Is the Housing Market in the United States Really Weakly-Efficient?

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Abstract

We analyze the directional predictability of a daily dataset of aggregate and regional (10 major metropolitan cities) housing markets of the United States using the quantilogram – a model-free procedure. We overwhelmingly reject the weak-form of the efficient market hypothesis (EMH), which has been derived thus far by the extant literature based on unit root tests and long-memory models.

JEL Codes: C22, R31

Keywords: Correlogram, dependence, quantiles, efficiency, housing markets, US

1. Introduction

Evidence in favour of the stationarity of (aggregate and regional) house prices in the United States (US), based on a large number of studies using unit root tests and long-memory models (with and without structural breaks), is weak, if not non-existent (see for example, Gupta and Miller (2012a, b), Canarella et al., (2012), and Canarella et al., (forthcoming) for a detailed literature review in this regard). US housing prices being random-walks, thus confirms the weak-form of the efficient market hypothesis (EMH), which states that asset (housing) prices fully and instantaneously reflect all available and relevant information (Samuelson, 1965; Fama, 1965). Under weak-form efficiency where the information set consists of past returns, future returns are unpredictable purely based on past price information. Hence, return predictability can be related to the violation of the weak-form of housing market efficiency.

Given that housing prices are known to lead business cycles in the US (Balcilar et al., 2014; Nyakabawo et al., 2015), and hence accurate prediction of housing returns is of paramount importance, we revisit the issue of the weak-form of EMH, using a unique database that comprises daily data (as developed by Bollerslev et al., (2016)) of the housing market. If indeed housing returns are predictable at the highest possible (daily) frequency, then one can obtain the future path of business cycles also at daily frequency based on models of nowcasting (Bańbura et al., 2011), and hence, should be of tremendous value to policymakers. As far as the econometric framework is concerned, we use the correlogram of quantile hits (i.e., quantilogram) as proposed by Linton and Whang (2007) to answer our question, which in turn, is a model-free econometric procedure involving a simple diagnostic statistic based on a sample correlation. While other tests of model-free directional predictability are available, we prefer the approach of Linton and Whang (2007) due its advantages from a conceptual perspective, since using the quantile in connection with counts is relatively more desirable.

At this stage, it must also be emphasized that we look at directional predictability instead of the conditional mean of housing returns, since direction of changes provide important insights to market participants for making investment decisions, and policy authorities for designing appropriate policies aiming to stabilize macroeconomic fluctuations. Further, predicting the direction of large housing return changes are likely to have information of possible future housing market crashes, and the associated likelihood of market contagion, as observed recently during the

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Global Financial Crisis of 2007-2008 in the US. To the best of our knowledge, this is the first attempt to test for the weak-form of the EMH using quantiles-based tests of directional predictability by relying on daily data on house prices of the US. The remainder of the paper is organized as follows: Section 2 presents the basics of the quantilogram, while Section 3 discusses the data and empirical results, with Section 4 concluding the paper.

2. Methodology

Suppose that $y_1, y_2, \ldots$ are random variables from a process without unit-roots with marginal distribution μ_α for $0 < \alpha < 1$ in quantiles. We test the null hypothesis that some conditional quantiles are time invariant, which can be written more formally as:
For some α:

$$E[\psi_\alpha(y_t - \mu_\alpha)|\mathcal{F}_{t-1}] = 0 \; a.s., where \; \psi_\alpha(x) = 1(x < 0) - \alpha \qquad (1),$$

denoted the check function, while $\mathcal{F}_{t-1} = \sigma(y_{t-1}, y_{t-2}, \ldots)$. Under this null hypothesis, if we exceed the unconditional α-quantile today, there is a small likelihood that we will exceed this threshold α in the next observation. This hypothesis can be further extended from a particular quantile to a set of quantiles and to the entire sample.

If we compare (1) with the usual weak form EMH that for some μ,

$$E[y_t - \mu|\mathcal{F}_{t-1}] = 0 \qquad (2),$$

We could infer that the median of the population is time- varying and the mean is invariant and vice versa. Under symmetry there is a one to one relationship between (2) and (1), with $\alpha = 1/2$. Linton and Whang (2007) suggest a formal procedure to examine the null hypothesis (1) by first estimating $\mu_\alpha$using quantile estimator $\hat{\mu}_\alpha$which is defined by:

$$\hat{\mu}_\alpha = arg \min_{\mu \in \mathbb{R}} \sum_{t=1}^{T} \rho_\alpha(y_t - \mu), where \; \rho_\alpha(x) = x[\alpha - 1(x < 0)]$$

Then letting:

$$\hat{\rho}_{\alpha k} = \frac{\frac{1}{T-k}\sum_{t=1}^{T-k} \psi_\alpha(y_t - \hat{\mu}_\alpha)\psi_\alpha(y_{t+k} - \hat{\mu}_\alpha)}{\sqrt{\frac{1}{T}\sum_{t=1}^{T} \psi_\alpha^2(y_t - \hat{\mu}_\alpha)}\sqrt{\frac{1}{T-k}\sum_{t=1}^{T-k} \psi_\alpha^2(y_{t+k} - \hat{\mu}_\alpha)}}, k = 1,2, \ldots,$$

for any $\alpha \in [0,1]$. Note that $-1 \leq \hat{\rho}_{\alpha k} \leq 1$ for any $\alpha,$ and k, given that this refers to the sample correlation on $\psi_\alpha(y_t - \hat{\mu}_\alpha)$. Under the null hypothesis (1), the population quantity is:
$E[\psi_\alpha(y_t - \mu_\alpha)\psi_\alpha(y_{t+k} - \mu_\alpha)] = E[\psi_\alpha(y_t - \mu_\alpha)E[\psi_\alpha(y_{t+k} - \mu_\alpha)|\mathcal{F}_{t+k-1}] = 0$ for all k.
Thus, $\hat{\rho}_{\alpha k}$ should approximate zero.

To test the null hypothesis of no directional predictability at α up to *p* lags (i.e. $\rho_{\alpha k}$ =0 for *k*=1,. . ., *p*), Linton and Whang (2007) suggest a quantile version of Box-Ljung Q test (*QQ*):

$$QQ_\alpha(p) = T(T+2)\sum_{k=1}^{p} \hat{\rho}_{\alpha k}^2 / (T-k) \qquad (3)$$

Note that for the $QQ_\alpha(p)$ test, if hypothesis null cannot be rejected, there is insufficient evidence against serial dependence (at α), but if the null hypothesis is rejected, the underlying series is serially dependent.

