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# A Nationwide or Localized Housing Crisis? Evidence from Structural Instability in US Housing Price and Volume Cycles

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**Abstract** This study provides fresh implications for the puzzle of the recent housing boom-bust cycle in the United States. It extracts housing factors from housing price and volume time series at state and regional levels under a dynamic factor model, which considers three varieties of structural instability in local housing markets. The findings suggest that state-level housing price cycles are more unstable than housing volume cycles, and the probability of rejecting stability for the Northeast is the highest among four regional housing markets. In general, the housing market forecasts based on 1988–2012 full-sample factors and time-varying coefficients across pre- and post-1999 subperiods are superior to alternatives. The factor-based forecast results provide new evidence for a nationwide housing crisis in 2007–2008, and thus suggest possible effectiveness of monetary policies in stabilizing recent housing boom-bust cycles.

**Keywords** Housing crisis · Structural instability · Housing boom-bust cycle · Housing factor · Dynamic factor model

## 1 Introduction

> Although the house price bubble appears obvious in retrospect–all bubbles appear obvious in retrospect–in its earlier stages, economists differed considerably about whether the increase in house prices was sustainable… whether the bubble was national or confined to a few local markets…

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~ Ben S. Bernanke, former Chairman of the Board of Governors of the Federal Reserve, at the Annual Meeting of the American Economic Association in January 2010

This study examines the nature of the recent bubble-like boom-bust cycle in the US from a forward-looking perspective, particularly for the housing crisis since 2007. The answer to this question means much to households and real estate investors since a nationwide housing crisis implies few risk diversification opportunities. Otherwise, if the US housing crisis is only localized, it is possible to substitute housing assets in non-crisis regions for those suffering a price collapse. In addition, it provides important implications for policy-making effectiveness. On the one hand, a localized housing crisis is indicative of the limited power of monetary policies in stabilizing housing market dynamics since they could be influenced by different shocks. On the other hand, a nationwide housing crisis suggests an active role of the government in mitigating unfavorable fluctuations in local housing markets.

This paper utilizes a dynamic factor model, which makes factor-based forecasts for the US housing market in the spirit of Banerjee et al. (2008), Hendry and Clements (2004), and Stock and Watson (2002b, 2007) who all propose well-estimated factors under instability. The framework is capable of incorporating a large number of housing prices and housing volumes,[1] extracting housing factors to represent their co-movements, and taking a variety of structural instability into consideration. The three scenarios of structural instability consist of a structural break in the housing-factor loadings, a break in housing factor dynamics, or a break in the idiosyncratic dynamics of housing markets. The research differs from the housing literature as it investigates both housing prices and volumes at disaggregate levels from a forward-looking perspective, motivated by Leamer (2007) and Moench and Ng (2011). As a result, it estimates the housing factors that govern the cross-state co-movements in terms of prices and volumes.

The sample period spans from 1988 to 2012, covering two boom-bust housing cycles: the previous one in the 1990s and the recent one in the 2000s. This study chooses 1999 to serve as the single break, which is suggested by many empirical studies. In order to examine the nature of the housing boom-bust cycle after 1999, this study compares predictive performances of three scenarios: first, the forecast using housing factors estimated from the full sample and full-sample estimates of the factor loadings (“full–full”); second, using housing factors estimated from the full sample and split-sample estimates of the factor loadings (“full-split”); third, using split-sample estimates of housing factors and factor loadings (“split–split”).

The main contributions of this study lie in the implications for the nature of the recent housing boom-bust cycle through comparison analyses among the three scenarios of factor-based forecasts. If full–full forecasts are the best ones, it suggests that forecasts of disaggregate housing market dynamics are not improved as instability across the two subsamples is considered. If split–split forecasts are the best ones, it implies that the estimated housing factors significantly differ across the pre-1999 and post-1999 subperiods. If full-split forecasts are the best ones, it indicates that instability of housing

[1] This study uses housing starts to proxy for housing volumes of 51 states and 4 Census regions in the US.

market dynamics matters from a forward-looking perspective, but extracted housing factors over subsamples are qualitatively the same compared to those estimated over the whole sample period from the forecast viewpoint. Thus, the housing factors over the entire period are sufficient to reflect various common shocks to local housing markets.

Overall, the results suggest that state-level housing price cycles are more unstable than housing volume cycles. The probability of rejecting stability for the Northeast is the highest among 4 regional housing markets. This study provides confirmative evidence for difficulties in predicting disaggregate housing markets dynamics owing to instability. The results show that we gain more as we make forecasts by using common factors estimated based on the housing time series spanning over a long period (full sample) and time-varying coefficients across subperiods. In particular, in the post-1999 subperiod, full-split forecasts yield better performances than the other two methods for all state-level housing markets. The findings suggest that no new shock emerges to influence cross-state co-movements after 1999, aligning with the argument made by Stock and Watson (2012) who attempt to quantify the uniqueness of the 2007–2009 recession. If there is a dynamic distinction between crisis states with dramatic housing boom-bust cycles and non-crisis states with milder housing market fluctuations in the post-break period, a new common shock occurs after 1999. The results of forecast comparisons give support to the absence of new factors which uniquely belong to the post-break subperiod. Thus, the co-movements across state-level housing markets remain after the structural break, and the post-1999 boom-bust cycle is nationwide. Important, the ways state-level housing markets respond to the old common shocks in the post-1999 are different from those in the pre-1999 since the factor loadings alter across subsamples in full-split forecasts. Based on the superiority of full-split forecasts over alternatives, the study provides supportive evidence on the nationwide nature of the recent housing boom-bust cycle, and the result reconciles with the argument by Del Negro and Otrok (2007).

The remainder of this paper is organized as follows. Section 2 reviews the literature which motivates this study. Section 3 presents the data and methods. Section 4 discusses the main findings regarding housing market instability and factor-based forecasts. Finally, Sect. 5 makes concluding remarks.

## 2 Motivation

This study is primarily motivated by and builds upon four strands of literature: studies using dynamic factor models to investigate macroeconomic aggregates, financial and local housing markets, analyses about forecasts of housing market dynamics, papers addressing structural instability of housing markets, and the literature emphasizing the housing volume. The following paragraphs cite a few highly relevant papers that support this research or whose results can be contrasted with our own.

Numerous empirical studies use dynamic factor models to forecast macroeconomic aggregates. For instance, Ng (2012) adopts probit forecasting models, which incorporate various risk factors, to predict the duration and turning points of the US recession. Poncela et al. (2011) compare forecasting performances of dynamic factor models with other three competing frameworks for the US macroeconomy. Stock and

Watson (2012) quantify the extent to which the 2007–2009 recession differs from previous ones; they use a high-dimensional dynamic factor model which incorporates 200 macroeconomic variables and 6 housing factors. Some authors observe macro-economies of countries other than the US. For example, Boysen-Hogrefe (2013) analyzes the European debt crisis under a dynamic factor model with time-varying loadings and 2 factors. Koop and Korobills (2011) improve forecasts of the UK macroeconomy by developing dynamic model averaging and model selection in order to solve the problem of over-parameterization in block-factor models. Lee (2012) addresses business cycle co-movements in Europe by using a dynamic factor model with time-varying parameters. Zaher (2007) considers 167 monthly data of UK economic and financial variables, and argues that dynamic factors models outperform alternatives. Recently, some authors have applied factor-based models to study financial and commodity markets. For instance, Akay et al. (2013) use a dynamic factor model with Markov regime-switching components to discuss contagion and time-varying risk-adjusted return for the hedge fund. Berger and Pozzi (2013) use a latent factor model to investigate time-varying linkages of stock markets across five developed countries. Cordis and Kirby (2011) analyze stock markets by establishing regime-switching factor models. Garcia-Martos et al. (2011) extract common factors from electricity prices to forecast electricity markets.

