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Price Exuberance and Contagion across Housing Markets: Evidence from US Metropolitan Areas

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ABSTRACT

Contagion occurs when cross-market correlation increases because of a shock to one market. Identifying shocks as episodes of house price exuberance, we provide evidence for contagion effects among the largest metropolitan markets in the US. We find that changes in income, interest rates, and unemployment also create contagion effects. These empirical findings are consistent with a model in which shocks to house prices and economic variables relax household down payment constraints and increase household mobility and housing demand. These effects are explored in an equilibrium framework in which house prices and household choices are determined endogenously, and we account for this endogeneity in our empirical study. Our results are robust to various empirical specifications, and we discuss the implications of these findings for households and investors.

Keywords: Contagion, Exuberance, Housing Markets, Macroeconomic Fundamentals, DCC-GARCH, GSADF

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1. Introduction

Contagion is a significant increase in cross-market co-movements after a shock to one or a group of markets (Forbes and Rigobon, 2002). The concept of contagion has been traditionally applied in studies of stock market dynamics as it helps understand how financial crises are transmitted across stock markets (see, e.g., Chiang et al., 2007).

Contagion has rarely been studied in the context of regional housing markets, yet contagion effects in these markets have wide-ranging implications. Housing is the dominant asset in the financial portfolio of most homeowners, and fluctuations in house prices have a substantial effect on their balance sheet.[1] Thus, the extent to which housing markets are correlated, and the presence of contagion effects – the incremental increase in correlation following a shock to one market – can have a significant impact on the lifetime wealth of households relocating across metropolitan areas as well as on their consumption and investment decisions. Furthermore, correlations have an impact on down payment constraints and on the housing demand of households (Sinai and Souleles, 2005, 2013; Han, 2010).

There is a small but growing strand of literature in household finance that analyzes the effect of cross-market correlations on the tenure choice of households. Sinai and Souleles (2005) present a theoretical framework to show that homeownership serves as a hedge for households relocating to other metropolitan statistical areas (MSAs). Higher correlation in house prices between the current and the destination MSA lowers the volatility of the lifetime wealth of relocating homeowners and increases their net risk of renting (defined as the difference between the volatility of renting and that of owning a home). Sinai and Souleles (2005) find empirical support for this hedging

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[1] Iacoviello (2011) reports that about one-half of the total household net worth in the United States is held in residential assets. Indeed, for the median homeowner, about two-thirds of their household wealth is tied to their house (Tracy and Schneider, 2001).

hypothesis. They show that the probability of owning a home and the price-to-rent ratio increase when the net risk of renting increases. Hence, housing markets and household tenure choices are affected by hedging considerations and the spatial correlations across markets. In a related study, Han (2010) differentiates between a financial risk effect of homeownership related to house price volatility and a hedging effect related to correlations. She finds evidence for a hedging effect according to which the demand for homes increases for households for which the current home serves as a hedge against future housing costs.

In this paper, we contribute to the current literature on spatial house price dynamics by developing and empirically testing the predictions of a model of contagion in regional housing markets. We advance the aforementioned literature by presenting a model in which correlations arise endogenously through the location and home buying choices of households. We identify a shock to one market as a period of explosive behavior in house prices. When house prices increase rapidly in one area, they relax the down payment constraint of households residing in this area. The accumulated equity resulting from the price appreciation allows households to relocate within the same or to another area. As we show theoretically, if the price dynamics in both areas are driven by the demand characteristics of the agents who can relocate, we will observe a higher correlation across markets. We test this hypothesis by applying techniques initially developed in studies of financial market contagion (Forbes and Rigobon, 2002; Corsetti et al., 2005; Chiang et al., 2007).

Our empirical study is structured as follows. We begin our analysis by deriving a time-varying measure of housing market interdependence. For that purpose, we estimate a dynamic conditional correlation model based on the multivariate GARCH specification proposed by Engle (2002). We then identify shocks to individual housing markets by date-stamping periods of exuberance for the nine largest US MSAs using the methods introduced by Phillips, Wu and Yu (2011) and Phillips,

Shi and Yu (2015). This methodology has been used to identify bubbles in US and international housing markets. Pavlidis et al. (2016) date-stamp the periods of explosive behavior in 22 countries and explore the macroeconomic factors contributing to their emergence. While we use the same technique to identify explosive periods, we recognize that they lead to an increase in home equity and thus explore empirically whether these shocks create contagion effects. A contagion effect exists when the correlation between two markets increases following a shock to one of the markets. As a first step, we estimate a static panel model by allowing both for MSA and time fixed effects while controlling for the impact of common factors such as industrial production, income, inflation, the stock market as well as demographic and economic variables related to housing demand and supply. We find evidence of contagion, which is robust to various model specifications, including dynamic panel data estimates that control for the potential endogeneity of exuberance. Following periods of price exuberance in one market, the dynamic correlation between markets increases with the change being highly statistically significant across all specifications.

The rest of the paper is structured as follows. Section 2 presents a theoretical framework which explains how contagion across MSAs can arise when one MSA experiences a housing market boom. Section 3 presents the data and preliminary evidence of contagion. A detailed discussion of the empirical methods and results is presented in Sections 4, 5, and 6. Section 4 starts with an analysis of dynamic conditional correlations; Section 5 presents the methods to identify and date-stamp price exuberance; and Section 6 examines the effect of price exuberance on contagion using static and dynamic panels. Section 7 discusses the economic mechanisms causing contagion, and Section 8 concludes.

2. Price Exuberance and Contagion: Theoretical Framework

In this section, we develop a stylized model highlighting a channel through which price exuberance in one area can lead to contagion effects across areas. Our framework is most closely related to the model by Stein (1995) in that households value the opportunity to relocate yet may be liquidity constrained due to down payment requirements. A housing boom in one area relaxes this liquidity constraint of households allowing them either to relocate within their initial area of residence or move to another area. When a boom occurs in one area only, it relaxes the down payment constraint in that area. Hence, the factors that govern demand across areas originate from the area which has experienced the housing boom. The theoretical model in this section captures this basic intuition. In this model, we show that if we observe an episode of explosive behavior in one area, we will also observe an increased correlation in returns with areas that have not registered a house price boom.

Our setup also relates to the real hedging framework by Sinai and Souleles (2005, 2013) in which households have the choice of selling their home in one area and buying a home in another. They show theoretically that owning a home can serve as a hedge against moving. That is, by being homeowner, households can smooth the shock of relocating on their lifetime wealth and consumption. The effectiveness of this hedge depends on the correlation between the growth in house prices in the destination and the origin areas. Using MSA-level data on house prices from OFHEO and data from the US Department of Treasury's County-to-County Migration Patterns, Sinai and Souleles (2013) demonstrate that households tend to move between MSAs with more correlated housing markets. In our model, the decisions of households and house prices are endogenously determined in a setting in which households want to relocate but face down-payment constraints. Allowing for the correlation between areas to be endogenously determined, we show that the erstwhile empirical findings by Sinai and Souleles (2013) – the tendency of households to

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move across more correlated areas – can appear as an equilibrium phenomenon. Furthermore, we show that a boom to one market increases correlation across markets, i.e., housing booms can cause contagion.

2.1. Assumptions

The model has three time periods, 0, 1 and 2 (as in Stein, 1995), and families live in two residential markets, A, and B (as in Sinai and Souleles, 2005). At time 0, each family is endowed with one unit of housing stock, and we normalize the prices to be $P_0^A = P_0^B = 1$. In period 1, the price in area $i = A, B$ is P_1^i and the house price growth rate is $r_1^i = P_1^i - 1$ for this period. We assume without loss of generality that $r_1^A \geq r_1^B$, that is if there was a housing market boom, it occurred in area A, while in area B there could or could not have been a boom. In these areas, families have outstanding mortgage debt of K which is a random variable distributed on an interval $[K_L, K_H]$ according to a probability distribution function of $G(K)$. In period 1 housing equity of households is $P_1^i - K$ and in this period some households decide to sell their home. They buy another home in period 2 in the same area or in the other area. While we assume that moving is beneficial, i.e. it confers additional utility, moving is also subject to a down-payment requirement. As in Stein (1995), we denote by γ the down-payment requirement which we express as a percentage of the value of the home acquired in period 2. Thus, households need to put down an amount of at least $\gamma P_2^j H^j$ whereby P_2^j is the equilibrium price per unit of size and H^j is the size of the home in area $j = A, B$ that the household buys in period 2. Hence, people are constrained in the value of the home they can move into whereby their liquidity constraint is given by the inequalities

$$\gamma P_2^j H^j \leq P_1^i - K$$

where $i = A, B$ and $j = A, B$. As in Stein (1995), the constraint on the size (and total value) of a home a household can move into, causes only some of the households to move. We therefore

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denote by m_A and m_B the fraction of households from area A and B, respectively, who are willing and able to move.[2] As the households from area A have accumulated more equity (by assumption $P_1^A \geq P_1^B$) the inequality $m_A \geq m_B$ holds.[3] In addition, we assume that an exogenously given fraction of $1/(1 + \theta)$ of these households relocate within the same geographical area while the remaining fraction $\theta/(1 + \theta)$ moves to the other area, whereby $\theta \geq 0$.

Furthermore, we assume that demand for homes in area A and area B in period 2 depends on the demographic profiles of households in these areas and is given by the random variables X_A and X_B, respectively. These random variables, which assume only non-negative values, encapsulate factors bearing on housing demand such as expectations about future employment opportunities as well as consumption preferences of the residents in these areas. We also assume for simplicity that $var(X_A) = var(X_B) := \sigma^2$ and $cov(X_A, X_B) = 0$ although the latter assumption is not essential and is chosen for analytical tractability. The equilibrium prices in period 2 in the two areas depend on the random variables X_A and X_B and are given by the equations:

$$P_2^A = \frac{1}{1+\theta} m_A X_A + \frac{\theta}{1+\theta} m_B X_B \tag{1}$$

$$P_2^A = \frac{\theta}{1+\theta} m_A X_A + \frac{1}{1+\theta} m_B X_B \tag{2}$$

Equation (1) signifies that the demand in area A is composed of the demand of households which relocate within the same area (first term) and households which migrate from area B (second term). The first additive term in equation (1) is the product of three components: the fraction $\frac{1}{1+\theta}$

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[2] In the Appendix, we consider the optimal relocation and housing choice problem of a household with the preferences assumed in Stein (1995) and we determine how m_A and m_B depend on these preferences as well as the liquidity and budget constraints of the household.

[3] The shares m_A and m_B of households who relocate depend on the preferences and on the liquidity constraint of the household. The liquidity constraint depends both on the prices in period 1, P_1^A and P_1^B and on the prices in period 2, P_2^A and P_2^B.

representing the households from area A which, conditional on moving, are staying within the same area; m_A, representing the fraction of the area A households which are moving; and X_A representing the random variable causing variation in the housing demand of households from area A. The second term is the fraction of household $\frac{\theta}{1+\theta}$ which, conditional on moving, are migrating from area B to area A, multiplied by the fraction of area B household m_B which are moving to area A, multiplied by the demand of area B households, X_B. The equilibrium price in area B, represented in equation (2), is defined analogously.