Instead of employing the inference strategy suggested in Linton and Whang (2007), which at times leads to inclusive results, we conduct the test by means of the quantile wild bootstrapping (QWB) method outlined in Fen et al., (2011), which has been shown, via simulations by Su et al., (2017), to have accurate size without compromising on power, and hence, avoids inconclusive outcomes.

3. Data and Results

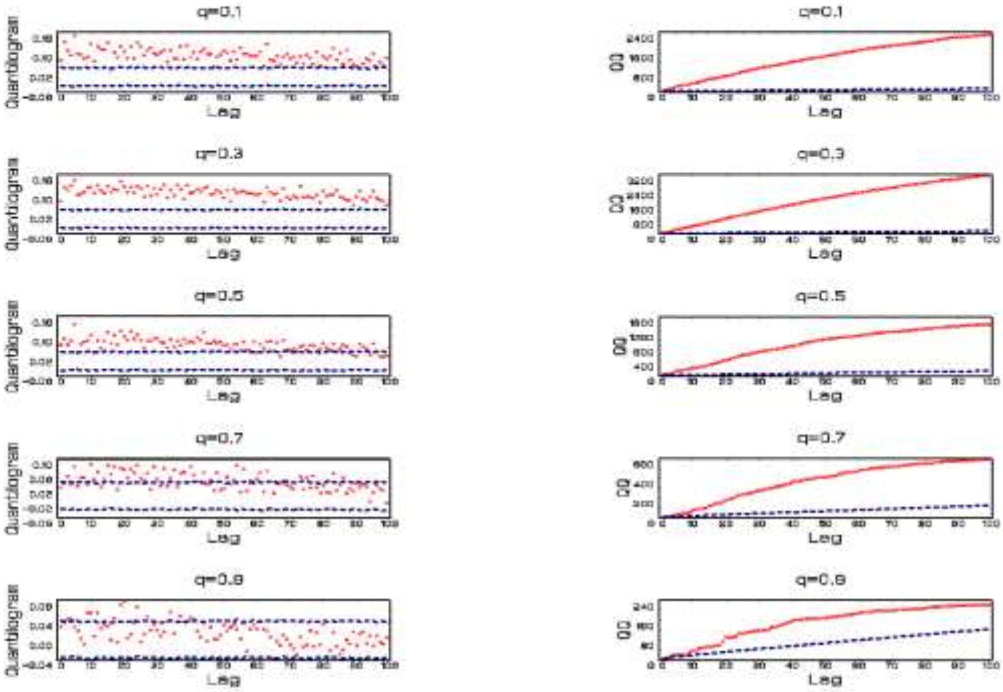
We use daily log-returns data based on a new data set of daily housing price series constructed by Bollerslev et al., (2016) using the repeat sales method and comprehensive housing transaction data from DataQuick. The daily housing price series covers 10 major Metropolitan Statistical Areas (MSAs) of the US, which we denote by $P_{i,t}$. Following Bollerslev et al., (2016), we compute the daily Composite 10 Housing Price Index ($P_{c,t}$) as a proxy for the aggregate housing price as a weighted average $(P_{c,t} = \sum_{i=1}^{10} w_i \, P_{i,t})$. The 10 MSAs and the specific values of the weights (w_i) are: 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 (see, Bollerslev et al., (2016) for further details).[1] Based on data availability, we cover the period of 5th June, 2001 to 11th October, 2012, i.e., a total of 2806 observations. The data for the aggregate and regional housing returns have been summarized in Table A1, and plotted in Figure A1 in the Appendix of the paper. The overwhelming rejection of the null of normality, provides strong underlying reasons to use a quantiles-based approach of directional predictability.

In Figure 1, we report the full-sample results of the quantilogram and the corresponding quantiles-based portmanteau test for the aggregate US housing returns, with lags (p) up to 100 trading days at five quantiles (α = 0.1, 0.3, 0.5, 0.7, 0.9). We also show the QWB-based 95% confidence intervals (centred at zero) for the quantilogram and the QWB-based 5% critical values for the portmanteau test, based on 1000 bootstrap replications. In general, there is significant and positive serial dependence, and the dependence appears to be strong and persistent, implying that when there are large gains in housing returns in one period, the chances of having large gains in the next few periods is also high. More importantly, aggregate housing returns of the US economy is strongly predictable, and hence we find evidence against the weak-form of EMH observed in the extant literature, derived using models-based tests of stationarity.[2]

[1] The data is downloadable from: http://qed.econ.queensu.ca/jae/datasets/bollerslev001/.

[2] In fact, Wang (2014) discusses in detail that the daily house price indices are indeed non-stationary in levels based on unit root tests, and hence, the housing market can be again be concluded to be weakly-efficient. In addition note that, to ensure that our results are not driven by the daily frequency of the data, we also applied the quantilogram on the log-returns of the monthly version of the index (derived from the FRED database of the Federal Reserve Bank of St. Louis), and reached similar conclusions, i.e., the null of no-predictability was strongly rejected. Complete details of these results are available upon request from the authors.

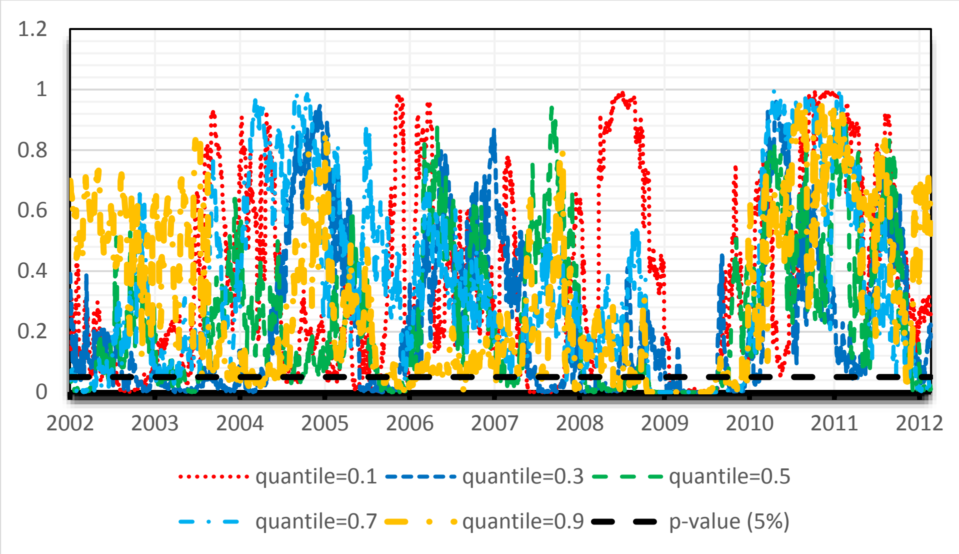
Figure 1. Quantilogram and quantile portmanteau test for daily Composite 10 Housing Price Index returns (at quantiles $\alpha = 0.1, 0.3, 0.5, 0.7$, and 0.9 for $p = 1, \ldots, 100$):



Note: Left column: Dots show the values of quantilogram; dashed lines represent the 95% confidence intervals centered at zero. Right column: Dots show the values of the QQ test; dashed lines give the bootstrapped 5% critical values.

