Spatial Effects and House Price Dynamics in the U.S.A.

Jeffrey Cohen[1]

Yannis M. Ioannides[2]

and

Win (Wirathip) Thanapisitikul[3]

February 17, 2015

Abstract

This paper examines spatial effects in house price dynamics. Using panel data from 363 US Metropolitan Statistical Areas for 1996 to 2013, we find that there are spatial diffusion patterns in the growth rates of urban house prices. Lagged price changes of neighboring areas show greater effects after the 2007-08 housing crash than over the entire sample period of 1996-2013. In general, the findings are robust to controlling for potential endogeneity, and for various spatial weights specifications (including contiguity weights and migration flows). These results underscore the importance of considering spatial spillovers in MSA-level studies of housing price growth.

[1] Center for Real Estate, University of Connecticut. Jeffrey.Cohen@business.uconn.edu
[2] Department of Economics, Tufts University. Yannis.Ioannides@tufts.edu
[3] Associated with Tufts University, when the research started, now with Lazada.co.th

Introduction

Spatial effects in economic processes have recently attracted particular attention by economists. For instance, during period of housing booms, house prices in metropolitan areas in the Northeast of the U.S. show distinct patterns as they appreciated at similarly high rates, while house prices in metropolitan areas in the Midwest did not experience comparably high appreciation rates during those same periods. Thus, house price dynamics might have spatial features. Spatial features of the housing bust associated with the Great Recession of 2007-2009 are currently receiving particular attention. This paper looks empirically at such spatial aspects in house price dynamics in more detail and by utilizing data that include several housing market booms and busts including the Great Recession.

Economists have accounted for the role of space in house price dynamics at various levels of aggregation. Some studies look at spatial effects at the level of submarkets within a particular Metropolitan Statistical Area (MSA for short). The fact that different urban neighborhoods are often developed at the same time, and dwellings in them may share similar structural characteristics and that neighborhoods may offer similar amenities suggest that house prices may react similarly to exogenous shocks. Basu and Thibodeau (1998) confirm this intuition by using data from submarkets within metropolitan Dallas. Also working at a similar local level, Clapp and Tirtiroglu (1994) estimate a spatial diffusion process in house price for towns in the Hartford, CT, MSA. They find that lagged house price changes in a submarket affect the current house price of a contiguous submarket positively and more strongly than the lagged house price changes for noncontiguous submarkets. However, such evidence of spatial effects at the submarket level of aggregation may be MSA-specific, and the conclusions for a single MSA may not necessarily be valid for other MSAs. Further, there could be spatial effects between submarkets that are geographically contiguous and belong to the same economic area and housing market, but not in the same MSA.

A second level of aggregation at which economists have examined spatial effects is at the Census division. Pollakowski and Ray (1997) find that although house prices in one division are affected by lagged house prices in other divisions, there is no clear spatial diffusion pattern that describes such processes. That is, lagged house price changes of adjacent Census divisions do not provide greater explanatory power in explaining current house prices than those in non-adjacent divisions. However, when those authors look at house prices within the greater New York's primary metropolitan statistical areas (PMSAs), they find evidence of spatial pattern consistent with that by Clapp and Tirtiroglu (1994).

Given mixed results from previous research on spatial diffusion patterns in house prices at different aggregation levels, this paper has the following aims; one, to examine house price interactions at the MSA level of aggregation across the entire continental U.S; two, to bring geographic distances into the analysis in addition to adjacency as measures of proximity. The paper employs the consolidated house price index, which has been published (since March 1996) by the Office of Federal Housing Enterprise Oversight (OFHEO). The data cover almost 400 MSAs across the entire U.S., with data for many MSAs going back to as early as 1975 (Calhoun, 1996). We use these data along with appropriate geographic information to study house price dynamics across the entire U.S. at the MSA level of aggregation and to compare the results with other levels of aggregation.

The organization of this paper is as follows: section 1 reviews the existing literature; section 2 introduces the econometric models used in this study; section 3 describes the data and methodology; section 4 presents the results, section 5 estimates impulse response functions, and section 6 concludes.

1. Literature Review

The modern view of housing emphasizes its role as an asset in household portfolios [Henderson and Ioannides (1983)]. Economists predict that asset prices in informationally efficient markets react rapidly to new information. Over the last twenty years, however, empirical studies have established that this might not be the case for housing markets (Rayburn *et al*., 1987, Guntermann and Norrbin, 1991). Economists have come to believe that households may be backward-looking in housing markets. Therefore, past house price changes can be used to explain future prices changes. Case and Shiller (1989) use their own house price indices for four major cities and find that one-year house price lag in a city is statistically and economically significant in forecasting that city's current house price.

Informational inefficiency in housing markets, as exhibited by temporal and spatial persistence in house prices, is not surprising when one considers the potential frictions affecting real estate markets. For instance, real estate markets do not clear immediately after a shock to the economy. The process of matching buyers with sellers of existing houses takes time. It also takes time for developers to bring new houses to the market, after an increase in demand, and to liquidate inventories when demand weakens.

Speculative inventory holding is very costly. Transaction costs in housing markets are also higher than other asset markets. Case *et al*. (2005) find that selling costs, such as five to six percent brokerage fees typically charged in the U.S., are high. In addition, both the physical and the psychological costs of moving (e.g. moving across neighborhoods and changing schools) are high. Such high transaction costs limit arbitrage opportunities for rational investors, and thus lead to pricing inefficiencies.

Brady (2014) reviews some recent studies on spatial aspects of housing prices that have incorporated Vector Autoregressions (VAR) as an approach to model simultaneity.[4] In earlier work, Anselin (2001) and Pace *et al*. (1998) introduce general methodologies for incorporating the time dimension in spatial models.[5] These papers followed Clapp and Tirtiroglu (1994), which was one of the pioneering works on spatial effects in house price dynamics that we referred to earlier, using house price data from Hartford, CT. These authors regress excess returns, defined as the difference between the return of a submarket within an MSA and the return at the MSA level, on the lagged excess returns of a group of neighboring towns and on a "control group" of non-neighboring towns. The authors find that estimated coefficients were significant for excess returns in neighboring towns, but insignificant for non-neighboring towns. Their results suggest that house price diffusion patterns exist within an MSA and are consistent with one form of a positive feedback hypothesis, where individuals would be expected to place more weight on past

---

[4] These include Pesaran and Chudik (2010), Holly et al (2011), Beenstock and Felsenstein (2007), and Kuethe and Pede (2011).

[5] One advantage of our approach over the approaches of Pace et al (1998), Anselin (2001), and others that utilize a VAR approach is that ours is well-suited for a study where contemporaneous spatial lags are not present. Our approach is also parsimonious, which is helpful in estimating versions of the model with time lags that contain several types of spatial lags.

price changes in their own and neighboring submarkets and less weight on those further away.

Pollakowski and Ray (1997) also examine house price spatial diffusion patterns, but at a much higher aggregation level. Using vector autoregressive models with quarterly log house price changes from the nine U.S. Census divisions, these authors are unable to identify a clear spatial diffusion pattern. Past growth rates in neighboring Census divisions were correlated with a particular division's current growth rates for some divisions. However, upon examining neighboring PMSAs within the greater New York CMSA, like Clapp and Tirtiroglu (1994), the authors find evidence in support of a positive feedback hypothesis. Shocks in housing prices in one metropolitan area are likely to Granger-cause subsequent shocks in housing prices in other metropolitan areas.

More recently, Brady (2008), using spatial impulse response function and VAR models, finds that spatial autocorrelations in house prices across counties in California are highly persistent over time. The average housing price in a Californian county is positively affected by bordering counties for up to 30 months. Brady (2011) examines how fast and how long a change in housing prices in one region affect its neighbors. Using an impulse response function with a panel of California counties, he finds that the diffusion of regional housing prices across space lasts up to two and half years. Brady (2014) estimates the spatial diffusion of housing prices across U.S. states over 1975-2011 using a single equation spatial autoregressive model. He shows that for the 1975 to 2011 period spatial diffusion of housing prices is statistically significant and persistent across US states and so is in the four US Census regions for the United States. He shows that the persistence of spatial diffusion may be more pronounced after 1999 than before.

Holly *et al*. (2010) also find spatial correlations in both housing prices across the eight Bureau of Economic Analysis (BEA) regions and housing prices across the contiguous states within the U.S. They find evidence of house price departures from the long run growth rates for markets in California, Massachusetts, New York, and Washington, even after accounting for spatial effects between states. Holly *et al*. (2010) work with data for the UK, but also allow for spillover from the US economy in order to explain the spatial and temporal diffusion of shocks in real house prices within the UK economy at the level of regions to illustrate its use. They model shocks that involve a region specific and a spatial effect. By focusing on London they allow for lagged effects to echo back to London, which in turn is influenced by international economic conditions via its link to New York and other financial centers. They show that New York house prices have a direct effect on London house prices. Their use of generalized spatio-temporal impulse responses allows them to highlight the diffusion of shocks both over time and over space.

An interesting recent development in this literature is the utilization of data on individual transactions. DeFusco *et al.* (2013) use micro data on the complete set of housing transactions between 1993 and 2009 in 99 US metropolitan areas to investigate contagion in the last housing cycle. By defining contagion as the price correlation between two different housing markets following a shock to one market that is above and beyond that which can be justified by common aggregate trends, their estimations allow them to determine the timing of local housing booms in a non-*ad hoc* way. The evidence for contagion is strong during the boom but not the bust phase of the cycle. They show that these effects are due to interactions between closest neighboring metropolitan area, with the price elasticity ranging from 0.10 to 0.27. The impact of larger markets on smaller markets imply greater elasticities. They show local fundamentals and expectations of future fundamentals are limited in accounting for their estimated effects, suggesting a potential role for non-rational forces.

