT	Vermont	0.23***	0.04	0.0000
LA	Louisiana	1.80***	0.51	0.0000	AK	Alaska	1.03	0.78	0.1900
TX	Texas	1.97**	0.93	0.0350	ID	Idaho	0.09	0.12	0.4480
CO	Colorado	3.06***	0.90	0.0010	NH	New Hampshire	0.12	0.21	0.5830

Notes: */**/*** denotes 10/5/1% significance level.
Standard errors are robust to group (conventional) heteroscedasticity.
Uncertainty series from Mumtaz 1977Q2 – 2015Q3.

Table 5: Estimation results for state-specific uncertainty coefficient, 1977Q2-2015Q3 (Horizon 2)

Housing returns factor (*fmed*)					Stochastic volatility (*svmed*)				
State		Coeff	SE	p-value	State		Coeff	SE	p-value
WY	Wyoming	-4.52***	0.81	0.0000	HI	Hawaii	12.07***	0.72	0.0000
OR	Oregon	-3.08***	0.96	0.0010	MI	Michigan	5.51***	0.71	0.0000
NH	New Hampshire	-2.99***	1.16	0.0100	NC	North Carolina	3.54***	0.27	0.0000
MI	Michigan	-2.53***	0.93	0.0060	AR	Arkansas	3.01***	0.34	0.0000
IL	Illinois	-2.52***	0.66	0.0000	MS	Mississippi	2.98***	0.30	0.0000
NV	Nevada	-2.47**	1.17	0.0340	WI	Wisconsin	2.97***	0.24	0.0000
DC	Distr. of Columbia	-2.33**	1.16	0.0450	TX	Texas	2.92***	0.33	0.0000
HI	Hawaii	-2.27**	1.03	0.0280	IN	Indiana	2.69***	0.25	0.0000
RI	Rhode Island	-2.01*	1.17	0.0850	MO	Missouri	2.68***	0.25	0.0000
IA	Iowa	-1.81***	0.49	0.0000	ND	North Dakota	2.67***	0.32	0.0000
WI	Wisconsin	-1.19**	0.51	0.0190	MN	Minnesota	2.61***	0.50	0.0000
DE	Delaware	-0.97**	0.41	0.0170	OR	Oregon	2.56***	0.37	0.0000
KY	Kentucky	-0.92***	0.33	0.0050	FL	Florida	2.29***	0.18	0.0000
AK	Alaska	0.34	1.13	0.7630	IL	Illinois	2.13***	0.26	0.0000
AL	Alabama	-0.48	0.31	0.1230	GA	Georgia	2.10***	0.26	0.0000
AR	Arkansas	0.54	0.96	0.5740	VA	Virginia	1.95***	0.21	0.0000
AZ	Arizona	0.65	1.07	0.5450	WV	West Virginia	1.87***	0.47	0.0000
CA	California	0.40	1.15	0.7300	NV	Nevada	1.85***	0.37	0.0000
CT	Connecticut	0.98	1.17	0.4000	OH	Ohio	1.80***	0.20	0.0000
FL	Florida	-0.39	0.99	0.6940	AZ	Arizona	1.72***	0.23	0.0000
GA	Georgia	0.40	0.71	0.5740	NM	New Mexico	1.69***	0.17	0.0000
ID	Idaho	-0.33	0.87	0.7050	PA	Pennsylvania	1.67***	0.19	0.0000
IN	Indiana	-0.87	0.56	0.1220	CT	Connecticut	1.66***	0.31	0.0000
KS	Kansas	-0.39	0.63	0.5290	OK	Oklahoma	1.62***	0.11	0.0000
MA	Massachusetts	1.46	1.15	0.2050	KY	Kentucky	1.53***	0.12	0.0000
MD	Maryland	-0.13	1.12	0.9070	CO	Colorado	1.44***	0.19	0.0000
ME	Maine	-0.16	1.15	0.8880	NJ	New Jersey	1.43***	0.22	0.0000
MN	Minnesota	0.13	0.71	0.8590	WA	Washington	1.42***	0.33	0.0000
MO	Missouri	-0.59	0.67	0.3760	SC	South Carolina	1.41***	0.17	0.0000
MS	Mississippi	-0.55	0.99	0.5740	DE	Delaware	1.37***	0.19	0.0000
MT	Montana	-0.81	0.81	0.3170	SD	South Dakota	1.29***	0.14	0.0000
NC	North Carolina	-0.52	0.55	0.3480	TN	Tennessee	1.27***	0.21	0.0000
ND	North Dakota	-0.12	1.04	0.9050	MA	Massachusetts	1.25***	0.15	0.0000
NE	Nebraska	0.54	0.60	0.3670	RI	Rhode Island	1.19***	0.23	0.0000
NJ	New Jersey	-0.83	1.14	0.4690	NY	New York	1.18***	0.09	0.0000
NY	New York	0.01	0.73	0.9890	IA	Iowa	1.14***	0.15	0.0000
OH	Ohio	-0.42	0.45	0.3520	WY	Wyoming	1.10***	0.11	0.0000
PA	Pennsylvania	1.28	0.80	0.1110	LA	Louisiana	1.08***	0.40	0.0070
SC	South Carolina	0.13	0.64	0.8340	ME	Maine	1.07***	0.33	0.0010
SD	South Dakota	-1.05	0.71	0.1400	UT	Utah	1.06***	0.20	0.0000
TN	Tennessee	-0.71	0.53	0.1770	AL	Alabama	0.98***	0.06	0.0000
UT	Utah	-0.18	1.16	0.8760	MD	Maryland	0.97***	0.18	0.0000
VA	Virginia	0.98	0.65	0.1340	CA	California	0.89***	0.09	0.0000
VT	Vermont	-0.54	0.84	0.5180	KS	Kansas	0.80**	0.33	0.0150
WA	Washington	0.42	0.98	0.6690	MT	Montana	0.79***	0.08	0.0000
WV	West Virginia	-0.66	0.95	0.4830	NE	Nebraska	0.64***	0.16	0.0000
NM	New Mexico	1.57**	0.65	0.0170	DC	Dist. of Columbia	0.25***	0.03	0.0000
OK	Oklahoma	1.98***	0.76	0.0090	VT	Vermont	0.19***	0.04	0.0000
TX	Texas	2.03**	1.02	0.0470	AK	Alaska	0.83	0.92	0.3690
LA	Louisiana	2.18***	0.65	0.0010	ID	Idaho	0.10	0.14	0.4590
CO	Colorado	2.63***	0.97	0.0070	NH	New Hampshire	0.17	0.20	0.4190

Notes: */**/*** denotes 10/5/1% significance level.
Standard errors are robust to group (conventional) heteroscedasticity.
Uncertainty series from Mumtaz 1977Q2 – 2015Q3.

Table 6: Estimation results for state-specific uncertainty coefficient, 1977Q2-2015Q3 (Horizon 3)

