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High Frequency Impact of Monetary Policy and Macroeconomic Surprises on US MSAs, Aggregate US Housing Returns and Asymmetric Volatility[#]

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Abstract

This paper explores the impact of monetary policy and macroeconomic surprises on the U.S housing market returns and volatility at the Metropolitan Statistical Area (MSA) and aggregate level using a GJR (or threshold generalized autoregressive conditional heteroscedasticity (GARCH)) model of Glosten, Jagannathan and Runkle (1993). Using daily data and sampling periods which cover both the conventional and unconventional monetary policy periods, empirical results show that monetary policy surprises have a greater impact on the volatility of housing market returns across time with particularly pronounced effect during the conventional monetary policy period. We also show that macroeconomic surprises do not have a significant impact on housing returns for most MSAs for the full sample, conventional and unconventional monetary policy periods.

***Keywords**:* Monetary policy and macroeconomic surprises; Asymmetric GARCH; Housing market returns and volatility.
***JEL Classifications**:* C32, E32, E44, E52, R31.

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1. Introduction

Residential homes are the largest financial asset holding in the portfolios of most U.S households (specifically, about half of total household net worth), hence changes in homeowner equity can impact the individual's wealth and the overall economy (Iacoviello, 2012). The housing market has an impact on the consumers through the wealth effect, and on the financial sector through the mortgage market and activities from the management of investor portfolios. Thus, house price movements are vital in driving the broader macroeconomic outcomes. There is a general consensus that housing prices are a good indicator of economic recovery as they reflect the level of consumers' confidence (Wang, 2014). As such, timely measures of housing price movements contain important information concerning the current state of the economy.

This highlights the need to fully understand the house price movements and the factors that drive the housing markets. Housing, being a consumption as well as an investment asset, intuitively is driven by interest rates and the news reflecting macroeconomic fundaments (Kishor and Marfatia, 2017). Moreover, the arrival of new information about the factors that drive house prices and the timing of measuring the house price data is mostly non-synchronous. This makes it necessary to undertake a high-frequency analysis of house price responses to macroeconomic and policy announcements. This paper investigates the high-frequency impact of the surprise component of monetary policy (Federal funds rate) as well as macroeconomic surprises on 10 U.S Metropolitan Statistical Areas (MSAs) housing market returns and volatility. The study further investigates this impact on an aggregate level, and analyzes how the results compare to the impact on stocks using the Standard & Poor's 500 (S&P500), and also aggregate Real Estate Investment Trusts (REITs) market. Given the typical nature of volatility clustering of ~~high~~ high-frequency asset returns, we apply the GJR (Glosten-Jagannathan-Runkle or threshold generalized autoregressive conditional heteroscedasticity

(GARCH)) model of Glosten et al., (1993) to examine the impact of monetary policy and macroeconomic surprises on the returns and volatility in the housing market at both individual MSA and aggregate level, using daily data of the housing market.

One of the main contributions of this paper is that it uses new high-frequency daily data of the housing market, which is not easily available. Apart from this dataset, Wang (2014) notes that housing market data is mostly available in relatively low monthly and quarterly frequencies, compared to other financial assets. Such low-frequency data tends to underestimate housing market risk as it ignores the information in the within variations in housing prices (Wang, 2014). In addition, the use of high-frequency daily housing data allows us to estimate a more accurate measure of not only housing returns but also of the volatility in the housing markets. Understanding the dynamics of housing volatilities and its response to the surprise component of monetary policy and macroeconomic surprises is important since housing asset plays a significant role in the investor's optimal portfolio decision (Yao and Zhang, 2005).

In the present study, the sample period varies for the different MSAs, mostly starting in 1995 - 2012 for most MSAs and the aggregate sample period starting in 2001 – 2012. This sample period allows us to cover the period when the Federal Reserve applied conventional monetary policy as well as the period when the short-term nominal interest rates were at or near the zero lower bound and unconventional monetary policy tools were implemented. In order to fully uncover how these changes in policy tools impact housing markets, we undertake the analysis for the full sample period, the conventional monetary policy period which constitutes the start of the dataset to December 2008, and the sample period from 2009-2012 representing the period the Federal Reserve started to use unconventional methods of monetary policy.

In efficient markets, asset prices respond to new information, therefore it is important to measure the surprise component of that information and the uncertainty that results from it (Scotti, 2016). According to Kroencke et al., (2016), there exist two transmission channels through which asset markets can be affected by macroeconomic information risk. Firstly, news on macroeconomic data is sometimes published randomly and secondly, the arrival of news announcements of macroeconomic variables and policy actions occurs on a pre-scheduled date, therefore the exact value of these factors can only be predicted. In light of this, it is essential to measure expectations contained in the macroeconomic and policy announcements.

One of the reliable and trusted sources of the predicted values macroeconomic announcements is the consensus estimations of professionals (Marfatia et al., 2017). Based on the semi-strong form of the efficient market hypothesis, the pricing of an asset already includes forecasted values after the publication of consensus data, but not the unanticipated difference between the predicted and the announced, which is the surprise component. To measure the monetary policy surprise, it is found that the Federal (Fed) funds futures rate is a natural market-based proxy of the otherwise unobserved market expectations of the Federal Reserve policy actions (Kuttner 2001; Kishor and Marfatia, 2013). All the expectations of the future changes in the interest are expected to be captured by the Fed funds futures rate. Therefore, any change in this futures rate after the Federal Open Market Committee (FOMC) meeting is because the announcement rate change (or no change) measures the unexpected (surprise) changes in the monetary policy. These monetary policy surprises are found to have a statistically significant impact on the returns on financial assets (Marfatia et al., 2017).

It is not surprising that several studies focus on analyzing the impact of domestic and U.S monetary policy and macroeconomic news surprises on bonds, commodity, currency, equity markets, and REITs market (see for example, Kishor and Marfatia, 2013; Cakan et al., 2015; Caporale et al., 2017; Scotti, 2016). However, in spite of the central role of housing markets, there is almost no literature on the study of the high-frequency impact of both monetary policy and macroeconomic surprises on the general housing market. However, there is a relatively spares literature focusing on the real estate investment trusts (REITs) market returns (see for example, Bredin et al., 2011; Xu and Yang, 2011; Claus et al., 2014; Kroencke et al., 2016; Marfatia et al., 2017)[1], which to some extent, is understandable, given that daily data on house prices was not available until recently.[2] REITs market is indeed associated with the real estate market, but characteristically different from it, and is much similar to standard equity markets like S&P500 with REIT market capturing partial[3] movements in primarily non-residential (commercial) properties which include apartments, industrial properties, offices, and retail properties (Ghysels et al., 2013). Institutions and individuals can take positions in the commercial real estate market by investing in publicly-traded REIT companies. Market-based indices can be obtained from the trading of individual REIT stocks. These indices are usually constructed as value-weighted averages of firm-specific REIT returns. Residential house prices movements tend to capture housing wealth, with REITs associated with the financial wealth variability, but the former is the dominant part in household's net worth. Also, as pointed out by Iacoviello (2012), 80 percent of housing wealth is made up by the stock of owner-occupied homes, with the remaining 20 percent of the residential real estate held by nonfarm noncorporate businesses, which is made up by the rental housing stock. Hence, by looking at housing price reactions to monetary policy and macroeconomic surprises, we are essentially concentrating on owner-occupied homes used mainly for residential purposes (i.e., consumption), and also to a limited degree for investment.

[1] Gabriel and Lutz (2017) analysed the impact of unconventional monetary policy surprises on mortgage default risks.
[2] Of course there is a large literature that has analysed the impact of macroeconomic and monetary policy shocks on the US housing market at monthly, quarterly and annual frequencies using Vector Autoregressive (VAR) models (see for example, Simo-Kengne et al., (2014), Rahal (2016), Plakandaras et al., (2017) and Gupta and Marfatia (forthcoming) for detailed reviews in this regard).
[3] Note that REITs represent quite a small fraction of estimated value of non-residential real estate market. Hence, REITs may not constitute a representative sample of the U.S. commercial real estate market as a whole.

