



# High-Frequency Volatility Forecasting of US Housing Markets

Mawuli Segnon<sup>1</sup> · Rangan Gupta<sup>2</sup> · Keagile Lesame<sup>2</sup> · Mark E. Wohar<sup>3</sup> 

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## Abstract

We propose a logistic smooth transition autoregressive fractionally integrated [STARFI ( $p, d$ )] process for modeling and forecasting US housing price volatility. We discuss the statistical properties of the model and investigate its forecasting performance by assuming various specifications for the dynamics underlying the variance process in the model. Using a unique database of daily data on price indices from ten major US cities, and the corresponding daily Composite 10 Housing Price Index, and also a housing futures price index, we find that using the Markov-switching multifractal (MSM) and FIGARCH frameworks for modeling the variance process helps improving the gains in forecast accuracy.

**Keywords** US housing prices · GARCH processes · MSM processes · Model confidence set

## Introduction

The housing market plays an important role in the economy of the United States (US), since it constitutes a significant share of many households' asset holding

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✉ Mawuli Segnon  
segnon@uni-muenster.de

Rangan Gupta  
rangan.gupta@up.ac.za

Keagile Lesame  
keagilel@gmail.com

Mark E. Wohar  
mwohar@unomaha.edu

<sup>1</sup> Department of Economics, University of Münster, Münster, Germany

<sup>2</sup> Department of Economics, University of Pretoria, Pretoria, South Africa

<sup>3</sup> Department of Economics, University of Nebraska at Omaha, Omaha, NE 68182, USA

and net worth. According to the Financial Accounts data of the US corresponding to the fourth quarter of 2018, residential real estate represents about 83.7% of total household non-financial assets, 28.3% of total household net worth and 24.6% of household total asset.<sup>1</sup> Therefore, as pointed out by Shiller (1998), the risk or volatility of house prices is among the largest personal economic risks faced by the individual. Note that, housing assets differ from financial assets, such as stocks, since they serve the dual role of investment and consumption (Henderson and Ioannides 1987). Naturally, the effects of housing on savings and portfolio choices are extremely important questions, and hence, understanding the source of the housing market price volatility is important because it has individual portfolio implications, as it affects households' investment decisions regarding tenure choice and housing quantity (Miles 2008a). Moreover, the housing market affects the economy not only through wealth effects (Case et al. 2013), but also through influences on other markets such as the mortgage market, mortgage insurance and mortgage backed bonds, as well as consumer durables (Miller and Peng 2006). Finally, knowledge about house price volatility is also an important input into housing policy (Zhou and Haurin 2010).<sup>2</sup> In light of these points, the variations in the housing market are important to key components of the overall economy and the welfare of the society.

Given this, a growing number of studies have attempted to model and predict volatility (using univariate models and also with econometric frameworks including wide array of factors) at the aggregate and regional (state and metropolitan statistical areas (MSAs)-levels) of the US (see for example, Dolde and Tirtiroglu (2002), Crawford and Fratanoni (2003), Miller and Peng (2006), Miles (2008a), Miles (2008b), Miles (2011), Zhou and Haurin (2010), Elder and Villupuram (2012), Li (2012), Ajmi et al. (2014), Engsted and Pedersen (2014), Barros et al. (2015), Bork and Møller (2015), Fairchild et al. (2015), André et al. (2017), Chen (2017), and Nyakabawo et al. (2018)). All these studies find the existence of Autoregressive Conditional Heteroskedasticity (ARCH) and long memory effects in housing price returns volatility, and a relatively good forecasting performance of the Generalized Autoregressive Conditional Heteroskedasticity (GARCH)-type models.

Our objective is to introduce a new class of volatility processes for modeling and forecasting volatility of US housing markets, namely the Markov-switching multifractal (MSM) process, recently introduced by Calvet and Fisher (2004). The multifractal processes originally stem from the statistical physics and have been adapted to finance by Mandelbrot et al. (1997), Calvet and Fisher (2001, 2004) and Lux (2008). The MSM processes successfully find applications in forecasting returns volatility in stock, exchange-rate, and commodity markets and outperform the GARCH-type models at long forecasting horizons. We adopt three different loss functions and the model confidence set (MCS) test to evaluate and compare the MSM forecasting performance with those of GARCH-type models at short and long

<sup>1</sup> See: <https://www.federalreserve.gov/releases/z1/20190920/html/b101h.htm>.

<sup>2</sup> For example, consider the following case: if low-valued houses' values are relatively volatile, then policies that encourage low-income renter households to become homeowners should be evaluated in light of the house price risk that they would bear.

horizons. The choice of the MSM process is motivated by the previous findings by Crawford and Fratanoni (2003) and Barros et al. (2015) who provide evidence of nonlinearities and long memory properties of house prices. In fact, the unique framework of the MSM model allows for regime switching of heterogeneous persistence creating an apparent long memory. These features are relevant for capturing the dynamics underlying the US housing price volatility. In addition, given that the MSM model requires high-frequency data in general, we deviate from the existing studies on volatility of the US housing market, which are based on monthly or quarterly datasets, by using a unique database of house prices available at daily frequency for the 10 major (Boston, Chicago, Denver, Las Vegas, Los Angeles, Miami, New York, San Diego, San Francisco, and Washington D.C.) Metropolitan Statistical Areas (MSAs) of the US, as well as a composite version for proxying the price of house in the country overall. In this regard, a recently developed daily house price futures data is also used for the sake of robustness. Given the importance of housing price volatility, we believe the usage of daily house price data for forecasting US housing market volatility is likely to be more informative to economic agents and policy authorities in making their respective decisions in a timely manner than those derived from low-frequency data. The daily estimates and forecasts of volatility will provide high-frequency leading information to consumers, investors and policymakers, as to where the economy is headed in the future, as researchers could use this information in a nowcasting framework (Banbura et al. 2011) to forecast important decision-making variables that are measured only at lower-frequencies, using mixed data sampling (MIDAS) regressions (see Andreou et al. (2010)).

The remainder of the paper is organized as follows: Section “Data Analysis” introduces our data sets. The modeling framework is provided in Section “Modeling Framework”. We discuss the statistical properties of our models in Section “Statistical Properties”. Forecasting methodologies and empirical results are presented in Section “Empirical Study”, and Section “Conclusion” concludes.

## Data Analysis

Our data set consists of daily housing price indices for 10 major US MSAs with different start and end dates, namely Boston (5/1/1995 - 11/10/2012), Los Angeles (5/1/1995 - 23/10/2012), Chicago (3/9/1999 - 12/10/2012), Denver (5/5/1999 - 17/10/2012), Miami (3/4/1998 - 15/10/2012), Las Vegas (5/1/1995 - 17/10/2012), San Diego (4/1/1996 - 23/10/2012), San Francisco (5/1/1995 - 18/10/2012), New York (5/1/1995 - 23/10/2012) and Washington D.C. (5/6/2001 - 11/10/2012). This unique data is sourced from Bollerslev et al. (2016), whereby the authors use comprehensive housing transaction data from DataQuick, and then apply the repeat sales method to derive these indices. The data set is downloadable from: <http://qed.econ.queensu.ca/jae/datasets/bollerslev001/>. Following Wang (2014), we compute the daily Composite 10 Housing Price Index, as a proxy for the aggregate housing price of the US, as a weighted average of the house prices of the 10 MSAs. The specific values of the weights used were Boston (0.212), Chicago (0.074), Denver (0.089), Las Vegas (0.037), Los Angeles (0.050), Miami (0.015), New York (0.055),

San Diego (0.118), San Francisco (0.272), and Washington D.C. (0.078), representing the total aggregate value of the housing stock in the 10 MSAs in the year 2000. This aggregate index has the daily sample period of 5/6/2001 - 11/10/2012. Since these indices are a bit outdated, even though they do cover the period of turmoil in the US housing market in the wake of the subprime mortgage crisis, we also use the CME-S&P Case-Shiller House Price Index (HPI) Continuous Futures (CS-CME), derived from Datastream as maintained by Thomson Reuters, and covers the period of 2/8/2007 - 29/8/2018. We compute the continuously compounded returns as

$$r_t = [\ln(p_t) - \ln(p_{t-1})], \quad (1)$$

where  $p_t$  denotes the housing price in USD at a time  $t$ .

Figures 1, 2, 3, 4 depict the time evolution of house price returns for 10 US cities, the aggregate index and their squared returns. The descriptive statistics of our data sets are reported in Table 1. Except for Chicago, Miami and future housing price index, we observe a negative skewness in the data for other major cities. All the data

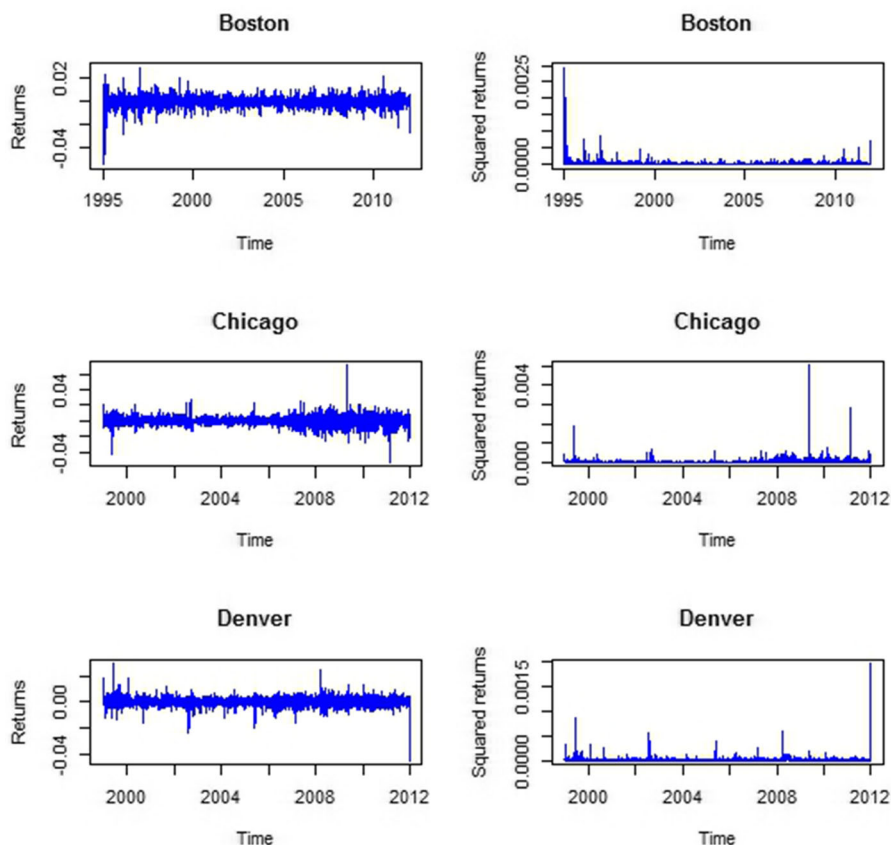
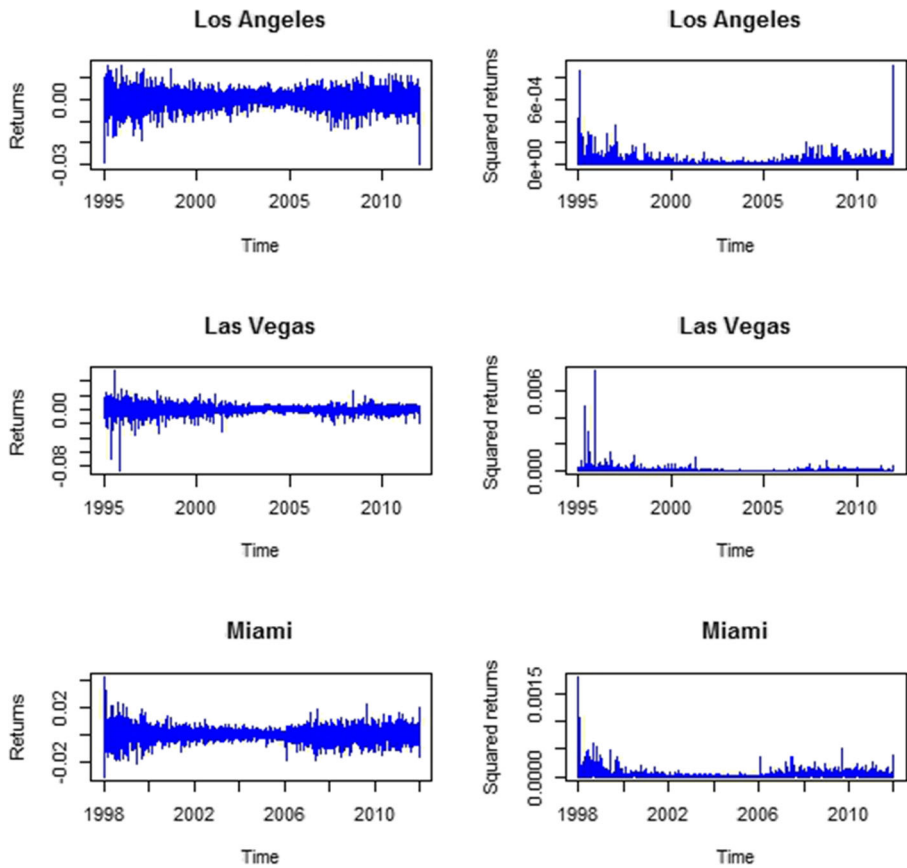


