

Volume 33, Issue 1

Housing bubble implications: The perspective of housing price predictability

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Abstract

The paper extracts housing bubble implications from the perspective of housing price predictability. Specifically, it examines predictive powers of the good-time-to-buy (GTTB) index and the federal funds rate in nationwide and state-level housing price returns by means of out-of-sample tests suggested in Rapach and Wohar (2006). The GTTB index is used to proxy for households' expectations, and the interest rate represents the economic fundamental. The empirical results indicate the predictive advantage of the GTTB index over the federal funds rate, and suggest higher vulnerability to bubble-like housing cycles in the housing markets of California, New York, New Jersey, Washington, Massachusetts and Arizona than other states. Overall, the study sheds insights into divergent predictability patterns between in-sample and out-of-sample forecasts, those between aggregate and disaggregate housing price dynamics, and those across state-level housing markets.

Housing bubble implications: The perspective of housing price predictability

1. Introduction

The predictability of asset price dynamics is a highly appealing issue for researchers, policy-makers and investors. A useful signal of asset price movements facilitates risk management by protecting investors from big losses during asset market crises. Noticeably, while the prediction of stock returns is intensively documented by numerous studies, the literature on housing price forecasts is relatively rare. Motivated by the recent dramatic housing boom-and-bust cycle, a growing body of literature has been devoted to predicting asset price returns although it is always a challenge to deliver a satisfactory forecast. Also, comparisons between in-sample and out-of-sample housing price forecasts, and predictive differences between aggregate and disaggregate housing price returns are hardly addressed.

Thus, this study adds to the thin literature on prediction of housing price returns by investigating predictive powers of two potential housing price predictors, households' expectations and the interest rate, respectively. On the one hand, the federal funds rate is chosen to proxy for the monetary policy shock, and it represents the economic fundamental. On the other hand, the good-time-to-buy (GTTB) index, which is computed as the sum of 100 and the percentage difference between responses of "buy" and "sell" in the Survey of Consumers administered by University of Michigan, is utilized to represent households' expectations about housing price dynamics.

Furthermore, the paper aims to extract important housing bubble implications by means of comparing housing price forecasting abilities of these two potential predictors. As documented in Stiglitz (1990) and Himmelberg *et al.* (2005), a housing bubble refers to that a high price surge is primarily caused by investors' unrealistic beliefs in even higher selling prices in the future rather than economic fundamentals. Similarly, Case and Shiller (2003) document that a housing bubble occurs as economic fundamentals fail to explain a temporary price climb which is mainly driven by peoples' over-optimistic expectations of future housing price appreciation. Thus, households' expectations from the demand side have attracted considerable attention of many researchers who attempt to explore the underlying causes of the recent bubble-like housing boom-bust cycle after the NBER-dated recession in 2001. In addition, there has been a vast of literature which discusses the critical roles of interest rates in driving housing price dynamics. Specifically, whether low interest rates are attributed to the recent surge in housing prices is an ongoing debate.

Noticeably, a weak predictive power of the federal funds rate and a strong forecasting ability of the GTTB index in housing market dynamics jointly imply high vulnerability to a bubble-like housing cycle. As defined in the housing market literature, a housing bubble is likely to occur as the economic fundamental fails to explain the housing asset dynamics. Although the study does not deliver direct evidence of the existence of housing bubbles during the recent decade, it provides informative implications of housing bubbles in the state-level housing markets.

Spotlighting the out-of-sample forecastability comparison across states, this paper utilizes three out-of-sample predictability tests: the Theil's U ratio, the encompassing test in McCracken (2004) ($MSE-F$ statistic), and the encompassing test in Clark and McCracken(2001) ($ENC-NEW$ statistic) , which were employed to evaluate stock return predictability in Rapach and Wohar(2006). It examines both the nationwide and state-level housing price return predictabilities in the sixteen most populous US states according to 2010 population survey conducted by the U.S. Census Bureau.

The empirical findings suggest that the housing price predictive ability of the GTTB index is generally superior to that of the federal funds rate. Besides, there are differences between in-sample and out-of-sample predictabilities for many state-level housing markets. Moreover, the federal funds rate displays a stronger power in predicting the nationwide(aggregate) housing price return than the state-level(disaggregate) ones. The $ENC-NEW$ statistic indicates that the nationwide housing price return is predictable by the interest rate up to 5-period ahead, while the economic fundamental fails to predict the disaggregate housing price returns in more than half of the selected sixteen state-level housing markets. Also, importantly, there also exists a divergent predictability pattern across states. The housing price returns in California, New York, New Jersey, Washington, Massachusetts and Arizona exhibit unpredictability as the federal funds rate works as the predictor, but they are forecastable as the GTTB index is used as the predictor.

The paper is organized as follows: Section 2 reviews the literature which motivates this study. Section 3 presents the housing market data and the two predictors, and it briefly outlines the forecasting models. Section 4 reports the primary empirical findings: the predictability phenomena of housing price returns in the nationwide and the selected 16 state-level housing markets. Finally, Section 5 makes concluding remarks.

2. Motivation

This paper is mainly motivated by three strands of the literature: the important role of households' expectations in the housing markets, the driving force of the interest rate in the housing boom-and-bust cycle, and divergent forecastability patterns between aggregate and disaggregate housing price dynamics as well as those across state-level housing markets.

First of all, both theoretical and empirical studies discuss that people's expectation has an important impact on housing price dynamics. The recent theoretical examples are Piazzesi and Schneider(2009) and Sommervoll *et al.* (2010), etc.; some recent empirical studies consist of Davis and Palumbo (2008), Glaeser *et al.* (2008), Huang(2012), among others. For instance, Piazzesi and Schneider (2009) establish a search model to address that few optimistic traders are sufficient to lead to a substantial housing price boom. Also, Sommervoll *et al.* (2010) develop a housing market model with interactions among heterogeneous agents to address how housing market cycles are associated with adaptive expectations. Concerning empirical studies, Davis and Palumbo (2008) argue that the housing price movement is driven by the demand side much more intensively during 1998-2004 than previous periods. Also, Glaeser *et al.* (2008) suggest that self-sustaining over-optimism results in an endogenous self-reinforcing bubble with irrational expectations. Recently, Huang (2012) proposes that the volatility feedback effect, which reflects the dynamics of investors' updated expectations about housing asset returns, plays an influential role in driving the US housing price dynamics during the post-1999 period.