This study is particularly motivated by the empirical literature which applies factor-based models to investigate local housing markets. For instance, Fadiga and Wang (2009) specify the common cyclical and trend components in the four regional housing markets in the US, and point out that they share three common cyclical and two common trend components under a multivariate state-space model. As Holly et al. (2010) address, there are unobserved common factors and spatial effects across state-level housing markets, which are governed by error terms of the housing price regression on some economic fundamentals. Extending the framework of Holly et al. (2010), Baltagi and Li (2014) suggest that spatial dependence at city levels is larger than that at state levels, and show the interesting fact that factor loadings alter over time horizons: estimated factor loadings of the bubble housing markets[2] are negative in 1975–2003, but many of them turn out positive when the estimation period covering 1975–2011. Moench and Ng (2011) extend the dynamic hierarchical factor model to analyze associations between housing and consumption, emphasizing the distinction between national and regional common factors extracted from disaggregate housing markets in the US. Del Negro and Otrok (2007) adopt a dynamic factor model to describe how changes in 48 state-level house price indexes are governed by two factors: a latent national factor and a state-level factor. Their research suggests that house price dynamic differences can be largely explained in terms of the states' exposures to the national factor during the recent housing boom. Stock and Watson (2009) utilize a dynamic model with time-varying volatility to observe co-movements across state-level housing permits.

The literature discussing co-movements across state- and MSA-level housing markets also provides light on policy-making implications: strong cross-market interplay

[2] The examples are MSAs in New York, Massachusetts and California, as noted by the authors.

is indicative of relative effectiveness of monetary policies in stabilizing housing cycles. In addition, the nature of the recent housing bubble is intensely debated by empirical studies. For instance, Del Negro and Otrok (2007) suggest the occurrence of a national bubble: the housing boom in 2001–2005 was a "national" phenomenon. More recently, Flor and Klarl (2017) advocate that the decline in the mortgage rate enhanced similarity between the MSAs and the national housing cycle in the pre-2006 period and thus monetary policy played a role during the housing boom. Otherwise, Miles (2015) suggests that regional housing markets were driven by "local" bubbles in the early years of the housing bubble 2001–2005, followed by a "national" housing bust in 2005–2012.

Regarding forecasts of housing markets, Crawford and Fratantoni (2003) claim the difficulty in predicting the prices of individual houses, but they argue the possibility of forecasting an aggregate housing price index. Campbell and Cocco (2007) and Miller et al. (2011a, b) show that the predictable component of the housing price influences macroeconomic aggregates more strongly than does the unpredictable one. Hassani et al. (2017) compare forecasting performances for national and regional house sales and suggest the superiority of the nonparametric approach of singular spectrum analyses. Huang (2013b) examines housing price predictability at nationwide and state levels, and finds that households' expectation has a stronger predictive power than interest rates. Rapach and Strauss (2009) propose that housing price forecastability differs across states, and suggest that the presence of local housing bubbles is associated with low price predictability.

However, as stated by Stock and Watson (2007), factor-based forecasts with structural breaks have hardly been studied. Among few examples, Breitung and Eickmeier (2011) develop a generalized LM test of structural breaks in dynamic factor models and observe whether there are structural breaks in the US and European business cycles. To take structural instability into consideration, this study uses the 1st quarter of 1999 (1999Q1) as the breakpoint to divide the entire sample into two sub-periods, 1988Q2–1998Q4 and 1999Q1–2012Q2, in an attempt to incorporate a structural break in forecasts of housing price dynamics. The breakpoint helps us examine whether the recent housing boom-bust cycle is national or localized. The papers that focus on methodological specifications for structural breaks of housing markets are rare: most related studies only approximate the breakpoint of the recent housing dynamics. Among few examples, Goodman and Thibodeau (2008) point out that homeownership increased substantially from 1999 to 2005; Huang (2013a) chooses 1999 as the permanent structural break in the US housing price dynamics; Lai and Van Order (2010) suggest that the momentum behavior of housing prices increased after 1999; Shiller (2006) finds that US second home mortgages doubled since 1999; Shiller (2008) advocates that the US housing boom showed a nationwide spillover since 1999. Although none of these studies propose a method to specify structural breaks in the housing market, they implicitly suggest that the US housing market displays noticeably different patterns in the post-1999 compared to the pre-1999 subperiod.

This study extracts housing factors from local housing prices and housing starts. The importance of housing volumes is advocated in the recent literature on housing market dynamics. For instance, using US data, Akkoyun et al. (2013) discuss correlation differences between housing prices and transaction volumes at different frequencies.

Clayton et al. (2010) propose a positive correlation between housing prices and volumes as they characterize the housing market cycle from 1990 to 2002. Croce and Haurin (2009) suggest performances of consumer sentiment in forecasting dynamics of three housing volumes: housing permits, housing starts and sales. Leamer (2007) documents that instead of the price cycle, the housing volume cycle matters to the US business cycle. For European countries, Oikarinen (2012) shows positive linkages between housing price changes and housing sales and negative relations between housing price levels and transactions; Wit et al. (2013) find a positive correlation between housing price growth and housing transactions in the Dutch housing market.

In particular, housing starts are commonly used to represent housing boom-bust cycles (Baffoe-Bonnie (1998), Edelstein and Tsang (2007), Hao and Ng (2011), Moench and Ng (2011), Silos and Vilan (2009), Stock and Watson (2012), Topel and Rosen (1988, etc.). One of the pioneering papers is Topel and Rosen (1988). They point out that housing starts are used to characterize booms and busts of the US housing markets. In the spirit of Topel and Rosen (1988), Edelstein and Tsang (2007) define housing investments as the units of new housing starts. Moench and Ng (2011) emphasize that the housing starts and permits are informative for the future market conditions as they incorporate housing volumes into their analyses about US local housing markets. Thus, the paper chooses housing starts to proxy for housing volume cycles, motivated by the existing literature.

## 3 Dynamic Factor Model

The static version of the factor model takes the following form:

$$X_t = \Lambda_t F_t + e_t, \tag{1}$$

where $X_t$=$(X_{1t},\ldots, X_{nt})'$, $F_t$ is the $r$-vector of static factors; $\Lambda_t$ is the $n \times r$ matrix of factor loadings; $e_t$=$(e_{1t},\ldots, e_{nt})'$ is the $n$-vector of idiosyncratic disturbances. Noticeably, Eq. (1) differs from standard formulations of the DFM by allowing for possibly time-varying factor loadings.