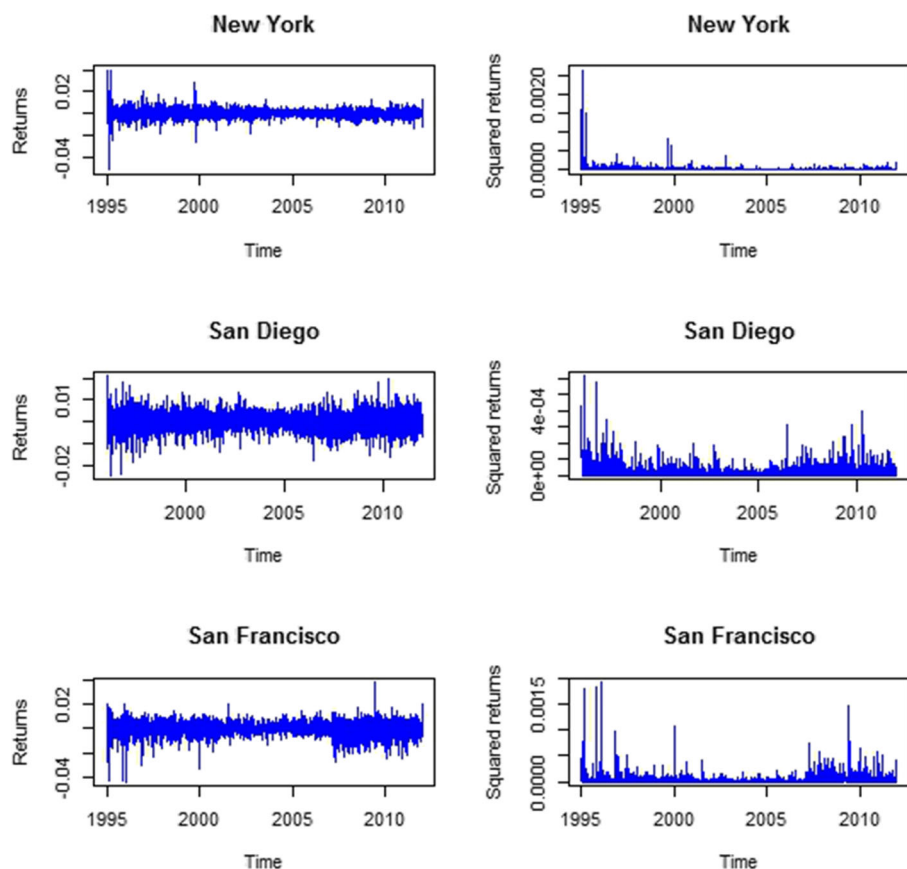
Fig. 1 Daily housing returns and squared returns



**Fig. 2** Daily housing returns and squared returns

sets are characterized by excess kurtosis suggesting a deviation from the normality. This observation can be confirmed by the Jarque-Bera test, which rejects the null hypothesis of the normality at all significant levels. The ARCH test for heteroscedasticity at lag 1 rejects the null of no conditional heteroscedasticity in the data. The results of the augmented Dickey-Fuller (ADF) unit-root test of Dickey and Fuller (1979) and its modified version to account for serial correlations (Phillips-Perron test) in Phillips and Perron (1988) reject the null hypothesis of unit-root. We also apply the KPSS test for stationarity to confirm the verdict of the unit root tests.

We investigate the long memory effects in the US housing price changes by adopting the Detrended Fluctuation Analysis (DFA) (see Weron (2002)) to compute the Hurst exponent indices (see, Table 1). The Hurst indices help to quantify the degree of persistence in data and serve as standard measures of long-term dependence. Except for Las Vegas, San Francisco, U.S. Aggregate and future housing price changes the values for log-price changes are close to 0.5, implying absence of long memory features in housing price returns. For absolute and squared returns the Hurst index values



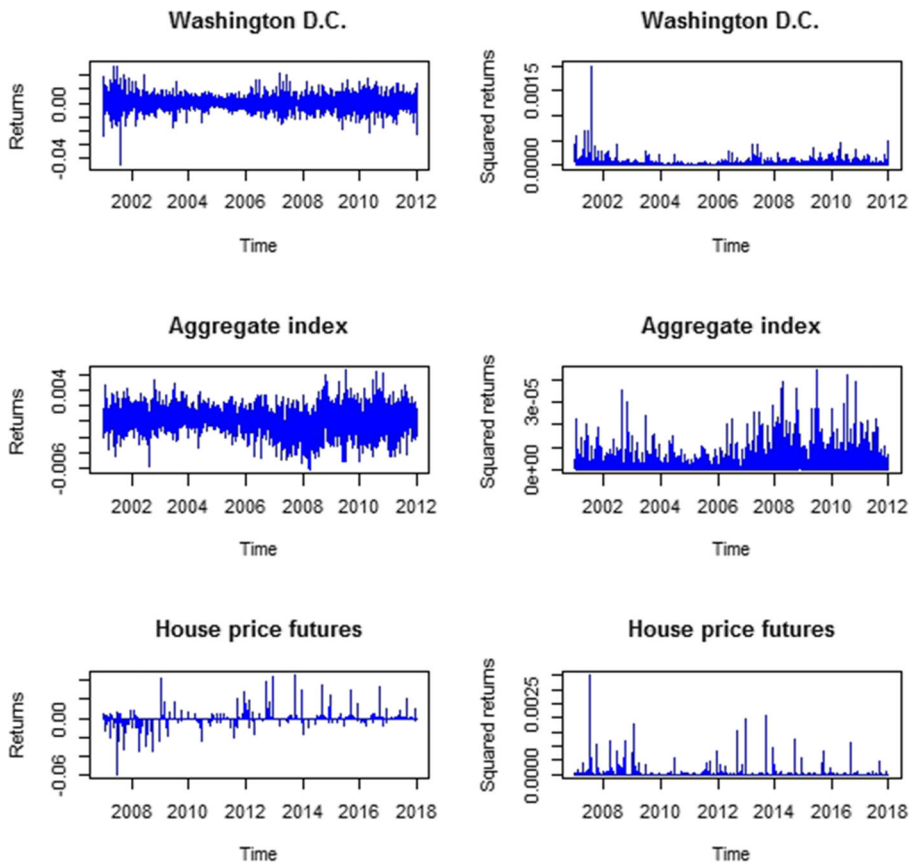
**Fig. 3** Daily housing returns and squared returns

are significantly above 0.5, indicating the presence of long memory in housing price volatility.

We also compute the so-called Hill estimator for the tail index (see Hill (1975)) in order to quantify the decay of the unconditional distribution of housing price returns in its extremal region. The estimate for the tail index (see Table 1) is in the vicinity of 3 or above and this result is in harmony with typical findings for financial assets, (see Lux and Ausloos (2002)). Again, this is a clear indication of non-Normality as the slow decay of the distribution of returns implies that large price changes occur with much higher probability than under a Gaussian shape.

We also investigate the nonlinearity in the mean process using the White (see Lee et al. (1993)) and Teraesvirta neural network tests (see, Table 1). Based on the results of Teraesvirta neural network test (see Teraesvirta et al. (1993)) only Las Vegas, San Diego and San Francisco exhibit linearity in “mean”. These results confirm that U.S. housing price indices are characterized by nonlinearities.

Figures 5, 6, 7, 8 show the autocorrelation functions for log-returns and squared log-returns. We observe that the squared log-returns are highly correlated. However,



**Fig. 4** Daily housing returns and squared returns for Washington D. C. and daily Composite 10 housing price and house price futures index returns and squared returns

the Ljung-Box tests also reject the null hypothesis of no serial correlation for log-returns at the 5% significance level for Denver and San Diego. This indicates the presence of some serial dependence and predictability in the returns of housing prices for those cities. Overall, the U.S. housing price indices, therefore, share the typical salient features of financial assets that are captured by the catchwords “fat tails” and “clustered volatility”, but some of them show some deviation from the “efficiency” of stock or foreign exchange markets (their complete lack of predictability). These findings have motivated the choice of our proposed processes.<sup>3</sup>

<sup>3</sup> It must be realized that, the features of market efficiency, long-memory, nonlinearity, and non-normality, as observed traditionally for other asset markets, are however not likely due to the usage of high-frequency data of the housing market. In fact, these features have also been reported for low-frequency (monthly, quarterly, and annual) data for the US by studies such as Canarella et al. (2012, 2019), Barros et al. (2015), Balcilar et al. (2015), Gupta and Majumdar (2015).

Table 1 Daily descriptive statistics

	Boston	Chicago	Denver	Los Ange- les	Las Vegas	Miami	New York	San Diego	San Francisco	Washington D.C.	Aggregate index	House price futures
No of Obs	4424	3265	3344	4425	4399	3587	4163	4442	4442	2816	2806	2790
Returns												
Mean	1.721E-4	9.291E-6	9.898E-5	1.721E-4	1.098E-5	1.331E-4	1.696E-4	2.175E-4	1.594E-4	1.528E-4	9.811E-5	2.355E-5
SD	3.995E-3	5.933E-3	3.302E-3	3.812E-3	5.686E-3	5.051E-3	3.799E-3	4.106E-3	5.296E-3	5.057E-3	1.627E-32	3.417E-3
Skewness	-1.119	0.131	-0.823	-0.510	-1.613	0.085	-0.041	-0.179	-0.955	-0.192	-0.211	0.847
Kurtosis	18.344	13.417	20.027	6.015	28.151	6.950	19.231	4.916	9.036	6.824	3.770	104.283
Hurst exponent	0.480	0.465	0.532	0.575	0.583***	0.554	0.499	0.559	0.603***	0.544	0.802***	0.775***
Hurst exponent <sup>2</sup>	0.751	0.825	0.778	0.848	0.745	0.826	0.795	0.723	0.761	0.823	0.676	0.775
Hurst exponent <sub>abs</sub>	0.724	0.813	0.752	0.807	0.728	0.812	0.778	0.709	0.745	0.803	0.669	0.673
Tail index	3.595	4.182	2.696	3.350	4.141	4.170	3.117	4.996	3.629	4.006	5.922	5.042
Test for dependency and normality												
<i>LB</i> (8)	39.008 (0.000)	24.934 (0.002)	11.918 (0.155)	43.951 (0.000)	36.467 (0.000)	21.984 (0.005)	22.909 (0.004)	9.477 (0.304)	138.048 (0.000)	26.117 (0.001)	335.500 (0.000)	17.805 (0.023)
Arch(1)	32.834	17.076	206.938	12.622	137.564	104.074	30.273	11.373	6.814	53.604	4.757	0.808
JB	4.432E+4	1.477E+4	4.077E+4	1.178E+5	1.868E+3	2.337E+3	4.876E+4	659.067	7.386E+3	1.734E+3	90.064	1.193E+6
Test for unit root and stationarity												
ADF	-46.334	-38.895	-38.267	-46.131	-46.904	-40.947	-45.888	-45.055	-48.447	-38.353	-66.538	-36.348
PP	-64.349	-56.503	-55.473	-65.475	-68.550	-60.874	-65.931	-65.024	-71.134	-54.086	-99.830	-51.828
KPSS	0.183	0.063	0.133	0.431	0.721	0.438	0.248	0.377	0.295	0.411	0.032	0.262
Test for nonlinearity												
White test	3.170 (0.205)	0.616 (0.735)	6.864 (0.032)	2.295 (0.317)	9.281 (0.010)	13.243 (0.001)	9.249 (0.001)	1.172 (0.557)	9.316 (0.009)	7.495 (0.023)	15.854 (0.000)	14.283 (0.001)
Teraesvirta test	5.701 (0.058)	15.314 (0.000)	68.878 (0.000)	4.796 (0.091)	0.381 (0.827)	23.922 (0.000)	15.935 (0.000)	4.579 (0.101)	1.647 (0.439)	17.728 (0.000)	12.855 (0.002)	5.819 (0.055)

