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House price fluctuations and the business cycle dynamics*

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Abstract

This paper investigates the impact of house price movements on output in a space-time dynamic framework. The transmission of house price fluctuations to the macroeconomy both across space and over time is explicitly considered through spatial econometric modeling techniques. Using 373 metropolitan areas in the US from 2001 to 2013, it is shown that house price fluctuations have detrimental effect on output growth and spillover from one location to another. The loss of output due to house price fluctuations is more pronounced during the recent financial crisis. The time varying recursive estimation of the space-time econometric model shows that the coefficient of spatial correlation has been increasing over time, reflecting an increasing trend in house price synchronization.

Keywords: House price fluctuations; output growth; space-time modeling
JEL classification: E30; E32

1 Introduction

The recent financial crisis caused by the US housing market crash has led many researchers in the field to consider the housing sector as a source of macroeconomic fluctuations, see, for example, Cesa-Bianchi (2013), Iacoviello and Neri (2010), and Liu et al. (2013). Many of the existing studies on the interactions between the US housing market and the macroeconomy present two important findings. First, house price

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fluctuations spill over to the macroeconomy over time (Holly et al. 2010 and Iacoviello and Neri 2010). Second, house price fluctuations show spatial effects where price fluctuations from one location transmit to the other locations (Kuethe and Pede 2011 and Valentini et al. 2013).[1] Motivated by this evidence, two interesting questions arise. (1) How big are the spillovers from the housing market to the real economy? And (2) what is the nature of housing market spillover from one location to the others?

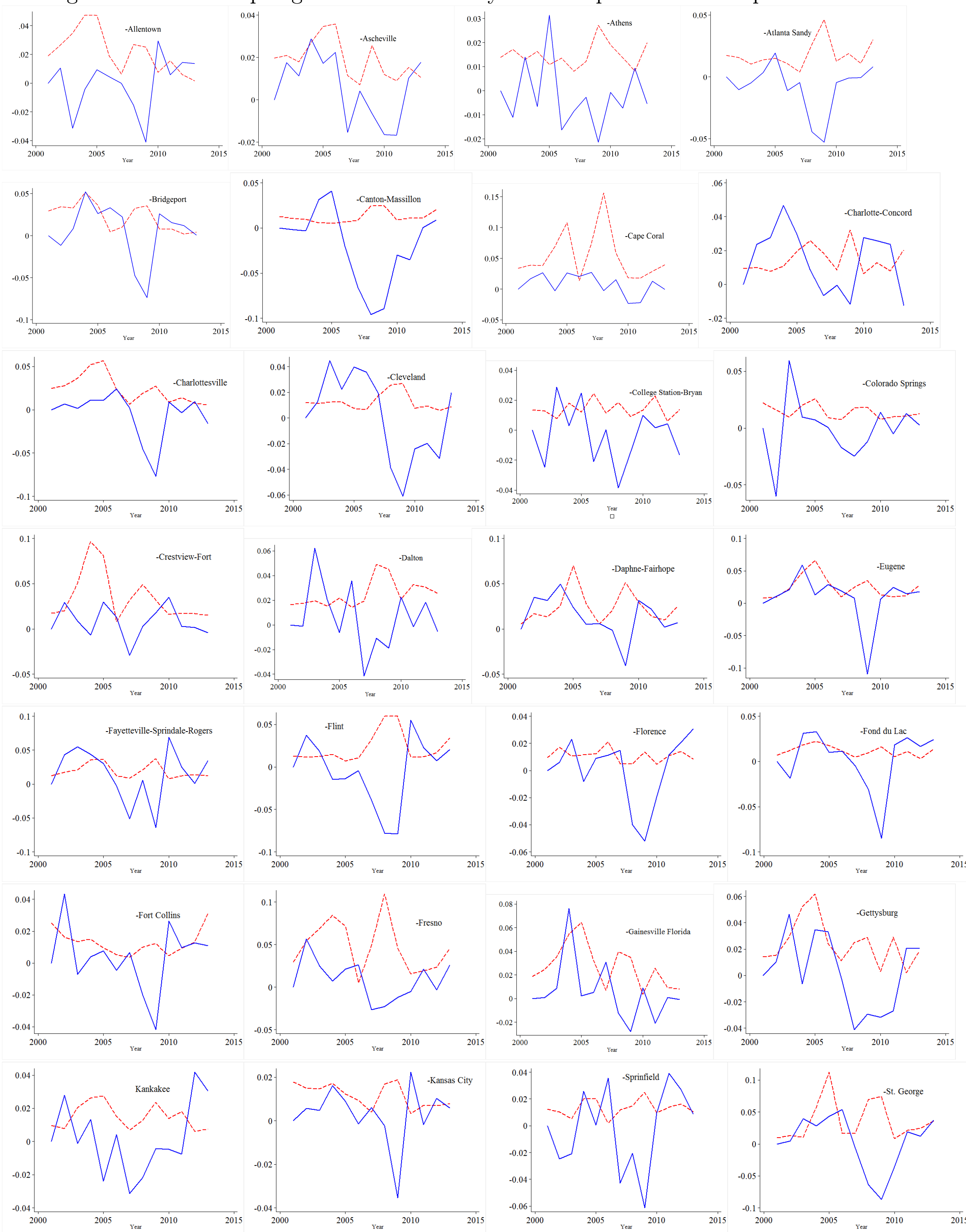
This paper investigates the impact of house price fluctuations on the macroeconomy in a joint space-time dynamic framework. The transmission of house price fluctuations to the real economy both across location (space) and over time is explicitly considered through spatial econometric modeling techniques. Recent advances in spatial econometrics provide very interesting and powerful tool for examining the linkages between the housing market and the real economy both across space and over time. Because fluctuations in house prices affect the wider economy, proper understanding of the interactions between house price fluctuations and the real economy is very important for economic stabilization policies.

In equilibrium models of the housing market and the macroeconomy (see e.g. Cesa-Bianchi 2013; Iacoviello and Neri 2010; Iacoviello 2005 and Monacelli 2009) house price changes affect macroeconomic aggregates through the collateral constraint. Given financial market imperfections, changes in house prices affect household's wealth and the capacity of borrowing, investment, and consumption. More specifically, an increase in house price improves the household's wealth status and enhances borrowing capacity, investment and consumption. A boom and subsequent downturn in the housing market amplifies cyclical fluctuations in the real economy. Earlier theoretical works by Bernanke et al. (1999) also stress the important linkages between asset prices (house prices) and the real economy. Similarly, Liu et al. (2013) also argue that housing market shocks are important sources of macroeconomic fluctuations.

A strand of empirical studies (among many others, see Hirata et al. 2013; Leamer 2007 and Bordo and Jeanne 2002) show that house prices exhibit frequent boom and bust and such housing busts can be very costly in terms of output loss. Figure 1 plots the standard deviation of house prices and output growth for a randomly selected samples of 28 US metropolitan statistical areas during the period 2001 to 2013. The graph shows that a high fluctuation in house prices is associated with a lower output growth rate during the sample period. This empirical evidence is also supported by earlier studies. Leamer (2007), for example, shows strong linkages between movements in the housing markets and business cycles in the US. Stephens (2012) also argues that fluctuations in house prices hurt the wider economy in different ways. During boom period, there is a temptation for individuals to overextend borrowing. House price volatility also creates risk of unsustainable house price for lenders.

[1] Location in this particular context refers to any economic unit, e.g. country, region, ZIP code or metropolitan city.

Figure 1: Plot of output growth and volatility of house prices for a sample of 28 MSAs



- - -Standard deviation of prices —Output growth

Moreover, an increase in house price volatility increases the probability of negative home equity, and mortgage foreclosure losses become worse.[2] In another literature, Cunningham and Kolet (2007) also document that the magnitude and duration of housing cycles vary widely across geographical areas and over time

Many theoretical and empirical works also show that housing markets are characterized by spatial patterns. Can (1992) states that the value of a house at a particular location is dependent on the value of houses at nearby locations. Buyers and sellers, for example, may use similar sale prices in a neighborhood as references for a transaction sales price, see Anselin (2003). This indicates that the price of a particular house will affect the price of neighboring houses, indicating that appropriate modeling of the interactions between the housing market and macroeconomic fluctuations calls for both the spatial and temporal dynamics. Meen (1999) also states that a perturbation in house prices in a given location spills over to other locations, leading to a global effect on house prices in all other locations. Anselin and Lozano-Gracia (2009) argue that spatial patterns in the housing market could arise from a combination of spatial heterogeneity and spatial dependence.[3] For example, spatial heterogeneity may result from spatially differentiated characteristics of demand, supply, and institutional barriers. In a cross-country framework, Cesa-Bianchi (2013) and others document that movements in house prices are highly synchronized across countries and house price fluctuations transmit from one country to the other through, for example, trade and interest rates. Holly et al. (2010) and Baltagi and Li (2014) also document that US housing markets show significant spatial effects.

