Dinâmica dos preços da casa metropolitana dos EUA

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RESUMO

Usando dados para as 50 maiores áreas estatísticas metropolitanas dos EUA (MSAs), este estudo contribui para a literatura sobre a heterogeneidade regional na dinâmica dos preços das casas de várias maneiras. Utilizamos avanços recentes na econometria de painéis que permitem a heterogeneidade regional, a dependência transversal e os dados não estacionários, mas cointegrados. Testamos formalmente as diferenças regionais e exploramos as relações entre a elasticidade-preço do fornecimento de habitação e a elasticidade dos preços, bem como o tamanho e a duração da bolha. A estimativa da elasticidade a longo prazo dos preços das casas em relação à renda pessoal agregada é de 0,86 em todas as MSAs, mas varia consideravelmente entre as cidades. A dinâmica de momentum e reversão de curto prazo também mostra uma heterogeneidade regional substancial. A dinâmica está significativamente associada à elasticidade-preço do fornecimento de habitação. A elasticidade de renda de longo prazo geralmente é maior, o impulso de curto prazo é mais forte e o ajuste para o nível de preços fundamentais a longo prazo é mais fraco nas MSAs mais inelisáveis. Assim, enquanto os ciclos de preços das casas em torno de níveis de preços fundamentais a longo prazo normalmente estão altamente sincronizados em todos os MSAs dentro da mesma região, as bolhas dos preços das casas tendem a ser maiores e mais duradouras nas MSAs com o fornecimento de alojamento mais inelástico.

Palavras-chave: preço da casa, dinâmica, dados do painel, dependência transversal, bolha

U.S. Metropolitan House Price Dynamics

ABSTRACT

Using data for the 50 largest U.S. Metropolitan Statistical Areas (MSAs), this study contributes to the literature on regional heterogeneity in house price dynamics in several ways. We use recent advances in panel econometrics that allow for regional heterogeneity, cross-sectional dependence, and non-stationary but cointegrated data. We formally test for regional differences and explore the relationships between the price elasticity of housing supply and the income elasticity of prices, as well as bubble size and duration. The estimated mean long-term elasticity of house prices with respect to aggregate personal income is 0.86 across MSAs, but varies considerably between cities. Short-term momentum and reversion dynamics also show substantial regional heterogeneity. The dynamics are significantly associated with the price elasticity of housing supply. The long-term income elasticity generally is greater, short-term momentum is stronger, and adjustment towards the long-term fundamental price level is weaker in the more supply-inelastic MSAs. Hence, while house price cycles around long-term fundamental price levels typically are highly synchronized across MSAs within the same region, house price bubbles tend to be larger and longer-lasting in the MSAs with more inelastic housing supply.

Keywords: house price, dynamics, panel data, cross-sectional dependence, bubble

1. INTRODUCTION

It is widely recognized that various panel tests, such as unit root and cointegration tests, have higher power than corresponding tests on individual time series or equations, and that panel estimations yield more efficient coefficient estimates. Therefore, a number of studies use panel data to investigate the housing market. Two common problems in these panel analyses of housing market dynamics are the implicit assumption of homogeneous dynamics across regions or countries and the potential bias caused by spatial (i.e., cross-sectional) dependence in the data.

The assumption of regional homogeneity is likely to be unrealistic, given that urban economic theory and empirical evidence suggest that there can be considerable regional differences in housing market dynamics. In particular, the elasticity of supply of housing – a key determinant of the dynamics – is shown to be determined largely by local factors that differ substantially across cities (Saiz, 2010; Paciorek, 2013). In addition to variations in supply elasticity, regional differences in housing demand elasticities can cause notable differences in the elasticities of house prices with respect to fundamentals, such as income. In addition, theoretical models and empirical evidence indicate regional heterogeneity in the persistence of house price growth ("momentum") and in the adjustment speed of house prices towards their long-term fundamental levels (Lamont and Stein, 1999; Capozza et al., 2004; Glaeser et al., 2008).

Significant differences in house price dynamics across regions have several practical implications: (1) Predictions concerning the influences of nationwide policies that affect housing demand could be misleading if homogeneous dynamics are assumed within a country. (2) Local policy tools, too, can be suboptimal if based on dynamics estimated at the national level or on average dynamics across a group of cities. (3) The riskiness of regional housing markets should be assessed taking into account regional variations in dynamics. (4) House price predictions (and, by implication, regional growth prospects given the effect that rising housing prices have on regional growth) should also be based on regional dynamics. This is relevant to the important role that housing plays in spatial equilibrium models (Glaeser et al., 2008; Glaeser and Gottlieb, 2009).

Given that conventional panel data models that assume similar slope coefficients across regions are likely to be too restrictive, some studies have allowed for regional heterogeneity in house price dynamics. Abraham and Hendershott (1996), Lamont and Stein (1999), Capozza et al. (2004), and Harter-Dreiman (2004) all provide pioneering work that allows for at least some degree of heterogeneity. Abraham and Hendershott (1996) estimate separate models for house price dynamics in U.S. coastal and inland cities. Similarly, Harter-Dreiman (2004) estimates separate models for supply-constrained and unconstrained cities, and for large and small cities. Lamont and Stein (1999) allow for regional variation in the coefficient on income change, but not in the other slope coefficients, in an equation for house price growth in U.S. cities. Capozza et al. (2004) let both the momentum effect and adjustment speed towards fundamental price levels differ across U.S. metropolitan areas, while not permitting heterogeneity in the long-term elasticities. These early studies generally ignore complications regarding the suitability of the estimators for non-stationary and cross-sectionally dependent data.

Oikarinen and Engblom (2016) and Lai and Van Order (2017) represent more recent studies using panel models that allow for heterogeneity in slope coefficients. Oikarinen and Engblom (2016) investigate regional differences in price dynamics across Finnish cities. They estimate long-term dynamics separately for each city instead of relying on a panel estimator, but use fixed interaction

effects to allow for different short-term parameter estimates across cities. Lai and Van Order (2017), who base their long-term price model on the Gordon dividend discount model, use the Pesaran et al. (1999) pooled mean group and mean group estimators – that allow for heterogeneity in the slope coefficients across regions – to study variation in the shorter-term momentum and reversion dynamics across 45 U.S. Metropolitan Statistical Areas (MSAs).

Oikarinen and Engblom (2016) and Lai and Van Order (2017) both go beyond previous studies by formally testing for the significance of regional differences. Based on the Hausman test, Lai and Van Order (2017) conclude that the long-run variables share the same parameters across MSAs. They also report notable variation in the short-term dynamics between non-bubble and bubble MSAs, but do not test for the significance of this variation in a panel context. Oikarinen and Engblom (2016) argue that the overall Likelihood Ratio test statistics – which do not reject the hypothesis of homogeneity of short-term dynamics across cities – may be diluted, since for most cities the parameter estimates lie close to the mean value across cities, and show that in several cases an individual city-specific parameter estimate differs significantly from the mean.