To the best of our knowledge, this is the first paper to analyze monetary policy (both conventional and unconventional) and macroeconomic surprises on high-frequency movements (returns and volatility) of the housing markets of 10 US MSAs, besides the aggregate market. The remainder of the paper is organized as follows: Section 2 presents the data, while Section 3 discusses the model and empirical results, with Section 4 concluding the paper.

2. Data

This study uses daily housing returns based on a new set daily housing price series constructed by Bollerslev et al., (2016) using the repeat sales method[4] (Shiller, 1991) and comprehensive housing transaction data from DataQuick. The daily housing price series covers the all of the 10 MSAs. Following Wang (2014), we use the daily Composite 10 Housing Index ($P_{c,t} = \sum_{i=1}^{10} w_i\, P_{i,t}$) as a proxy for the aggregate housing price computed as a weighted average. 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 Wang (2014)). The S&P500 equity and S&P REIT indices data are obtained from Datastream of Thomson Reuters.

For the macroeconomic surprises, we follow the daily macroeconomic index by Scotti (2016) which is constructed using a dynamic factor model and business condition indexes to estimate the weights of the contribution of the economic indicator, which include: quarterly Gross Domestic Product (GDP), monthly industrial production (IP), employees on non-

[4] Repeat sales methodology is used to estimate house price changes by evaluating repeat transactions of the same house, assuming that the quality of the same house remains the same over time unless there are records of significant renovations and reconstruction. The advantages of this method is that it controls for the heterogeneity in characteristics of houses and the estimation only requires data transaction prices and sales dates for properties (Wang, 2014).

agriculture payroll, monthly retail sales and the monthly Institute of Supply Management (ISM) manufacturing index to these business condition indexes. The weights are then used to average surprises to construct the macroeconomic surprise index (see Scotti, 2016 for details on the construction of the index).

For the monetary policy surprise, we use the monetary policy shock measure by Nakamura and Steinsson (2018). They construct a monetary policy shock dataset using data on changes in the prices of federal funds futures rate over a 30-minute window around FOMC announcements (see Appendix A in Nakamura and Steinsson (2018)).

Summary statistics of the housing log returns, S&P500 log returns, monetary policy and macroeconomic surprises for the 10 MSA and aggregate daily data are presented in Table A1 in the Appendix, along with the respective length of data availability. Figure A1 in Appendix plots of the data used. Note that, our data heterogeneously covers the period of June, 1995 to October, 2012, with the end–point being a month after the third phase of the Quantitative Easing was announced by the Federal Reserve on 13th September of 2012, and with tapering talks starting in the June of the following year. The sample period of the daily housing indices is understandably determined by its availability based on the work of Bollerslev et al., (2016), who purchased the data from DataQuick.[5] The sample mean for the daily housing returns as well as the mean macroeconomic surprise is generally positive, while the mean of monetary policy surprise and S&P500 returns are negative, with all the variables being non-normal as suggested by the Jarque-Bera test. Interestingly, the REITs return is more volatile than equity and aggregate housing market returns over the common sample period.

[5] One of the limitations of our analysis is that our sample period ends in 2012. However, the endpoint corresponds to the paper by Bollerslev et al., (2016), from where we obtained the data set. The authors of this paper confirmed that they do not have access to an updated version of this data, and we could not obtain updated data from the primary source due to the tremendously high expense involved in securing the daily housing transaction data from the primary source. Having said this, we believe that we do cover the sample period associated with the most turbulent episodes of the US housing market and the corresponding policies implemented to calm the real estate sector.

3. Methodology and Empirical Results

In this paper, we use the ~~the~~ GJR (or threshold GARCH)~~GJR~~ proposed by Glosten et al., (1993) to examine the impact of monetary policy and macroeconomic surprises on housing market returns and volatility at the daily frequency for both individual MSA and aggregate levels. The GJR model is preferred for this analysis because it is designed to capture an important phenomenon in the conditional variance of assets, which is the leverage effect captured by the asymmetric terms. Since future increases in the volatility of returns are associated with present falls in asset prices, in order to capture the statistical leverage effect, which is the propensity for the volatility to rise more subsequent to large negative shocks than to large positive shocks, we use the following GJR specification following Wang (2014):

$$R_t = \mu + \rho R_{t-1} + \gamma_0 MP_{t-1} + \gamma_1 MS_{t-1} + \varepsilon_t \qquad (1)$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-1}^2 d_{t-1} + \beta_0 h_{t-1} + d_1 MP_{t-1} + d_2 MS_{t-1} \qquad (2)$$

R_t represents the U.S housing return series, MP is the federal funds rate monetary policy surprise, MS represents the macroeconomic news surprise and ε_t is the stochastic disturbance term that is assumed to be normally distributed with zero mean. The conditional variance h_t depends on the mean volatility level (α_0), the lagged error (ε_{t-1}^2) and the lagged conditional variance (h_{t-1}). The asymmetric effect is captured by the $\varepsilon_{t-1}^2 d_{t-1}$ term, where $d_t = 1$ if $\varepsilon_t^2 < 0$; and $d_t = 0$ otherwise. The shocks have an asymmetric impact on conditional variance if α_2 is statistically significant. Note that, the GJR model requires α_0, α_1, and α_2 should be positive (McAleer, 2014).

Given that the model used here is multivariate, a natural question to ask is: why a multivariate asymmetric conditional volatility model, such as an extension of GJR to VARMA-GARCH as in McAleer, et al., (2009), was not considered? This is because, the monetary policy and macroeconomic news surprise variables are shocks, and hence, are considered to be exogenous to the movements in the housing markets. Therefore, we do not need to set-up a system-based model with all variables as endogenous to each other. In our case, the GJR model with the monetary policy and macroeconomic news shocks treated as right-hand side exogenous variables serves our purpose without concerns of endogeneity (see, for example, Cakan et al., (2015)).

Table 1 present the summary of estimation results revealing the positive and negative impact of monetary policy and macroeconomic surprises on housing returns and volatility. The full set of GJR estimation results of the impact of monetary policy and macroeconomic surprises on housing returns and volatility is presented in Table A2 in the Appendix. The results show that for the full sample, monetary policy shocks do not statistically impact housing returns for 6 of the 10 U.S MSAs[6]. Similarly, for the period when the conventional monetary policy was implemented, evidence suggests that monetary policy shocks do not statistically impact housing returns for 7 of the 10 U.S MSAs[7], with a positive and statistically significant relationship for Miami. For the unconventional monetary policy period, monetary policy shocks also do not statistically impact most of the U.S MSAs, except for Washington which shows a significant relationship.

[TABLE 1]

The full sample results for the impact of macroeconomic surprises on housing returns at the MSA level shows that macroeconomic surprises do not statistically impact housing returns for most of the MSAs, with the exception of Los Angeles and New York which show a positive and significant impact at a 10 percent level of significance. For the conventional monetary policy period, macroeconomic surprises have a negative and statistically significant (10% level)

[6]Boston, Chicago, Denver, New York, San Diego, San Francisco.
[7] Boston, Chicago, Denver, New York, San Diego, San Francisco and Washington.

impact on housing returns for Washington only, and the rest are insignificant. The results show that macroeconomic surprises do not statistically impact housing returns for all MSAs, for the period of the unconventional monetary policy.

The estimated parameter of the lagged conditional variance (α_2) is positive and statistically significant for Miami, New York, San Francisco and Washington for the full sample period, Boston during the conventional and unconventional monetary policy period and aggregate returns as well as S&P500 returns for all three periods. The positive coefficient α_2 implies that bad news increases volatility more than good news (α_1). This means that policy shocks have an asymmetric impact on conditional variance for these MSAs. The results show that monetary policy surprises have a negative and statistically significant impact on housing returns volatility at a 5 percent level of significance for Boston, Miami and Washington for the full sample period, while it has a positive and statistically significant impact for Denver and New York. For the conventional monetary policy period, the policy surprises have a negative and statistically significant impact on housing return volatility for Boston, Los Angeles and Washington, with Miami, New York, San Diego showing a positive and statistically significant impact. In the unconventional monetary policy period, monetary policy surprises have a mostly positive but insignificant impact on housing returns volatility.