Housing returns factor (*fmed*)					Stochastic volatility (*svmed*)				
State		Coeff	SE	p-value	State		Coeff	SE	p-value
WY	Wyoming	-4.91***	0.92	0.0000	HI	Hawaii	16.69***	0.92	0.0000
OR	Oregon	-3.56***	1.07	0.0010	MI	Michigan	6.21***	0.80	0.0000
NH	New Hampshire	-3.03**	1.32	0.0220	MO	Missouri	3.86***	0.30	0.0000
IL	Illinois	-2.95***	0.78	0.0000	WI	Wisconsin	3.81***	0.29	0.0000
NV	Nevada	-2.93**	1.30	0.0250	NC	North Carolina	3.80***	0.31	0.0000
MI	Michigan	-2.79***	1.02	0.0060	MS	Mississippi	3.76***	0.36	0.0000
DC	Distr. of Columbia	-2.55**	1.31	0.0520	AR	Arkansas	3.47***	0.38	0.0000
RI	Rhode Island	-2.40**	1.33	0.0710	TX	Texas	3.37***	0.37	0.0000
HI	Hawaii	-2.28**	1.07	0.0340	MN	Minnesota	3.14***	0.59	0.0000
IA	Iowa	-1.99***	0.53	0.0000	OR	Oregon	3.08***	0.41	0.0000
WI	Wisconsin	-1.52**	0.63	0.0150	IN	Indiana	2.97***	0.28	0.0000
IN	Indiana	-1.05*	0.63	0.0920	ND	North Dakota	2.64***	0.32	0.0000
KY	Kentucky	-1.03***	0.38	0.0070	IL	Illinois	2.59***	0.31	0.0000
DE	Delaware	-0.74*	0.38	0.0510	FL	Florida	2.55***	0.19	0.0000
AK	Alaska	0.61	1.30	0.6390	VA	Virginia	2.37***	0.25	0.0000
AL	Alabama	-0.57	0.38	0.1320	GA	Georgia	2.30***	0.28	0.0000
AR	Arkansas	0.33	1.08	0.7610	NM	New Mexico	2.28***	0.18	0.0000
AZ	Arizona	0.54	1.21	0.6570	WV	West Virginia	2.09***	0.55	0.0000
CA	California	0.32	1.29	0.8070	CT	Connecticut	2.07***	0.36	0.0000
CT	Connecticut	1.19	1.32	0.3710	OH	Ohio	2.04***	0.23	0.0000
FL	Florida	-0.63	1.10	0.5670	NV	Nevada	2.00***	0.38	0.0000
GA	Georgia	0.43	0.78	0.5810	OK	Oklahoma	1.99***	0.14	0.0000
ID	Idaho	-0.41	0.99	0.6770	AZ	Arizona	1.95***	0.26	0.0000
KS	Kansas	-0.41	0.77	0.5950	DE	Delaware	1.93***	0.22	0.0000
MA	Massachusetts	1.78	1.31	0.1750	WA	Washington	1.91***	0.39	0.0000
MD	Maryland	-0.64	1.16	0.5810	PA	Pennsylvania	1.82***	0.22	0.0000
ME	Maine	-0.37	1.30	0.7750	KY	Kentucky	1.76***	0.14	0.0000
MN	Minnesota	0.12	0.83	0.8830	CO	Colorado	1.70***	0.20	0.0000
MO	Missouri	-0.85	0.85	0.3150	SC	South Carolina	1.62***	0.19	0.0000
MS	Mississippi	-0.61	1.16	0.5970	LA	Louisiana	1.59***	0.52	0.0020
MT	Montana	-1.04	0.93	0.2650	NJ	New Jersey	1.45***	0.23	0.0000
NC	North Carolina	-0.64	0.61	0.2900	MA	Massachusetts	1.44***	0.18	0.0000
ND	North Dakota	-0.12	1.09	0.9150	SD	South Dakota	1.41***	0.15	0.0000
NE	Nebraska	0.57	0.58	0.3230	NY	New York	1.38***	0.11	0.0000
NJ	New Jersey	-0.93	1.27	0.4630	UT	Utah	1.36***	0.25	0.0000
NY	New York	0.15	0.85	0.8570	TN	Tennessee	1.36***	0.22	0.0000
OH	Ohio	-0.49	0.50	0.3270	IA	Iowa	1.26***	0.16	0.0000
PA	Pennsylvania	1.08	0.91	0.2390	AL	Alabama	1.21***	0.08	0.0000
SC	South Carolina	0.08	0.72	0.9130	ME	Maine	1.18***	0.35	0.0010
SD	South Dakota	-1.20	0.77	0.1210	WY	Wyoming	1.18***	0.13	0.0000
TN	Tennessee	-0.84	0.55	0.1290	CA	California	1.17***	0.11	0.0000
UT	Utah	-0.48	1.36	0.7250	KS	Kansas	1.12***	0.41	0.0060
VA	Virginia	0.88	0.66	0.1810	RI	Rhode Island	1.06***	0.24	0.0000
VT	Vermont	-0.75	0.97	0.4420	MT	Montana	0.92***	0.10	0.0000
WA	Washington	0.47	1.14	0.6800	MD	Maryland	0.75***	0.16	0.0000
WV	West Virginia	-0.74	1.08	0.4950	NE	Nebraska	0.53***	0.16	0.0010
NM	New Mexico	1.99***	0.70	0.0040	DC	Distr. of Columbia	0.29***	0.03	0.0000
OK	Oklahoma	2.46***	0.88	0.0050	VT	Vermont	0.21***	0.05	0.0000
TX	Texas	2.50**	1.15	0.0290	AK	Alaska	0.66	1.17	0.5710
LA	Louisiana	2.52***	0.82	0.0020	ID	Idaho	0.15	0.16	0.3430
CO	Colorado	2.67**	1.08	0.0130	NH	New Hampshire	0.24	0.23	0.2940

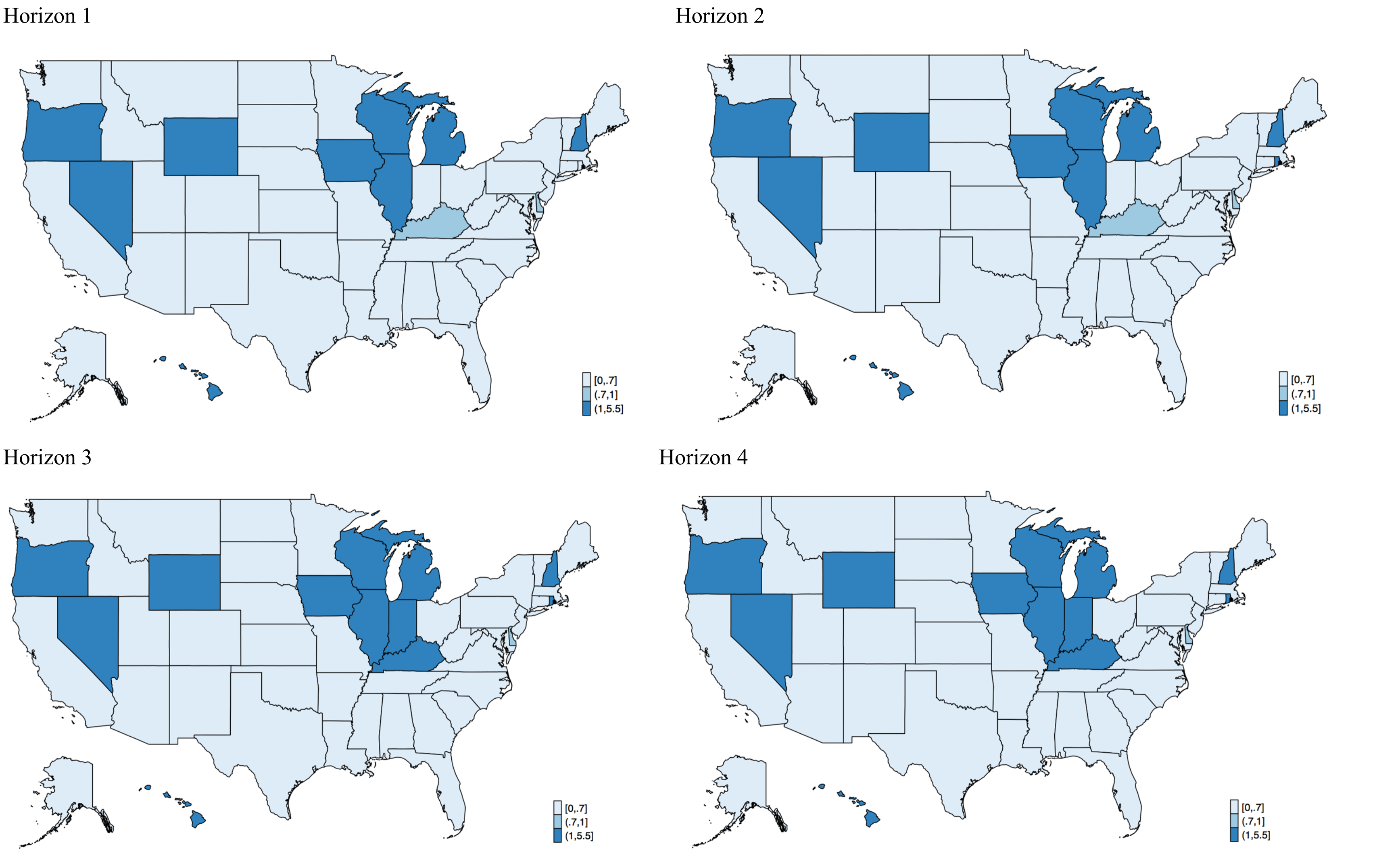
Notes: */**/*** denotes 10/5/1% significance level.
Standard errors are robust to group (conventional) heteroscedasticity.
Uncertainty series from Mumtaz 1977Q2 – 2015Q3.

