



# High-Frequency Contagion between Aggregate and Regional Housing Markets of the United States with Financial Assets: Evidence from Multichannel Tests

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## Abstract

This study examined contagion involving the aggregate and regional housing markets of the United States (US) with other asset markets using multichannel tests during the 2007–2008 global financial crisis based on a unique high-frequency, i.e., daily data set. To arrive at bias free results several contagion tests: *the Forbes and Rigobon (FR) correlation test for contagion*, *the Fry, Martin and Tang coskewness (CS) test for contagion*, *the Hsiao cokurtosis (CK) test for contagion* and *the Hsiao covolatility (CV) test for contagion* were employed. At the country level, the linear (correlation) channel indicates that contagion is present from (to) average housing returns to (from) the S&P500, with the correlation contagion also running from average housing returns to REITs. Moreover, the coskewness, cokurtosis and covolatility channels are strongly active with contagion running only from average housing returns to the S&P500, bond returns and REITs. At the Metropolitan Statistical Area (MSA) level, our results indicate that the linear (correlation) channel of contagion is relatively inactive, but the coskewness, cokurtosis and covolatility channels are strongly active with contagion running mostly from housing returns to the S&P500. Our results have important implications for investor and policymakers, given the possibility of differential results based on tests and whether we rely on regional or aggregate data.

**Keywords** Contagion · real estate · multichannel tests · United States

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## Introduction

The most frequently used strategy by investors in risk reduction is that of diversification. In order to minimize losses, investors spread their capital investments across different types of assets (markets) either within the same economy (country) or across different economies (countries). Studies however, have shown that, in the days of worsening financial challenges, there may exist a significant change of correlations within the same asset markets between different countries or between different asset markets within the same country. This condition further diminishes the effectiveness of diversification as a strategy for risk aversion in capital investments, a phenomenon known as contagion. Contagion usually results in a downward comovement of assets prices in markets in times of financial crises (Hui & Chan, 2013).

Dornbusch et al., (2000) defined contagion in three categories, namely; Broad, Restrictive and Very restrictive definitions, with the very restrictive being, the most universally adopted definition. In the broad definition, contagion is the cross-country transmission of shocks or the general cross-country spillover effects. Restrictive definition considers contagion as the transmission of shocks to other countries or the cross-country correlation, beyond any fundamental link among the countries and beyond common shocks. In the very restrictive definition, contagion occurs when cross-country correlations increase during “crisis times” relative to correlations during “tranquil times”.

Recent events of global financial crisis and indeed the European debt crisis has propelled keen interest among researchers for a need to clearly understand the concept of contagion, with several of such studies affirming the presence of contagion in the domestic financial markets of the United States (US), and across international real estate markets like Australia and the United Kingdom (UK) (Bouri et al., 2020). Several studies have investigated contagion involving bonds, stocks, currencies, commodities and more recently, hedge funds. For example Bond et al., (2006), Fry et al., (2010), Wilson & Zurbruegg (2004), Wilson et al., (2007), Yunus & Swanson (2007), Liow (2008), Kallberg et al., (2002), Gerlach et al., (2006), Guo et al., (2011), Hoesli & Reka (2013, 2015) etc. have worked on contagion either across real estate markets or between real estate and stock markets.

A test for contagion involves a comparison of the cross-correlation between the changes in the returns of asset of two markets during the crisis period relative to the pre-crisis period (King & Wadhvani, 1990). Though contagion has various definitions, our study adopted that of Forbes & Rigobon (2002) known as “shift-contagion”, which defines contagion as a significant increase in cross-market linkages after a shock has occurred to one or more markets. This definition clearly distinguishes contagion from “normal” interdependence which is a high level of interconnectedness across markets during all states of the world. The concept of “shift-contagion” connotes a high volatility event that causes instability between interconnected markets.

The global financial crises of 2007–2008 that originated from the US subprime mortgage market is said to be the most solemn recession since World War II. Devastating impacts of this crises spread across various sectors of the US financial markets through the Collateralized Mortgage Obligations (CMOs), which are a type of collateralized debt obligations (CDOs) (Apergis et al., 2019). The impacts of the

2007–2008 recession triggered series of studies involving financial sectors within the US, and internationally. For example, Apergis et al., (2019), investigated whether contagion occurred during the recent global financial crisis across European and US financial markets. Dooley & Hutchison (2009) explore the effect of various news announcements on CDS spreads during the crisis, Jorion & Zhang (2007, 2009) use stock and CDS data to investigate the effects and various channels of credit contagion.

This study is aimed at examining the contagion in the US real estate market during the global financial crisis. We examined two cases of contagion: (i) contagion between average housing returns and S&P500, bond returns and Real Estate Investment Trusts (REITs) at the country level, and (ii) contagion between housing returns and S&P500 across the major cities. This study is unique and differs from several other studies on contagion in three distinct ways: in the methodology employed, the uniqueness in terms of the data frequency used, in particular that involving the daily data of the aggregate and regional housing markets. In terms of the overall and regional date, i.e., 10 major Metropolitan Statistical Areas (MSAs) of the US (Boston, Chicago, Denver, Las Vegas, Los Angeles, Miami, New York, San Diego, San Francisco and Washington), we rely on the important contribution of Bollerslev et al., (2016). Their construction of daily data is based on a comprehensive database consisting of all publicly recorded residential property transactions. The daily house price indexes are based on the same “repeat-sales” methodology of Shiller (1991), just as the popular S&P/Case-Shiller indexes, traditionally published at a monthly frequency. As the name suggests, a repeat sales model estimate house price changes by looking at repeated transactions of the same house. This provides some control for the heterogeneity in the characteristics of houses, while only requiring data on transaction prices and dates.

At this stage, it is important to point out that low frequency of reporting ignores the potential information available in the daily records of housing transactions, and is likely to induce “aggregation biases” if the true index changes at a higher frequencies than the measurement period (Calhoun et al., 1995). Furthermore along these lines, aggregating the indexes to lower frequencies also reduces their volatility, thereby underestimating the true risk of the housing market (Wang, 2014; Nyakabawo et al., 2018). In addition, more timely house prices, are also of direct interest to policy makers, central banks, developers and lenders, as well as, of course, potential buyers and sellers (Bollerslev et al., 2016). This is vindicated by the results obtained by Bollerslev et al., (2016), whereby the authors show that the new daily indexes result in improved forecasts over longer monthly horizons for both the composite and city-specific housing returns, thus directly underscoring the informational advantages over the existing monthly published indexes. Moreover, the use of high-frequency (daily) housing data allows us to estimate more accurate measures of not only housing returns but also the higher moments, particularly volatility, in the housing markets (Segnon et al., 2021), with Bollerslev et al., (2016) depicting strong evidence of volatility clustering within and across the different house price indexes, which in turn can be satisfactorily described by a relatively simple multivariate Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. While, there are indeed lot of advantages of using daily data, and better estimates of volatility, i.e., risks in the housing market from the perspective of investment and policy deci-

sions, predicting the mean of the housing returns might turn out to be a difficult exercise, especially given the fact that housing returns are driven by large number of predictors, which in turn are only available at lower frequency (see Gupta et al., (2022) for a detailed review of this literature). Not surprisingly, Bollerslev et al., (2016) found that the new daily house price indexes exhibit only mild predictability in the mean. This might, possibly wrongly, suggest that the daily housing market is efficient (Tiwari et al., 2020a, b), and cannot be affected by policies, among other variables. To validate or reject this line of reasoning, one would then need to rely on the complicated Unrestricted Reverse-Mixed Data Sampling (UR-MIDAS) approach (see, Feroni et al., (2018)), whereby one explains high-frequency dependent variable with low-frequency data. Also, if the daily data is not publicly available and updated frequently, making policy decisions will not be straightforward, and reliance needs to be placed again on low-frequency indexes. In this regard, it must be pointed out that, the transaction data used in the daily index estimation is obtained by Bollerslev et al., (2016) from DataQuick, a property information company, whereby the data is proprietary. Hence, even though the Federal Reserve can buy and access this data at a cost, it would not be that easily accessible to regular buyers and sellers in the market in terms of its affordability, and they would need to rely on large investment houses to make the decisions for them.