With regards to the effect of macroeconomic surprises on the volatility of housing returns, the results show a positive and statistically significant impact at a 1% level for Denver, but negative and statistically significant for Miami and New York for the full sample. For the conventional monetary policy period, macroeconomic surprises have a positive and statistically significant effect on housing returns volatility for Denver and Miami at a 1% level of significance. In the case of New York, the macroeconomic surprises have a negative impact on housing returns volatility, but only at a 10% level of significance.

For the aggregate housing market, results indicate that monetary policy surprises have a positive and statistically significant impact on housing returns for the full sample period and conventional monetary policy period. For the unconventional monetary policy period, monetary policy surprises have an insignificant impact on housing returns. Macroeconomic surprises have no significant impact on aggregate housing returns across all sample periods.

The estimated parameter of the lagged conditional variance is positive and statistically significant, which suggests that volatility will increase more following a negative return shock and confirms volatility asymmetry for daily aggregate housing returns. This is in line with results Wang (2014). At an aggregate level, monetary policy surprises have a negative and statistically impact (10% level of significance) on daily aggregate housing returns during the conventional monetary policy period only.

For comparison, we also evaluate the impact of monetary policy and macroeconomic surprises on REIT and S&P500 returns and volatility. Results show that monetary policy surprises negatively impact REIT returns for the full sample and unconventional monetary policy period, but does not impact the volatility of REIT returns for all the periods. However, during the conventional monetary policy period, monetary policy surprises have an insignificant impact on REIT. This corroborates the findings of Claus et al., (2014) who show that REIT prices have an insignificant response to monetary policy shocks during normal monetary policy settings, but significant during the zero lower bound period. Macroeconomic surprises have a positive and statistically significant impact on REIT returns during the full sample and conventional monetary policy period, but a negative and significant impact on REIT volatility during the full sample period. Volatility asymmetry exists, similar to the aggregate housing market. Wang (2014) obtains similar results. In terms of the S&P500 returns, results show that monetary policy surprises have a negative and statistically significant (5% level) impact on stock returns during the full sample and conventional monetary policy period.

However, macroeconomic surprises show a positive and statistically significant impact on stock returns during the conventional and unconventional monetary policy periods. Similar to the aggregate housing market, the stock market also shows evidence of volatility asymmetry. The results show that monetary policy surprises have a positive and significant impact on stock returns volatility during the conventional monetary policy period. However, the macroeconomic surprise has a negative and statistically significant impact on stock returns volatility for all the sample periods.

Overall, evidence suggests that monetary policy surprises, rather than macroeconomic news surprises, generally have a more significant impact on housing returns, especially volatility. In some MSAs, the volatility is increasing as in the case of Chicago, Denver, Miami (full sample period), New York and San Diego and in some cases decreasing as in the case of Boston, Las Vegas, Los Angeles, Miami (unconventional monetary policy period) and Washington. The results show that mostly coastal MSAs exhibit lower return volatility compared to the most inland MSAs which showed an increase in volatility. Although there are a few exceptions, in general, monetary policy surprises affect housing returns volatility more during the conventional monetary policy period. The fact that monetary policy surprises are more important at higher frequency than macroeconomic news surprises is an indication that agents put more weight on monetary policy movements at the shorter-run. This is possibly also a reason we see more impact on volatility, i.e., the risk-profile of the housing market, than returns, which are likely to be affected by such decisions in the longer-term. Finally, the increase in volatility of the inland MSAs~~,~~ could be due to them being global cities~~,~~ and tends to behave just like equities.

4. Conclusion

In this paper, we employ a GJR model to analyze the impact of monetary policy and macroeconomic surprises on daily housing returns and volatility for 10 U.S MSAs and on aggregate housing returns. We further compare the results with the impact on the aggregate stock market using S&P500 returns. We use a set of newly constructed daily housing price series, which allows us to investigate the volatility asymmetries and volatility relationship of the housing market and monetary policy and macroeconomic surprises.

The evidence suggests that at the MSAs level, monetary policy surprises have a positive and significant impact on housing returns for Denver and Miami during the period of conventional monetary policy and for Washington during the unconventional monetary policy period. Furthermore, monetary policy surprises have a positive and significant impact on housing volatility for the full sample period for Denver, New York and San Francisco, and then for Chicago, Miami and New York and San Diego as well during the conventional monetary policy period. During the unconventional monetary policy period, the policy surprises have a positive impact on Washington only. At an aggregate level, monetary policy surprises have a positive impact on housing returns during the full sample and conventional monetary policy period. This is in contrast to the aggregate stock market where we find a significant response of market returns in all three periods and the volatility response only in and the conventional monetary policy period.

In terms of macroeconomic surprises, the results suggest that they have a positive and significant impact on housing returns during the full sample period for Los Angeles and New York. Macroeconomic surprises have a positive impact on housing volatility in Las Vegas and Miami during the conventional monetary policy period and unconventional monetary policy period for Las Vegas only.

The results show that monetary policy has a negative and significant impact mostly on housing volatility across the various periods for Boston, Las Vegas, Los Angeles, Miami, New York and Washington. On aggregate, results show that monetary policy surprises have a negative and statistically significant impact on housing returns volatility during the conventional monetary policy period compared to the stock market where it shows an impact on stock returns during the full sample and conventional.

The evidence suggests that macroeconomic surprises do not have a negative and statistically significant impact on housing returns both at the MSA and aggregate level. However, in terms of volatility, macroeconomic surprises have a negative and statistically significant impact for Miami only during the full sample period. At the aggregate level, macroeconomic surprises show a negative and significant impact on the stock market during the full sample, unconventional and conventional monetary policy period.

Overall, at the MSA level monetary policy and macroeconomic surprises do not have a significant impact on housing returns for most MSAs for the full sample, conventional and unconventional monetary policy period. However, the results show that in relation to volatility, monetary policy surprises have a significant impact on housing returns volatility for 5 MSAs in the full sample, 5 in the conventional monetary policy period, but a mostly positive and insignificant impact in the unconventional monetary policy period. Macroeconomic surprises largely have an insignificant impact on housing returns volatility across all sample periods and most MSAs.

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Table 1: GJR model estimation summary results of significant results of the impact of monetary and macroeconomic surprises on housing returns and volatility

Panel A: Positive Effects

Metropolitan Area	Sample period	Monetary policy surprise		Macroeconomic surprise	
		Returns	*Volatility*	*Returns*	*Volatility*
Chicago	P_2	____	2.500** (0.012)	____	____
Denver	P_1	____	16.023*** (0.000)	____	____
	P_2	2.589** (0.010)	____	____	____
Las Vegas	P_2	____	____	____	1.777* (0.076)
	P_3	____	____	____	3.336*** (0.001)
Los Angeles	P_1	____	____	1.683* (0.092)	____
Miami	P_2	2.278** (0.023)	22.676*** (0.000)	____	2.905*** (0.004)
New York	P_1	____	85.501*** (0.000)	2.472** (0.013)	3.238*** (0.001)
	P_2	____	6.238*** (0.000)	____	____
San Diego	P_1	____	6.490*** (0.000)	____	____
	P_2	____	4.719*** (0.000)	____	____
Washington	P_3	1.717* (0.090)	____	____	____
Aggregate housing returns	P_1	4.041*** (0.000)	____	____	____
	P_2	3.333*** (0.000)	____	____	____
REIT Returns	P_1	____	____	3.178*** (0.002)	____
	P_3	____	____	3.664*** (0.000)	____
S&P500 returns	P_1	____	____	6.027*** (0.000)	____
	P_2	____	2.157** (0.031)	2.272** (0.023)	____
	P_3	____	____	3.211*** (0.001)	____

Notes: P_1 = full sample period; P_2 = conventional monetary policy period and P_3 =unconventional monetary policy period. GJR(1,1) specification used: *Mean equation:* $R_t = \mu + \rho R_{t-1} + \gamma_0 MP_{t-1} + \gamma_1 MS_{t-1} + \varepsilon_t$. *Volatility equation:* $h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-1}^2 d_{t-1} + \beta_0 h_{t-1} + d_1 MP_{t-1} + d_2 MS_{t-1}$. R_t represents the U.S housing return series, MP is the federal funds rate monetary policy surprise, MS represents the macroeconomic surprise and ε_t is the stochastic disturbance term that is assumed to be normally distributed with zero mean. The conditional variance h_t depends on the mean volatility level (α_0), the lagged error (ε_{t-1}^2) and the lagged conditional variance (h_{t-1}). The asymmetric effect is captured by the $\varepsilon_{t-1}^2 d_{t-1}$ term, where $d_t = 1$ if $\varepsilon_t^2 < 0$; and $d_t = 0$ otherwise. The standard errors are given in parenthesis. Level of significance: ***1 percent; ** 5 percent, *10 percent.