Bayer *et al*. (2014) utilize data from a detailed register of housing transactions in the greater Los Angeles metropolitan Area from 1988 to 2012. Properties in their data set contain full geographic information, which allows them to readily merge with 2011 county tax assessor data and obtain information on property attributes, and for some of the data, additional information may be obtained from the Home Mortgage Disclosure Act (HMDA) forms on purchaser/borrower income and race. Bayer *et al*. find evidence of strong spillovers within neighborhoods: homeowners were much more likely to speculate both after a neighbor had successfully “flipped” a home and when a home had been successfully flipped in their neighborhood. Social contagion appears to be at work and to involve amateur investors, whose share of the market reached a record high at the same time as the market reached its peak, with equity losses following in the ensuing crash.

2. Econometric Models

As should be apparent in the above literature survey, one can postulate that housing prices (in our case, at the MSA level) in a given period depend on lagged housing prices, and MSA specific effects. By differencing the housing prices, we are left with a dependent variable of the annual house price growth rate of MSA_i at year t.[6] We utilize this measure to calculate one-year through four-year lagged house prices growth of MSA_i in year t. Similarly, we calculate the one-year, two-year, three-year, and four-year time lags of the spatial lags of the dependent variable. These spatial lags are obtained using the contiguity neighbor weights, the inverse distance weights for several distance intervals, and the migration weights. The results presented in the tables are for the growth-rate regressions, and the growth-rate regressions with the spatial lags for the adjacent weights, due to potential multicollinearity concerns between the inverse distance weighted house price lags for various intervals that lead to many insignificant t-statistics.

The growth rate of house prices in MSA_i is defined in the standard fashion as the difference in logs, $G_{i,t} = \log(HPI_{i,t}) - \log(HPI_{i,t-1})$. We compute the annual growth rate, $G_{i,t}$, by using values for each year's first quarter. It is important to note that such differencing eliminates unobserved additive heterogeneity at the log house price levels.

Baseline Model: Own-Lag Effects

We use a autoregressive model up to order 4, AR(4), for the house price annual growth rates as a baseline for comparison against spatial effects. The yearly growth rates $G_{i,t}$ are regressed against their four own lags,

$$G_{i,t} = \beta_0 + \beta_1 G_{i,t-1} + \beta_2 G_{i,t-2} + \beta_3 G_{i,t-3} + \beta_4 G_{i,t-4} + \varepsilon_{i,t} \quad , \qquad (1)$$

where $\varepsilon_{i,t}$, the error term, may include MSA-specific time-invariant fixed effects. Our choice of 4-year lags is based on the literature discussed above where other researchers

[6] The MSA fixed effects would then drop out, although for completeness we present two sets of results – one with and one without MSA fixed effects.

have found significant correlation between lagged and current growth-rates. In our estimation of model (1), all four lags are statistically significant; our results based on the Akaike Information Criterion (AIC) imply the four lag specification is preferred over models with additional lags.[7]

Incorporating Geography into the Model by Means of Cross-Lag Effects

We control for spatial effects in several ways. First, we add as a regressor in the r.h.s. of (1) the average annual growth rate in the HPI of all MSAs that border MSA_i at time period t, $A_{i,t}$, and up to four of its lags.[8] That is, we estimate dynamic fixed effect spatial autoregressive models up to order 4, SAR(4):[9]

$$G_{i,t} = \eta + \beta \,\vec{\phi}_{i,t} + \lambda \,\vec{\delta}_{i,t} + \varepsilon_{i,t}\,, \tag{2}$$

where η is a constant intercept, $\vec{\phi}_{i,t}$ is a vector of four own-lag growth rates, $\vec{\delta}_{i,t}$ is a vector of the four lags of the mean annual growth rate of all MSAs that border MSA_i, and β and λ are the respective vectors of parameters.

Second, we introduce physical distances between MSAs in order to examine whether spatial dependence in MSA house prices is related to distance among them. For each MSA_i, we group the remaining 362 MSAs into 5 groups. Group 1 includes all MSAs that are less than 100 km away from MSA_i, Group 2 includes all MSAs that are between 100 km and under 200 km from MSA_i, and Groups 3, 4, and 5 include MSAs that are between [200 km to 350 km), [350 km to 500 km), and [500 km to 1000 km) from MSA_i,

---

[7] One could argue that the lagged dependent variables can give rise to time series autocorrelation. It is for this reason that we have utilized the Heteroskedasticity Autocorrelation Consistent (HAC) estimator.

[8] Using adjacency as a measure of geographical proximity has also been used in previous literature. Dobkins and Ioannides (2001) use adjacency for comparing MSA population growth rates. Pollakowski and Ray (1997) and Holly *et al.* (2011) use it at the regional and the state level, respectively.

[9] Anselin (2001) and Pace et al (1998) provide overviews of space-time models.

respectively. The inverse distance weighted (IDW) growth rates for each of the 5 intervals for each MSA_i at time period t are calculated. The use of inverse distance weights imposes a particular spatial attenuation of interactions. The lagged IDW growth rates for each of the 6 intervals are then incorporated into (1), such that we have,

$$G_{i,t} = \eta + \beta \vec{\phi}_{i,t} + \lambda \vec{\delta}_{i,t} + \mu \vec{\omega}_{i,t} + \varepsilon_{i,t}, \qquad (3)$$

where $\vec{\omega}_{i,t}$ is a vector of the four lags for the annual inverse distance weighted growth rate of all MSAs in each of the 5 distance intervals relative to MSA *i*.

Finally, we add an additional set of spatial weights based on migration data. Specifically, we denote the (i,j) element of $\alpha_{i,t}$ as $\psi_t G_{i,t}$, where ψ_t is a 363 by 363 matrix in year t of the total migration – the sum of migration inflows and outflows – between MSA_j and MSA_i. We then modify equation (3) to incorporate the time lags of the migration weighted housing price growth rates:

$$G_{i,t} = \eta + \beta \vec{\phi}_{i,t} + \lambda \vec{\delta}_{i,t} + \mu \vec{\omega}_{i,t} + \gamma \alpha_{i,t} + \varepsilon_{i,t}, \qquad (4)$$

In this specification, the time period of our analysis covers 1996-2011, because these are the years covered by the migration data set.

Given the potential for multicolinearity among the inverse distance spatial lags (since one might speculate greater migration flows occur between larger cities that are far away), we estimate an alternative to equation (4). This estimation equation includes spatial lags for contiguous neighbors and for migration spatial lags:

$$G_{i,t} = \eta + \beta \vec{\phi}_{i,t} + \lambda \vec{\delta}_{i,t} + \gamma \alpha_{i,t} + \varepsilon_{i,t}, \qquad (5)$$

MSA-specific effects

The housing literature suggests that it may be important to consider MSA-specific effects in house prices dynamics. We recall the maxim “location-location-location” in connection with real estate and apply it at the MSA level. Indeed, intuitively, growth rates in house prices in MSA’s in a relatively warm state such as California could have different fundamental characteristics than houses in colder MSA’s in New England. In addition, Gyourko *et al*. (2006) identify “superstar cities,” defined as cities with extraordinarily high growth in real income and fixed housing supply, whose housing prices exhibit greater volatility and faster appreciation rates. There may well be unobservable idiosyncratic differences among different MSAs. Further, results reported in Thanapisitikul (2008) suggest widely varying patterns in boom and bust periods of the housing price cycle across MSAs. In addition to estimating these models without fixed effects, we also adopt fixed effects in the stochastic structure of Equations (2), (3), and (4) because such effects could capture MSA-specific patterns that may be correlated with other regressors.

Since the own-lags of the dependent variable are included as regressors, our model is susceptible to endogeneity bias. This is in principle quite important, especially because we use annual growth rates and not longer time unit of analysis such as five-year growth rates in house prices. Such bias may be due to a common component in the current period, which may arise from an exogenous shock in the previous period. Following Arellano and Bond (1991) and Glaeser and Gyourko (2006), we use the Arellano-Bond estimator. Briefly, this procedure utilizes the generalized method of moments (GMM) to instrument the dependent variable's own lag, $G_{i,t-1}$, with $G_{i,t-2}$. This process is repeated for the dependent variable's own second, third, and fourth lags. That is, $G_{i,t-2}$ is instrumented by $G_{i,t-3}$, $G_{i,t-3}$ by $G_{i,t-4}$, and $G_{i,t-4}$ by $G_{i,t-5}$. The same procedure is repeated for the possibly endogenous spatial regressors.

It is important to note that the Arellano-Bond estimator, like all instrumental estimation methods, hinges on two assumptions. First, $G_{i,t-h}$ must be correlated with $G_{i,t-h-1}$, where h denotes a lag. Second, the instrument, $G_{i,t-h-1}$, must be *uncorrelated* with the model's error term.[10] One potential problem that may arise is when the instruments of the spatial regressors are correlated with the time lag of the dependent variable, which could result in multicollinearity. As discussed in Brady (2008), this issue is less of a concern when there is high variability in the dependent variable. Since we use data from 363 MSAs, in which the variability in house price growth rates is high, this helps mitigate the problem of multicollinearity in the instruments and the in time lags of the dependent variable.