The price data used in this study are the state and regional housing prices from Freddie Mac. These Freddie Mac house price indexes are deflated by the core CPI (Consumer Price Index for all urban consumers: all items less food and energy) which comes from U.S. Department of Labor: Bureau of Labor Statistics. The state and regional volume data chosen for the study are Privately Owned Housing Starts Authorized by Building Permits: 1-Unit from U.S. Department of Commerce: Census Bureau. Because the volume data are available from 1988, the analyzed period spans from 1988 to 2012Q2.[3] All time series are seasonally-adjusted by the Census X-12 approach. All 51 states are selected and the four regions are the Northeast, the Midwest, the South, and the West. There are 55 house price series and 54 housing vol-

[3] Because state-level housing price and starts are available monthly but regional data are available only quarterly, quarterly values of state-level time series are computed by averaging the monthly values over the corresponding quarter.

ume series (excluding Washington, DC[4]). For each state and region, the real housing price (volume) growth is computed as the difference in the logs of the real housing price (volume). This study incorporates 109 housing market variables, state-level and regional housing price and volume growths, into the estimation of housing factors.

Following the literature on dynamic factor models, this study assumes finite-order autoregressive dynamics for the housing factors and the idiosyncratic term:

$$F_t = \Phi_t F_{t-1} + \eta_t \tag{2}$$

$$e_{it} = a_{it}(L)\, e_{it-1} + \varepsilon_{it}, \quad i = 1, \ldots, n \tag{3}$$

where $\eta_t$ is the $r$-vector of factor innovations with $\mathrm{E}(\eta_t | F_{t-1}, F_{t-2}, \ldots, X_{it-1}, X_{it-2}, \ldots) = 0$. Equation (1)–(3) describe the static factor model derived from the dynamic factor framework if finite lag lengths and VAR factor dynamics are assumed. In the dynamic version, $F_t$ contains lags of the dynamic factors and $\Phi_t$ is a companion matrix so that the static factor follows the 1st-order dynamics.

Suppose that $E(\varepsilon_{is} | F_t, F_{t-1}, \ldots, X_{it}, X_{it-1}, \ldots) = 0$ and $E(\eta_s | F_t, F_{t-1}, \ldots, X_{it}, X_{it-1}, \ldots) = 0$ for $s > t$, and that the idiosyncratic errors $\{\varepsilon_{it}\}$ are uncorrelated with the factor disturbances $\{\eta_t\}$ at all leads and lags. Then, given the data and factors over time $t$, and the assumption that the potentially time-varying parameters are available, the $h$-step ahead conditional expectation of $X_{it+h}$ is as follows:

$$\begin{aligned} X_{it+h|t} &= E(X_{it+h} | F_t, F_{t-1}, \ldots, X_{it}, X_{it-1}, \ldots) \\ &= E(\Lambda_{t+h} F_{t+h} + e_{t+h} | F_t, F_{t-1}, \ldots, X_{it}, X_{it-1}, \ldots) \\ &= \beta_{it}^{h\prime} F_t + a_{it}^{h}(L) e_{it} \end{aligned} \tag{4}$$

where $\beta_{it}^{h\prime} = \Lambda_{it+h} \prod_{s=t+1}^{t+h} \Phi_s$ and $a_{it}^{h}(L) e_{it} = E[a_{it+h}(\mathrm{L}) e_{t+h-1} | F_t, F_{t-1}, \ldots, X_{it}, X_{it-1}, \ldots] = E[e_{it+h} | e_{it}, e_{it-1}, \ldots]$, where the latter is obtained by making the assumption that $\{e_{it}\}$ and $\{\eta_t\}$ are independent and that expectations are linear.

Motivated by the literature on structural breaks in housing market dynamics, this study assumes a single break at time $t = \tau$ and considers three scenarios, which incorporate a break in $\Lambda$, $\Phi$, or $a_{it}(L)$, respectively. The three scenarios are presented as follows:

***Scenario 1: A single break in factor loadings, $\Lambda$, of the forecast regression***
Specifically, $\Lambda_{it} = \Lambda_{i1}$, $t < \tau$, and $\Lambda_{it} = \Lambda_{i2}$, $t \geq \tau$. In the scenario, Eq. (4) is modified to be the following:

$$X_{it+h|t} = \begin{cases} \beta_{i1}^{h\prime} F_t + a_i^h(L)\, e_{it}, t < \tau & \mathit{where} \quad \beta_{i1}^{h\prime} = \Lambda_{i1} \Phi^h \\ \beta_{i2}^{h\prime} F_t + a_i^h(L)\, e_{it}, t \geq \tau, & \mathit{where} \quad \beta_{i2}^{h\prime} = \Lambda_{i2} \Phi^h \end{cases} \tag{5}$$

[4] Housing starts in DC are zero in most periods from 1995 to 1997, and thus the model excludes its housing volume.

**Scenario 2: A single break in the factor autoregressive process, Φ, of the forecast regression** Specifically, $\Phi_t = \Phi_1$, $t < \tau$, and $\Phi_t = \Phi_2$, $t \geq \tau$. In the scenario, Eq. (4) is modified as follows:

$$X_{it+h|t} = \begin{cases} \beta_{i1}^{h\prime} F_t + a_i^h(L) e_{it}, t < \tau \quad where \quad \beta_{i1}^{h\prime} = \Lambda_i \Phi_1^h \\ \beta_{i2}^{h\prime} F_t + a_i^h(L) e_{it}, t \geq \tau, \quad where \quad \beta_{i2}^{h\prime} = \Lambda_i \Phi_2^h \end{cases} \tag{6}$$

***Scenario 3: A single break in innovations' autoregressive dynamics, $a_{it}(L)$, of the forecast regression*** Specifically, $a_{it}(L) = a_{i1}(L)$, $t < \tau$, and $a_{it}(L) = a_{i2}(L)$, $t \geq \tau$. In the scenario, Eq. (4) is modified to be the following:

$$X_{it+h|t} = \begin{cases} \beta_{i1}^{h\prime} F_t + a_{i1}^h (L) \, e_{it}, \, t < \tau \\ \beta_{i2}^{h\prime} F_t + a_{i2}^h (L) \, e_{it}, \, t \geq \tau \end{cases} \tag{7}$$

where $\beta_i^{h\prime} = \Lambda_i \Phi_h$.

Although the scenario of instability is not known a priori, we are able to identify the feature of observed structural instability by working backwards (Stock and Watson (2008). This study conducts 4-period ahead predictions (i.e., $p = 4$) for the US housing market. The 4-period ahead forecast, $X_{it+4}^{(4)}$, corresponds to housing price (volume) growths over the next 4 periods. All forecasts are obtained by the following forecasting regression:

$$X_{it+4}^{(4)} = \mu_i + \beta_i' \hat{F}_t + \sum_{j=0}^{p-1} \alpha_{ij}^4 \widehat{e_{it-j}} + error \tag{8}$$

## 4 Empirical Findings

The paper has three main tasks. First, it determines the number of housing factors for (sub)samples. Second, it conducts instability tests for in-sample factor-loadings and the three scenarios of out-of-sample forecasts for price and volume cycles. The three scenarios are: the forecast using housing factors estimated from the full sample and full-sample estimates of the factor loadings ("full–full"), that using housing factors estimated from the full sample and split-sample estimates of the factor loadings ("full-split"), and that using split-sample estimates of housing factors and factor loadings ("split–split"). Third, it compares the forecasting performances of the three scenarios in the pre- and post-break subsamples.