The study by Holly et al. (2010) is the only one to date to take account of cross-sectional dependence, and they show that cross-sectional dependence can be an important issue in panel analyses of house price dynamics. They use the common correlated effects mean group (CCEMG) estimator of Pesaran (2006) that permits regional heterogeneity in slope coefficients and asymptotically eliminates cross-sectional dependence in large panels. While allowing heterogeneity across U.S. states in long-term house price elasticity with respect to aggregate income and in short-term dynamics, Holly et al. (2010) concentrate on the estimation of average values of the coefficients rather than the extent of regional variation and its causes.

The aim of this study is to add to the scarce literature on regional heterogeneity in house price dynamics using recent advances in panel econometrics. In contrast to Holly et al. (2010), we focus on analyzing regional variation in dynamics. We investigate the extent of city-level differences in long-term income elasticity and in short-term dynamics using quarterly data for the 50 largest U.S. MSAs for the period 1980 through 2012. The analysis is a test of the validity of the conventionally used panel models that assume homogeneous dynamics across regions. We apply several estimators that take account of cross-sectional dependence in the data: the augmented mean group (AMG) estimator of Eberhardt and Teal (2010), the CCEMG, and the Dynamic CCEMG (DCCEMG) of Chudik and Pesaran (2015), in particular.

We contribute to the literature in several ways. First, no study before this concentrates on the extent of variation in both long- and short-term city-level house price dynamics applying a panel estimator that permits slope coefficients to be heterogeneous across regions and is consistent in the presence of cross-sectional dependence. Second, we are the first to test formally for the significance of regional differences in both long-term and short-term price dynamics. Third, we analyze the differences across MSAs by relating the MSA-specific dynamics to supply restrictions and by investigating the deviations of house prices from long-term fundamental levels over time. Finally, this is the first study to apply the DCCEMG estimator – that is consistent in the presence of lagged dependent variables – to housing market dynamics.

We estimate the long-term elasticity of house prices with respect to aggregate personal income to average 0.86 across MSAs, but to vary considerably between cities. As expected, we find the MSA-level long-term income elasticity to generally be inversely related to the elasticity of housing supply.

Also, momentum and reversion dynamics show substantial regional heterogeneity that can influence the duration and magnitude of house price cycles.

We show that house price cycles around long-term fundamental price levels generally are highly synchronized across MSAs within the same region, while there are substantially greater differences in the timing and magnitude of these cycles between more distant cities. The results also indicate that conventional panel estimators that do not consider cross-sectional dependence can yield overly large estimates for the house price momentum effect as well as inconsistent parameter signs.

Moreover, we provide evidence supporting the theoretical considerations of Glaeser et al. (2008) regarding both the size and the duration of price bubbles: the notable overvaluations relative to long-term fundamental price levels have occurred in relatively supply inelastic MSAs, and the duration of considerable overvaluations has generally been longer in the more supply-restricted MSAs.[1] This finding is particularly strong with respect to the price boom of the 2000s.

The next section presents a simple theoretical framework for our empirical analysis. Section three describes the data used in the empirical investigation, while section four discusses the empirical analysis. The final section concludes the study.

2. A SIMPLE THEORETICAL FRAMEWORK

The theoretical basis of our empirical analysis lies in a conventional housing market stock-flow model. Using the typical assumptions concerning housing demand and supply determinants in the stock-flow model we have:

$$d_{i,t}^{*} = \mathrm{f}(y_{i,t}, r_{i,t}, p_{i,t}) = \gamma_0 + \gamma_1 y_{i,t} - \gamma_2 r_{i,t} - \gamma_3 p_{i,t} \tag{1}$$

$$s_{i,t}^{*} = \mathrm{g}(p_{i,t}, c_{i,t}) = \phi_0 + \phi_1 p_{i,t} - \phi_2 c_{i,t} \tag{2}$$

In (1), the natural log of equilibrium demand for housing services (d^*) in city i and period t is determined by the log of aggregate real income (y) representing the purchasing power in the city, the real mortgage interest rate (r) reflecting the opportunity cost of capital, and the log of house price level (p). The parameter γ_1 represents the elasticity of housing demand with respect to aggregate income, γ_2 indicates the influence of the interest rate on housing demand, and γ_3 is the price elasticity of housing demand. The inverse of γ_3 gives the slope of the housing demand curve.

The steady-state level of log housing supply (s^*), in turn, is a function of the log house price level and log construction costs (c) in the city. In (2), ϕ_1 reflects the long-term price elasticity of supply of housing and ϕ_2 is the long-run supply elasticity with respect to construction costs. In the long-term (steady-state) market clearing equilibrium $d^* = s^*$. Using this equilibrium condition, we get:

$$\gamma_0 + \gamma_1 y_{i,t} - \gamma_2 r_{i,t} - \gamma_3 p_{i,t} = \phi_0 + \phi_1 p_{i,t} - \phi_2 c_{i,t} \tag{3}$$

Based on (3), we can derive the reduced form equation for the long-term equilibrium house price level (p^*) as a function of demand side factors and construction costs, as shown in (4). These three factors, y, r, and c, also are the key determinants of the long-term equilibrium for house prices in, for example, the

[1] In contrast with our approach, Glaeser et al. (2008) base their bubble measure on the extent of price growth, i.e., not on deviations from a fundamental price level. They show that the notable price run-ups of the 1980s and during 1996-2006 in the U.S. were experienced almost exclusively in cities where housing supply is relatively inelastic.