3. Data Description[11]

House Price Data

House price data are taken from the Office of Federal Housing Enterprise Oversight (OFHEO). We define a panel dataset that is comprised of annual (based on 1st quarter) house price indices from 363 MSAs within the continental U.S. The panel data run from the first quarter of 1975 until the first quarter of 2013 and they were first

[10] We examined the correlation between the instruments and the error term for the AB estimation of equation (1) below. The correlations range from 5.79x10^-19 to 1.07x10^-16. These correlations appear sufficiently small that we are confident the errors are uncorrelated with the instruments.
[11] See Table 1 for the complete list of MSAs included in this study, which are based on the U.S. Census Bureau's 2009 MSA definitions; and the summary statistics.

published in March of 1996. However, because OFHEO requires that an MSA must have at least 1,000 total transactions before the MSA's Housing Price Index (HPI) may be published, the panel is unbalanced, with only roughly half of the 363 MSAs have HPIs that begin in 1975. We are able to obtain a balanced panel beginning in 1995 through 2013. We use the first quarter data from each year during this period to construct the balanced panel. A map of the U.S. and all of the 363 MSA's is in Figure 1, and a list of the 363 MSA's is in Table 1.[12]

Spatial Data

We use three measures of spatial proximity. The first is a contiguity or adjacency matrix, *W* (363x363), and the second is a matrix of physical distances among metro areas, *D* (363x363).[13] The third is a set of migration weights with migration data. Provided by the Internal Revenue Service and compiled by Telestrian.

For the contiguity weights, any pair of MSAs that border one another, the value "1" is entered into *W*, otherwise the default value is "0". *W* is normalized such that the sum of each row equals one.

For the distance matrix, the U.S. Census Bureau provides centroids (reference points at the center of each polygon) for all of the 363 MSAs. The physical distances, measured in kilometers, between any pair of centroids define the entries in *D*.

---

[12] Note that since we focus on the continental U.S., Figure 1 includes some MSA's that we did not include in our sample, such as those in Alaska, Hawaii, and Puerto Rico. Also, Figure 1 shows Micropolitan Statistical Areas, but we restrict our attention to the MSA's due to data consistency and availability over our entire sample period of 1996-2013.

[13] All spatial distance data are calculated based on 2009 Tiger Line files from the U.S. Census Bureau, which include latitude and longitude for the MSA centroids. We use the Haversine distance formula to calculate the distances between each pair of MSA's. For the contiguity matrix, an ArcGIS script is used to identify whether any polygons (MSA boundary) pairs border one another.

The migration data are annual, covering the period 1996-2011 (16 years). The migration weights that MSA j have on MSA i in a given year are based on the sum of migration inflows and outflows between i and j in that year. Since our annual migration data cover the period 1996-2011, we construct a separate migration weights matrix for each of these years. We then row-normalize this migration weights matrix, and place them into a larger, block diagonal matrix that is dimension (16 times 363) by (16 times 363).

Consumer Price Index Data: The Consumer Price Index (CPI) data are taken from the Bureau of Labor Statistics (BLS). The data are the Urban Consumer CPI for All Items from 1995 to 2013, for each of 4 regions in the U.S. Each MSA is classified into one of these 4 regions, then the appropriate regional CPI is used to deflate its HPI. Using these regional CPI deflators avoids some limitations with the MSA-level CPI data that are noteworthy. First, the BLS only publishes CPI data for 27 metropolitan areas.[14] There are only 39 MSAs that fall inside (completely and partially) the boundaries of the 27 metropolitan areas. Therefore only 39 MSAs have an associated CPI, while many of the 39 MSAs also share common CPI. Second, the frequency of the published CPI varies (monthly, bimonthly, and semiannually) for different metropolitan areas. These variations do not necessary coincide with the timing of OFHEO's HPI, which is reported on a quarterly basis.

Descriptive statistics for the housing price growth and spatial lags of housing price growth are presented in Table 2. The typical MSA experienced year-over-year mean price growth of approximately 0.4%. Its neighbors' house price growth ranged from an average (mean and median) of between 2% and 3%, depending on the definitions

[14] See www.bls.gov for the list of the 27 metropolitan areas.

of neighbors. The largest year-over-year increase in an MSA over the years 1996-2013 was 28%, while the largest drop was 45%. This range is somewhat smaller for the neighboring MSA's maximum and minimum year-over-year price growth.

4. Empirical Results

4.1 Own-Lag Effects: Baseline Results

For our entire sample of 1996-2013, we first report the results of the own-lags regression.

Table 3 reports the baseline results from estimating equation (1) with only own-lags effects and MSA fixed effects, for the real (i.e., deflated) housing price growth regression. Column 1, Table 3, reports the coefficient estimates of the own-lagged model with fixed effects. The coefficients on the first 2 lags are positive, less than 1, and statistically significant. The coefficients on the 3 year and 4 year lags are negative, less than 1 in absolute value, and statistically significant. The sign of the one-year lag coefficient is consistent with previous literature, suggesting that the first own-lag of house prices has explanatory power in forecasting the next period's house prices. Since the third, and fourth own-lags are all also highly statistically significant but negative, once again this may suggest mean reversion.

Column 1 of Table 6 reports the results using the Arellano-Bond correction (and Table 4 presents results for the corresponding estimation approach including fixed effects). The signs for the first and third lag coefficients remain unchanged but the magnitudes are somewhat larger than those in column 1.[15] The 4-period lagged growth rate coefficient is now positive. All four coefficient estimates are highly statistically significant once again.

We introduce four time lags of the spatially lagged growth rates of all MSAs adjacent to MSA_i as additional regressors, as in equation (2). We perform a likelihood ratio test between the restricted model (OLS estimates of own-lags without the presence of adjacent spatial regressors) and the unrestricted models (equation (2)). The LR test statistic is approximately equal to 100, while the χ^2 statistic (critical value) with 4 degrees of freedom is 9.49. Hence, the LR test strongly rejects the null hypothesis at all levels of statistical significance that spatial dependence is *not* present in the residuals.

Column 3 of Table 3 presents the growth rates with fixed effects regression results, for the estimated coefficients of lags of contiguity weights spatial regressors. The first 3 of these coefficients are positive, while the second and fourth time lags are statistically significant at all significance levels.

A number of remarks are in order. First, spatial effects from growth rates of housing prices in neighboring MSAs are clearly present. Second, in general, lagged house price growth rates for adjacent MSAs have a comparable degree of explanatory power relative to the own-lags in explaining MSA_i's current growth rates. Third, including fixed effects does not substantially affect the estimates.[16] And fourth, the own-lag effects and

---

[15]Although the magnitude of the coefficient on the one-year lag is greater than 1.0, it is not statistically significantly greater than 1.0.
[16] For completeness, we include the fixed effects estimates in Table 3. Obviously, if the original model is a fixed effects specification with the house price index in levels, these fixed effects would drop out when obtaining the first differences.

cross-lag effects could be co-determined. Accordingly, we re-estimate these models with the Arellano-Bond estimator, which accounts for potential endogeneity of the regressors.

Column 3 of Table 4 reports the results including both the own-lags and the time lags of the spatial variables with the Arellano-Bond estimator. Here the first and third year time lags of the own lags are significant, and lag four of the spatial lags is negative and significant.[17]

We also estimated models where we add time lags of inverse distance weights spatial lags, as in equation (3). Once again, all four of the own-price lags are statistically significant, but all of the contiguity neighbor spatial lags, and all of the inverse distance spatial lags with the exception of the second and fourth year lags of the 500 to 1000 km spatial lags, are statistically insignificant. The results for equation (3) with the Arellano-Bond estimator are much worse, with none of the parameter estimates significant. We examined the correlations between the various inverse distance and contiguity spatial lag variables, and find that there is likely a high degree of multicollinearity that is leading to insignificant parameter estimates. Given the lack of significance of most of the parameters when we include inverse distance weighted spatial lags, we omit those results from the tables.[18]

Finally, we add time lags of spatial lags using migration weights, as in equation (5).[19] Since our migration data covers the years 1996-2011, we estimate equation (5) for this time period. Column 5 of Tables 3 and 4 present the results for equation (5) estimated by OLS and using the Arellano-Bond estimator, respectively, both including

---

[17] The one-period lag on both the own-lag and the spatial lag are greater than 1.0 in magnitude, but not statistically significantly greater than 1.0.
[18] These results are available from the authors upon request.
[19] We omit the inverse distance weighted spatial lags from this specification, due to severe multicolinearity among the inverse distance spatial lags.

fixed effects. In the OLS case for the time lags of the spatially lagged migration weights, the second time lag is positive and significant, while the fourth time lag is negative and significant; the other two time lags are insignificant. Given our earlier concerns of potential endogeneity, we re-estimated equation (5) using the Arellano-Bond estimator. Once again, all parameter estimates are highly insignificant. While one might anticipate that there can be persistence over time in MSA-to-MSA migration that leads to time series autocorrelation and contributing to the high standard errors (and in turn, low t-statistics), all of these estimates are based on Heteroskedasticity and Autocorrelation Consistent (HAC) standard errors. Thus, it is likely in the full sample that when we include time lags of both types of spatial lags and control for potential endogeneity, there is little evidence of spatial spillovers. One might conjecture, however, that this result does not hold during the period following a "bust", so we turn our attention to the post-2007 period.

4.2.2 Post-2007 Results

Since one might expect the results to differ after the bust of 2007-08, we re-estimated the models described above, for the period 2008-2013 (and for equation (5), for the period 2008-2011).

For the model with both spatial lags and own-lags (equation 2) where we estimate using the Arellano-Bond procedure (column 4 of Table 4), 3 out of 4 of the own-lags in the post-2007 period are larger in magnitude than for the entire sample. More importantly, there is no immediate spatial contagion in this post-2007 model, since the one-, two-, and four-period lags of the spatial lag are insignificant, but the three-period lag of the spatial lag is significant.[20] This implies that contagion was more important after the crisis of 2007-08.