Regarding the proxy for people's expectations, Croce and Haurin(2009) propose that the GTTB index measures the forward-looking consumer sentiment regarding housing ownership, and it is capable of predicting the housing market dynamics which are jointly characterized by some housing volume variables (i.e., housing permits, housing starts, new and existing home sales). Inspired by Croce and Haurin(2009) with respect to the choice of proxy for households' expectations, this study further examines whether the GTTB index is also able to predict both the aggregate and state-level housing price dynamics.

The second strand of the literature discusses whether the surge in housing prices is attributable to persistently relaxed monetary policies after the 2001 recession. It is an ongoing debate among policy-makers and scholars. On the one hand, Jarocinski and Smets(2008), Leamer(2007), and Taylor(2007) all emphasize that low interest rates during 2003-2005 led to the recent housing boom. Likewise, Edelstein and Tsang (2007), Goodhart and Hofmann(2007), Himmelberg *et al.*(2005), Jin and Zeng (2004), Lai and Van Order (2010), McDonald and Stokes(2012), and Shiller(2009), all advocate that the influential roles of interest rates in the recent remarkable housing market cycle. On the other hand, some recent studies, which consist of Case and Shiller (2003), Campbell *et al.* (2009), Dynan *et al.* (2006), Kuttner(2012), Mayer and Quigley (2003), Veld *et al.* (2011), all argue a minor role of interest rates in the housing boom and bust. Certainly, there are alternative variables which can proxy for the macroeconomic fundamentals. However, motivated by the vast literature which claims the critical role of interest rates in driving the recent housing price movements, the paper investigates the predictive power of the federal funds rate in the dynamics of housing price returns.

Finally, there exists a growing body of the literature on different dynamic patterns among state-level housing price returns. Three representative studies are worth our more discussions. Firstly, Negro and Otrok (2007) suggest that state-level housing markets experience considerable "local" bubble patterns, but the recent housing boom during 2000-2005 can be regarded as a "national" phenomenon. In addition, they argue that the influence of monetary policy shocks on housing market dynamics is quite limited compared to considerable housing upward movements. Secondly, Rapach and Strauss (2009) propose that housing price forecastability varies substantially across the US states. They specify that the five states, which are California, Massachusetts, New Jersey, New York and Washington, display remarkably different housing price fluctuations from the others. Thirdly, Holly

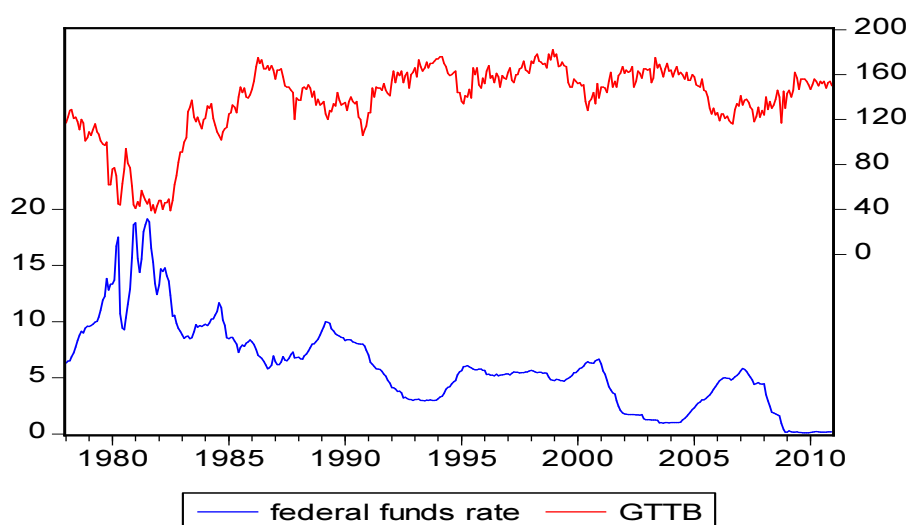
et al.(2010) suggest that house prices in California, New York and Massachusetts deviate from the long-term equilibrium price more significantly than those in Connecticut, Rhode Island, Oregon and Washington. This paper is motivated by the above representative studies in terms of the divergent dynamic patterns of state-level housing markets, and it attempts to examine whether the out-of-sample forecastability phenomena at state levels corresponds to the findings in the existing literature.

3. Data and Methodology

The Freddie Mac's Conventional Mortgage Home Price Indexes (CMHPIs) are chosen to represent the housing market dynamics because the time span of CMHPIs is longer than other alternative housing price indexes for both state-level and aggregate housing prices at the monthly frequency. The seasonal-adjusted housing prices are obtained by means of US Census Bureau's X-12-ARIMA seasonal adjustment method. The Consumer Price Index(CPI) for all urban consumers: all items less food and energy from the Department of Labor: Bureau of Labor Statistics(BLS) is used as the deflator to have a real housing price¹. Each of the real housing price returns is computed as the log first difference of the real housing price.

Based on 2010 state-level population data from the US Census Bureau, the study selects the sixteen most populous states as the state-level housing markets investigated. The analyzed period spans from 1978M1 to 2010M12 because the monthly GTTB index is available from 1978.2. The descriptive statistics of the aggregate and state CMHPIs are exhibited in Table 1. The most volatile housing markets are California, Arizona, Florida, Michigan, New York, Washington, Massachusetts, New Jersey, ranked by their standard deviations.

**Figure 1 Predictors of housing price returns:
The GTTB index (right-axis) & the federal funds rate (left-axis)**



The two chosen predictors are the interest rate and the GTTB index. The interest rate is the effective federal funds rate which comes from the dataset of Federal Reserve Bank of St. Louis. The GTTB (good-time-to-buy) index comes from the Survey of Consumers administered by the Survey Research Center of University of Michigan³. It proxies for people's expectation of housing price returns and buying conditions of the housing markets in the US. The asked question in the survey is "Generally speaking, do you think now is a good time or a bad time to buy a house?". Based on the

¹ Prices of food and energy, which are subject to various supply shocks, are not good proxies for changes in price levels because they are highly volatile and non-persistent. Thus, the core CPI, which is CPI for all urban consumers: all items less food and energy, is used to represent the aggregate price dynamics in a more appropriate manner in some recent empirical studies, such as Davis and Heathcote (2007) and Huang(2012). Similarly, Negro and Otrok(2007) use inflation in the personal consumption expenditure basket less food and energy to obtain state-level real housing price growths.