2.2. Housing Booms and Correlations

With these preliminaries, the correlation between the growth rates of home values in period 2 is given by

$$cov(r_2^A, r_2^B) = cov\left(\frac{P_2^A}{P_1^A} - 1, \frac{P_2^B}{P_1^B} - 1\right) = \frac{1}{(P_1^A P_1^B)^2} cov(P_2^A, P_2^B)$$

For the covariance between the prices in period 2 we obtain

$$cov(P_2^A, P_2^B) = \frac{1}{(1+\theta)^2} E[(m_A X_A + \theta m_B X_B) \times (\theta m_A X_A + m_B X_B)]$$

$$= \frac{\theta}{(1+\theta)^2}(m_A^2 X_A^2 + m_B^2 X_B^2) = \frac{\theta \sigma^2}{(1+\theta)^2}(m_A^2 + m_B^2)$$

For the correlation we obtain

$$corr(P_2^A, P_2^B) = \frac{cov(P_2^A, P_2^B)}{\sigma^2 \sqrt{m_A^2 + \theta^2 m_B^2}\sqrt{\theta^2 m_A^2 + m_B^2}} = \frac{\theta}{(1+\theta)^2} \frac{m_A^2 + m_B^2}{\sqrt{m_A^2 + \theta^2 m_B^2}\sqrt{\theta^2 m_A^2 + m_B^2}}$$

Dividing both sides by m_B^2 yields

$$corr(P_2^A, P_2^B) = \frac{\theta}{(1+\theta)^2} \frac{\left(\frac{m_A}{m_B}\right)^2 + 1}{\sqrt{\left(\frac{m_A}{m_B}\right)^2 + \theta^2} \times \sqrt{\theta^2 \left(\frac{m_A}{m_B}\right)^2 + 1}}$$

The ratio $\frac{m_A}{m_B}$ indicates the extent to which the down-payment constraint in area A is relaxed relative

to area B. A boom in area A not accompanied by a boom in area B would result in a ratio $\frac{m_A}{m_B}$ that

is higher compared to the scenarios where there is no boom in area A or where there is a boom in

both areas. We show that the following result holds true.

Proposition 1. *The correlation between the house price growth in the two areas is increasing in*

the ratio $\frac{m_A}{m_B}$. Hence the correlation between areas A and B is higher in the scenario in which there

is a boom in area A but not in area B.

Proof. Let $q = \left(\frac{m_A}{m_B}\right)^2$. For the partial derivative of the correlation with respect to q we obtain

$$\frac{\partial corr(P_2^A, P_2^B)}{\partial q} = \frac{\theta}{(1+\theta)^2} \times \frac{q\theta^4 - 2q\theta^2 + q - \theta^4 + 2\theta^2 - 1}{2(q+\theta^2)(q\theta^2+1)\sqrt{q+\theta^2}\sqrt{q\theta^2+1}}$$

$$= \frac{\theta}{(1+\theta)^2} \times \frac{(q-1)(\theta^2-1)^2}{2(q+\theta^2)(q\theta^2+1)\sqrt{q+\theta^2}\sqrt{q\theta^2+1}}$$

As $m_A \geq m_B$ we have $q \geq 1$ and $\frac{\partial corr(P_2^A, P_2^B)}{\partial q} \geq 0$ with the strict inequality applying when m_A

exceeds m_B.

3. Data and Preliminary Evidence of Contagion

3.1. Data

In this study, we use the seasonally adjusted monthly Zillow Single-Family Home Value Index

(ZHVI)[4] over the sample period April 1996 - January 2018 to capture regional housing prices. The ZHVI is based on a hedonic index methodology which uses information on home attributes to create a value estimate for individual properties (a Zestimate) and aggregate these estimates in an index. The ZHVI exhibits similar dynamics and is highly correlated with indices based on alternative methodologies, e.g. repeat-sales indices, such as the S&P Core Logic index.[5] We include in our sample the nine most populated MSAs in the US: New York, Los Angeles, Chicago, Dallas, Washington, Miami, Philadelphia, Atlanta, and Boston.[6]

In addition to housing prices, we obtain data on industrial production, income and inflation from FRED, and housing supply data from the US Census Bureau. We also collect income per capita by MSA from the Bureau of Economic Analysis and annual population figures by MSAs from the US Census Bureau. Furthermore, we include in our analysis the monthly employment and unemployment rates that we obtained from the US Bureau of Labor Statistics, as well as the monthly average mortgage interest rate on thirty-year fixed-rate mortgages obtained from Freddie Mac.[7]

As a proxy for the stock market, we use the Standard and Poor's 500 (S&P 500) index, retrieved from Thomson Reuters DataStream, and our measure of inflation is based on the monthly seasonally adjusted Consumer Price Index (CPI), retrieved from the St Louis Fed's database

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[4] We retrieved the data from Zillow, https://www.zillow.com/research/data/
[5] Guerrieri et al. (2013) study the correlation between appreciation rates during the period 2000-2006. Their findings indicate that ZHVI and the Case-Shiller index exhibit a pair-wise correlation of 0.96. See, for example, Dorsey et al. (2010), Guerrieri et al. (2013) and Damianov and Escobari (2016) for a detailed discussion on the similarities and differences of these indices.
[6] Population is based on the United States Census Bureau as of July 1, 2018. While the Houston MSA is also ranked among the ten, we do not include it due to data availability in the Zillow pricing index.
[7] The data on the 30-year fixed mortgage interest rate are based on the Primary Mortgage Market Survey and is collected from the website of Freddie Mac, available at http://www.freddiemac.com/pmms/pmms_archives.html

FRED. The summary statistics of the MSA housing returns, industrial production growth, income growth, inflation, and the S&P 500 returns are presented in Table 1.[8]

[Table 1, about here]

In terms of house price growth, we observe that Los Angeles is the best-performing market while Chicago is the worst. We also observe, consistent with studies from other sample periods, that the return on the S&P 500 has the largest volatility of all these series, with a standard deviation of 3.74.

3.2. House price volatility and correlations

The time-series plots of housing returns in New York and Los Angeles are presented in Figure 1. We observe that large return changes are often followed by further large return changes, which is indicative of "clustering of return volatility". Our approach characterizes clustering volatility and allows us to analyze contagion effects which is the main objective of our study.

[Figure 1, about here]

Table 2 reports pair-wise unconditional correlations between MSAs for the nine metropolitan areas in our sample as well as the pair-wise unconditional correlations between each MSA and industrial production, income, inflation, and the S&P 500. Spearman's rank correlations are reported in the upper triangular cells, while Pearson's correlation coefficients are reported in the lower triangular cells. We observe that unconditional correlations between each pair of MSAs are positive, relatively large and statistically significant at the 1 percent level.

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[8] We report continuously compounded returns, given by $r_t = [\ln(P_t) - \ln(P_{t-1})] \times 100$, where P_t is value of each respective index for month t.

[Table 2, about here]

4. Contagion across Housing Markets

4.1. The Dynamic Conditional Correlation Framework

The unconditional correlations reported in Table 2 provide a single statistic for the entire sample. They are indicative of interdependence but do not provide evidence for contagion. To analyze contagion, we rely on a framework that allows correlations across housing markets to change over time as well as to be conditional on observables. As in Chiang et al. (2007), we estimate a dynamic conditional correlations model.

Our dynamic conditional correlation (DCC) framework follows Engle (2002) and is built on a Multivariate GARCH (MGARCH). These MGARCH models have been previously used to investigate volatility spillovers in equity markets[9] and to examine the predictability of future stock return volatility.[10] Further, they have also been extensively employed in the economics and finance literature.[11]

There are a number of advantages in using Engle's (2002) DCC-GARCH approach to capture contagion in our setting. First, it allows us to include common factors (such as industrial production, income, inflation, or stock market returns) that potentially affect home prices. Second, the model estimates time-varying correlation coefficients of the standardized residual, accounting for heteroscedasticity directly. This addresses the well-known issue of estimation bias in the presence of heteroskedasticity raised in Forbes and Rigobon (2000, 2002). Third, we are able to

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[9] See, e.g., Lin et al. (1994), Karolyi (1995), Koutmos and Booth (1995), Karolyi and Stulz (1996), Booth et al. (1997), Worthington and Higgs (2004), and Cha and Jithendranathan (2009).
[10] Additional applications include Tse (2000), and Scheicher (2001).
[11] See, for example, Elder and Serletis (2009), Sadorsky (2006), Cifarelli and Paladino (2010), and Malik and Hammoudeh (2007).

include multiple housing markets without the need to estimate too many coefficients. This presents an advantage over alternative multivariate GARCH models that require the estimation of a large number of coefficients in the variance-covariance matrix (e.g., Engle and Kroner, 1995).[12] Fourth, our approach does not have a volatility clustering bias because volatility is allowed to vary over time. Furthermore, the time-varying correlation coefficients model would account for the possibility of regime shifts.[13] Finally, the methodology allows us to create a panel of estimates of the dynamic correlations across housing markets and test for housing market contagion by exploring whether correlations change in response to shocks to regional housing markets.

Let P_{it} and $r_{it}=[\ln(P_{it})- \ln(P_{i,t-1})]\times 100$ be the real home price and its return, respectively, in housing market i in period t. We use the vector of returns to estimate the following AR(1) mean specification:

$$r_t = \mu + \varphi r_{t-1} + \gamma r_{t-1}^{\text{Industrial Production}} + \epsilon_t, \tag{3}$$

where $r_t = (r_{1,t}, r_{2,t}, r_{3,t}, r_{4,t}, \ldots, r_{n,t})'$ is the vector of n housing appreciation rates at time t. Moreover, $\mu = (\mu_1, \mu_2, \mu_3, \ldots, \mu_n)'$ is the vector of n constants, and $\epsilon_t = (\epsilon_{1t}, \epsilon_{2t}, \epsilon_{3t}, \ldots, \epsilon_{n,t})'$ is the vector of n random errors that are distributed $\epsilon_t | \Omega_{t-1} \sim N(0, H_t)$ where Ω_{t-1} refers to the information set at the end of period t-1. In our main autoregressive specification, we use industrial production as a common factor. However, as robustness checks, we also examine specifications in which we consider income, inflation and US stock returns (i.e. the S&P 500 index) as alternative

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[12] For limitations of these models, see Sadorsky (2012) and Bauwens et al. (2006).
[13] The DCC-GARCH approach has also been used to estimate the relationship between risk and return (see, e.g., Engle, 2004; and Cifarelli and Paladino, 2010).

common factors.[14] The AR(1) specification allows us to additionally account for momentum effects through the vector of autoregressive coefficients (see, Sinai and Souleles, 2005, 2013).[15]

We model the variance-covariance matrix of shocks to have the following structure:

$$H_t = D_t R_t D_t \,, \tag{4}$$

where D_t and R_t both depend on time. Hereby D_t is the $n \times n$ diagonal matrix of time-dependent standard deviations fitted by univariate GARCH models which takes the following form:

$$\begin{pmatrix} h_{11,t}^{1/2} & 0 & \cdots & 0 \\ 0 & h_{22,t}^{1/2} & \ldots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \ldots & h_{nn,t}^{1/2} \end{pmatrix}. \tag{5}$$

Further, R_t is the $n \times n$ time-varying conditional correlation matrix of the innovations ϵ_t given by:

$$\begin{pmatrix} 1 & \rho_{12,t} & \ldots & \rho_{1n,t} \\ \rho_{21,t} & 1 & \ldots & \rho_{2n,t} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{n1,t} & \rho_{n2,t} & \ldots & 1 \end{pmatrix}. \tag{6}$$

Following Engle (2002), we estimate the conditional variance-covariance matrix H_t in two steps. In the first step, we fit a univariate GARCH for each housing market to obtain estimates of conditional standard deviation $h_{ii,t}^{\frac{1}{2}}$ of the diagonal elements of D_t in Equation (4). In the second step, we transform the residuals obtained from the first stage employing, $u_{i,t} = \varepsilon_{i,t} \times h_{ii,t}^{-\frac{1}{2}}$. The

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[14] We are grateful to an anonymous referee for suggesting these alternative common factors.
[15] Damianov and Escobari (2021) estimate a similar model, but focus on correlations between price tiers *within* the same housing market and do not study contagion.