For the time lags of the migration weighted spatial lags estimated with the Arellano-Bond approach in equation (5), shown in column 6 of Table 4, the own-price lags are insignificant, but the two- and three-period lagged migration weighted prices are significant. Since virtually all MSA fixed effects are highly insignificant, we estimated equation (5) again without fixed effects, in column 6 of Table 6. In this model, 3 out of the 4 migration lags are significant, and the first two own-price lags are significant. [21]

5. Impulse Response Functions

Given the significance of several of the time lags of the spatial lags, an examination of the impulse responses allows us to generate insights on the adjustment process to shocks with and without consideration of spatial spillovers. Here we report two sets of simulations that utilize the results from the previous section in order to help us conceptualize how a unit shock (100 percent) on house prices in one area propagates across time and space, *ceteris paribus*. The first set of simulations examine how house prices in one area respond to a shock in the same area, considering the spatial structure of the models and based on parameter estimates from the 1996-2013 regressions. The results from the first simulation will serve as a benchmark against the results based on parameter

[20] None of the four spatial lags are statistically significant in the full sample, while one of the spatial lags are statistically significant in the post-2007 sample.

[21] With the inverse distance weights model in equation (3) for post-2007, only 3 of the time-lagged inverse distance spatial lags are significant, and all of the own time lags are statistically significant. This is a slight improvement over the results for the entire sample, but still somewhat disappointing, likely due to the multicollinearity between the inverse distance-weighted spatial lags. In the version of the model with the Arellano-Bond estimator for post-2007, the one-year and two-year own time lags are the only two statistically significant variables in the model. These detailed coefficient estimates are available from the authors upon request.

estimates from the post-2007 period, which is the focus of the second simulation. Both sets of simulations focus on the house price dynamics in a particular MSA. One considers the situation where there are no spatial effects and the second simulation is based on regression parameter estimates where there are a variety of types of spatial effects.

Simulation 1: 1996-2013

We report the impulse response function of house prices in an MSA, to an exogenous unit shock that occurred in X, and follow the effect the shock has on house prices in X over time.[22] These impulse responses are based on several different model specifications presented above, using the 1996-2013 data. These impulse response functions are presented in Figure 2a (based on the model with only own time-lag effects), Figure 2b (based on the model with own time-lag effects and lagged neighbor effects), and Figure 2c (based on the model with own time-lag effects, lagged neighbor-effects, and lagged migration weighted spillover effects). These impulse response functions demonstrate that the adjustment to the unit shock is smaller when based on the model without spatial effects (0.79) compared with the model with contiguity neighbor spatial effects (0.83) and both contiguity and migration spatial effects (0.84). Also, in all cases, home prices overreact positively to an exogenous positive shock on house prices, and then the positive reactions turn negative, before becoming positive again and finally returning to equilibrium growth rates. But in the simulations based on the parameter estimates from the models with spatial effects, this process is slightly faster, with the prices becoming negative more quickly, and a more rapid return to equilibrium.

[22] We also include confidence intervals, for two standard deviations, in these impulse response figures.

Simulation 2: 2008-2013

In this second simulation, we use the parameter estimates based on estimation covering the period 2008-2013, for the model with no spatial effects, and separately, for the model with lagged contiguity neighbor spatial effects, and separately with both lagged contiguity and lagged migration spatial effects.[23] There is a stark difference in the own-lag effect simulation (Figure 3a), with a very precipitous fall-off in the response in the first few periods. When we consider the spatial effects in our estimation, the corresponding impulse responses are much smoother. In other words, based on post-2007 estimations with spatial effects, the impulse responses exhibit greater persistence. This is in contrast with the impulse responses from the estimates on the entire 1996-2013 period, where the differences in the impulse responses based on the spatial and non-spatial models are small but not very pronounced. Clearly, considering spatial effects during periods of a bust is more important than when considering all parts of the housing cycle. By ignoring spatial effects in examining the impacts of a shock during a “bust”, one misses the persistence in this shock (as in Figures 3b and 3c) that otherwise may not be apparent.

6. Conclusions

We find that studying house price dynamics at low levels of aggregation such as the MSA level can be more informative than those at the national and the Census region levels. This is because at the large level of aggregation the regional own-lag effects

[23] Since the migration data ends in 2011, the estimation for the spatial model including the migration weights for post-2007 covers the period 2008-2011.

obscure the own-lag effects and spatial effects of MSAs within the respective Census division.

Using panel data from 363 MSAs across the U.S. from 1996 to 2013, we find that there is a notable spatial diffusion pattern in inter-MSAs house prices. Specifically, information on lagged price changes in neighboring (i.e., contiguous) MSAs, in addition to an MSA's own time-lagged price changes, help explain current house price changes. Consideration of migration flows can also be a driver for spatial interconnectivity in housing prices across MSA's. Such spatial attenuation is intuitively appealing, but has not been documented in earlier research. We use our estimation results to obtain impulse response functions for the house price dynamics.

Overall, we find that spatial effects play a significant role in explaining house prices even after controlling for own-lag effects. These spatial effects are particularly pronounced when considering the post-2007 sample period. In other words, our results imply greater spatial contagion following the 2007-08 crisis.

Our finding of very significant spatial effects underscores the need to incorporate the spatial dimension into existing house price dynamic equilibrium models, such as Glaeser and Gyourko's (2006). A worthwhile direction for future research is full structural form estimations of house price dynamics, with key regressors such as income, mortgage rates and interest rates, taxes, and housing supply changes.

The spatial threshold effects in spatial house price interactions that we identify suggest that policy makers and economic agents must take into account spatial attenuation and interactions when making economic decisions. For instance, it may be important to consider the spatial diffusion pattern in inter-MSAs house prices when formulating business development policies as the impact of such policy in some areas may spillover into the housing markets of neighboring areas.

Our results on the richness of the dynamics in house prices are relevant in assessing arguments about housing price bubbles. Consider Robert Shiller's *New York Times* article "How a Bubble Stayed under the Radar," [Shiller (2008)] on detecting housing bubbles. Shiller argues that the fundamental problem in verifying the existence of a housing market bubble is that

> "[the] information obtained by any individual — even one as well-placed as the chairman of the Federal Reserve — is bound to be incomplete. If people could somehow hold a national town meeting and share their independent information, they would have the opportunity to see the full weight of the evidence. Any individual errors would be averaged out, and the participants would collectively reach the correct decision."

Shiller goes on to state that

> "Of course, such a national town meeting is impossible. Each person makes decisions individually, sequentially, and reveals his decisions through actions — in this case, by entering the housing market and bidding up home prices" [*ibid.*]

Our paper provides some evidence on Shiller's argument. Specifically, information from neighboring areas is very important. Naturally, overreactions are smaller when people can share information, even if the combined information is still incomplete.

References

Anselin, Luc. 2001. Spatial econometrics. *A companion to Theoretical Econometrics, 310330*.

Arellano, Manuel, and Stephen Bond. 1991. "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations," *Review of Economic Studies*. 58(2):277-97.

Bayer, Patrick, Kyle Mangum, and James Roberts. 2014. "Speculative Fever: Micro Evidence for Investor Contagion in the Housing Bubble." Duke working paper, preliminary. June.

Basu, Sabyasachi, and Thomas G. Thibodeau. 1998. "Analysis of Spatial Autocorrelation in House Prices," *Journal of Real Estate Finance and Economics*. 17: 61-85.

Beenstock, Michael, and Daniel Felsenstein. 2007. "Spatial Vector Autoregressions." *Spatial Economic Analysis* 2(2): 167-196.

Brady, Ryan B. 2008. "Measuring the Persistence of Spatial Autocorrelation: How Long does the Spatial Connection between Housing Markets Last?" United States Naval Academy Department of Economics Working Papers 2008-19.

Brady, Ryan B. 2011. "Measuring the Diffusion of Housing Prices across Space and over Time." *Journal of Applied Econometrics*, 26: 213-231.

Brady, Ryan B. 2014. "The Spatial Diffusion of Regional Housing Prices across U.S. States." *Regional Science and Urban Economics*. 46:150-166.

Calhoun, Charles A. 1996. "OFHEO House Price Indexes: HPI Technical Description." Office of Federal Housing Enterprise Oversight.

Case, Karl E., and Robert J. Shiller. 1989. "The Efficiency of the Market for Single-Family Homes," *American Economic Review*. 79(1):125-37.

Case, Karl E., John M. Quigley, and Robert J. Shiller. 2005. "Stock Market Wealth, Housing Market Wealth, Spending and Consumption", working paper, http://www.escholarship.org/uc/item/28d3s92s .

Clapp, John M., and Dogan Tirtiroglu. 1994. "Positive Feedback Trading and Diffusion of Asset Price Changes: Evidence from Housing Transactions." *Journal of Economic Behavior and Organization*. 24(3):337-55.

Cutler, David M., James M. Poterba, and Lawrence H. Summers. 1991. "Speculative Dynamics and the Role of Feedback Traders," *American Economic Review*. 80(2): 63-68.

DeFusco, Anthony, Wenjie Ding, Fernando Ferreira, and Joseph Gyourko. 2013. "The Role of Contagion in the Lst American Housing Cycle." Wharton School working paper.

Dobkins, Linda H., & Ioannides, Yannis M. Ioannides. 2001. "Spatial Interactions among US Cities: 1900–1990" *Regional Science and Urban Economics*. *31*(6): 701-731.

Glaeser, Edward L., and Joseph Gyourko. 2006. "Housing Dynamics," National Bureau of Economic Research, Inc, NBER Working Paper No. W12787.

Guntermann, Karl L., and Stefan C. Norrbin. 1991. Empirical Tests of Real Estate Market Efficiency," *Journal of Real Estate Finance and Economics*, 4(3): 297-313.

Henderson, J. Vernon, and Yannis M. Ioannides. 1983. "A Model of Housing Tenure Choice," *American Economic Review*. 73(1): 98-113.

Holly, Sean, M. Hashem Pesaran, and Takashi Yamagata. 2011. "Spatial and Temporal Diffusion of House Prices in the UK." *Journal of Urban Economics*. 69(1):2-23.