Table 6: Estimation results for state-specific uncertainty coefficient, 1977Q2-2015Q3 (Horizon 4)

Housing returns factor (*fmed*)					Stochastic volatility (*svmed*)				
State		Coeff	SE	p-value	State		Coeff	SE	p-value
WY	Wyoming	-5.30***	1.02	0.0000	HI	Hawaii	18.26***	1.10	0.0000
OR	Oregon	-3.61***	1.09	0.0010	MI	Michigan	6.09***	0.82	0.0000
IL	Illinois	-3.53***	0.93	0.0000	MO	Missouri	5.36***	0.36	0.0000
NV	Nevada	-2.98**	1.39	0.0310	WI	Wisconsin	4.68***	0.34	0.0000
NH	New Hampshire	-2.80**	1.41	0.0470	NC	North Carolina	4.46***	0.35	0.0000
MI	Michigan	-2.73***	1.05	0.0090	AR	Arkansas	4.06***	0.40	0.0000
RI	Rhode Island	-2.61*	1.42	0.0650	TX	Texas	3.80***	0.40	0.0000
DC	Distr. of Columbia	-2.49*	1.39	0.0740	MS	Mississippi	3.68***	0.39	0.0000
IA	Iowa	-2.41***	0.62	0.0000	MN	Minnesota	3.49***	0.65	0.0000
HI	Hawaii	-2.32**	1.09	0.0340	IN	Indiana	3.43***	0.32	0.0000
WI	Wisconsin	-1.88**	0.75	0.0120	IL	Illinois	3.23***	0.38	0.0000
IN	Indiana	-1.25*	0.72	0.0820	OR	Oregon	3.10***	0.40	0.0000
KY	Kentucky	-1.11***	0.43	0.0100	VA	Virginia	3.03***	0.31	0.0000
DE	Delaware	-0.83*	0.45	0.0650	FL	Florida	2.96***	0.21	0.0000
AK	Alaska	0.90	1.39	0.5180	GA	Georgia	2.82***	0.33	0.0000
AL	Alabama	-0.65	0.44	0.1440	NM	New Mexico	2.82***	0.19	0.0000
AR	Arkansas	0.25	1.17	0.8330	ND	North Dakota	2.72***	0.31	0.0000
AZ	Arizona	0.44	1.30	0.7330	DE	Delaware	2.63***	0.27	0.0000
CA	California	0.20	1.38	0.8840	OH	Ohio	2.63***	0.28	0.0000
CT	Connecticut	1.08	1.42	0.4470	WA	Washington	2.56***	0.45	0.0000
FL	Florida	-0.76	1.21	0.5270	WV	West Virginia	2.36***	0.63	0.0000
GA	Georgia	0.51	0.90	0.5710	OK	Oklahoma	2.27***	0.15	0.0000
ID	Idaho	-0.50	1.05	0.6360	LA	Louisiana	2.27***	0.65	0.0000
KS	Kansas	-0.40	0.87	0.6410	CT	Connecticut	2.25***	0.37	0.0000
MA	Massachusetts	1.89	1.40	0.1760	AZ	Arizona	2.15***	0.28	0.0000
MD	Maryland	-0.98	1.28	0.4450	NV	Nevada	2.14***	0.40	0.0000
ME	Maine	-0.47	1.39	0.7350	KY	Kentucky	1.96***	0.16	0.0000
MN	Minnesota	0.12	0.90	0.8950	CO	Colorado	1.95***	0.21	0.0000
MO	Missouri	-1.05	1.04	0.3140	MA	Massachusetts	1.75***	0.21	0.0000
MS	Mississippi	-0.71	1.22	0.5620	UT	Utah	1.75***	0.32	0.0000
MT	Montana	-1.30	1.06	0.2200	PA	Pennsylvania	1.74***	0.24	0.0000
NC	North Carolina	-0.76	0.70	0.2770	NJ	New Jersey	1.73***	0.26	0.0000
ND	North Dakota	-0.20	1.12	0.8560	SD	South Dakota	1.73***	0.17	0.0000
NE	Nebraska	0.60	0.62	0.3270	TN	Tennessee	1.66***	0.25	0.0000
NJ	New Jersey	-0.88	1.37	0.5210	NY	New York	1.58***	0.12	0.0000
NY	New York	0.26	0.96	0.7840	IA	Iowa	1.55***	0.19	0.0000
OH	Ohio	-0.63	0.63	0.3150	SC	South Carolina	1.53***	0.19	0.0000
PA	Pennsylvania	0.58	0.95	0.5390	AL	Alabama	1.43***	0.09	0.0000
SC	South Carolina	-0.03	0.71	0.9610	WY	Wyoming	1.30***	0.15	0.0000
SD	South Dakota	-1.37	0.88	0.1180	KS	Kansas	1.28***	0.47	0.0060
TN	Tennessee	-1.03	0.64	0.1070	CA	California	1.27***	0.12	0.0000
UT	Utah	-0.68	1.49	0.6480	ME	Maine	1.25***	0.35	0.0000
VA	Virginia	0.95	0.81	0.2390	RI	Rhode Island	1.14***	0.25	0.0000
VT	Vermont	-0.93	1.06	0.3810	MT	Montana	1.08***	0.11	0.0000
WA	Washington	0.66	1.29	0.6100	MD	Maryland	0.83***	0.19	0.0000
WV	West Virginia	-0.90	1.20	0.4530	NE	Nebraska	0.52***	0.16	0.0010
CO	Colorado	2.56**	1.16	0.0280	DC	Distr. of Columbia	0.32***	0.03	0.0000
NM	New Mexico	2.61***	0.82	0.0010	VT	Vermont	0.23***	0.05	0.0000
OK	Oklahoma	2.63***	1.00	0.0080	AK	Alaska	0.21	1.28	0.8730
TX	Texas	2.69**	1.24	0.0300	ID	Idaho	0.21	0.17	0.2100
LA	Louisiana	2.77***	1.00	0.0050	NH	New Hampshire	0.33	0.23	0.1530

Notes: */**/*** denotes 10/5/1% significance level.
Standard errors are robust to group (conventional) heteroscedasticity.
Uncertainty series from Mumtaz 1977Q2 – 2015Q3.

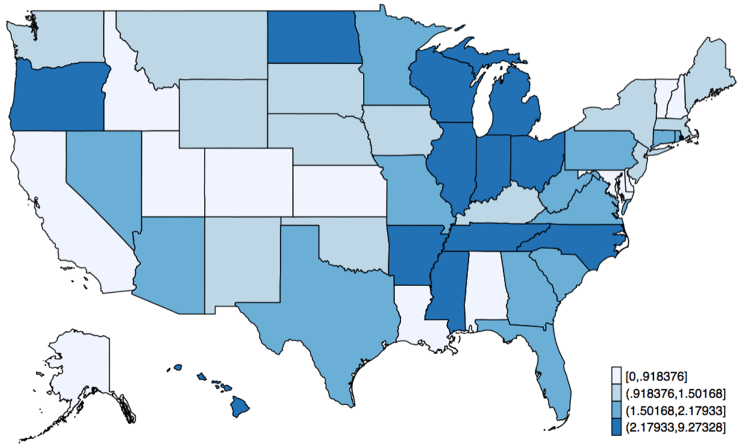
Figure 1: The impact of macroeconomic uncertainty on housing returns factor, 1977Q2-2015Q3



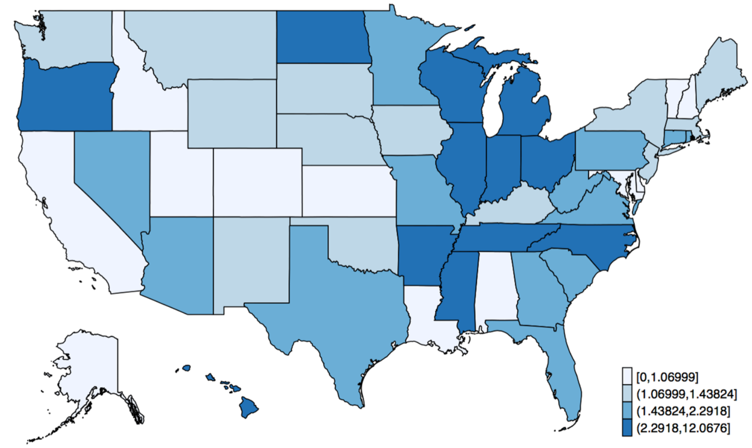
Note: Macroeconomic uncertainty taken from Mumtaz (2018)

Figure 2: The impact of macroeconomic uncertainty on stochastic volatility factor, 1977Q2-2015Q3

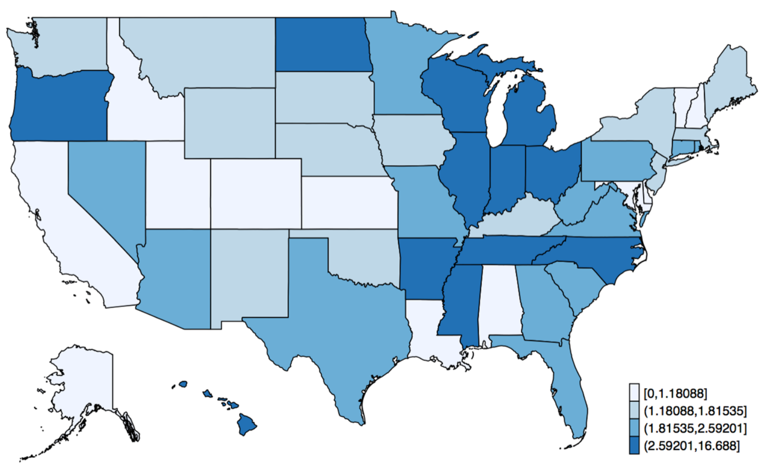
Horizon 1



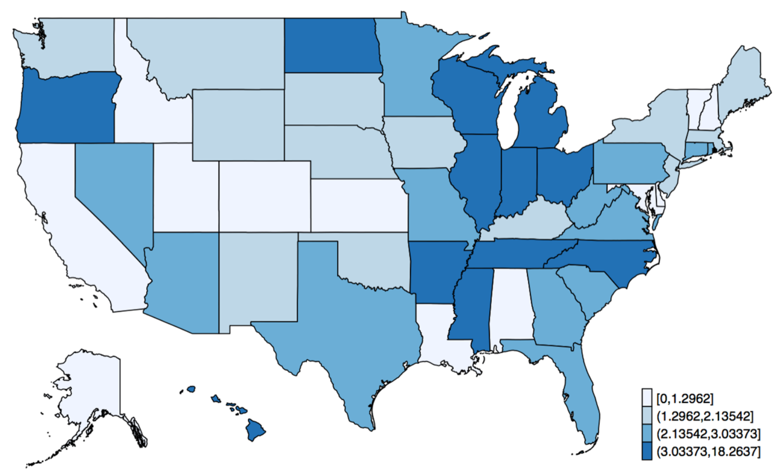
Horizon 2



Horizon 3



Horizon 4



Note: Macroeconomic uncertainty taken from Mumtaz (2018)