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scaled error term $u_{i,t}$ is then employed to calculate the parameters of dynamic conditional correlation. Engle's (2002) conditional correlation GARCH (1,1) is given by:

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha u_{t-1}u'_{t-1} + \beta Q_{t-1}, \tag{7}$$

where Q_t is the time-dependent $n{\times}n$ conditional variance-covariance matrix of u_t, and $\bar{Q} = E[u_t u'_t]$ is the unconditional variance-covariance matrix of u_t. Note that α and β are nonnegative and we add the restriction $\alpha + \beta < 1$ to make sure that the process is stationary. As Q_t would not have ones on its main diagonal, we rescale Q_t to obtain a proper correlation matrix. Therefore, R_t can be represented as:

$$R_t = diag\left(\frac{1}{q_{11,t}^{1/2}}, \frac{1}{q_{22,t}^{1/2}}, \cdots, \frac{1}{q_{nn,t}^{1/2}}\right) Q_t \, diag\left(\frac{1}{q_{11,t}^{1/2}}, \frac{1}{q_{22,t}^{1/2}}, \cdots, \frac{1}{q_{nn,t}^{1/2}}\right). \tag{8}$$

Equation (8) presents ones on the main diagonal and less than one in absolute value on the off-diagonal elements given that Q_t is positive definite. In the bivariate case, we can express off-diagonal elements of correlation R_t as:

$$\rho_{12,t} = \frac{(1-\alpha-\beta)\bar{q}_{12} + \alpha u_{1,t-1}u_{2,t-1} + \beta q_{12,t-1}}{[(1-\alpha-\beta)\bar{q}_{11} + \alpha u_{1,t-1}^2 + \beta q_{11,t-1}]^{\frac{1}{2}} \, [(1-\alpha-\beta)\bar{q}_{22} + \alpha u_{2,t-1}^2 + \beta q_{22,t-1}]^{\frac{1}{2}}}, \tag{9}$$

where $\bar{q}$ and q_{t-1} represent the off-diagonal elements of $\bar{Q}$ and Q_t respectively. Following Engle (2002), in the second step we maximize the following log-likelihood function:

$$L_t(\Theta, \vartheta) = \left[-\frac{1}{2}\sum_{t=1}^{T}\left(nlog(2\pi) + log|D_t|^2 + \varepsilon'_t D_t^{-2}\varepsilon_t\right)\right]$$
$$+ \left[-\frac{1}{2}\sum_{t=1}^{T}\left(log|R_t| + u'_t R_t^{-1}u_t - u'_t u_t\right)\right], \tag{10}$$

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where the first element on the right-hand side is the sum of the univariate GARCH likelihoods. The second term is the function to be maximized in order to obtain the estimates of ϑ and the correlation coefficients. Hence, θ denotes the estimates from the mean and variance equations from the first step.

4.2. Dynamic Correlation and Momentum Estimates

Table 3 reports the DCC-GARCH estimation results. Panel A presents the estimates for the housing returns of Equation (1), while Panel B reports the conditional variance equations. These estimates show evidence of statistically significant ARCH and GARCH effects in addition to capturing the volatility among housing markets and industrial production. Panel C reports the estimates of the multivariate equation, which consists of ARCH (α) and GARCH (β) parameters.

[Table 3, about here]

The estimation results for the mean equations show that the autoregressive terms are all positive and highly statistically significant for all MSAs, which we interpret as strong evidence for momentum in housing markets. Higher appreciation rates in the previous period leads to higher appreciation in the current period. Interestingly, the magnitude of the influence of previous housing returns on current values is fairly homogenous across markets, ranging from the point estimate of 0.876 for Dallas to 0.943 for Los Angeles. The observed statistically significant autoregressive coefficients are in line with informationally inefficient housing markets, consistent with results reported in literature (e.g., Case and Shiller, 1989, 1990; Hjalmarsson and Hjalmarsson, 2009). These results can be explained by market frictions or by home sellers' strategic behavior.[16] More

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[16] Damianov and Escobari (2016), and Fu and Ng (2001) show that housing markets respond slowly to new information. Moreover, Guren (2018) reports that home sellers set their asking prices close to the existing average housing price which also creates momentum in the market.

recently, Das et al. (2020) also argue that noisy traders, illiquidity, market entry barriers, indivisible assets, high transaction costs, lack of transparency, heterogeneous assets, information asymmetries, and limits-to-arbitrage make housing markets inefficient. Conversely, the autoregressive term in the industrial production equation, reported in the last column, is not statistically significant. Note that the conditional mean equations show that lagged industrial production growths have a positive and highly statistically significant effect on housing returns for Philadelphia, Atlanta and Boston.

The measure of short-term persistence (a) in the variance equations of Panel B captures the conditional volatility. The variance equations show that these lagged conditional volatilities (or ARCH coefficients) are statistically significant at the 1% or the 5% levels across all metropolitan areas and for industrial production. Moreover, own conditional GARCH effects (b), in addition to explaining conditional volatility, also capture the importance of long-term persistence. Our estimates of these lagged shock-squared terms are statistically different from zero for every housing market except New York and Dallas. Overall, these estimates provide strong evidence for conditional volatility in housing returns and for the GARCH specification.

When examining Panel B, we find that the sum of the ARCH and GARCH coefficients is less than one for each of the MSAs and for industrial production. The volatilities are time-varying as we observe that the ARCH and GARCH components in the variance equations are statistically significant. We can interpret this as evidence of time-varying risk in the monthly return series of housing and industrial production.

Panel C presents the point estimates of the mean-reverting process, α and β. Both coefficients are statistically significant at the 1% level, which is interpreted as strong evidence of time-varying co-movement across MSAs and industrial production. Note that the sum of these coefficients is less

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than one, indicating that the dynamic conditional correlations are mean reverting. The Wald statistic shows significance at the 1% level, providing strong evidence against the null hypothesis that both coefficients are jointly zero (i.e., $\alpha = \beta = 0$). Using income, inflation and S&P 500 as alternative common factors showed qualitatively similar results.

[Figure 2, about here]

To illustrate the dynamics of the conditional correlations, Figure 2 presents the time series graphs of the pairwise correlations between New York, Los Angeles, Chicago, Dallas, and industrial production. Consistent with the unconditional correlations, the dynamic correlation estimates are positive for each pair of MSAs, and for the correlation with industrial production.

5. Date Stamping Price Exuberance in Housing Markets

5.1. Identification Strategy

In this section we present our empirical strategy for identifying price exuberance periods for each of the housing markets studied. The methods we use follow Phillips, Wu, and Yu (2011, hereafter PWY) and Phillips, Shi, and Yu (2015, hereafter PSY). PWY test for the existence of a single episode of exuberance behavior using a forward expanding sample sequence, while PSY test for the existence of multiple periods of exuberance employing a double recursive approach. Both tests involve a rolling window Augmented Dickey-Fuller (ADF) style regression that shifts the sample subperiods. Consider the following ADF regression:

$$\Delta P_t = a_{r_1,r_2} + \beta_{r_1,r_2} P_{t-1} + \sum_{i=1}^{k} \varphi_{r_1,r_2}^i \Delta P_{t-i} + \varepsilon_t, \tag{11}$$

where, as defined earlier, P_t is the real housing price index at time t for housing market i. To simplify notation, we drop the subscript i when modeling price exuberance and denote by ΔP_t the first difference of P_t. The error term is assumed to follow a normal distribution, i.e., $\varepsilon \sim$

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$iidN(0, \sigma_{r_1, r_2}^2)$. The starting r_1 and ending r_2 points of the rolling window are denoted as fractions of the total sample, where $r_2 = r_1 + r_w$ and $r_w > 0$. For our specification in Equation (11), we are interested in the sequence of test statistics $ADF_{r_1}^{r_2} = \hat{\beta}_{r_1, r_2} / s.e. (\hat{\beta}_{r_1, r_2})$, that depend on the fractions of the total sample r_1 and r_2. Note that the well-known standard ADF test statistic for the unit root null hypothesis is just ADF_0^1.

The PWY test relies on recursive (right-tailed) estimations of Equation (9). To test for exuberance behavior, PWY proposes using the following supreme ADF (SADF) statistic:

$$SADF (r_0) = \sup_{r_2 \in [r_0, 1]} ADF_0^{r_2}. \qquad (12)$$

When the SADF test statistic of Equation (12) exceeds the right-tail critical value, the unit root null hypothesis is rejected in favor of (mildly) explosive pricing behavior in P_t. The justification for using the SADF statistics is that price exuberance generally collapses periodically, and conventional unit root tests are not satisfactorily effective to detect such price exuberance (Evans, 1991). Homm and Breitung (2012) conduct extensive simulations and find that the SADF test has greater power compared to similar econometric approaches (see, e.g., Bhargava, 1986; the modified Kim, 2000; and the modified Busetti and Taylor, 2004). Moreover, PSY and Homm and Breitung (2012) argue that PWY performs satisfactorily against other recursive techniques for structural breaks and provides a fairly efficient procedure for detecting economic exuberance in real-time when dealing with one or two periods of economic exuberance. Further, our approach can identify economic exuberance that may arise from various sources, such as mildly explosive pricing behaviors that are induced by changing fundamentals (e.g., time-varying discount factor).

One concern with the PWY procedure is that it lacks power or may be inconsistent when the sample includes multiple origin and collapses of the exuberances. Hence, it is not particularly suitable for analyzing long period of data or fast-changing dynamics. Phillips, Shi, and Yu (2015) propose a generalized SADF (GSADF) procedure to test and identify the origination and termination of multiple periods of exuberances. the PSY procedure implements recursive right-tailed ADF test and uses flexible rolling windows where both the start and end dates of the windows change. In particular, the GSADF statistics is given by:

$$GSADF\left(r_0\right) = \sup_{\substack{r_1 \in [0, r_2 - r_0] \\ r_2 \in [r_0, 1]}} ADF_{r_1}^{r_2}. \tag{13}$$

We use Equation (13) to identify exuberance, i.e., when the $GSADF_{r_0}$ statistics is greater than the corresponding right tail critical value. In addition, we use the methods proposed in PSY to further date-stamp the origination and termination of exuberance episodes. Consider the following backward sup ADF statistics (BSADF):

$$BSADF_{r_2}\left(r_0\right) = \sup_{r_1 \in [0, r_2 - r_0]} SADF_{r_1}^{r_2}. \tag{14}$$

Equation (14) relies on a backward expanding sample where the origination of the subsample fluctuates from 0 to $r_2 - r_0$ and the termination point of the sample is fixed at r_2. The origination of an exuberance period, denoted by $\hat{r}_e$, is captured as the first observation whose BSADF statistic exceeds the corresponding critical value. Formally, the origination of exuberance $\hat{r}_e$ is given by

$$\hat{r}_e = \inf_{r_2 \in [r_0, 1]} \left\{r_2 : BSADF_{r_2}\left(r_0\right) > scv_{r_2}^{\alpha}\right\}. \tag{15}$$

The termination date of an exuberance episode, denoted by $\hat{r}_f$, is the first observation after $\hat{r}_e + 4/T$ where the BSADF falls below the corresponding critical value.[17] Hence, the timing of the termination point $\hat{r}_f$ is given by,

$$\hat{r}_f = \inf_{r_2 \in [\hat{r}_e + 3/T, 1]} \{r_2 : BSADF_{r_2}(r_0) < scv_{r_2}^{\alpha}\}, \tag{16}$$

where T is the sample size, $SCV_{r_2}^{\alpha}$ is the $100(1-\alpha)\%$ critical value of the SADF based on $\lfloor r_2 T \rfloor$ observations at a significance level α.[18] The distributions of the $GSADF_{r_0}$ and $BSADF_{r_2}(r_0)$ statistics of Equations (13) and (14) are non-standard. Therefore, we use Monte Carlo simulations to calculate the critical values.