### 4.1 How Many Housing Factors?

This study adopts two approaches to estimate the number of housing factors. Table 1 shows the first estimation: Panel information criteria ($\mathrm{IC_p}$) suggested by Bai and Ng (2002), and the results point out that there are four factors for the full sample and

**Table 1** Number of factors estimated using Bai and Ng (2002) criteria

| Sample | Period | ICp1 | ICp2 | ICp3 |
|---|---|---|---|---|
| Full | 1988Q1–2012Q2 | 4 | 3 | 10 |
| Pre-1999 | 1988Q1–1998Q4 | 4 | 3 | 10 |
| Post-1999 | 1999Q1–2012Q2 | 2 | 2 | 10 |

ICp refers to the Panel Information Criteria suggested in Bai and Ng (2002)

**Table 2** Canonical correlations between subsample and full-sample estimates of the factors

| Estimated number of factors | | Pre-1999 | | | | Post-1999 | | | |
|---|---|---|---|---|---|---|---|---|---|
| Full | Subsample | 1 | 2 | 3 | 4 | 1 | 2 | 3 | 4 |
| 3 | 3 | 1 | 0.98 | 0.86 | | 1 | 1 | 0.73 | |
| 4 | 3 | 1 | 0.98 | 0.93 | | 1 | 1 | 0.74 | |
| 4 | 4 | 1 | 0.98 | 0.97 | 0.8 | 1 | 1 | 0.74 | 0.26 |

The table shows the squared canonical correlations (Stock and Watson 2002a, b) between the estimated factors in the indicated subsample and the factors estimated over the full sample. Factors are estimated using principal components

2–4 factors for subsamples. Table 2 exhibits the second approach proposed by Stock and Watson (2002a, b), and close-to-unity canonical correlations suggest that the full-sample and subsample factors are spanned over the same factor space. The result indicates that the squared canonical correlations decline substantially as four factors are considered for both the full and subsamples, particularly for the post-1999 subsample (drop from the 3rd canonical correlation of 0.74 to the 4th one of only 0.26), corresponding to the estimates based on Bai and Ng (2002). Based on the results of the two approaches, this study chooses four factors for the full sample and three factors for the two subsamples.

### 4.2 Structural Instability of Housing Price Cycles and Volume Cycles

Table 3 shows Chi squared Chow statistics based on Newey–West (1987) to test stability for three scenarios. The results suggest that in general housing prices are more unstable than housing starts. With respect to factor loadings (in-sample), there are 32 states with instable prices, but only 17 states with instable housing-start dynamics at the 5% significance level. Regarding 4-period ahead forecasts, all states display instability of factor-loading forecasts (except for Connecticut, Maine, and New York for housing prices; North Dakota for housing volumes). Also, most states display unstable forecasts of factor autoregressive process across subperiods, except for California, Connecticut, Georgia, Maine, New York, Oklahoma, and Washington DC for house prices; Connecticut, Hawaii, and North Dakota for housing starts. Otherwise, the instability test results of the third scenario, instability in idiosyncratic dynamics, are mixed. There are in total 19 states showing stable forecasts of idiosyncratic housing price dynamics, and only 14 states displaying stable forecasts of idiosyncratic volume movements. Still, state-level housing markets showing instable idiosyncratic

**Table 3** Chow statistics testing the stability of the factor loadings and three scenarios instability in 4-step-ahead forecasting equations

| States and regions | Factor loadings | | Scenario 1 | | Scenario 2 | | Scenario 3 | |
|---|---|---|---|---|---|---|---|---|
| | Price | Volume | Price | Volume | Price | Volume | Price | Volume |
| AK | 11.7* | 2.5 | 61** | 101.8** | 38.4** | 31.4** | 9.2 | 33.9** |
| AL | 8.9 | 2.8 | 82.6** | 96.8** | 35.6** | 32.9** | 65.3** | 27** |
| AR | 22.3** | 2.1 | 80.9** | 114.4** | 45.4** | 41** | 6.1 | 25** |
| AZ | 50.8** | 12.7* | 67.3** | 106.6** | 51.7** | 79.9** | 11.3* | 39.9** |
| CA | 16.4** | 7.8 | 37.6** | 69.6** | 6 | 17.8** | 22.3** | 18** |
| CO | 24.3** | 11.9* | 127.7** | 82.1** | 27.8** | 57.6** | 22.6** | 51.9** |
| CT | 13.7** | 42.4** | 16.3 | 40.8** | 8.9 | 10.1* | 3.7 | 21.5** |
| DC | 3.3 | – | 21.9** | – | 12.2* | – | 3.1 | – |
| DE | 15.2** | 7 | 55.1** | 112.7** | 39.6** | 50.3** | 20.7** | 18.5** |
| FL | 82.4** | 15.7** | 88** | 228.9** | 69.4** | 44.5** | 38.8** | 31.1** |
| GA | 12.9* | 24** | 121.7** | 69.7** | 11.8* | 44.9** | 45.8** | 17.5** |
| HI | 23.2** | 5.2 | 66.3** | 28.6** | 23.7** | 10.5* | 27.7** | 6.4 |
| IA | 2 | 15.8** | 167.5** | 77.3** | 17.2** | 21.5** | 58.7** | 21.8** |
| ID | 29.3** | 1.5 | 241.2** | 102.8** | 91.6** | 58.9** | 25.2** | 51.8** |
| IL | 138.4** | 18.8** | 159.1** | 171.4** | 52.6** | 44.5** | 58.4** | 33.9** |
| IN | 23.5** | 1.8 | 100.8** | 154.7** | 37.1** | 46.6** | 59.2** | 32.6** |
| KS | 2.3 | 10.6* | 56.1** | 146.5** | 18.4** | 49.6** | 11.5* | 14.1* |
| KY | 46.2** | 14.7** | 112.4** | 70.9** | 20.2** | 26.7** | 17.2** | 25.6** |
| LA | 17** | 2.6 | 53** | 119** | 33.9** | 84.1** | 4.2 | 34.9** |
| MA | 37.4** | 14.8** | 62.5** | 31.3** | 36** | 17.7** | 4.7 | 11.8* |
| MD | 22.1** | 1.1 | 79.7** | 46.4** | 45.7** | 28.7** | 27.2** | 22** |
| ME | 16.1** | 6.8 | 21.2* | 61.2** | 6.5 | 35** | 2.4 | 15.7** |
| MI | 15** | 9 | 198.7** | 62.5** | 26.9** | 45.3** | 142.2** | 31.2** |
| MN | 26.1** | 3.3 | 81.5** | 168.2** | 25.2** | 50.4** | 36.9** | 51.7** |
| MO | 2 | 12.4* | 111.2** | 80** | 24.2** | 31.4** | 18.1** | 21.7** |
| MS | 23.1** | 15.4** | 29.8** | 111** | 16.8** | 49.9** | 5.2 | 33.1** |
| MT | 9.3 | 11.5* | 130.5** | 63** | 89.7** | 21.7** | 8 | 16.7** |
| NC | 10* | 2.4 | 32.6** | 69.5** | 18.1** | 41.3** | 12.9* | 19.9** |
| ND | 31.9** | 1.2 | 40** | 8 | 28.2** | 5.2 | 29.5** | 1.5 |
| ne | 7.7 | 10.4* | 117.3** | 94.4** | 22.6** | 32.8** | 49.6** | 38.4** |
| NH | 22.2** | 6.3 | 39.3** | 124.4** | 29.8** | 34.2** | 3.3 | 21.8** |
| NJ | 50.4** | 13.9** | 47.5** | 71.9** | 16.2** | 15.9** | 6.8 | 15.2** |
| NM | 4.4 | 23.3** | 125.8** | 85.9** | 78.3** | 69.8** | 18.6** | 25.1** |
| NV | 62.8** | 7.9 | 107.4** | 183.3** | 79** | 50.9** | 41.1** | 35.1** |
| NY | 10.6* | 30.6** | 10.8 | 84.3** | 0.6 | 22.5** | 6 | 7.9 |