In spite of some of the associated disadvantages involving the usage of daily data, particularly in terms of its availability, if and when accessible, its advantages, as outlined above, more than outweighs the concerns associated with its usage. And this is more so, in our context, where we aim to study contagion across the housing and other asset markets (and not so much forecasting its mean returns and volatility), with data available at high frequency for the latter set. In this context, usage of daily data is highly important to accurately depict the underlying interrelationships, given that the dynamic dependencies in the new daily housing price series were found to closely mimic those of other aggregate asset price indexes, and also helps us avoid the issues of aggregation, which is known to increase degree of correlation of assets (Bollerslev et al., 2016). Note that, we do not rely on the analysis based on data at the country-level only, since it is well-known that the US housing market at the city-level cannot be dubbed as homogenous (Canarella et al., 2012; Kim & Rous, 2012). To the best of our knowledge, this is the only study that has diligently treated contagion holistically using a wide array of statistical tests associated with alternative channels of contagion across major assets traded within the US, and also involving regional analysis.

Specifically, we use the Forbes & Rigobon (2002) correlation test for contagion to investigate the linear (returns) channel of contagion. This test corrects the biasness associated with Pearson correlation coefficient due to heteroskedasticity. Since correlations alone may not be able to capture the complete contagion patterns, we extend our analysis to higher order comovements such as coskewness, cokurtosis and covolatility. Specifically, we employ the Fry et al., (2010) coskewness test to investigate contagion between returns and squared returns (volatilities). Furthermore, we employ Fry-McKibbin & Hsiao (2018) cokurtosis and covolatility tests for contagion to detect possible contagion links between returns and skewness (cubed returns), and between volatilities of two markets, respectively. Furthermore, we estimate long run correlations using the Müller and Watson (2018) long-run covariability test. In

addition, we also analyse a regime switching skew-normal (RSSN) model of crisis and contagion introduced by Chan et al., (2019) to examine contagion and/or structural breaks in our data sample. To the best of our knowledge, our work is the first that integrates all the aforementioned tests to fully examine contagion patterns in the US real estate market. Secondly, despite the fact that 2007–2008 financial crisis originated in the US, most studies on the crisis examine its continental or global impacts. Contrary, our study examines the home impacts of this crisis on the country and metropolitan level. Thirdly, we use high-frequency house price data at both aggregate and 10 Metropolitan Statistical Areas (MSAs) levels. The rest of the paper is organized as follows: Literature is reviewed in the next section. Methodological approaches employed are discussed in Sect. 3. Data and empirical analyses are presented in Sect. 4 while Sect. 5 concludes.

## Literature review

Several authors investigate links between events of financial crises and their corresponding effects on the financial markets generally. Most of such works have confirmed contagion between these crises and the financial markets in both the US and indeed the world at large. Yunus (2009) examined the degree of interdependence among the securitized property markets of six major countries and the US and established that the property markets of Australia, Hong Kong, Japan, the UK and the U.S. were correlated from January 1990 to August 2007. During their investigation of the dynamic conditional correlations (DCCs) between housing returns and retail property returns, and the existence of volatility spillover between the two property markets of Hong Kong, Hui & Zheng (2012), found more contagion in property market than the residential market and confirmed a unilateral volatility spillover from residential property to retail property in the Hong Kong market.

Hui & Chan (2012) examined contagion during the great recession of 2008 between U.S., U.K., China and Hong Kong using the coskewness and cokurtosis tests. The result of this study revealed monumental evidence of contagion between these countries with the highest contagion existing between China and Hong Kong, and between U.S. and U.K. Zhou (2010) used the wavelet analysis and examined the correlation among international securitized real estate markets and the cross-market comovement between the stock and securitized real estate markets. During the Asian financial crisis and the global credit crisis Ryan (2011) applied vector autoregression (VAR) models to examine the extent of correlation between international listed property markets. Their result showed evidence of contagion between the markets which triggered the evaporation of diversification benefits during the crisis in both hedged and un-hedged cases. Apergis et al., (2019) investigated contagion in the events of recent global recession in European and US financial markets using correlation, coskewness, cokurtosis and covolatility tests. Findings from the study revealed evidence of contagion between the financial markets in this period.

Bouri et al., (2020) analyzed contagion between Real Estate Investments Trusts (REITs) and the equity markets of nineteen countries between 1998 and 2018 using the local Gaussian correlation approach during the dotcom, global financial, Euro-

pean sovereign debt crises and the recent Brexit period in the UK. The study uncovered substantial evidence of correlation between equities and REITs during the global financial and sovereign debt crises. The result of the study further revealed a similar contagion across REITs of the US and the other countries, and between US REITs and equities of the remaining eighteen countries. Cotter & Stevenson (2006) documented through the use of a multivariate VAR-GARCH (Vector Auto-Regression - Generalized Auto-Regressive Conditional Heteroskedasticity) model that contagion exists between REIT sub-sections and equity in the US. Hiang (2012) applied the DCC-GJR-GARCH (Dynamic Conditional Correlation - Glosten, Jagannathan and Runkle - Generalized Auto-Regressive Conditional Heteroskedasticity) model and established conditional correlation is time-varying in eight Asian countries over 1995–2009 in a study for the co-movements between real estate and stock markets.

Concentrating now more within the US, Hoesli & Reka (2015) used quantile regressions and copulas to confirm a strong contagion between real estate, i.e., REITs, and financial markets in the US during 1999–2011. This result confirmed the earlier findings of Hoesli & Reka (2013) for the US, besides the UK. Caporin et al. (2020) studied contagion between Real Estate Investment Trusts (REITs) and the equity market in the US using Bayesian nonparametric quantile-on-quantile (QQ) regressions with heteroskedasticity. Their study found a hike in contagion between REITs and stock markets during the period of January 2003, to December, 2017.<sup>1</sup>

As can be seen from the review above, while dealing with contagion between the real estate sector and financial markets, primarily equities, studies have used REITs to proxy for the former. This is understandable, since daily house price data is not generally available. While REITs market is indeed associated with the real estate market, but is characteristically different from it, and is much similar to a standard stock markets, with REITs market capturing partial<sup>2</sup> movements in primarily non-residential (commercial) properties which include apartments, industrial properties, offices, and retail properties (Ghysels et al., 2013). Usage of this high-frequency data set on housing market when analysing contagion with other financial markets, and in particular, the stock market at aggregate and MSA-level is what makes our analysis unique in providing a correct picture of contagion involving the broader real estate sector of the US.

## Methodological approaches

This section describes several of the tests that have been developed to examine whether a significant increase in cross-market linkages is observed after a shock to an individual market has occurred. The Forbes & Rigobon (2002) test for contagion is based on the Pearson correlation coefficient and finds evidence of contagion,

<sup>1</sup> In this regard, these authors used the framework developed by Caporin et al., (2018), who studied shift-contagion in euro bond yield spreads.