5.2. Price Exuberance Episodes

[Table 4, about here]

Panel A of Table 4 uses Equations (12) and (13) to report the SADF and GSADF test statistics for our housing markets. In addition, Panel B presents the corresponding finite sample critical values, obtained via Monte Carlo simulations with 2,000 replications. In order to obtain the critical values, we use an initial window size of 20 observations, which corresponds to 8% of our sample.[19] Consistent across both sets of statistics, the results show strong statistical evidence of exuberance behavior in each of our real housing price series. For example, for the New York market, the SADF test statistic exceeds the 1% right-tail critical value (SADF: 14.382>2.124), while the GSADF test statistic also exceeds its corresponding 1% right-tail critical value (GSADF: 14.941>2.999). Hence, the test identifies multiple episodes of exuberance. Overall, this interpretation holds for all

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[17] We use 4/T in Equation (14) to make sure that episodes of exuberance last at least four months.
[18] We use $\lfloor \rfloor$ to denote the floor function that gives the integer part of $r_2 T$.
[19] The results are robust to different window sizes and lags.

of our housing markets. Further, in order to date stamp each of the periods of exuberance in our MSAs, we compare the sequence of BSADF statistics obtained using Equation (14) with the corresponding sequence of 95% critical values.

6. Can Price Exuberance and Macroeconomic Factors Explain Contagion?

We now turn to examining the potential causes for contagion across housing markets, focusing on price exuberance along with factors that are known to affect house price dynamics.

6.1. Panel Estimation

Our empirical specifications are set to examine the impact of exuberance on the time-varying correlations of each pair of housing returns from our set of nine metropolitan areas. We begin by estimating a pooled Ordinary Least Squares (OLS) and a fixed effects (FE) model. Furthermore, to account for the potential endogeneity of price exuberance periods, we estimate various dynamic panel specifications that employ the difference Generalized Method of Moments (GMM) estimator described in Holtz-Eakin et al. (1988) and Arellano and Bond (1991) and the system GMM estimator as presented in Blundell and Bond (1998).

Our dependent variable captures the dynamic conditional correlations obtained as the off-diagonal elements of R_t in Equation (8). We create a panel of correlations by pooling across all housing market pairs. The empirical model is given as follows:

$$\rho_{ijt} = \lambda \rho_{ij,t-1} + \kappa Z_{ijt} + \eta_{ij} + v_{ijt}, \tag{17}$$

where ρ_{ijt} is the pair-wise dynamic conditional correlation between appreciation rates of housing markets i and j. Moreover, Z_{ijt} is an indicator variable equal to one during month t if exuberance exists, as defined in Equations (15) and (16), in one of the two MSAs i or j, but not both. Hence,

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Z_{ijt} is equal to zero if none or both MSAs i and j are in a price exuberance period; η_{ij} is the time invariant effect, while v_{ijt} is the remainder stochastic term.

Our approach focuses on estimating the scalars λ and κ. While the coefficient of the lagged dependent variable $\rho_{ij,t-1}$ is not our primary interest, including dynamics helps us to recover consistent estimates of the impact of house price exuberance on contagion. In our estimation of Equation (17), we allow Z_{ijt} to be endogenous. This includes the possibility of reverse causality, where an increase in ρ might lead to a period of exuberance. Modeling Z_{ijt} as potentially endogenous means that it can be correlated with the v_{ijt} and earlier shocks. However, Z_{ijt} needs to be uncorrelated with shocks in the next period $v_{ij,t+1}$ and subsequent shocks. Formally:

$$\left. \begin{array}{ll} E\big(Z_{ijs}v_{ijt}\big) = 0, & s \leq t \\ E\big(Z_{ijs}v_{ijt}\big) \neq 0, & s > t \end{array} \right\} \quad \forall \, ij. \tag{18}$$

The identification assumes that the stochastic term v_{ijt} is serially uncorrelated, assumption that we formally test when presenting the results. Moreover, note that even though we model the variable that captures exuberance periods Z_{ijt} as potentially endogenous, this does not prevent households and other economic agents from rationally predict housing price appreciation. Under rational expectation they use Equation (17) and the dynamics of Z_{ijt} and ρ_{ijt}. Consistent with literature that uses dynamic panels, we assume that agents cannot predict only the surprise component of ρ_{ijt}.

Our empirical strategy follows the difference GMM dynamic panel estimator proposed by Holtz-Eakin et al. (1988) and Arellano and Bond (1991) to obtain consistent estimates of λ and κ. This model is based on taking first differences in Equation (17) to sweep out the time-invariant effect η_{ij} to obtain:

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$$\Delta\rho_{ijt} = \lambda\Delta\rho_{ij,t-1} + \kappa\Delta Z_{ijt} + \Delta v_{ijt}. \tag{19}$$

We need to construct a vector of instruments W to employ the moments $E(\Delta v_{ijt}W) = 0$ from the difference Equation (17). Following Arellano and Bond (1991), we use lagged levels of $\rho_{ij,t-1}$ and Z_{ijt} as instruments. Because we can use multiple lags as instruments, our model is overidentified, which allows us to test the validity of the instrument list.

Blundell and Bond (1998) point out a shortcoming in this difference estimator. If the dynamic conditional correlation or the variable that captures the exuberance periods are persistent, then lagged values of these variables are weak instruments. To overcome this, we additionally employ the system GMM estimator presented in Blundell and Bond (1998) that combines Equations (17) and (19). The new specification requires additional moments for the equation in levels, $E[(\eta_{ij} + v_{ijt})M] = 0$. For the addition instruments M, we use lags of the first differences of the dynamic correlation coefficients and the exuberance periods, i.e., lags of $\Delta\rho_{ij,t-1}$ and ΔZ_{ijt}.

Note that including η_{ij} in Equation (17) helps to control for proximity between MSAs. This is important as Cohen et al. (2016) find that there are significant spatial diffusion patterns in the growth rates of urban house prices. Their result implies that two MSAs that are closer to each other are likely to exhibit a higher ρ_{ijt}. Because the physical distance between housing markets i and j does not change over time, proximity is controlled for with our fixed effects. Moreover, unlike Cohen et al. (2016) that use 363 MSAs to capture spatial effects, with some of their MSAs being in close proximity, in our sample we only have nine MSAs that are relatively far from each other. We argue that any remaining time-varying special effect is likely to be small.

6.2. Dynamic Correlations and Price Exuberance

We begin by pooling the time-varying conditional correlations between all MSA pairs to create a panel of correlations. We then combine these data with the housing market exuberance dummy variables obtained with the GSADF. In order to account for macro fundamental effects, we also include population, income per capita, mortgage interest rates, housing starts, unemployment and employment rates as control variables.[20] As our left-hand side variable in Equation (17) is the correlation between housing markets i and j, for the macro fundamentals on the right-hand side we take the averages of our control variables for the corresponding housing markets i and j.

Static Panel Results

Table 5 reports the static panel data estimates of Equation (17). Different columns report different alternative common factors, starting with industrial production (columns 1 through 3), income (columns 4 and 5), inflation (columns 6 and 7), and the S&P 500 (columns 8 and 9). Moreover, we use different sets of fixed effects across. Right-hand side regressors include population, MSAs income per capita, mortgage interest rates, housing starts, change in employment, and the unemployment rate. For comparison purposes columns 1, 4, 6 and 8 report estimates without MSA FE. In our preferred model of column 3, we observe that when MSA i exhibits price exuberance, the correlation to MSA j increases by 1.20%. This result is robust as the exuberance dummy is positive and highly statistically significant across all specifications. Moreover, the magnitude of the effect is stable, being slightly greater only when the specification does not control for MSA FE. This is not surprising given the additional unaccounted variation in the pooled models in which we do not control for the time-invariant effect η_{ij}.

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[20] We follow Case and Shiller (2003) in the selection of the fundamental variables.

[Table 5, about here]

From the statistically significant constant term in column 2 (0.795), we observe that the average co-movement between housing markets is positive and relatively high. Moreover, when one of the MSAs experiences price exuberance, the average bivariate time-varying correlation increases to about 0.807, with the difference (0.012) being statistically significant at the 1% level. The results provide robust empirical evidence that when one of the MSAs in a pair goes through a period of price exuberance, the time-varying correlation of housing returns between that pair increases.

Our preferred specification presented in column 3 of Table 5, shows that positive changes in population have a negative and statistically significant effect on correlations. This effect is different from the positive point estimate in the pooled OLS of column 2, which appears to be biased due to the omitted MSAs fixed effects. From a theoretical viewpoint we expect that correlations across cities would increase with the increase in population flows between the two cities. Our measure of population, however, captures the absolute annual growth within each city rather than population flows. Thus, from a theoretical viewpoint, the overall effect of population growth on correlations is indeterminate as it depends on the source of population growth which we, unfortunately, do not observe. Previous literature has considered the effect of population on house prices, yet the empirical results are mixed. Mankiw and Weil (1989) and Heiborn (1994) find that population has a positive effect on house prices. Moreover, Engelhardt and Poterba (1991) and Berg (1996) report that the effect of demographic variables on housing prices is not statistically significant while Hort (1998) concludes that some demographic variables can have a puzzling effect on house prices. Given our focus on correlations, it is difficult to directly compare our results to previous work which focused on direct effects on housing prices rather than contagion.

Consistent across all columns, real income has a positive and highly statistically significant effect on correlations. However, the relatively small point estimates show the marginal effect of income is not economically significant. Also consistent across all specifications, fixed mortgage interest rate has a statistically significant negative affect. From the point estimate in our preferred specification in column 3, we can see that if the fixed mortgage interest rate increases by one percentage point, the correlation between housing returns decreases by about 0.0143. These findings are consistent with our theoretical framework. When interest rates increase, affordability constraints become more binding.

An increase in housing starts, which serves as a proxy for housing supply, leads to a reduction in contagion. This is true for all our specifications in Table 5; however, the magnitude of the effect is relatively small and not economically significant. For the change in employment, the positive and significant effect in the column 8 is consistent with the theory that higher employment creates a higher demand for housing and elevates the correlation between housing returns. However, after controlling the MSA fixed effect (columns 3, 5, 7 and 9), the coefficients are no longer statistically significant. Similar results apply for the unemployment rate, which is statistically significant in the pooled OLS specifications (columns 4, 6, and 9), but not when including MSA FE. The observed negative effect is consistent with our theoretical argument that lower unemployment rate relaxes affordability constraints, which in turn increases contagion.