**Table 3** continued

| States and regions | Factor loadings | | Scenario 1 | | Scenario 2 | | Scenario 3 | |
|---|---|---|---|---|---|---|---|---|
| | Price | Volume | Price | Volume | Price | Volume | Price | Volume |
| OH | 81** | 12.1* | 296.6** | 182.6** | 67.9** | 56.1** | 142.2** | 51.4** |
| OK | 19.4** | 5.8 | 78.5** | 131.4** | 11.4* | 62.1** | 14.5* | 22.2** |
| OR | 47.5** | 14.2** | 84** | 69.5** | 32.1** | 40** | 45.6** | 23.5** |
| PA | 27.3** | 22.4** | 108.7** | 33.6** | 75.3** | 14.8** | 17.1** | 2.9 |
| RI | 38.4** | 16.9** | 137.4** | 39.7** | 27.2** | 22** | 33** | 6.6 |
| SC | 24.9** | 13* | 56.7** | 120.6** | 17.9** | 52.7** | 40.7** | 49** |
| SD | 10.4* | 17.6** | 31.5** | 124.6** | 14.5** | 24.9** | 2.2 | 14.2* |
| TN | 17.8** | 4.8 | 49** | 79.2** | 24.9** | 55.7** | 24.4** | 9.9 |
| TX | 3.6 | 2.1 | 32.9** | 215** | 21.9** | 89.9** | 16.5** | 55** |
| UT | 2.3 | 14** | 137.5** | 61.2** | 76.3** | 47.4** | 2.9 | 12.9* |
| VA | 8.2 | 10.2* | 98.4** | 121.7** | 55.1** | 15.7** | 26.9** | 32.4** |
| VT | 5.5 | 8.1 | 24** | 33.5** | 20.5** | 28.5** | 5.1 | 2.2 |
| WA | 13.8** | 5.6 | 119.1** | 59.8** | 60.5** | 27.8** | 58.5** | 14.2* |
| WI | 37.1** | 6.3 | 148.3** | 125.1** | 50.2** | 32** | 60.8** | 26.2** |
| WV | 2.2 | 1.4 | 132.5** | 77.9** | 63.6** | 50.2** | 16.3** | 12.1* |
| WY | 9.5* | 15.2** | 93.4** | 236.5** | 56.9** | 95.6** | 24.5** | 6 |
| Northeast | 17.1** | 28** | 41.9** | 95.4** | 25.1** | 45.7** | 13.8* | 28.6** |
| Midwest | 3.7 | 3.9 | 100.9** | 116.3** | 43.6** | 69.8** | 10.2 | 33.9** |
| South | 6.2 | 6.2 | 23.5** | 137.1** | 12.9* | 46.3** | 6.5 | 30.6** |
| West | 4.7 | 8.2 | 31.2** | 57.6** | 10.3* | 34** | 13.4* | 13.3* |

The table shows Chi squared Chow statistics computed by Newey–West (1987) standard errors. Structural instability exists as the Chow statistics exceed standard *5 and **1% critical values. Factor loading regression: $X_{it}=\Lambda_i'\hat{\hat{F}}_t+e_{it}$; Forecasting regression:$X_{it+4}^{(4)}=\mu_i+\beta_i'\hat{F}_t+\sum_{j=0}^{p-1}\alpha_{ij}^4\widehat{e_{it-j}}+error$. Scenario 1: A single break in factor loadings, $\Lambda$; Scenario 2: A single break in the factor dynamics, $\Phi$; Scenario 3: A single break in factor dynamics, $a_{it}\ (L)$

dynamics dwarf those lacking this instability feature. The results provide evidence that it is challenging to make forecasts of housing price and volume cycles for most states primarily due to instability in factor loadings and factor autoregressive process.

Table 4 reveals instability patterns across different regional housing markets. Not surprisingly, the probability of rejecting the null hypothesis of stability for the Northeast (80%), which contains many states with high fluctuations in housing market dynamics, is the highest among the 4 regions. The West has the second highest probability (61%), and the South has the lowest one (51%). Instability in the Northeastern housing market occurs in the first and second scenarios, factor loadings and housing factor dynamics, but is not the case in the idiosyncratic dynamics (the probability is only 45% for the Northeast). The results echo the ideas in the real estate literature, which points out that the Northeast and the West have nonlinear housing market dynamics and are more subject to housing bubbles than the Midwest and the South (e.g., Huang 2014; Kim and Bhattacharya 2009; Moench and Ng 2011; etc.).

**Table 4** Summary of Chow tests by 4 housing regions: null-hypothesis rejection proportion at the 5% significance level

| Regions | States number | Factor loading | Scenario 1 | Scenario 2 | Scenario 3 |
|---|---|---|---|---|---|
| Northeast | 20 | 0.8 | 0.9 | 0.85 | 0.45 |
| Midwest | 26 | 0.58 | 0.96 | 0.96 | 0.88 |
| South | 35 | 0.51 | 1 | 1 | 0.83 |
| West | 28 | 0.61 | 1 | 0.96 | 0.82 |

### 4.3 A Nationwide or Localized Housing Bubble? Implications from Three-Scenario Forecast Comparisons

Table 5 displays how much forecasts of housing cycles can be improved as structural instability is considered by showing relative mean square errors (MSEs), the ratios of two residuals from two different in-sample regressions. Specifically, this study computes the ratios for MSEs of full-split forecasts (computed by the residuals from split-sample regressions onto full-sample factors) over those of full–full forecasts (computed by the residuals from full-sample regressions onto full-sample factors). Less-than-unity ratios indicate that full-split forecasts have lower MSEs and thus outperform full–full forecasts. Similarly, as the MSEs of the split–split predictions are smaller than those of the full-split methods, split–split forecasts outperform full-split forecasts.

Regarding housing price cycles, the MSE ratios of all states show that full-split forecasts outperform full–full forecasts because all the ratios are smaller than unity before 1999. In particular, price full-split forecasts of Nevada, Florida and Arizona are improved the most significantly compared with full–full scenarios because their ratios are quite low (0.13, 0.14, and 0.22, respectively). On the other hand, price full-split forecasts of Alaska, Connecticut, Maine, Oklahoma, and South Dakota show little improvement (by less than 20%) compared with full–full scenarios. Also, in the post-1999 subperiod, price full-split predictions are better than full–full scenarios for all states, even though improvement in full-split forecasts of some states (Illinois, Massachusetts, New York, Pennsylvania, Washington DC, and Wisconsin) is marginal (by less than 10%). Nevertheless, the comparison results between full-split and split–split forecasts are mixed. In the pre-1999 subperiod, among the 19 states and 2 regions whose full-split forecasts are better than split–split forecasts, split–split forecasts are improved marginally (by less than 10% in MSEs) compared with full-split scenarios for 7 states and 2 regions. In the post-1999 subperiod, full-split forecasts serve as the best method among all scenarios for all states.[5]

Similar to housing price cycles, the relative MSEs of all states show that full-split forecasts of housing volume cycles outperform full–full forecasts (except for Rhode Island and Vermont in the post-1999 subsample). In general, the forecast improvement in the pre-1999 subperiod is more substantial than in the post-1999 subperiod given that MSE ratios are lower for the former than the latter. In addition, full-split forecasts are

[5] MA is the only exception whose MSE ratio of split-split/full-split is less than unity (0.90) after 1999.