5. Conclusion

In this chapter, we aim to analyze the state-level impact of uncertainty on first- and second-moment movements in real housing returns. For this purpose, we begin by estimating a dynamic factor model with time-varying loadings and stochastic volatility (DFM-TV-SV) using Bayesian methods to disentangle the national and local factors affecting real housing returns and volatility in the 50 US states and DC. As the common components of housing returns and volatility tend to play an important role in driving the corresponding state-level values, failing to filter them out would result in an underestimation of the impact of state-level uncertainty. We then use panel data methods with heterogeneous coefficients to relate the first and second-moments of the local factors with corresponding state-level uncertainty. The latter is estimated using the average forecast error variance from a factor augmented forecasting regression with stochastic volatility in the regression residuals and the error term for the factor dynamics. The model incorporates a large set regional variables and 248 US-level data series. In our analysis, we use a narrower measure of uncertainty at one to four quarters forecast horizons, incorporating 8 financial and macroeconomic state-level variables, besides the overall US data used in the factor regressions, over the 1977Q2 to 2015Q3 period, and a broader measure incorporating 21 financial and macroeconomic state-level variables over the period 1991Q1 to 2015Q3. We find that, when considering the narrower uncertainty measure, all but three states register a positive and highly significant relationship between macroeconomic uncertainty and the stochastic volatility measure. Hawaii, followed by Michigan, ranks highest in terms of the uncertainty spillover effect. At the same time, the negative impact of increased uncertainty on the housing returns factor is less severe, with only 12 to 14 states recording a statistically significant negative impact across the different horizons. Amongst the 12 states most affected by increased uncertainty are 6 states from the Great Lakes/Midwest region, including Michigan, Indiana, Ohio, Wisconsin, Illinois and Minnesota. Of the states in this region, Michigan, Illinois, Iowa, Wisconsin and Indiana also record a negative and significant relationship between uncertainty and housing returns. Apart from the Midwest, a number of Southern states, known to be lower income states, also record large and significant positive spillover effects from macroeconomic uncertainty unto housing market volatility. Lower income households have fewer recourse options in the face of uncertainty and are often impacted more severely. The Southwestern states of Texas, Arizona and Nevada, together with Oregon on the West coast also count amongst the states with large spillover effects. When considering the shorter sample period from 1991Q1 onwards, and using the broader measure of uncertainty, we note that now all states in the West, with the exception of Washington, are also affected by large spillover effects from macroeconomic uncertainty to house price volatility, especially at 3 and 4-quarter horizons. In addition, states in the Midwest and Southeastern regions are persistent in recording large spillover effects.

Our results have important implications for households, mortgage lenders and investors. As indicated at the onset, the housing market plays an important role in the US economy, since it constitutes a significant share of many households' asset holding and net worth. Therefore, the risk or volatility of house prices is among the largest personal economic risks faced by households. In the event of falling house prices and borrower financial difficulties, mortgage lenders may face defaults on their loans. Housing market turmoil and uncertainty may also create financing difficulties, especially for lenders relying on short-term funding. Investors are affected by shocks to returns, but also, depending on their investment horizon, by house price volatility. Understanding the sensitivity of house prices to uncertainty relative to that of other assets is also essential for portfolio diversification. The fact that uncertainty primarily impacts real housing returns volatility, implies that investors need to pay close attention to movements in state-level variability of a range of macroeconomic and financial variables when taking their housing market-related decisions. At the same time, our results tend to suggest that in the majority of states, households and mortgage lenders should be more worried about heightened second-moment effects of uncertainty on the housing market, than about the negative effect on real returns. Both are likely to have a recessionary impact on the regional economy, but of varying degree.

As part of future research, it would be interesting to extend our analysis to a nonlinear set-up, given that the literature has shown that the effect of uncertainty on the housing market (and the economy in general) could be nonlinear, i.e. state-contingent. Preliminary evidence, based on the symbolic transfer entropy causality test for panel data due to Camacho et al. (2021), which is robust in the presence of cross-sectional heterogeneity, structural breaks, nonlinearity, and outliers, are reported in Table A7 in the Appendix of this chapter. They suggest that our linear model-based overall results showing a stronger influence of uncertainty on second moment movements in real housing returns continue to hold even in a nonlinear context. Nevertheless, more detailed state-level analysis could be of high value to households, mortgage lenders and investors, given the existence of heterogeneity. At the same time, given that in-sample predictability does not guarantee out-of-sample gains, conducting a real-time forecasting analysis could also be an area of further investigation.

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Appendix

Table A1: Estimation results for overall uncertainty impact, 1991Q1-2015Q3 (Horizons 1 to 4)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent: Housing returns factor (*fmed*)				Dependent: Stochastic volatility (*svmed*)			
u1	-0.068				0.052^{***}			
	(-0.51)				(2.05)			
u2		-0.0032				0.103^{***}		
		(-0.03)				(4.02)		
u3			-0.038				0.127^{***}	
			(-0.30)				(3.99)	
u4				-0.116				0.134^{***}
				(-0.96)				(4.19)
_cons	-0.540	1.650	5.510	12.29	-0.731	-2.322^{**}	-3.153^{*}	-3.811^{**}
	(0.20)	(0.35)	(0.88)	(1.33)	(-1.33)	(-2.38)	(-1.85)	(-2.02)
Obs	4950	4950	4950	4950	4950	4950	4950	4950
Groups	50	50	50	50	50	50	50	50
$Chi^2(100)$	512.57^{***}	500.66^{***}	462.90^{***}	449.98^{***}	93768^{***}	94053^{***}	92448^{***}	90853^{***}

t statistics in parentheses
t statistics based on standard errors that are robust to group (bootstrap) heteroscedasticity.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Chi^2 is a test for parameter constancy.

Table A2: Estimation results for state-specific uncertainty coefficient, 1991Q1-2015Q3 (Horizon 1)