To examine if the dependence is stable across time, we also run rolling version of the quantiles-based portmanteau test ($QQ_\alpha(p)$) with a 1-year window (i.e, 250 daily returns) moving up by each day. We report the results using $p = 50$ at the 5% significance level with various quantiles, i.e., α in Figure 2. As can be seen, consistent with the full-sample portmanteau test, the results are similar across the quantiles in terms of rejection of the null hypothesis over time. While evidence of directional predictability is observed in general over the entire sample period, it is particularly strong during the Global Financial Crisis, which might be a result of herding in the market in the face of uncertainty (Akinsomi et al., 2018), with lagged returns playing an important and persistent role. The housing market is found to behave more efficiently from 2010 onwards, with it recovering in the wake of unconventional measures of monetary policy (Huber and Punzi, forthcoming).

Figure 2. Rolling quantile portmanteau test of daily Composite 10 Housing Price Index returns (at quantiles $\alpha = 0.1, 0.3, 0.5, 0.7$, and 0.9 for $p = 50$):



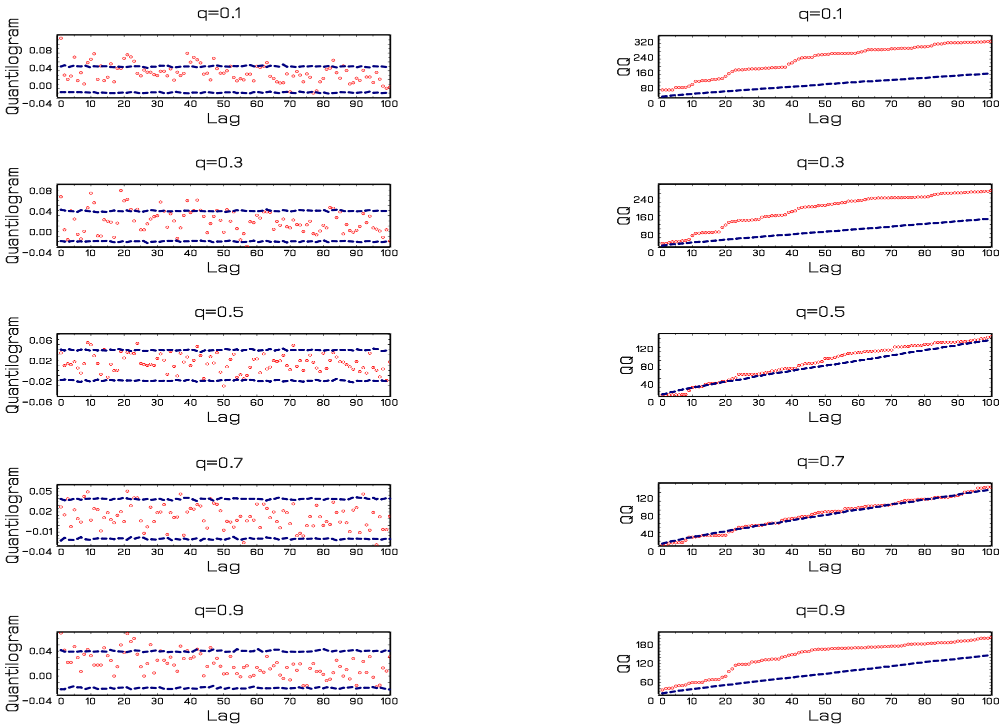
Note: Curve lines show the p-value of the quantiles- based portmanteau test of 1-year rolling subsamples with 1-day shifts. Dashed lines give the 5% significance level.

In Figures 3(a)-3(j), we report the results for the 10 MSAs. As can be seen, barring instances for the quantiles of 0.5 and 0.7 at lower lags for majority of the cities, and in addition the quantiles of 0.3 and 0.9 for San Diego, and 0.9 for Washington, D.C., there is strong evidence of predictability of housing returns even at the city-level. The results for the aggregate housing returns seems to be driven primarily by Las Vegas, Los Angeles and San Francisco. In sum, just like for the aggregate US housing market, weak-form of the EMH is also rejected in general for the 10 major MSAs.[3]