**Table 5** Relative MSEs of 4-step ahead Forecasts: Housing Prices and Volumes

| States and regions | Pre-1999 | | | | Post-1999 | | | |
|---|---|---|---|---|---|---|---|---|
| | Price | | Volume | | Price | | Volume | |
| | FS/FF | SS/FS | FS/FF | SS/FS | FS/FF | SS/FS | FS/FF | SS/FS |
| AK | 0.89 | 0.85 | 0.52 | 1.51 | 0.82 | 1.28 | 0.65 | 0.89 |
| AL | 0.43 | 0.46 | 0.49 | 0.81 | 0.67 | 1.32 | 0.56 | 1.17 |
| AR | 0.65 | 0.71 | 0.72 | 0.75 | 0.64 | 1.39 | 0.60 | 1.22 |
| AZ | 0.22 | 0.96 | 0.26 | 1.32 | 0.75 | 1.36 | 0.53 | 1.20 |
| CA | 0.42 | 1.28 | 0.59 | 1.18 | 0.67 | 1.36 | 0.58 | 1.06 |
| CO | 0.64 | 0.93 | 0.38 | 1.12 | 0.53 | 1.22 | 0.54 | 1.22 |
| CT | 0.83 | 0.89 | 0.48 | 0.82 | 0.82 | 1.07 | 0.55 | 1.01 |
| DC | 0.68 | 1.52 | – | – | 0.95 | 1.45 | – | – |
| DE | 0.43 | 1.11 | 0.57 | 1.29 | 0.79 | 1.10 | 0.61 | 1.18 |
| FL | 0.14 | 1.01 | 0.46 | 1.15 | 0.74 | 1.17 | 0.49 | 1.46 |
| GA | 0.45 | 0.82 | 0.31 | 1.05 | 0.60 | 1.05 | 0.61 | 1.12 |
| HI | 0.74 | 1.21 | 0.89 | 1.10 | 0.76 | 1.40 | 0.83 | 0.89 |
| IA | 0.53 | 0.87 | 0.68 | 1.20 | 0.58 | 0.99 | 0.76 | 1.14 |
| ID | 0.33 | 1.20 | 0.43 | 0.93 | 0.68 | 1.22 | 0.78 | 1.18 |
| IL | 0.27 | 0.91 | 0.37 | 1.09 | 0.95 | 1.19 | 0.36 | 1.45 |
| IN | 0.48 | 0.57 | 0.56 | 1.12 | 0.43 | 1.06 | 0.62 | 1.15 |
| KS | 0.74 | 1.14 | 0.79 | 0.78 | 0.59 | 1.09 | 0.59 | 1.26 |
| KY | 0.66 | 0.65 | 0.52 | 1.13 | 0.59 | 1.09 | 0.60 | 0.99 |
| LA | 0.65 | 0.83 | 0.30 | 1.02 | 0.80 | 1.15 | 0.55 | 1.15 |
| MA | 0.79 | 0.87 | 0.51 | 0.96 | 0.95 | 0.90 | 0.61 | 1.21 |
| MD | 0.36 | 0.98 | 0.54 | 1.53 | 0.78 | 1.10 | 0.58 | 1.20 |
| ME | 0.82 | 1.02 | 0.46 | 1.38 | 0.70 | 1.41 | 0.78 | 1.07 |
| MI | 0.33 | 1.12 | 0.27 | 1.17 | 0.72 | 1.35 | 0.56 | 1.09 |
| MN | 0.43 | 1.37 | 0.46 | 1.22 | 0.84 | 1.11 | 0.45 | 1.45 |
| MO | 0.59 | 1.25 | 0.47 | 1.06 | 0.67 | 1.15 | 0.67 | 1.21 |
| MS | 0.75 | 0.72 | 0.61 | 0.90 | 0.75 | 1.04 | 0.65 | 1.17 |
| MT | 0.67 | 0.77 | 0.52 | 0.98 | 0.74 | 1.46 | 0.73 | 1.36 |
| NC | 0.68 | 0.83 | 0.38 | 1.09 | 0.75 | 1.07 | 0.73 | 1.35 |
| ND | 0.54 | 0.68 | 0.88 | 1.10 | 0.83 | 1.15 | 0.95 | 1.03 |
| NE | 0.62 | 0.85 | 0.51 | 1.28 | 0.55 | 1.17 | 0.70 | 1.17 |
| NH | 0.64 | 0.97 | 0.55 | 1.00 | 0.73 | 1.06 | 0.55 | 1.05 |
| NJ | 0.71 | 0.95 | 0.70 | 1.05 | 0.82 | 0.99 | 0.33 | 1.06 |
| NM | 0.47 | 0.83 | 0.48 | 0.86 | 0.70 | 1.32 | 0.57 | 1.10 |
| NV | 0.13 | 1.21 | 0.37 | 0.89 | 0.71 | 1.27 | 0.56 | 1.14 |
| NY | 0.66 | 1.20 | 0.60 | 1.15 | 0.93 | 1.14 | 0.79 | 1.00 |
| OH | 0.28 | 0.56 | 0.51 | 1.15 | 0.60 | 1.29 | 0.39 | 1.32 |