Housing returns factor (*fmed*)					Stochastic volatility (*svmed*)				
State		Coeff	SE	p-value	State		Coeff	SE	p-value
FL	Florida	-3.86***	0.74	0.0000	ID	Idaho	0.49***	0.06	0.0000
ND	North Dakota	-1.81**	0.66	0.0060	NC	North Carolina	0.40***	0.07	0.0000
WA	Washington	-0.86***	0.33	0.0100	CA	California	0.38***	0.07	0.0000
TN	Tennessee	-0.81**	0.39	0.0370	LA	Louisiana	0.33***	0.09	0.0000
GA	Georgia	-0.71**	0.30	0.0210	AK	Alaska	0.24**	0.10	0.0170
NC	North Carolina	-0.63***	0.24	0.0090	AZ	Arizona	0.21***	0.06	0.0010
UT	Utah	-0.47*	0.28	0.0890	TN	Tennessee	0.21***	0.03	0.0000
NM	New Mexico	-0.35*	0.19	0.0660	MS	Mississippi	0.21***	0.06	0.0000
AK	Alaska	0.80	0.50	0.1080	OK	Oklahoma	0.19***	0.07	0.0100
AL	Alabama	-0.02	0.20	0.9270	OR	Oregon	0.16***	0.04	0.0000
AR	Arkansas	0.39	0.54	0.4660	NE	Nebraska	0.15***	0.05	0.0030
AZ	Arizona	-0.26	0.32	0.4120	IL	Illinois	0.15**	0.06	0.0200
CA	California	0.52	0.72	0.4730	MN	Minnesota	0.12*	0.06	0.0570
CT	Connecticut	-0.08	0.25	0.7450	CT	Connecticut	0.12***	0.04	0.0010
HI	Hawaii	0.03	0.61	0.9630	UT	Utah	0.10***	0.04	0.0030
IA	Iowa	-0.08	0.07	0.2460	VA	Virginia	0.10***	0.02	0.0000
ID	Idaho	-0.42	0.70	0.5550	MT	Montana	0.08***	0.01	0.0000
IL	Illinois	-0.04	0.32	0.8950	PA	Pennsylvania	0.07**	0.04	0.0560
KS	Kansas	-0.13	0.17	0.4690	RI	Rhode Island	0.06***	0.01	0.0000
KY	Kentucky	0.25	0.16	0.1100	MI	Michigan	0.02*	0.01	0.0880
MA	Massachusetts	0.12	0.32	0.7010	MD	Maryland	0.0*	0.01	0.0560
MD	Maryland	-0.02	0.19	0.9130	NJ	New Jersey	0.01**	0.00	0.0240
ME	Maine	0.12	0.21	0.5920	FL	Florida	0.17	0.13	0.1830
MI	Michigan	-0.08	0.10	0.4540	HI	Hawaii	0.13	0.09	0.1640
MN	Minnesota	0.20	0.30	0.5100	GA	Georgia	0.04	0.06	0.5550
MO	Missouri	-0.27	0.45	0.5530	AL	Alabama	0.02	0.04	0.6410
MS	Mississippi	-0.37	0.38	0.3210	SC	South Carolina	0.02	0.03	0.6400
NE	Nebraska	0.18	0.24	0.4500	NV	Nevada	0.01	0.02	0.4700
NH	New Hampshire	0.19	0.20	0.3570	KS	Kansas	0.01	0.03	0.7010
NJ	New Jersey	-0.05	0.15	0.7480	CO	Colorado	0.01	0.03	0.7590
NV	Nevada	0.02	0.09	0.8270	WA	Washington	0.01	0.06	0.8740
NY	New York	-0.20	0.24	0.3970	SD	South Dakota	0.01	0.03	0.8510
OH	Ohio	0.33	0.23	0.1460	WY	Wyoming	-0.01	0.01	0.1450
OK	Oklahoma	-0.01	0.41	0.9760	MA	Massachusetts	-0.01	0.02	0.5330
OR	Oregon	0.10	0.20	0.6360	ME	Maine	-0.01	0.01	0.2410
PA	Pennsylvania	0.86	0.56	0.1210	NY	New York	-0.02	0.02	0.3150
RI	Rhode Island	-0.40	0.32	0.2040	NH	New Hampshire	-0.02	0.03	0.4310
SC	South Carolina	-0.15	0.26	0.5680	NM	New Mexico	-0.02	0.01	0.1070
SD	South Dakota	0.15	0.19	0.4240	KY	Kentucky	-0.04	0.04	0.3330
TX	Texas	0.44	0.27	0.1060	AR	Arkansas	-0.05	0.07	0.4870
VA	Virginia	0.18	0.19	0.3320	WV	West Virginia	-0.12	0.13	0.3570
WV	West Virginia	-0.81	0.60	0.1790	VT	Vermont	-0.01	0.00	0.0010
WY	Wyoming	-0.01	0.10	0.9600	DE	Delaware	-0.02	0.01	0.0010
DE	Delaware	0.32***	0.11	0.0050	WI	Wisconsin	-0.06	0.03	0.0690
VT	Vermont	0.32*	0.17	0.0650	IA	Iowa	-0.06	0.01	0.0000
MT	Montana	0.49***	0.17	0.0050	TX	Texas	-0.11	0.03	0.0000
WI	Wisconsin	0.61***	0.12	0.0000	MO	Missouri	-0.15	0.09	0.0950
CO	Colorado	0.69**	0.28	0.0130	IN	Indiana	-0.29	0.06	0.0000
IN	Indiana	1.08***	0.25	0.0000	OH	Ohio	-0.30	0.08	0.0000
LA	Louisiana	1.10***	0.17	0.0000	ND	North Dakota	-0.33	0.11	0.0020

Notes: */**/*** denotes 10/5/1% significance level.
Standard errors are robust to group (conventional) heteroscedasticity.
Uncertainty series from Mumtaz 1991Q1 – 2015Q3.

Table A3: Estimation results for state-specific uncertainty coefficient, 1991Q1-2015Q3 (Horizon 2)

Housing returns factor (*fmed*)					Stochastic volatility (*svmed*)				
State		Coeff	SE	p-value	State		Coeff	SE	p-value
FL	Florida	-3.86***	0.74	0.0000	ID	Idaho	0.49***	0.06	0.0000
ND	North Dakota	-1.81**	0.66	0.0060	NC	North Carolina	0.40***	0.07	0.0000
WA	Washington	-0.86***	0.33	0.0100	CA	California	0.38***	0.07	0.0000
TN	Tennessee	-0.81**	0.39	0.0370	LA	Louisiana	0.33***	0.09	0.0000
GA	Georgia	-0.71**	0.30	0.0210	AK	Alaska	0.24**	0.10	0.0170
NC	North Carolina	-0.63***	0.24	0.0090	AZ	Arizona	0.21***	0.06	0.0010
UT	Utah	-0.47*	0.28	0.0890	TN	Tennessee	0.21***	0.03	0.0000
NM	New Mexico	-0.35*	0.19	0.0660	MS	Mississippi	0.21***	0.06	0.0000
AK	Alaska	0.80	0.50	0.1080	OK	Oklahoma	0.19***	0.07	0.0100
AL	Alabama	-0.02	0.20	0.9270	OR	Oregon	0.16***	0.04	0.0000
AR	Arkansas	0.39	0.54	0.4660	NE	Nebraska	0.15***	0.05	0.0030
AZ	Arizona	-0.26	0.32	0.4120	IL	Illinois	0.15**	0.06	0.0200
CA	California	0.52	0.72	0.4730	MN	Minnesota	0.12*	0.06	0.0570
CT	Connecticut	-0.08	0.25	0.7450	CT	Connecticut	0.12***	0.04	0.0010
HI	Hawaii	0.03	0.61	0.9630	UT	Utah	0.10***	0.04	0.0030
IA	Iowa	-0.08	0.07	0.2460	VA	Virginia	0.10***	0.02	0.0000
ID	Idaho	-0.42	0.70	0.5550	MT	Montana	0.08***	0.01	0.0000
IL	Illinois	-0.04	0.32	0.8950	PA	Pennsylvania	0.07**	0.04	0.0560
KS	Kansas	-0.13	0.17	0.4690	RI	Rhode Island	0.06***	0.01	0.0000
KY	Kentucky	0.25	0.16	0.1100	MI	Michigan	0.02*	0.01	0.0880
MA	Massachusetts	0.12	0.32	0.7010	MD	Maryland	0.0*	0.01	0.0560
MD	Maryland	-0.02	0.19	0.9130	NJ	New Jersey	0.01**	0.00	0.0240
ME	Maine	0.12	0.21	0.5920	FL	Florida	0.17	0.13	0.1830
MI	Michigan	-0.08	0.10	0.4540	HI	Hawaii	0.13	0.09	0.1640
MN	Minnesota	0.20	0.30	0.5100	GA	Georgia	0.04	0.06	0.5550
MO	Missouri	-0.27	0.45	0.5530	AL	Alabama	0.02	0.04	0.6410
MS	Mississippi	-0.37	0.38	0.3210	SC	South Carolina	0.02	0.03	0.6400
NE	Nebraska	0.18	0.24	0.4500	NV	Nevada	0.01	0.02	0.4700
NH	New Hampshire	0.19	0.20	0.3570	KS	Kansas	0.01	0.03	0.7010
NJ	New Jersey	-0.05	0.15	0.7480	CO	Colorado	0.01	0.03	0.7590
NV	Nevada	0.02	0.09	0.8270	WA	Washington	0.01	0.06	0.8740
NY	New York	-0.20	0.24	0.3970	SD	South Dakota	0.01	0.03	0.8510
OH	Ohio	0.33	0.23	0.1460	WY	Wyoming	-0.01	0.01	0.1450
OK	Oklahoma	-0.01	0.41	0.9760	MA	Massachusetts	-0.01	0.02	0.5330
OR	Oregon	0.10	0.20	0.6360	ME	Maine	-0.01	0.01	0.2410
PA	Pennsylvania	0.86	0.56	0.1210	NY	New York	-0.02	0.02	0.3150
RI	Rhode Island	-0.40	0.32	0.2040	NH	New Hampshire	-0.02	0.03	0.4310
SC	South Carolina	-0.15	0.26	0.5680	NM	New Mexico	-0.02	0.01	0.1070
SD	South Dakota	0.15	0.19	0.4240	KY	Kentucky	-0.04	0.04	0.3330
TX	Texas	0.44	0.27	0.1060	AR	Arkansas	-0.05	0.07	0.4870
VA	Virginia	0.18	0.19	0.3320	WV	West Virginia	-0.12	0.13	0.3570
WV	West Virginia	-0.81	0.60	0.1790	VT	Vermont	-0.01	0.00	0.0010
WY	Wyoming	-0.01	0.10	0.9600	DE	Delaware	-0.02	0.01	0.0010
DE	Delaware	0.32***	0.11	0.0050	WI	Wisconsin	-0.06	0.03	0.0690
VT	Vermont	0.32*	0.17	0.0650	IA	Iowa	-0.06	0.01	0.0000
MT	Montana	0.49***	0.17	0.0050	TX	Texas	-0.11	0.03	0.0000
WI	Wisconsin	0.61***	0.12	0.0000	MO	Missouri	-0.15	0.09	0.0950
CO	Colorado	0.69**	0.28	0.0130	IN	Indiana	-0.29	0.06	0.0000
IN	Indiana	1.08***	0.25	0.0000	OH	Ohio	-0.30	0.08	0.0000
LA	Louisiana	1.10***	0.17	0.0000	ND	North Dakota	-0.33	0.11	0.0020

Notes: */**/*** denotes 10/5/1% significance level.
Standard errors are robust to group (conventional) heteroscedasticity.
Uncertainty series from Mumtaz 1991Q1 – 2015Q3.