DiPasquale and Wheaton (1992) four-quadrant model. In (4) and in the rest of the paper, we drop the subindex *i* from *r*, since the rate is the same across the cities within our U.S. sample.

$$p_{i,t}^{*} = \mathrm{h}(d_{i,t}^{*}, s_{i,t}^{*}) = \beta_0 + \beta_1 y_{i,t} - \beta_2 r_t + \beta_3 c_{i,t} \tag{4}$$

where

$$\beta_0 = (\gamma_0 - \phi_0) / (\gamma_3 + \phi_1)$$
$$\beta_1 = \gamma_1 / (\gamma_3 + \phi_1)$$
$$\beta_2 = \gamma_2 / (\gamma_3 + \phi_1)$$
$$\beta_3 = \phi_2 / (\gamma_3 + \phi_1)$$

Note that "long-term" refers to a time period within which housing supply is able to fully adjust to changes in its determinants. In a frictionless and informationally efficient market, the adjustment to the new equilibrium would be instantaneous – prices and supply would react immediately to a shock so that (2) and (4) would hold in every period. In the housing market, however, the adjustment is typically highly sluggish due to the notable frictions such as construction lag, high transaction costs, imperfect and costly market information, and liquidity constraints. Because of the market frictions, the adjustment towards equilibrium in (4) is expected to be slow and the price level may deviate notably from p^* in the short term even if market participants are fully rational (DiPasquale and Wheaton, 1994). In addition, behavioral factors such as feedback effects and loss aversion may affect short-term house price dynamics (e.g., DiPasquale and Wheaton, 1994; Genesove and Mayer, 2001; Dusansky and Koç, 2007; Røed Larsen and Weum, 2008). Taking account of these short-term features of housing market adjustment, urban house price movements can be presented in an error-correction form, where the current period price change is determined by the lagged price change, the lagged changes in market fundamentals, and by the previous period deviation of house price level from its long-term equilibrium level:

$$\Delta p_{i,t} = \lambda_{0i} + \lambda_1 \Delta y_{i,t-1} - \lambda_2 \Delta r_{t-1} + \lambda_3 \Delta c_{i,t-1} + \lambda_4 \Delta p_{i,t-1} - \lambda_5 (p - p^*)_{i,t-1} + \varepsilon_{i,t} \tag{5}$$

The kind of specification shown in (5) is typical in empirical examinations of house price dynamics (e.g., Lamont and Stein, 1999; Harter-Dreiman, 2004). This specification allows for fixed effects (λ_{0i}), momentum effects, and error correction. The inclusion of Δp_{t-1} on the right hand side caters for the potential feedback in housing demand that can cause positive momentum effects in house price movements: high house price growth in the previous period induces greater price growth expectations for the current period thus increasing demand for housing and consequently the house price growth rate. Previous empirical examinations provide strong support for such momentum effects (Case and Shiller, 1989; Capozza et al., 2004; Dusansky and Koç, 2007; Røed Larsen and Weum, 2008; Beracha and Skiba, 2011). The error-correction term [$\lambda_5(p - p^*)_{i,t-1}$] captures the sluggish adjustment of house prices towards the long-term equilibrium price level. The parameter λ_5 shows the speed of price adjustment towards p^* per period. Obviously, both λ_4 and λ_5 are expected to be between zero and one. Finally, ε, is assumed to be white noise and have a zero mean.

Generally, empirical estimations of housing market dynamics that have been based on panel data are in line with (4) and (5) in that the long-term coefficients on market fundamentals and the short-term dynamics are assumed to be the same across regions. Nevertheless, some regional heterogeneity is typically allowed by including region-specific fixed effects [i.e., the constant terms differ across regions: λ_{0i} in (5); this also would reflect β_{0i} instead of β_0 in (4)]. However, as we show above, the slope

coefficients in (4) are dependent on the price elasticity of housing supply. Given that theory expects supply elasticity to vary substantially across cities and empirical evidence supports these theoretical models (Saiz, 2010; Paciorek, 2013), the assumption of similar coefficients across regions seems unrealistic. In addition, the demand elasticities (γ_1 ,γ_2, γ_3) may vary across cities. Moreover, there are good reasons to expect that the strength of the momentum effect (λ_4) and the speed of adjustment towards long-term equilibrium (λ_5) differ across housing markets (Capozza et al., 2004; Glaeser et al., 2008).

Therefore, we hypothesize that there are significant differences in long- and short-term house price dynamics across cities, and rewrite the equations for the long-term equilibrium house price level and the short-term price change by adding the subscript *i* to all the parameters in the equations, thus allowing for heterogeneity of slope coefficients across cities:

$$p_{i,t}^* = \mathrm{h}(d_{i,t}^*, s_{i,t}^*) = \beta_{0i} + \beta_{1i} y_{i,t} - \beta_{2i} r_t + \beta_{3i} c_{i,t}, \tag{6}$$

$$\Delta p_{i,t} = \lambda_{0i} + \lambda_{1i}\Delta y_{i,t-1} - \lambda_{2i}\Delta r_{i,t-1} + \lambda_{3i}\Delta c_{i,t-1} + \lambda_{4i}\Delta p_{i,t-1} - \lambda_{5i}(p - p^*)_{i,t-1} + \varepsilon_{i,t} \tag{7}$$

In our empirical analysis, we examine the extent of regional heterogeneity across U.S. metropolitan area housing markets. We also relate regional differences in house price dynamics to MSA-specific factors, the supply elasticity of housing in particular.

3. DATA

Our empirical analysis is based on quarterly data for the 50 largest (as of 2012) U.S. MSAs for the period 1980 through 2012. For house prices, we use the Federal Housing Finance Agency (FHFA) all transactions house price indexes. The mortgage interest rate data are also from FHFA. Annual construction cost data, in turn, are sourced from the RS Means database. The quarterly construction cost values are interpolated based on changes in the shelter only component of the urban CPI produced by the Bureau of Labor Statistics. Finally, the aggregate income series is from the Bureau of Economic Analysis. As the income series is annual, we interpolate quarterly values based on changes in the national GDP, which is also from the Bureau of Economic Analysis. In contrast with the house price, aggregate income, and construction cost series that are at the MSA level, the mortgage interest rate data are nationwide. All the variables are specified in real terms. House prices and construction costs are deflated by the national urban CPI less shelter, while aggregate income and interest rates are deflated by the national urban CPI for all items. All the series except for the mortgage rate are in natural log form. Table 1 provides summary statistics for the variables.

There are significant regional variations in the mean growth rates of house prices and aggregate income. During 1980-2012, the mean real house price growth was negative in 18 MSAs, most of which are inland. The greatest price growth (annualized growth rate of 2.7%) was observed in Boston, with San Francisco, San Jose and New York having figures close to that of Boston. The mean real aggregate income growth, in turn, was positive in all the MSAs, being the lowest in Detroit and the highest in Austin. The regional variation in construction cost growth is much milder and statistically insignificant. The extremes with respect to Δc are Phoenix – having the only negative value (-0.1% annualized) – and New York (1.0%). The summary statistics indicate that, while construction cost and interest rate movements should not cause notable deviations in house price growth across MSAs at least over the

long run, aggregate income trends should account for a major part of the variation in the long-term growth of fundamental house price levels.[2]

While there are significant differences across MSAs in the long-term means of some variables, Table 1 shows that the mean correlation coefficients between MSAs are significantly positive for each variable. For construction cost growth the mean correlation coefficient is even close to one.