While much of the existing research on the interactions between house prices and the real economy focuses on the temporal dynamics, the links between house prices and the real economy in a space-time setup have been less thoroughly researched. This paper aims to fill part of this gap.

We use rich house price data sets across 373 US metropolitan statistical areas (MSAs) during the period 2001 to 2013. The disaggregated panel data at MSA level feature some important advantages over aggregate (state and national) level data. First, house price fluctuations are local outcomes and are specific to particular economic areas, e.g. MSAs, see Baltagi and Li (2014). Second, MSAs in the sample are subject to similar policy shocks (monetary policy, for example), taxes, and financial market conditions. House prices at MSA level also exhibit much more fluctuations both across space and over time than the smoother national or state level data can provide, and this helps to exploit cross-sectional variation.

We begin with a standard dynamic panel analysis. One advantage of the dynamic panel specification is its ability to control for fixed effects. We estimate our dynamic panel model both with and without fixed effects. The estimation results suggest that high fluctuations in house prices lower output growth. Our dynamic panel analysis is related to that of Muñoz (2003) who examines the dynamics of US house prices using state level

[2]See Miller and Peng (2006) and Penning-Cross (2013) for further discussions.

[3]See Anselin (1988) for details regarding spatial dependence and spatial heterogeneity.

data.

Next, a space-time model for house prices and output growth is specified. Using a spatial connectivity weight matrix, the house price-output growth model is estimated. Estimation results of the spatial model suggest that house price fluctuations have a statistically significant negative effect on output growth. It is shown that the negative effect of house price fluctuations on output growth are more pronounced during the recent financial crisis.

As an alternative specification, we estimate the spatial model using a direct and indirect effects approach. This is important because the recent literature in spatial econometrics points out that standard estimation of spatial econometric models may lead to misleading inference (LeSage and Pace 2009). Appropriate estimation involves decomposition of spatial impacts into direct and indirect effects using a partial derivatives impact approach. We decompose the impacts of house price fluctuations on output growth into direct and indirect effects. It is shown that both the direct and indirect impacts of house price fluctuations on real output are negative and significant. House price fluctuation in a particular MSA, in addition to hampering its own growth, transmits to neighboring MSAs.

Another major contribution of this paper is the application of a recursive estimation of the house price spatial econometric model which provides an alternative measure of house price synchronization. This technique enables investigation of the dynamics of house price movements across space and over time where the spatial correlation coefficient is allowed to vary over time and capture major changes in the economy. For this purpose, we use a relatively longer time series of house price data. We consider quarterly house price data for 373 MSAs during 1987:Q1 to 2014:Q3. The estimation result shows that the spatial correlation coefficient across MSAs has been increasing over time, indicating an increasing synchronization of house prices across MSAs during the sample period.

The remainder of this paper is organized as follows. Section 2 presents a brief summary of the literature review. Different existing theoretical and empirical studies are discussed. Section 3 presents a space-time model for house prices and output growth. Section 4 presents the data. Some stylized facts of the data are briefly presented and discussed. Section 5 presents the empirical results, and the final section provides the conclusion.

2 Brief literature review

Numerous studies on the interactions between house prices and the macroeconomy have been conducted. Most studies focus on the temporal analysis of the interactions between house prices and the real economy. Few studies have been conducted on the relationship between house price fluctuations and real output in a space-time dynamic framework. Studies that investigate the relationship between house price dynamics and the real economy found that house prices play important role in the real economy and show significant spatial patterns.

Cesa-Bianchi (2013) investigates the international spillovers of housing demand shocks on the real economy. Using a global vector autoregressive model on 33 advanced and emerging economies over the period 1983 to 2009, finds that US house demand shocks spill over to the real economy. Further, house demand shocks originating from the US transmit to the other advanced economies. Using 379 US metropolitan areas in a standard panel data model, Miller et al. (2011) investigate the effect of house prices on output growth. They find that house price changes have significant effect on output growth. Further, they show that the collateral effect (change in actual consumption) of house prices has a stronger effect than the wealth effect (change in desired consumption). Holly et al. (2010) employ an error correction model with a cointegrating relationship between real house prices and real income that explicitly considers heterogeneity and cross sectional dependence. Using 49 US states during 1975-2003, they identify that real house prices rise in line with real income and show significant spatial effects. Baltagi and Li (2014) replicate Holly et al. (2010). First, they consider 381 MSAs instead of state level data. Second, they use extended data during 1975-2011 instead of 1975-2003. They show that real house prices and real income are co-integrated and the degree of spatial dependence is stronger at MSA level than state level.

Iacoviello and Neri (2010), using a theoretical dynamic stochastic general equilibrium (DSGE) model, study sources and consequences of fluctuations in the US housing market. They find that slow technological progress in the housing sector explains the upward trend in real housing prices. Over the business cycle, housing demand and housing technology shocks explain one-quarter each of the volatility of housing investment and housing prices.

Another direction of the literature in house prices has been the use of spatial econometrics in standard hedonic price models. Anselin and Lozano-Gracia (2009) briefly discuss the motivation and application of spatial econometric methods in hedonic house price models. They state that there are two motivations for incorporating spatial effects in standard hedonic models. The first is the need to account for interaction effects and/or market heterogeneity. The second is to capture spatial autocorrelation in omitted variables or unobserved externalities and heterogeneities. Osland (2010) applies spatial econometrics on standard hedonic house price models. Using municipality level data in the Southwestern part of Norway during 1997 to 2002, the author shows that the spatial model alternatives have higher explanatory power than the standard model. Clapp et al. (2002) use local polynomial regression model to predict spatial pattern of house prices. They show that the local polynomial regression model performs better in predicting the spatial pattern of house prices across space.

In a more recent study, Dubé and Legros (2014) emphasize the importance of the time dimension in spatial econometric estimation of hedonic house price models. Using house price data in Paris between 1990 and 2001, they find that ignoring the time dimension in spatial econometric estimation of hedonic house price models could generate divergence in the estimated autoregressive coefficients. Can (1992) formally considers spatial dependence and spatial heterogeneity in the standard hedonic house price models. It is shown that models that include both spatial dependence and spatial heterogeneity are superior to the standard hedonic house price models. Using data for the year 1980 of 563 single-family houses sold in the Franklin county of the Columbus metropolitan area, she finds significant spatial effects in hedonic house price models.

3 Empirical methods

3.1 Model specification

Anselin (1988) states that spatial dependence in a regression framework reflects a situation where the values of a variable at one location depend on the values of the observation at other locations. A number of studies show that location is one of the most important determinants of house prices, see, for example, Can (1992) and many others.

Consider two neighboring MSAs i and j. Suppose the output growth process in a particular MSA i at particular time period t is given by

$$g_{it} = f(g_{jt},\, v_{it},\, v_{jt},\, g_{it-1},\, x_{it}), \tag{1}$$

where g_{it} denotes the growth rate of per capita GDP for MSA i during time t, v_{it} denotes the standard deviation of house prices as described in equation (6) below, g_{it-1} denotes the lagged output growth rate, x_{it} denotes a set of control variables, unemployment, for example.

For a set of N MSAs $i = 1, \ldots, N$, equation (1) can be written as

$$g_{it} = \rho \sum_{j \neq i}^{N} W_{ij} g_{jt} + \alpha_1 v_{it} + \lambda \sum_{j \neq i}^{N} W_{ij} v_{jt} + \alpha_2 g_{it-1} + \alpha_3 x_{it} + c + \varepsilon_{it}, \tag{2}$$

or in matrix form

$$g_t = \rho W g_t + \alpha_1 v_t + \lambda W v_t + \alpha_2 g_{t-1} + \alpha_3 x_t + c + \varepsilon_t, \tag{3}$$

where ρ is the spatial correlation coefficient, W is a spatial weight matrix connecting MSAs i and j, α_1, λ, α_2, and α_3 are unknown parameters, c is a constant, and ε_t is an $i.i.d$ white noise.

Equation (3) states that the growth regression relationship is between the $NX1$ vector of time t growth rates (g_t), neighboring MSAs' growth rate in the current time period (Wg_t), own volatility of house prices in the current time period (v_t), neighboring MSAs' volatility of house prices in the current time period (Wv_t), growth rates in the previous time period (g_{t-1}), and set of controls, e.g. unemployment. The model in (3) is known as the spatial Durbin (SDM) model.

The parameters of interest are ρ, α_1, and λ. The parameter ρ measures the extent of spatial dependence in the dependent variable. A positive value of ρ indicates that output growth in neighboring MSAs affects a particular MSA's growth rate positively. A number of studies show that growth rates in neighboring units have positive effect on the growth rate of a particular economic unit. Ertur and Koch (2007), for example, find that the growth rates of neighboring countries play an important role in the growth rate of a particular country through technological interdependence, see also Abate (2015).