² The quarterly GTTB index is available for the period of 1956-1977.

³ The details of the survey are documented in Curtin (1982).

responses to the question, the GTTB index is computed as follows:

$$GTTB\ index = 100 + \%Good\ time - \%Bad\ time$$

Therefore, GTTB ranges from 0 to 200. Thus, a high GTTB index represents that people are optimistic for expected housing asset returns. The dynamics of the two alternative predictors are displayed in Figure 1. Noticeably, both predictors are at aggregate levels, so the empirical results reflect the association between nationwide and state-level variables of our interest to some extent.

Based on Rapach and Wohar(2006), the model is a simple linear regression with one predictor:

$$y_{t+k} = \alpha + \beta x_t + \varepsilon_{t+k} \quad (1)$$

where y_{t+k} is the housing price return at period $t+k$; which is defined as the log first difference of the real housing price; x_t is the single predictor; ε_{t+k} represents the forecast error. To mitigate the concern about serial correlation in ε_{t+k} , Newey and West(1987) standard errors of the t -statistics are adopted.

Furthermore, to avoid size distortions (i.e., t -statistic increases along with k when testing the null hypothesis of no predictability: $\beta=0$), the bootstrap procedure is implemented based on Kilian (1999), Kothari and Shanken (1997), Mark (1995) and Nelson and Kim (1993) as follows:

$$y_t = a_0 + u_{0,t} \quad (2)$$

$$x_t = b_0 + b_1 x_{t-1} + \dots + b_p x_{t-p} + u_{1,t} \quad (3)$$

where $u_t = (u_{0,t}, u_{1,t})'$ is *i.i.d.* with covariance matrix Σ .

Equation (2) and (3) are estimated by the OLS (i.e., ordinary least squares) method and the OLS residuals (i.e., $\hat{u}_t = \{\hat{u}_{0,t}, \hat{u}_{1,t}\}_{t=1}^{t=T-p}$) are generated. The optimal lag order p is chosen by Akaike information criterion (AIC) criteria, and it is restricted to the maximum order of four. The pseudo-series of disturbance terms, $\{\hat{u}_t^*\}_{t=1}^{T+100}$, are produced by $T+100$ times of randomly draws from the OLS residuals. The procedures of establishing $\{y_t^*, x_t^*\}_{t=1}^{T+100}$, and the approaches of obtaining the empirical distribution of the in-sample t -statistic and each out-of-sample statistics follow Rapach and Wohar (2006).

There are two out-of-sample forecasting models: the unrestricted model with non-zero β and the unrestricted forecast error $\hat{\varepsilon}_{1,t+k}$, as well as the restricted model with zero β and the restricted forecast error $\hat{\varepsilon}_{0,t+k}$. The zero β implies that the predictor lack a predictive power for the housing price return. The whole sample is divided into two parts: period R and period $T-R$. Thus, R refers to the "sample-split" parameter because we assume the observations in the first R periods are available to be used in the out-of-sample forecast. In this study, the total observation T is 396 (i.e., $T=396$, from 1978M1 to 2010M10); R is set to be half of the total observation T (i.e., $R=396/2=198$) as suggested in Rapach and Strauss(2009)⁴.

The out-of-sample forecasts are generated recursively. The first sets of forecasts for both restricted and unrestricted models are generated by estimating Equation (1) via OLS using the first R -period observations. Then the fitted model is used to establish a forecasting housing price return $\hat{y}_{1,R+k} = \hat{\alpha}_{1,R} + \hat{\beta}_{1,R} x_R$ for the unrestricted model and $\hat{y}_{0,R+k} = \hat{\alpha}_{0,R} + \hat{\beta}_{0,R} x_R$ for the restricted model. Thus, $\hat{\varepsilon}_{1,R+k} = y_{R+k} - \hat{y}_{1,R+k}$, and $\hat{\varepsilon}_{0,R+k} = y_{R+k} - \hat{y}_{0,R+k}$ are the forecast errors of the unrestricted and restricted models, respectively. Next, the second set of forecasts is estimated by means of the data available up to period $R+1$. Then the parameters, which are separately estimated in the two models, and the predictor x_{R+1} are used jointly to construct $\hat{y}_{i,(R+1)+k}$ and $\hat{\varepsilon}_{i,(R+1)+k}$ for $i=0$ (restricted model), 1 (unrestricted). This process is repeated for both models and finally two sets of $(T-R-k+1)$ recursive forecast errors, $\{\hat{\varepsilon}_{i,t+k}\}_{t=R}^{t=T-k}$ for $i=0,1$, are generated.

The three out-of-sample tests consist of Theil's U ratio, the McCracken(2004) $MSE-F$ statistic, and the Clark and McCracken(2001) $ENC-NEW$ statistic. They are briefly outlined in Equation (4)-(6). First, Theil's U ratio compares mean squared errors of the restricted and unrestricted models:

⁴ Rapach and Strauss (2009) choose half of the whole sample as R .

$$\text{Theil's } U = \frac{\text{MSE}_1}{\text{MSE}_0} \quad (4)$$

where $\text{MSE}_i = \sum_{t=R}^{T-k} (\hat{\varepsilon}_{1,t+k})^2$, $i=0,1$

Second, the *MSE-F* statistic tests the null hypothesis that the mean squared errors of the unrestricted and restricted models are equal (i.e., $\text{MSE}_1 = \text{MSE}_0$) against the alternative one that the unrestricted MSE is smaller than the restricted MSE (i.e., $\text{MSE}_1 < \text{MSE}_0$). Let $\hat{d}_{t+k} = (\hat{\varepsilon}_{0,t+k})^2 - (\hat{\varepsilon}_{1,t+k})^2$ and $\bar{d} = (T - R - k + 1)^{-1} \sum_{t=R}^{T-k} \hat{d}_{t+k} = \text{MSE}_0 - \text{MSE}_1$, $\text{MSE}_i = \sum_{t=R}^{T-k} (\hat{\varepsilon}_{i,t+k})^2$, $i=0,1$.