Note: \*\*\* indicates 1% significance of Hurst coefficients based on the simulated boundary values of Weron (2002) for Wiener Brownian motion. The values in parentheses are the p-values of Ljung-Box test, white and Teraesvirta neutral network tests for nonlinearity



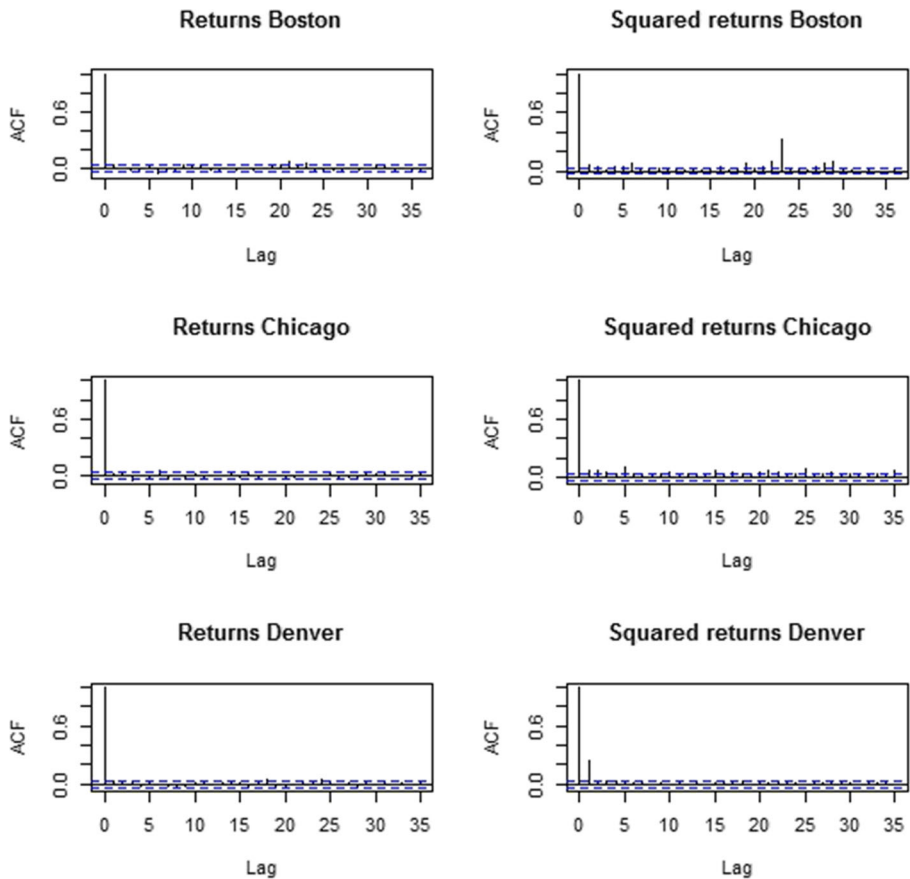


Fig. 5 ACFs for housing returns and squared returns

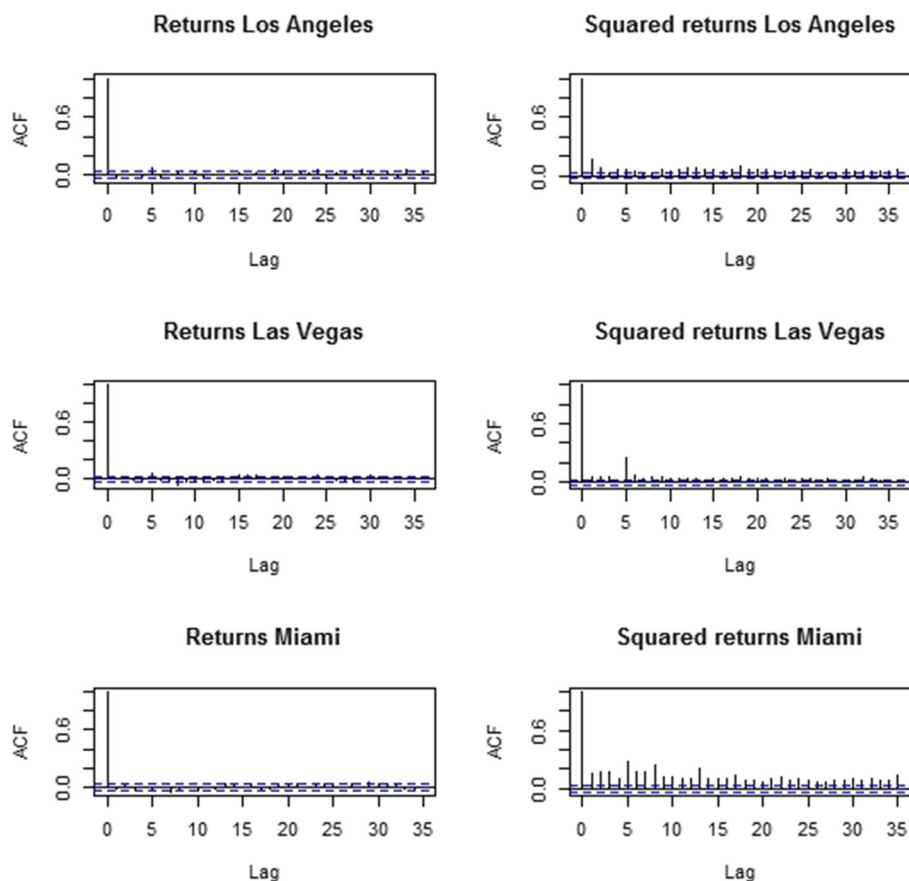
## Modeling Framework

We assume that returns  $\{r_t\}$  in US housing markets follow a smooth transition autoregressive fractionally integrated process [STARFI( $p, d$ )] that satisfies the following equation:

$$\Phi_{s_t; \eta}(L)(1 - L)^d r_t = \epsilon_t, \quad (2)$$

where  $\epsilon_t | \Omega_{t-1} \sim N(0, \sigma_t^2)$ .

$\Omega_{t-1}$  is the  $\sigma$ -field generated by the past information  $\{\epsilon_{t-1}, \epsilon_{t-2}, \dots\}$ . The lag polynomials in Eq. 2 are defined as:  $\Phi_{s_t; \eta}(L) = 1 - \phi_1(s_t; \eta_1)L - \dots - \phi_p(s_t; \eta_p)L^p$  where the autoregressive coefficients  $\phi_i(s_t, \eta_i) = \phi_{i0} + \phi_{i1}G(s_t, \tau, c)$ , for  $i = 1, \dots, p$ , are nonlinear functions that have to be defined,  $s_t$  denotes the state variable



**Fig. 6** ACFs for housing returns and squared returns

and  $\eta_i = (\phi_{i0}, \phi_{i1}, \tau, c)'$  a vector of parameters, and  $d$  is a real number.  $L$  is the lag operator and  $(1 - L)^d$  is the fractional differencing operator that is given by

$$(1 - L)^d = \sum_{k=0}^{\infty} \frac{\Gamma(k - d)L^k}{\Gamma(-d)\Gamma(k + 1)}, \quad (3)$$

with  $\Gamma(\cdot)$  being the gamma function.

The transition function  $G(s_t, \tau, c)$  follows the first-order Logistic function that is given:

$$G(s_t, \tau, c) = \frac{1}{1 + \exp(-\tau(s_t - c))}, \quad \tau > 0. \quad (4)$$

**Remark 1** The STARFI(p,d) reduces to the STAR(p) when  $d = 0$ . The logistic function exhibits the following properties:  $\lim_{s_t \rightarrow -\infty} G(s_t, \tau, c) = 0$ ,  $\lim_{s_t \rightarrow \infty} G(s_t, \tau, c) = 1$ ,  $G(s_t, 0, c) = 1/2$ ,  $\lim_{\tau \rightarrow -\infty} G(s_t, \tau, c) = 0$  and  $\lim_{\tau \rightarrow \infty} G(s_t, \tau, c) = 1$ .