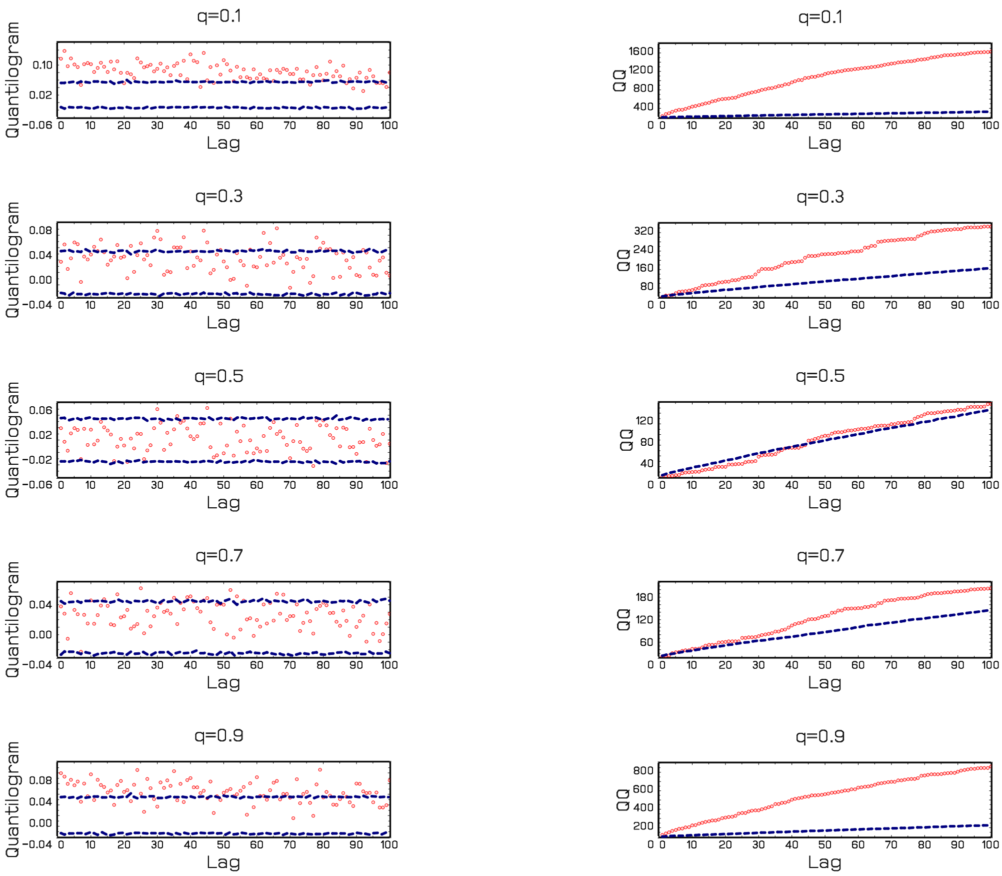
[3] We also conducted the rolling quantiles-based portmanteau test for the 10 MSAs, and found the pattern of rejection of the null hypothesis to be similar as that for the overall housing returns. We have suppressed these results in the main text to save space, however complete details are available upon request from the authors.

Figure 3. Quantilogram and quantile portmanteau test for housing returns of the 10 MSAs:

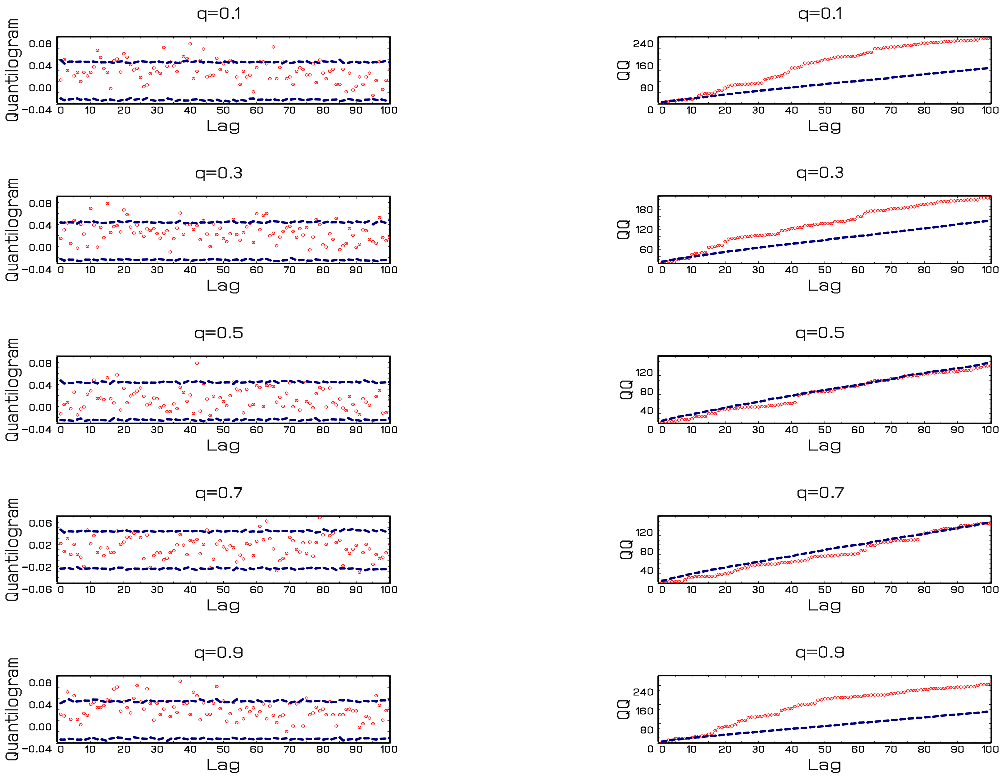
3(a). Boston



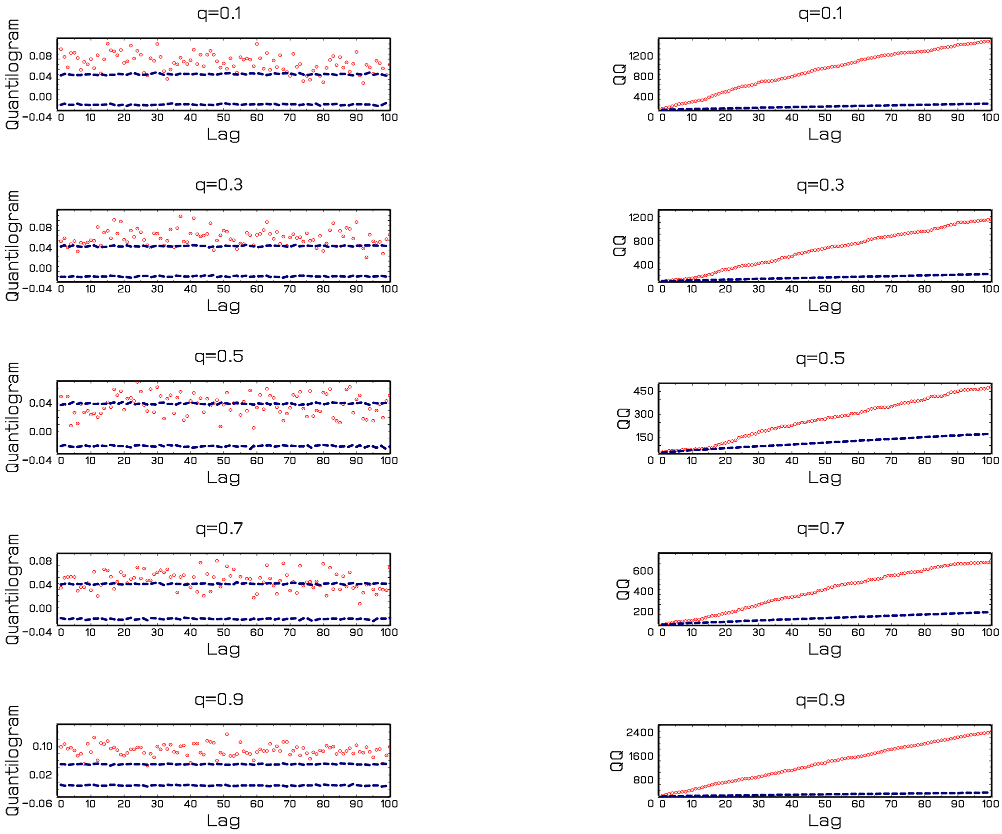
3(b). Chicago



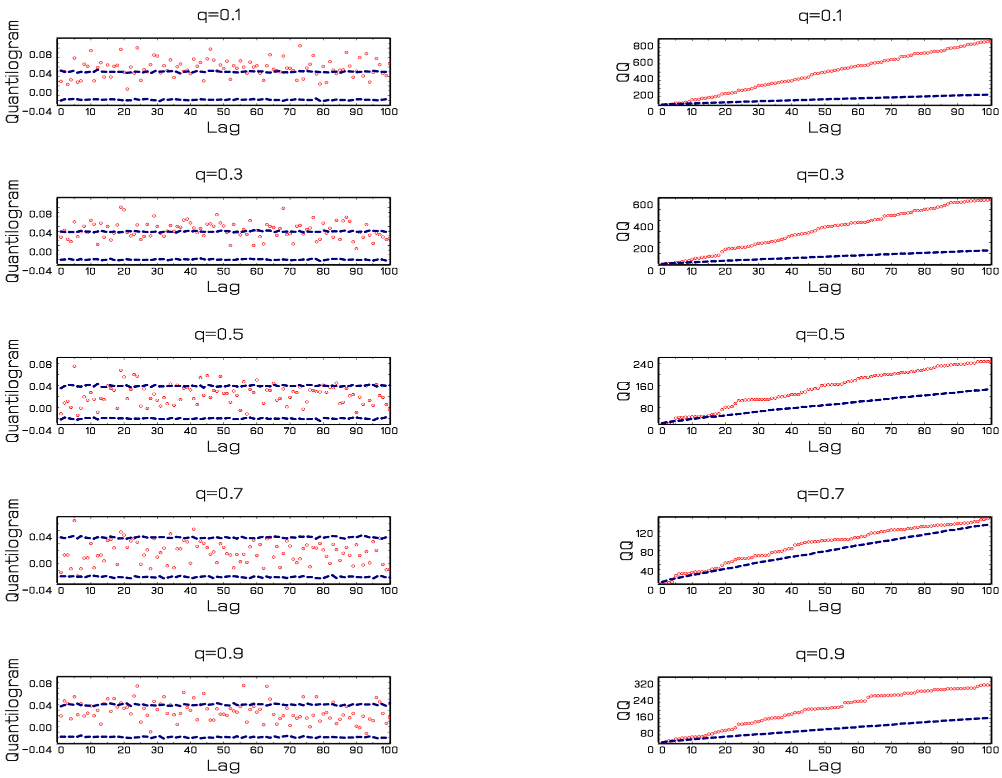
3(c). Denver



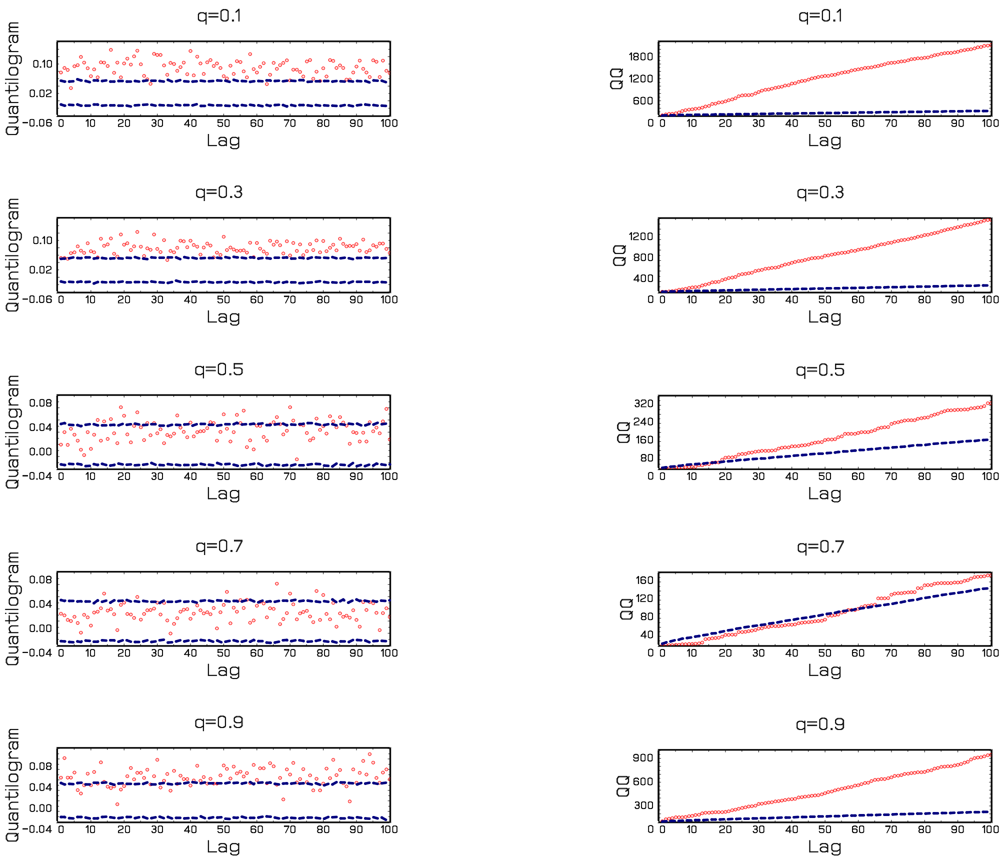
3(d). LasVegas



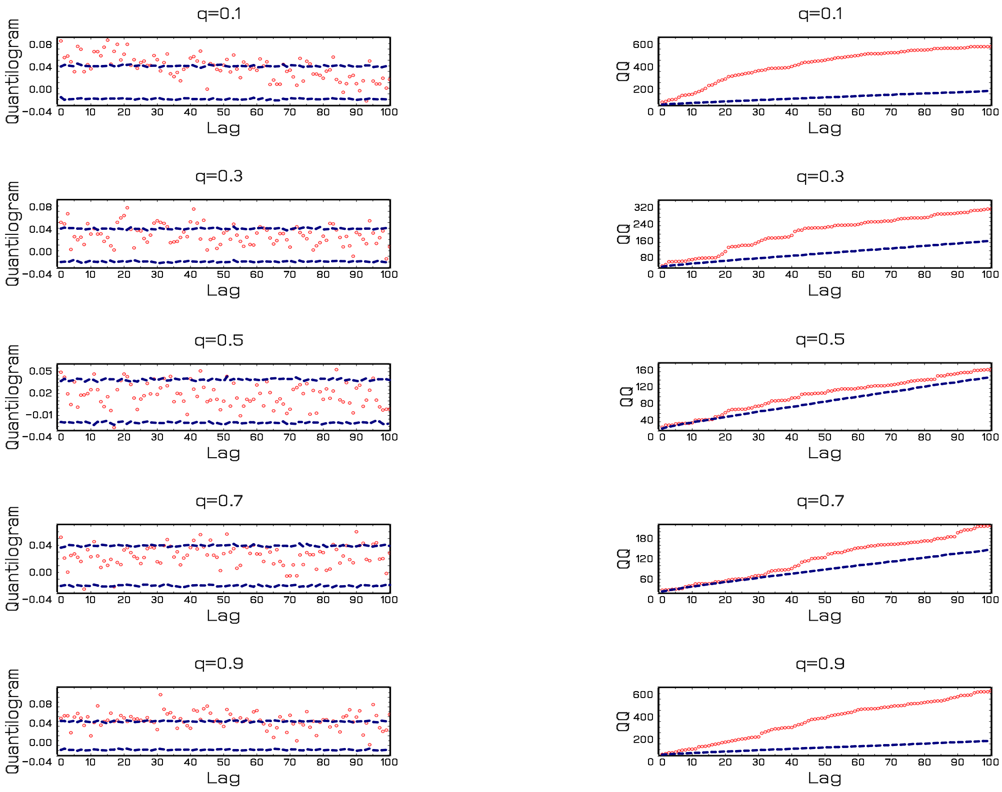
3(e). Los Angeles



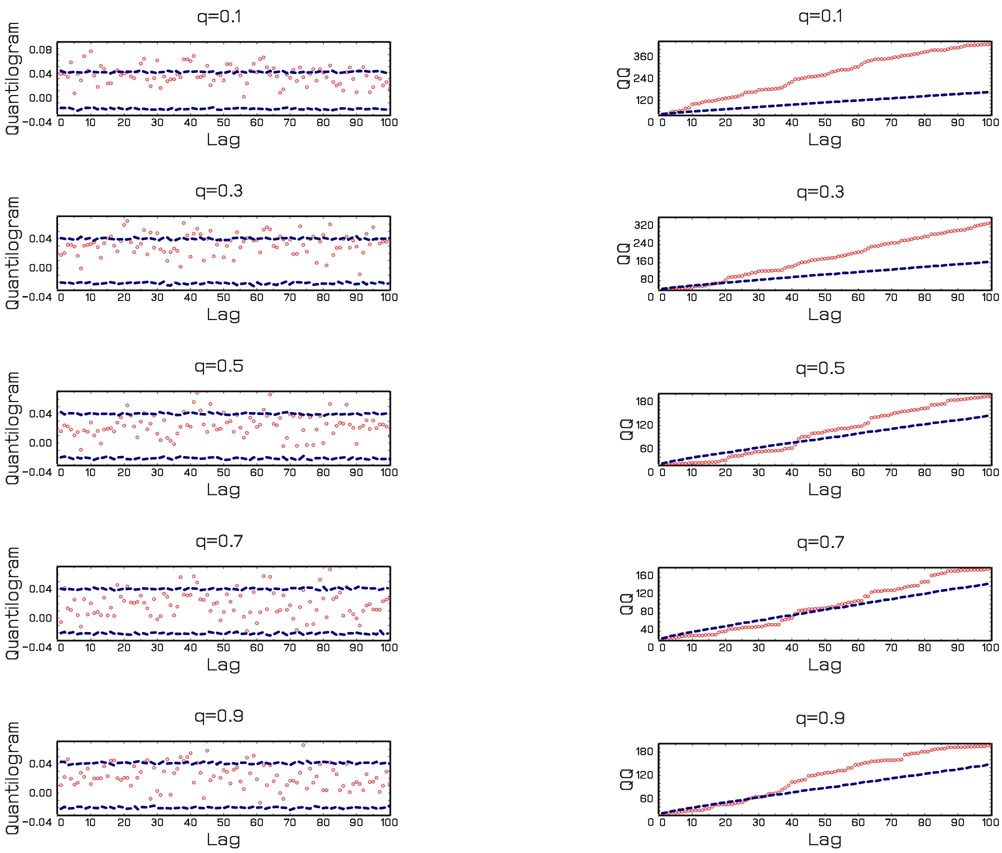
3(f). Miami



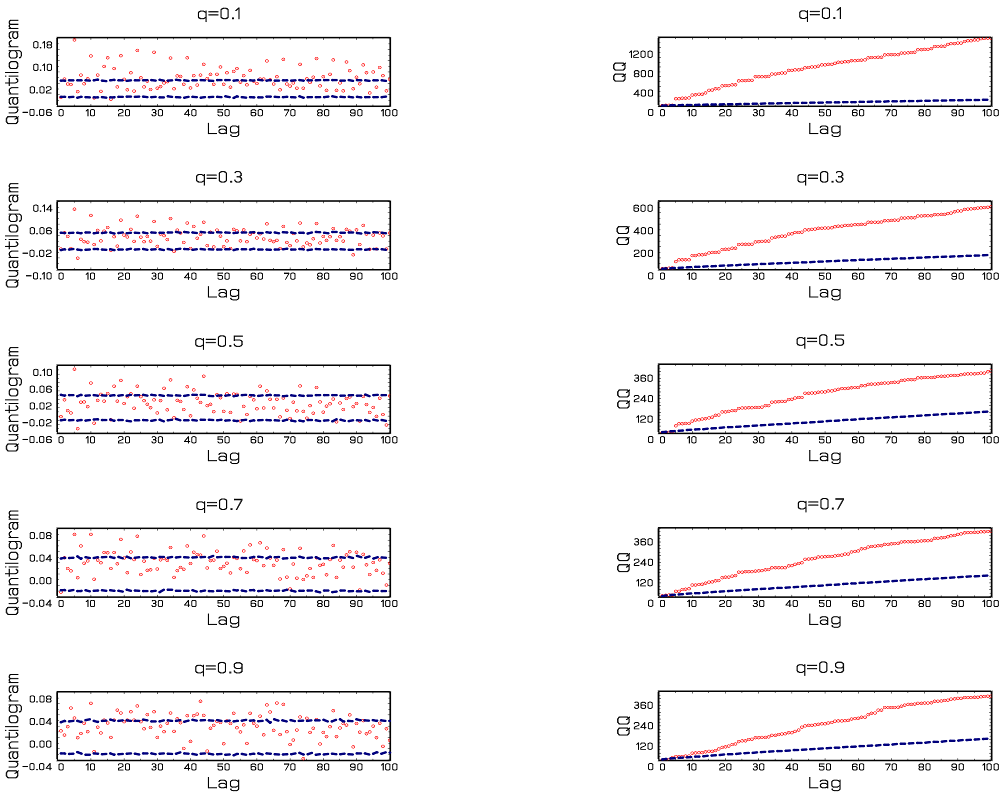
3(g). New York



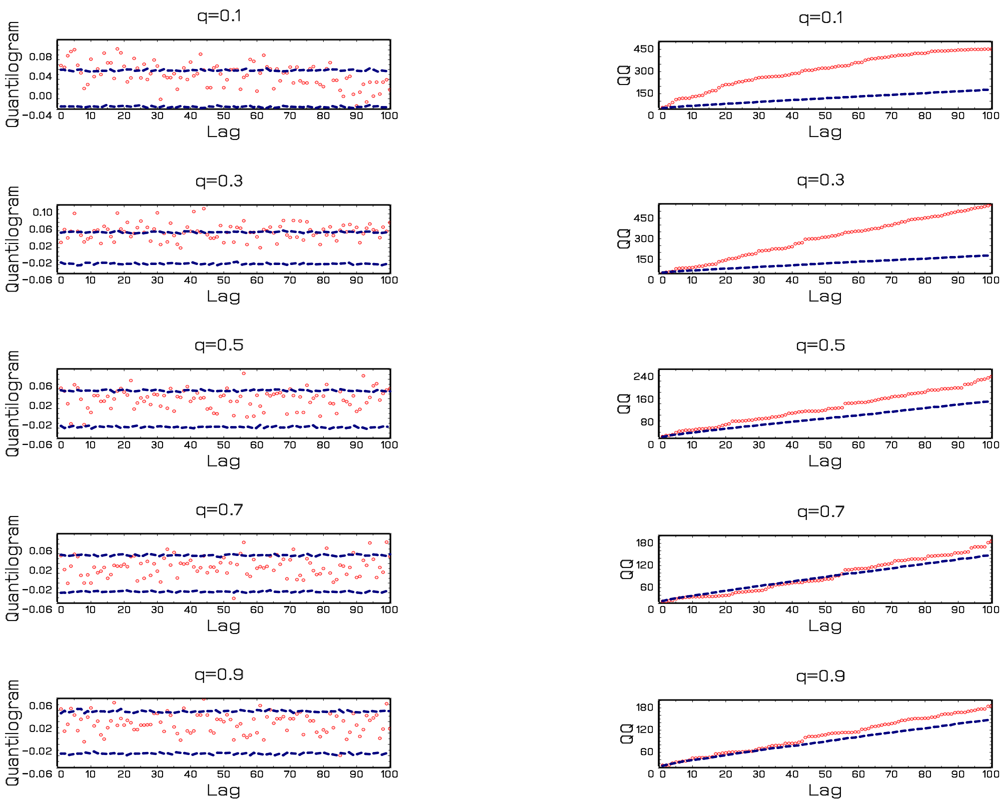
3(h). San Diego



3(i). San Francisco



3(j). Washington, D.C.



Note: See Notes to Figure 1.

4. Conclusion

Unit root tests and long-memory models tend to suggest that house prices in the US are non-stationary, i.e., the housing market is weakly efficient. We revisit this issue in this paper by using the quantilogram, which in turn, is a model-free econometric procedure involving a simple diagnostic statistic based on a sample correlation. When the quantilogram is applied on a unique database of daily housing returns for the aggregate US economy and 10 major cities, we find strong evidence of predictability, and hence, reject the notion of weak-form of market efficiency obtained in the extant literature thus far. Our results are in line with violation of the semi-strong version of efficiency obtained from tests of predictability of housing returns at monthly, quarterly and annual housing frequencies, derived based on wide-array of predictors (Ghysels, et al., 2013; Plakandaras et al., 2015). Our results should be of tremendous value to policymakers, as they can conduct high-frequency predictability of economic activity based on lagged values of daily housing returns.