The sample period 1980-2012 includes notable price cycles in many of the cities, especially during the 2000s but also in the late 1980s through early 1990s. The difference between coastal and inland cities generally is clearly visible from Figure 1 and particularly prominent concerning the later price cycle. The house price level is generally more cyclical in the coastal cities, and the price increases of the 2000s were substantial in the coastal cities in particular. Regarding coastal cities, Houston and New Orleans are exceptions to the general rule of a notable price increase before the global financial crises. The graphs also show that house price development across MSAs located within the same part of the country is typically highly similar. In contrast, there are substantial differences between different regions of the U.S.

4. EMPIRICAL ANALYSIS

The econometric analysis of macro (or "market") level panel data must address some common complications. A well-established aspect of house price dynamics is cross-sectional (or spatial) dependence; if cross-sectional dependence is present in the data, then conventional estimators are not consistent. Cross-sectional dependence can be particularly relevant to housing market dynamics, since the spatial equilibrium condition implies that house price developments affect each other across cities (Glaeser and Gottlieb, 2009). Holly et al. (2010) provide evidence of notable cross-sectional dependence in house prices across U.S. states and show that neglecting the influence of cross-sectional dependence can considerably bias coefficient estimates. Another common problem is non-stationarity of data.

Fortunately, recent advances in panel econometrics have produced estimators that are consistent in the presence of cross-sectional dependence and non-stationary variables. Our empirical analysis is based on these kinds of modern techniques of panel econometrics, in particular those introduced by Pesaran (2006, 2007), Eberhardt and Teal (2010), and Chudik and Pesaran (2015). These approaches are designed for data with cross-sectional dependence, and the estimators are suitable for non-stationary data that are cointegrated. Moreover, these methods allow for regional heterogeneity in slope coefficients, which is important given the potentially substantial differences in house price dynamics across regions and the aim of this study. Our empirical analysis includes three phases:

1) Checking the order of integration of the data.
2) Estimating the long-run equation (6). This phase also includes testing for panel cointegration as a specification check for the estimated long-run house price equation and investigating the extent of regional heterogeneity in the long-run parameters.
3) Estimating the short-term house price equation (7) and examining the significance of heterogeneity in dynamics across MSAs.

[2] This is in line with the findings of Van Nieuwerburgh and Weill (2010): an increase in wage dispersion has been the main factor driving house price dispersion across U.S. cities.

In each phase, we report the cross-sectional dependence of model residuals to investigate whether it is appropriate to apply test procedures and estimators that allow for such dependence. We also examine if the models designed for cross-sectionally dependent data are able to remove such dependence from the residuals. Furthermore, the final part of this section studies the implications of the estimation results for price cycles and the relationship between price dynamics and the supply elasticity of housing.

4.1. Unit root tests

We start with panel unit root tests to examine the stationarity of the data. As the residual series from conventional augmented Dickey-Fuller (ADF) regressions exhibit highly significant cross-sectional correlation (see Table 2),[3] we report results based on the cross-sectional augmented IPS (CIPS) panel unit root test (Pesaran, 2007). The CIPS test filters out the cross-sectional dependence by augmenting the conventional ADF regressions with cross-sectional averages and is thus not biased by the presence of spatial dependence in the data. Furthermore, the CIPS test is based on the cross-sectional augmented ADF (CADF) regressions that are conducted separately for each MSA, thereby allowing for regional heterogeneity. Table 2 presents the CIPS test statistics both with and without a trend in the CADF regressions and with lag lengths varying between 0 and 4. The null hypothesis is that of non-stationarity, which is accepted for p and y in all cases. For c the evidence is mixed. Since the r series is the same for all MSAs, the unit root test for r is just the conventional ADF test for individual series, which accepts the null hypothesis of non-stationarity. Since the data clearly seem to include non-stationary components, there is a need to test for cointegration and apply an estimator that is suitable for non-stationary data in the second phase of the empirical analysis. As expected, all the variables are stationary in differences.

4.2. Long-term dynamics

Next, we estimate the long-term equations for house prices that correspond to (6). We estimate the long-term model with the Eberhardt and Teal (2010) Augmented Mean-Group (AMG) estimator that is designed for non-stationary data with cross-sectional dependence.[4] This estimator has previously been used to examine phenomena such as the determinants of default risk (Saldías, 2013) and interest rates (Lanzafame, 2016), and the relationship between energy intensity, income, urbanization, and industrialization (Sadorsky, 2013). The present study is the first to apply this estimator to analyze house price dynamics. In the AMG estimator, each regression in the estimated panel model is augmented with a "common dynamic process" to account for cross-sectional dependence. This common dynamic process is estimated first using a standard pooled OLS regression:

[3] This is in line with the findings of Holly et al. (2010) regarding state-level U.S. data.

[4] We also applied the CCEMG estimator. However, we do not report those results as the parameter estimates, especially on y, were implausible in many cases (for instance, there were negative coefficients in several MSAs). This complication of the CCEMG estimator with the long-term model is likely due to the substantial multicollinearity between the independent variables and the additional regressors included to capture the "common dynamic process". It is well known that strong multicollinearity increases the likelihood of obtaining incorrect signs and leads to more imprecise parameter estimates. In contrast, in the short-term model, the correlation between the independent variables and the additional regressors is considerably smaller on average. Furthermore, based on factor analysis the nature of the common correlated components differs substantially between the levels models and the model with differenced variables. While the AMG estimator works well for the levels model, the (D)CCEMG estimator is found to be more suitable for the difference model. The factor analysis results and correlation matrices are available upon request.

$$\Delta p_{i,t} = \delta_1 \Delta y_{i,t} - \delta_2 \Delta r_t + \delta_3 \Delta c_{i,t} + \sum_{t=2}^{T} \mu_t \Delta D_t + e_{i,t} \quad (8)$$

In (8), D_t are quarterly dummies, T is the length of the sample period, and e is the error term. In the second stage, the 50 MSA-specific OLS regressions for the levels are augmented with the *T-1* coefficient estimates, $\hat{\mu}_t$:

$$p_{i,t} = \beta_{0i} + \beta_{1i} y_{i,t} - \beta_{2i} r_t + \beta_{3i} c_{i,t} + d_i \hat{\mu}_t + e_{i,t} \quad (9)$$

In (9), $\hat{\mu}_t$ represents an estimated cross-group average of the evolution of unobservables over time (referred to as the common dynamic process). The model also contains MSA-specific intercepts (β_{0i}) to cater for any unobserved time-invariant fixed effects.