Panel B: Negative Effects

Metropolitan Area	Sample period	Monetary policy surprise		Macroeconomic surprise	
		Returns	*Volatility*	*Returns*	*Volatility*
Boston	P_1	______	-3.676*** (0.000)	______	______
	P_2	______	-3.973*** (0.000)	______	______
Las Vegas	P_1	______	-3.331*** (0.000)	______	______
	P_2	______	-2.063** (0.039)	______	______
	P_3	______	-1.650* (0.099)	______	______
Los Angeles	P_2	______	-1.721* (0.085)	______	______
Miami	P_1	______	-2.018** (0.044)	______	-3.218*** (0.001)
New York	P_1	______	-1.993** (0.046)	______	______
	P_2	______	-1.925* (0.054)	______	______
Washington	P_2	______	-5.368*** (0.000)	-1.908* (0.056)	______
	P_1	______	-5.221*** (0.000)	______	______
Aggregate Returns	P_2	______	-1.828* (0.068)	______	______
REIT Returns	P_1	-1.747* (0.081)			-13.763*** (0.000)
	P_3	-2.186** (0.029)			
S&P500 Returns	P_1	-3.435*** (0.001)	______	______	-2928.55*** (0.000)
	P_2	-2.243** (0.025)	______	______	-5.810*** (0.000)
	P_3	______	______	______	-1.983** (0.047)

Notes: P_1 = full sample period; P_2 = conventional monetary policy period and P_3 =unconventional monetary policy period. GJR(1,1) specification used: *Mean equation:* $R_t = \mu + \rho R_{t-1} + \gamma_0 MP_{t-1} + \gamma_1 MS_{t-1} + \varepsilon_t$. *Volatility equation:* $h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-1}^2 d_{t-1} + \beta_0 h_{t-1} + d_1 MP_{t-1} + d_2 MS_{t-1}$. R_t represents the U.S housing return series, MP is the federal funds rate monetary policy surprise, MS represents the macroeconomic surprise and ε_t is the stochastic disturbance term that is assumed to be normally distributed with zero mean. The conditional variance h_t depends on the mean volatility level (α_0), the lagged error (ε_{t-1}^2) and the lagged conditional variance (h_{t-1}). The asymmetric effect is captured by the $\varepsilon_{t-1}^2 d_{t-1}$ term, where $d_t = 1$ if $\varepsilon_t^2 < 0$; and $d_t = 0$ otherwise. The standard errors are given in parenthesis. Level of significance: ***1 percent; ** 5 percent, *10 percent.

Appendix

Table A1: Summary statistics for the 10 U.S MSA and aggregate housing returns

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
REITs returns	6/6/2001- 10/11/2012	2806	-21.945	17.124	0.019	2.222	-0.185	17.863	0.000
S&P500 returns	6/6/2001- 10/11/2012	2806	-9.470	10.246	0.004	1.331	-0.360	10.148	0.000
Monetary policy surprise	1/6/1995- 10/11/2012	4424	-0.413	0.125	-0.000	0.013	-18.355	510.165	0.000
Macroeconomic surprise	1/6/1995- 10/11/2012	4424	-1.649	2.451	0.000	0.139	0.373	52.795	0.000

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

Table A2: GJR model estimation results of the impact of monetary policy and macroeconomic surprises on housing returns and volatility for 10 US metropolitan statistical areas and the aggregate housing returns

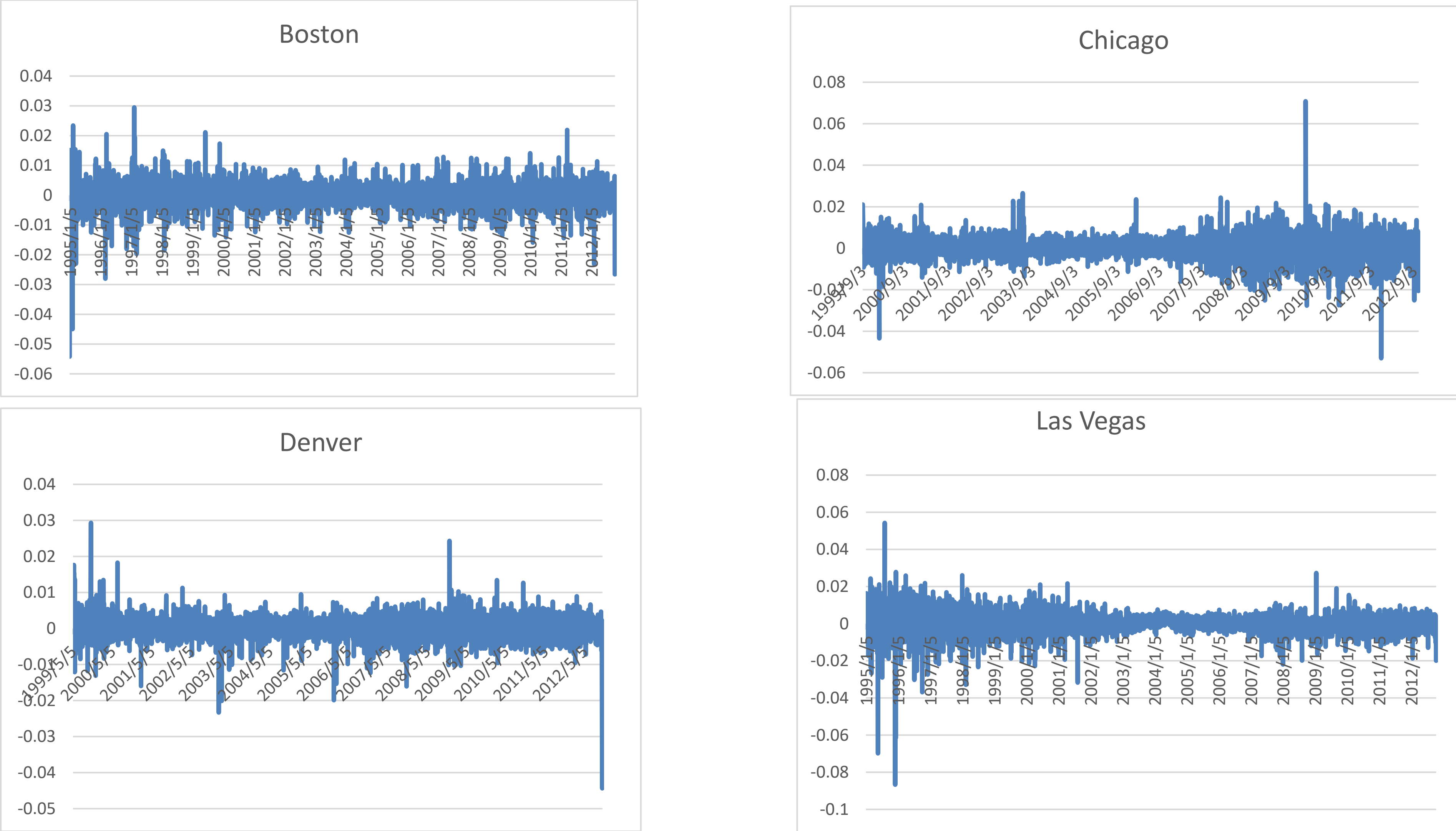
Metropolitan Area			**Full sample**			**Conventional monetary policy period**			**Unconventional monetary policy period**		
			Coefficient	*z-Statistic*	*p-value*	*Coefficient*	*z-Statistic*	*p-value*	*Coefficient*	*z-Statistic*	*p-value*
Boston	*Mean*	γ_0	-0.105	-0.197	0.844	-0.164	-0.315	0.753	3.796	0.399	0.690
		γ_1	0.038	0.819	0.413	0.034	0.652	0.514	0.054	0.516	0.606
	Volatility	α_0	0.000	6.973***	0.000	0.002	7.675***	0.000	0.007	5.099***	0.000
		α_1	0.148	3.558***	0.000	0.012	3.043***	0.002	0.055	2.463**	0.014
		α_2	0.049	1.183	0.237	0.035	5.733***	0.000	0.080	2.496**	0.013
		β_0	0.949	276.741***	0.000	0.955	279.981***	0.000	0.871	45.828***	0.000
		d_1	-0.254	-3.676***	0.000	-0.250	-3.937***	0.000	-0.020	-0.019	0.985
		d_2	0.002	0.313	0.754	0.005	1.080	0.280	0.007	0.408	0.684
Chicago	*Mean*	γ_0	-0.365	-0.433	0.665	-0.503	-0.911	0.362	6.434	0.228	0.820