Holly, Sean, M. Hashem Pesaran, and Takashi Yamagata. 2010. "A Spatio-Temporal Model of House Prices in the USA." *Journal of Econometrics.* 158:160-173.

Kuethe, Todd H., and Valerien O. Pede, 2011. Regional housing price cycles: a spatio-temporal analysis using US state-level data. *Regional Studies*. *45*(5):563-574.

Pace, R. Kelley, Ronald Barry, John M. Clapp, and Mauricio Rodriquez. 1998. "Spatial Temporal autoregressive Models of Neighborhood Effects." *Journal of Real Estate Finance and Economics*, 17(1): 15-33.

Pesaran, M. Hashem, and Alexander Chudik. 2010. "Econometric Analysis of High Dimensional VARs Featuring a Dominant Unit" ECB Working Paper No. 1194.

Pollakowski, Henry O., and Traci S. Ray. 1997. "Housing Price Diffusion Patterns at Different Aggregation Levels: An Examination of Housing Market Efficiency." *Journal of Housing Research*. 8(1):107-24.

Rayburn, William, Michael Devaney, and Richard Evans. 1987. "A Test of Weak-Form Efficiency in Residential Real Estate Returns," *American Real Estate and Urban Economics Association Journal*. 15(3):220-33.

Shiller, Robert J. 2008. "How a Bubble Stayed Under the Radar," *The New York Times*, p. B1, March 2.

Thanapisitikul, Wirathip. 2008. "U.S. House Prices: Dynamics and Spatial Interactions, 1975-2007," B.S. Thesis, Tufts University.

Figure 1 – Metropolitan Statistical Areas of the U.S. (2009 definitions), U.S. Census Bureau

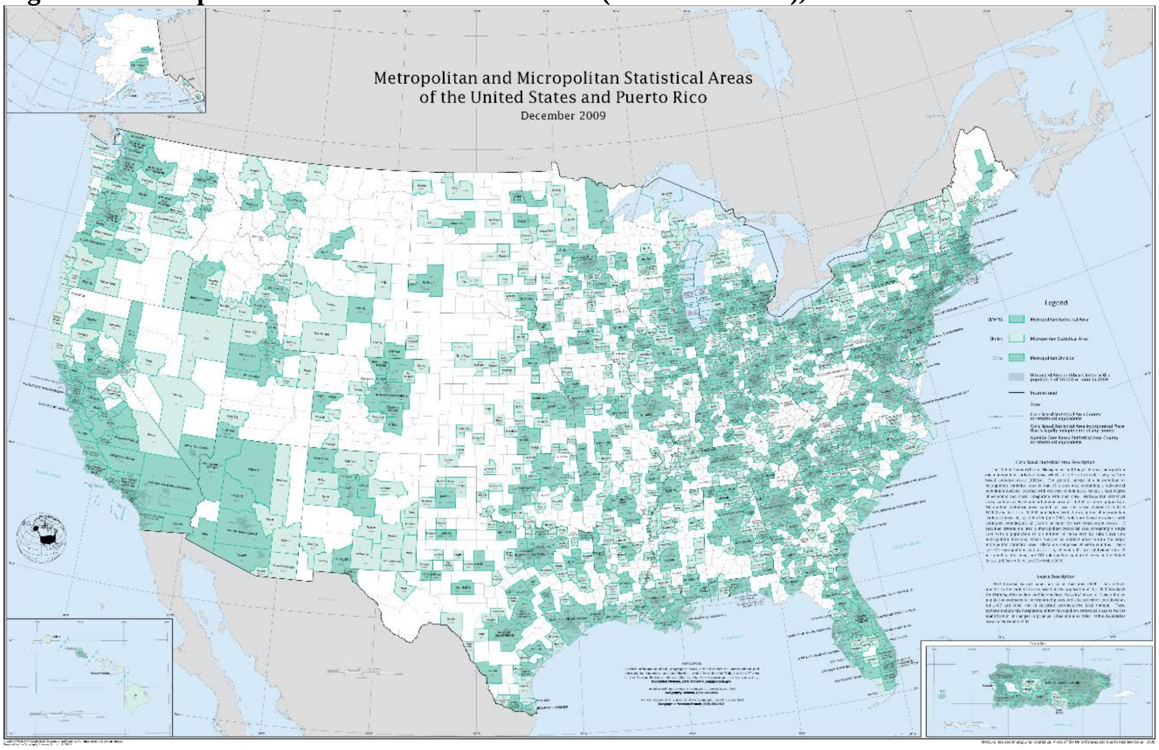


Figure 2a: Impulse Response, Own Time-lags only, Full Sample Regressions

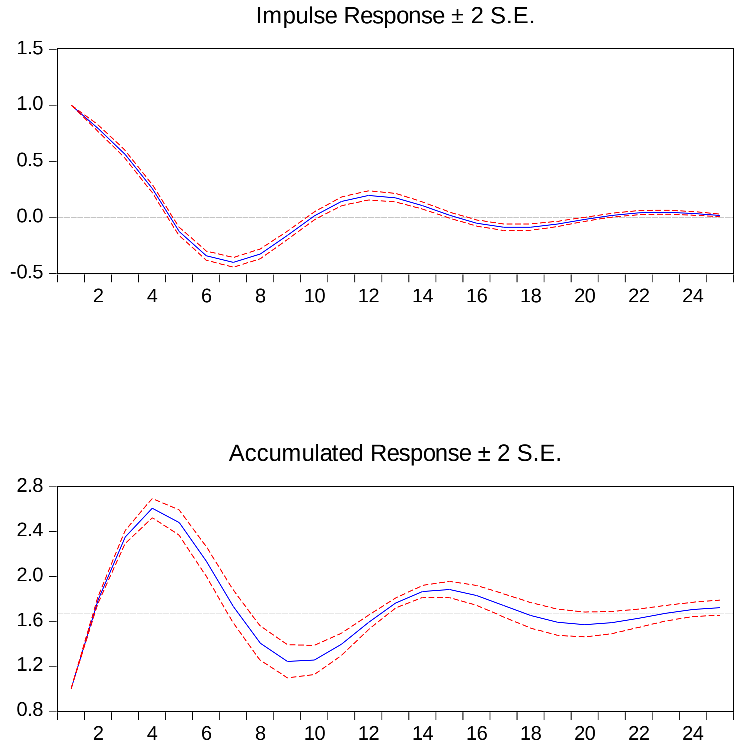


Figure 2b: Impulse Response, Own-Time-lags and Time-lags of Contiguous Neighbors, Full Sample Regressions

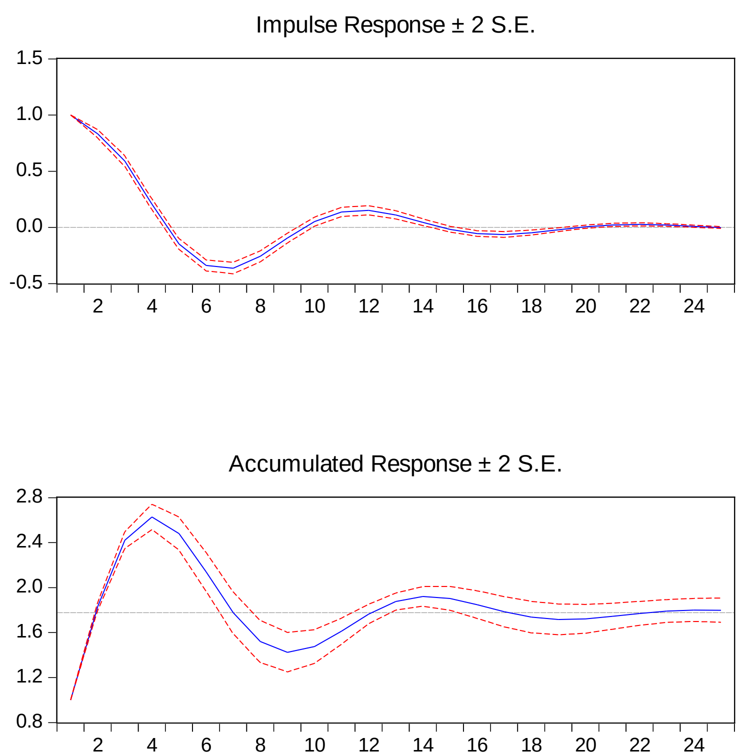
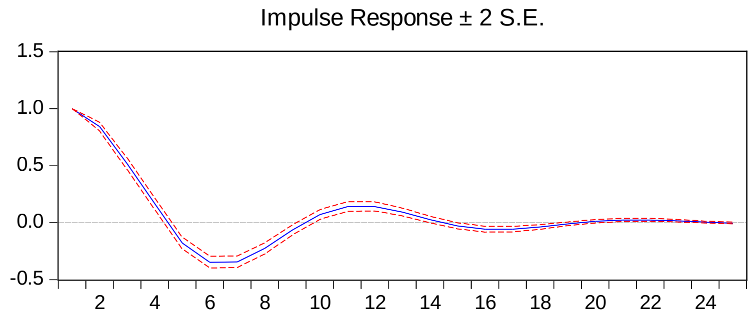


Figure 2c – Impulse Response, Own-Time-lags, Time-lags of Continuous Neighbors and Total Migration Flow Weighted Neighbors, Full Sample Regressions