Table A1 in the Appendix, reports additional static panel data model results where we take lags of exuberance, change of population, real income per capita, fixed mortgage interest rate, change in employment, and unemployment rate to reduce potential endogeneity in the regressors. The results are consistent with the ones reported in Table 5.

Dynamic Panel Results

The dynamic panel data results, that model price exuberance as potentially endogenous, are reported in Table 6. Comparing with the point estimates from Table 5, we see that the sign on exuberance is the same. In terms of magnitude, the dynamic panel estimates on exuberance are about half the size of the static panels. The difference in marginal impact provides evidence that exuberance can be endogenous.

[Table 6, about here]

To validate the dynamic specifications, we consider the serial correlation and the Hansen tests. For the serial correlation test, the relatively high p-values in both columns validate the assumption of no second-order serial correlation. Further, the relatively high p-values associated with the Hansen test indicate that the instrument lists are not correlated with the residuals. Finally, the large p-value of the Difference Hansen test in columns 2, 4, 6, and 8 provides support to the additional instruments used in the equations in levels. i.e., they are not correlated with the residuals. Overall, these tests provide strong empirical support for the validity of our dynamic specifications.

6.3. Further Robustness Checks: Analysis of Subperiods

In this section, we explore whether contagion effects exist in the different phases of the real estate cycle: expansion, bust, and recovery phase. For that purpose, we divide our sample in three subsamples. The first subsample (Jan 1999-Jul 2006) represents the expansion period around the turn of the century; the second subsample (Aug 2006-Feb 2012) represents the housing bust associated with the Global Financial Crisis; and the final subsample (Mar 2012-Dec 2016) represents the latest housing recovery period. To define these housing market subperiods, we used the S&P/Case-Shiller U.S. National Home Price Index according to which the peak of the expansion period is in July 2006 and the through of the bust is in February 2012.

[Table 7, about here]

We report the result from these different subsamples in Table 7. The dependent variable is the correlation between housing markets, and we include the same fundamental macro controls we used before (i.e., population, income per capita, mortgage interest rate, housing starts, change in employment, and unemployment rate). Consistent with our previous results, across all subperiods, we find that the correlation across housing markets is greater during periods of price exuberance.

7. Discussion

What is the economic mechanism that causes the empirically observed contagion effects? One of the main consequences of price exuberance is the accumulation of housing equity by homeowners and the relaxation of their down payment constraints. Housing booms allow households to move up the property ladder and relocate either to the same or to another MSA. As we have demonstrated theoretically in Section 2, when only one MSA in a pair goes through a housing boom, the demand in both areas would bear the characteristics of the households that experienced the highest appreciation of their homes. This effect, which operates via the demand for housing, leads to a higher correlation of returns across the two markets.

The affordability channel explanation is overall consistent with the additional results from our panel regressions. Indeed, an increase in the real income per capita relaxes affordability constraints, and we find that it leads to higher correlations. Conversely, increases in the interest rate and the unemployment rate exacerbate affordability constraints, and we indeed find that they have a negative effect on correlations.

There is a body of empirical literature that has developed in recent years which further supports the theoretical channel presented here. For example, Milcheva and Zhu (2016) find that the co-

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movements across national housing markets depend on cross-border bank flows. Thus, there is evidence that affordability constraints and funding risks are associated with house price spillovers. Further, a significant determinant of home buying decisions are the expectations formed by households about future house price growth. Using the Michigan Survey of Consumers, Piazzesi and Scheinder (2009) find that households' belief affects house price appreciation. They point to the formation of a "momentum" cluster of respondents which form adaptive expectations, and find that the size of this cluster has doubled toward the end of the housing market boom (i.e. during the 2004-2005 period). Furthermore, using a search model, they show that the presence of a small number of optimistic investors can have a large effect on house prices without them buying a large share of the housing stock. Thus, it is presumably sufficient for only a small fraction of households to relocate across MSAs in order for contagion effects to develop. We note that for households which indeed relocate, these contagion effects might be greater than the ones we estimated here. Sinai and Souleles (2013) find that households tend to move to MSAs that are highly correlated with the MSA in which they currently reside. This behavior creates higher demand for housing and leads to higher correlations as the exuberance in one housing market is driven by the exuberance in another housing market.

The main focus of the existing literature (Sinai and Souleles, 2005, 2013; Han 2010; Damianov and Escobari 2021) has been on studying the hedging incentives of households. In this literature, correlations are treated as being exogenous, and the analysis explores how they impact the volatility of lifetime wealth of households engaging in real hedging strategies.[21] The current paper provides, to the best of our knowledge, the first framework in which correlations are determined

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[21] Damianov and Escobari (2021) examine correlations across price tiers in the same metropolitan area rather than correlations across MSAs.

endogenously. We establish, both theoretically and empirically, that correlations depend on the price exuberance in MSAs.

8. Conclusion

This paper analyzes the determinants of contagion across MSAs in the United States whereby contagion is defined as an increase in the pairwise correlation across markets after a shock to one market. We establish empirically that price exuberance – defined as a period of explosive growth in home values – is a source of contagion in residential housing markets. The contagion effects are statistically and economically significant, and are present after accounting for the potential endogeneity of price exuberance. Using an equilibrium model of house price dynamics, we show that contagion can arise due to the easing of affordability (down payment) constraints of households. The affordability channel of contagion is further supported by our estimates of the effects of the economic variables used in our study. We find that an increase in income as well as a decrease in unemployment and interest rates also tend to contribute to contagion.

Our results have practical implications for homeowners and investors. It is well established that household decisions are driven in part by hedging incentives (Sinai and Souleles, 2005, 2013; Han, 2010; Damianov and Escobari, 2021). The contagion effects established here, indicating increases in correlations across housing markets, serve to lower the volatility of lifetime wealth for households seeking to relocate to another metropolitan area. While high correlation levels lower the risk for households which are moving (i.e., economic agents who have a long position in one market and a short in another) they magnify portfolio risk for investors in the housing market (i.e., economic agents with long positions in both markets). These investors have only limited opportunities for geographical diversification due to the established contagion effects.

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Declarations

Conflict of Interest none.

REFERENCES

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies*, 58(2), 277-297.

Bauwens, L., Laurent, S., & Rombouts, J. V. (2006). Multivariate GARCH models: A survey. *Journal of Applied Econometrics*, 21(1), 79-109.

Berg, L. (1996). *Age Distribution, Saving and Consumption in Sweden* (Working Paper No. 22). Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1405

Bhargava, A. (1986). On the theory of testing for unit roots in observed time series. *The Review of Economic Studies*, 53(3), 369-384.

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, 87(1), 115-143.

Booth, G. G., Martikainen, T., & Tse, Y. (1997). Price and volatility spillovers in

    Scandinavian stock markets. *Journal of Banking & Finance*, 21(6), 811-823.

Busetti, F., & Taylor, A. R. (2004). Tests of stationarity against a change in

    persistence. *Journal of Econometrics*, 123(1), 33-66.

Case, K. E., & Shiller, R. J. (1989). The efficiency of the market for single family

    homes. *Regional Science and Urban Economics*, 79(1), 125–137.

Case, K. E., & Shiller, R. J. (1990). Forecasting prices and excess returns in the housing

    market. *Real Estate Economics*, *18*(3), 253-273.

Case, K. E., & Shiller, R. J. (2003). Is there a bubble in the housing market?. *Brookings papers*

    on economic activity, *2003*(2), 299-362.

Cha, H. J., & Jithendranathan, T. (2009). Time-varying correlations and optimal allocation in

    emerging market equities for the US investors. *International Journal of Finance &*

    Economics, 14(2), 172-187.

Chiang, T. C., Jeon, B. N., & Li, H. (2007). Dynamic correlation analysis of financial

    contagion: Evidence from Asian markets. *Journal of International Money and*

    Finance, 26(7), 1206-1228.

Cifarelli, G., & Paladino, G. (2010). Oil price dynamics and speculation: A multivariate

    financial approach. *Energy Economics*, 32(2), 363-372.

Cohen, J. P., Ioannides, Y. M. & Thanapisitikul, W. (2016). Spatial effects and house price

    dynamics in the USA. *Journal of Housing Economics*, 31, 1-13.

Corsetti, G., Pericoli, M., & Sbracia, M. (2005). Some contagion, some interdependence: more

    pitfalls in tests for financial contagion. *Journal of International Money and Finance*,

    24(8), 1177-1199.

Damianov, D. S., & Escobari, D. (2016). Long-run equilibrium shift and short-run dynamics of US home price tiers during the housing bubble. *The Journal of Real Estate Finance and Economics*, 53(1), 1-28.

Damianov, D. S., & Escobari, D. (2021). Getting on and moving up the property ladder: Real hedging in the US housing market before and after the crisis. *Real Estate Economics*, 1-37.

Das, P., Füss, R., Hanle, B., & Russ, I. N. (2020). The cross-over effect of irrational sentiments in housing, commercial property, and stock markets. *Journal of Banking & Finance*, 114, 1-14.

Dorsey, R. E., Hu, H., Mayer, W. J., & Wang, H. C. (2010). Hedonic versus repeat-sales housing price indexes for measuring the recent boom-bust cycle. *Journal of Housing Economics*, 19(2), 75-93.

Elder, J., & Serletis, A. (2009). Oil price uncertainty in Canada. *Energy Economics*, 31(6), 852-856.

Engelhardt, G. V., & Poterba, J. M. (1991). House prices and demographic change: Canadian evidence. *Regional Science and Urban Economics*, 21(4), 539-546.

Engle, R. F. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics*, *20*(3), 339-350.

Engle, R. F. (2004). Risk and volatility: Econometric models and financial practice. *The American Economic Review*, 94(3), 405–420.

Engle, R. F., & Kroner, K. F. (1995). Multivariate simultaneous generalized ARCH. *Econometric Theory*, 11(1), 122-150.

Evans, G. W. (1991). Pitfalls in testing for explosive bubbles in asset prices. *The American Economic Review*, 81(4), 922-930.

Forbes, K. J., & Rigobon, R. (2000). *Contagion in Latin America: Definitions, Measurement, and Policy Implications*. National Bureau of Economic Research Working Paper 7885).

Forbes, K. J., & Rigobon, R. (2002). No contagion, only interdependence: measuring stock market comovements. *The Journal of Finance*, 57(5), 2223-2261.

Fu, Y., & Ng, L. K. (2001). Market efficiency and return statistics: Evidence from real estate and stock markets using a present-value approach. *Real Estate Economics*, 29(2), 227-250.

Guerrieri, V., Hartley, D., & Hurst, E. (2013). Endogenous gentrification and housing price dynamics. *Journal of Public Economics*, 100, 45-60.

Guren, A. M. (2018). House price momentum and strategic complementarity. *Journal of Political Economy*, 126(3), 1172-1218.

Han, L. (2010). The effects of price risk on housing demand: empirical evidence from US markets. *The Review of Financial Studies*, 23(11), 3889-3928.

Hjalmarsson, E., & Hjalmarsson, R. (2009). Efficiency in housing markets: Which home buyers know how to discount? *Journal of Banking & Finance*, *33*(11), 2150-2163.

Heiborn, M. (1994). *Demographic Factors and the Demand for Housing. Department of Economics*. Uppsala University, Working paper 1994: 30, Uppsala.