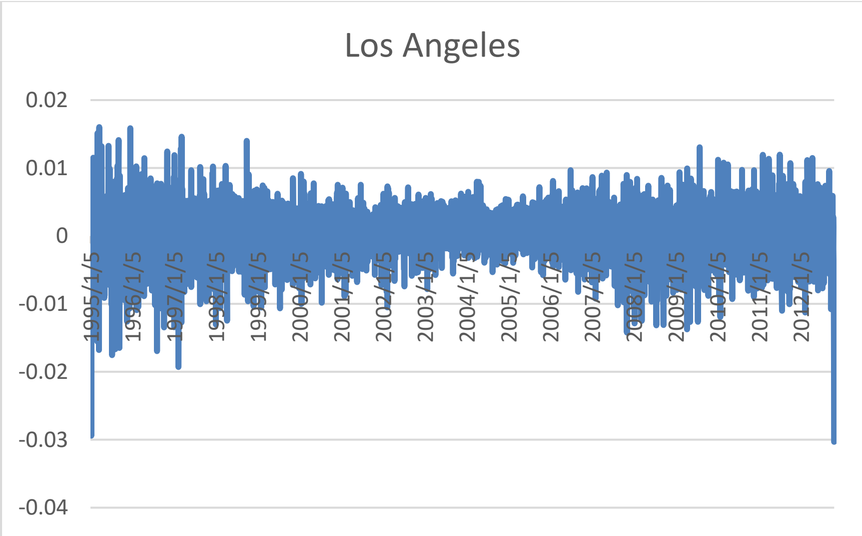
		γ_1	-0.092	-1.553	0.120	-0.080	-0.564	0.573	0.052	0.182	0.855
	Volatility	α_0	0.000	4.311***	0.000	0.171	3.297***	0.001	0.447	1.070	0.285
		α_1	0.139	2.536**	0.011	0.057	2.650***	0.008	-0.009	-0.443	0.658
		α_2	0.046	0.910	0.363	-0.045	-1.600	0.110	0.034	0.796	0.426
		β_0	0.948	254.890***	0.000	0.508	3.529***	0.000	0.465	0.928	0.354
		d_1	-0.021	-0.224	0.823	0.844	2.500**	0.012	5.184	1.626	0.104
		d_2	-0.003	-0.306	0.759	-0.009	-0.116	0.908	-0.198	-0.481	0.631
Denver	*Mean*	γ_0	-0.006	-0.056	0.956	-0.135	-0.190	0.849	0.822	0.028	0.977
		γ_1	0.028	0.474	0.635	0.088	2.589**	0.010	-0.020	-0.151	0.880
	Volatility	α_0	0.000	3.714***	0.000	0.003	7.999***	0.000	0.111	1.462	0.144
		α_1	0.150	3.038***	0.002	0.072	9.978***	0.000	0.041	0.436	0.663
		α_2	0.050	0.703	0.482	-0.031	-4.418***	0.000	-0.027	-0.286	0.775
		β_0	0.528	3.906***	0.000	0.916	114.012***	0.000	0.528	1.657*	0.098
		d_1	0.502	16.023***	0.000	-0.058	-1.046	0.296	2.311	1.212	0.225
		d_2	0.082	5.125***	0.000	0.013	4.025***	0.000	0.175	2.745***	0.006
Las Vegas	*Mean*	γ_0	0.435	0.621	0.534	0.525	0.796	0.426	0.836	0.078	0.938
		γ_1	-0.027	-0.600	0.549	-0.015	-0.314	0.754	-0.013	-0.136	0.892
	Volatility	α_0	0.000	4.204***	0.000	0.000	3.344***	0.001	0.201	4.543***	0.000
		α_1	0.012	6.661***	0.000	0.013	5.646***	0.000	-0.024	-0.907	0.364
		α_2	0.001	1.049	0.294	0.001	0.861	0.389	0.018	0.504	0.614
		β_0	0.986	964.517***	0.000	0.985	803.190***	0.000	-0.085	-0.374	0.709
		d_1	-0.148	-3.331***	0.000	-0.100	-2.063**	0.039	-8.078	-1.650*	0.099
		d_2	0.007	1.277	0.202	0.011	1.777*	0.076	0.158	3.336***	0.001
Los Angeles	*Mean*	γ_0	0.159	0.456	0.648	0.046	0.121	0.904	5.581	0.545	0.585
		γ_1	0.056	1.683*	0.092	0.055	1.598	0.110	0.108	0.811	0.417
	Volatility	α_0	0.000	4.731***	0.000	0.001	4.855***	0.000	0.114	0.915	0.360
		α_1	0.013	3.150***	0.002	0.010	2.509**	0.012	0.002	0.030	0.976
		α_2	0.027	5.200***	0.000	0.023	4.112***	0.000	0.076	1.297	0.195
		β_0	0.966	308.731***	0.000	0.969	265.843***	0.000	0.432	0.729	0.466
		d_1	-0.069	-1.223	0.221	-0.094	-1.721*	0.085	1.270	0.431	0.667
		d_2	0.006	1.267	0.205	0.007	1.480	0.139	-0.041	-0.473	0.636
Miami	*Mean*	γ_0	0.466	0.939	0.347	0.547	2.278**	0.023	4.835	0.782	0.434
		γ_1	0.015	0.279	0.780	0.012	0.150	0.881	-0.007	-0.045	0.965
	Volatility	α_0	0.000	6.317***	0.000	0.127	22.525***	0.000	0.187	0.745	0.456
		α_1	0.144	0.498	0.618	0.155	5.198***	0.000	0.021	0.403	0.687
		α_2	0.047	6.332***	0.000	-0.014	-0.357	0.721	-0.02	-0.436	0.663
		β_0	0.985	488.550***	0.000	0.455	213.733***	0.000	0.364	0.434	0.665
		d_1	-0.091	-2.018**	0.044	0.617	22.676***	0.000	1.885	0.267	0.789
		d_2	-0.018	-3.218***	0.001	0.157	2.905***	0.004	-0.087	-0.740	0.459
New York	*Mean*	γ_0	-0.506	-0.638	0.523	-0.165	-0.247	0.805	0.768	0.185	0.853
		γ_1	0.113	1.651*	0.099	0.078	0.929	0.353	0.052	0.486	0.627
	Volatility	α_0	0.000	14.041***	0.000	0.112	9.212***	0.000	0.081	1.587	0.113
		α_1	0.148	5.448***	0.000	0.097	3.445***	0.001	0.021	0.470	0.638
		α_2	0.049	1.853*	0.064	-0.005	-0.191	0.848	-0.094	-2.129**	0.033
		β_0	0.533	10.327***	0.000	0.539	12.681***	0.000	0.479	1.395	0.163
		d_1	0.512	14.382***	0.000	0.556	6.238***	0.000	1.062	0.263	0.793
		d_2	-0.068	-1.993**	0.046	-0.082	-1.925*	0.054	0.017	0.351	0.726
San Diego	*Mean*	γ_0	-0.308	-0.603	0.546	-0.301	-0.578	0.563	2.760	0.136	0.892
		γ_1	0.042	0.598	0.549	0.023	0.293	0.769	0.016	0.078	0.937
	Volatility	α_0	0.000	4.232***	0.000	0.114	4.377***	0.000	0.144	2.076**	0.038
		α_1	0.145	2.835***	0.005	0.028	0.817	0.414	0.017	0.341	0.733
		α_2	0.046	0.775	0.438	-0.039	-1.104	0.270	-0.087	-1.629	0.103
		β_0	0.496	4.509***	0.000	0.472	3.706***	0.000	0.460	1.683*	0.092
		d_1	0.608	6.490***	0.000	0.524	4.719***	0.000	1.771	0.482	0.630
		d_2	-0.009	-0.243	0.808	-0.004	-0.105	0.917	-0.011	-0.088	0.930
	Mean	γ_0	-0.635	-1.471	0.141	-0.628	-1.229	0.219	-6.044	-0.120	0.905
		γ_1	-0.020	-0.169	0.866	-0.006	-0.045	0.964	-0.050	-0.178	0.859