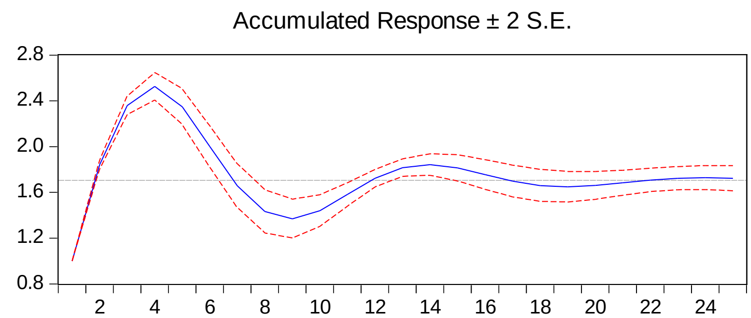


Figure 3a: Impulse Response, Own Time-lags only, Post-2007 Regressions

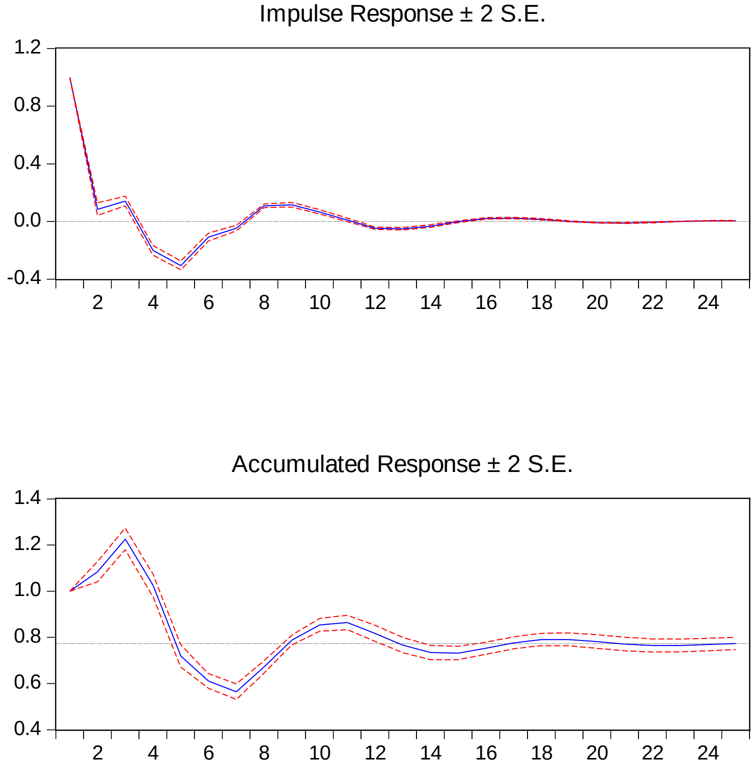


Figure 3b: Impulse Response, Own-Time-lags and Time-lags of Contiguous Neighbors, Post-2007 Regressions

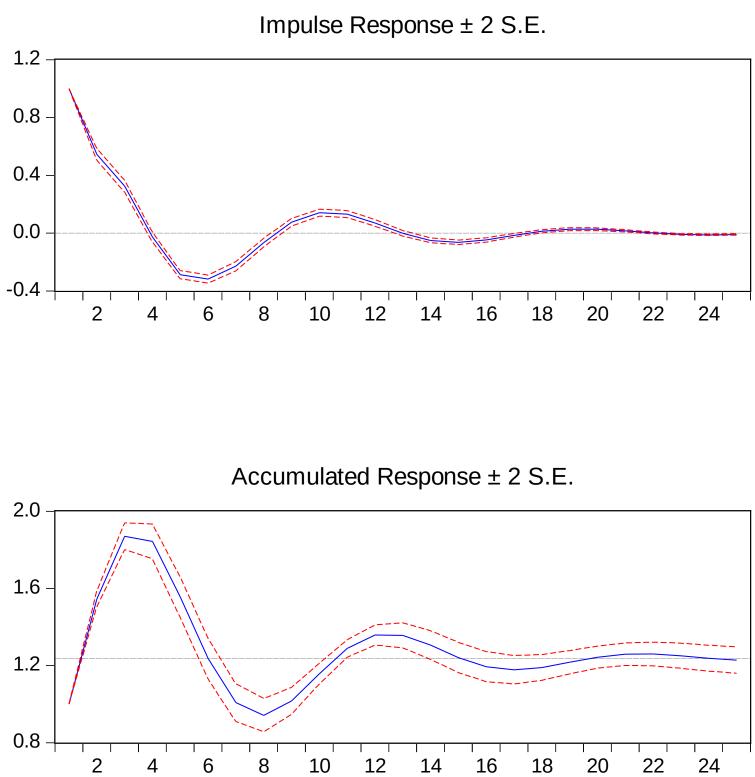


Figure 3c: Impulse Response, Own-Time-lags, Time-lags of Continuous Neighbors and Total Migration Flow Weighted Neighbors, Post-2007 Regressions

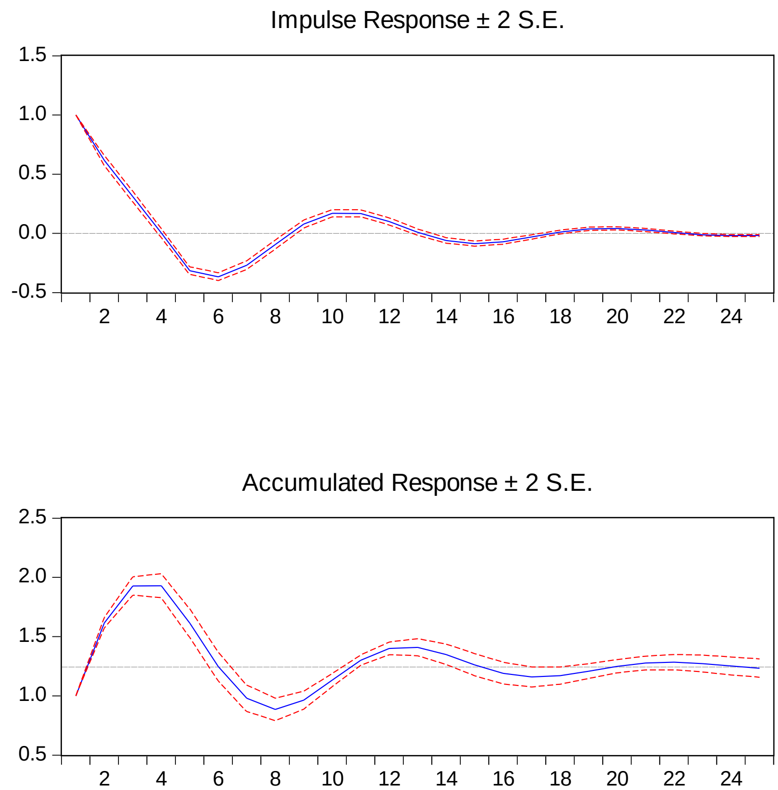


Table 1: 363 MSA's in the continental U.S. (2009 U.S. Census Delineations)