We follow Holly et al. (2010) and investigate model stationarity (i.e., whether the models are cointegrated) based on the CIPS test. This works as a specification check for the estimated relations: if the null hypothesis of non-stationarity is rejected, we can conclude that the estimated relationship is a long-term equilibrium equation. The long-run equation (10) that is tested for stationarity does not incorporate the effects of the common dynamic process:

$$\hat{\epsilon}_{i,t} = p_{i,t} - \hat{\beta}_{0i} + \hat{\beta}_{1i} y_{i,t} - \hat{\beta}_{2i} r_t + \hat{\beta}_{3i} c_{i,t} \; [= (p - p^*)_{i,t}] \quad (10)$$

For cointegration to be present, $\hat{\epsilon}$ needs to be stationary. Indeed, the hypothesis of non-stationarity of $\hat{\epsilon}$ is rejected for each model reported in Table 3 regardless of the imposed lag length in the CADF regressions. Again, regional heterogeneity in the CADF coefficients is allowed in the CIPS test.

Table 3 reports the estimated mean group (i.e., the mean of $\beta_{j,i}$ across MSAs) coefficients for the long-term price equation based on four different estimators. The reported standard errors are computed following Pesaran and Smith (1995). All of the coefficient estimates in the AMG model have the expected signs and are statistically significant. The standard mean-group (MG) estimator of Pesaran and Smith (1995), which allows for regional heterogeneity but does not include the common dynamic process [i.e., does not cater for cross-sectional dependence because it excludes $d_i \hat{\mu}_t$ from (9)] results in somewhat different results. For instance, the sign on *r* is positive instead of negative. The AMG estimator is more reliable as it eliminates almost all of the cross-sectional dependence – the remaining cross-sectional correlation in the residuals is only 0.01, while the corresponding correlation in the MG model is as high as 0.60.

Based on the AMG model, the mean of the MSA-specific long-term elasticities of house prices with respect to aggregate income is 0.86. Corresponding estimates for *c* and *r* are 0.56 and –0.01, respectively. Higher aggregate income increases demand for housing and thereby the price level, while higher interest rates do the opposite. Higher construction costs, in turn, reduce housing supply, which causes higher house price levels.

A concern with the AMG estimation results is the potential endogeneity of the regressors with respect to *p*. Therefore, we also apply the panel mean-group Fully-Modified OLS (FMOLS-MG) estimator of Pedroni (2000, 2001) to the data. The individual FMOLS estimates are super-consistent and robust in the presence of variable endogeneity, when the variables are non-stationary and cointegrated (Pedroni, 2007). However, as the FMOLS-MG estimator does not cater for cross-sectional dependence – which in our case is evident in the reported residual correlations in Table 3 – we also report the panel mean-group FMOLS estimation results when the MSA-specific regressions are augmented with a common dynamic process as in (9) (FMOLS-AMG). Again, the augmented model can remove (almost) all of the

cross-sectional correlation in residuals. The FMOLS-AMG estimates are very close to the AMG ones, which suggests that potential endogeneity bias is not an issue in the AMG estimates. In contrast, cross-sectional dependence appears to be an important issue in the FMOLS estimations, too, since the FMOLS-MG estimates differ substantially from the FMOLS-AMG ones.

The models also allow us to investigate formally whether the regional differences in the long-term slope coefficients are statistically significant. For the MG and AMG models we use the Swamy test of slope homogeneity of Pesaran and Yamagata (2008).[5] For the FMOLS models, in turn, the size-adjusted F-test proposed by Pedroni (2007) is used. These tests clearly rejects the null hypothesis of homogeneous slope coefficients in all models, indicating that the regional differences in long-term dynamics are indeed of importance.

Regarding differences across MSAs, we concentrate on the variation in income elasticity. Aggregate income is the determinant of p^* that is trending, while c and r do not exhibit notable long-term trends but are rather mean-reverting. Also, y is the fundamental whose growth over time varies significantly across MSAs. That is, the growth in y together with income elasticity determine MSA-specific house price growth and its variation across MSAs over the long run.

Income elasticity exhibits substantial regional differences. The largest observed elasticity is 2.01 for Detroit, while the smallest is 0.14 for Dallas. Detroit differs quite substantially from the other MSAs, since the second largest value is 1.64 for Los Angeles. The considerable variation in income elasticity across MSAs must be explained by regional variation in the supply elasticity of housing and in the price and income elasticities of housing demand: as shown above, $\beta_1 = \gamma_1 / (\gamma_3 + \phi_1)$. Given the large regional variation in the price elasticity of supply of housing (Saiz, 2010), it is expected that the supply side accounts for a major part of the differences in β_1. The influence of supply elasticity is also of particular interest, as it is the supply elasticity in particular that can be affected directly by national and especially local policies and regulations. Moreover, many leading urban economists emphasize today the influence of housing supply elasticity as a key determinant not only of house price dynamics but also of metropolitan growth dynamics in general (e.g., Glaeser et al., 2006; Glaeser and Gottlieb, 2009; Saiz, 2010; Gyourko et al., 2013). In particular, more inelastic housing supply and thereby greater income elasticity of house prices can work as a significant counterforce for city growth and regional centralization.

Figure 2 illustrates the relationship between the price elasticity of supply reported by Saiz (2010) and the estimated elasticity of house price level with respect to aggregate income at the MSA level.[6] The income elasticities are based on AMG estimation, but the results would be the same based on the FMOLS-AMG estimator (the correlation between these two models' MSA-specific income elasticities is 0.99). As expected, generally the more inelastic housing supply is, the greater is the income elasticity. The simple correlation between these two elasticities is -0.72 (-0.76 without Detroit). The strong negative relationship between income elasticity of house prices and supply elasticity, in

[5] This test has the correct size and satisfactory power in panels with exogenous regressors and in dynamic panels if the autoregressive coefficient is not too close to unity. The long-term models reported in Table 3 may include endogenous regressors, However, the very small p-values (<0.001) in the Swamy and F-tests are a clear indication of heterogeneous slope coefficients.

[6] All of the figures, coefficients, and correlations that include the supply elasticity exclude Sacramento, CA, since Saiz (2010) does not report the elasticity for this MSA.

particular, is why supply elasticity significantly affects metropolitan growth dynamics (Saks, 2008; Gyourko et al., 2013).

4.3. Short-term dynamics

In the third step, we focus on short-term house price dynamics, with the momentum effect and adjustment speed towards long-run equilibrium being our main interests. In the error-correction part of the short-term model, we use the MSA-specific deviation of the house price level from its long-term equilibrium level [given by (10)] based on the AMG estimates.[7] For comparison purposes, we estimate equation (7) with several alternative estimators to see the impact of the potential biases on the estimates computed with conventional estimators that do not cater for cross-sectional dependence.