The parameter α_1 links the fluctuation of house prices in a particular MSA i to that of the growth rate of output in that MSA itself. Different previous works show that an increase in the fluctuations of house prices affects average growth rate negatively, see Bordo and Jeanne (2002).

The effect of average house price movements from neighboring MSAs is measured by the parameter λ. A high house price fluctuation observed in nearby MSAs might have negative effect on the economic growth of a particular MSA while a relatively stable house price changes in nearby MSAs may have positive effects on output growth rate of a particular MSA. The temporally lagged growth rate is included in the model to account for the fact that past growth may contain some information about the economy.

The other important model in spatial regression specifications is the spatial autorgeressive (SAR) model of the form

$$g_t = \rho W g_t + \alpha_1 v_t + \alpha_2 g_{t-1} + \alpha_3 x_t + c + \varepsilon_t. \tag{4}$$

This model is a special case of the model in (3) with $\lambda = 0$. This model states that spatial dependence occurs through the dependent variable, see LeSage and Pace (2009) for details as well as further discussion on the spatial error (SER) model where spatial dependence occurs through the error terms. Setting the restriction $\rho = 0$, and $\lambda = 0$ in equation (3) produces the standard panel data specifications of the form

$$g_t = \alpha_1 v_t + \alpha_2 g_{t-1} + \alpha_3 x_t + c + \varepsilon_t. \tag{5}$$

All the different spatial econometric models discussed above can be estimated using maximum likelihood, instrumental variable estimation, and generalized method of moments, see Elhorst (2010) for details.

4 Data

This study covers 373 MSAs in the US during the period 2001 to 2013. The US Office of Management and Budget (OMB) defines metropolitan areas based on a core area containing a large population nucleus together with adjacent communities having a high degree of economic and social integration with that core.

We draw data for house prices, per capita GDP, and unemployment from different sources. All-transactions quarterly house price index for 373 MSAs from 2001 to 2013 is interpolated from the Federal Housing Finance Agency (FHFA). The all-transactions house price index data of the FHFA is widely used in previous studies, see e.g. Bork and Møller (2015), Baltagi and Li (2014) and Miller et al. (2011) among many others. The house price indexes are constructed using repeated sales and refinancing on the same single-family properties.[4] The MSA level data are available on a quarterly level back to the mid-1980s.

Then, the volatility of house prices v_{it} for MSA i at particular year t is calculated as the standard deviation of prices over four quarters for each year:

$$v_{it} = std.dev(log(p_{q1i}, p_{q2i}, p_{q3i}, p_{q4i})), \quad i = 1, ..., 373; \; t = 2001, ..., 2013 \tag{6}$$

where $p_{q1i}, ..., p_{q4i}$ is the house price index at each quarter for MSA i. Note that v_{it} is normalized by the mean price of each MSA to control for size of each MSA.

The per capita gross domestic product (GDP) for each MSAs is drawn from the Bureau of Economic Analysis (BEA) from 2001 to 2013. The metropolitan area GDP is the sub-state counterpart of the Nation's gross domestic product (GDP).

Unemployment data is collected from the Bureau of Labor Statistics (BLS). The unemployment data for each MSA is available on a monthly frequency. The annual unemployment rate is constructed using this monthly data for each MSA from 2001 to 2013.

Prior to the empirical analysis of house prices and output dynamics, it is of interest to look at some features of the data. Table 1 presents the summary of the data series across all the MSAs. GDP, GDP growth, and house prices are in log terms. Panel I of the table reports the descriptive statistics of GDP, GDP growth, house prices, and house price volatility across all MSAs from 2001 to 2013. The mean price volatility across all MSAs during 2001 to 2013 has been above 2% per year. Growth rate of per capita GDP across all the MSAs has been above 0.5% per year during the sample period. Cross correlations of variables across all MSAs during the sample period is reported in panel II. As shown, house price volatility has an average negative correlation of -0.019 with output growth over the sample period. Similarly, output level and house price fluctuations have an average

[4] See also appendix A.2.1 for details.

negative cross correlation of -0.090 during the sample period.

Panel III of Table 1 reports metropolitan cities with highest and lowest house price fluctuations and GDP growth rates. The highest mean volatility for the entire period has been in Merced, California with average mean volatility of above 6%. The lowest mean volatility has been observed in Cedar Rapids, Iowa where the mean volatility has been around 0.65%. The highest mean real GDP per capita growth rate have been observed in Corpus Christi, Texas with a mean real income growth rate above 5.7%. The lowest mean income growth rate, on the other hand, have been observed in the city of Canton-Massillon, Ohio where the mean growth rate for the entire sample period has been around -2.2%.

Table 1: Data summary: 373 MSAs from 2001 to 2013

		GDP	GDP growth	House price	House price volatility	Unemployment
Panel I						
	Mean	10.564	0.0055	5.764	0.0209	1.803
	Median	10.557	0.0045	5.729	0.0151	1.775
	Std.dev	0.265	0.0357	0.179	0.0187	0.386
Panel II						
	GDP	1	0.1160	0.186	-0.0900	-0.1333
	GDP growth		1	-0.064	-0.0192	-0.1466
	House price			1	0.3250	-0.2166
	House price volatility				1	0.0549
	Unemployment					1
Panel III						
	Highest growth MSAs/value	Corpus Christi, Texas/0.0577				
	Lowest growth MSAs/value	Canton-Massillon, Ohio/-0.0216				
	Highest volatile region/value	Merced, California/0.0628				
	Lowest variance region/value	Cedar Rapids, Iowa/0.0065				

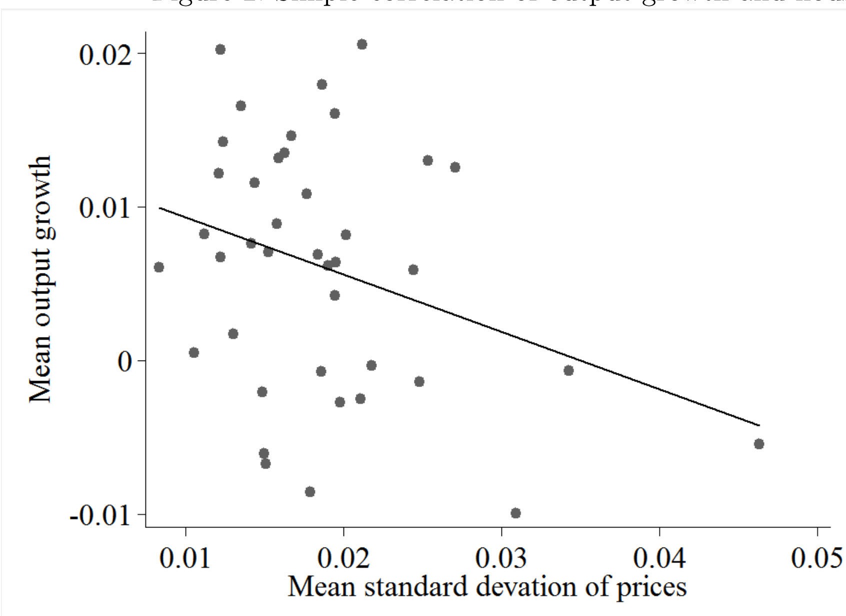
Notes: Panel I reports the descriptive statistics of GDP, GDP growth, house price, house price volatility and unemployment. Panel II reports the cross correlations of GDP, GDP growth, house price, house price volatility and unemployment. Panel III reports metropolitan areas with highest and lowest GDP growth and house price volatility.

5 Results

5.1 Dynamic panel analysis

Prior to the empirical estimation, different panel unit root tests were performed. Under heterogeneous panels, Levin et al. (2002), LCC hereafter, and Im et al. (2003), IPS hereafter, present unit root testing procedures.[5] Whereas the LCC specification is based on the assumption that the error terms are independent and the persistence parameter is the same across sections, the IPS specification allows heterogeneous panels based on the mean of individual unit root statistics. Both the LCC and IPS panel unit root tests reject the null hypothesis of unit roots in output growth, price volatility, and unemployment rate, see Table 2.

Figure 2: Simple correlation of output growth and house price volatility



Note. The figure shows plot of average output growth and average standard deviation of house prices across 373 MSAs during 2001-2013. The average growth and standard deviation of house prices for each MSA is computed over the sample period 2001-2013. We report a sample of 40 MSAs for clarity. The pattern is more or less similar for all 373 MSAs.

Table 3 presents the maximum likelihood results of the dynamic panel specification. The dependent variable is the annual growth rate of per capita GDP computed as the log difference. The independent variables are volatility of house prices measured as the standard deviation of log prices as defined in equation (6), the unemployment rate, and previous growth rate as well as dummy for the year 2007. Specifications in panel A are results for the whole sample period, whereas specifications in panel B are results for the

[5]See appendix A.2 for details.

sub-sample period 2007-2013. Such sub-period specification helps in understanding the interactions between changes in house prices and output growth during the recent financial crisis.