<sup>2</sup> 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.

if the cross-correlation has increased significantly between the pre- and the post-crisis period. The statistic tests whether a shock in the returns of the source market transmitted to the returns of the recipient market. Fry et al., (2010) propose another test for contagion based on the second order of moments, namely skewness. Their coskewness based test checks for contagion between the returns of one market to the volatility of the second market. Using the framework developed by Fry et al., (2010), Fry-McKibbin & Hsiao (2018) create another line of tests based on higher order of moments, i.e. kurtosis and volatility. The cokurtosis test examines the relationship between one market's returns and another market's skewness. The covolatility test explores how shocks transmit from the volatility of one market to the volatility of the second market. Finally, Chan et al., (2019) propose a regime switching skew-normal (RSSN) model of crisis and contagion. Their tests measure contagion in terms of changes in the comoments of correlation and coskewness in the non-crisis regime compared to a crisis regime. Furthermore, the authors develop tests for structural breaks in the moments of the mean, variance and skewness.

### The Forbes & Rigobon (2002) correlation test for contagion

Tests for contagion based on the cross-market Pearson correlation coefficient are biased due to the presence of heteroskedasticity in market returns. An increase in market volatility can affect estimates of cross-correlation coefficients. This can be problematic because tests that do not adjust for the aforementioned bias in the correlation coefficient, often find evidence of contagion. The authors show how the variance affects the correlation coefficient, a way to calculate this bias and how to correct it. They test for contagion from market  $i$  to market  $j$ . Furthermore, they make the assumptions that there are no omitted variables and endogeneity. They divide the sample into two sets so that the variance of the first group  $\sigma_x^2$  is lower and the variance of the second group  $\sigma_y^2$  is higher. In terms of testing for contagion, the low-variance group refers to the tranquil period prior to the crisis, while the high-variance group refers to the period after the occurrence of the shock. The correlation between the asset returns for the two markets is  $\rho_x$  for the non-crisis period (low-variance group) and  $\rho_y$  post-crisis period (high-variance group). If a shock occurs in market  $i$  and there is an increase in the volatility of the asset returns then:  $\sigma_{y,i}^2 > \sigma_{x,i}^2$ , while the transmission channels between market  $i$  and market  $j$  remain the same, then  $\rho_y > \rho_x$  gives the false appearance of contagion. As a result, tests for contagion based on cross-correlation can lead to the wrong conclusion, because the estimates of the correlation coefficient are biased and conditional on the variance of the market returns. Forbes and Rigobon find a way to adjust for this bias by defining contagion as an increase in the unconditional correlation coefficient, which is given by the following equation:

$$v_y = \frac{\rho_y}{\sqrt{1 + \delta(1 - \rho_y^2)}}, \text{ where } \delta = \frac{\sigma_{y,i}^2 - \sigma_{x,i}^2}{\sigma_{x,i}^2}. \quad (1)$$

The unconditional correlation  $v_y$  is the conditional correlation  $\rho_y$  scaled by the non-linear function  $\delta$ , which is the relative change in variance in the asset returns of the source country. During periods of high volatility in market  $i$ , the conditional correlation between the two markets will be greater than the unconditional correlation. Even if the unconditional correlation coefficient remains constant during both pre- and post-crisis periods, the conditional correlation coefficient will increase after a shock has occurred, due to bias caused by the presence of heteroskedasticity in the market returns. They estimate a VAR model and use the variance-covariance estimates from this model to calculate the cross-correlation coefficient between the market where the shock originated and each of the other markets. These are based on the unconditional correlation coefficient from Eq. (1). They use  $t$ -tests to examine if there is a significant increase in any of the correlation coefficients during the crisis period. If  $v_y$  is the adjusted correlation during the crisis period and  $\rho_x$  is the correlation during the non-crisis period, the null and the alternative hypotheses are hypotheses are:

$$H_0 : v_y = \rho_x, H_1 : v_y > \rho_x \quad (2)$$

The null hypothesis indicates that no contagion has occurred, while the alternative hypothesis means that contagion has taken place. The  $t$ -statistic used for testing the above hypotheses is given by the following equation:

$$FR(i \rightarrow j) = \frac{\frac{1}{2} \ln \left( \frac{1+\hat{v}_y}{1-\hat{v}_y} \right) - \frac{1}{2} \ln \left( \frac{1+\hat{\rho}_x}{1-\hat{\rho}_x} \right)}{\sqrt{\frac{1}{T_y-3} + \frac{1}{T_x-3}}}, \quad (3)$$

where  $T_y$  and  $T_x$  are the sample sizes of the crisis period and pre-crisis period respectively. The standard error in Eq. (3) derives from assuming that the two samples are drawn from independent normal distributions. It is important to note that Forbes & Rigobon (2002) focus on fixing only one of the problems with the cross-correlation coefficient: heteroskedasticity. Adjustment also needs to be made for the bias caused by the presence of endogeneity or omitted variables.

### The Fry et al., (2010) coskewness test for contagion

Correlations alone may not be able to capture the complete contagion pattern; therefore, the authors extend to higher order moments, such as coskewness, to obtain more details. They argue that after a shock has occurred, risk-averse investors would shift towards positive skewness by trading off smaller returns for positive skewness. The aim of the asymmetric dependence tests of contagion by Fry et al., (2010) is to identify whether there is a statistically significant change in coskewness between the pre- and post-crisis period after controlling for the market fundamentals. They test for contagion from market  $i$  to market  $j$ , where  $x$  is the low volatility pre-crisis period and  $y$  is the high volatility post-crisis period. The asset returns are  $r_i$  and  $r_j$  for markets  $i$  and  $j$  respectively. The means are  $\mu_x$  and  $\mu_y$ , while the standard deviations are denoted by  $\sigma_x$  and  $\sigma_y$ , for the tranquil period and for the period after the shock



respectively. The correlation between the two asset returns is denoted as  $\rho_x$  (low variance period) and  $\rho_y$  (high variance period). Finally, the sample sizes of the pre-crisis and crisis periods are  $T_x$  and  $T_y$ , respectively.

They developed two variants of the coskewness-based test,  $CS_{12}$  and  $CS_{21}$ , which build on the Forbes & Rigobon (2002) test and are specified depending on whether the asset prices at the source market of the crisis are expressed in terms of returns or squared returns in order to calculate coskewness. The coskewness statistics for testing for contagion from market  $i$  to market  $j$  (or specifically, from the value of  $i$  to the volatility of  $j$  and from the volatility of  $i$  to the value of  $j$ ) are given by the following equations:

$$CS_{12}(i \rightarrow j; r_i^1, r_j^2) = \left( \frac{\widehat{\psi}_y(r_i^1, r_j^2) - \widehat{\psi}_x(r_i^1, r_j^2)}{\sqrt{\frac{4\widehat{v}_y+2}{T_y} + \frac{4\widehat{\rho}_x^2+2}{T_x}}} \right)^2 \tag{4}$$

The  $CS_{12}$  test for contagion tests whether there is a significant decrease of the returns in the source market and an increase of the volatility in the second market. This implies that the crisis in the source market has been identified with positive skewness (i.e., investors seek low-risk assets and accept lower returns), while contagion in the second market takes the form of increased volatility.