Table A4: Estimation results for state-specific uncertainty coefficient, 1991Q1-2015Q3 (Horizon 3)

Housing returns factor (*fmed*)					Stochastic volatility (*svmed*)				
State		Coeff	SE	p-value	State		Coeff	SE	p-value
FL	Florida	-1.90^{***}	0.42	0.0000	AZ	Arizona	0.56^{***}	0.12	0.0000
AZ	Arizona	-1.60^{***}	0.62	0.0100	NC	North Carolina	0.52^{***}	0.06	0.0000
UT	Utah	-1.44^{**}	0.63	0.0220	CT	Connecticut	0.50^{***}	0.10	0.0000
MI	Michigan	-1.20^{***}	0.41	0.0030	OK	Oklahoma	0.46^{***}	0.10	0.0000
WA	Washington	-1.05^{**}	0.43	0.0140	MN	Minnesota	0.45^{***}	0.12	0.0000
GA	Georgia	-0.65^{*}	0.34	0.0590	ID	Idaho	0.44^{***}	0.08	0.0000
NC	North Carolina	-0.55^{**}	0.25	0.0280	LA	Louisiana	0.40^{***}	0.11	0.0000
NV	Nevada	-0.42^{**}	0.21	0.0490	CA	California	0.37^{***}	0.06	0.0000
AK	Alaska	0.14	0.14	0.3270	OH	Ohio	0.29^{***}	0.10	0.0040
AL	Alabama	-0.18	0.51	0.7280	FL	Florida	0.28^{***}	0.08	0.0000
AR	Arkansas	0.10	0.27	0.6960	VA	Virginia	0.27^{***}	0.04	0.0000
CA	California	0.06	0.33	0.8500	OR	Oregon	0.27^{***}	0.05	0.0000
CT	Connecticut	-0.71	0.62	0.2470	MS	Mississippi	0.26^{***}	0.06	0.0000
HI	Hawaii	0.17	0.35	0.6260	IL	Illinois	0.24^{***}	0.08	0.0020
IA	Iowa	-0.17	0.15	0.2780	AL	Alabama	0.22^{**}	0.11	0.0440
ID	Idaho	-0.40	0.39	0.3010	MI	Michigan	0.22^{***}	0.07	0.0030
IL	Illinois	-0.38	0.35	0.2760	GA	Georgia	0.17^{**}	0.08	0.0330
KS	Kansas	-0.12	0.39	0.7540	SC	South Carolina	0.13^{**}	0.05	0.0120
KY	Kentucky	0.45	0.34	0.1860	IN	Indiana	0.13^{*}	0.08	0.0920
MA	Massachusetts	0.09	0.44	0.8340	TN	Tennessee	0.11^{***}	0.02	0.0000
MD	Maryland	-0.24	0.41	0.5570	MT	Montana	0.10^{***}	0.03	0.0000
ME	Maine	0.28	0.49	0.5610	UT	Utah	0.10^{***}	0.04	0.0080
MN	Minnesota	0.15	0.39	0.7000	NV	Nevada	0.07^{*}	0.04	0.0840
MO	Missouri	0.03	0.41	0.9390	ND	North Dakota	0.06^{**}	0.03	0.0330
MS	Mississippi	-0.48	0.36	0.1830	PA	Pennsylvania	0.05^{**}	0.02	0.0210
MT	Montana	0.27	0.37	0.4710	MD	Maryland	0.04^{**}	0.02	0.0150
ND	North Dakota	0.05	0.18	0.7870	NJ	New Jersey	0.04^{**}	0.01	0.0110
NE	Nebraska	0.11	0.24	0.6490	RI	Rhode Island	0.02^{***}	0.01	0.0080
NH	New Hampshire	0.24	0.53	0.6540	HI	Hawaii	0.10	0.11	0.3610
NJ	New Jersey	-0.41	0.41	0.3200	CO	Colorado	0.08	0.07	0.2920
NM	New Mexico	-0.75	0.51	0.1420	WV	West Virginia	0.07	0.06	0.2710
OK	Oklahoma	0.34	0.43	0.4270	WA	Washington	0.05	0.09	0.5610
OR	Oregon	-0.39	0.27	0.1390	AK	Alaska	0.03	0.10	0.7300
RI	Rhode Island	-0.33	0.28	0.2340	AR	Arkansas	0.01	0.04	0.7550
SC	South Carolina	-0.36	0.40	0.3650	WI	Wisconsin	0.01	0.09	0.8990
SD	South Dakota	0.26	0.47	0.5790	KS	Kansas	0.01	0.08	0.9370
TN	Tennessee	-0.33	0.28	0.2320	TX	Texas	0.00	0.06	0.9390
TX	Texas	0.47	0.42	0.2730	SD	South Dakota	-0.01	0.08	0.8680
VA	Virginia	0.45	0.47	0.3410	MA	Massachusetts	-0.01	0.07	0.8270
WV	West Virginia	-0.03	0.18	0.8750	NE	Nebraska	-0.02	0.06	0.7290
WY	Wyoming	-0.05	0.25	0.8400	KY	Kentucky	-0.02	0.09	0.7860
PA	Pennsylvania	0.55^{*}	0.31	0.0760	NH	New Hampshire	-0.04	0.05	0.3850
DE	Delaware	0.56^{*}	0.30	0.0640	VT	Vermont	-0.04^{***}	0.01	0.0000
NY	New York	0.62^{*}	0.34	0.0690	WY	Wyoming	-0.05^{**}	0.02	0.0140
OH	Ohio	0.70^{**}	0.29	0.0170	NM	New Mexico	-0.06^{*}	0.04	0.0680
IN	Indiana	0.76^{***}	0.30	0.0100	ME	Maine	-0.07^{*}	0.04	0.0880
VT	Vermont	0.84^{**}	0.39	0.0300	NY	New York	-0.07^{***}	0.02	0.0000
WI	Wisconsin	1.26^{***}	0.33	0.0000	DE	Delaware	-0.08^{***}	0.02	0.0010
CO	Colorado	1.58^{***}	0.56	0.0050	IA	Iowa	-0.12^{***}	0.03	0.0000
LA	Louisiana	1.71^{***}	0.32	0.0000	MO	Missouri	-0.19^{**}	0.10	0.0530

Notes: $^{*}/^{**}/^{***}$ denotes 10/5/1% significance level.
Standard errors are robust to group (conventional) heteroscedasticity.
Uncertainty series from Mumtaz 1991Q1 – 2015Q3.