The *MSE-F* statistic is represented as follows:

$$\text{MSE-F} = (T - R - k + 1) \bar{d} / \text{MSE}_1 \quad (5)$$

Third, the *ENC-NEW* statistic tests the null hypothesis that the restricted model forecasts encompass the unrestricted ones, and it is of the following form:

$$\text{ENC-NEW} = (T - R - k + 1) \bar{c} / \text{MSE}_1 \quad (6)$$

where $\hat{c}_{t+k} = (\hat{\varepsilon}_{0,t+k})(\hat{\varepsilon}_{0,t+k} - \hat{\varepsilon}_{1,t+k})$ and $\bar{c} = (T - R - k + 1)^{-1} \sum_{t=R}^{T-k} \hat{c}_{t+k}$.

If the predictor has a predictive power in housing price returns and the unrestricted model forecasts are superior to the restricted model forecasts (i.e., $\text{MSE}_1 < \text{MSE}_0$), Theil's *U* ratio is less than unity, and both of the *MSE-F* and *ENC-NEW* statistics are positive.

4. Empirical Results

This section presents the main findings about housing price return forecastability as the two alternative predictors, which are the GTTB index and the federal funds rate, are employed in the in-sample and out-of-sample forecasts. Besides, the housing-bubble implications derived from divergent forecastability patterns across state-level housing markets are addressed.

4.1 The GTTB index

The most important finding lies in the strong predictive powers of the GTTB index: it is capable of forecasting the housing price returns in all the state-level housing markets except the three states: Texas, Illinois, and Michigan (shown in Table 2, the bold statistics indicate the significant forecastability). Noticeably, the predictive powers of the index remain significant up to the 25-year horizon for Pennsylvania, Ohio, North Carolina, Virginia, Washington and Indiana whose in-sample and out-of-sample housing price returns are both forecastable. On the other hand, California, New York and Massachusetts, which are considered to be more likely to have housing bubbles in existing studies (e.g., Rapach and Strauss(2009), Holly, Pesaran and Yamagata (2010), among others), display short-term forecastability because their housing price returns are only significantly predictable in less than ten year horizons. Particularly, the in-sample forecastability only lasts for one period in New York, and all in-sample forecasts in California are not significant.

Noticeably, there are marked differences between in-sample and out-of-sample forecastability patterns in some states, such as California, New York, and Florida: their 5-year-ahead out-of-sample forecasts are significant but the in-sample ones are otherwise. Moreover, the nationwide CMHPI displays significant out-of-sample forecastability up to the 20-year horizon, but none of its in-sample forecastability is significant. It implies robust out-of-sample tests facilitate our investigations into housing price return forecastability while the conventional in-sample *t*-statistics fail to provide the information. The results suggest that the two out-of-sample tests adopted in the study (McCracken(2004) *MSE-F* statistic and the Clark and McCracken(2001) *ENC-NEW* statistic) contribute to empirical studies on housing-price predictability. Furthermore, the results suggest that the GTTB index not only works as a good predictor of housing *volumes* as Croce and Haurin(2009) propose, but also has good performances in the out-of-sample forecasts of housing *price returns*.

4.2 The federal funds rate

The empirical results of the federal fund rate suggest, in contract to the GTTB index, all in-sample forecastability patterns at the state levels are not significant except the 1-year-horizon forecast in Michigan (shown in Table 3). Other than the three states (Texas, Illinois, and Michigan), there are more states whose housing price returns are unpredictable for the interest rate than the GTTB index: California, New York, New Jersey, Washington, Massachusetts and Arizona. Regarding

out-of-sample forecasting performances, the interest rate works as a significant predictor only in the 25-year horizon out-of-sample forecast for Washington. In New Jersey, out-of-sample forecastability remains significant up to the 3-year horizon.

The empirical findings deliver interesting monetary-policy implications. Both in-sample and out-of-sample housing price dynamics in California, New York, Massachusetts and Arizona are not significantly predictable through the interest rate at all horizons. Importantly, the lack of housing-price predictability for the federal funds rate suggests weak predictive powers of monetary policies which are adopted to stabilize the housing boom-bust cycle to some extent. Thus, the housing markets in these four states are vulnerable to housing bubbles as the government fails to mitigate dramatic fluctuations of housing prices. Noticeably, these four states are all considered to be more likely to experience bubble-like price dynamics than other states by growing empirical studies. Furthermore, the findings are consistent with the literature which attributes the recent housing bubble-like boom-bust cycle to limited influences of monetary policies on housing price dynamics and disconnections between housing markets and the economic fundamental.

5. Conclusion

This paper examines housing price return predictability at the nationwide and state levels from both in-sample and out-of-sample perspectives, utilizing the GTTB index and the federal funds rate as two alternative predictors. Specifically, two robust out-of-sample tests, the McCracken(2004) *MSE-F* statistic and the Clark and McCracken(2001) *ENC-NEW* statistic which are employed to discuss stock return predictability in Rapach and Wohar(2006), are adopted to evaluate out-of-sample forecastability of housing price returns. The main contributions of this study lie in three dimensions. Firstly, it provides confirmative evidence of stronger predictive powers of households' expectations than those of the interest rate in housing markets. Next, this study detects the discrepancy between in-sample and out-of-sample forecastability for both predictors. Finally and also importantly, consistent with the existing literature on divergent state-level housing price dynamics, the findings indicate that some state-level markets, which consist of California, New York, New Jersey, Washington, Massachusetts and Arizona, are more vulnerable to bubble-like housing cycles than other states analyzed.