$$CS_{21}(i \rightarrow j; r_i^2, r_j^1) = \left( \frac{\widehat{\psi}_y(r_i^2, r_j^1) - \widehat{\psi}_x(r_i^2, r_j^1)}{\sqrt{\frac{4\widehat{v}_y+2}{T_y} + \frac{4\widehat{\rho}_x^2+2}{T_x}}} \right)^2 \tag{5}$$

where

$$\widehat{\psi}_y(r_i^m, r_j^n) = \frac{1}{T_y} \sum_{t=1}^{T_y} \left( \frac{y_{i,t} - \widehat{\mu}_{y,i}}{\widehat{\sigma}_{y,i}} \right)^m \left( \frac{y_{j,t} - \widehat{\mu}_{y,j}}{\widehat{\sigma}_{y,j}} \right)^n \tag{6}$$

$$\widehat{\psi}_x(r_i^m, r_j^n) = \frac{1}{T_x} \sum_{t=1}^{T_x} \left( \frac{x_{i,t} - \widehat{\mu}_{x,i}}{\widehat{\sigma}_{x,i}} \right)^m \left( \frac{x_{j,t} - \widehat{\mu}_{x,j}}{\widehat{\sigma}_{x,j}} \right)^n \tag{7}$$

and  $\widehat{v}_y$  is the FR adjusted unconditional correlation coefficient. The  $CS_{21}$  test for contagion tests whether there is a significant increase of the volatility in the source market and a significant decrease of the average returns in the second market, which means that the increased volatility in the source market affects investors in the second market, who prefer low-risk assets with lower returns seeking positive skewness. To test whether there is a significant change in coskewness, they formulate the following hypotheses:

$$H_0 : \psi_y (r_i^m, r_j^n) = \psi_x (r_i^m, r_j^n) \quad (8)$$

$$H_1 : \psi_y (r_i^m, r_j^n) \neq \psi_x (r_i^m, r_j^n).$$

Under the null hypothesis of no contagion, tests of contagion based on changes in coskewness are asymptotically distributed as:

$$CS_{12} (i \rightarrow j), CS_{21} (i \rightarrow j) \xrightarrow{d} X_1^2 \quad (9)$$

The framework Fry et al. present can also be used to create more tests for contagion using higher co-moments such as cokurtosis.

### The Fry-McKibbin & Hsiao (2018) cokurtosis test for contagion

The coskewness test is not always enough to capture the full scope contagion. Additional transmission channels may be detected by raising the order of moment by one. The author tests for contagion from market  $i$  to market  $j$ , where  $x$  is the tranquil period prior to the crisis (low variance), while  $y$  is the period during the crisis (high variance). The asset returns are  $r_i$  and  $r_j$  for markets  $i$  and  $j$  respectively. The correlation between the two asset returns is denoted as  $\rho_x$  (tranquil period) and  $\rho_y$  (crisis period). Finally, the sample sizes of the pre-crisis and crisis periods are  $T_x$  and  $T_y$  respectively.

Two types of cokurtosis tests were created by using the framework developed by Fry et al., (2010) for the coskewness tests, which are based on the Forbes & Rigobon (2002) test for contagion. The first type of statistic  $CK_{j3}$  is to detect the shocks originating from the asset returns of the source market  $i$  to the cubed returns (skewness) of market  $j$ . The second type of statistic  $CK_{3i}$  is to measure the shock transmitting from the cubed asset returns (skewness) of the source market  $i$  to the returns of market  $j$ . The cokurtosis statistics for testing for contagion from market  $i$  to market  $j$  are given by the following two equations:

$$CS_{13} (i \rightarrow j; r_i^1, r_j^3) = \left( \frac{\hat{\xi}_y (r_i^1, r_j^3) - \hat{\xi}_x (r_i^1, r_j^3)}{\sqrt{\frac{18\hat{\sigma}_y^2+6}{T_y} + \frac{18\hat{\sigma}_x^2+6}{T_x}}} \right)^2 \quad (10)$$

and

$$CS_{31} (i \rightarrow j; r_i^3, r_j^1) = \left( \frac{\hat{\xi}_y (r_i^3, r_j^1) - \hat{\xi}_x (r_i^3, r_j^1)}{\sqrt{\frac{18\hat{\sigma}_y^2+6}{T_y} + \frac{18\hat{\sigma}_x^2+6}{T_x}}} \right)^2, \quad (11)$$

where

$$\widehat{\xi}_y (r_i^m, r_j^n) = \frac{1}{T_y} \sum_{t=1}^{T_y} \left( \frac{y_{i,t} - \widehat{\mu}_{y,i}}{\widehat{\sigma}_{y,i}} \right)^m \left( \frac{y_{j,t} - \widehat{\mu}_{y,j}}{\widehat{\sigma}_{y,j}} \right)^n - (3\widehat{v}_y), \tag{12}$$

$$\widehat{\xi}_x (r_i^m, r_j^n) = \frac{1}{T_x} \sum_{t=1}^{T_x} \left( \frac{x_{i,t} - \widehat{\mu}_{x,i}}{\widehat{\sigma}_{x,i}} \right)^m \left( \frac{x_{j,t} - \widehat{\mu}_{x,j}}{\widehat{\sigma}_{x,j}} \right)^n - (3\widehat{\rho}_x) \tag{13}$$

and  $\widehat{v}_y$  is the FR adjusted unconditional correlation coefficient. To test whether there is a significant change in cokurtosis, the following hypotheses are made:

$$H_0 : \xi_y (r_i^m, r_j^n) = \xi_x (r_i^m, r_j^n) \tag{14}$$

$$H_1 : \xi_y (r_i^m, r_j^n) \neq \xi_x (r_i^m, r_j^n).$$

Under the null hypothesis of no contagion, tests of contagion based on changes in cokurtosis are asymptotically distributed as:

$$CS_{13} (i \rightarrow j), CS_{31} (i \rightarrow j) \underset{d}{\sim} X_1^2 \tag{15}$$

**.The Fry-McKibbin & Hsiao (2018) covolatility test for contagion**

Changes in the relation between the volatility of the returns of one market with the volatility of the returns of another market from negative to positive after the shock has occurred, reveals the volatility smile effect through the covolatility channel in the crisis period. During the crisis period, a high covolatility means that the returns are high risk, which is undesirable by the investors. The author tests for contagion from market  $i$  to market  $j$ , where  $x$  is the tranquil period, while  $y$  is the volatile period after the crisis has occurred. The asset returns are  $r_i$  and  $r_j$  for markets  $i$  and  $j$  respectively. The correlation between the two asset returns is denoted as  $\rho_x$  and  $\rho_y$  for the pre- and post-crisis period respectively. Finally, the sample sizes of the two periods are  $T_x$  and  $T_y$ . The covolatility test detects shocks transmitted from the volatility of returns of the source market  $i$  to the volatility of returns of another market  $j$ . The covolatility statistic for testing for contagion from market  $i$  to market  $j$  is given by the following equation:

$$CV_{22} (i \rightarrow j; r_i^2, r_j^2) = \left( \frac{\widehat{\xi}_y (r_i^2, r_j^2) - \widehat{\xi}_x (r_i^2, r_j^2)}{\sqrt{\frac{4\widehat{v}_y^4 + 16\widehat{v}_y^2 + 4}{T_y} + \frac{4\widehat{\rho}_x^4 + 16\widehat{\rho}_x^2 + 4}{T_x}}} \right)^2, \tag{16}$$

where

$$\widehat{\xi}_y(r_i^2, r_j^2) = \frac{1}{T_y} \sum_{t=1}^{T_y} \left( \frac{y_{i,t} - \widehat{\mu}_{y,i}}{\widehat{\sigma}_{y,i}} \right)^2 \left( \frac{y_{j,t} - \widehat{\mu}_{y,j}}{\widehat{\sigma}_{y,j}} \right)^2 - (1 + 2\widehat{v}_y^2), \quad (17)$$

$$\widehat{\xi}_x(r_i^2, r_j^2) = \frac{1}{T_x} \sum_{t=1}^{T_x} \left( \frac{x_{i,t} - \widehat{\mu}_{x,i}}{\widehat{\sigma}_{x,i}} \right)^2 \left( \frac{x_{j,t} - \widehat{\mu}_{x,j}}{\widehat{\sigma}_{x,j}} \right)^2 - (1 + 2\widehat{\rho}_x^2). \quad (18)$$