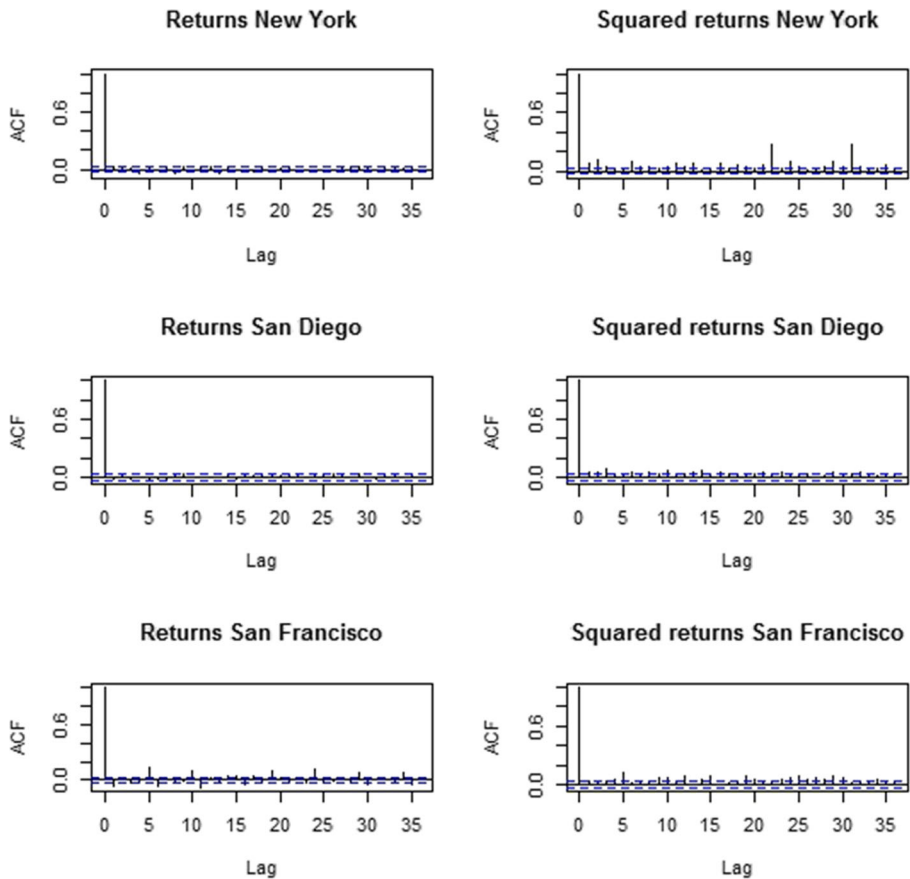


Fig. 7 ACFs for housing returns and squared returns

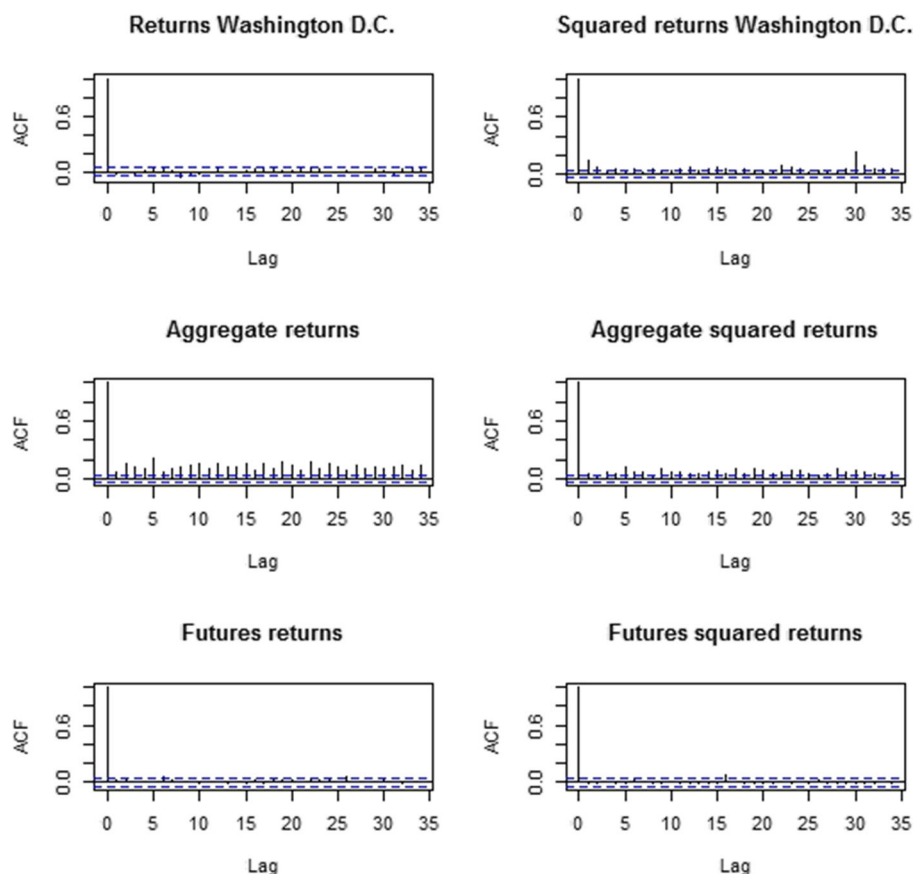
In general, the innovation process,  $\epsilon_t$ , in Eq. 2 can be modeled as follows:

$$\epsilon_t = u_t \sigma_t, \quad (5)$$

where  $u_t$  is a sequence of independent identically distributed normal random variables with zero mean and unit variance.

Our findings in Section 2 show that US housing markets share the same salient features of financial assets. In addition, the recent research findings in modeling and forecasting financial market volatility that the Markov-switching multifractal (MSM) model can better reproduce the stylized facts of financial markets and provides more accurate forecast than the GARCH-type models. Motivated by all these facts, we choose the MSM and GARCH-type processes for capturing the time-varying dynamics of  $\sigma_t$ :

1. *Markov-switching multifractal (MSM) model*: In this framework we assume that the dynamics underlying the housing markets volatility are driven by a



**Fig. 8** ACFs for Washington D. C., daily composite and future housing returns and their squared returns

hidden Markov chain vector,  $M_t$ , that consists of  $k$  independent random volatility components,  $M_t^{(1)}, M_t^{(2)}, \dots, M_t^{(k)}$ , and the volatility is formalized as:

$$\sigma_t = \bar{\sigma} \sqrt{\prod_{j=1}^k M_t^{(j)}}, \quad (6)$$

where  $\bar{\sigma}$  is a scaling factor and  $k$  the number of volatility components.

The dynamics governing the random volatility components (also called multipliers) determines the unique framework that characterizes the multifractal models. At date  $t$ , each multiplier  $M_t^{(j)}$  is drawn from the base distribution  $F_M$  (to be specified) with positive support and unit expectation. Depending on its rank within the hierarchy of multipliers,  $M_t^{(j)}$  changes from one period to the next, with probability  $\gamma_j$ , and remains unchanged with probability  $1 - \gamma_j$ , providing a spectrum of low and high frequencies of multiplier renewal.

The  $k$  transition probabilities are specified as

$$\gamma_j = 2^{j-k}, j = 1, \dots, k. \quad (7)$$

The transition matrix related to the  $j$ th multiplier is given by

$$\begin{pmatrix} 1 - 0.5\gamma_j & 0.5\gamma_j \\ 0.5\gamma_j & 1 - 0.5\gamma_j \end{pmatrix} \quad (8)$$

To finalize the specification of the MSM model we draw each multiplier,  $M_t^{(j)}$  (in the event of a change) from a two-point distribution with support  $\{m_0, 2 - m_0\}$ ,  $1 < m_0 < 2$ , and probability 0.5, implying the unconditional expectation  $\mathbb{E}(M_t^{(j)}) = 1$ . The transition matrix of the vector  $M_t \equiv (M_t^{(1)}, \dots, M_t^{(k)})'$  becomes the  $2^k \times 2^k$  matrix  $P = P_1 \otimes P_2 \otimes \dots \otimes P_k$ , where  $\otimes$  denotes the Kronecker product. Using the binomial base distribution<sup>4</sup> for the single multipliers implies the finite support  $\Gamma \equiv \{m_0, 2 - m_0\}^k$  for  $M_t$  and allows implementing of the maximum likelihood approach.

*Remark 2* A higher  $k$  increases the number of regimes (which is  $2^k$ ), and generates proximity to long memory over a longer number of lags, but comes at an additional computational cost in our maximum likelihood approach. In contrast to the traditional Markov switching models, in which the number of parameters to be estimated doubles with an additional regime, the number of parameters in MSM model remains constant with an increasing number of regimes. We note that the non-parametric specification of the transition probability does not guarantees the convergence of the process in continuous time limit. Furthermore, we point out that the MSM processes exhibit only *apparent* long memory with an asymptotic hyperbolic decay of the autocorrelation of absolute powers over a finite horizon and does not obey the traditional definition of long memory (see Beran (1994)).

## 2. GARCH-type models:

- A more general class of short-memory GARCH(1, 1) models proposed by Hentschel (1995) can be formalized as

$$\frac{\sigma_t^\delta}{\delta} = \omega + \alpha_{t-1}^\delta f^\nu(u_t) + \beta \frac{\sigma_{t-1}^\delta - 1}{\delta}, \quad (9)$$

where  $u_t$  has zero mean and unit variance,  $\omega > 0, \alpha > 0, \beta > 0, f(u_t) = |u_t - b| - c(u_t - b)$ , the transformation  $f^\nu(\cdot)$  controls the impact of shocks  $u_t$  on the transformed conditional volatility  $\sigma_t, \delta > 0$  determines the shape of the Box-Cox transformation of the conditional standard deviation and  $\nu$  serves to transform the absolute value function  $f(\cdot)$ . This class of GARCH-type models includes, among others, the specifications of Bollerslev (1986) (standard GARCH), (Glosten et al. 1993) (GJR-GARCH), (Nelson 1991)

<sup>4</sup>Liu et al. (2007) find that assuming other base distributions, such as lognormal and gamma, makes little difference in empirical applications.

(EGARCH), and (Ding et al. 1993) (APARCH). These models are robust and able to capture the most stylized facts of US housing markets.

- Motivated by the properties observed in log changes of US housing prices and the findings in Barros et al. (2015) we also adopt the FIGARCH model developed by Baillie et al. (1996) that generalizes the standard GARCH framework by introducing fractional differences in the GARCH process and thereby enables the model to reproduce the long-term dependence of US housing price volatility as documented in the high Hurst coefficients of absolute and squared returns. The conditional variance in the FIGARCH(1,d,1) model can be formalized as

$$\sigma_t^2 = \omega + \left[ 1 - \beta(L) - \phi(L)(1-L)^d \right] \epsilon_t^2 + \beta \sigma_{t-1}^2, \quad (10)$$

where  $\omega > 0$ ,  $\phi < 1$ ,  $\beta < 1$ ,  $0 \leq d \leq 1$ .  $L$  denotes the lag operator and  $d$  is the parameter of fractional differentiation. The lag polynomials  $\beta(L) = \beta$  and  $\phi(L) = 1 - \phi(L)$ . The parameters have to fulfill the following conditions:

$$\beta - d \leq \phi \leq \frac{(2-d)}{3} \quad (11)$$

and

$$d \left[ \phi - \frac{(1-d)}{2} \right] \leq \beta(d - \beta + \phi). \quad (12)$$

**Remark 3** We refer the readers to Conrad and Haag (2006) for generalized restrictions on the parameters in the FIGARCH model. Long-term dependence shows up in the fact, that, in principle, all available past data should be used in the construction of forecasts of future volatility (while in GARCH, its short-term dependence makes it sufficient to use the filtered realization of the conditional variance,  $\sigma_t$ , at the forecast origin, time  $t$ ).

## Statistical Properties

In this section we show that our proposed models for modeling and forecasting US housing market volatility are stationary, ergodic and exhibit high-order moments.

**Assumption 1** The roots of the characteristic polynomials  $\Phi_{s_t; \eta}(L)$  lie outside the unit circle, the parameter  $d \in (-0.5, 0.5)$  and the logistic transition function is well defined.

**Assumption 2** The random volatility components  $M_t^1, M_t^2, \dots, M_t^k$  with  $E(M_t^j) = 1$ ,  $j = 1, \dots, k$ , are nonnegative and independent of each other at any time and  $\gamma_j \in (0, 1)$ .

**Proposition 1** Under Assumption 1 and 2, the STARFI( $p, d$ )-MSM( $k$ ) model given by Eqs. 2, 6 and 7 has a unique, second-order stationary solution. It follows that  $\{r_t, \epsilon_t, \sigma_t\}$  are strictly stationary, ergodic and invertible.

*Proof* Under Assumption 2, the conditions of *Theorem 1* in (see Shiryaev (1995), Chapter 1, section 12) are satisfied. It follows that the chain underlying the dynamics of multipliers  $M_t^j$  is geometrically ergodic. The ergodic distribution is given by  $\pi_l = 1/2^k$ ,  $l = 1, \dots, 2^k$ . Under Assumptions 1 and 2,  $\{r_t, \epsilon_t, \sigma_t\}$  are strictly stationary, ergodic and invertible.  $\square$

**Proposition 2** *Under Assumption 1, the STARFI(p,d)-GARCH-class model given by Eqs. 2, 5 and 9 has a unique,  $\alpha\delta$ -order stationary solution. It follows that  $\{r_t, \epsilon_t, \sigma_t\}$  are strictly stationary, ergodic and invertible.*

*Proof* Under Assumption 1 and the conditions of *Theorem 2.1* in Ling and McAleer (2002) with a constant mean process replaced by a stationary univariate STARFI(p,d) process,  $\{r_t, \epsilon_t, \sigma_t\}$  are strictly stationary, ergodic and invertible.  $\square$

**Proposition 3** *Under Proposition 2, it follows that the  $2m$ th moments of  $\{r_t, \epsilon_t\}$  are finite, where  $m$  is a strictly integer.*

*Proof* Under Proposition 1 and the conditions of *Theorem 1* in (see Shiryaev (1995), Chapter 1, section 12), the  $2m$ th moments of  $\{r_t, \epsilon_t\}$  are finite.  $b > 1$ , it is obvious that all the elements of the transition matrix of the chain underlying the multipliers are strictly positive,  $\gamma_j \in (0, 1)$   $\square$

**Proposition 4** *Under Proposition 2, it follows that the  $m\delta$ th moments of the  $\{r_t, \epsilon_t\}$  exist.*

*Proof* Under Proposition 2 and the conditions of *Theorem 2.2* in Ling and McAleer (2002), the  $m\delta$ th moments of the  $\{r_t, \epsilon_t\}$  exist.  $\square$

Denoting  $\rho(n) = \text{cov}(r_t, r_{t-n})/\text{var}(r_t)$  the autocorrelation function of the process defined by Eq. 2.  $\rho_q(n) = \text{cov}(|\epsilon_t|^q, |\epsilon_{t-n}|^q)/\text{var}(|\epsilon_t|^q)$  the autocorrelation of  $\epsilon_t$  for every moment  $q$  and every integer  $n$ . Consider two arbitrary numbers  $\kappa_1$  and  $\kappa_2$  in the open interval  $(0, 1)$ . The following set of integers  $S_k = \{n : \kappa_1 k \leq \log 2(n) \leq \kappa_2 k\}$  contains a large range of intermediate lags.