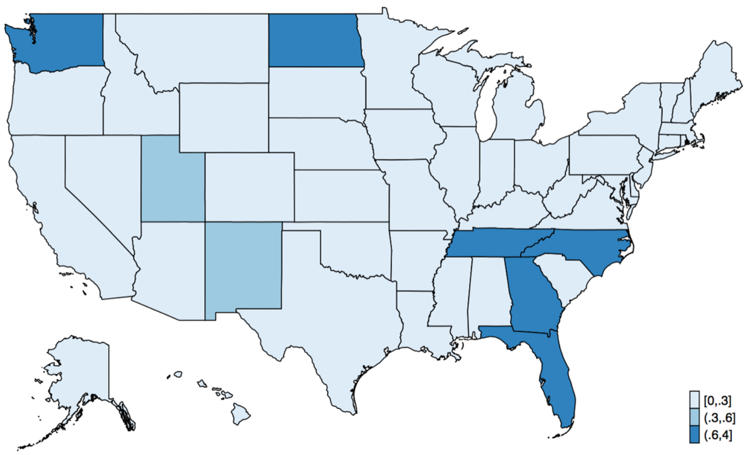
Table A5: Estimation results for state-specific uncertainty coefficient, 1991Q1-2015Q3 (Horizon 4)

Housing returns factor (*fmed*)					Stochastic volatility (*svmed*)				
State		Coeff	SE	p-value	State		Coeff	SE	p-value
FL	Florida	-2.26***	0.49	0.0000	AZ	Arizona	0.61***	0.14	0.0000
AZ	Arizona	-2.15***	0.74	0.0040	NC	North Carolina	0.59***	0.07	0.0000
MI	Michigan	-1.83***	0.58	0.0020	OK	Oklahoma	0.59***	0.12	0.0000
NV	Nevada	-1.49***	0.44	0.0010	MN	Minnesota	0.48***	0.13	0.0000
UT	Utah	-1.20**	0.51	0.0190	LA	Louisiana	0.39***	0.12	0.0010
WA	Washington	-1.09**	0.44	0.0130	AL	Alabama	0.38***	0.12	0.0020
GA	Georgia	-0.66*	0.38	0.0860	VA	Virginia	0.37***	0.06	0.0000
NC	North Carolina	-0.62**	0.29	0.0310	OH	Ohio	0.34***	0.11	0.0030
OR	Oregon	-0.55*	0.30	0.0680	ID	Idaho	0.34***	0.08	0.0000
AK	Alaska	0.12	0.13	0.3310	MI	Michigan	0.34***	0.11	0.0030
AL	Alabama	-0.37	0.57	0.5130	FL	Florida	0.33***	0.09	0.0000
AR	Arkansas	0.07	0.24	0.7680	OR	Oregon	0.31***	0.05	0.0000
CA	California	0.03	0.49	0.9480	CT	Connecticut	0.23**	0.10	0.0220
CT	Connecticut	-0.38	0.70	0.5820	CA	California	0.22***	0.04	0.0000
DE	Delaware	0.30	0.46	0.5050	MS	Mississippi	0.22***	0.05	0.0000
HI	Hawaii	0.25	0.37	0.4920	NV	Nevada	0.21***	0.08	0.0050
IA	Iowa	-0.22	0.20	0.2790	GA	Georgia	0.21**	0.09	0.0200
ID	Idaho	-0.66	0.47	0.1670	IN	Indiana	0.18***	0.05	0.0010
IL	Illinois	-0.40	0.27	0.1350	IL	Illinois	0.17***	0.06	0.0050
IN	Indiana	0.28	0.22	0.1940	CO	Colorado	0.15**	0.08	0.0470
KS	Kansas	-0.13	0.53	0.8110	SC	South Carolina	0.14***	0.05	0.0080
KY	Kentucky	0.10	0.25	0.6900	TN	Tennessee	0.09***	0.02	0.0000
MA	Massachusetts	0.04	0.46	0.9270	MT	Montana	0.06**	0.03	0.0380
MD	Maryland	-0.22	0.39	0.5690	ND	North Dakota	0.04**	0.02	0.0150
ME	Maine	0.25	0.58	0.6640	UT	Utah	0.04**	0.02	0.0480
MN	Minnesota	0.11	0.38	0.7730	PA	Pennsylvania	0.02**	0.01	0.0260
MO	Missouri	0.22	0.44	0.6160	NJ	New Jersey	0.02*	0.01	0.0980
MS	Mississippi	-0.46	0.35	0.1880	HI	Hawaii	0.07	0.11	0.5250
MT	Montana	-0.12	0.39	0.7510	KY	Kentucky	0.07	0.07	0.3390
ND	North Dakota	0.06	0.12	0.6250	WI	Wisconsin	0.06	0.11	0.5560
NE	Nebraska	0.07	0.21	0.7260	WA	Washington	0.06	0.09	0.4810
NH	New Hampshire	0.15	0.71	0.8340	TX	Texas	0.06	0.06	0.3330
NJ	New Jersey	-0.39	0.42	0.3560	WV	West Virginia	0.04	0.04	0.2740
NM	New Mexico	-0.94	0.70	0.1820	MD	Maryland	0.02	0.01	0.1030
OK	Oklahoma	0.48	0.49	0.3310	AK	Alaska	0.02	0.10	0.8400
PA	Pennsylvania	0.30	0.19	0.1180	AR	Arkansas	0.01	0.03	0.7250
RI	Rhode Island	-0.16	0.17	0.3610	RI	Rhode Island	0.01	0.01	0.1230
SC	South Carolina	-0.38	0.43	0.3770	MA	Massachusetts	0.00	0.09	0.9860
SD	South Dakota	0.25	0.63	0.6940	KS	Kansas	-0.01	0.12	0.9220
TN	Tennessee	-0.32	0.27	0.2460	SD	South Dakota	-0.02	0.11	0.8800
TX	Texas	0.35	0.44	0.4300	NE	Nebraska	-0.05	0.05	0.3450
VA	Virginia	0.50	0.67	0.4520	NH	New Hampshire	-0.05	0.05	0.3500
WV	West Virginia	-0.01	0.12	0.9300	MO	Missouri	-0.08	0.10	0.4270
WY	Wyoming	-0.23	0.37	0.5260	VT	Vermont	-0.05	0.02	0.0010
NY	New York	0.79**	0.33	0.0170	DE	Delaware	-0.06	0.03	0.0250
OH	Ohio	0.83**	0.35	0.0190	NM	New Mexico	-0.07*	0.04	0.0900
VT	Vermont	1.09**	0.49	0.0260	NY	New York	-0.08***	0.02	0.0000
WI	Wisconsin	1.39***	0.43	0.0010	WY	Wyoming	-0.09***	0.03	0.0050
CO	Colorado	1.58**	0.63	0.0130	ME	Maine	-0.13**	0.06	0.0270
LA	Louisiana	1.81***	0.42	0.0000	IA	Iowa	-0.16***	0.04	0.0000

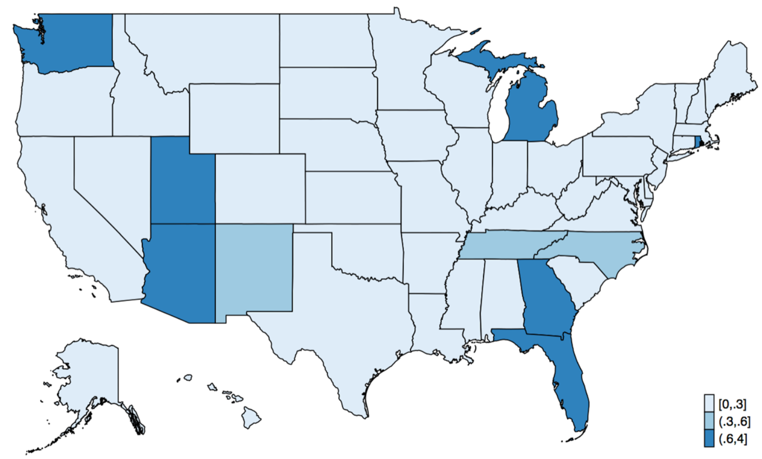
Notes: */**/*** denotes 10/5/1% significance level.
Standard errors are robust to group (conventional) heteroscedasticity.
Uncertainty series from Mumtaz, 1991Q1 – 2015Q3.

Figure A1: The impact of macroeconomic uncertainty on housing returns factor, 1991Q1-2015Q3