To test whether there is a significant change in covolatility, the following hypotheses are made:

$$H_0 : \xi_y(r_i^2, r_j^2) = \xi_x(r_i^2, r_j^2) \quad (19)$$

$$H_1 : \xi_y(r_i^2, r_j^2) \neq \xi_x(r_i^2, r_j^2).$$

Under the null hypothesis of no contagion, tests of contagion based on changes in covolatility are asymptotically distributed as:

$$CV_{22}(i \rightarrow j) \underset{d}{\sim} X_1^2 \quad (20)$$

.It is important to note that both the Fry et al. coskewness test and the Fry-McKibbin & Hsiao (2018) cokurtosis and covolatility tests are based on the Forbes & Rigobon (2002) adjusted correlation coefficient; therefore, they follow the same assumptions of no omitted variables and absence of endogeneity.

## Data and Empirical analysis

### Data

We use daily housing price data which were sourced from Bollerslev et al., (2016) and covered the 10 US MSAs. These data were constructed by Bollerslev et al., (2016) based on the repeat sales method, and comprehensive transaction data from DataQuick. This database contains detailed transactions of more than one hundred million properties in the US. For most of the areas, the historical transaction records goes back to the late 1990s, with some large metropolitan areas, such as Boston and New York, having transactions recorded as far back as 1987. Properties are uniquely identified by property IDs, which enables one to identify sale pairs. Bollerslev et al., (2016) rely on US Standard Use Codes contained in the DataQuick database to identify transactions of single-family residential homes.

The monthly estimation approach of the S&P/Case-Shiller repeat-sales indexes is not computationally feasible at the daily frequency,<sup>3</sup> as it involves the simultaneous

<sup>3</sup> The daily home price indexes are designed to mimic the popular S&P/Case-Shiller house price indexes for the “typical” prices of single-family residential real estate. They are based on a repeat sales method

estimation of several thousand parameters. To overcome this difficulty, Bollerslev et al., (2016) use an expanding-window estimation procedure: conditional on a start-up period, the authors begin by estimating daily index values for the final month in an initial sample, imposing the constraint that all of the earlier months have only a single monthly index value. Restricting the daily values to be the same within each month for all but the last month drastically reduces the dimensionality of the estimation problem. They then expand the estimation period by one month, thereby obtaining daily index values for the new “last” month. The authors continue this expanding estimation procedure through to the end of our sample period. Finally, following the S&P/Case-Shiller methodology, Bollerslev et al., (2016) normalize all of the individual indexes to 100 based on their average values in the year 2000.

To compute the daily composite 10 housing price index as a proxy for the aggregate housing price, we use the weighted average following Bolleslev et al. (2016) with weights assigned as follows: 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 (0.078). The data on S&P500, 10-year government bond price, and REITs were sourced from Datastream of Thomson and Reuters.

The covering period for the study span from 4th June 2001 to 10th October 2012 representing the period of the great recession of 2008 in the US. The crisis event is set to September 15, 2008, which is the date when Lehman Brothers filed for Chap. 11 bankruptcy. Therefore, the sample is divided into two sub-periods; the tranquil (pre-crisis) period from June 4, 2001 to September 15, 2008 and the crisis period from September 16, 2008 to October 10. The data were collected in their clean forms devoid of the inherent problems associated with time series such as missing values and outliers. The analysis of the data as earlier mentioned was through multiple channels in order to arrive at inferences that are free from biases and impulsive conclusions.

## Empirical analysis

The tests of contagion described in Sect. 3 are employed to identify potential linkages, which appeared during the global financial crisis. There are two cases of contagion examined: (i) contagion at the country level between average housing returns and S&P500, bond returns and REITs at the country level, and (ii) contagion at the metropolitan level (MSA) between housing returns and S&P500.

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and the transaction dates and prices for all houses that sold at least twice during the sample period. Specifically, for a house  $j$  that sold at times  $s$  and  $t$  at prices  $H_{j,s}$  and  $H_{j,t}$ , the repeat sales model postulates that,  $\beta_t H_{j,t} = \beta_s H_{j,s} + \sqrt{2}\sigma_w w_{j,t} + \sqrt{(t-s)}\sigma_v v_{j,t}$ ,  $0 \leq s < t \leq T$  with the value of the house price index at time  $\tau$  is defined by the inverse of  $\beta\tau$ . The last two terms on the right-hand side account for “errors” in the sale pairs, with  $\sqrt{2}\sigma_w w_{j,t}$  representing the “mispricing error” and  $\sqrt{(t-s)}\sigma_v v_{j,t}$  representing the “interval error.” Mispricing errors are included to allow for imperfect information between buyers and sellers, potentially causing the actual sale price of a house to differ from its “true” value. The interval error represents a possible drift over time in the value of a given house away from the overall market trend, and is therefore scaled by the (square root of the) length of the time-interval between the two transactions. The error terms  $w_{j,t}$  and  $v_{j,t}$  are assumed independent and identically standard normal distributed. The model and the corresponding error structure naturally lend itself to estimation by a three-stage generalized least square type procedure.

**Table 1** Contagion between average housing returns, stock returns, bond returns and REITs returns

$(i \rightarrow j)$	$FR(i \rightarrow j)$	$CS12(i \rightarrow j)$	$CS21(i \rightarrow j)$	$CK13(i \rightarrow j)$	$CK31(i \rightarrow j)$	$CV22(i \rightarrow j)$	Long run correlation
$AHR \rightarrow S\&P500$	<b>-1.7611</b> [0.0391]	<b>210.1041</b> [0.0000]	<b>85.4688</b> [0.0000]	<b>568.6830</b> [0.0000]	<b>131.8938</b> [0.0000]	<b>164.7500</b> [0.0000]	0.432 (-0.003 0.733)
$S\&P500 \rightarrow AHR$	<b>-1.8084</b> [0.0353]	0.0002 [0.9896]	0.6261 [0.4288]	0.0001 [0.9910]	0.0131 [0.9088]	0.0199 [0.8877]	
$AHR \rightarrow BR$	0.0844 [0.5336]	<b>357.7044</b> [0.0000]	<b>16.1323</b> [0.0001]	<b>1056.8500</b> [0.0000]	<b>154.7712</b> [0.0000]	<b>4809.4000</b> [0.0000]	-0.319 (-0.659 0.102)
$BR \rightarrow AHR$	0.0451 [0.5180]	0.0161 [0.8989]	0.3754 [0.5401]	0.0105 [0.9184]	0.0038 [0.9509]	0.0481 [0.8263]	
$AHR \rightarrow REITs$	<b>-1.7700</b> [0.0384]	<b>962.1400</b> [0.0000]	<b>96.2292</b> [0.0000]	<b>984.4740</b> [0.0000]	<b>207.6240</b> [0.0000]	<b>264.1501</b> [0.0000]	0.839 (0.516 0.947)
$REITs \rightarrow AHR$	-1.5111 [0.0654]	0.0001 [0.9941]	0.0002 [0.9889]	0.0000 [0.9949]	0.2526 [0.6152]	0.0329 [0.8561]	