Table 2: LCC and IPS unit root tests

Variable	Test statistics	
	LCC	IPS
Volatility	-28.039***	-6.064***
GDP growth	-26.896***	-9.969***
Unemployment	-18.995***	-9.267***

Notes: *** denotes significance at 1% level.

Table 3: Dynamic panel results

	Panel A: 2001-2013		Panel B: 2007-2013	
	(1)	(2)	(3)	(4)
Constant	0.007 (0.001)***	0.033 (0.003)***	0.006 (0.001)***	0.015 (0.005)***
Volatility	-0.063 (0.027)**	-0.069 (0.029)**	-0.489 (0.039)***	-0.473 (0.042)***
$Growth_{-1}$	0.144 (0.015)***	0.092 (0.016)***	0.072 (0.019)***	0.046 (0.020)***
Dummy for 2007	-0.012 (0.002)***	-0.016 (0.002)***	-0.003 (0.002)	-0.005 (0.003)**
Unemployment		-0.014 (0.002)***		-0.005 (0.002)**
Log likelihood	9347.64	8298.36	4920.06	4354.53
N	4849	4849	2611	2611

Notes: (***, **) denotes significance at (1%, 5%) level. Standard errors are in parenthesis. The dependent variable is the change in (log) GDP per capita.

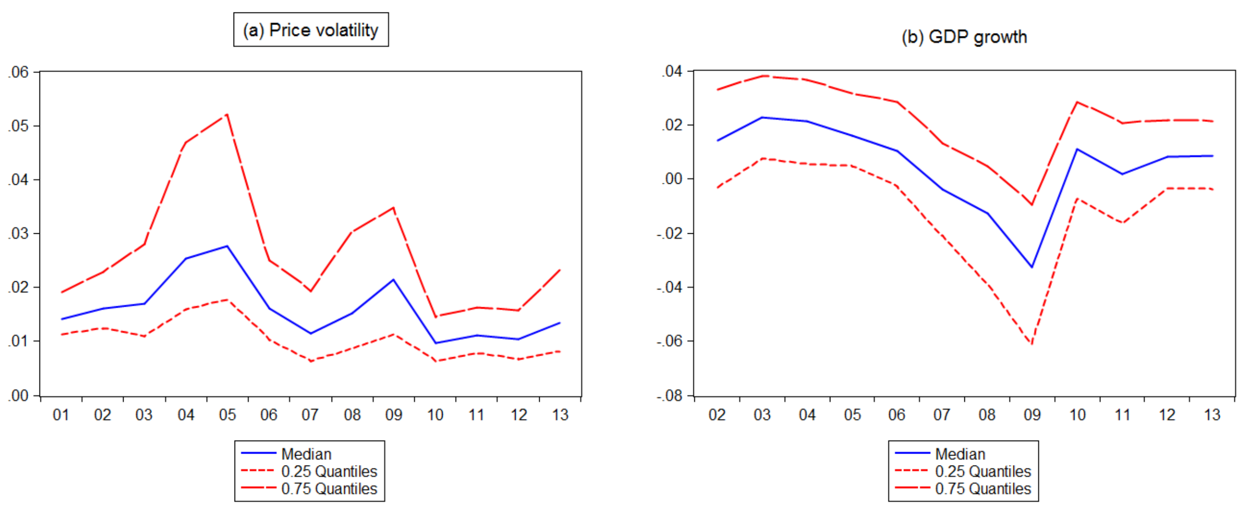
Column (1) of Table 3 reports the specification without unemployment rate. The coefficient estimate of house price volatility shows a statistically significant negative effect on the output growth rate. Figure 2 shows the scatter plot of average volatility and average output growth rate over the entire period for a randomly selected 40 MSAs. The graph shows a clear negative relationship between volatility and output growth.

A change in output might affect local industry structure and frictions in the labor market and may cause migration of the labor force. To capture this effect, we include unemployment rate as an additional control variable in column (2) of Table 3. The effect of house price volatility on output increases (in absolute value) slightly. The unemployment rate also takes a statistically significant negative coefficient estimate, reflecting the standard relationship between unemployment and output growth.

Column (3) and (4) in panel B of Table 3 present the specification during the sample period 2007-2013. Interestingly, the coefficient of volatility on output growth shows an increase (in absolute) value during the period 2007-2013. This reflects that the loss in output due to price fluctuations is more pronounced during crisis periods. The remaining variables, past growth, and unemployment rate take predicted signs across all specifications.

Further, Figure 3 illustrates the dramatic changes in house prices and output growth rate during the recent boom and bust of the housing markets. The figure displays the median (blue line) of house price volatility with the first and third quantiles (red lines) across the 373 MSAs during 2001 to 2013. The figure shows that high price fluctuations are accompanied by lower output growth rates. This result supports the inverse relationship between house price fluctuations and output growth illustrated in Figure 1 in Section 1. Further, the figure shows that growth rate in per capita GDP was at its lowest value in 2009.

Figure 3: Plots of price fluctuations and output growth across all MSAs during the period 2001-2013



5.2 Spatial modeling of house prices and the business cycle

In this section, we analyze the spatial dependence of house price fluctuations and output growth rate across 373 US MSAs during the period 2001 to 2013. The section starts with a discussion on the spatial weight matrix used in the empirical estimation. The empirical analysis focuses on the two models given in equations (3) and (4). The final section presents a time varying estimation of the spatial dependence.

A fundamental issue in the analysis of spatial econometric models in (3) and (4) is the specification of the spatial weight matrix that defines a neighborhood structure. More precisely, each MSA is connected to a set of neighboring MSAs by means of a spatial pattern introduced exogenously in W. Elements w_{ij} indicate the way MSA i is spatially connected to MSA j. To avoid self neighborhood, the elements w_{ii} on the main diagonal are set to zero by convention.

There is little guiding theory in the selection of the appropriate weight matrix in practice (Anselin 2002). Most commonly used weight matrices in spatial econometrics are binary contiguity weight matrix, inverse distance weight matrix, and the k-nearest neighbor weight matrices, see Anselin (1992). More complex spatial weight matrices can be created based on additional theory and assumptions, such as those based on economic distance (Holly et al., 2010). In this paper, we use a k-nearest neighbor row normalized distance weight matrix. More specifically, the weight matrix in standardized form is specified as

$$w(k)_{ij} = w(k)^*_{ij} / \sum w(k)^*_{ij} \;\; with \;\; w(k)^*_{ij} = \begin{cases} 0 & if \;\; i = j \\ 1 & if \;\; d_{ij} < d_i(k) \\ 0 & if \;\; d_{ij} > d_i(k) \end{cases},$$

where d_{ij} is the great circle distance between metropolitan city centroids, and $d_i(k)$ is the $k - th$ order smallest distance between metropolitan city i and j so that each MSA has k neighbors.[6] In this paper, we consider $k = 10$. One advantage of choosing the k-nearest weight matrix instead of the inverse distance weight matrix is that the latter specification results in an unacceptably large number of neighbors for the smaller units, see Anselin (2002).

The estimation results of the spatial models are reported in Table 4. Panel A of the table reports the full sample estimation results, and panel B reports the estimation results of the period 2007-2013. In both samples, we estimate both the SAR and SDM. The coefficient estimate of house price volatility shows significant negative effect on output growth across all specifications. Particularly, house price fluctuations result in, respectively, a 21.4% and 27.4% decline in output growth under the SDM SAR specifications during the sample period 2007-2013. As discussed previously, changes in house prices can have significant consequences on output through consumption and investment spending. The spatial autoregressive coefficient (ρ) has a positively significant coefficient estimate, suggesting growth spillover effects across MSAs in the US during the sample period. Many empirical works, see e.g. Abate (2015), Ertur and Koch (2007), and LeSage and Fischer (2008), document a positive significant growth spillover effects across countries as well as regions.

[6] The great-circle distance, the shortest distance between any two points is determined as: $d_{ij} = radious\, x\, cos - 1[cos \mid longtuide_i - longtude_j \mid coslatitude_i coslatitude_j + sinlatitude_i sinlatitude_j]$. We extrapolate the longitude and latitude coordinates for each MSA from the Census Bureau.