Holtz-Eakin, D., Newey, W., & Rosen, H. S. (1988). Estimating vector autoregressions with panel data. *Econometrica*, 1371-1395.

Homm, U., & Breitung, J. (2012). Testing for speculative bubbles in stock markets: a comparison of alternative methods. *Journal of Financial Econometrics*, 10(1), 198-231.

Hort, K. (1998). The determinants of urban house price fluctuations in Sweden 1968-1994. *Journal of Housing Economics*, 7(2), 93-120.

Iacoviello, M. (2011). Housing wealth and consumption. International Finance Discussion Papers Number 10278. Board of Governors of the Federal Reserve System.

Karolyi, G. A. (1995). A multivariate GARCH model of international transmissions of stock returns and volatility: The case of the United States and Canada. *Journal of Business & Economic Statistics*, 13(1), 11-25.

Karolyi, G. A., & Stulz, R. M. (1996). Why do markets move together? An investigation of US-Japan stock return comovements. *The Journal of Finance*, 51(3), 951-986.

Kim, J. Y. (2000). Detection of change in persistence of a linear time series. *Journal of Econometrics*, *95*(1), 97-116.

Koutmos, G., & Booth, G. G. (1995). Asymmetric volatility transmission in international stock markets. *Journal of International Money and Finance*, 14(6), 747-762.

Lin, W. L., Engle, R. F., & Ito, T. (1994). Do bulls and bears move across borders? International transmission of stock returns and volatility. *Review of Financial Studies*, *7*(3), 507-538.

Malik, F., & Hammoudeh, S. (2007). Shock and volatility transmission in the oil, US and Gulf equity markets. *International Review of Economics & Finance*, 16(3), 357-368.

Mankiw, N. G., & Weil, D. N. (1989). The baby boom, the baby bust, and the housing market. *Regional Science and Urban Economics*, 19(2), 235-258.

Milcheva, S., & Zhu, B. (2016). Bank integration and co-movements across housing

    markets. *Journal of Banking & Finance*, *72*, S148-S171.

Pavlidis, E., Yusupova, A., Paya, I., Peel, D., Martínez-García, E., Mack, A., & Grossman, V.

    (2016). Episodes of exuberance in housing markets: in search of the smoking gun. *The*

    Journal of Real Estate Finance and Economics, *53*(4), 419-449.

Phillips, P. C., Shi, S., & Yu, J. (2015). Testing for multiple bubbles: Historical episodes of

    exuberance and collapse in the S&P 500. *International Economic Review*, 56(4), 1043-

    1078.

Phillips, P. C., Wu, Y., & Yu, J. (2011). Explosive behavior in the 1990s Nasdaq: When did

    exuberance escalate asset values? *International Economic Review*, 52(1), 201-226.

Piazzesi, M., & Schneider, M. (2009). Momentum traders in the housing market: survey

    evidence and a search model. *American Economic Review*, *99*(2), 406-11.

Sadorsky, P. (2006). Modeling and forecasting petroleum futures volatility. *Energy*

    Economics, *28*(4), 467-488.

Sadorsky, P. (2012). Correlations and volatility spillovers between oil prices and the stock

    prices of clean energy and technology companies. *Energy Economics*, *34*(1), 248-255.

Scheicher, M. (2001). The comovements of stock markets in Hungary, Poland and the Czech

    Republic. *International Journal of Finance & Economics*, 6(1), 27-39.

Sinai, T., & Souleles, N. S. (2005). Owner-occupied housing as a hedge against rent risk. *The*

    Quarterly Journal of Economics, *120*(2), 763-789.

Sinai, T., & Souleles, N. S. (2013). Can owning a home hedge the risk of moving? *American*

    Economic Journal: Economic Policy, *5*(2), 282-312.

Stein, J. C. (1995). Prices and trading volume in the housing market: A model with down-payment effects. *The Quarterly Journal of Economics*, *110*(2), 379-406.

Tracy, J., & Schneider, H. (2001). Stocks in the household portfolio: A look back in the 1990s. *Current Issues in Economics and Finance* 7, 1-6.

Tse, Y. K. (2000). A test for constant correlations in a multivariate GARCH model. *Journal of Econometrics*, 98(1), 107-127.

Worthington, A., & Higgs, H. (2004). Transmission of equity returns and volatility in Asian developed and emerging markets: a multivariate GARCH analysis. *International Journal of Finance & Economics*, 9(1), 71-80.

Appendix

In this Appendix, we present the solution of the household relocation problem for households endowed with the preferences given in Stein (1995). The household's utility is a function of the amount of housing they consume (H_i) and food (F_i), $i = A, B$. Relocating brings additional value of $\ln(\theta) > 0$ so that the household utility function is given by

$$U_i = \alpha \ln(H_i) + (1 - \alpha)\ln(F_i) + M\ln(\theta)$$

where M is an indicator variable equal to 1 if the household relocates within the same or the other geographical area and zero if the household does not relocate. The household makes this choice facing the budget constraint

$$P_2^i H_i + F_i \leq I_i$$

where I_i is the income of the household, and the liquidity (down payment) constraint is

$$\gamma P_2^i H_i \leq P_1^k - K$$

If the liquidity constraint is not binding, a household which relocates will buy a home of size $H_i = \alpha \frac{I_i}{P_2^i}$ and will consume $(1 - \alpha)I_i$ units of food, realizing a utility of

$$\ln\left(\frac{\theta \alpha^\alpha (1 - \alpha)^{1-\alpha} I_i}{\left(P_2^i\right)^\alpha}\right)$$

The liquidity constraint is not binding when $\gamma P_2^i(\alpha \frac{I_i}{P_2^i}) \leq P_1^j - K \Leftrightarrow \gamma \alpha I_i \leq P_1^j - K$.

The (reservation) utility associated with no trade equals $\ln I_i^{(1-\alpha)}$, and hence, when the liquidity constraint is not binding, the household will relocate when

$$\frac{\theta \alpha^\alpha (1-\alpha)^{1-\alpha} I_i}{\left(P_2^i\right)^\alpha} \geq I_i^{(1-\alpha)} \Leftrightarrow$$

$$I_i \geq \alpha (1-\alpha)^{\frac{1-\alpha}{\alpha}} \theta^{\frac{1}{\alpha}} P_2^i$$

When the liquidity constraint is binding, the household would choose a home of size $\overline{H_\iota} = \frac{P_1^j - K}{\gamma P_2^i}$.

In this case it is optimal to relocate if

$$\frac{\theta \overline{H_\iota}^\alpha \left(I_i - P_2^i \overline{H_\iota}\right)^{1-\alpha}}{\left(P_2^i\right)^\alpha} \geq I_i^{(1-\alpha)}.$$

We note that the left hand-side of the above equality is increasing in $\overline{H_\iota}$ as the liquidity constraint is binding. We denote by $\overline{K^\iota}$ the threshold mortgage debt for which the above constraint is satisfied with equality. The fraction of household who are willing to relocate is $m_i = G(\overline{K^\iota})$. Because by assumption $P_1^A \geq P_1^B$ it follows that $\overline{K^A} \geq \overline{K^B}$ and hence $m_A \geq m_B$.

Figure 1. Monthly Housing Returns Over Time
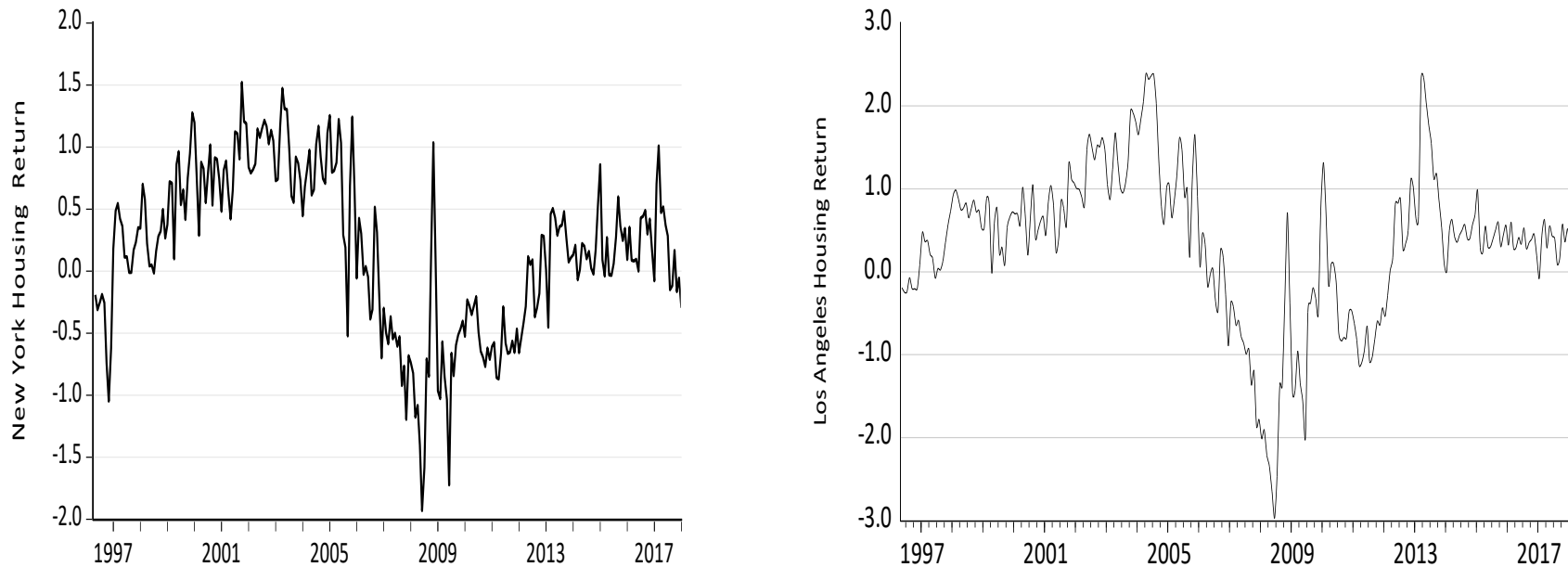
Notes: Monthly housing returns in New York (left-hand side) and Los Angles (right-hand side). The sample spans from April 1996 to January 2018. New York and Los Angeles home price data obtained from Zillow. We use the monthly seasonally adjusted Consumer Price Index, from the St Louis Fed's database FRED, to obtain the series in real terms. CPI is equal to 100 in April 1996. Logarithmic returns calculated as $r_t = [\ln(P_t)-\ln(P_{t-1})] \times 100$, where P_t is the real housing price at month t. Real housing returns are in percentage terms.