Notes: The null hypothesis is “no contagion”. The figures denote the test statistics values, while those in square brackets are the p-values. Figures in bold indicate the rejection of the null hypothesis at the 5% significance level. AHR, BR and REITs stand for average housing returns, bond returns and REITs returns, respectively. Long run correlation corresponds to the posterior median of long run correlation coefficient for periods longer than 5.7 years calculated as suggested by Müller and Watson (2018); corresponding 67% confidence intervals are in parentheses

To compute the Forbes & Rigobon (2002) test statistics as well as the adjusted unconditional correlation coefficient needed for the coskewness, cokurtosis and covolatility tests, the market returns are filtered with a Vector Autoregressive (VAR) model. The number of lags in each VAR model is chosen using the BIC, while the Lagrange Multiplier autocorrelation test is applied to test for no autocorrelations in the residuals at the 1% significance level. The residuals estimated from each VAR model are used in computing the Forbes and Rigobon statistic in (4), the coskewness statistics in (5) and (6), the cokurtosis statistics in (11) and (12), and the covolatility statistic in (17), while the assumptions of no omitted variables or the presence of endogeneity across markets are maintained. Tables 1 and 2 present the contagion results at the country and MSA levels, respectively. The figures are test statistics, while those in brackets are p-values. The null hypothesis is ‘no contagion’ and the rejection of the null hypothesis implies that contagion has occurred. To fix ideas, we also report the long-run covariability between variables calculated using the methodology suggested by Müller and Watson (2018).

### Contagion results at the country level

Table 1 presents the empirical results of the contagion tests at the country level between average housing returns and S&P500, bond returns and REITs. Furthermore, the last column of Table 1 reports the point estimates of long run correlations along with their 67% confidence intervals. The long run correlation between average housing returns and REITs is high and positive (0.839) with narrow and informative confidence interval. Average housing returns and S&P500 are also positively correlated in the long run, although the confidence intervals indicate substantial uncertainty. Contrary, the long run correlation between average housing returns and bond returns appears to be negative but with wide confidence interval. Our results suggest

**Table 2** Contagion between MSA's housing returns (HR) and S&P500 returns

	Boston	Chicago	Denver	Las Vegas	Los Angeles	Miami	New York	San Diego	San Francisco	Washington
Panel A: The Forbes & Rigobon (2002) $FR(i \rightarrow j)$ correlation-based contagion test results										
$HR \rightarrow S\&P500$	0.3470 [0.6357]	-0.7861 [0.2159]	-1.0424 [0.1486]	1.4479 [0.9262]	-1.2879 [0.0989]	<b>-2.0122</b> [0.0221]	-1.6239 [0.0522]	0.2727 [0.6074]	0.3827 [0.6490]	-0.1197 [0.4523]
$S\&P500 \rightarrow HR$	0.2147 [0.5850]	-0.5662 [0.2856]	-0.8580 [0.1955]	1.3676 [0.9143]	-1.2046 [0.1142]	<b>-2.0067</b> [0.0224]	-1.5754 [0.0576]	0.2287 [0.5905]	0.3842 [0.6496]	-0.2946 [0.3842]
Panel B: The Fry et al., (2010) $CS12(i \rightarrow j)$ coskewness-based test result										
$HR \rightarrow S\&P500$	<b>253.3290</b> [0.0000]	<b>35.7610</b> [0.0000]	<b>898.8823</b> [0.0000]	<b>615.0940</b> [0.0000]	<b>307.4825</b> [0.0000]	<b>185.4000</b> [0.0000]	<b>126.4298</b> [0.0000]	<b>292.4041</b> [0.0000]	<b>268.7037</b> [0.0000]	<b>676.9427</b> [0.0000]
$S\&P500 \rightarrow HR$	0.0071 [0.9327]	0.0230 [0.8794]	0.0000 [0.9996]	0.1100 [0.7402]	0.0215 [0.8835]	0.0162 [0.8988]	0.0025 [0.9599]	0.0021 [0.9633]	0.0245 [0.8755]	0.0677 [0.7947]
Panel C: The Fry et al., (2010) $CS21(i \rightarrow j)$ coskewness-based test result										
$HR \rightarrow S\&P500$	<b>48.9251</b> [0.0000]	<b>5.3450</b> [0.0208]	<b>147.2118</b> [0.0000]	<b>246.6855</b> [0.0000]	<b>56.7037</b> [0.0123]	<b>14.5893</b> [0.0001]	<b>13.8099</b> [0.0002]	<b>8.0119</b> [0.0046]	<b>8.0076</b> [0.0047]	<b>31.1918</b> [0.0000]
$S\&P500 \rightarrow HR$	0.6901 [0.4061]	0.6187 [0.4315]	0.0164 [0.8980]	1.5741 [0.2096]	0.6872 [0.4071]	1.9013 [0.1679]	0.8643 [0.3525]	1.0782 [0.2991]	<b>8.4654</b> [0.0036]	0.6085 [0.4353]
Panel D: The Fry-McKibbin & Hsiao (2018) $CK13(i \rightarrow j)$ and REIRScokurtosis-based test results										
$HR \rightarrow S\&P500$	<b>630.9400</b> [0.0000]	<b>164.3500</b> [0.0000]	<b>811.4422</b> [0.0000]	<b>886.1200</b> [0.0000]	<b>239.1680</b> [0.0000]	<b>186.8019</b> [0.0000]	<b>196.7581</b> [0.0000]	<b>420.2602</b> [0.0000]	<b>124.7800</b> [0.0000]	<b>819.8128</b> [0.0000]
$S\&P500 \rightarrow HR$	0.0021 [0.9631]	0.8219 [0.3646]	0.0232 [0.8790]	0.0641 [0.8002]	0.0090 [0.9244]	0.0106 [0.9180]	0.0058 [0.9393]	0.0003 [0.9853]	0.0034 [0.9538]	0.0528 [0.8183]
Panel E: The Fry-McKibbin & Hsiao (2018) $CK31(i \rightarrow j)$ cokurtosis-based test results										
$HR \rightarrow S\&P500$	<b>69.4456</b> [0.0000]	<b>993.2633</b> [0.0000]	<b>570.6017</b> [0.0000]	<b>203.3711</b> [0.0000]	<b>317.1073</b> [0.1511]	<b>90.1719</b> [0.0000]	<b>631.1601</b> [0.0000]	<b>16.7507</b> [0.0000]	<b>7.6148</b> [0.0058]	<b>33.6007</b> [0.0000]
$S\&P500 \rightarrow HR$	<b>6.6781</b> [0.0098]	<b>13.8771</b> [0.0002]	0.2080 [0.6484]	3.4365 [0.0638]	1.0082 [0.3153]	0.2282 [0.6329]	2.3466 [0.1256]	0.2847 [0.5936]	<b>5.7742</b> [0.0163]	0.0249 [0.8746]

Table 2 (continued)