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Table 1
Summary of descriptive statistics: Freddie Mac's Conventional Mortgage Home Price Indexes (CMHPIs) of the 16th populous states

	US	California	Texas	New York	Florida	Illinois	Pennsylvania	Ohio	Michigan	Georgia	North Carolina	New Jersey	Virginia	Washington	Massachusetts	Indiana	Arizona
		CA	TX	NY	FL	IL	PA	OH	MI	GA	NC	NJ	VA	WA	MA01	IN	AZ
Mean	0.018	0.068	-0.051	0.129	-0.030	-0.042	0.033	-0.088	-0.093	-0.069	-0.006	0.118	0.052	0.084	0.181	-0.082	-0.053
Median	0.069	0.143	0.009	0.092	0.004	0.064	0.016	-0.003	0.082	0.041	0.049	0.091	0.091	0.127	0.128	-0.023	0.055
Maximum	1.182	2.322	1.443	2.755	2.372	2.966	2.042	2.845	5.707	1.953	2.135	2.824	1.434	2.670	2.189	2.911	3.147
Minimum	-1.510	-3.176	-3.290	-2.840	-3.420	-3.222	-2.586	-4.040	-6.519	-2.955	-1.988	-2.089	-2.150	-3.785	-1.741	-2.338	-3.942
Std. Dev.	0.476	0.966	0.517	0.800	0.907	0.663	0.575	0.557	0.896	0.582	0.473	0.735	0.638	0.785	0.754	0.510	0.956
Skewness	-0.710	-0.759	-1.137	0.005	-0.752	-1.220	-0.449	-1.327	-0.448	-1.164	-0.287	0.101	-0.412	-0.796	0.126	0.135	-0.341
Kurtosis	3.609	3.884	7.639	4.175	5.083	8.377	5.186	13.201	18.080	6.334	5.876	2.873	3.253	6.811	2.598	10.317	5.194
Jarque-Bera	39.412	50.957	440.369	22.777	108.880	575.235	92.113	1833.123	3765.562	272.746	141.911	0.936	12.255	281.404	3.708	884.503	87.113
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.626	0.002	0.000	0.157	0.000	0.000
Sum	7.249	27.114	-20.126	51.005	-11.897	-16.661	13.262	-34.731	-36.761	-27.294	-2.248	46.847	20.421	33.242	71.787	-32.532	-21.002
Sum Sq. Dev.	89.441	368.931	105.546	252.639	325.031	173.547	130.407	122.686	317.109	133.696	88.290	213.275	160.631	243.644	224.645	102.538	361.132

Notes: This table lists the sample mean, median, maximum, minimum, sample SD, skewness, kurtosis, and the Jarque-Bera (*JB*) statistics for the monthly housing price returns of the 16th populous states in the US. The source of the state-level housing price indexes is Freddie Mac's Conventional Mortgage Home Price Index (CMHPI), and the analyzed period is 1978M1-2010M12.