Table 4: Spatial panel model results

	Panel A: 2001-2013		Panel B: 2007-2013	
	SDM	SAR	SDM	SAR
Constant	0.005 (0.002)**	0.007 (0.001)***	0.001 (0.003)	0.006 (0.002)***
Volatility	-(0.072) (0.036)**	-0.045 (0.025)**	-0.214 (0.051)***	-0.274 (0.038)***
$Growth_{-1}$	-0.085 (0.071)	-0.731 (0.105)***	0.0576 (0.019)**	0.051 (0.017)***
Unemployment	0.052 (0.016)***	-0.002 (0.001)***	-0.002 (0.001)**	-0.002 (0.001)*
$W*$Volatility	0.029 (0.047)		-0.133 (0.068)**	
$W*Growth_{-1}$	0.109 (0.027)***		-0.009 (0.034)	
$W*$Unemployment	0.0007 (0.001)		0.005 (0.002)**	
ρ	0.564 (0.018)***	0.579 (0.018)***	0.537 (0.026)***	0.549 (0.025)
Log likelihood	9754.22	9745.59	5113.65	5109.00
Wald test $\rho = 0$	944.51 (0.000)	1061.81 (0.000)	424.77 (0.000)	479.10 (0.000)
Log likelihood ratio	17.26 (0.001)		9.29 (0.000)	
N	4849	4849	2611	2611

Notes: *** (**, *) denotes significance at 1% (5%, 10%) level. Standard errors are in parenthesis. P-values are in parenthesis for the log likelihood ratio tests. The dependent variable is the change in (log) GDP per capita.

5.3 Alternative regression frameworks

The empirical analysis so far suggests a negative relationship between output growth and house price movements. The loss of output due to price fluctuations tends to be higher during the recent financial crisis. In this section, we reexamine the overall robustness of the main results. We first consider a direct and indirect impacts approach following LeSage and Pace (2009). We then consider fixed effects alternative regression frameworks to account for MSA specific characteristics that may not be captured by the explanatory variables.

5.3.1 Direct and indirect impacts

LeSage and Pace (2009) argue that appropriate estimation of spatial econometric models such as in equations (3) and (4) involves decomposition of spatial impacts into direct and indirect effects using the partial derivatives impact approach. Taking the SDM in (3) as a point of departure, it can be rewritten as

$$g_t = (I - \rho W)^{-1}(\alpha_1 v_t + \lambda W v_t + \alpha_2 g_{t-1} + \alpha_3 x_t + c + \varepsilon_t). \quad (7)$$

The matrix of the partial derivatives of output growth, g_t, with respect to an explanatory variable, v_t, for example, for all spatial units $i = 1, ..., N$ is

$$\begin{bmatrix} \frac{\partial g_t}{\partial v_{1t}} & . & . & . & \frac{\partial g_t}{\partial v_{Nt}} \end{bmatrix} = (I - \rho W)^{-1} \begin{bmatrix} \alpha_1 & w_{12}\lambda & . & . & . & w_{1N}\lambda \\ w_{21}\lambda & \alpha_1 & . & . & . & w_{2N}\lambda \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ w_{N1}\lambda & w_{N2}\lambda & . & . & . & \alpha_1 \end{bmatrix}.$$

The direct effect is the average of the diagonal elements, and the indirect effect is the average of the off diagonal elements (LeSage and Pace 2009). The direct and indirect effects approach here enables us to isolate the effects of house price fluctuations on the real economy into direct and indirect effects. A surprise movement in house price in a particular MSA may affect the growth rate in that MSA itself (direct effect) and potentially affect the growth rate of other MSAs (indirect effect).

Table 5: Spatial panel model results: Direct and indirect effects

	Panel A: 2001-2013		Panel B: 2007-2013	
	SDM	SAR	SDM	SAR
Direct effect volatility	-0.073 (0.030)**	-0.048 (0.022)**	-0.232 (0.042)***	-0.286 (0.033)***
Indirect effect volatility	-0.012 (0.074)	-0.062 (0.028)**	-0.499 (0.108)***	-0.331 (0.045)***
Total effect volatility	-0.085 (0.071)	-0.110 (0.050)**	-0.731 (0.105)***	-0.617 (0.073)***
Direct effect growth	0.052 (0.016)***	0.072 (0.015)***	0.061 (0.019)***	0.054 (0.019)***
Indirect effect growth	0.289 (0.057)***	0.092 (0.019)***	0.049 (0.069)	0.062 (0.022)***
Total effect growth	0.341 (0.057)***	0.164 (0.034)***	0.110 (0.067)	0.116 (0.041)***
Direct effect unemployment	-0.002 (0.001)**	-0.002 (0.001)***	-0.002 (0.001)*	-0.002 (0.001)
Indirect effect unemployment	-0.001 (0.003)	-0.003 (0.001)***	0.007 (0.004)*	-0.002 (0.001)
Total effect unemployment	-0.003 (0.003)	-0.005 (0.002)***	0.005 (0.004)	-0.004 (0.002)
ρ	0.565 (0.018)***	0.579 (0.018)***	0.537 (0.026)***	0.549 (0.025)***
Log likelihood	9754.22	9745.59	5113.65	5109.00
Log likelihood ratio	17.26 (0.000)		9.29(0.009)	
N	4849	4849	2611	2611

Notes: *** (**, *) denotes significance at 1% (5%, 10%) level. Standard errors are in parenthesis for estimation results. P-values are in parenthesis for the log likelihood ratio tests. The dependent variable is the change in (log) GDP per capita.

Panel A of Table 5 reports the direct effect, indirect effect, and total effect of house price volatility, lagged growth, and unemployment rate for the sample period 2001-2013. The direct effects of house price fluctuations are negative and significant across all specifications. The indirect effects also have a statistically significant negative coefficient estimate under the SAR model. The main message here is that house price volatility, in addition to its negative effect on the growth rate of a particular MSA, spills over to the nearby MSAs and hampers growth. The spatially lagged growth rate also shows a positively significant coefficient estimate.

Panel B of Table 5 reports the estimation results of the spatial models for the period 2007 to 2013. Both the direct and indirect effects of house price volatility are negative and significant. The magnitude, however, has increased (in absolute value) compared to the full sample period results. The loss of output from house price fluctuations during the crisis period is more pronounced.

5.3.2 MSA fixed effects specification

In order to account for MSA specific features that may not be captured by the explanatory variables, we re-estimate a fixed effects model. To be consistent, we present the fixed effects results for both non spatial (standard panel) and spatial panel models.

Table 6 reports the fixed effects estimation results of the standard panel model. Whereas the full sample results are reported in panel A, the results for the sub-sample period 2007-2013 are reported in panel B. The relationship between movements in house prices and output growth remains negative even after controlling for MSA specific fixed effects under both samples.

Table 6: Dynamic panel results with fixed effects

	Panel A: 2007-2013	Panel B: 2007-2013
Constant	0.049 (0.004)***	0.035 (0.007)***
Volatility	-0.119 (0.035)***	-0.679 (0.054)***
$Growth_{-1}$	0.031 (0.016)**	-0.076 (0.021)***
Dummy for 2007	-0.019 (0.002)***	-0.008 (0.003)***
Unemployment	-0.025 (0.002)***	-0.015 (0.004)***
Observations	4849	2611

Notes: ***, ** denotes significance at 1% ,5% level. Standard errors are in parenthesis. The dependent variable is the change in (log) GDP per capita.

Table 7 reports the MSA specific fixed effects spatial model results. Similar to Table 6, the full sample results are reported in panel A, the results for the sub-sample period 2007-2013 are reported in panel B. As shown, house price volatility has a statistically significant negative effect on output growth across all specifications under both sample periods. We also estimate MSA specific fixed effects spatial model under a direct and indirect effects approach. Both the direct and indirect effects of house price movements have a statistically negative effect on output growth after controlling for MSA specific fixed effects during the sub-sample period 2007-2013, see Table A.1 in the appendix.

Table 7: Spatial panel model results: MSA fixed effects

	Panel A: 2001-2013		Panel B: 2007-2013	
	SDM	SAR	SDM	SAR
Volatility	-0.099 (0.043)**	-0.062 (0.029)**	-0.306 (0.061)***	-0.372 (0.046)***
$Growth_{-1}$	-0.044 (0.015)**	-0.015 (0.014)	-0.113 (0.019)***	-0.088 (0.017)***
Unemployment	-0.018 (0.003)***	-0.012 (0.001)***	-0.020 (0.005)***	-0.009 (0.002)***
$W*$Volatility	0.057 (0.056)		-0.099 (0.083)	
$W*Growth_{-1}$	0.156 (0.028)***		0.126 (0.035)***	
$W*$Unemployment	0.013 (0.004)***		0.019 (0.005)***	
ρ	0.577 (0.018)***	0.586 (0.018)***	0.562 (0.025)***	0.571 (0.024)***
Log likelihood	9952.85	9934.27	5347.95	5336.18
Wald test $\rho = 0$	1036.68 (0.000)***	1112.13 (0.000)***	502.03 (0.000)***	558.60 (0.000)***
Log likelihood ratio	37.17 (0.000)***		23.55 (0.000)***	
N	4849	4849	2611	2611