	Boston	Chicago	Denver	Las Vegas	Los Angeles	Miami	New York	San Diego	San Francisco	Washington
Panel F: The Fry-MeKibbin & Hsiao (2018) CV22 cointegration-based test results										
$HR \rightarrow S \& P_{500}$	<b>143.8700</b> [0.0000]	<b>522.3200</b> [0.0000]	<b>170.7374</b> [0.0000]	<b>849.1200</b> [0.0000]	<b>538.3649</b> [0.0000]	<b>132.0041</b> [0.0000]	<b>234.2530</b> [0.0000]	<b>421.1302</b> [0.0000]	<b>112.2312</b> [0.0000]	<b>465.1985</b> [0.0000]
$S \& P_{500} \rightarrow HR$	0.0897 [0.7646]	0.4813 [0.4878]	0.0150 [0.9024]	0.2148 [0.6430]	0.0418 [0.8379]	0.0001 [0.9920]	0.4219 [0.5160]	0.3514 [0.5533]	0.5451 [0.4603]	3.3900 [0.0656]
Panel G: The long run correlation										
Long run correlation	0.115 (-0.273 0.516)	0.304 (-0.129 0.645)	0.454 (0.003 0.757)	0.513 (0.041 0.807)	0.429 (-0.004 0.724)	0.510 (0.030 0.804)	0.333 (-0.103 0.653)	0.333 (-0.099 0.653)	0.571 (0.118 0.846)	0.502 (0.022 0.791)
	0.079 [-0.365 0.550]	0.319 [-0.160 0.704]	0.365 [-0.128 0.713]	0.500 [-0.001 0.839]	0.411 [-0.073 0.762]	0.429 [-0.041 0.786]	0.362 [-0.129 0.712]	0.304 [-0.184 0.680]	0.477 [-0.006 0.818]	0.160 [-0.158 0.600]
	0.696 [0.331 0.902]	0.960 [0.885 0.980]	0.379 [-0.045 0.707]	0.721 [0.379 0.918]	0.924 [0.700 0.970]	0.894 [0.624 0.962]	0.813 [0.462 0.942]	0.845 [0.512 0.972]	0.887 [0.596 0.961]	0.733 [0.379 0.921]

Notes: The null hypothesis is "no contagion". The figures denote the test statistics values, while those in parenthesis are the p-values. Figures in bold indicate the rejection of the null hypothesis at the 5% significance level. Long run correlation corresponds to the posterior median of long run correlation coefficient between state-level housing returns and S&P500 returns for periods longer than 5.7 years calculated as suggested by Müller and Watson (2018); corresponding 67% confidence intervals are in parentheses.



that average housing returns covariate with stock, bond and REITs markets in the long run.

Forbes & Rigobon (2002) test examines if shocks transmit from the returns of one market to the returns of the second market, based on a significant increase in cross-correlation. The empirical findings reported in Table 1, illustrate that there are no contagion effects between average housing returns and bond returns. However, our results reveal that contagion transmits from (to) the average housing returns to (from) the S&P500. Furthermore, correlation contagion is also present from average housing returns to the REITs returns.

Fry et al., (2010) argue that correlations are not enough to fully reveal the patterns of contagion, and that important information can be obtained from higher order of moments, such as skewness, which shifts from negative to positive figures after a crisis event. They develop two types of tests based on coskewness: the CS12 statistic tests for contagion, transmitting from the returns of the source market to the volatility (squared returns) of the recipient market, and the CS21 statistic tests for contagion, originating from the volatility of the first market to the returns of the second market, displaying opposite directions of contagion. The CS12 (CS21) test results reported in Table 1 show that there is a statistically significant increase in cross-market linkages from average housing returns (volatility) to the volatility (returns) of S&P500, bonds and REITs. Interestingly, average housing volatility and returns are not affected by the volatility and returns of stock, bond and REITs markets.

Fry-McKibbin & Hsiao (2018) suggest a test for contagion based on cokurtosis. Asset returns typically have 'fat tails' and after a shock occurs, kurtosis rises. The authors develop two types of tests based on cokurtosis: the CK13 statistic tests for contagion transmitting from the returns of the source market to the skewness (cubic returns) in the recipient market, while the CK31 statistic tests for contagion originating from the skewness of the first market to the returns of the second market. By examining the results of the CK13 test for contagion, significant from can be observed between average housing returns to the skewness of S&P500, bonds and REITs markets. On the other hand, CK31 test results indicate that contagion is also transmitted to the S&P500 returns, bond returns and REITs returns from the skewness of the average housing returns. Moreover, stock, bond and REITs do not affect average average housing returns through the cokurtosis channel. It is evident that, the cokurtosis channel of contagion is important during the global financial crisis with the average stock returns acting as the source market.

Another test developed by Fry-McKibbin & Hsiao (2018) is based on covolatility. The CV22 statistic tests for contagion transmitting from the volatility (squared returns) of the source market to the volatility in the recipient market. The results for the CV22 test suggest that contagion transmits only from the average housing returns volatility to the volatilities of S&P500, bonds and REITs. Clearly, the covolatility channel is active with the average housing returns being the source market and the stock, bond and REITs being the recipient markets.

We have also employ the contagion and/or structural break test suggested by Chan et al., (2019). Test results (reported in Table A.1 in the Appendix) support the hypothesis of structural breaks in mean and volatility but provide no evidence of contagion. However, joint tests support the hypothesis of contagion and structural breaks.

Overall, at the country level, our results suggest that, (i) the linear (correlation) channel indicates that contagion is present from (to) average housing returns to (from) the S&P500; correlation contagion also runs from average housing returns to REITs, (ii) the coskewness, cokurtosis and covolatility channels are strongly active with contagion running only from average housing returns to the S&P500, bond returns and REITs.

### Contagion results at the MSA level

Table 2 presents the empirical results of the contagion tests between housing returns and S&P500 for ten MSAs. Panel A reports the results from the correlation based tests for contagion, while Panels B to F refer to contagion results from tests which utilize information from higher moments. Panel G reports the point estimates of long run correlations along with their 67% confidence intervals.

The long run correlations between MSA's housing returns (HR) and S&P500 returns are all positive ranging from 0.115 to 0.571. However, confidence intervals are quite wide, indicating substantial uncertainty.

Forbes & Rigobon (2002) test results reported in Panel A, suggest that contagion at the returns level is present only in one MSA, Miami. Specifically, for Miami MSA we can observe statistically significant (at the 5% level) bidirectional contagion effects between housing returns and S&P500 returns.

Panels B and C report the results of the coskewness tests suggested by Fry et al., (2010). The CS12 test results for contagion reported in Panel B, indicate transmission from housing returns to the volatility (squared returns) of the S&P500 for all MSAs. On the other hand, the test suggest that there is no evidence of contagion from the S&P500 returns to the volatility of housing returns. The CS21 statistic test results in Panel C, show that there is a statistically significant increase in cross-market linkages from the volatility of housing returns to the returns of the S&P500 for all MSAs. However, our results suggest no statistically significant contagion effects from the S&P500 returns to the volatility of housing returns. The only exception is the MSA of San Francisco. Our results reveal that in the case of the coskewness channel of contagion housing market is the source and the stock market in recipient.

Panels D and E report the results of the coskewness CK13 and CK31 contagion tests (Fry-McKibbin & Hsiao, 2018), respectively. The CK13 tests results indicate statistically significant contagion transmitting from housing returns to the skewness of the S&P500, while contagion originating from the S&P500 returns to the skewness of housing returns is not found. On the other hand, CK31 test results indicate that contagion is also transmitted from the skewness of housing returns to the S&P500 returns in all MSAs. Furthermore, the CK31 test suggest that contagion effects from the S&P500 skewness to the housing returns are present only in three MSAs, Boston, Chicago and San Francisco.

Lastly, Panel F report the results of the covolatility CV22 test developed by Fry-McKibbin & Hsiao (2018). The CV22 test results suggest statistically significant contagion effects from the volatility of housing returns to the volatility of the S&P500 for all MSAs. Contrary, the results show that contagion does not occur from the volatility S&P500 to the volatility of housing returns.