San Francisco	*Volatility*	α_0	0.000	6.149***	0.000	0.197	39.966***	0.000	0.344	2.171**	0.030
		α_1	0.012	5.446***	0.000	0.049	1.474	0.141	0.006	0.068	0.945
		α_2	0.013	4.185***	0.000	-0.057	-1.697	0.090	-0.113	-1.406	0.160
		β_0	0.512	557.713***	0.000	0.530	173.892***	0.000	0.530	2.256**	0.024
		d_1	1.094	1.525	0.127	1.008	1.487	0.137	2.772	0.532	0.595
		d_2	-0.028	-0.406	0.685	-0.026	-0.373	0.709	-0.054	-0.189	0.850
Washington	*Mean*	γ_0	0.003	0.002	0.998	-0.235	-0.166	0.869	0.983	1.717*	0.09
		γ_1	-0.062	-0.998	0.318	-0.136	-1.908*	0.056	0.195	1.445	0.149
	Volatility	α_0	0.000	5.275***	0.000	0.001	4.179***	0.000	0.101	1.638	0.102
		α_1	0.033	0.895	0.371	0.030	3.836***	0.000	0.084	2.127**	0.034
		α_2	0.007	203.129***	0.000	0.016	1.613	0.107	-0.026	-0.582	0.560
		β_0	0.958	203.181***	0.000	0.955	162.503***	0.000	0.579	2.506**	0.012
		d_1	-0.684	-5.221***	0.000	-0.691	-5.368***	0.000	1.691	0.743	0.458
		d_2	0.006	0.557	0.577	0.005	0.418	0.676	-0.067	-0.719	0.472
Aggregate housing returns	*Mean*	γ_0	0.937	4.041***	0.000	0.791	3.333***	0.001	4.197	0.868	0.385
		γ_1	-0.006	-0.256	0.798	-0.023	-0.896	0.370	0.057	1.094	0.274
	Volatility	α_0	0.000	4.630***	0.000	0.000	2.317**	0.021	0.000	2.852***	0.004
		α_1	0.000	0.000	0.999	-0.000	-0.350	0.726	-0.023	-9.167***	0.000
		α_2	0.016	4.899***	0.000	0.012	3.679***	0.000	0.029	5.248***	0.000
		β_0	0.985	275.219***	0.000	0.991	242.318***	0.000	0.999	289.440***	0.000
		d_1	-0.020	-1.578	0.115	-0.019	-1.828	0.068*	0.019	0.272	0.786
		d_2	0.002	1.536	0.125	0.001	1.205	0.228	0.003	0.741	0.459
REITs Returns	*Mean*	γ_0	-0.060	-1.747**	0.081	-3.653	-1.399	0.162	-57.822	-2.186**	0.029
		γ_1	0.005	3.178***	0.002	-0.031	-0.201	0.841	1.086	3.664***	0.000
	Volatility	α_0	0.000	16.311***	0.000	0.021	3.988***	0.000	0.028	2.295**	0.022
		α_1	0.237	9.380***	0.000	0.079	4.478***	0.000	0.091	3.448***	0.001
		α_2	0.154	4.002***	0.000	0.106	4.414***	0.000	0.051	1.850*	0.064
		β_0	0.442	20.043***	0.000	0.862	60.002***	0.000	0.875	51.032***	0.000
		d_1	0.000	0.347	0.729	1.477	0.638	0.524	24.824	1.299	0.194
		d_2	-0.000	-13.373***	0.000	0.084	1.102	0.270	0.046	0.200	0.842
S&P500	*Mean*	γ_0	-6.465	-2.540**	0.011	-5.999	-2.243**	0.025	-24.576	-1.494	0.135
		γ_1	0.520	3.641***	0.000	0.412	2.272**	0.023	0.729	3.211***	0.001
	Volatility	α_0	0.000	14.959***	0.000	0.008	5.749***	0.000	0.024	5.020***	0.000
		α_1	0.178	6.949***	0.000	-0.022	-2.779***	0.005	-0.033	-2.214**	0.027
		α_2	0.159	4.869***	0.000	0.117	9.525***	0.000	0.196	7.762***	0.000
		β_0	0.934	121.592***	0.000	0.956	114.092***	0.000	0.916	62.959***	0.000
		d_1	1.910	1.647	0.100	2.439	2.157**	0.031	5.948	0.793	0.428
		d_2	-0.222	-5.804***	0.000	-0.187	-5.810***	0.000	-0.207	-1.983**	0.047

Note: GJR(1,1) specification used: *Mean equation:* $R_t = \mu + \rho R_{t-1} + \gamma_0 MP_{t-1} + \gamma_1 MS_{t-1} + \varepsilon_t$.*Volatility equation:* $h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-1}^2 d_{t-1} + \beta_0 h_{t-1} + d_1 MP_{t-1} + d_2 MS_{t-1}$. R_t represents the U.S housing return series, MP is the federal funds rate monetary policy surprise, MS represents the macroeconomic surprise and ε_t is the stochastic disturbance term that is assumed to be normally distributed with zero mean. The conditional variance h_t depends on the mean volatility level (α_0), the lagged error (ε_{t-1}^2) and the lagged conditional variance (h_{t-1}). The asymmetric effect is captured by the $\varepsilon_{t-1}^2 d_{t-1}$ term, where $d_t = 1$ if $\varepsilon_t^2 < 0$; and $d_t = 0$ otherwise. Level of significance: ***1 percent; ** 5 percent, *10 percent.