**Proposition 5** *Under Assumption 1, it follows that  $\rho(n) \sim c|n|^{2d-1}$  as  $n \rightarrow \infty$ , where  $c$  is a constant.*

*Proof* Under Proposition 2 and *Theorem 2.4* in Hosking (1981),  $\rho(n)$  is proportional to  $|n|^{2d-1}$ .  $\square$

**Proposition 6** *Under Assumption 2, it follows that  $\ln \rho_q(n) \sim -\psi(q) \ln n$  as  $k \rightarrow \infty$ , where  $\psi(q) = \log_2 \left( \frac{E(M^q)}{[E(M^{q/2})]^2} \right)$ .*

*Proof* Under Proposition 2 and the proof of the Proposition 1 in Calvet and Fisher (2004),  $\rho(n)$  is proportional to  $\psi(q) \ln n$ .  $\square$

*Remark 4* The MSM processes exhibit only *apparent* long memory with an asymptotic hyperbolic decay of the autocorrelation of absolute powers over a finite horizon and does not obey the traditional definition of long memory, that means, asymptotic power-law behavior of autocorrelation functions in the limit or divergence of the spectral density (see Beran (1994)).

*Remark 5* We note that the FIGARCH process is not covariance stationary. However, there exist many attempts to demonstrate the strict stationarity of the FIGARCH process with infinity variance. We refer the reader to Bougerol and Picard (1992), Giraitis et al. (2000), Kazakevicius and Leipus (2002) and Douc et al. (2008) for more details.

## Estimation

We estimate all the models using the maximum likelihood approach. Given the fact that  $u_t$  in Eq. 5 is assumed to follow a standard normal distribution, the information matrix of the STARFI-GARCH-type models and STARFI-MSM model are block-diagonal and allow to estimate the models using a two-stage procedure without loss of efficiency (see Lundbergh and Terasvirta (1999)). In the first stage we adopt the Non-linear Squares (NLS) to estimate the parameters of the conditional mean process. The optimal lag  $p$  in STARFI model is determined based on the Akaike information criterion. We note that here that under normality assumption the NLS is equivalent to MLE (see Wooldridge (1994)).

*Remark 6* Based on the fact that under Assumption 1, the STARFI process defined in Eq. 2 is strictly stationary and ergodic and the necessary and sufficient conditions for the existence of moments are satisfied, the  $\hat{\epsilon}_t$  are the consistent estimates of the  $\epsilon_t$  (see Chan and McAleer (2002)).

In the second stage we use the computed residuals to estimate the parameters of the conditional variance via the maximum likelihood method. In the GARCH-type models we fix the optimal lag  $p = q = 1$ . It well documented that using  $p = q = 1$  is enough to effectively capture the dynamics underlying the variance process (see Bollerslev et al. (1994)). The parameters are well-estimated and asymptotically efficient. To save place we do not report them, but can be submitted under request.

## Empirical Study

We investigate the forecasting performance of our models using three loss functions, namely the root mean squared error, mean absolute error and the value-at-risk (VaR)



based loss function. In addition, we apply the model confidence set (MCS) test of Hansen et al. (2011) to identify models that perform well in our portfolio of models. We adopt a rolling forecasting scheme that consists of removing one earlier observation and adding a new one day by day, so that the estimation sample size remains constant over the out-of-sample. For all 10 US cities and their composite index we use observations until 31/12/2007 as in-sample and those from 01/01/2008 to the end of each data set as out-sample. For each run, we produce forecasts up to 20 days ahead. For house price futures data set we take the first half of the observations as in-sample and the remaining as out-of-sample.

### Forecasting Evaluation Criteria

The root mean square error, the mean absolute deviation and the mean of the VaR-based loss function that are given by

$$\text{RMSE}_h^{j,k} = \left( \frac{1}{n} \sum_{i=1}^n \left( \sigma_{T+i,h,k}^2 - \hat{\sigma}_{T+i,h,j,k}^2 \right)^2 \right)^{1/2}, \quad (13)$$

$$\text{MAE}_h^{j,k} = \frac{1}{n} \sum_{i=1}^n |\sigma_{T+i,h,k}^2 - \hat{\sigma}_{T+i,h,j,k}^2|, \quad (14)$$

and

$$\text{MVaR}_h^{j,k}(\alpha) = n^{-1} \sum_{i=1}^n \left( \alpha - I_{T+h,j,k}^\alpha \right) \left( \epsilon_{T+h,j,k} - \text{VaR}_{T+h,j,k}^\alpha \right), \quad (15)$$

respectively.  $j$  denotes a particular model in our portfolio and  $k$  represents a particular U.S. city or index,  $n$  is the number of out-sample forecast observations,  $T$  the forecast origin and  $h$  the forecasting horizon.  $\hat{\sigma}_{T+i,h,j,k}^2$  denotes the volatility forecast obtained using a GARCH-type model or MSM model,  $\sigma_{T+i,h,k}^2$  is the daily actual volatility that is approximated by the daily squared returns,  $I_{T+h,j,k}^\alpha = \mathbf{1}(\epsilon_{T+h,j,k} < \text{VaR}_{T+h,j,k}^\alpha)$ ,  $\text{VaR}_{T+h,j,k}^\alpha = F_{T+h}^{-1}(\alpha) \hat{\sigma}_{T+h,j,k}$  is the conditional value-at-risk, and  $F_{T+h}(\cdot)$  is the forecast cumulative distribution of the standardized returns. As with RMSE and MAE, a smaller value for the  $\text{MVaR}(\alpha)$  points to a good predictive performance. VaR forecasts provide an assessment of the loss that occurs in the  $\alpha$  percent worst cases, and are used to determine the necessary level of underlying equity for risky assets to cover the risk of extreme market movement. The asymmetry of Eq. 15 helps to avoid making type I-errors (failing to forecast a large negative change) to be more important than issuing an erroneous warning signal.

We note that the VaR-based loss function defined in Eq. 15 is not differentiable due to the presence of the indicator function. The non-differentiability of  $\text{MVaR}(\alpha)$  may cause a problem in the implementation of the MCS test of Hansen et al. (2011) that is based on the framework of White (2000). To obtain consistent results we also use

a smooth approximation<sup>5</sup> to  $\text{MVaR}(\alpha)$ , denoted as  $\text{MSVaR}(\alpha)$ , that is differentiable and given by

$$\text{MSVaR}_h^{j,k}(\alpha) = n^{-1} \sum_{i=1}^n \left[ \alpha - g_v \left( \epsilon_{T+h,j,k}, \text{VaR}_{T+h,j,k}^\alpha \right) \right] \left( \epsilon_{T+h,j,k} - \text{VaR}_{T+h,j,k}^\alpha \right), \quad (16)$$

$g_v(y, z) = [1 + \exp(v(y - z))]^{-1}$ . The parameter,  $v > 0$ , governs the smoothness and for a higher value of  $v$   $\text{MSVaR}(\alpha)$  gets closer to  $\text{MVaR}(\alpha)$ .

To draw meaningful inferences about the relative forecasting performance of our proposed models for forecasting housing market volatility, we apply the model confidence set (MCS) test that was recently developed by Hansen et al. (2011). The basic idea of the MCS approach is to derive from an initial set of competing models,  $\mathcal{M}_0$  without a predefined benchmark model, a set of superior models,  $\mathcal{M}^*$  at forecasting horizon  $h$ , with a given confidence level. Formally, we have

$$\mathcal{M}^* = \{i \in \mathbb{M}_0 | \mathbb{E} \left( d_{i,j}^h \right) \leq 0 \forall j \in \mathcal{M}_0\},$$

where  $d_{i,j}^h = L_{i,h} - L_{j,h}$  is the loss differential between models  $i$  and  $j$ .  $L_{i,h}$  denotes a specific loss function of a particular model  $i$ . Based on the expected loss functions, competing models are ranked and the worst performing model at each step is eliminated. This sequential elimination continues until the null hypothesis of equal loss differentials for all models cannot be rejected:

$$H_0 : \mathbb{E} \left( d_{i,j}^h \right) \leq 0 \forall i, j \in \mathcal{M}.$$

The test statistic used under the null is either the range statistic,  $T_r$ , or the semi-quadratic statistic,  $T_{sq}$ , that are given by

$$T_r = \max_{i,j \in \mathcal{M}} \frac{|\bar{d}_{i,j}|}{\sqrt{\hat{v} \hat{\sigma}(\bar{d}_{i,j})}}, \quad T_{sq} = \sum_{i \neq j} \frac{(\bar{d}_{i,j})^2}{\sqrt{\hat{v} \hat{\sigma}(\bar{d}_{i,j})}}.$$

The p-values can easily be obtained via a stationary bootstrap procedures that are developed based on the framework in White (2000). We refer the reader to Hansen et al. (2011) for details on the framework of the MCS approach concerning the impact of the (i) forecasting schemes used, (ii) the relationships between models under comparison and (iii) the differentiation of the loss functions used.

## Forecasting Results

Tables 2, 3, 4 report MSE, MAE,  $\text{MVaR}(1\%)$  and  $\text{MSVaR}(1\%)$  of housing price volatility forecasts for our six volatility models used in this analysis and across US cities or indices. For the MCS test we have used both the differentiable and non-differentiable VaR-based loss function. We only report the MCS test results for

<sup>5</sup> As mentioned by Granger (1999) the issue associated with the non-differentiability may be just a technicality due to the fact that it should always be possible to find a smooth function which is arbitrarily close to the non-smooth one.