The contagion and/or structural break tests developed by Chan et al., (2019) are also applied to the MSAs data. Contagion test results (reported in Table A.2 in the [Appendix](#)) suggest no contagion but provide support to the hypothesis of structural breaks in mean. However, joint tests support the hypothesis of contagion and structural breaks.

Overall, at the MSA level, our results suggest that, (i) the linear (correlation) channel of contagion is relatively inactive, (ii) the coskewness, cokurtosis and covolatility channels are strongly active with contagion running mostly from housing returns to the S&P500.

## Conclusion

This study examines the correlation, coskewness, cokurtosis, covolatility channels of contagion triggered by the recent global financial crisis between a unique database of daily data on aggregate and MSA-level housing returns with that of stock, bond and REITs markets in the US. Furthermore, we investigate the long run correlations and test for breaks in first and higher-order moments.

We find that during the recent global financial crisis all channels of contagion were active. However, the correlation channel was relatively weak compared to the higher comovements channels of contagion. Additionally, our results document that contagion worked primarily from real estate to the stock, bond and REITs markets.

At the country level, the correlation channel worked from average housing returns to stock and REITs markets and from stock market to average housing returns. Bond market seems to be not active in correlation contagion. In the case of the coskewness, cokurtosis and covolatility channels, the real estate operated as the source in the contagion process while stock, bond and REITs markets were just the recipients. Specifically, by examining the coskewness channel, we find that average housing returns (volatility) contagiously affected volatility (returns) of the recipient markets. Cokurtosis tests of contagion suggest that average housing returns (skewness) transmitted to the skewness (returns) of the stock, bond and REITs markets. Covolatility test of contagion indicates that average housing volatility spread to the volatilities of the other markets under study.

At the metropolitan (MSA) level, we find no correlation contagion in all MSAs except Miami. As in the case of contagion at the country level, coskewness, cokurtosis and covolatility channels were active for all MSAs when the direction of contagion runs from metropolitan housing returns to the stock market. That is, again, metropolitan real estate acted primarily as the source in the contagion process. Evidence of metropolitan real estate acting as a recipient market was scarce.

The empirical findings provide insight about how different contagion channels operate across financial markets and states. This is crucial for policymakers because enables them to understand the sources and nature of contagion dynamics and effects in order to design, communicate and introduce appropriate policy responses. Furthermore, our findings carry important information for investors, with regard to the identification of the active linkages among the markets, and the nature and the direction of the contagion flows. But as we show, to draw appropriate inferences both in terms of policy and investment decisions, it is important to rely on higher moment tests, besides investigating regional and aggregate data.

Now, as indicated by Bollerslev et al., (2016), the usage of daily data makes the housing returns less predictable, naturally this makes the analysis of contagion based on correlation-type tests less reliable, compared to the ones associated with higher-moments, which in turn are now better captured by the daily indexes. In other words, policy authorities, would need to rely on coskewness, cokurtosis, and covolatility to detect contagion between the housing market with other assets, when drawing policy decisions, i.e., whether or not to intervene into the asset market and change the interest rates to prevent possibly overheating of the housing market (André et al., 2022) and the spillover of risks into bonds, equities and REITs. In other words, the Federal Reserve will only be able to impact the process of contagion by affecting the transmission channels associated with extreme risks and asymmetry (as outlined in Plakandara et al. (2022)) when using information derived from daily data of the housing market, as opposed to the control of housing returns, which is traditionally what is believed to be affected by monetary authorities, when we look at low-frequency analyses (see Cepni & Gupta (2021) for an elaborate review in this context). Having said this, since contagion is a concern during episodes of crises, correlation-based tests of it using models of conditional mean, as used by us here, might not be completely informative, and one might need to rely on quantiles-based approaches, which allows us to study the entire conditional distribution of returns, including the tails capturing extreme market behaviour (Caporin et al., 2021).

As part of future analysis, contingent on the availability of high-frequency house price data (see for instance, the CME-S&P/Case-Shiller HPI Continuous Futures (CS-CME)), it would be interesting to perform a similar analysis around the outbreak of the COVID-19 pandemic.

## Appendix

**Table A1** Empirical results from a regime switching skew-normal model of contagion and/or structural breaks

Tests	Method	S&P500	Bond returns	REITs	Average housing returns	All (joint test)
Contagion						
Correlation	<i>P</i>	0.4790	0.6300	0.4870		0.0000
Coskewness	<i>BF</i>	5.1076	5.1128	5.0930		32.7918
Correlation & Coskewness	<i>BF</i>	7.2405	7.2214	7.2271		44.7315
Structural breaks						
Mean	<i>p</i>	<b>1.0000</b>	<b>1.0000</b>	<b>1.0000</b>	<b>1.0000</b>	<b>1.0000</b>
Variance	<i>p</i>	<b>1.0000</b>	<b>1.0000</b>	<b>1.0000</b>	<b>1.0000</b>	<b>1.0000</b>
Skewness	<i>BF</i>	4.7532	4.7643	4.7216	4.7680	20.3936
Mean, variance and Skewness	<i>BF</i>	<b>-38.4514</b>	<b>-41.8598</b>	<b>-49.2772</b>	<b>-38.7422</b>	-
Joint contagion and structural breaks tests	<i>BF</i>	-25.4768	-29.0332	-36.3990		-
						45.6590

**Notes:** Contagion is measured with respect to the average housing returns. *BF* and *p* denote that a decision is based on Bayes Factor and on probability, respectively. Figures in bold indicate evidence of contagion and/or structural break

**Table A2** Empirical results from a regime switching skew-normal model of contagion and/or structural breaks

Tests	Method	Boston	Chicago	Denver	Las Vegas	Los Angeles	Miami	New York	San Diego	San Francisco	Washington
<b>Contagion</b>											
Correlation	<i>p</i>	0.5039	0.5105	0.4990	0.5030	0.5098	0.4982	0.4945	0.5052	0.4994	0.5016
Coskewness	<i>BF</i>	5.1104	5.1101	5.1108	5.1007	5.1109	5.1106	5.1109	5.1107	4.9901	5.1103
Correlation & Coskewness	<i>BF</i>	7.3608	7.3822	7.3667	7.4278	7.3880	7.3478	7.3610	7.3733	7.3814	7.4073
<b>Structural breaks</b>											
Mean	<i>p</i>	<b>1.0000</b>	<b>1.0000</b>	<b>1.0000</b>	<b>1.0000</b>	<b>1.0000</b>	<b>1.0000</b>	<b>1.0000</b>	<b>1.0000</b>	<b>1.0000</b>	<b>1.0000</b>
Variance	<i>p</i>	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Skewness	<i>BF</i>	4.7683	4.7677	4.7690	4.7685	4.7689	4.7684	4.7690	4.7594	4.7680	4.7595
Mean, variance and Skewness	<i>BF</i>	-442.6231	-415.1762	-398.0941	-349.1684	-511.5694	-436.0712	-442.7221	-437.9488	-469.8522	-404.0205
Joint contagion and structural breaks tests		-429.5963	-402.1356	-385.0341	-336.1103	-498.6004	-423.0439	-429.6721	-424.8888	-456.8627	-390.9183

**Notes:** Contagion is measured with respect to the average housing returns. *BF* and *p* denote that a decision is based on Bayes Factor and on probability, respectively. Figures in bold indicate evidence of contagion and/or structural break

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