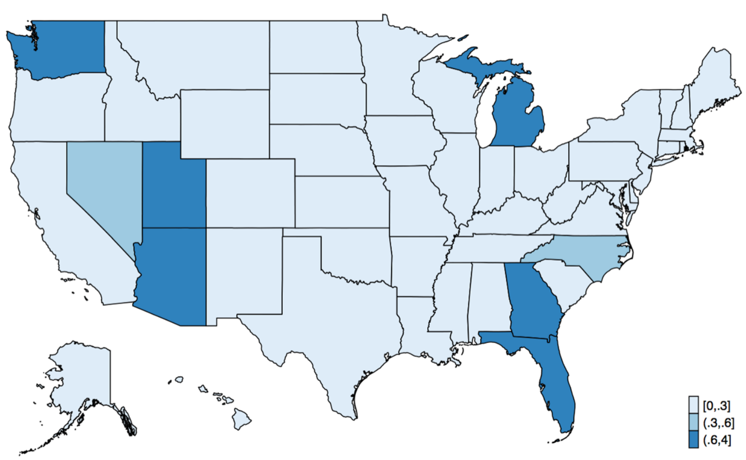
Horizon 1



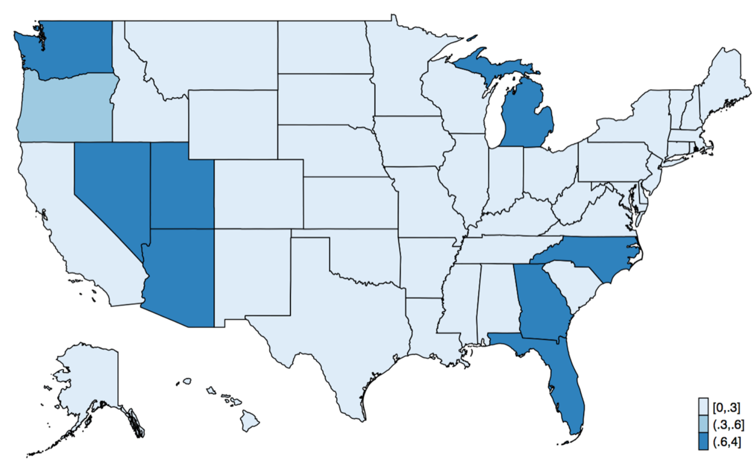
Horizon 2



Horizon 3



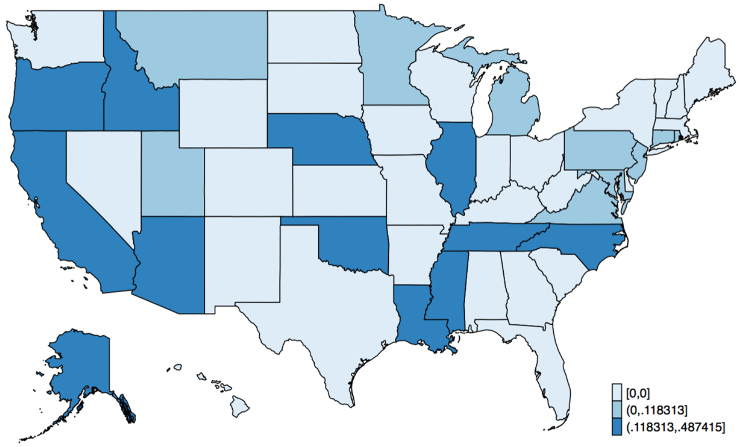
Horizon 4



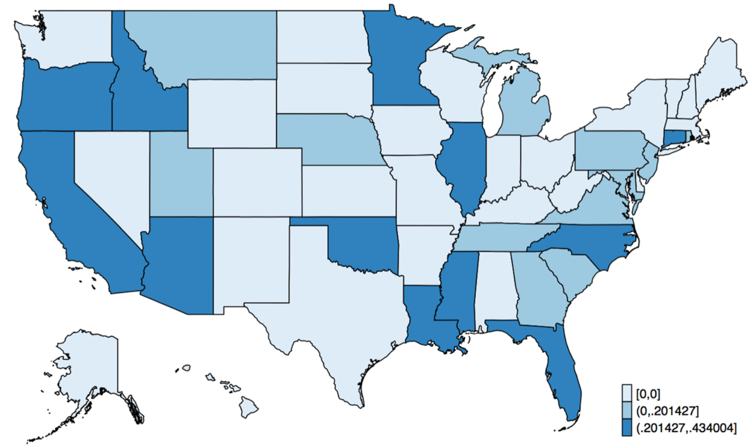
Note: Macroeconomic uncertainty taken from Mumtaz (2018)

Figure A2: The impact of macroeconomic uncertainty on stochastic volatility factor, 1991Q1-2015Q3

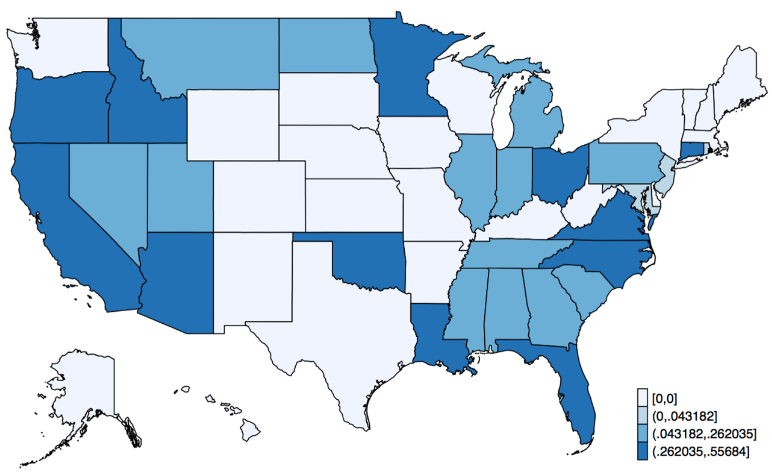
Horizon 1



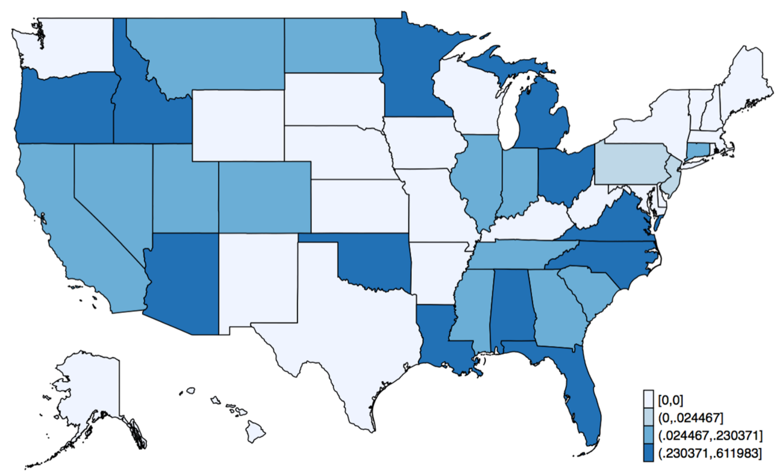
Horizon 2



Horizon 3



Horizon 4



Note: Macroeconomic uncertainty taken from Mumtaz (2018)

Table A6: Estimation results for overall uncertainty impact, using the Jurado et. al. (2015) dataset, 1977Q2-2015Q3 (Horizons 1 to 4)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent: Housing returns factor (*fmed*)				Dependent: Stochastic volatility (*svmed*)			
u1	-0.406				-0.386^{***}			
	(-1.26)				(-3.28)			
u2		-0.740^{***}				0.044		
		(-3.15)				(0.21)		
u3			-0.765^{**}				0.318	
			(-2.08)				(1.06)	
u4				-0.894^{**}				0.475
				(-2.40)				(1.25)
_cons	0.298	0.687^{*}	0.562	1.056^{**}	0.990^{***}	0.774^{***}	0.463	3.74
	(1.17)	(1.59)	(1.11)	(1.85)	(8.57)	(5.07)	(1.95)	(1.09)
Obs	7854	7854	7854	7854	7854	7854	7854	7854
Groups	51	51	51	51	51	51	51	51
$Chi^2(100)$	197.51^{***}	209.05^{***}	208.85^{***}	202.37^{***}	13009^{***}	13105^{***}	13238^{***}	12977^{***}

t statistics in parentheses
t statistics based on standard errors that are robust to group (bootstrap) heteroscedasticity.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Chi^2 is a test for parameter constancy.

Table A7: The Symbolic Transfer Entropy (STE) test

Panel (a). Mumtaz (2018) uncertainty data: 1977Q2-2015Q3

Direction of Causality $x \rightarrow y$	Test statistic	p-value
$u1 \rightarrow fmed$	0.0002	0.2400
$u2 \rightarrow fmed$	0.0003	0.0900
$u3 \rightarrow fmed$	0.0001	0.4700
$u4 \rightarrow fmed$	0.0001	0.4100
$u1 \rightarrow svmed$	0.0005	0.0100
$u2 \rightarrow svmed$	0.0010	0.0000
$u3 \rightarrow svmed$	0.0011	0.0000
$u4 \rightarrow svmed$	0.0015	0.0000

Panel (b). Mumtaz (2018) uncertainty data: 1991Q1-2015Q3

Direction of Causality $x \rightarrow y$	Test statistic	p-value
$u1 \rightarrow fmed$	0.0002	0.4200
$u2 \rightarrow fmed$	0.0002	0.4100
$u3 \rightarrow fmed$	0.0002	0.3600
$u4 \rightarrow fmed$	0.0000	0.9100
$u1 \rightarrow svmed$	0.0004	0.0600
$u2 \rightarrow svmed$	0.0004	0.2100
$u3 \rightarrow svmed$	0.0014	0.0000
$u4 \rightarrow svmed$	0.0021	0.0000

Panel (c). Jurado et al., (2015) uncertainty data: 1977Q2-2015Q3

Direction of Causality $x \rightarrow y$	Test statistic	p-value
$u1 \rightarrow fmed$	0.0004	0.0600
$u2 \rightarrow fmed$	0.0000	0.9400
$u3 \rightarrow fmed$	0.0001	0.4300
$u4 \rightarrow fmed$	0.0000	0.9100
$u1 \rightarrow svmed$	0.0003	0.0900
$u2 \rightarrow svmed$	0.0005	0.0100
$u3 \rightarrow svmed$	0.0008	0.0000
$u4 \rightarrow svmed$	0.0010	0.0000

Note: x is the independent variable and y is the dependent variable.