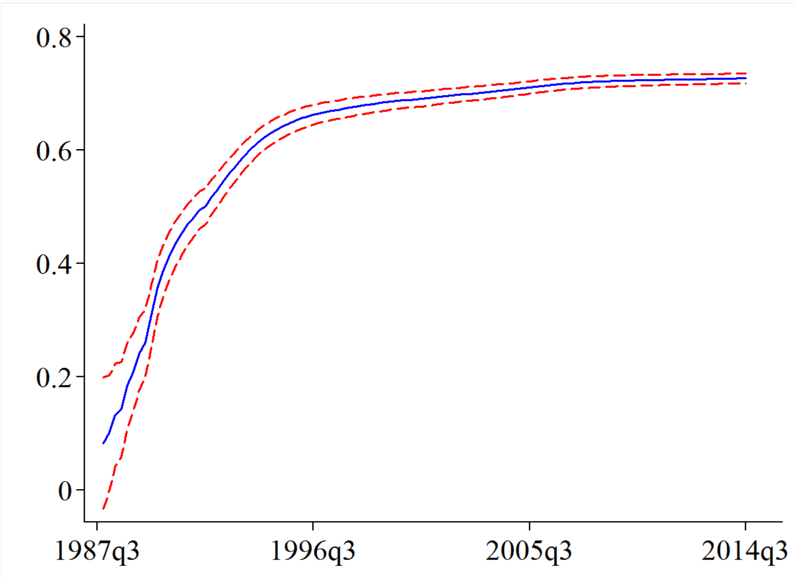
Notes: *** (**, *) denotes significance at 1% (5%, 10%) level. Standard errors are in parenthesis. P-values are in parenthesis for the log likelihood ratio tests. The dependent variable is the change in (log) GDP per capita.

5.4 Time varying space-time model results

The results presented so far outline a substantial change over time of the role played by the network interactions in house price and the macroeconomy dynamics. This suggests the need to examine spatial dependence of house prices over time. For this end, a rolling windows recursive estimation is employed to capture the structural changes in house price dynamics over time.

Quarterly house price data for 373 MSAs during 1987:Q1 to 2014:Q3 is used in the recursive sample estimation. We use rolling windows of 10 quarters and row normalized 10 nearest weight matrix. The rolling estimation resulted in 108 coefficient estimates. The rolling estimates of the spatial correlation coefficient is reported (blue line), together with 95% confidence bands (red lines), in Figure 4.

Figure 4: Recursive estimation results of log house prices across 373 MSAs during 1987:Q1 to 2014:Q3



The figure shows that the network coefficient has been increasing over time. Particularly in the mid 1990s the spatial correlation coefficient shows a substantial increase, implying an increasing integration of house prices across US MSAs. This reflects the enormous increase in the correlation of house prices in the US across different states after the deregulation of interstate banking in the US during 1995 to 1999, see Landier et al. (2015) for details. Cotter et al. (2011) have also documented an increasing trend in house price correlation across US cities during the real estate boom.

The time varying spatial correlation coefficient captures the dynamics of house prices both across MSAs and over time. This paper is the first to document an increasing house price integration across US MSAs and over time using time varying space-time econometric model.

6 Conclusion

This paper examines the interactions between house price fluctuations and output growth rate across 373 MSAs in US over the period 2001-2013. In order to examine the dynamics of house price fluctuations and output growth in the recent crisis period, we use a sub-sample period of 2007-2013. We examine the dynamics of house prices and output growth in standard panel data models as well as spatial panel models. The paper adds to the literature on housing markets and the real economy in three important dimensions: (a) it explicitly allows spatial lag variables (b) uses direct and indirect effects estimation and (c) uses time varying spatial econometric model.

The standard dynamic panel results suggest a significant negative association between a movement in house prices and output growth. The negative impact of house price fluctuations on output growth is larger during the recent financial crisis.

Next, using a spatial weight matrix, we analyze the dynamics of house prices and output growth by allowing spatial interaction effects. We consider spatial autoregressive and spatial Durbin models. Estimation results of the spatial autoregressive and spatial Durbin models show that spatially lagged house price movements and output growth rates are very important in examining the interactions between housing market and the wider economy. The negative effects of house price volatility on output growth gets larger during the recent crisis.

As an alternative specification, we follow LeSage and Pace (2009) and use the direct and indirect effects approach. The partial derivative impacts approach shows that house price fluctuations have both direct and indirect negative effect on output growth rate. This result has two important implications for stabilization policies. First, achieving stable house prices helps to stabilize the wider economy. Second, nearby economic units have important roles in stabilizing/destabilizing a given economy. Moreover, in order to account for MSA specific factors that may not be captured by the explanatory variables, we re-estimate a fixed effects model. The main results remain the same after controlling for MSA specific characteristics.

Another major contribution of this paper is the recursive estimation of the house price spatial econometric model. This method provides an alternative measure of house price co-movements across metropolitan areas over time. For this purpose, we use relatively longer time series house price data. We consider quarterly house price data for 373 MSAs during 1987:Q1 to 2014:Q3. The estimation result shows that the spatial correlation coefficient across metropolitan areas has been increasing over time, indicating an increasing synchronization of house prices across MSAs during the sample period.

This paper opens up an important research path in understanding the interactions of the housing market and the macroeconomy. One possible direction of future work can be investigating the channels through which house price volatility affects output growth in a space-time dynamic framework. Housing market bubbles can also be examined in a joint space-time effects specification.

Appendix A.

A.1 Metropolitan Statistical Areas; definition and criteria

Metropolitan Statistical Areas (MSAs) are defined by the Office of Management and Budget (OMB). Each metropolitan statistical area must have at least 10,000 inhabitants in the urban center and adjust areas that are connected to the urban centers by commuting.

The Federal Housing Finance Agency (FHFA) requires that an MSA must have at least 1,000 total transactions before it may be published. Additionally, an MSA must have had at least 10 transactions in any given quarter for that quarterly value to be published.

A.2 Panel unit root test

Levin et al. (2002) and Im et al. (2003) are the commonly used unit root testing precedures inheterogeneous panel. The formal testing procedure is based on an equation of the form

$$\triangle y_{it} = \alpha_i + \beta_i y_{it-1} + \delta_{it} + \sum_{k=1}^{K_i} \gamma_i^{(k)} \triangle y_{it-k} + \varepsilon_{it} \qquad (A.1)$$

where y_{it} denotes the variable y observed for the i^{th} cross-sectional unit at time t. In the case of Levin et al. unit root test specification, the error terms (ε_{it}) are assumed to be independent and the persistent parameter is the same across sections.

A.3 Spatial panel model results: Direct and indirect effects with fixed effects

Table A.1: Spatial panel model results: Direct and indirect effects with fixed effects

	Panel A: 2001-2013		Panel B: 2007-2013	
	SDM	SAR	SDM	SAR
Direct effect volatility	-0.099(0.035)**	-0.065(0.0267)**	-0.327(0.050)***	-0.390(0.041)***
Indirect effect volatility	0.001(0.092)	-0.0856(0.036)**	-0.596(0.128)***	-0.481(0.059)***
Total effect volatility	-0.099(0.089)	-0.151(0.062)**	-0.924(0.127)***	-0.871(0.093)***
Direct effect growth	-0.032(0.016)*	-0.014(0.016)	-0.107(0.021)***	-0.090(0.019)***
Indirect effect growth	0.313(0.057)***	-0.019(0.021)	0.155(0.069)*	-0.1112(0.028)***
Total effect growth	0.281(0.059)***	-0.033(0.037)	0.0481(0.071)	-0.202(0.047)***
Direct effect unemployment	-0.0176(0.003)***	-0.013(0.002)***	-0.019(0.005)***	-0.009(0.003) **
Indirect effect unemployemnt	0.007(0.005)	-0.017(0.003)***	0.017(0.007)*	-0.011(0.004)**
Total effect unemployment	-0.0106(0.005)*	-0.029(0.005)***	-0.002(0.006)	-0.020(0.006)**
ρ	0.577(0.018)***	0.586(0.018)***	0.562(0.025)***	0.571(0.024)***
Log likelihood	9952.85	9934.27	5347.95	5336.18
Wald test $\rho = 0$	1036.68(0.000)***	1112.13(0.000)***	502.03(0.000)***	558.60(0.000)***
Log likelihood ratio	37.17(0.000)***		23.55(0.000)***	
N	4849	4849	2611	2611

Notes: *** (**, *) denotes significance at 1% (5%, 10%) level. Standard errors are in parenthesis for estimation results. P-values are in parenthesis for the log likelihood ratio tests.

References

Abate, G.D., 2015. On the Link between Volatility and Growth: A spatial econometrics approach, Spatial Economic Analysis, DOI:10.1080/17421772.2015.1045021.

Anselin, L., 1988. Spatial econometrics: Methods and models. Dordrecht, Kluwer.

Anselin, L., 2002. Under the hood: Issues in the specification and interpretation of spatial regression models, Agricultural Economics 27, 247-267.

Anselin, L., 1992. Space and applied econometrics, Special Issue Regional Science and Urban Economics, 22.