Figure 2. Dynamic correlations of New York with Los Angeles, Chicago, Dallas, and Industrial Production
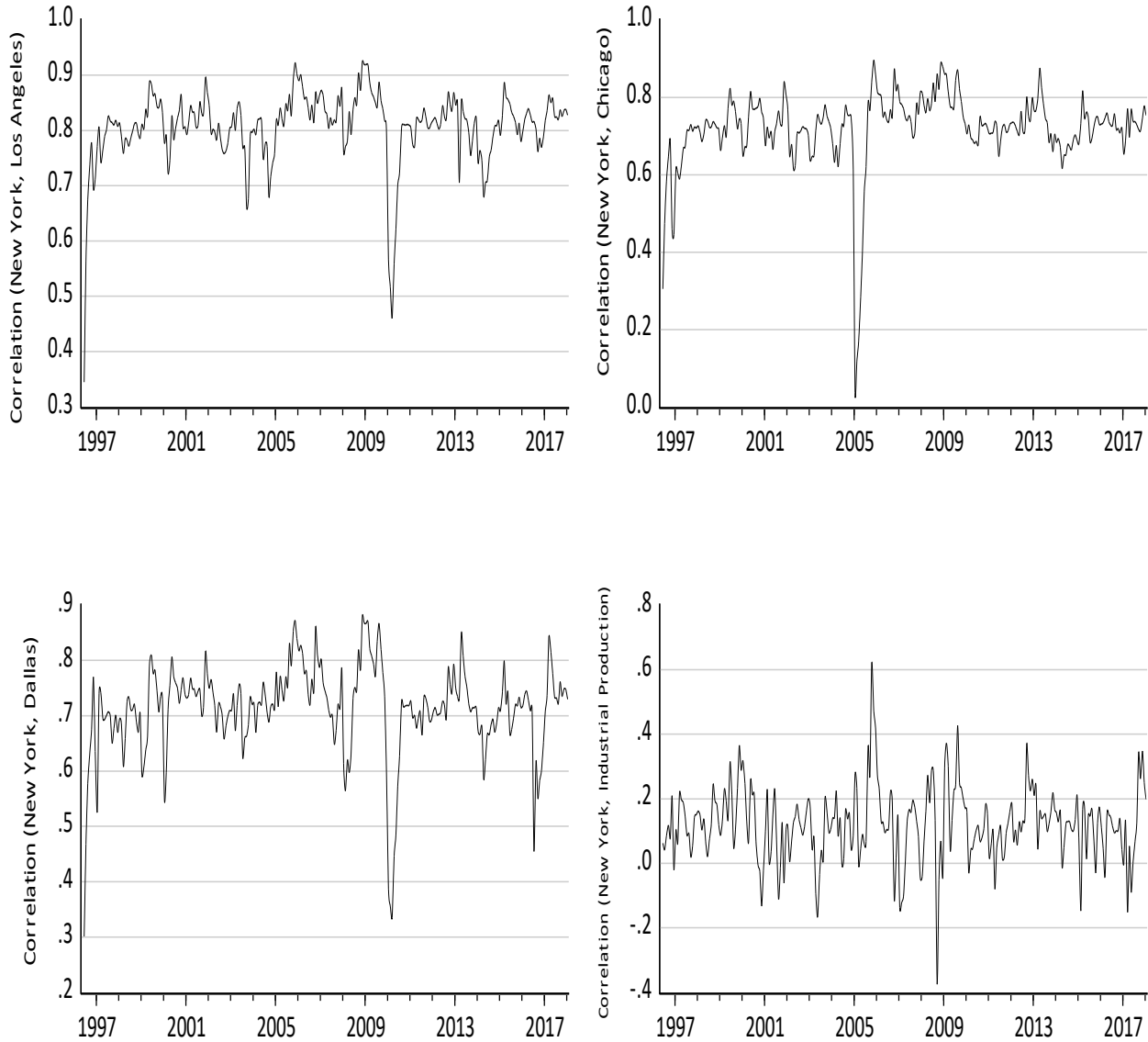
Notes: The figures represent the time series of the DCC-GARCH estimates of the dynamic conditional correlations of returns between the housing market of New York with Los Angeles (first quadrant), Chicago (second quadrant), Dallas (third quadrant), and Industrial Production (fourth quadrant).

Table 1. Summary Statistics (April 1996 - January 2018)

	Obs.	Mean	Std.Dev.	Min.	Max.	P25	P75
New York	261	0.173	0.658	-1.932	1.522	-0.297	0.699
Los Angeles	261	0.330	0.939	-2.975	2.390	-0.165	0.865
Chicago	261	-0.019	0.613	-1.951	1.176	-0.395	0.403
Dallas	261	0.120	0.609	-3.000	2.120	-0.178	0.472
Washington	261	0.160	0.789	-2.666	1.923	-0.225	0.696
Miami	261	0.210	1.131	-3.657	2.635	-0.233	0.945
Philadelphia	261	0.092	0.540	-1.401	1.458	-0.231	0.428
Atlanta	261	0.036	0.642	-2.004	1.232	-0.242	0.459
Boston	261	0.223	0.619	-1.549	1.470	-0.151	0.664
Industrial Production	261	0.117	0.657	-4.393	2.048	-0.210	0.536
Income	261	0.152	0.750	-6.003	4.677	-0.027	0.390
Inflation	261	0.178	0.281	-1.786	1.367	0.053	0.315
S&P 500	261	0.204	3.743	-20.93	11.00	-1.338	2.457

Notes: Housing returns in the nine MSAs are calculated as $r_t = [\ln(P_t) - \ln(P_{t-1})] \times 100$, where P_t is the real house price index for month t. Growth in industrial production, growth in disposable personal income, the return on the S&P 500 index, and the rate of inflation are calculated analogously.

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Table 2. Unconditional Correlations between MSAs, Industrial Production, Income, Inflation, and the S&P 500 index

Correlations	New York	Los Angeles	Chicago	Dallas	Washington	Miami	Philadelphia	Atlanta	Boston	Industrial Production	Income	Inflation	S&P 500
New York	1.000	0.839*	0.793*	0.493*	0.880*	0.752*	0.891*	0.553*	0.812*	0.022	0.223*	-0.327*	-0.059
Los Angeles	0.843*	1.000	0.762*	0.507*	0.912*	0.848*	0.854*	0.573*	0.716*	0.087	0.202*	-0.332*	-0.016
Chicago	0.817*	0.787*	1.000	0.570*	0.731*	0.722*	0.748*	0.693*	0.692*	-0.052	0.240*	-0.413*	-0.002
Dallas	0.534*	0.559*	0.548*	1.000	0.468*	0.511*	0.518*	0.805*	0.587*	0.032	0.243*	-0.599*	0.041
Washington	0.871*	0.919*	0.703*	0.491*	1.000	0.835*	0.886*	0.494*	0.725*	0.038	0.177*	-0.296*	-0.073
Miami	0.806*	0.898*	0.756*	0.543*	0.876*	1.000	0.789*	0.560*	0.525*	0.005	0.147	-0.265*	0.020
Philadelphia	0.887*	0.849*	0.756*	0.494*	0.885*	0.792*	1.000	0.523*	0.691*	0.046	0.233*	-0.377*	-0.035
Atlanta	0.679*	0.699*	0.809*	0.706*	0.587*	0.706*	0.631*	1.000	0.651*	0.009	0.261*	-0.533*	0.087
Boston	0.824*	0.752*	0.737*	0.585*	0.739*	0.648*	0.693*	0.726*	1.000	0.023	0.244*	-0.431	-0.074
Industrial Production	0.102	0.200	0.063	0.098	0.137	0.212*	0.077	0.110	0.116	1.00			
Income	0.127	0.099	0.186*	0.108	0.102	0.094	0.146	0.120	0.118		1.00		
Inflation	-0.355*	-0.291*	-0.402*	-0.524*	-0.315*	-0.207*	-0.426*	-0.468*	-0.447*			1.00	
S&P 500	-0.004	0.078	0.058	0.052	0.014	0.103	0.010	0.090	-0.025				1.000

Notes: Pearson's correlation coefficients and Spearman's rank correlation are reported in the lower-triangular cells, and the upper-triangular cells, respectively. * indicates statistical significance at the 1% level.

Table 3. DCC-GARCH Estimates

MSA:	New York	Los Angeles	Chicago	Dallas	Washington	Miami	Philadelphia	Atlanta	Boston	Industrial Production
Panel A: Mean Equations										
μ	0.017	0.031	0.002	0.033	0.021	0.023	0.019	0.006	0.037*	0.196***
	(0.0192)	(0.0216)	(0.0201)	(0.0208)	(0.0199)	(0.0219)	(0.0197)	(0.0200)	(0.020)	(0.0375)
φ	0.937***	0.943***	0.921***	0.876***	0.935***	0.959***	0.909***	0.937***	0.897***	0.093
	(0.0143)	(0.0122)	(0.0198)	(0.0239)	(0.0126)	(0.0123)	(0.0175)	(0.0164)	(0.0147)	(0.0835)
γ	0.019	0.0368	0.001	0.018	0.040	0.032	0.013***	0.040***	0.025***	
	(0.0301)	(0.0316)	(0.0311)	(0.0312)	(0.0312)	(0.0327)	(0.0294)	(0.0304)	(0.0297)	
Panel B: Variance Equations										
c	0.070***	0.019**	0.073***	0.100 ***	0.026**	0.007**	0.0765***	0.042*	0.036**	0.135***
	(0.0223)	(0.0078)	(0.0231)	(0.0176)	(0.0117)	(0.0034)	(0.0198)	(0.0287)	(0.0146)	(0.0344)
a	0.141***	0.056***	0.207***	0.212***	0.076***	0.045***	0.136***	0.111**	0.088***	0.573***
	(0.0437)	(0.0189)	(0.0679)	(0.0601)	(0.0252)	(0.0158)	(0.0350)	(0.0504)	(0.0319)	(0.1340)
b	0.296	0.825***	0.285*	0.164	0.727***	0.916***	0.292*	0.589**	0.636***	0.244**
	(0.1942)	(0.0657)	(0.1614)	(0.1162)	(0.1098)	(0.034)	(0.1547)	(0.2523)	(0.1333)	(0.1029)
Panel C: Multivariate Equations										
α					0.131***					
					(0.0156)					
β					0.510***					
					(0.0354)					
χ^2					10471.12					
χ^2 (p-value)					0					

Notes: The table reports estimates of the Dynamic Conditional Correlation GARCH model. The figures in parentheses are standard errors. For each MSA the mean return equations are: $r_t = \mu + \varphi r_{t-1} + \gamma r_{t-1}^{\text{Industrial Production}} + \epsilon_t$, where $r_t = (r_{1,t}, r_{2,t}, r_{3,t}, r_{4,t}, \ldots, r_{n,t})'$ is the vector of *n* housing appreciation rates at time *t*. $\mu_t = (\mu_{1t}, \mu_{2t}, \mu_{3t}, \ldots, \mu_{n,t})'$ is the vector of *n* constants, $\epsilon_t = (\epsilon_{1t}, \epsilon_{2t}, \epsilon_{3t}, \ldots, \epsilon_{n,t})'$ is the vector of *n* random errors, n=9 and $\epsilon_t | \Omega_{t-1} \sim N(0, H_t)$. The variance equations: $h_t^\tau = c^\tau + a^\tau h_{t-1}^\tau + b^\tau (\epsilon_{t-1}^\tau)^2$ for MSA $\tau = (i, j, \ldots, n)$. The null hypothesis for the χ^2 test is $H_0: \alpha = \beta = 0$. * significant at 10%; ** significant at 5%; *** significant at 1% levels.

Table 4. Estimates of Price Exuberance.