**Table 2** The results of RMSE, MAE and MVAR

Models	RMSE			MAE			MVAR			SMVaR		
	h=1	h=10	h=20	h=1	h=10	h=20	h=1	h=10	h=20	h=1	h=10	h=20
Boston												
GARCH	0.032	0.034	0.034	0.017	0.017	0.017	0.115	0.142	0.143	0.115	0.142	0.144
GJR	0.033	0.034	0.034	0.017	0.017	0.017	0.110	0.143	0.144	0.109	0.142	0.144
EGARCH	0.033	0.034	0.034	0.017	0.018	0.018	0.115	0.134	0.135	0.115	0.134	0.134
APARCH	0.033	0.034	0.034	0.017	0.018	0.018	0.126	0.134	0.136	0.126	0.134	0.135
FIGARCH	0.033	0.035	0.034	0.015	0.016	0.016	0.122	0.169	0.170	0.122	0.168	0.169
MSM	0.031	0.034	0.034	0.015	0.017	0.017	0.107	0.133	0.133	0.106	0.133	0.133
Chicago												
GARCH	0.177	0.192	0.191	0.062	0.068	0.068	0.200	0.279	0.284	0.200	0.279	0.284
GJR	0.178	0.191	0.191	0.062	0.069	0.069	0.194	0.279	0.284	0.193	0.278	0.284
EGARCH	0.182	0.189	0.189	0.061	0.066	0.067	0.215	0.264	0.277	0.215	0.264	0.277
APARCH	0.179	0.192	0.191	0.061	0.066	0.066	0.228	0.301	0.309	0.227	0.301	0.308
FIGARCH	0.190	0.193	0.194	0.055	0.057	0.057	0.320	0.501	0.597	0.320	0.500	0.596
MSM	0.181	0.189	0.190	0.055	0.060	0.059	0.204	0.267	0.282	0.204	0.267	0.282
Denver												
GARCH	0.023	0.023	0.062	0.010	0.011	0.012	0.077	0.085	0.119	0.077	0.085	0.119
GJR	0.022	0.023	0.062	0.010	0.011	0.012	0.077	0.085	0.120	0.077	0.085	0.119
EGARCH	0.023	0.023	0.062	0.010	0.011	0.012	0.082	0.087	0.119	0.082	0.086	0.118
APARCH	0.023	0.023	0.062	0.011	0.011	0.013	0.087	0.087	0.117	0.087	0.086	0.116
FIGARCH	0.023	0.024	0.062	0.010	0.010	0.012	0.078	0.085	0.119	0.077	0.084	0.119
MSM	0.022	0.024	0.062	0.010	0.011	0.013	0.084	0.092	0.122	0.084	0.092	0.122
Las Vegas												
GARCH	0.039	0.040	0.040	0.019	0.020	0.020	0.118	0.143	0.153	0.118	0.143	0.153
GJR	0.040	0.040	0.040	0.020	0.020	0.021	0.116	0.144	0.154	0.115	0.143	0.154
EGARCH	0.041	0.040	0.040	0.021	0.021	0.021	0.134	0.144	0.149	0.134	0.143	0.149
APARCH	0.041	0.039	0.040	0.020	0.020	0.020	0.143	0.141	0.149	0.142	0.141	0.149
FIGARCH	0.042	0.040	0.040	0.016	0.016	0.016	0.176	0.196	0.212	0.175	0.196	0.211
MSM	0.038	0.040	0.040	0.018	0.021	0.021	0.118	0.142	0.146	0.118	0.142	0.146
Los Angeles												
GARCH	0.024	0.025	0.027	0.015	0.016	0.016	0.102	0.117	0.128	0.102	0.117	0.128
GJR	0.024	0.025	0.027	0.016	0.016	0.016	0.107	0.118	0.126	0.107	0.118	0.126
EGARCH	0.025	0.025	0.027	0.017	0.017	0.017	0.108	0.116	0.124	0.108	0.116	0.124
APARCH	0.026	0.062	0.135	0.015	0.050	0.106	0.122	0.192	0.248	0.121	0.192	0.248
FIGARCH	0.026	0.027	0.028	0.015	0.015	0.015	0.134	0.155	0.174	0.133	0.154	0.174
MSM	0.024	0.025	0.027	0.015	0.016	0.016	0.102	0.115	0.124	0.102	0.115	0.124

Note: The entries are RMSE, MAE, and MVAR(5%) and MSVaR(5%) for all six models. For  $v \geq 6950$  the differences between the non-differentiable and differentiable VaR-based loss functions are vanishing. All the numbers reported here have to be multiplied by  $10^{-3}$

**Table 3** The results of RMSE, MAE and MVAR

Models	RMSE			MAE			MVaR			SMVaR		
	h=1	h=10	h=20	h=1	h=10	h=20	h=1	h=10	h=20	h=1	h=10	h=20
Miami												
GARCH	0.042	0.045	0.045	0.027	0.029	0.029	0.128	0.147	0.155	0.128	0.147	0.154
GJR	0.042	0.045	0.045	0.027	0.029	0.029	0.125	0.144	0.156	0.125	0.144	0.155
EGARCH	0.044	0.045	0.045	0.029	0.029	0.029	0.132	0.139	0.143	0.132	0.139	0.143
APARCH	0.045	0.045	0.045	0.028	0.028	0.028	0.145	0.146	0.146	0.145	0.146	0.146
FIGARCH	0.047	0.048	0.048	0.026	0.026	0.026	0.215	0.237	0.263	0.214	0.236	0.262
MSM	0.041	0.045	0.045	0.026	0.028	0.028	0.130	0.142	0.142	0.130	0.142	0.142
New York												
GARCH	0.016	0.017	0.018	0.010	0.010	0.011	0.082	0.098	0.103	0.082	0.098	0.103
GJR	0.016	0.017	0.019	0.010	0.011	0.011	0.084	0.098	0.104	0.084	0.098	0.103
EGARCH	0.017	0.017	0.019	0.010	0.011	0.011	0.088	0.097	0.102	0.088	0.097	0.102
APARCH	0.016	0.017	0.018	0.010	0.010	0.011	0.087	0.098	0.103	0.087	0.098	0.103
FIGARCH	0.017	0.018	0.019	0.009	0.009	0.009	0.096	0.116	0.132	0.096	0.115	0.131
MSM	0.016	0.017	0.018	0.010	0.011	0.011	0.086	0.099	0.101	0.086	0.099	0.101
San Diego												
GARCH	0.032	0.033	0.033	0.019	0.019	0.019	0.107	0.132	0.135	0.107	0.132	0.135
GJR	0.032	0.033	0.033	0.019	0.019	0.019	0.107	0.132	0.133	0.107	0.132	0.132
EGARCH	0.033	0.033	0.033	0.020	0.020	0.020	0.123	0.131	0.131	0.123	0.130	0.131
APARCH	0.033	0.056	0.108	0.019	0.041	0.073	0.129	0.156	0.185	0.129	0.156	0.185
FIGARCH	0.033	0.033	0.033	0.018	0.018	0.018	0.133	0.139	0.140	0.133	0.138	0.140
MSM	0.032	0.033	0.033	0.019	0.019	0.019	0.113	0.129	0.130	0.113	0.129	0.130
San Francisco												
GARCH	0.081	0.083	0.084	0.042	0.043	0.042	0.216	0.259	0.258	0.216	0.258	0.258
GJR	0.081	0.083	0.084	0.043	0.043	0.042	0.209	0.252	0.253	0.209	0.251	0.253
EGARCH	0.082	0.083	0.083	0.045	0.046	0.046	0.216	0.229	0.227	0.216	0.229	0.227
APARCH	0.082	0.083	0.083	0.045	0.045	0.045	0.232	0.235	0.236	0.232	0.235	0.236
FIGARCH	0.086	0.086	0.088	0.039	0.038	0.038	0.404	0.429	0.454	0.404	0.429	0.453
MSM	0.078	0.083	0.084	0.039	0.042	0.041	0.177	0.237	0.248	0.176	0.237	0.248
Washington D.C.												
GARCH	0.042	0.044	0.043	0.026	0.028	0.027	0.132	0.161	0.163	0.132	0.161	0.163
GJR	0.042	0.044	0.043	0.027	0.028	0.028	0.130	0.162	0.160	0.130	0.162	0.159
EGARCH	0.043	0.044	0.043	0.027	0.029	0.028	0.139	0.160	0.160	0.138	0.160	0.159
APARCH	0.044	0.045	0.043	0.026	0.027	0.027	0.156	0.163	0.161	0.156	0.162	0.161
FIGARCH	0.045	0.046	0.045	0.024	0.024	0.024	0.177	0.236	0.251	0.177	0.236	0.250
MSM	0.041	0.044	0.043	0.025	0.027	0.027	0.134	0.153	0.154	0.134	0.153	0.154

Note: The entries are RMSE, MAE, and MVaR(5%) and MSVaR(5%) for all six models. For  $v \geq 6950$  the differences between the non-differentiable and differentiable VaR-based loss functions are vanishing. All the numbers reported here have to be multiplied by  $10^{-3}$

**Table 4** The results of RMSE, MAE and MVaR

Models	RMSE			MAE			MVaR			SMVaR		
	h=1	h=10	h=20	h=1	h=10	h=20	h=1	h=10	h=20	h=1	h=10	h=20
Aggregate index												
GARCH	0.005	0.006	0.006	0.003	0.003	0.003	0.046	0.066	0.068	0.045	0.064	0.067
GJR	0.005	0.006	0.006	0.003	0.003	0.003	0.044	0.064	0.067	0.043	0.063	0.065
EGARCH	0.006	0.006	0.006	0.004	0.004	0.004	0.047	0.050	0.051	0.046	0.049	0.051
APARCH	0.006	0.019	0.043	0.003	0.015	0.035	0.150	0.159	0.183	0.147	0.158	0.182
FIGARCH	0.006	0.006	0.006	0.003	0.003	0.003	0.071	0.077	0.082	0.069	0.075	0.080
MSM	0.005	0.006	0.006	0.003	0.003	0.003	0.047	0.054	0.058	0.046	0.053	0.057
House price futures												
GARCH	0.103	0.106	0.106	0.019	0.019	0.019	0.085	0.086	0.086	0.085	0.086	0.086
GJR	0.098	0.106	0.106	0.018	0.019	0.019	0.085	0.087	0.087	0.085	0.087	0.087
EGARCH	2.719	0.509	0.476	0.165	0.049	0.047	0.121	0.097	0.097	0.121	0.097	0.097
APARCH	0.100	0.302	0.182	0.019	0.111	0.063	0.085	0.168	0.139	0.085	0.168	0.139
FIGARCH	0.079	0.107	0.108	0.016	0.028	0.029	0.089	0.109	0.114	0.087	0.109	0.114
MSM	0.099	0.107	0.106	0.010	0.014	0.015	0.038	0.084	0.085	0.038	0.084	0.085

Note: The entries are RMSE, MAE, and MVaR(5%) and MSVaR(5%) for all six models. For  $\nu \geq 6950$  the differences between the non-differentiable and differentiable VaR-based loss functions are vanishing. All the numbers reported here have to be multiplied by  $10^{-3}$

$\nu \geq 6950$ . The p-values of the MCS test and the rank of the models are reported in Tables 5, 6, 7, 8, 9, 10.

Based on the RMSE criterion, all the models perform well at different forecasting horizons and across all indices. However, based on the MCS test results we observe that in most cases the MSM model clearly outperforms other competitive models at the 1-day forecasting horizon. At the 10-days forecasting horizon and beyond the MCS test results indicate that for Denver, Las Vegas all the volatility models are in the optimal set at the 95% confidence level suggesting that for these US cities all models perform equally well.

According to the MAE criterion and the MCS test results, FIGARCH seems to be the best model followed by the MSM model across indices and performs better than short-memory GARCH-type models at the different horizons. Based on the MVaR(1%) criterion and the MCS test results the MSM model outperforms its competitors at the 10-days ahead and beyond across all indices. The second best model seems to be the EGARCH model. Note that the differences in forecasting performance between the MSM and GARCH-type models across US cities or indices appear so pronounced under the MVaR criterion. The MSM model provides better average MVaR results and as for the smooth MSVaR criterion, practically no differences are detected compared to the non-differentiable MVaR as the smoothness parameter  $\nu$  increases.