Anselin, L., 2003. Spatial Externalities and Spatial Econometrics, International Regional Science Review 2, 153–166.

Anselin, L., and Le Gallo, J., 2006. Interpolation of Air Quality Measures in Hedonic House Price Models: Spatial Aspects, Spatial Economic Analysis 1, 31-52.

Anselin, L. and Lozano-Gracia N., 2009. Spatial Hedonic Models, In T.C. Mills and K. Patterson (Eds.), Palgrave Handbook of Econometrics: Applied Econometrics. Basingstoke, Palgrave Macmillan 2, 1213–1250.

Baltagi, B.H., and Li, J. 2014. Further evidence on the spatio-temporal model of house prices in the united states, Journal of Applied Econometrics 29, 515–522.

Bernanke, Ben, Mark Gertler, and Simon Gilchrist. 1999. The financial accelerator in a quantitative business cycle framework. In Handbook of macroeconomics. Vol. 1C, ed. John B. Taylor and Michael Woodford, 253–57. Amsterdam: Elsevier Science, North-Holland.

Bork, L., Møller, S.V., 2015. Forecasting house prices in the 50 states using Dynamic Model Averaging and Dynamic Model Selection, International Journal of Forecasting 31, 63-78.

Bordo, M.D., Jeanne, O., 2002. Boom-busts in Asset Prices, Economic Instability and Monetary Policy, NBER Working Papers 8966.

Can, A., 1992. Specification and estimation of hedonic housing price models, Regional Science and Urban Economics 22, 453-474.

Cesa-Bianchi, A., 2013. Housing cycles and macroeconomic fluctuations: A global perspective, Journal of International Money and Finance 37, 215-238.

Clapp, J. M., Kim, H. and Gelfand, A. E., 2002. Predicting Spatial Patterns of House Prices Using LPR and Bayesian Smoothing, Real Estate Economics 30, 505-532.

Cotter, J., Stuart, G., and Richard, R., 2011. Integration and Contagion in US Housing Markets, Geary WP 2011/31.

Cunningham, R. and I. Kolet. 2007. Housing Market Cycles and Duration Dependence in the United States and Canada, Bank of Canada Working Paper No. 2007-2.

Dubéa, J. and Lagros, D., 2014. Spatial econometrics and the hedonic pricing model: what about the temporal dimension? Journal of Property Research 31, 333-359.

Elhorst, P., 2010. Applied spatial econometrics: raising the bar, Spatial Economic Analysis 5, 928.

Ertur, C. and Koch, W., 2007. Growth, Technological Interdependence and Spatial Externalities: Theory and Evidence, Journal of Applied Econometrics 22, 1033-1062.

Hirata, H., Kose, M.A., Otrok, C., Terrones, M.E., 2013. Global house price fluctuations: synchronization and determinants, IMF Working Paper, WP/13/38.

Holly, S., Pesaran, M. H. and Yamagata, T., 2010. A spatio-temporal model of house prices in the USA, Journal of Econometrics 158, 160-173.

Iacoviello, M., 2005. House Prices, Borrowing Constraints, and Monetary Policy in the Business Cycle, American Economic Review 95, 739-764.

Iacoviello, M., Neri, S., 2010. Housing market spillovers: evidence from an estimated dsge model, American Economic Journal: Macroeconomics 2, 125-164.

Landier, A., David, S., D. and Thesmar, D., 2015. Banking Integration and House Price Comovement: Historical Evidence from the Deregulation of Interstate Banking. http://faculty.haas.berkeley.edu/dsraer/correlation_v12.pdf.

Leamer, E.E., 2007. Housing is the business cycle. In: Proceedings, Federal Reserve Bank of Kansas City, Federal Reserve Bank of Kansas City, 149–233.

LeSage, J. and Fischer, M. (2008) Spatial Growth Regressions: Model Specication, Estimation and Interpretation, Spatial Economic Analysis , Taylor and Francis Journals 3, 275-304.

LeSage, J. and Pace, R., 2009. Introduction to Spatial Econometrics. Boca Raton: Taylor and Francis.

Levin, Andrew, Lin, Chien-Fu, Chu, James Chia-Shang., 2002. Unit root tests in panel data: asymptotic and finite sample properties, Journal of Econometrics 108, 1-24.

Liu, Z., Pengfei, W. and Tao, Z., 2013. Land Price Dynamics and Macroeconomic Fluctuations, Econometrica 3, 434-447.

Im, Kyung So, Hashem Pesaran, M., Shin, Yongcheol., 2003. Testing for unit roots in heterogeneous panels, Journal of Econometrics 1, 53-74.

Kuethe, T. and Pede, V., 2011. Regional Housing Price Cycles: A Spatio-temporal Analysis Using US State-level Data, Regional Studies 45, 563-574.

Meen, G., 1999. Regional house prices and the ripple effect: a new interpretation, Housing Studies 14, 733-753.

Miller, N., Peng, L., and Sklarz, M., 2011. House Prices and Economic Growth, Journal of Real Estate Finance Economics 42, 522–541.

Miller, N. and Peng, L., 2006. Exploring metropolitan housing price volatility, Journal of Real Estate Finance and Economics 33, 5-18.

Monacelli, T., 2009. New Keynesian models,durable goods, and collateral constraints, Journal of Monetary Economics 56, 242–254.

Muñoz, Sònia (2004) Real effects of regional house prices: dynamic panel estimation with heterogeneity, London School of Economics and Political Science, Discussion paper, 493.

Osland, L., 2010. An Application Relation of Spatial Econometrics Price to Hedonic House Modeling, Journal of Real Estate Research 32, 289–320.

Penning-Cross, A., 2013. Subprime and prime Mortgages: Loss Distributions, OFHEO working paper 03–1.

Stephens, M., 2012. Tackling Housing Market Volatility in the UK, Part I: Long- and Short-term Volatility, International Journal of Housing Policy 12, 367–380.

Valentini, P., Ippoliti, L and Fontanella, L., 2013. Modeling US housing prices by spatial dynamic structural equation models, The Annals of Applied Statistics 7, 763- 798.

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Indirect effect volatility	0.001(0.092)	-0.0856(0.036)**	-0.596(0.128)***	-0.481(0.059)***
Total effect volatility	-0.099(0.089)	-0.151(0.062)**	-0.924(0.127)***	-0.871(0.093)***
Direct effect growth	-0.032(0.016)*	-0.014(0.016)	-0.107(0.021)***	-0.090(0.019)***
Indirect effect growth	0.313(0.057)***	-0.019(0.021)	0.155(0.069)*	-0.1112(0.028)***
Total effect growth	0.281(0.059)***	-0.033(0.037)	0.0481(0.071)	-0.202(0.047)***
Direct effect unemployment	-0.0176(0.003)***	-0.013(0.002)***	-0.019(0.005)***	-0.009(0.003) **
Indirect effect unemployemnt	0.007(0.005)	-0.017(0.003)***	0.017(0.007)*	-0.011(0.004)**
Total effect unemployment	-0.0106(0.005)*	-0.029(0.005)***	-0.002(0.006)	-0.020(0.006)**
ρ	0.577(0.018)***	0.586(0.018)***	0.562(0.025)***	0.571(0.024)***
Log likelihood	9952.85	9934.27	5347.95	5336.18
Wald test $\rho = 0$	1036.68(0.000)***	1112.13(0.000)***	502.03(0.000)***	558.60(0.000)***
Log likelihood ratio	37.17(0.000)***		23.55(0.000)***	
N	4849	4849	2611	2611

Notes: *** (**, *) denotes significance at 1% (5%, 10%) level. Standard errors are in parenthesis for estimation results. P-values are in parenthesis for the log likelihood ratio tests.