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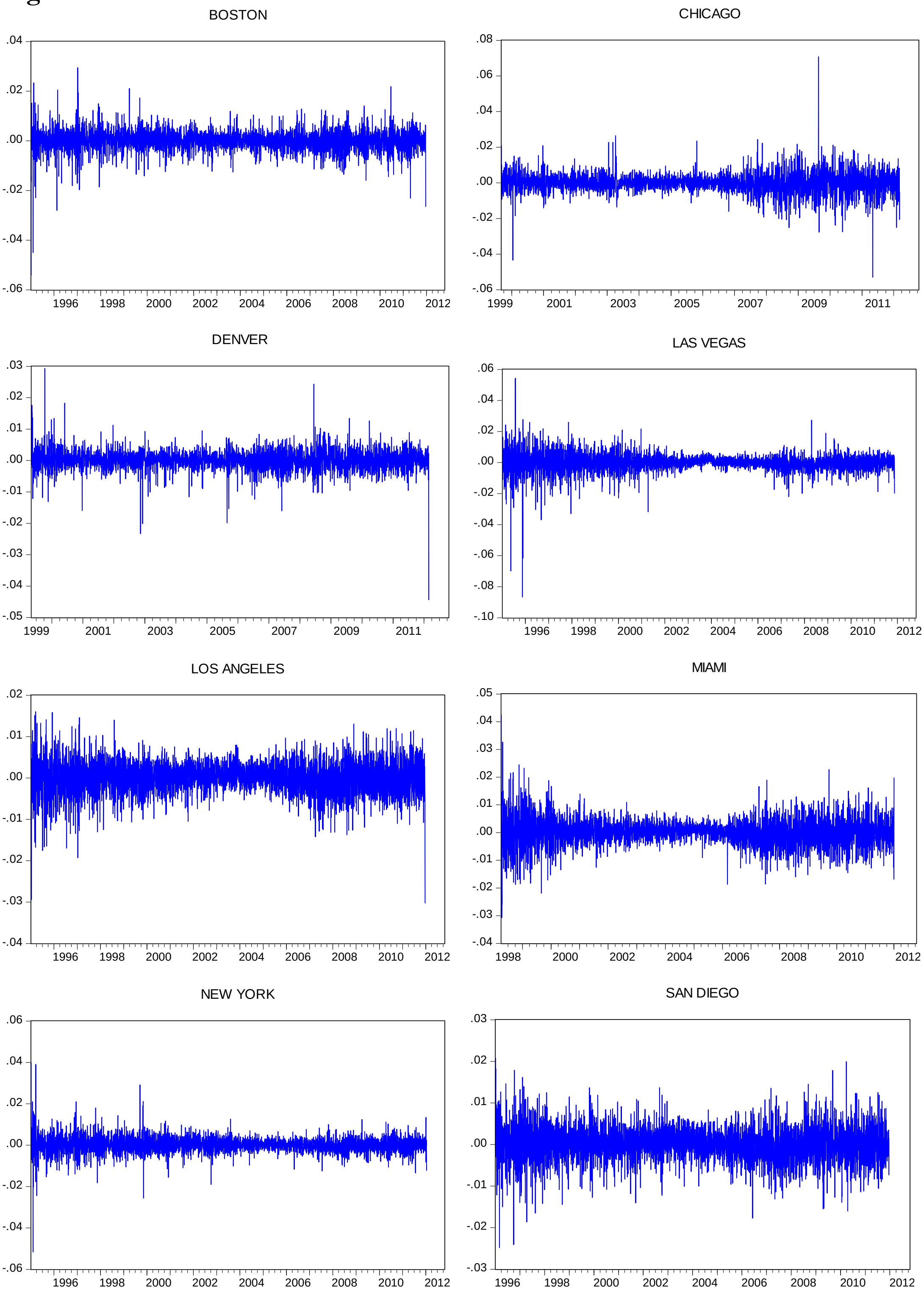
APPENDIX:

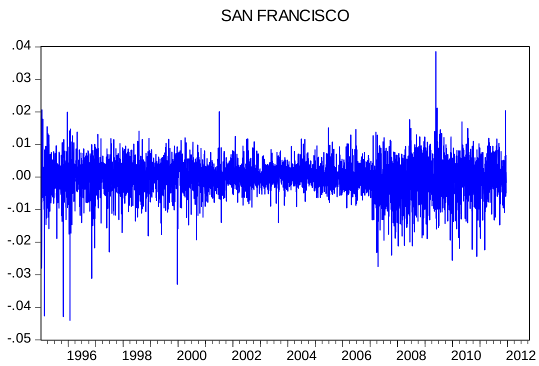
Table A1: Summary statistics for housing returns of the 10 MSAs and aggregate US

Housing returns	Sample Period	Observations	Minimum	Maximum	Average	Standard Deviation	Skewness	Kurtosis	Jarque-Bera (*p*-value)
Boston	1/6/1995 - 10/11/2012	4424	-5.419	2.947	0.017	0.400	-1.119	18.344	0.000
Chicago	9/7/1999- 10/12/2012	3265	-5.300	7.081	0.001	0.593	0.131	13.417	0.000
Denver	5/6/1999 – 10/17/2012	3344	-4.434	2.930	0.010	0.330	-0.823	20.027	0.000
Las Vegas	1/6/1995 – 10/17/2912	4399	-8.667	5.425	0.001	0.569	-1.613	28.151	0.000
Los Angeles	1/6/1995– 10/23/2012	4425	-3.030	1.602	0.017	0.381	-0.510	6.015	0.000
Miami	4/6/1998- 10/15/2012	3587	-3.073	4.261	0.013	0.505	0.085	6.950	0.000
New York	1/6/1995- 10/23/2012	4442	-5.162	3.988	0.017	0.380	-0.041	19.232	0.000
San Diego	1/5/1996- 10/23/2012	4163	-2.478	2.082	0.022	0.411	-0.179	4.916	0.000
San Francisco	1/6/1995- 10/18/2012	4422	-4.403	3.855	0.016	0.530	-0.955	9.036	0.000
Washington	6/6/2001- 10/23/2012	2816	-4.477	2.650	0.015	0.506	-0.192	6.825	0.000
Aggregate housing returns	6/6/2001- 10/11/2012	2806	-0.627	0.663	0.010	0.163	-0.211	3.770	0.000

Note: The Jarque-Bera test has the null hypothesis of normality.

Figure A1. Data Plots:

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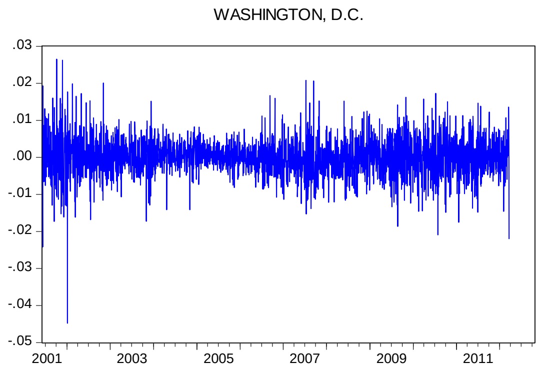
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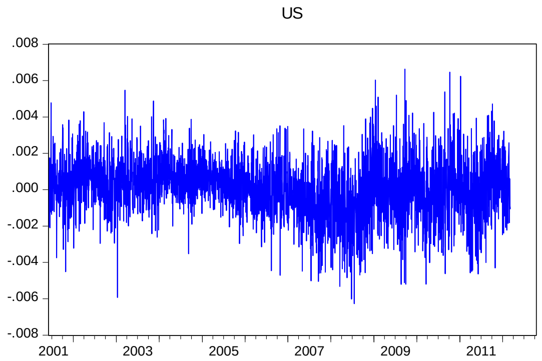
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