**Table 5** MCS test results using squared and absolute loss functions

Squared loss function			Absolute loss function					
Horizons			h=1		h=10		h=20	
Model	$p_{V_{MCS}}$	Model	$p_{V_{MCS}}$	Model	$p_{V_{MCS}}$	Model	$p_{V_{MCS}}$	Model
<b>Boston</b>								
FIGARCH	0.000	FIGARCH	0.015	EGARCH	0.000	EGARCH	0.000	EGARCH
EGARCH	0.000	GJR	0.682*	APARCH	0.000	APARCH	0.000	APARCH
APARCH	0.000	GARCH	0.249*	MSM	0.000	GJR	0.000	GJR
GARCH	0.000	MSM	0.274*	GJR	0.000	MSM	0.000	MSM
GJR	0.000	APARCH	0.274*	APARCH	0.736*	GARCH	0.000	GARCH
MSM	1.000*	EGARCH	1.000*	EGARCH	0.963*	FIGARCH	0.000	FIGARCH
					1.000*	1.000*	1.000*	1.000*
<b>Chicago</b>								
FIGARCH	0.030	FIGARCH	0.000	EGARCH	0.000	EGARCH	0.000	EGARCH
EGARCH	0.348*	APARCH	0.123*	GJR	0.002	GJR	0.001	GJR
MSM	0.433*	GJR	0.099	GARCH	0.002	GARCH	0.001	GARCH
APARCH	0.433*	GARCH	0.127*	APARCH	0.002	APARCH	0.001	APARCH
GJR	0.614*	MSM	0.678*	FIGARCH	0.849*	MSM	0.001	MSM
GARCH	1.000*	EGARCH	1.000*	MSM	1.000*	FIGARCH	1.000*	FIGARCH
<b>Denver</b>								
EGARCH	0.000	FIGARCH	0.438*	APARCH	0.000	MSM	0.000	MSM
FIGARCH	0.000	MSM	0.832*	EGARCH	0.000	APARCH	0.000	APARCH
APARCH	0.000	GARCH	0.832*	GARCH	0.000	GARCH	0.000	GARCH
GARCH	0.000	APARCH	0.984*	GJR	0.000	EGARCH	0.002	EGARCH
GJR	0.000	GJR	0.984*	FIGARCH	0.001	GJR	0.002	GJR
MSM	1.000*	EGARCH	1.000*	MSM	1.000*	FIGARCH	1.000*	FIGARCH

**Table 5** (continued)

Squared loss function			Absolute loss function									
Horizons												
h=1			h=10		h=20		h=1		h=10		h=20	
Model	$p^{v_{MCS}}$		Model	$p^{v_{MCS}}$	Model	$p^{v_{MCS}}$	Model	$p^{v_{MCS}}$	Model	$p^{v_{MCS}}$	Model	$p^{v_{MCS}}$
Las Vegas												
APARCH	0.001		EGARCH	0.063*	EGARCH	0.076*	EGARCH	0.000	MSM	0.000	MSM	0.000
EGARCH	0.001		GJR	0.499*	GJR	0.246*	APARCH	0.000	EGARCH	0.000	EGARCH	0.000
FIGARCH	0.001		FIGARCH	0.586*	FIGARCH	0.445*	GARCH	0.000	GARCH	0.000	GJR	0.000
GJR	0.001		GARCH	0.586*	GARCH	0.445*	GJR	0.000	APARCH	0.000	GARCH	0.000
GARCH	0.001		MSM	0.586*	MSM	0.547*	MSM	0.000	GJR	0.000	APARCH	0.000
MSM	1.000*		APARCH	1.000*	APARCH	1.000*	FIGARCH	1.000*	FIGARCH	1.000*	FIGARCH	1.000*
Los Angeles												
FIGARCH	0.000		APARCH	0.000	APARCH	0.000	EGARCH	0.000	APARCH	0.000	APARCH	0.000
APARCH	0.000		FIGARCH	0.000	FIGARCH	0.000	GJR	0.000	EGARCH	0.000	EGARCH	0.000
EGARCH	0.000		GJR	0.366*	GARCH	0.231*	GARCH	0.007	GARCH	0.000	GARCH	0.000
GJR	0.004		GARCH	0.366*	GJR	0.377*	APARCH	0.007	GJR	0.000	MSM	0.000
GARCH	0.410*		MSM	0.748*	MSM	0.509*	MSM	0.041	MSM	0.000	GJR	0.000
MSM	1.000*		EGARCH	1.000*	EGARCH	1.000*	FIGARCH	1.000*	FIGARCH	1.000*	FIGARCH	1.000*

Note: MCS p-values for forecasts from six volatility models at different forecasting horizons. The p-values are computed via a stationary bootstrap (B=10000) using the range statistic  $T_r$ . The forecasts in  $M_{95}^*$  are identified by one asterisk

**Table 6** MCS test results using squared and absolute loss functions

Squared loss function			Absolute loss function									
Horizons			h=10		h=20		h=1		h=10		h=20	
Model	$p_{VMCS}$	Model	$p_{VMCS}$	Model	$p_{VMCS}$	Model	$p_{VMCS}$	Model	$p_{VMCS}$	Model	$p_{VMCS}$	
Miami												
FIGARCH	0.000	FIGARCH	0.000	FIGARCH	0.000	EGARCH	0.000	EGARCH	0.000	EGARCH	0.000	
EGARCH	0.000	GARCH	0.144*	GARCH	0.080	APARCH	0.000	APARCH	0.000	GJR	0.000	
APARCH	0.000	APARCH	0.280*	GJR	0.310*	GARCH	0.000	GARCH	0.000	GARCH	0.000	
GARCH	0.000	GJR	0.872*	APARCH	0.749*	GJR	0.000	MSM	0.000	APARCH	0.000	
GJR	0.000	MSM	0.872*	MSM	0.749*	FIGARCH	0.956*	APARCH	0.000	MSM	0.001	
MSM	1.000*	EGARCH	1.000*	EGARCH	1.000*	MSM	1.000*	FIGARCH	1.000*	FIGARCH	1.000*	
New York												
EGARCH	0.000	FIGARCH	0.280*	FIGARCH	0.048	EGARCH	0.000	MSM	0.000	MSM	0.000	
FIGARCH	0.000	EGARCH	0.568*	GJR	0.091	APARCH	0.000	EGARCH	0.000	EGARCH	0.000	
APARCH	0.000	GJR	0.770*	EGARCH	0.155*	GJR	0.000	GJR	0.000	GJR	0.000	
GARCH	0.000	APARCH	0.963*	APARCH	0.566*	GARCH	0.000	APARCH	0.000	APARCH	0.000	
GJR	0.000	MSM	0.963*	GARCH	0.755*	MSM	0.000	GARCH	0.000	GARCH	0.000	
MSM	1.000*	GARCH	1.000*	MSM	1.000*	FIGARCH	1.000*	FIGARCH	1.000*	FIGARCH	1.000*	
San Diego												
APARCH	0.000	APARCH	0.000	APARCH	0.000	EGARCH	0.000	APARCH	0.000	APARCH	0.000	
EGARCH	0.000	FIGARCH	0.007	FIGARCH	0.000	APARCH	0.002	EGARCH	0.000	EGARCH	0.000	
FIGARCH	0.000	GJR	0.011	GJR	0.125*	GJR	0.002	MSM	0.000	MSM	0.000	
GJR	0.020	GARCH	0.103*	EGARCH	0.346*	GARCH	0.077	GJR	0.000	GJR	0.000	
GARCH	0.024	EGARCH	0.105*	GARCH	0.346*	MSM	0.344*	GARCH	0.000	GARCH	0.000	
MSM	1.000*	MSM	1.000*	MSM	1.000*	FIGARCH	1.000*	FIGARCH	1.000*	FIGARCH	1.000*	



**Table 6** (continued)

Squared loss function			Absolute loss function									
Horizons												
h=1			h=10		h=20		h=1		h=10		h=20	
Model	p <sub><i>MCS</i></sub>		Model	p <sub><i>MCS</i></sub>	Model	p <sub><i>MCS</i></sub>	Model	p <sub><i>MCS</i></sub>	Model	p <sub><i>MCS</i></sub>	Model	p <sub><i>MCS</i></sub>
San Francisco												
FIGARCH	0.000		FIGARCH	0.000	FIGARCH	0.000	APARCH	0.000	EGARCH	0.000	EGARCH	0.000
APARCH	0.000		MSM	0.260*	MSM	0.051	EGARCH	0.000	APARCH	0.000	APARCH	0.000
EGARCH	0.000		GARCH	0.260*	GARCH	0.101	GJR	0.000	GJR	0.000	GJR	0.000
GARCH	0.000		GJR	0.260*	GJR	0.364*	GARCH	0.000	GARCH	0.000	GARCH	0.000
GJR	0.000		APARCH	0.844*	APARCH	0.742*	MSM	0.328*	MSM	0.000	MSM	0.000
MSM	1.000*		EGARCH	1.000*	EGARCH	1.000*	FIGARCH	1.000*	FIGARCH	1.000*	FIGARCH	1.000*
Washington D. C.												
FIGARCH	0.000		FIGARCH	0.000	FIGARCH	0.000	EGARCH	0.000	GJR	0.000	EGARCH	0.000
APARCH	0.000		APARCH	0.169*	APARCH	0.276*	GJR	0.000	EGARCH	0.000	GJR	0.000
EGARCH	0.000		EGARCH	0.550*	EGARCH	0.389*	GARCH	0.000	MSM	0.000	GARCH	0.000
GARCH	0.000		GJR	0.599*	GARCH	0.389*	APARCH	0.001	GARCH	0.000	MSM	0.000
GJR	0.000		GARCH	0.599*	GJR	0.649*	MSM	0.001	APARCH	0.001	APARCH	0.001
MSM	1.000*		MSM	1.000*	MSM	1.000*	FIGARCH	1.000*	FIGARCH	1.000*	FIGARCH	1.000*

Note: MCS p-values for forecasts from six volatility models at different forecasting horizons. The p-values are computed via a stationary bootstrap (B=10000) using the range statistic  $T_r$ . The forecasts in  $M_{95}^*$  are identified by one asterisk

**Table 7** MCS test results using squared and absolute loss functions

Squared loss function			Absolute loss function									
Horizons												
h=1			h=10		h=20		h=1		h=10		h=20	
Model	$pV_{MCS}$		Model	$pV_{MCS}$	Model	$pV_{MCS}$	Model	$pV_{MCS}$	Model	$pV_{MCS}$	Model	$pV_{MCS}$
Aggregate index												
APARCH	0.000		APARCH	0.000	APARCH	0.000	EGARCH	0.000	APARCH	0.000	APARCH	0.000
FIGARCH	0.000		FIGARCH	0.000	FIGARCH	0.000	APARCH	0.000	EGARCH	0.000	EGARCH	0.000
EGARCH	0.002		GARCH	0.000	GARCH	0.000	MSM	0.000	MSM	0.000	MSM	0.000
MSM	0.174*		GJR	0.000	GJR	0.000	FIGARCH	0.015	GARCH	0.002	GARCH	0.011
GJR	0.174*		MSM	0.006	MSM	0.002	GARCH	0.485*	GJR	0.002	GJR	0.011
GARCH	1.000*		EGARCH	1.000*	EGARCH	1.000*	GJR	1.000*	FIGARCH	1.000*	FIGARCH	1.000*
House price futures												
EGARCH	0.042		EGARCH	0.004	EGARCH	0.012	EGARCH	0.000	APARCH	0.000	APARCH	0.000
GARCH	0.042		APARCH	0.004	APARCH	0.012	APARCH	0.000	EGARCH	0.000	EGARCH	0.000
APARCH	0.269*		FIGARCH	0.022	FIGARCH	0.029	GARCH	0.000	FIGARCH	0.000	FIGARCH	0.000
MSM	0.269*		MSM	0.748*	GARCH	0.671*	GJR	0.000	GJR	0.000	GJR	0.000
GJR	0.269*		GARCH	0.748*	MSM	0.980*	FIGARCH	0.000	GARCH	0.000	GARCH	0.000
FIGARCH	1.000*		GJR	1.000*	GJR	1.000*	MSM	1.000*	MSM	1.000*	MSM	1.000*

Note: MCS p-values for forecasts from six volatility models at different forecasting horizons. The p-values are computed via a stationary bootstrap (B=10000) using the range statistic  $T_r$ . The forecasts in  $\mathcal{M}_{95\%}^*$  are identified by one asterisk