Table 2 Predictability tests: the GTTB predictor

Horizon	US CMHPI	CA	TX	NY	FL	IL	PA	OH	MI	GA	NC	NJ	VA	WA	MA	IN	AZ																	
1																																		
In-sample																																		
Slope coefficient	-0.090832	-0.0794325	0.0465575	0.02751	0.0949294	0.0405505	0.0534737	0.0637339	-0.0125804	0.02265345	0.08202947	0.06453057	0.05569876	0.08833451	0.03201979	0.06656638	0.04461737																	
t-statistic	-5.403725	1.0	-5.400178	1.0	5.943472	0.295	2.220476	0.018	2.819636	0.02	0.5043172	0.295	7.713078	0	8.1304110	0	-1.567013	0.91	2.513592	0.04	5.170173	0	5.871584	0	5.843915	0	5.824751	0	2.8113397	0.01	9.2540680	0	3.0156253	0
Rsquared	0.06916278	0.0691695	0.0664889	0.012393	0.01828274	0.00648895	0.1314746	0.1459845	0.00619407	0.0182235	0.06386983	0.0064968	0.0795128	0.0794982	0.01982521	0.178919	0.02266592																	
Out-of-sample																																		
Theils U	1.00251	0.924	0.9568589	0	1.079692	1	0.979825	0	0.98723218	0.07	1.077692	1	0.9377916	0	0.94633276	0	1.095784	1	0.98843038	0.04	0.97527542	0	0.9460124	0	0.9518602	0	0.9883253	0.01	0.96958668	0	0.93846533	0	0.98574163	0.01
MSE-F	-3.978381	0.924	18.164365	0	-14.149015	1	8.196156	0	5.128532	0.07	-14.149015	1	27.02775	0	22.977607	0	-32.32613	1	4.688779	0.04	10.111596	0	25.661701	0	20.431013	0	4.601259	0.01	12.552548	0	26.681341	0	5.7402747	0.01
EDC-new	21.548589	0	13.601391	0	-6.108525	1	4.533946	0.05	2.714358	0.031	-6.108525	1	16.909514	0	32.064801	0	-3.027617	0.99	3.104844	0.18	12.829187	0	17.078397	0	12.062282	0	10.064461	0	6.9261705	0.03	48.949654	0	3.2210713	0.018
2																																		
In-sample																																		
Slope coefficient	-0.0793915	-0.1508922	0.0682929	0.05364	0.0861254	0.0682929	0.0163859	0.0127606	-0.0373078	0.04834051	0.07258264	0.01298216	0.0118053	0.01515271	0.06228060	0.01283319	0.0801366																	
t-statistic	-3.070220	0.98	-2.968065	1.0	0.2962798	0.36	1.07473	0.1660	1.882922	0.49	0.2962798	0.36	5.844360	0	3.3103189	0	-0.945219	0.790	1.9334539	0.43	2.2332114	0.02	3.532607	0.02	3.445164	0.02	2.587392	0.06	1.9727764	0.035	3.9425727	0	2.420779	0.014
Rsquared	0.0887285	0.06346956	0.0596769	0.013887	0.02342978	0.00596769	0.1391898	0.1678748	0.00791026	0.0204022	0.0719702	0.00798758	0.08954027	0.08688254	0.019356121	0.2022608	0.02498573																	
Out-of-sample																																		
Theils U	1.007807	0.682	0.96216862	0.01	1.051925	0.98	0.978061	0.07	0.98636303	0.021	1.051925	0.98	0.9351243	0	0.93314657	0	1.104801	0.99	0.98510747	0.021	0.9634701	0.03	0.93541428	0	0.94879467	0	0.98356662	0.01	0.97033893	0.02	0.92172324	0	0.98581121	0.02
MSE-F	-3.778956	0.682	15.672103	0.01	-18.70261	0.98	8.891434	0.07	5.4570649	0.021	-18.70261	0.98	28.138969	0	29.80972	0	-35.386139	0.99	5.970921	0.021	12.59139	0.03	28.003	0	21.726652	0	6.6042321	0.01	12.165693	0.02	34.179207	0	5.6826643	0.02
EDC-new	25.227138	0	11.880881	0.03	-8.231057	0.99	4.884198	0.035	2.883396	0.072	-8.231057	0.99	17.431833	0	38.21034	0	-3.503972	0.99	3.9599719	0.053	15.143576	0.01	18.466357	0.01	12.828952	0.02	11.221088	0.04	6.6623264	0.019	6.120552	0.03	3.150239	0.051
3																																		
In-sample																																		
Slope coefficient	-0.1172949	-0.2168833	0.07398012	0.07965	0.01234467	0.07398012	0.015764018	0.08261776	-0.03725819	0.075222199	0.016640722	0.01935921	0.016274538	0.01985705	0.09128236	0.00556148	0.03105208																	
t-statistic	-2.917270	0.984	-2.487204	0.987	0.19261262	0.427	1.087357	0.16900	1.859114	0.659	0.19261262	0.427	5.6091944	0	3.9704835	0	-0.8598764	0.7190	2.294372	0.026	2.451645	0.019	3.4755708	0.02	3.211773	0.01	2.703494	0.01	1.8201010	0.045	4.2107854	0	2.191751	0.03
Rsquared	0.09397601	0.06293793	0.00578766	0.01557	0.02609596	0.00578766	0.1423693	0.1986169	0.00801052	0.02074780	0.00907154	0.02299582	0.08072142	0.09646411	0.019071364	0.23145756	0.02496364																	
Out-of-sample																																		
Theils U	1.004339	0.308	0.9167445	0.08	1.067249	0.99	0.976235	0.04	0.98612176	0.042	1.067249	0.99	0.93358629	0	0.92151647	0	1.112949	0.98	0.98311349	0.021	0.96392404	0.03	0.93541428	0	0.94879467	0	0.98356662	0.01	0.97033893	0.02	0.92172324	0	0.98581121	0.02
MSE-F	-1.778014	0.308	13.458734	0.08	-23.80563	0.99	9.609573	0.04	5.5273084	0.042	-23.80563	0.99	28.70751	0	33.64182	0	-37.56979	0.98	6.7563911	0.021	14.888463	0.04	29.546074	0	22.78422	0	8.2118757	0.02	11.68076	0.09	44.719809	0	5.617764	0.027
EDC-new	27.099649	0	10.374578	0.025	-10.43136	1	5.231934	0.04	2.916792	0.113	-10.43136	1	17.599565	0.04	42.457728	0	-3.835456	0.95	4.550805	0.05	16.949028	0.05	19.227914	0.01	13.420497	0.01	11.680169	0.06	6.3435721	0.037	7.4134652	0	3.0845307	0.101
5																																		
In-sample																																		
Slope coefficient	-0.1796445	-0.3327457	0.01894254	0.012749	0.02265389	0.01894254	0.02621339	0.02979546	-0.07939254	0.01331562	0.01708293	0.01982675	0.02759913	0.02231592	0.014522021	0.02982467	0.02291282																	
t-statistic	-2.602836	0.976	-2.088839	0.96	0.1869540	0.431	1.17789	0.16400	1.879765	0.058	0.1869540	0.431	5.3140797	0	4.109428	0	-0.7804689	0.740	2.8135806	0.018	2.824620	0.008	3.450540	0	3.070118	0.06	3.209247	0.06	1.5844595	0.08	4.6801757	0	2.1698391	0.032
Rsquared	0.1062396	0.05956233	0.00484777	0.019222	0.03250972	0.00484777	0.1522432	0.27021979	0.01511998	0.04214474	0.0164454	0.04966997	0.11942094	0.10722457	0.00830248	0.3184852	0.02567921																	
Out-of-sample																																		
Theils U	0.98632449	0.074	0.9762073	0.037	1.082054	0.989	0.975613	0.048	0.98434068	0.061	1.082054	0.989	0.9300294	0.02	0.9139667	0	1.125287	0.92	0.9789825	0.048	0.9458987	0.08	0.93062139	0.01	0.94228398	0.09	0.97133679	0.01	0.97414487	0.029	0.8642577	0	0.98429564	0.059
MSE-F	5.3882361	0.074	9.52519165	0.037	-26.47742	0.989	9.769446	0.048	6.1894991	0.061	-26.47742	0.989	30.145773	0.02	38.029827	0	-40.74401	0.92	8.735316	0.048	18.661195	0.08	29.849288	0.01	24.347041	0.09	11.58349	0.03	10.30809	0.029	65.346384	0	6.210773	0.059
EDC-new	26.951331	0.011	1.861309	0.103	-12.47204	0.997	5.30236	0.109	3.2573889	0.173	-12.47204	0.997	18.25203	0.02	47.86773	0	-4.421289	0.93	5.562988	0.1	19.23447	0.09	18.667277	0.01	14.203478	0.021	13.289935	0.03	5.642352	0.11	10.21836	0	3.370902	0.15
10																																		
In-sample																																		
Slope coefficient	-0.37217803	-0.48683794	0.06733641	0.019083	0.0560102	0.06733641	0.05292771	0.057910407	-0.23780146	0.02779999	0.03617146	0.05802013	0.05648538	0.06901249	0.02273619	0.0654233	0.05488524																	
t-statistic	-2.362891	0.954	-1.2427613	0.866	0.5557451	0.302	0.95422	0.24400	1.840125	0.076	0.5557451	0.302	4.1168054	0	3.6730779	0.03	-0.9478826	0.760	2.774713	0.016	3.8989198	0.05	2.970240	0.013	2.8323559	0.017	4.5821838	0	1.073402	0.199	6.3550666	0	2.2321570	0.048
Rsquared	0.1404513	0.02288849	0.05261936	0.015726	0.04857656	0.05261936	0.1802022	0.3630148	0.02538066	0.06667897	0.088616	0.09489544	0.1807759	0.1675455	0.012171368	0.4790511	0.05104068																	
Out-of-sample																																		
Theils U	0.94541177	0.05	1.058955	0.152	1.081419	0.893	0.993257	0.155	0.9794924	0.085	1.081419	0.893	0.91585231	0.01	0.86122389	0.02	1.139305	0.92	0.96781284	0.059	0.92216163	0.02	0.92868066	0.02	0.93041615	0.018	0.94456093	0.03	0.9314279	0.142	0.7836887	0	0.97621215	0.079
MSE-F	13.712415	0.05	-2.2520331	0.152	-27.24087	0.893	2.561232	0.155	7.959805	0.085	-27.24087	0.893	36.133155	0.01	65.49595	0.02	-45.094810	0.92	12.712812	0.059	32.741847	0.012	29.981681	0.02	29.15053	0.018	22.716185	0.03	2.689772	0.142	122.28933	0	9.278014	0.079
EDC-new	30.617586	0.024	1.845556	0.293	-12.02362	0.975	1.689139	0.294	4.1616792	0.187	-12.02362	0.975	21.195397	0.05	71.900978	0.01	-4.1625794	0.637	7.739028	0.123	28.261926	0.022	17.94413	0.06	16.542414	0.05	20.245204	0.04	1.647298	0.281	163.7326	0	4.9751888	0.192
15																																		
In-sample																																		
Slope coefficient	-0.5478849	-0.54064412	0.01267286	0.019554	0.08663839	0.01267286	0.07922964	0.082802572	-0.42514903	0.042																								