Abilene, TX
Akron, OH
Albany, GA
Albany-Schenectady-Troy, NY
Albuquerque, NM
Alexandria, LA
Allentown-Bethlehem-Easton, PA-NJ
Altoona, PA
Amarillo, TX
Ames, IA
Anderson, IN
Anderson, SC
Ann Arbor, MI
Anniston-Oxford, AL
Appleton, WI
Asheville, NC
Athens-Clarke County, GA
Atlanta-Sandy Springs-Marietta, GA
Atlantic City-Hammonton, NJ
Auburn-Opelika, AL
Augusta-Richmond County, GA-SC
Austin-Round Rock, TX
Bakersfield, CA
Baltimore-Towson, MD
Bangor, ME
Barnstable Town, MA
Baton Rouge, LA
Battle Creek, MI
Bay City, MI
Beaumont-Port Arthur, TX
Bellingham, WA
Bend, OR
Billings, MT
Binghamton, NY
Birmingham-Hoover, AL
Bismarck, ND
Blacksburg-Christiansburg-Radford, VA
Bloomington, IN
Bloomington-Normal, IL
Boise City-Nampa, ID
Boston-Cambridge-Quincy, MA-NH
Boulder, CO
Bowling Green, KY
Bradenton-Sarasota-Venice, FL
Bremerton-Silverdale, WA
Bridgeport-Stamford-Norwalk, CT
Brownsville-Harlingen, TX
Brunswick, GA
Buffalo-Niagara Falls, NY
Burlington, NC
Burlington-South Burlington, VT
Canton-Massillon, OH
Cape Coral-Fort Myers, FL
Cape Girardeau-Jackson, MO-IL
Carson City, NV
Casper, WY
Cedar Rapids, IA
Champaign-Urbana, IL
Charleston, WV
Charleston-North Charleston-Summerville, SC
Charlotte-Gastonia-Concord, NC-SC
Charlottesville, VA
Chattanooga, TN-GA
Cheyenne, WY
Chicago-Naperville-Joliet, IL-IN-WI
Chico, CA
Cincinnati-Middletown, OH-KY-IN
Clarksville, TN-KY
Cleveland, TN
Cleveland-Elyria-Mentor, OH
Coeur d'Alene, ID
College Station-Bryan, TX
Colorado Springs, CO
Columbia, MO
Columbia, SC
Columbus, GA-AL
Columbus, IN
Columbus, OH
Corpus Christi, TX
Corvallis, OR
Cumberland, MD-WV
Dallas-Fort Worth-Arlington, TX
Dalton, GA
Danville, IL
Danville, VA
Davenport-Moline-Rock Island, IA-IL
Dayton, OH
Decatur, AL
Decatur, IL
Deltona-Daytona Beach-Ormond Beach, FL
Denver-Aurora-Broomfield, CO
Des Moines-West Des Moines, IA
Detroit-Warren-Livonia, MI
Dothan, AL
Dover, DE
Dubuque, IA
Duluth, MN-WI
Durham-Chapel Hill, NC
Eau Claire, WI
El Centro, CA
El Paso, TX
Elizabethtown, KY
Elkhart-Goshen, IN
Elmira, NY
Erie, PA
Eugene-Springfield, OR
Evansville, IN-KY
Fargo, ND-MN
Farmington, NM
Fayetteville, NC
Fayetteville-Springdale-Rogers, AR-MO
Flagstaff, AZ
Flint, MI
Florence, SC
Florence-Muscle Shoals, AL
Fond du Lac, WI
Fort Collins-Loveland, CO
Fort Smith, AR-OK
Fort Walton Beach-Crestview-Destin, FL
Fort Wayne, IN
Fresno, CA
Gadsden, AL
Gainesville, FL
Gainesville, GA
Glens Falls, NY
Goldsboro, NC
Grand Forks, ND-MN
Grand Junction, CO
Grand Rapids-Wyoming, MI
Great Falls, MT
Greeley, CO
Green Bay, WI
Greensboro-High Point, NC
Greenville, NC
Greenville-Mauldin-Easley, SC
Gulfport-Biloxi, MS
Hagerstown-Martinsburg, MD-WV
Hanford-Corcoran, CA
Harrisburg-Carlisle, PA
Harrisonburg, VA
Hartford-West Hartford-East Hartford, CT
Hattiesburg, MS
Hickory-Lenoir-Morganton, NC
Hinesville-Fort Stewart, GA
Holland-Grand Haven, MI
Hot Springs, AR
Houma-Bayou Cane-Thibodaux, LA
Houston-Sugar Land-Baytown, TX
Huntington-Ashland, WV-KY-OH
Huntsville, AL
Idaho Falls, ID
Indianapolis-Carmel, IN
Iowa City, IA
Ithaca, NY
Jackson, MI
Jackson, MS
Jackson, TN
Jacksonville, FL
Jacksonville, NC
Janesville, WI
Jefferson City, MO
Johnson City, TN
Johnstown, PA
Jonesboro, AR
Joplin, MO
Kalamazoo-Portage, MI
Kankakee-Bradley, IL
Kansas City, MO-KS
Kennewick-Pasco-Richland, WA
Killeen-Temple-Fort Hood, TX
Kingsport-Bristol-Bristol, TN-VA
Kingston, NY
Knoxville, TN
Kokomo, IN
La Crosse, WI-MN
Lafayette, IN
Lafayette, LA
Lake Charles, LA
Lake Havasu City-Kingman, AZ
Lakeland-Winter Haven, FL
Lancaster, PA
Lansing-East Lansing, MI
Laredo, TX
Las Cruces, NM
Las Vegas-Paradise, NV
Lawrence, KS
Lawton, OK
Lebanon, PA
Lewiston, ID-WA
Lewiston-Auburn, ME
Lexington-Fayette, KY
Lima, OH
Lincoln, NE
Little Rock-North Little Rock-Conway, AR
Logan, UT-ID
Longview, TX
Longview, WA
Los Angeles-Long Beach-Santa Ana, CA
Louisville-Jefferson County, KY-IN
Lubbock, TX
Lynchburg, VA
Macon, GA
Madera-Chowchilla, CA
Madison, WI
Manchester-Nashua, NH
Manhattan, KS
Mankato-North Mankato, MN
Mansfield, OH
McAllen-Edinburg-Mission, TX
Medford, OR
Memphis, TN-MS-AR
Merced, CA
Miami-Fort Lauderdale-Pompano Beach, FL
Michigan City-La Porte, IN
Midland, TX
Milwaukee-Waukesha-West Allis, WI
Minneapolis-St. Paul-Bloomington, MN-WI
Missoula, MT
Mobile, AL
Modesto, CA
Monroe, LA
Monroe, MI
Montgomery, AL
Morgantown, WV
Morristown, TN
Mount Vernon-Anacortes, WA
Muncie, IN
Muskegon-Norton Shores, MI
Myrtle Beach-North Myrtle Beach-Conway, SC
Napa, CA
Naples-Marco Island, FL
Nashville-Davidson--Murfreesboro--Franklin, TN
New Haven-Milford, CT
New Orleans-Metairie-Kenner, LA
New York-Northern New Jersey-Long Island, NY-NJ-PA
Niles-Benton Harbor, MI
Norwich-New London, CT
Ocala, FL
Ocean City, NJ
Odessa, TX
Ogden-Clearfield, UT
Oklahoma City, OK
Olympia, WA
Omaha-Council Bluffs, NE-IA
Orlando-Kissimmee, FL
Oshkosh-Neenah, WI
Owensboro, KY
Oxnard-Thousand Oaks-Ventura, CA
Palm Bay-Melbourne-Titusville, FL
Palm Coast, FL
Panama City-Lynn Haven-Panama City Beach, FL
Parkersburg-Marietta-Vienna, WV-OH
Pascagoula, MS
Pensacola-Ferry Pass-Brent, FL
Peoria, IL
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD
Phoenix-Mesa-Scottsdale, AZ
Pine Bluff, AR
Pittsburgh, PA
Pittsfield, MA
Pocatello, ID
Port St. Lucie, FL
Portland-South Portland-Biddeford, ME
Portland-Vancouver-Beaverton, OR-WA
Poughkeepsie-Newburgh-Middletown, NY
Prescott, AZ
Providence-New Bedford-Fall River, RI-MA
Provo-Orem, UT
Pueblo, CO
Punta Gorda, FL
Racine, WI
Rapid City, SD
Reading, PA
Redding, CA
Reno-Sparks, NV
Richmond, VA
Riverside-San Bernardino-Ontario, CA
Roanoke, VA
Rochester, MN
Rochester, NY
Rockford, IL
Rocky Mount, NC
Rome, GA
Sacramento--Arden-Arcade--Roseville, CA
Saginaw-Saginaw Township North, MI
Salem, OR
Salinas, CA
Salisbury, MD
Salt Lake City, UT
San Angelo, TX
San Antonio, TX
San Diego-Carlsbad-San Marcos, CA
San Francisco-Oakland-Fremont, CA
San Jose-Sunnyvale-Santa Clara, CA
San Luis Obispo-Paso Robles, CA
Sandusky, OH
Santa Barbara-Santa Maria-Goleta, CA
Santa Cruz-Watsonville, CA
Santa Fe, NM
Santa Rosa-Petaluma, CA
Savannah, GA
Scranton--Wilkes-Barre, PA
Seattle-Tacoma-Bellevue, WA
Sebastian-Vero Beach, FL
Sheboygan, WI
Sherman-Denison, TX
Shreveport-Bossier City, LA
Sioux City, IA-NE-SD
Sioux Falls, SD
South Bend-Mishawaka, IN-MI
Spartanburg, SC
Spokane, WA
Springfield, IL
Springfield, MA
Springfield, MO
Springfield, OH
St. Cloud, MN
St. George, UT
St. Joseph, MO-KS
St. Louis, MO-IL
State College, PA
Stockton, CA
Sumter, SC
Syracuse, NY
Tallahassee, FL
Tampa-St. Petersburg-Clearwater, FL
Terre Haute, IN
Texarkana, TX-Texarkana, AR
Toledo, OH
Topeka, KS
Trenton-Ewing, NJ
Tucson, AZ
Tulsa, OK
Tuscaloosa, AL
Tyler, TX
Utica-Rome, NY
Valdosta, GA
Vallejo-Fairfield, CA
Victoria, TX
Vineland-Millville-Bridgeton, NJ
Virginia Beach-Norfolk-Newport News, VA-NC
Visalia-Porterville, CA
Waco, TX
Warner Robins, GA
Washington-Arlington-Alexandria, DC-VA-MD-WV
Waterloo-Cedar Falls, IA
Wausau, WI
Weirton-Steubenville, WV-OH
Wenatchee-East Wenatchee, WA
Wheeling, WV-OH
Wichita Falls, TX
Wichita, KS
Williamsport, PA
Wilmington, NC
Winchester, VA-WV
Winston-Salem, NC
Worcester, MA
Yakima, WA
York-Hanover, PA
Youngstown-Warren-Boardman, OH-PA
Yuba City, CA
Yuma, AZ

Table 2: Descriptive Statistics, Year-Over-Year Housing Price Growth and Spatial Lags, 1996-2013

Sample: 1 8712 IF YEAR>1995 AND YEAR<2014

	HOUSE_PRICE_GROWTH_REAL	WX_NEIGHBOR	WX_MIGRATION
Mean	0.004303	0.024086	0.027653
Median	0.008713	0.026198	0.035223
Maximum	0.284685	0.316475	0.235201
Minimum	-0.458622	-0.458622	-0.173963
Std. Dev.	0.061543	0.051705	0.044549
Skewness	-0.544800	-0.226287	-0.414428
Kurtosis	8.171865	7.775563	3.767376
Jarque-Bera	7605.418	6264.698	347.3548
Probability	0.000000	0.000000	0.000000
Sum	28.11633	157.3766	180.6839
Sum Sq. Dev.	24.74392	17.46535	12.96570
Observations	6534	6534	6534

Table 3 - Full Sample, 1996-2013*, MSA Fixed Effects (FE), HAC consistent std errors
Dependent Variable: House Price Index Growth between year t and t-1, for MSA i