In Table 4, the OLS model refers to the conventional pooled fixed-effects Ordinary Least Squares estimator that corresponds to equation (5), which does not allow for regional heterogeneity in the slope coefficients. For the other models, the coefficient estimates reported in Table 4 represent the mean coefficients across MSAs. The RE model is the Random Effects estimator that allows for heterogeneity in dynamics through random intercepts and slope coefficients. The MG estimator also allows for regional heterogeneity in the estimates. These three "conventional" estimators yield momentum parameters of around 0.3 and significant but very slow adjustment speeds of prices (approximately 2-3% per quarter) towards the steady-state level. The other estimated parameters, except those on Δc, are also statistically significant, but the coefficients on Δc and Δr have unexpected signs. As expected, the residual cross-sectional correlation in these models is large (around 0.4), indicating notable cross-sectional dependence.

Given that the conventional panel OLS, RE, and MG estimates can be biased in the presence of cross-sectional dependence, Table 4 also reports the results based on the AMG and CCEMG estimators. The CCEMG estimator aims to remove the biasing impact of the unobservable common factor by including the cross-sectional averages of the dependent and independent variables as additional regressors (Pesaran, 2006). The CCEMG estimator seems to do a better job with the short-term dynamics than the AMG estimator, since the latter model's residuals still exhibit some cross-sectional correlation. Also, the sign of the coefficient on Δc is inconsistent with theory in the AMG model. The coefficients computed with CCEMG exhibit several notable differences compared with those estimated with the OLS, RE, and MG estimators: (1) the momentum parameter is much smaller; (2) the adjustment speed towards the long-run equilibrium level is notably greater; (3) the coefficient on lagged income is substantially larger; (4) the sign of the coefficient on Δc is in line with theory; and (5) the coefficient on Δr is insignificant. The remaining cross-sectional correlation in the CCEMG model is negligible (-0.01).

As all of the estimators used for models [1] through [5] in Table 4 can, in principle, suffer from the "Nickell bias" (Nickell, 1981) due to the inclusion of the one-period lagged dependent variable as an explanatory variable, we further present results from an estimation conducted with the Chudik and Pesaran (2015) Dynamic CCEMG estimator. This estimator is consistent in the presence of the lagged dependent variable. There are some slight differences between the CCEMG and DCCEMG results, but

[7] The deviation from long-run fundamental price level for each MSA is computed as in (10), i.e., excluding the influence of the common dynamic process. The common dynamic process itself is not a fundamental factor for house prices and in many cases could "explain" a high price level in a given MSA by high price levels in other MSAs even if market fundamentals do not justify such price levels. The deviations based on the FMOLS-AMG model are similar.

generally these two models are very much alike, and the differences in the coefficient estimates are not statistically significant. This indicates that, while cross-sectional dependence appears to cause notable bias in the OLS, RE and MG coefficient estimates, the biases induced by the lagged dependent variable in the CCEMG estimates are not large (given our data). Model [6] estimated with DCCEMG is our preferred one in any case given its desirable properties when estimating short-term dynamics.

The quarterly adjustment speed of prices towards the steady-state level is 7% and highly significant in model [6]. The negative sign on the adjustment coefficient – higher house price levels compared with long-term equilibrium levels predict lower future price growth – further implies that the estimated long-term model works as it should: house prices tend towards the long-term steady-state level. Interestingly, the notably smaller coefficients on lagged price change (smaller momentum effect) in models [4] to [6], which cater for cross-sectional dependence, than in models [1] to [3], which do not, suggests that the relatively large momentum parameters often reported for U.S. MSAs in the previous literature may exaggerate the actual momentum effect. However, the parameter on lagged price change remains highly significant in models [4] to [6].

The Swamy test clearly rejects the hypothesis of slope homogeneity in models [3] through [6] for which the test is applicable. Similar to the long-term income elasticity, the momentum effect and equilibrium-adjustment speed vary considerably across MSAs and are significantly related to the supply elasticity. The momentum is generally greater and reversion towards fundamental price level slower in the MSAs with more inelastic supply of housing. The correlation of the momentum parameter with supply elasticity is -0.30 and that between reversion speed and supply elasticity is -0.28. This is in line with the often stated argument that the more supply-restricted regions are more prone to notable house price overshoots and subsequent price drops.

4.4. Price cycles around the fundamental price level

Figure 3 shows the deviation of house price levels from the estimated long-run relation in each MSA using the same long-run fundamental price levels as in the estimation of short-term dynamics. Similar to Figure 1, we have clustered the 50 MSAs into 12 different regional groups. This division illustrates how house price cycles around the long-term fundamental price level generally are highly synchronized across MSAs within the same region, while there typically are notably greater differences in the deviations from fundamental price level between cities located far from each other. The average correlation of deviations is 0.82 within geographic groups, while it is 0.58 between MSAs that do not belong in the same geographic group.

The theoretical model of Glaeser et al. (2008) suggests that, if housing supply is sufficiently elastic, then a “temporary burst of irrational exuberance” does not lead to large and long-lasting price increases; instead, the emerging bubble disappears fast. In contrast, if housing supply is inelastic and if we assume adaptive expectations (which are well supported by the empirical literature), a positive demand shock causes a greater short-term price reaction, expectations of future price increases remain high, and additional price growth is induced. The Glaeser et al. (2008) model further suggests that the degree of inelasticity needed for a bubble to survive increases over time, implying that long-lasting bubbles can take place only in cities with highly inelastic housing supply. Hence, bubbles are expected to be larger and longer-lasting in the comparatively inelastic MSAs. Eventually, prices have to converge back towards the fundamental level, but this convergence typically involves an undershoot; i.e., house prices tend to drop below the fundamental level after a notable overshoot. In line with their

theoretical considerations, Glaeser et al. (2008) show that the notable price run-ups of the 1980s in the U.S. were almost exclusively experienced in cities where housing supply is relatively inelastic. Similarly, the largest price increases from 1996 to 2006 took place, with a couple of exceptions, in the inelastic markets.

While Glaeser et al. (2008) concentrate on comparing *price growth rates* across cities, we provide further evidence on the relationship between supply elasticity and house price dynamics by investigating the relationship between elasticity of supply and *overvaluation* relative to long-term fundamental price levels. This is worthwhile, since greater price growth does not straightforwardly define a price bubble, as faster price growth can be related to more rapid income and population growth as well as to greater long-run income elasticity of housing prices. In theory, the faster run-ups in the more supply-restricted areas could be due to differing market fundamentals.