A.2.4 List of metropolitan statistical areas

Abilene, TX
Akron, OH
Albany, GA
Albany, OR
Albany-Schenectady-Troy, NY
Albuquerque, NM
Alexandria, LA
Allentown-Bethlehem-Easton, PA-NJ
Altoona, PA
Amarillo, TX
Ames, IA
Anchorage, AK
Ann Arbor, MI
Anniston-Oxford-Jacksonville, AL
Appleton, WI
Asheville, NC
Athens-Clarke County, GA
Atlanta-Sandy Springs-Roswell, GA
Atlantic City-Hammonton, NJ
Auburn-Opelika, AL
Augusta-Richmond County, GA-SC
Austin-Round Rock, TX
Bakersfield, CA
Baltimore-Columbia-Towson, MD
Bangor, ME
Barnstable Town, MA
Baton Rouge, LA
Battle Creek, MI
Bay City, MI
Beaumont-Port Arthur, TX
Beckley, WV
Bellingham, WA
Bend-Redmond, OR
Billings, MT
Binghamton, NY
Birmingham-Hoover, AL
Bismarck, ND
Blacksburg-Christiansburg-Radford, VA
Bloomington, IL
Bloomington, IN
Bloomsburg-Berwick, PA
Boise City, ID
Boulder, CO
Bowling Green, KY
Bremerton-Silverdale, WA
Bridgeport-Stamford-Norwalk, CT
Brownsville-Harlingen, TX
Brunswick, GA
Buffalo-Cheektowaga-Niagara Falls, NY
Burlington, NC
Burlington-South Burlington, VT
Casper, WY
California-Lexington Park, MD
Cambridge-Newton-Framingham, MA
Canton-Massillon, OH
Cape Coral-Fort Myers, FL
Cape Girardeau, MO-IL
Carbondale-Marion, IL
Carson City, NV
Fargo, ND-MN
Farmington, NM
Flagstaff, AZ
Cedar Rapids, IA
Chambersburg-Waynesboro, PA
Champaign-Urbana, IL
Charleston, WV
Charleston-North Charleston, SC
Charlotte-Concord-Gastonia, NC-SC
Charlottesville, VA
Chattanooga, TN-GA
Cheyenne, WY
Chico, CA
Cincinnati, OH-KY-IN
Clarksville, TN-KY
Cleveland, TN
Cleveland-Elyria, 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
Crestview-Fort Walton Beach-Destin, FL
Cumberland, MD-WV
Dalton, GA
Danville, IL
Daphne-Fairhope-Foley, AL
Davenport-Moline-Rock Island, IA-IL
Dayton, OH
Decatur, AL
Decatur, IL
Deltona-Daytona Beach-Ormond Beach, FL
Denver-Aurora-Lakewood, CO
Des Moines-West Des Moines, IA
Dothan, AL
Dover, DE
Dubuque, IA
Duluth, MN-WI
Durham-Chapel Hill, NC
East Stroudsburg, PA
Eau Claire, WI
El Centro, CA
Elizabethtown-Fort Knox, KY
Elkhart-Goshen, IN
Elmira, NY
El Paso, TX
Erie, PA
Eugene, OR
Evansville, IN-KY
Fairbanks, AK
Fayetteville-Springdale-Rogers, AR-MO
Fayetteville, NC
Flint, MI
Florence, SC
Florence-Muscle Shoals, AL
Fond du Lac, WI
Fort Collins, CO
Fort Smith, AR-OK
Fort Wayne, IN
Fresno, CA
Gadsden, AL
Gainesville, FL
Gainesville, GA
Gettysburg, PA
Glens Falls, NY
Goldsboro, NC
Grand Forks, ND-MN
Grand Island, NE

Grand Junction, CO

Grand Rapids-Wyoming, MI

Grants Pass, OR

Great Falls, MT

Greeley, CO

Green Bay, WI

Greensboro-High Point, NC

Greenville, NC

Greenville-Anderson-Mauldin, SC

Hanford-Corcoran, CA

Harrisburg-Carlisle, PA

Harrisonburg, VA

Hartford-West Hartford-East Hartford, CT

Hattiesburg, MS

Hickory-Lenoir-Morganton, NC

Hilton Head Island-Bluffton-Beaufort, SC

Hinesville, GA

Homosassa Springs, FL

Hot Springs, AR

Houma-Thibodaux, LA

Houston-The Woodlands-Sugar Land, TX

Huntington-Ashland, WV-KY-OH

Huntsville, AL

Idaho Falls, ID

Indianapolis-Carmel-Anderson, IN

Iowa City, IA

Ithaca, NY

Jackson, MI

Jackson, MS

Jackson, TN

Jacksonville, FL

Jacksonville, NC

Janesville-Beloit, WI

Jefferson City, MO

Johnson City, TN

Johnstown, PA

Jonesboro, AR

Joplin, MO

Kahului-Wailuku-Lahaina, HI

Kalamazoo-Portage, MI

Kankakee, IL

Kansas City, MO-KS

Kennewick-Richland, WA

Killeen-Temple, TX

Kingsport-Bristol-Bristol, TN-VA

Kingston, NY

Knoxville, TN

Kokomo, IN

Lafayette, LA

La Crosse-Onalaska, WI-MN

Lafayette-West Lafayette, IN

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-Henderson-Paradise, NV

Lawrence, KS

Lawton, OK

Lebanon, PA

Lewiston, ID-WA

Lewiston-Auburn, ME

Lexington-Fayette, K

Lima, OH

Lincoln, NE

Little Rock-North Little Rock-Conway, AR

Logan, UT-ID

Longview, TX

Longview, WA

Louisville/Jefferson County, KY-IN

Lubbock, TX

Lynchburg, VA

Macon, GA

Madera, 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

Michigan City-La Porte, IN

Midland, MI

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, MI

Myrtle Beach-Conway-N. Myrtle Beach, SC-NC

Naples-Immokalee-Marco Island, FL

Napa, CA

Nashville-Davidson–Murfreesboro–Franklin, TN

New Bern, NC

New Haven-Milford, CT

New Orleans-Metairie, LA

Niles-Benton Harbor, MI

North Port-Sarasota-Bradenton, FL

Norwich-New London, CT

Ocala, FL

Ocean City, NJ

Odessa, TX

Ogden-Clearfield, UT

Oklahoma City, OK

Olympia-Tumwater, WA

Omaha-Council Bluffs, NE-IA

Orlando-Kissimmee-Sanford, FL

Oshkosh-Neenah, WI

Owensboro, KY

Oxnard-Thousand Oaks-Ventura, CA

Palm Bay-Melbourne-Titusville, FL

Panama City, FL

Parkersburg-Vienna, WV

Pensacola-Ferry Pass-Brent, FL

Peoria, IL

Phoenix-Mesa-Scottsdale, AZ

Pine Bluff, AR

Pittsburgh, PA

Pittsfield, MA

Pocatello, ID

Portland-South Portland, ME

Portland-Vancouver-Hillsboro, OR-WA

Port St. Lucie, FL

Prescott, AZ

Providence-Warwick, RI-MA

Provo-Orem, UT

Pueblo, CO

Punta Gorda, FL

Racine, WI

Raleigh, NC

Rapid City, SD

Reading, PA

Redding, CA

Reno, NV

Richmond, VA

Riverside-San Bernardino-Ontario, CA

Roanoke, VA

Rochester, MN

Rochester, NY

Rockford, IL

Rocky Mount, NC

Rome, GA

St. Louis, MO-IL

Sacramento–Roseville–Arden-Arcade, CA

Saginaw, MI

St. Cloud, MN

St. George, UT

St. Joseph, MO-KS

Salem, OR

Salinas, CA

Salisbury, MD-DE

Salt Lake City, UT

San Angelo, TX

San Antonio-New Braunfels, TX

San Diego-Carlsbad, CA

San Jose-Sunnyvale-Santa Clara, CA

San Luis Obispo-Paso Robles-Arroyo Grande, CA

Santa Cruz-Watsonville, CA

Santa Fe, NM

Santa Maria-Santa Barbara, CA

Santa Rosa, CA

Savannah, GA

Scranton–Wilkes-Barre–Hazleton, PA

Seattle-Bellevue-Everett, WA

Sebastian-Vero Beach, FL

Sebring, FL

Sheboygan, WI

Sherman-Denison, TX

Shreveport-Bossier City, LA

Sierra Vista-Douglas, AZ

Sioux City, IA-NE-SD

Sioux Falls, SD

South Bend-Mishawaka, IN-MI

Spartanburg, SC

Spokane-Spokane Valley, WA

Springfield, IL

Springfield, MA

Springfield, MO

Springfield, OH

State College, PA

Staunton-Waynesboro, VA

Stockton-Lodi, CA

Sumter, SC

Syracuse, NY

Tacoma-Lakewood, WA

Tallahassee, FL

Tampa-St. Petersburg-Clearwater, FL

Terre Haute, IN

Texarkana, TX-AR

The Villages, FL

Toledo, OH

Topeka, KS

Trenton, NJ

Tucson, AZ

Tulsa, OK

Tuscaloosa, AL

Tyler, TX

Honolulu ('Urban Honolulu'), HI

Utica-Rome, NY

Valdosta, GA

Vallejo-Fairfield, CA

Victoria, TX

Vineland-Bridgeton, NJ

Virginia Beach-Norfolk-Newport News, VA-NC

Visalia-Porterville, CA

Waco, TX"

"Walla Walla, WA

Warner Robins, GA

Waterloo-Cedar Falls, IA

Watertown-Fort Drum, NY

Wausau, WI

Weirton-Steubenville, WV-OH

Wenatchee, WA

Wheeling, WV-OH

Wichita, KS

Wichita Falls, TX

Williamsport, PA

Wilmington, NC

Winchester, VA-WV

Winston-Salem, NC

Worcester, MA-CT

Yakima, WA

York-Hanover, PA

Youngstown-Warren-Boardman, OH-PA

Yuba City, CA

Yuma, AZ

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