	FE	FE post-2007	FE	FE post-2007	FE	FE, post-2007
constant	0.001337	-0.09922	0.001428	-0.102672	0.002258	-0.104176
	0.067945	***-6.627418***	***0.141102***	***-7.085534***	***0.225425***	***-6.72806***
Lagged Growth (t-1)	0.664548	0.084501	0.654179	0.098031	0.6436	-0.008955
	18.075	***3.878959***	***48.45978***	***4.236311***	***44.90283***	***-0.302542***
Lagged Growth (t-2)	0.137151	0.134437	0.117916	0.045018	0.088253	-0.06233
	3.45083	***7.44445***	***7.437054***	***2.303653***	***5.194735***	***-2.405071***
Lagged Growth (t-3)	-0.2712	-0.223971	-0.279876	-0.169536	-0.279778	-0.079483
	-9.952059	***-12.11822***	***-17.82169***	***-8.654643***	***-16.53972***	***-3.554155***
Lagged Growth (t-4)	-0.110793	-0.289164	-0.087911	-0.328221	-0.056998	-0.426242
	-4.281305	***-16.78527***	***-6.285872***	***-18.50129***	***-3.906895***	***-21.39453***
Spatial Lag Growth (t-1)			0.013824	-0.092147	-0.001834	-0.139438
			0.80296	***-3.224093***	***-0.081042***	***-3.364402***
Spatial Lag Growth (t-2)			0.077745	0.262061	-0.018413	0.017818
			3.725996	***10.97481***	***-0.63989***	***0.456435***
Spatial Lag Growth (t-3)			0.036482	-0.103675	0.023508	0.02102
			1.723244	***-4.256112***	***0.788195***	***0.614495***
Spatial Lag Growth (t-4)			-0.131844	0.01562	0.011832	-0.045569
			-6.753995	***0.686782***	***0.44643***	***-1.511414***
Spatial Migration Growth (t-1)					0.022077	0.245658
					0.789402	***6.136838***
Spatial Migration Growth (t-2)					0.187278	0.591801
					5.157995	***11.23098***
Spatial Migration Growth (t-3)					0.02896	-0.152578
					0.784019	***-3.296313***
Spatial Migration Growth (t-4)					-0.303739	0.017718
					-8.718272	***0.428054***
R-squared	**0.502698**	**0.689281**	**0.509927**	**0.711546**	**0.520496**	**0.735662**

Numbers in italics are t-statistics

*regressions using migration data cover the years 1996-2011

Table 4 - Full Sample, 1996-2013*, Arellano-Bond Estimation (A-B) with MSA Fixed Effects (FE), HAC consistent std errors
Dependent Variable: House Price Index Growth between year t and t-1, for MSA i

	FE, A-B	FE, A-B post-2007	FE, A-B	FE, A-B post-2007	FE, A-B	FE, A-B post-2007
constant	-0.00152	0.099145	0.004858	0.067773	0.021528	0.041663
	-0.036152	***1.244193***	***0.070456***	***0.924616***	***0.153006***	***0.697426***
Lagged Growth (t-1)	2.576564	2.364041	3.953734	1.990126	7.951231	1.736789
	3.523473	***3.319094***	***2.260661***	***2.991464***	***0.875746***	***3.064276***
Lagged Growth (t-2)	-1.221921	-0.739167	-2.15395	-0.683877	-4.876032	-0.697839
	-2.268756	***-2.50952***	***-1.770868***	***-2.613524***	***-0.786855***	***-3.142662***
Lagged Growth (t-3)	-0.474108	-0.463275	-0.395526	-0.229947	-0.443125	-0.051579
	-4.754495	***-5.6964***	***-3.408559***	***-4.018498***	***-1.42685***	***-0.81332***
Lagged Growth (t-4)	0.47611	0.506198	0.803613	0.304179	1.816345	0.141076
	2.006881	***2.129898***	***1.683968***	***1.437538***	***0.781162***	***0.805641***
Spatial Lag Growth (t-1)			-2.117542	-0.488302	-0.35422	-0.2989
			-1.66994	***-0.778034***	***-0.275332***	***-0.38956***
Spatial Lag Growth (t-2)			1.49605	0.445811	0.213277	0.088614
			1.755587	***1.794344***	***0.229249***	***0.303953***
Spatial Lag Growth (t-3)			-0.099678	-0.38837	0.203771	0.076521
			-0.895266	***-4.388573***	***0.594454***	***1.19069***
Spatial Lag Growth (t-4)			-0.603873	-0.005087	-0.26261	-0.13392
			-2.078652	***-0.025126***	***-0.674191***	***-0.540719***
Spatial Migration Growth (t-1)					-3.796618	-0.272306
					-0.702084	***-0.737046***
Spatial Migration Growth (t-2)					2.545577	0.638457
					0.747003	***2.925386***
Spatial Migration Growth (t-3)					-1.070816	-0.785693
					-0.699507	***-3.003323***
Spatial Migration Growth (t-4)					-0.791738	0.190893
					-0.982235	***1.852112***
J-Statistic	**0.0000000**	**1.30E-42**	**0.0000000**	**0.0000000**	**0.0000000**	**0.0000000**

Numbers in italics are t-statistics

*regressions using migration data cover the years 1996-2011

Table 5 - Full Sample, 1996-2013*, HAC consistent standard errors
Dependent Variable: House Price Index Growth between year t and t-1, for MSA i

	no FE	no FE, post-2007	no FE	no FE, post-2007	no FE	no FE, post-2007
constant	0.00382	-0.021939	0.004607	-0.023936	0.0060640	-0.02122
	3.487911	***-11.64791***	***4.37067***	***-13.48862***	***6.010982***	***-12.93094512***
Lagged Growth (t-1)	0.672533	0.478725	0.664584	0.540908	0.655723	0.602968
	18.70821	***10.82139***	***17.67518***	***11.85372***	***16.12177***	***11.51922068***
Lagged Growth (t-2)	0.136279	0.122189	0.117397	0.034178	0.089001	-0.05131
	3.556629	***2.747557***	***3.059331***	***0.717341***	***2.131005***	***-0.927563456***
Lagged Growth (t-3)	-0.270765	-0.307033	-0.278418	-0.231338	-0.277587	-0.1602
	-10.26015	***-10.63542***	***-9.8116***	***-6.937455***	***-8.964133***	***-4.201234687***
Lagged Growth (t-4)	-0.100301	-0.133555	0.076787	-0.145981	-0.044938	-0.158747
	-4.012427	***-4.768795***	***3.090475***	***-5.590306***	***-1.746022***	***-6.021921589***
Spatial Lag Growth (t-1)			0.008156	-0.242515	-0.004862	-0.121056
			0.376996	***-7.707917***	***-0.196076***	***-3.972923108***
Spatial Lag Growth (t-2)			0.07703	0.259168	-0.015511	0.062557
			2.703624	***7.022555***	***-0.486195***	***1.640124166***
Spatial Lag Growth (t-3)			0.034513	-0.131958	0.023463	0.035289
			1.295186	***-3.702765***	***0.842933***	***0.979088223***
Spatial Lag Growth (t-4)			-0.134064	-0.049341	0.009566	-0.058565
			-5.431445	***-1.879395***	***0.365081***	***-2.187505119***
Spatial Migration Growth (t-1)					0.01637	-0.22429
					0.430273	***-3.929054637***
Spatial Migration Growth (t-2)					0.180927	0.386892
					3.393715	***5.811981821***
Spatial Migration Growth (t-3)					0.025417	-0.327535
					0.564772	***-4.980840253***
Spatial Migration Growth (t-4)					-0.306861	-0.021957
					-6.189478	***-0.437442712***
R-squared	**0.497454**	**0.516028**	**0.504427**	**0.542619**	**0.514814**	**0.558572**

Numbers in italics are t-statistics

*regressions using migration data cover the years 1996-2011

Table 6 - Full Sample, 1996-2013*, Arellano-Bond Estimation (A-B), HAC consistent standard errors
Dependent Variable: House Price Index Growth between year t and t-1, for MSA i

	A-B	A-B post-2007	A-B	A-B post-2007	A-B	A-B post-2007
constant	0.00024	0.008734	0.003049	0.0004	0.029	-0.002939
	0.070567	***0.954072***	***0.764525***	***0.064379***	***0.369412***	***-0.429715***
Lagged Growth (t-1)	2.598048	1.824262	4.764851	-1.537327	16.97576	1.416775
	3.173747	***5.053834***	***1.584543***	***-5.636287***	***0.322928***	***5.253978***
Lagged Growth (t-2)	-1.240891	-0.646951	-2.737545	0.579006	-11.14589	-0.611359
	-2.060268	***-2.891036***	***-1.3034***	***3.155907***	***-0.3076***	***-3.27412***
Lagged Growth (t-3)	-0.477511	-0.367637	-0.411837	-0.209845	-0.671581	-0.053373
	-4.423051	***-6.631461***	***-2.717719***	***-3.821309***	***-0.499997***	***-0.867599***
Lagged Growth (t-4)	0.478403	0.311552	0.979804	0.149638	3.973364	0.036901
	1.855441	***2.834265***	***1.263967***	***1.956955***	***0.3074***	***0.546102***
Spatial Lag Growth (t-1)			-2.913751	-0.160447	-0.24491	-0.115934
			-1.237608	***-0.605338***	***-0.061662***	***-0.415584***
Spatial Lag Growth (t-2)			2.080433	0.357042	0.102184	0.048445
			1.28362	***1.9821***	***0.034427***	***0.251413***
Spatial Lag Growth (t-3)			-0.11955	-0.366757	0.46828	0.057297
			-0.792144	***-5.180469***	***0.283708***	***1.025973***
Spatial Lag Growth (t-4)			-0.746629	0.099668	-0.519224	-0.071217
			-1.477288	***1.02911***	***-0.335458***	***-0.779476***
Spatial Migration Growth (t-1)					-9.305953	-0.218052
					-0.289968	***-1.242968***
Spatial Migration Growth (t-2)					6.208285	0.611582
					0.297063	***2.965999***
Spatial Migration Growth (t-3)					-2.481894	-0.713281
					-0.292627	***-4.204313***
Spatial Migration Growth (t-4)					-1.436646	0.191768
					-0.350727	***2.384653***
J-statistic	**0.0000000**	**0.0000000**	**5.38E-43**	**0.0000000**	**0.0000000**	**0.0000**

Numbers in italics are t-statistics

*regressions using migration data cover the years 1996-2011