Figure A1: Daily housing returns for 10 U.S MSAs

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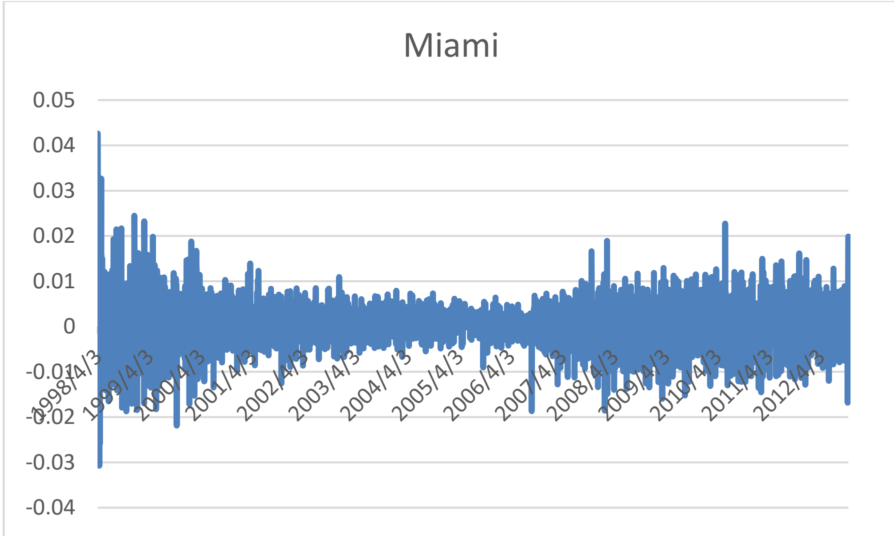
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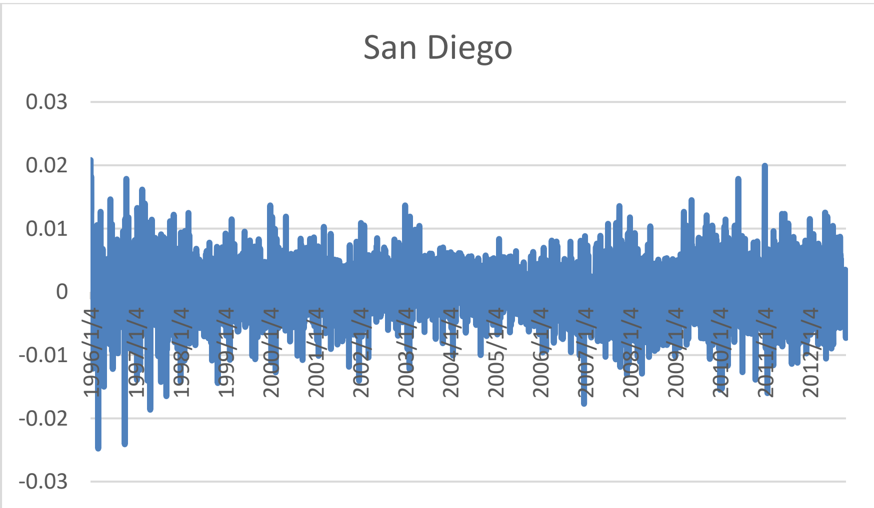
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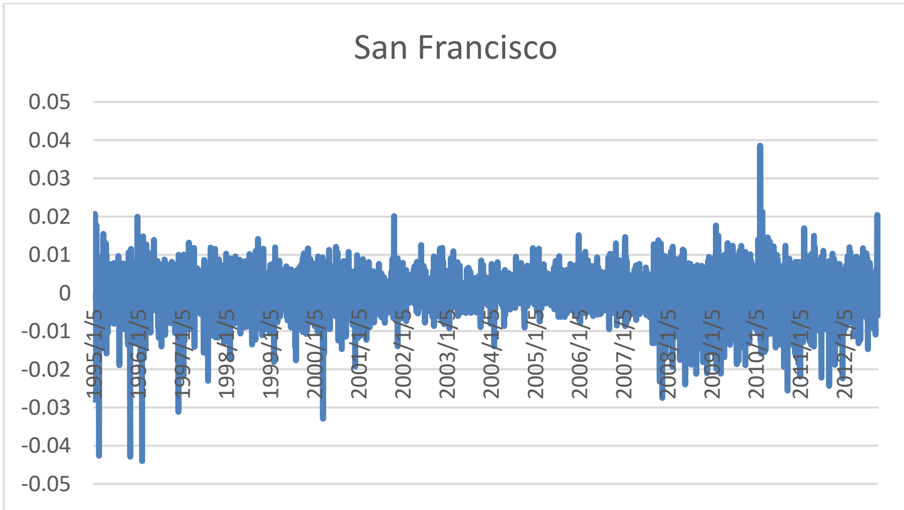
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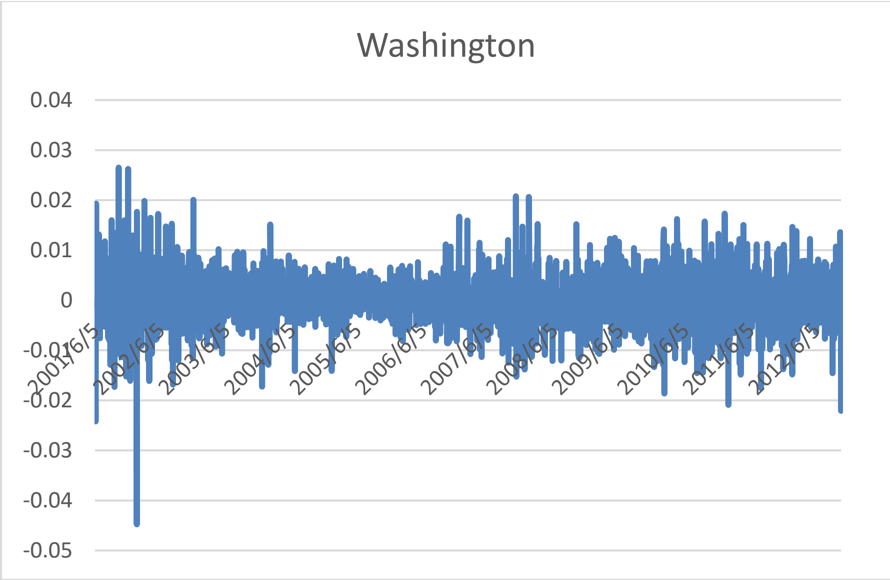
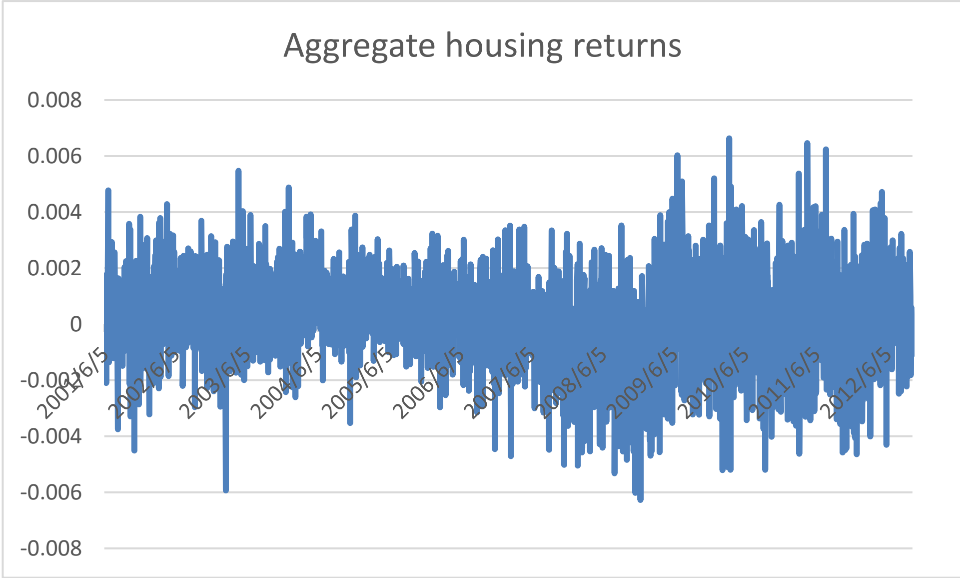
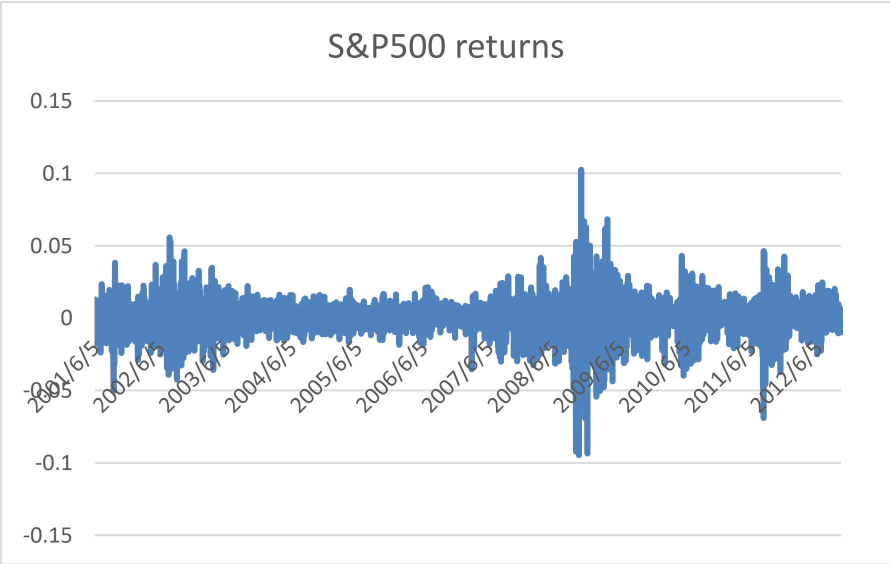
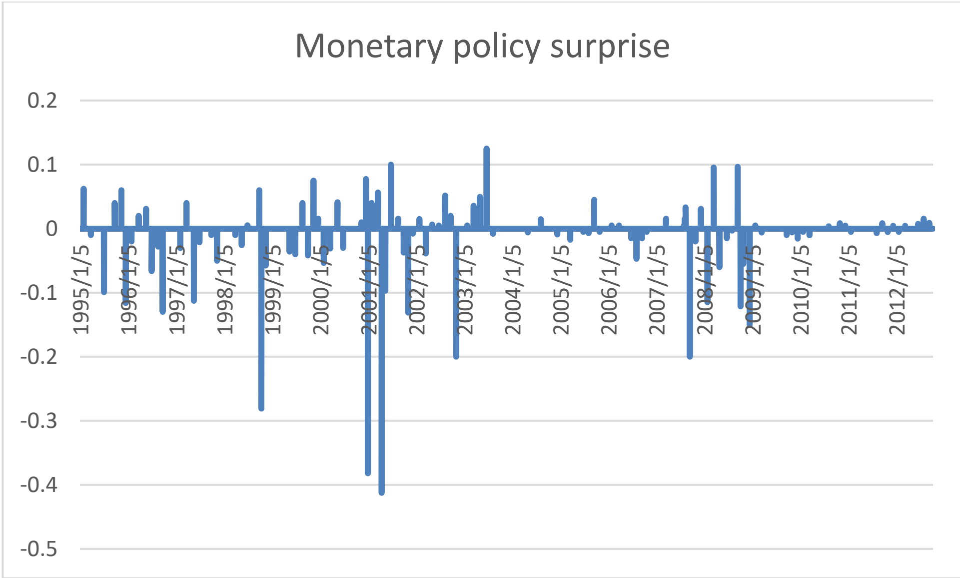
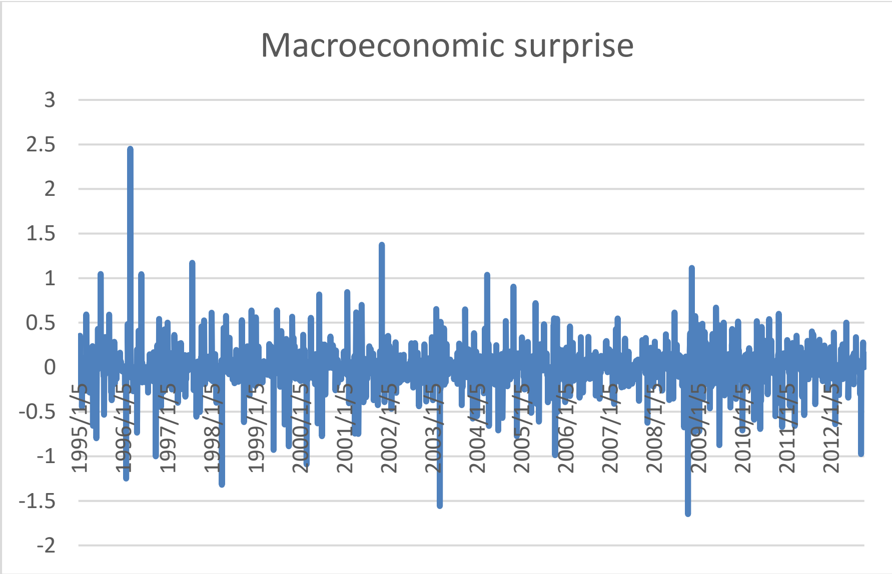
0.05
0.04
0.03
0.02
0.01
0
-0.01
-0.02
-0.03
-0.04
-0.05