Table 3 Predictability tests: the federal funds rate predictor

	US CDPH	CA	TX	NY	FL	IL	PA	OH	MI	GA	NC	NO	VA	WA	MA	IN	AZ	
1																		
Slope coefficient	-0.10270218	-0.00217827	0.056759	-0.00217827	-0.0908352	0.056759	-0.0908352	-0.05764967	0.01284972	-0.02184948	-0.0326724	-0.02184948	-0.0326724	-0.02597074	0.00467895	-0.0908352	-0.0676431	
t-statistic	-3.94910	1.0	-2.087307	0.597	0.9404172	0.295	-2.087307	0.597	-5.407525	1.0	0.9404172	0.295	-5.407525	1.0	0.9404172	0.295	-5.407525	1.0
Required	0.02868276	1.08546	0.648029	1.08546	0.06916278	0.648029	0.06916278	0.06818954	0.00723489	0.03200425	0.037801818	0.03200425	0.037801818	0.01638497	0.5797958	0.06916278	0.7473245	
Out-of-sample																		
Theil's U	1.085128	0.510	1.002582	0.452	1.037962	1.000	1.002582	0.452	1.002531	0.940	0.99710678	0.452	0.99710678	0.452	0.99710678	0.452	1.002531	0.940
MSE-F	-1.376787	0.510	-1.046169	0.452	-1.149015	1.000	-1.046169	0.452	-3.978630	0.940	-1.149015	0.452	-3.978630	0.940	-1.149015	0.452	-3.978630	0.940
ENC-new	7.6531453	0.002	0.6739902	0.176	0.6739902	0.000	0.6739902	0.176	21.548589	0.000	0.6739902	0.176	21.548589	0.000	0.6739902	0.176	21.548589	0.000
2																		
Slope coefficient	-0.04361658	-0.00416859	0.0729288	-0.00416859	-0.07999915	0.00416859	-0.07999915	-0.07999915	0.02719565	-0.04578029	-0.06598660	-0.04578029	-0.06598660	-0.05766601	0.01088394	-0.07999915	-0.0712363	
t-statistic	-1.728310	0.954	-0.1012211	0.547	0.2382788	0.396	-0.1012211	0.547	-3.070250	0.999	0.2382788	0.396	-3.070250	0.999	0.2382788	0.396	-3.070250	0.999
Required	0.03358049	1.1700719	0.567688	1.1700719	0.08872485	0.567688	0.08872485	0.08035071	0.00319309	0.01554005	0.04306509	0.01554005	0.04306509	0.022489	0.8062152	0.08872485	0.01361653	
Out-of-sample																		
Theil's U	1.06528	0.425	1.007354	0.571	1.051925	0.988	1.007354	0.571	1.009707	0.700	1.051925	0.988	1.009707	0.726	1.215992	1.000	1.3551	0.819
MSE-F	-2.04894	0.425	-2.859707	0.571	-18.760261	0.988	-2.859707	0.571	-3.778926	0.700	-18.760261	0.988	-3.778926	0.726	-63.44672	1.000	-1.191287	0.819
ENC-new	7.591743	0.013	-0.1735519	0.384	-0.231627	0.999	-0.1735519	0.384	35.227138	0.000	-0.231627	0.999	35.227138	0.000	7.632456	0.013	1.440295	0.175
3																		
Slope coefficient	-0.0616446	-0.0496956	0.0798117	-0.0496956	-0.1172949	0.0496956	-0.1172949	-0.1172949	0.04582507	-0.06193751	-0.1617	-0.06193751	-0.1617	-0.08810875	0.02048905	-0.1172949	-0.0280794	
t-statistic	-1.528070	0.906	-0.167674769	0.524	0.1926162	0.427	-0.167674769	0.524	-2.912970	0.990	0.1926162	0.427	-2.912970	0.990	0.1926162	0.427	-2.912970	0.990
Required	0.0528257	6.81E-63	3.787560	6.81E-63	0.09397401	3.787560	0.09397401	0.09397401	0.00594008	0.016780726	0.04959510	0.016780726	0.04959510	0.029287224	0.01338657	0.09397401	0.00897461	
Out-of-sample																		
Theil's U	1.008615	0.372	1.012849	0.667	1.067249	0.999	1.012849	0.667	1.044339	0.313	1.217518	1.000	1.044339	0.325	0.9606341	0.095	0.9606341	0.095
MSE-F	-2.538072	0.372	-4.910707	0.667	-23.85763	0.999	-4.910707	0.667	-1.7178014	0.313	-23.85763	0.999	-4.910707	0.313	-6.2488203	0.095	6.2488203	0.095
ENC-new	7.527327	0.049	-1.204664	0.642	-0.491396	1.000	-1.204664	0.642	27.099649	0.002	-0.491396	1.000	27.099649	0.002	8.0401592	0.049	0.7339064	0.361
5																		
Slope coefficient	-0.1127507	-0.00161294	0.01094425	-0.00161294	-0.1796445	0.01094425	-0.1796445	-0.1796445	0.07457732	-0.11273817	-0.1728214	-0.11273817	-0.1728214	-0.1459595	0.04192295	-0.1796445	-0.06746283	
t-statistic	-1.487390	0.873	-0.16757809	0.524	0.1868590	0.431	-0.16757809	0.524	-2.602365	0.980	0.1868590	0.431	-2.602365	0.980	0.1868590	0.431	-2.602365	0.980
Required	0.0592437	1.86E-62	4.008477	1.86E-62	0.1062396	4.008477	0.1062396	0.1062396	0.00468849	0.01762035	0.06023876	0.01762035	0.06023876	0.01625103	0.02119805	0.1062396	0.00559972	
Out-of-sample																		