**Table 5** continued

| States and regions | Pre-1999 | | | | Post-1999 | | | |
|---|---|---|---|---|---|---|---|---|
| | Price | | Volume | | Price | | Volume | |
| | FS/FF | SS/FS | FS/FF | SS/FS | FS/FF | SS/FS | FS/FF | SS/FS |
| OK | 0.93 | 0.89 | 0.49 | 1.25 | 0.82 | 1.04 | 0.61 | 1.24 |
| OR | 0.48 | 1.57 | 0.44 | 0.89 | 0.70 | 1.51 | 0.67 | 1.21 |
| PA | 0.41 | 1.20 | 0.40 | 1.51 | 0.90 | 1.17 | 0.98 | 0.95 |
| RI | 0.67 | 1.08 | 0.45 | 1.31 | 0.84 | 1.06 | 1.01 | 1.02 |
| SC | 0.57 | 1.07 | 0.38 | 0.80 | 0.72 | 0.99 | 0.62 | 1.44 |
| SD | 0.83 | 0.86 | 0.83 | 1.04 | 0.62 | 1.01 | 0.84 | 1.13 |
| TN | 0.59 | 0.83 | 0.47 | 1.02 | 0.57 | 1.06 | 0.68 | 1.16 |
| TX | 0.61 | 1.31 | 0.43 | 0.89 | 0.78 | 1.06 | 0.47 | 1.31 |
| UT | 0.57 | 0.84 | 0.42 | 0.92 | 0.75 | 1.38 | 0.63 | 1.15 |
| VA | 0.39 | 0.79 | 0.66 | 0.88 | 0.86 | 1.32 | 0.33 | 1.26 |
| VT | 0.69 | 1.03 | 0.67 | 1.14 | 0.89 | 1.49 | 1.08 | 1.01 |
| WA | 0.60 | 0.90 | 0.88 | 0.64 | 0.89 | 1.05 | 0.87 | 1.10 |
| WI | 0.43 | 1.00 | 0.65 | 1.08 | 1.00 | 1.08 | 0.59 | 0.99 |
| WV | 0.35 | 0.80 | 0.53 | 1.14 | 0.84 | 1.08 | 0.40 | 1.06 |
| WY | 0.37 | 1.00 | 0.88 | 0.64 | 0.81 | 1.32 | 0.70 | 1.28 |
| Northeast | 0.84 | 0.99 | 0.36 | 2.68 | 0.99 | 1.10 | 0.69 | 1.03 |
| Midwest | 0.66 | 1.17 | 0.50 | 1.50 | 0.71 | 1.15 | 0.41 | 1.24 |
| South | 0.80 | 0.94 | 0.33 | 1.25 | 0.92 | 1.14 | 0.51 | 1.33 |
| West | 0.80 | 1.01 | 0.47 | 0.86 | 0.65 | 1.44 | 0.57 | 1.20 |

Notes: The table shows relative MSEs for housing prices and volumes. The forecasting regressions (Eq. (8)) are estimated using: full-sample factor estimates and full-sample coefficients ("full–full", FF), full-sample factor estimates and split-sample coefficients ("full-split", FS), split-sample factor estimates and full-sample coefficients ("split–split", SS)

dominated by split–split forecasts in more states in the pre-1999 (17 states and 1 region) than the post-1999 (5 states). However, for a majority of states, full-split forecasts are superior to full–full and split–split scenarios in housing volume cycles. The superiority of full-split forecasts of local housing market dynamics suggests a nationwide nature of the recent housing boom-bust cycle. In general, superior forecast performances based on full-sample factors suggest that subsample factors do not capture new common shocks to state-level housing markets after 1999. In other words, there is no peculiar shock occurring during the recent dramatic housing boom-bust cycles after 1999. Since factor loadings differ across subsamples in the full-split scenario, the findings lend support to the idea that local housing markets respond to old common shocks in a different manner during the post-1999 subperiod.

If compared to the pre-break subperiod, cross-state linkages did not change and the dynamic distinction between crisis states and non-crisis states was trivial in the post-break period, there was no new common shock to state-level housing markets over the recent boom-bust cycle. Thus, the 2007 housing crisis prevailed in a nationwide scope.

The logic of this argument is supported by Stock and Watson (2012).[6] Moreover, this study' findings are consistent with those in Del Negro and Otrok (2007), who advocate that the house price swing from 2001 to 2005 is a national phenomenon. Overall, this study provides new evidence for a nationwide housing crisis and thus suggests an active role of the government in mitigating unfavorable fluctuations in US housing markets during the recent decade.

## 5 Conclusions

This study provides insights in regard to the question, raised by former Chairman of the Board of Governors of the Federal Reserve in 2010: "whether the bubble was national or confined to a few local markets". A dynamic factor model, which incorporates house prices and volumes in all states and the 4 Census regions in the US, is utilized for investigations into local housing markets from 1988 to 2012. Three varieties of structural instability in forecasts of housing markets are examined: a structural break in housing factor loadings, a break in housing factor dynamics, or a break in idiosyncratic dynamics of housing markets.

The findings suggest that state-level housing price cycles are generally more unstable than housing volume cycles. The evidence of dynamic instability for the Northeastern housing market is the strongest among 4 regional housing markets. The results underscore the difficulty in predicting disaggregate housing markets dynamics owing to instability. We can obtain superior forecasts by using housing factors estimated by housing prices and volumes over a long period (full sample) and time-varying coefficients across subperiods before and after 1999. In the post-1999 subperiod, the full-split forecast has the best performance among the three methods. To sum up, this study provides new evidence for the nationwide nature of the recent housing boom-bust cycle, and thus suggests few risk diversification opportunities in real estate investment and an active role of the Fed in stabilizing the nationwide housing market dynamics.

The paper yields risk management and policy-making implications from the nationwide housing cycle, and it extends the literature along several directions. First, it would be of interest for future research to explore underlying drivers of housing boom-bust cycles. In particular, adding some influential predictors, such as interest rates and housing-market expectation indexes, into the factor-based frameworks could enhance forecast performances of housing market dynamics. Second, the issue concerning effectiveness of monetary-policies in stabilizing housing cycles is worthy of discussions from other perspectives. Third, more of well-developed methods can be applied to examine instability and identify the breakpoints of housing markets. Finally, more efforts can be taken to analyze dynamic linkages across local housing markets. All these lines of future research are exciting.

[6] They examine how the recent recession in 2007–2009 differs from the previous business cycles under a dynamic factor framework, and they find no new common factor of macroeconomic variables in the post-2007 period. Hence, they suggest the recent recession results from larger versions of old economic shocks rather than unpredicted new ones.

## References


Akay, O., Senyuz, Z., & Yoldas, E. (2013). Hedge fund contagion and risk-adjusted returns: A Markov-switching dynamic factor approach. *Journal of Empirical Finance, 22,* 16–29.

Akkoyun, H. C., Arslan, Y., & Kanik, B. (2013). Housing prices and transaction volume. *Journal of Housing Economics, 22*(2), 119–134.

Baffoe-Bonnie, J. (1998). The dynamic impact of macroeconomic aggregates on housing prices and stock of houses: A national and regional analysis. *Journal of Real Estate Finance and Economics, 17*(2), 179–197.

Bai, J., & Ng, S. (2002). Determining the number of factors in approximate factor models. *Econometrica, 70*(1), 191–221.

Baltagi, B. H., & Li, J. (2014). Further evidence on the spatio-temporal model of house prices in the United States. *Journal of Applied Econometrics, 29*(3), 515–522.

Banerjee, A., Marcellino, A. M., & Masten, I. (2008). Forecasting macroeconomic variables using diffusion indexes in short samples with structural change. In D. Rapach & M. Wohar (Eds.), *Forecasting in the presence of structural breaks and model uncertainty*. Bingley: Emerald Group.

Berger, T., & Pozzi, L. (2013). Measuring time-varying financial market integration: An unobserved components approach. *Journal of Banking & Finance, 37*(2), 463–473.

Boysen-Hogrefe, J. (2013). A dynamic factor model with time-varying loadings for euro area bond markets during the debt crisis. *Economics Letters, 118*(1), 50–54.

Breitung, J., & Eickmeier, S. (2011). Testing for structural breaks in dynamic factor models. *Journal of Econometrics, 163*(1), 71–84.

Campbell, J. Y., & Cocco, J. F. (2007). How do house prices affect consumption? Evidence from micro data. *Journal of Monetary Economics, 54*(3), 591–621.

Clayton, J., Miller, N., & Peng, L. (2010). Price-volume correlation in the housing markets: Causality and co-movements. *Journal of Real Estate Finance and Economics, 40*(1), 14–40.