Figure 3 reveals that it is mostly the coastal cities that have experienced drastic house price overshoots and cycles around fundamental price levels. That is, quite intuitively, demand increases induce greater initial price growth in the more supply-restricted cities – that are typically coastal cities – which yields greater future price growth expectations for backward-looking agents. The greater expectations can fulfill themselves, up to a point, and subsequently drive house price levels farther away from long-term fundamental price levels. The correlation of momentum and reversion with supply elasticity provides further reasons for the observed notable price overshoots in the supply-inelastic MSAs.

Figure 4 illustrates the relationship between price bubbles and supply elasticity by showing that the notable price bubbles – defined as at least a 20% deviation above the estimated fundamental price level – have been concentrated in the relatively supply-inelastic MSAs.[8] The vertical dashed line shows the average supply elasticity (1.66), while the horizontal dashed line indicates the 20% threshold. In the 2000s, the large overshoots took place only in the MSAs with lower than average supply elasticity. Indeed, in 74% of cities with lower than average supply elasticity, the maximum price overshoot was more than 20%, and the simple correlation between the peak of overshoot and supply elasticity is -0.59 and statistically highly significant (allowing for non-linearity in the relationship, the association between the overshoot and supply elasticity is even slightly greater; see Figure 4). This relationship in the 2000s is somewhat stronger than that in the 1980s: for the 1980s, the corresponding correlation is -0.40, partly reflecting the impact of two high supply-elastic MSAs that experienced an overshoot of more than 20% (Houston and Oklahoma City, both in 1980). Table 5 summarizes the elasticity values and bubble figures of the 2000s.

We further test the implications of the Glaeser et al. (2008) model by regressing both bubble size and duration in the 2000s on supply elasticity (Table 6). In addition to the supply elasticity, the aggregate income growth rate is a likely factor contributing to the size and duration of the bubbles, as greater demand growth induces faster price growth and thereby greater expected growth (assuming adaptive expectations). Hence, Table 6 also reports simple cross-sectional OLS regressions for the bubble variables using the difference between the maximum level of y during 1996-2007 and y as of 1996Q1 ("growth of y") as an additional explanatory variable.[9] Year 1996 is selected as the base year for the growth rate as in Glaeser et al. (2008), since 1996 presents the turning point in real house price indices,

[8] In line with Glaeser et al. (2008), we chose the value 20% to ensure that house prices really are substantially above the long-run fundamental level.

[9] We also estimated models that include the squared explanatory variables. These models do not show evidence of significant non-linearity in the effects.

and 2007 generally is the last year when price peaks where observed in these MSAs. Both supply elasticity and growth in *y* are highly significant and together explain the bulk of bubble size and duration across MSAs. As expected, more inelastic supply and growth in housing demand (i.e., in *y*) both were positively associated with the size and duration of the bubble.

While these regressions are coarse and growth in *y* may be endogenous to price bubbles, it is reassuring that the coefficient on supply elasticity is not notably affected by the inclusion of demand growth in the regressions. The coefficient estimates suggest that a one-unit smaller supply elasticity caused a 9% larger price bubble and a one year longer bubble duration in the 2000s, on average. Obviously, given that the bubbles – defined here as at least 20% overpricing – have taken place only in the relatively inelastic cities, there is a highly significant correlation between the bubble duration and supply elasticity across all 50 MSAs. Therefore, Table 6 also reports a model for duration that includes only those 22 MSAs that experienced at least a 20% overshoot. While the coefficient on supply elasticity remains largely unchanged in this model, it is statistically insignificant. All in all our findings provide support for the theoretical model of Glaeser et al. (2008).[10]

5. CONCLUSIONS

We use recent advances in panel econometrics to investigate house price dynamics in the 50 largest U.S. MSAs. These methods allow for regional heterogeneity, take account of cross-sectional dependence, and are suitable for non-stationary but cointegrated data. The study adds to the literature on regional heterogeneity in house price dynamics and includes several innovations compared with the extant studies.

We estimate the mean long-term elasticity of house prices with respect to aggregate personal income to be 0.86 across MSAs, but to vary considerably between regions. The MSA-level long-term income elasticity is negatively and significantly associated with the price elasticity of housing supply: the income elasticity of prices is generally greater the more inelastic is housing supply. House price cycles around long-term fundamental price levels generally are highly synchronized across MSAs within the same region, while there are substantially greater differences in the timing and magnitude of these cycles between more distant cities. This points to important region-specific demand shocks that drive house price cycles in MSAs within the same geographic part of the country.

The short-term momentum and reversion dynamics also show substantial regional heterogeneity that can notably influence the extent of house price cycles. Momentum is stronger and adjustment towards the long-term fundamental price level is weaker in the more supply-restricted MSAs. The analysis provides empirical evidence supporting the theoretical model of Glaeser et al. (2008): house price bubbles tend to be larger and longer-lasting in the MSAs with more inelastic housing supply. Indeed, the notable overvaluations have concentrated on and have had longer duration in the relatively supply-inelastic MSAs during the sample period (1980-2012). This finding is particularly strong concerning the price boom of the 2000s. As productivity growth increases housing demand (through increases in

[10] In contrast to Glaeser et al. (2008) and our findings, Davidoff (2013) concludes that there is no evidence supporting the view that differences in supply elasticity caused cross-sectional variation among U.S. housing markets in the severity of the 2000s housing cycle. While Davidoff (2013) uses three different measures for the severity of the cycle – price growth rates, price growth rate volatilities, and the price difference between peak of the boom and the lowest price level in the consequent bust – he does not relate house price levels to a "fundamental" house price level.

regional income and population), the results imply that productivity shocks can have considerably different house price impacts in different MSAs both in the short- and in the long-term.

The analysis is also a test of the validity of conventional panel models – that assume homogeneous dynamics across regions and neglect cross-sectional dependence – in the analysis of housing market dynamics. Given the considerable variations across regions, the use of estimators that allow for heterogeneous dynamics is warranted. Allowing for regionally heterogeneous dynamics is likely to yield more accurate house price predictions and "bubble indicators", and is important with respect to efforts to have more reliable estimates of the housing market outcomes of nationwide and local policy actions, regional growth prospects, and the riskiness of regional housing markets. Our results also suggest that the ability to take account of cross-sectional dependence can significantly affect coefficient estimates. Conventional panel estimators that do not consider cross-sectional dependence can yield overly large estimates for the house price momentum effect, estimated adjustment speeds towards long-run equilibrium levels that are too slow, and incorrect parameter signs.

6. REFERENCES

ABRAHAM, J. M. and HENDERSHOTT, P. H. Bubbles in metropolitan housing markets. *Journal of Housing Research*, 7(2), 1996, 191-207.

BERACHA, E. and SKIBA, H. Momentum in residential real estate. *Journal of Real Estate Finance and Economics*, 43(3), 2011, 299-320.