Theil's U	1.006624	0.299	1.024885	0.721	1.083954	0.989	1.024885	0.721	0.9632649	0.65	1.205492	1.000	0.9632649	0.65	0.9632649	0.65	1.077024	0.556
MSE-F	-2.548615	0.299	-2.92763	0.721	-20.47422	0.989	-2.92763	0.721	5.3882361	0.65	-20.47422	0.989	-2.92763	0.65	-6.653808	0.556	5.3882361	0.65
ENC-new	6.671854	0.096	-3.401712	0.823	-12.47214	0.997	-3.401712	0.823	26.951331	0.006	-12.47214	0.997	26.951331	0.006	0.3441488	0.096	0.6711647	0.457
10																		
Slope coefficient	-0.2755044	0.05770760	0.00673204	0.05770760	-0.37217805	0.00673204	-0.37217805	-0.3453157	0.03846957	-0.2407439	-0.4083987	-0.2407439	-0.4083987	-0.3638381	0.07018148	-0.37217805	-0.248	
t-statistic	-1.570182	0.881	0.0281865	0.450	0.5557461	0.302	0.0281865	0.450	-2.368691	0.958	0.5557461	0.302	-2.368691	0.958	0.5557461	0.302	-2.368691	0.958
Required	0.065774	7.78E-61	0.065206194	7.78E-61	0.1404513	7.78E-61	0.1404513	0.1404513	0.002316981	0.02316981	0.09801652	0.02316981	0.09801652	0.063877317	0.00158431	0.1404513	0.016	
Out-of-sample																		
Theil's U	1.001680	0.181	1.063973	0.794	1.081419	0.893	1.063973	0.794	0.9654117	0.859	1.081419	0.893	1.063973	0.859	0.9749767	0.066	1.013494	0.313
MSE-F	-4.638472	0.181	-21.92804	0.794	-27.24087	0.893	-21.92804	0.794	13.712435	0.859	-27.24087	0.893	-21.92804	0.859	-4.958283	0.066	-1.958081	0.313
ENC-new	8.301826	0.155	-9.23861	0.931	-12.02362	0.975	-9.23861	0.931	30.617586	0.834	-12.02362	0.975	30.617586	0.834	13.19291	0.098	3.0040764	0.256
15																		
Slope coefficient	-0.4557549	0.06282545	0.01267286	0.06282545	-0.5175849	0.01267286	-0.5175849	-0.4810748	-0.05180182	-0.3701911	-0.6612828	-0.3701911	-0.6612828	-0.6834359	0.01604796	-0.5175849	-0.59	
t-statistic	-1.545578	0.868	0.0748427	0.454	0.6631279	0.307	0.0748427	0.454	-2.110695	0.931	0.6631279	0.307	-2.110695	0.928	0.6631279	0.307	-2.110695	0.928
Required	0.080909	0.00143743	0.00931453	0.00143743	0.1408485	0.00931453	0.1408485	0.1408485	0.0062236	0.02398562	0.12430409	0.02398562	0.12430409	0.11458218	0.00737403	0.1408485	0.034	
Out-of-sample																		
Theil's U	0.9522523	0.167	1.091641	0.759	1.094287	0.835	1.091641	0.759	0.9289117	0.849	1.094287	0.835	0.9289117	0.849	1.094287	0.835	1.094287	0.835
MSE-F	1.760165	0.167	-29.456158	0.759	-30.16947	0.835	-29.456158	0.759	18.541922	0.849	-30.16947	0.835	-29.456158	0.849	-55.80363	0.835	-1.2082526	0.849
ENC-new	8.986295	0.165	-42.5344	0.915	-13.32161	0.943	-42.5344	0.915	28.286819	0.844	-13.32161	0.943	28.286819	0.844	19.241101	0.098	-2.788989	0.519
20																		
Slope coefficient	-0.4401525	0.1238037	0.02075861	0.1238037	-0.7084764	0.02075861	-0.7084764	-0.6104996	-0.1454887	-0.4855817	-0.8700889	-0.4855817	-0.8700889	-1.020266	0.02772775	-0.7084764	-0.896413	
t-statistic	-1.580321	0.841	0.2209764	0.451	0.7800346	0.325	0.2209764	0.451	-1.924867	0.894	0.7800346	0.325	-1.924867	0.894	0.7800346	0.325	-1.924867	0.894
Required	0.059493	0.00214044	0.06525265	0.00214044	0.1371363	0.06525265	0.1371363	0.1371363	0.0239903	0.0076731	0.02361520	0.0239903	0.02361520	0.1267108	0.02361520	0.1371363	0.016	
Out-of-sample																		
Theil's U	0.9842269	0.158	1.115956	0.739	1.103027	0.793	1.115956	0.739	0.9488296	0.881	1.103027	0.793	0.9488296	0.881	1.115956	0.739	0.9488296	0.881
MSE-F	3.8261194	0.158	-35.06880	0.739	-31.692421	0.793	-35.06880	0.739	19.17789	0.881	-31.692421	0.793	-35.06880	0.881	-49.592481	0.881	-10.24869	0.354
ENC-new	8.949015	0.217	-44.77087	0.882	-13.94494	0.911	-44.77087	0.882	23.76626	0.119	-13.94494	0.911	23.76626	0.119	18.77886	0.124	-1.213214	0.400
25																		
Slope coefficient	-0.7944624	0.29294879	0.01733772	0.29294879	-0.8271448	0.01733772	-0.8271448	-0.697069	-0.22667626	-0.5802795	-1.025993	-0.5802795	-1.025993	-1.251239	0.4992129	-0.8271448	-1.284386	
t-statistic	-1.578236	0.850	0.4018024	0.406	0.9280737	0.258	0.4018024	0.406	-1.751976	0.861	0.9280737	0.258	-1.751976	0.861	0.9280737	0.258	-1.751976	0.861
Required	0.09711739	0.007																