Cordis, A. S., & Kirby, C. (2011). Regime-switching factor models in which the number of factors defines the regime. *Economics Letters, 112*(2), 198–201.

Crawford, G. W., & Fratantoni, M. C. (2003). Assessing the forecasting performance of regime-switching, ARIMA and GARCH models of house prices. *Real Estate Economics, 31*(2), 223–243.

Croce, R. M., & Haurin, D. R. (2009). Predicting turning points in the housing market. *Journal of Housing Economics, 18*(4), 281–293.

Del Negro, M., & Otrok, C. (2007). 99 luftballons: Monetary policy and the house price boom across U.S. States. *Journal of Monetary Economics, 54*(7), 1962–1985.

Edelstein, R. H., & Tsang, D. (2007). Dynamic residential housing cycles analysis. *Journal of Real Estate Finance and Economics, 35*(3), 295–313.

Fadiga, M. L., & Wang, Y. S. (2009). A multivariate unobserved component analysis of US housing market. *Journal of Economics and Finance, 33*(1), 13–26.

Flor, M. A., & Klarl, T. (2017). On the cyclicity of regional house prices: New evidence for U.S. metropolitan statistical areas. *Journal of Economic Dynamics and Control, 77,* 134–156.

Garcia-Martos, C., Rodriguez, J., & Sanchez, M. J. (2011). Forecasting electricity prices and their volatilities using unobserved components. *Energy Economics, 33*(6), 1227–1239.

Goodman, A. C., & Thibodeau, T. G. (2008). Where are the speculative bubbles in US housing markets? *Journal of Housing Economics, 17*(2), 117–137.

Hao, L., & Ng, E. C. Y. (2011). Predicting Canadian recessions using dynamic probit modelling approaches. *Canadian Journal of Economics, 44*(4), 1297–1330.

Hassani, H., Ghodsi, Z., Gupta, R., & Segnon, M. (2017). Forecasting home sales in the four Census regions and the aggregate US economy using singular spectrum analysis. *Computational Economics, 49*(1), 83–97.

Hendry, D. F., & Clements, M. P. (2004). Pooling of forecasts. *Econometrics Journal, 7*(1), 1–31.

Holly, S., Pesaran, M. H., & Yamagata, T. (2010). A spatio-temporal model of house prices in the USA. *Journal of Econometrics, 158*(1), 160–173.

Huang, M. (2013a). The role of people's expectation in the recent US housing boom and bust. *The Journal of Real Estate Finance and Economics, 46*(3), 452–479.

Huang, M. (2013b). Housing bubble implications: The perspective of housing price predictability. *Economics Bulletin, 33*(1), 586–596.

Huang, M. C. (2014). Monetary policy implications of housing shift-contagion across regional markets. *Journal of Economics and Finance, 38*(4), 589–608.

Kim, S. W., & Bhattacharya, B. (2009). Regional housing prices in the USA: An empirical investigation of non- linearity. *Journal of Real Estate Finance and Economics, 38*(4), 443–460.

Koop, G., & Korobills, D. (2011). UK macroeconomic forecasting with many predictors: Which model forecast best and when do they do so? *Economic Modelling, 28*(5), 2307–2318.

Lai, R. N., & Van Order, R. (2010). Momentum and house price growth in the U.S.: Anatomy of a bubble. *Real Estate Economics, 38*(4), 753–773.

Leamer, E. E. (2007). *Housing is the business cycle*. NBER Working Paper No. 13248, National Bureau of Economic Research.

Lee, J. (2012). Measuring business cycle co-movements in Europe: Evidence from a dynamic factor model with time-varying parameters. *Economics Letters, 115*(3), 438–440.

Miles, M. (2015). Regional house price segmentation and convergence in the US: A new approach. *Journal of Real Estate Finance and Economics, 50*(1), 113–128.

Miller, N., Peng, L., & Sklarz, M. (2011a). House prices and economic growth. *Journal of Real Estate Finance and Economics, 42*(4), 522–541.

Miller, N., Peng, L., & Sklarz, M. (2011b). The economic impact of anticipated house price changes—Evidence from home sales. *Real Estate Economics, 39*(2), 345–378.

Moench, E., & Ng, S. (2011). A hierarchical factor analysis of U.S. housing market dynamics. *Econometrics Journal, 14*(1), C1–C24.

Ng, E. C. Y. (2012). Forecasting US recessions with various risk factors and dynamic probit models. *Journal of Macroeconomics, 34*(1), 112–125.

Oikarinen, E. (2012). Empirical evidence on the reaction speeds of housing prices and sales to demand shocks. *Journal of Housing Economics, 21*(1), 41–54.

Poncela, P., Rodriguez, J., Sanchez-Mangas, R., & Senra, E. (2011). Forecast combination through dimension reduction techniques. *International Journal of Forecasting, 27*(2), 224–237.

Rapach, D. E., & Strauss, J. K. (2009). Differences in housing price forecastability across US states. *International Journal of Forecasting, 25*(2), 351–372.

Shiller, R. J. (2006). Long-term perspectives on the current boom in home prices. *Economists' Voice*, *3*(4), 1–11.

Shiller, R. J. (2008). Understanding recent trends in house prices and homeownership. In Jackson Hole Conference Series (Ed.), Housing, housing finance and monetary policy (pp. 85–123). Kansas City, MO.

Silos, P., & Vilan, D. (2009). Is more still better? Revisiting the sixth district coincident indicator. *Federal Reserve Bank of Atlanta Economic Review*, *94*(3), 1–8.

Stock, J. H., & Watson, M. W. (2002a). Macroeconomic forecasting using diffusion indexes. *Journal of Business and Economic Statistics, 20*(2), 147–162.

Stock, J. H., & Watson, M. W. (2002b). Forecasting using principal components from a large number of predictors. *Journal of the American Statistical Association, 97*(460), 1167–1179.

Stock, J. H., & Watson, M. W. (2007). Why has inflation become harder to forecast? *Journal of Money, Credit, and Banking, 39*(1), 3–33.

Stock, J. H., & Watson, M. W. (2008). Forecasting in dynamic factor models subject to structural instability. In J. Castle & N. Shephard (Eds.), *The methodology and practice of econometrics, a festschrift in honour of Professor David F. Hendry*. Oxford: Oxford University Press.

Stock, J. H., & Watson, M. W. (2009). The evolution of national and regional factors in U.S. housing construction. In T. Bollerslev, J. Russell, & M. Watson (Eds.), *Volatility and time series econometrics: Essays in Honour of Robert F. Engle*. Oxford: Oxford University Press.

Stock, J. H., & Watson, M. W. (2012). Disentangling the channels of the 2007–2009 recession. *Brookings Papers on Economic Activity*, *43*(1), 81–156.

Topel, R., & Rosen, S. (1988). Housing investment in the United States. *Journal of Political Economy, 96*(4), 718–740.

Wit, E. R., Englund, P., & Francke, M. K. (2013). Price and transaction volume in the Dutch housing markets. *Regional Science and Urban Economics, 43*(2), 220–241.

Zaher, F. (2007). Evaluating factor forecasts for the UK: The role of asset prices. *International Journal of Forecasting, 23*(4), 679–693.