Panel A: SADF and GSADF Test Statistics		
	SADF	GSADF
New York	14.382***	14.941***
Los Angeles	25.231***	25.231***
Chicago	10.521***	10.521***
Dallas	4.760***	10.942***
Washington	28.524***	28.524***
Miami	36.247***	36.401***
Philadelphia	17.147***	17.147***
Atlanta	5.128***	7.756***
Boston	11.184***	11.184***
Panel B: SADF and GSADF Critical Values		
	SADF	GSADF
90%	1.236	2.112
95%	1.482	2.446
99%	2.124	2.999

Notes: The table reports Supremum Augmented Dickey–Fuller (SADF) statistics, as proposed in Phillips et al. (2011), and Generalized SADF (GSADF) statistics, as proposed in Philips et al. (2015). The real Housing price indices are obtained by dividing the Zillow Single-Family Home Value Index (Obtained from Zillow) by the monthly seasonally adjusted Consumer Price Index (CPI, obtained from the Federal Reserve Bank of St. Louis). There are 262 monthly observations from April 1996 to January 2018. Critical values are obtained from Monte Carlo simulations with 2,000 replications. *** denotes statistical significance at the 1 percent level.

Table 5. Static Panel Data Estimates.

Common Factors:	Industrial Production			Income		Inflation		S&P 500	
Variables:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Exuberance	0.0248***	0.0121***	0.0120***	0.0247***	0.0131***	0.0342***	0.0207***	0.0262***	0.0137***
	(0.0033)	(0.0020)	(0.0022)	(0.0033)	(0.0022)	(0.0041)	(0.0032)	(0.0033)	(0.0021)
Change in Population (percent)	0.0437***		-0.0149***	0.0416***	-0.0163***	0.0438***	-0.0337***	0.0442***	-0.0148***
	(0.0028)		(0.0031)	(0.0028)	(0.0031)	(0.0036)	(0.0046)	(0.0028)	(0.0029)
Real Income Per capita/10^3	0.0088***		0.0042***	0.0098***	0.0043***	0.0080***	0.0067***	0.00876***	0.00411***
	(0.0004)		(0.0011)	(0.0004)	(0.0011)	(0.0005)	(0.0016)	(0.0004)	(0.0010)
Fixed Mortgage Interest Rate	-0.0116***		-0.0143***	-0.0130***	-0.0152***	-0.0259***	-0.0274***	-0.0110***	-0.0138***
	(0.0038)		(0.0026)	(0.0037)	(0.0026)	(0.0049)	(0.0038)	(0.0037)	(0.0025)
Housing Starts/10^3	-0.0062***		-0.0038	-0.0596***	-0.0034	-0.0631***	-0.0106***	-0.00621***	-0.00573
	(0.0026)		(0.0029)	(0.0026)	(0.0028)	(0.0033)	(0.0041)	(0.0026)	(0.0028)
Change in Employment (percent)	0.00105		-0.0004	0.0003	-0.0006	-0.0007	-0.0006	0.00282**	0.00101
	(0.0013)		(0.0010)	(0.0013)	(0.0010)	(0.00172)	(0.0015)	(0.0013)	(0.0009)
Unemployment Rate (percent)	-0.0014		0.00131	-0.0037**	0.00143	-0.0051**	0.00187	-0.00302*	-0.00121
	(0.0017)		(0.0014)	(0.0017)	(0.0014)	(0.0022)	(0.0021)	(0.0017)	(0.0013)
Constant		0.795***							
		(0.0008)							
MSA Fixed Effects	No	Yes	Yes	No	Yes	No	Yes	No	Yes
Month Fixed Effects	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,776	7,776	7,776	7,776	7,776	7,776	7,776	7,776	7,776
R-squared	0.209	0.567	0.637	0.237	0.635	0.194	0.491	0.217	0.655

Notes: The dependent variable is the pair-wise dynamic conditional correlation ρ_{ijt} between housing markets i and j. The housing markets considered are detailed in Table 1. The sample is from January 1999 to December 2016. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.

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Table 6. Dynamic Panel Data Estimates.

Common Factors:	Industrial Production		Income		Inflation		S&P 500	
Variables:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GMM Estimator:	Difference	System	Difference	System	Difference	System	Difference	System
Variables:								
$\rho_{ij,t-1}$	0.7500***	0.818***	0.741***	0.808***	0.7460***	0.7780***	0.744***	0.802***
	(0.0189)	(0.0199)	(0.0195)	(0.0200)	(0.0181)	(0.0219)	(0.0202)	(0.0199)
$\rho_{ij,t-2}$	0.0887***	0.0996***	0.086***	0.100***	0.0665***	0.0747***	0.0905***	0.0989***
	(0.0165)	(0.0160)	(0.0164)	(0.0171)	(0.0162)	(0.0162)	(0.0174)	(0.0175)
$\rho_{ij,t-3}$	-0.0588***	-0.0617***	-0.051***	-0.053***	-0.0713***	-0.0725***	-0.0736***	-0.0801***
	(0.0170)	(0.0162)	(0.0178)	(0.0179)	(0.0146)	(0.0166)	(0.0152)	(0.0141)
Z_{ijt} (Exuberance)	0.0050***	0.0051***	0.0054***	0.0057***	0.0110***	0.0118***	0.0063***	0.0059***
	(0.0019)	(0.0018)	(0.0019)	(0.0017)	(0.0029)	(0.0028)	(0.0021)	(0.0019)
Constant		0.114***		0.115***		0.1670***		0.141***
		(0.0139)		(0.0159)		(0.0120)		(0.0148)
Observations	7,632	7,668	7,632	7,668	7,632	7,668	7,632	7,668
Instruments	36	36	36	36	36	36	34	39
Serial Correlation	-0.96	-1.18	-0.96	-1.23	-1.26	-1.44	-0.91	-1.17
Serial Correlation (p-value)[a]	0.335	0.240	0.346	0.218	0.208	0.149	0.361	0.242
Hansen	35.54	33.92	35.28	32.41	34.57	32.12	35.85	35.85
Hansen (p-value)[b]	0.224	0.137	0.232	0.117	0.258	0.124	0.213	0.382
Diff. Hansen test		1.22		0.88		0.70		0.01
Diff. Hansen test (p-value)[c]		0.874		0.928		0.951		1.000

Notes: The dependent variable is the pair-wise dynamic conditional correlation ρ_{ijt} between housing markets i and j. The housing markets considered are detailed in Table 1. Z_{ijt} at time t is equal to one if exuberance period exists in one of the two MSAs i or j. Conversely, the exuberance period Z_{ijt} is equal to zero if there is exuberance in both MSAs or there is no exuberance in any of the two markets. The sample is from January 1999 to December 2016. The Windmeijer finite sample corrected standard errors of the two-step GMM estimates are reported in parentheses. *** p<0.01, **p<0.05, * p<0.10. [a] The null hypothesis is that the errors in the first-difference regression exhibit no second order serial correlation (valid specification). [b] The null hypothesis is that the instruments are not correlated with the residuals (valid specification). [c] The null hypothesis is that the additional instruments used in the levels Equations are not correlated with the residuals (valid specification).

Table 7. Panel Data Estimates of Subsamples.

Common Factors:	*Industrial Production*			*National Income*			*Inflation*			*S&P 500*		
Subperiod:	Jan 1999-Jul 2006	Aug 2006-Feb 2012	Mar 2012-Dec 2016	Jan 1999-Jul 2006	Aug 2006-Feb 2012	Mar 2012-Dec 2016	Jan 1999-Jul 2006	Aug 2006-Feb 2012	Mar 2012-Dec 2016	Jan 1999-Jul 2006	Aug 2006-Feb 2012	Mar 2012-Dec 2016
Variables:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Exuberance	0.0101***	0.0199***	0.0084***	0.0112***	0.0218***	0.0080***	0.0147***	0.0304***	0.0146***	0.0137***	0.0176***	0.0054*
	(0.0031)	(0.0054)	(0.0029)	(0.0030)	(0.0055)	(0.0031)	(0.0043)	(0.0077)	(0.0052)	(0.00302)	(0.00507)	(0.0029)
Macro Fundamentals	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSA Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,276	2,412	2,088	3,276	2,412	2,088	3,276	2,412	2,088	3,276	2,412	2,088
R-squared	0.634	0.703	0.772	0.640	0.693	0.764	0.534	0.580	0.564	0.639	0.729	0.790

Notes: The dependent variable is the pair-wise dynamic conditional correlation ρ_{ijt} between housing markets i and j. The housing markets considered are detailed in Table 1. The dummy variable Z_{ijt} at time t is equal to one if exuberance period exists in one of the two MSAs i or j. Conversely, Z_{ijt} is equal to zero if there is exuberance in both MSAs or if there is no exuberance in any of the two markets. The macroeconomic fundamentals include population, income per capita, mortgage interest rate, housing starts, change in employment and unemployment rate. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

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Table A.1. Static Panel Data Estimates.

Common Factors:	Industrial Production			Income		Inflation		S&P 500	
Variables:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Exuberance $_{t-1}$	0.0231***	0.0114***	0.0103***	0.0232***	0.0116***	0.0291***	0.0152***	0.0238***	0.0112***
	(0.0033)	(0.0020)	(0.0022)	(0.0032)	(0.0022)	(0.0040)	(0.0032)	(0.0033)	(0.0022)
Change in Population (percent) $_{t-1}$	0.0399***		-0.0137***	0.0379***	-0.0150***	0.0391***	-0.0294***	0.0402***	-0.0138***
	(0.0027)		(0.0028)	(0.0027)	(0.0028)	(0.0035)	(0.0043)	(0.0027)	(0.0027)
Real Income Per capita/10^3 $_{t-1}$	0.0085***		0.0053***	0.0095***	0.0054***	0.0077***	0.0079***	0.0085***	0.0047***
	(0.0004)		(0.0010)	(0.0004)	(0.0010)	(0.0005)	(0.0016)	(0.0004)	(0.0010)
Fixed Mortgage Interest Rate $_{t-1}$	-0.0128***		-0.0143***	-0.0142***	-0.0153***	-0.0211***	-0.0221***	-0.0115***	-0.0134***
	(0.0040)		(0.0027)	(0.0040)	(0.0027)	(0.0051)	(0.0040)	(0.0040)	(0.0026)
Housing Starts/10^3 $_{t-1}$	-0.0584***		-0.0070***	-0.0587***	-0.0068***	-0.0613***	-0.0142***	-0.0604***	-0.0071***
	(0.0025)		(0.0026)	(0.0024)	(0.0026)	(0.0032)	(0.0039)	(0.0025)	(0.0026)
Change in Employment (percent) $_{t-1}$	0.0025*		0.0009	0.0017	0.00058	0.0019	0.0014	0.0039***	0.0018*
	(0.0013)		(0.0010)	(0.0013)	(0.0010)	(0.0018)	(0.0016)	(0.0013)	(0.0009)
Unemployment Rate (percent) $_{t-1}$	-0.0026		0.0008	-0.0048***	0.0009	-0.0067***	0.0008	-0.0043**	-0.0019
	(0.0018)		(0.0015)	(0.0017)	(0.0015)	(0.0022)	(0.0022)	(0.0017)	(0.0014)
Constant		0.796***							
		(0.0008)							
MSA Fixed Effects	No	Yes	Yes	No	Yes	No	Yes	No	Yes
Month Fixed Effects	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,740	7,740	7,740	7,740	7,740	7,740	7,740	7,740	7,740
R-squared	0.209	0.566	0.636	0.237	0.634	0.191	0.488	0.215	0.654

Notes: The dependent variable is the pair-wise dynamic conditional correlation ρ_{ijt} between housing markets i and j. The housing markets considered are detailed in Table 1. The sample is from January 1999 to December 2016. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.