**Table 8** MCS test results using VaR-based loss function

Discrete VaR-based loss function				Continuous VaR-based loss function			
Horizons							
h=1				h=10			
h=20				h=1			
Model	p <sub>VaR</sub>	Model	p <sub>VaR</sub>	Model	p <sub>VaR</sub>	Model	p <sub>VaR</sub>
<b>Boston</b>							
APARCH	0.011	FIGARCH	0.012	FIGARCH	0.020	APARCH	0.012
FIGARCH	0.144*	GJR	0.029	GJR	0.074*	FIGARCH	0.142*
EGARCH	0.144*	GARCH	0.085*	GARCH	0.105*	EGARCH	0.142*
GARCH	0.144*	APARCH	0.933*	APARCH	0.665*	GARCH	0.142*
GJR	0.488*	EGARCH	0.933*	EGARCH	0.665*	GJR	0.491*
MSM	1.000*	MSM	1.000*	MSM	1.000*	MSM	1.000*
<b>Chicago</b>							
FIGARCH	0.001	FIGARCH	0.000	FIGARCH	0.000	FIGARCH	0.001
EGARCH	0.129*	APARCH	0.024	APARCH	0.031	EGARCH	0.133*
APARCH	0.161*	GJR	0.024	GJR	0.546*	APARCH	0.173*
MSM	0.331*	GARCH	0.024	GARCH	0.546*	MSM	0.336*
GARCH	0.331*	MSM	0.617*	MSM	0.665*	GARCH	0.336*
GJR	1.000*	EGARCH	1.000*	EGARCH	1.000*	GJR	1.000*
<b>Denver</b>							
APARCH	0.000	MSM	0.154*	MSM	0.006	APARCH	0.000
MSM	0.000	EGARCH	0.926*	GJR	0.776*	MSM	0.146*
EGARCH	0.022	APARCH	0.926*	GARCH	0.776*	EGARCH	0.895*
FIGARCH	0.080*	GARCH	0.926*	EGARCH	0.776*	APARCH	0.895*
GARCH	0.080*	GJR	0.926*	FIGARCH	0.776*	GARCH	0.895*
GJR	1.000*	FIGARCH	1.000*	APARCH	1.000*	GJR	0.895*
<b>h=20</b>							
Model	p <sub>VaR</sub>	Model	p <sub>VaR</sub>	Model	p <sub>VaR</sub>	Model	p <sub>VaR</sub>
FIGARCH	0.018	FIGARCH	0.015	FIGARCH	0.012	FIGARCH	0.015
GJR	0.065*	GJR	0.035	GJR	0.142*	GJR	0.035
GARCH	0.100*	GARCH	0.093*	GARCH	0.142*	GARCH	0.093*
APARCH	0.681*	APARCH	0.941*	APARCH	0.142*	APARCH	0.941*
EGARCH	0.681*	EGARCH	0.941*	EGARCH	0.491*	EGARCH	0.941*
MSM	1.000*	MSM	1.000*	MSM	1.000*	MSM	1.000*
FIGARCH	0.000	FIGARCH	0.000	FIGARCH	0.001	FIGARCH	0.000
APARCH	0.036	APARCH	0.019	APARCH	0.133*	APARCH	0.019
GJR	0.567*	GJR	0.019	GJR	0.173*	GJR	0.019
GARCH	0.567*	GARCH	0.019	GARCH	0.336*	GARCH	0.019
MSM	0.671*	MSM	0.595*	MSM	0.336*	MSM	0.595*
EGARCH	1.000*	EGARCH	1.000*	EGARCH	1.000*	EGARCH	1.000*
MSM	0.005	MSM	0.146*	MSM	0.000	MSM	0.146*
GJR	0.779*	GJR	0.895*	MSM	0.000	GJR	0.779*
GARCH	0.779*	GARCH	0.895*	EGARCH	0.020	GARCH	0.895*
EGARCH	0.779*	EGARCH	0.895*	FIGARCH	0.042	EGARCH	0.895*
FIGARCH	0.779*	GJR	0.895*	GARCH	0.042	GJR	0.895*
APARCH	1.000*	FIGARCH	1.000*	GJR	1.000*	FIGARCH	1.000*



**Table 9** MCS test results

Discrete VaR-based loss function		Continuous VaR-based loss function							
Horizons		h=10		h=20		h=1		h=10	
Model	$p_{V_{MCS}}$	Model	$p_{V_{MCS}}$	Model	$p_{V_{MCS}}$	Model	$p_{V_{MCS}}$	Model	$p_{V_{MCS}}$
<b>Miami</b>									
FIGARCH	0.000	FIGARCH	0.000	FIGARCH	0.000	FIGARCH	0.000	FIGARCH	0.000
APARCH	0.002	GARCH	0.390*	GJR	0.133*	APARCH	0.002	GARCH	0.386*
EGARCH	0.002	APARCH	0.410*	GARCH	0.151*	EGARCH	0.002	APARCH	0.419*
MSM	0.025	GJR	0.410*	APARCH	0.698*	MSM	0.030	GJR	0.419*
GARCH	0.025	MSM	0.410*	EGARCH	0.698*	GARCH	0.030	MSM	0.419*
GJR	1.000*	EGARCH	1.000*	MSM	1.000*	GJR	1.000*	EGARCH	1.000*
<b>New York</b>									
FIGARCH	0.003	FIGARCH	0.186*	FIGARCH	0.029	FIGARCH	0.004	FIGARCH	0.222*
EGARCH	0.003	MSM	0.837*	GJR	0.847*	EGARCH	0.004	MSM	0.856*
APARCH	0.012	GARCH	0.837*	APARCH	0.847*	APARCH	0.016	GARCH	0.856*
MSM	0.087*	GJR	0.837*	GARCH	0.847*	MSM	0.093*	GJR	0.856*
GJR	0.087*	APARCH	0.837*	EGARCH	0.847*	GJR	0.093*	APARCH	0.856*
GARCH	1.000*	EGARCH	1.000*	MSM	1.000*	GARCH	1.000*	EGARCH	1.000*
<b>San Diego</b>									
APARCH	0.032	APARCH	0.044	APARCH	0.004	APARCH	0.037	APARCH	0.049
FIGARCH	0.032	FIGARCH	0.425*	FIGARCH	0.288*	FIGARCH	0.037	FIGARCH	0.484*
EGARCH	0.032	GJR	0.769*	GARCH	0.425*	EGARCH	0.037	GJR	0.773*
MSM	0.100*	GARCH	0.769*	GJR	0.593*	MSM	0.105*	GARCH	0.773*
GJR	0.715*	EGARCH	0.769*	EGARCH	0.593*	GJR	0.681*	EGARCH	0.773*
GARCH	1.000*	MSM	1.000*	MSM	1.000*	GARCH	1.000*	MSM	1.000*

Table 9 (continued)

Discrete VaR-based loss function				Continuous VaR-based loss function							
Horizons											
h=1		h=10		h=20		h=1		h=10		h=20	
Model	$p^{V_{MCS}}$	Model	$p^{V_{MCS}}$	Model	$p^{V_{MCS}}$	Model	$p^{V_{MCS}}$	Model	$p^{V_{MCS}}$	Model	$p^{V_{MCS}}$
San Francisco											
FIGARCH	0.000	FIGARCH	0.000	FIGARCH	0.000	FIGARCH	0.000	FIGARCH	0.000	FIGARCH	0.000
APARCH	0.000	GARCH	0.001	GARCH	0.003	APARCH	0.000	GARCH	0.002	GARCH	0.002
EGARCH	0.000	GJR	0.003	GJR	0.004	EGARCH	0.000	GJR	0.003	GJR	0.003
GARCH	0.000	MSM	0.024	MSM	0.012	GARCH	0.000	MSM	0.024	MSM	0.012
GJR	0.000	APARCH	0.024	APARCH	0.012	GJR	0.000	APARCH	0.024	APARCH	0.012
MSM	1.000*	EGARCH	1.000*	EGARCH	1.000*	MSM	1.000*	EGARCH	1.000*	EGARCH	1.000*
Washington D. C.											
FIGARCH	0.001	FIGARCH	0.000	FIGARCH	0.000	FIGARCH	0.001	FIGARCH	0.000	FIGARCH	0.000
APARCH	0.001	GJR	0.391*	GARCH	0.322*	APARCH	0.001	GJR	0.390*	GARCH	0.336*
EGARCH	0.001	APARCH	0.391*	APARCH	0.322*	EGARCH	0.001	APARCH	0.390*	APARCH	0.336*
MSM	0.233*	EGARCH	0.391*	EGARCH	0.322*	MSM	0.227*	EGARCH	0.390*	EGARCH	0.336*
GARCH	0.233*	GARCH	0.391*	GJR	0.322*	GARCH	0.227*	GARCH	0.390*	GJR	0.336*
GJR	1.000*	MSM	1.000*	MSM	1.000*	GJR	1.000*	MSM	1.000*	MSM	1.000*

Note: MCS p-values for forecasts from six volatility models at different forecasting horizons. The p-values are computed via a stationary bootstrap (B=10000) using the range statistic  $T_r$ . The forecasts in  $\mathcal{M}_{95\%}^*$  are identified by one asterisk

**Table 10** MCS test results

Discrete VaR-based loss function				Continuous VaR-based loss function							
Horizons											
h=1		h=10		h=20		h=1		h=10		h=20	
Model	$p^{V_{MCS}}$	Model	$p^{V_{MCS}}$	Model	$p^{V_{MCS}}$	Model	$p^{V_{MCS}}$	Model	$p^{V_{MCS}}$	Model	$p^{V_{MCS}}$
Aggregate index											
APARCH	0.000	APARCH	0.000	APARCH	0.000	APARCH	0.000	APARCH	0.000	APARCH	0.000
FIGARCH	0.000	FIGARCH	0.001	FIGARCH	0.001	FIGARCH	0.001	FIGARCH	0.001	FIGARCH	0.001
MSM	0.025	GARCH	0.017	GARCH	0.004	MSM	0.021	GARCH	0.023	GARCH	0.006
EGARCH	0.068*	GJR	0.017	GJR	0.012	EGARCH	0.084*	GJR	0.023	GJR	0.017
GARCH	0.068*	MSM	0.023	MSM	0.016	GARCH	0.084*	MSM	0.033	MSM	0.020
GJR	1.000*	EGARCH	1.000*	EGARCH	1.000*	GJR	1.000*	EGARCH	1.000*	EGARCH	1.000*
House price futures											
EGARCH	0.000	APARCH	0.000	APARCH	0.000	EGARCH	0.000	APARCH	0.000	APARCH	0.000
APARCH	0.000	FIGARCH	0.000	FIGARCH	0.000	APARCH	0.000	FIGARCH	0.000	FIGARCH	0.000
FIGARCH	0.000	EGARCH	0.012	EGARCH	0.009	FIGARCH	0.000	EGARCH	0.013	EGARCH	0.010
GJR	0.000	GJR	0.051*	GJR	0.061*	GJR	0.000	GJR	0.057*	GJR	0.056*
GARCH	0.000	GARCH	0.690*	GARCH	0.731*	GARCH	0.000	GARCH	0.688*	GARCH	0.747*
MSM	1.000*	MSM	1.000*	MSM	1.000*	MSM	1.000*	MSM	1.000*	MSM	1.000*

Note: MCS p-values for forecasts from six volatility models at different forecasting horizons. The p-values are computed via a stationary bootstrap (B=10000) using the range statistic  $T_r$ . The forecasts in  $\mathcal{M}_{95\%}^*$  are identified by one asterisk

## Conclusion

In this paper we have shown that the US housing markets share the typical salient features of financial assets. However, we note that the persistence in US housing markets is more pronounced and that the tails have more probability mass than observed in the stock, foreign exchange and commodity markets. We have proposed various approaches for modeling and forecasting US housing market volatility and discussed the statistical properties of the models used. We have evaluated and compared the out-of-sample forecasting ability of the models via three loss functions and the model confidence set (MCS) test. We found that based on the RMSE criterion all models in most cases perform well. Using the asymmetric loss functions such as the MAE and MVAR, the MSM followed by the FIGARCH outperform the short-memory GARCH-type models. At this stage a caveat is in order.<sup>6</sup> As indicated at the onset, the MSM approach is more suited to high-frequency data, but in general, house price data is not available at a daily frequency when it comes to the coverage of the whole country, i.e., for the various states, MSAs, and also the aggregate US. Moreover, the data that we use is a bit outdated, and even though, we do make use of a more recent data set involving house price futures, the lack of wide-spread coverage of this (Case-Shiller-type) data is a concern, especially when compared to that of the low-frequency data maintained by the Federal Housing Finance Agency (FHFA). This is more so, since the US housing market is known to be heterogenous, and cannot be generalized with a single housing index (Apergis and Payne 2012; Montañés and Olmos 2013; Barros et al. 2014; Miles 2015). Given this, unless new high-frequency house price data becomes available for the states, MSAs, and the overall US, we must be cautious about generalizing our findings. Contingent on the availability of high-frequency house price data, an interesting analysis in the future would be to revisit our results in terms of the superiority of the MSM approach.

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