Washington
0.04
0.03
0.02
0.01
0
-0.01
-0.02
-0.03
-0.04
-0.05
2001/6/5
2002/6/5
2003/6/5
2004/6/5
2005/6/5
2006/6/5
2007/6/5
2008/6/5
2009/6/5
2010/6/5
2011/6/5
2012/6/5


Aggregate housing returns
0.008
0.006
0.004
0.002
0
-0.002
-0.004
-0.006
-0.008
2001/6/5
2002/6/5
2003/6/5
2004/6/5
2005/6/5
2006/6/5
2007/6/5
2008/6/5
2009/6/5
2010/6/5
2011/6/5
2012/6/5


S&P500 returns
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
2001/6/5
2002/6/5
2003/6/5
2004/6/5
2005/6/5
2006/6/5
2007/6/5
2008/6/5
2009/6/5
2010/6/5
2011/6/5
2012/6/5


Monetary policy surprise
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
-0.5
1995/1/5
1996/1/5
1997/1/5
1998/1/5
1999/1/5
2000/1/5
2001/1/5
2002/1/5
2003/1/5
2004/1/5
2005/1/5
2006/1/5
2007/1/5
2008/1/5
2009/1/5
2010/1/5
2011/1/5
2012/1/5


Macroeconomic surprise
3
2.5
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
1995/1/5
1996/1/5
1997/1/5
1998/1/5
1999/1/5
2000/1/5
2001/1/5
2002/1/5
2003/1/5
2004/1/5
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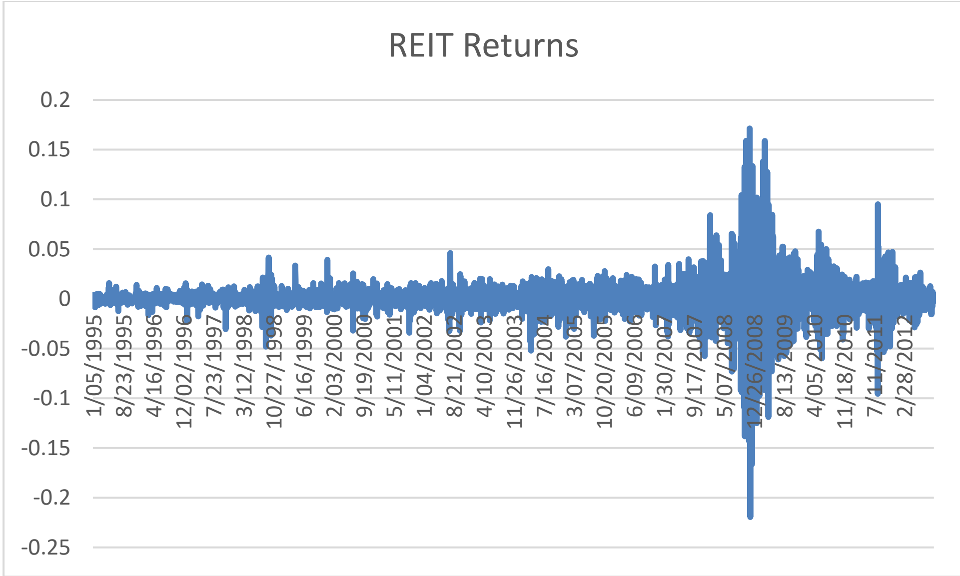
2006/1/5
2007/1/5
2008/1/5
2009/1/5
2010/1/5
2011/1/5
2012/1/5


REIT Returns
0.2
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
-0.2
-0.25
1/05/1995
8/23/1995
4/16/1996
12/02/1996
7/23/1997
3/12/1998
10/27/1998
6/16/1999
2/03/2000
9/19/2000
5/11/2001
1/04/2002
8/21/2002
4/10/2003
11/26/2003
7/16/2004
3/07/2005
10/20/2005
6/09/2006
1/30/2007
9/17/2007
5/07/2008
12/26/2008
8/13/2009
4/05/2010
11/18/2010
7/11/2011
2/28/2012