CAPOZZA, D. R., HENDERSHOTT, P. H. and MACK, C. An anatomy of price dynamics in illiquid markets: analysis and evidence from local housing markets. *Real Estate Economics*, 32(1), 2004, 1-32.

CASE, K. E. and SHILLER, R. J. The efficiency of the market for single-family homes. *American Economic Review*, 79(1), 1989, 125-137.

CHUDIK, A. and PESARAN, M. H. Common correlated effects estimation of heterogeneous dynamic panel data models with weakly exogenous regressors. *Journal of Econometrics*, 188(2), 2015, 393-420.

DAVIDOFF, T. Supply elasticity and the housing cycle of the 2000s. *Real Estate Economics*, 41(4), 2013, 793-813.

DIPASQUALE, D. and WHEATON, W. C. The markets for real estate assets and space: a conceptual framework. *Real Estate Economics*, 20(1), 1992, 181-197.

DIPASQUALE, D. and WHEATON, W. C. Housing market dynamics and the future of housing prices. *Journal of Urban Economics*, 35(1), 1994, 1-27.

DUSANSKY, R. and KOÇ, Ç. The capital gains effect in the demand for housing. *Journal of Urban Economics*, 61(2), 2007, 287-298.

EBERHARDT, M. and TEAL, F. Productivity analysis in global manufacturing production. Economics Series Working Papers 515, University of Oxford, Department of Economics, 2010.

GENESOVE, D. and MAYER, C. Loss aversion and seller behavior: evidence from the housing market. *Quarterly Journal of Economics*, 116(4), 2001, 1233-1260.

GLAESER, E. L. and GOTTLIEB, J.D. The wealth of cities: agglomeration economies and spatial equilibrium in the United States. *Journal of Economic Literature*, 47(4), 2009, 983-1028.

GLAESER, E. L., GYOURKO, J. and SAIZ, A. Housing supply and housing bubbles. *Journal of Urban Economics*, 64(2), 2008, 198-217.

GLAESER, E. L., GYOURKO, J. and SAKS, R. E. Urban growth and housing supply. *Journal of Economic Geography*, 6(1), 2006, 71-89.

GYOURKO, J., MAYER, C. and SINAI, T. Superstar cities. *American Economic Journal*: *Economic Policy*, 5(4), 2013, 167-199.

HARTER-DREIMAN, M. Drawing inferences about housing supply elasticity from house price responses to income shocks. *Journal of Urban Economics*, 55(2), 2004, 316-337.

HOLLY, S., PESARAN, M. H. and YAMAGATA, T. A spatio-temporal model of house prices in the USA. *Journal of Econometrics*, 158(1), 2010, 160-173.

LAI, R. N., and VAN ORDER, R. U.S. house prices over the last 30 years: bubbles, regime shifts and market (in)efficiency. *Real Estate Economics*, 45(2), 2017, 259-300.

LAMONT, O. and STEIN, J. C. Leverage and house-price dynamics in U.S. cities. *Rand Journal of Economics*, 30(3), 1999, 498-514.

LANZAFAME, M. Inflation targeting and interest rates: a panel time-series approach. *Oxford Economic Papers*, 68(2), 2016, 484-505.

NICKELL, S. Biases in dynamic models with fixed effects. *Econometrica*, 49(6), 1981, 1417-1426.

OIKARINEN, E. and ENGBLOM, J. Differences in housing price dynamics across cities: a comparison of different panel model specifications. *Urban Studies*, 53(11), 2016, 2312-2329.

PACIOREK, A. Supply constraints and housing market dynamics. *Journal of Urban Economics*, 77, 2013, 11-26.

PEDRONI, P. Fully modified OLS for heterogeneous cointegrated panels. In: B. H. Baltagi (Editor), *Nonstationary Panels, Cointegration in Panels and Dynamic Panels*, Amsterdam: Elsevier, 2000.

PEDRONI, P. Purchasing power parity tests in cointegrated panels. *Review of Economics and Statistics*, 83(4), 2001, 727-731.

PEDRONI, P. Social capital, barriers to production and capital shares: implications for the importance of parameter heterogeneity from a nonstationary panel approach. *Journal of Applied Econometrics*, 22(2), 2007, 429-451.

PESARAN, M. H. Estimation and inference in large heterogeneous panels with a multifactor error structure. *Econometrica*, 74(4), 2006, 967-1012.

PESARAN, M. H. A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Econometrics*, 22(2), 2007, 265-312.

PESARAN, M. H., SHIN, Y. and SMITH, R. P. Pooled mean group estimation of dynamic heterogeneous panels. *Journal of the American Statistical Association*, 94(446), 1999, 621-634.

PESARAN, M. H. and SMITH, R. P. Estimating long-run relationships from dynamic heterogeneous panels. *Journal of Econometrics*, 68(1), 1995, 79-113.

PESARAN, M. H. and YAMAGATA, T. Testing slope homogeneity in large panels. *Journal of Econometrics*, 142, 2008, 50-93.

RØED LARSEN, E. and WEUM, S. Testing the efficiency of the Norwegian housing market. *Journal of Urban Economics*, 64(2), 2008, 510-517.

SADORSKY, P. Do urbanization and industrialization affect energy intensity in developing countries? *Energy Economics*, 37, 2013, 52-59.

SAIZ, A. The geographic determinants of housing supply. *The Quarterly Journal of Economics*, 125(3), 2010, 1253-1296.

SAKS, R. E. Job creation and housing construction: Constraints on metropolitan area employment growth. *Journal of Urban Economics*, 64(1), 2008, 178-195.

SALDÍAS, M. A market-based approach to sector risk determinants and transmission in the euro area. *Journal of Banking and Finance*, 37(11), 2013, 4534-4555.

VAN NIEUWERBURGH, S. and WEILL, P. Why has house price dispersion gone up? *Review of Economic Studies*, 77(4), 2010, 1567-1606.

Table 1. Summary statistics

Variable	**Mean across all MSAs**	**Standard deviation of MSA-specific means**	**Mean of minimums across MSAs**	**Mean of maximums across MSAs**	**Equality of means (p-value)**
Real house price growth (Δp)	0.001	0.024	-0.003	0.007	0.091*
Real aggregate income growth (Δy)	0.006	0.010	0.002	0.012	0.000***
Real construction cost growth (Δc)	0.001	0.010	-0.000	0.003	0.991
Real interest rate (r)	0.074	0.026	0.074	0.074	1.000
Real interest rate change (Δr)	-0.000	0.008	-0.000	-0.000	1.000
Correlations[a]	Δp	Δy	Δc	Δr	
Δp	1.000				
Δy	0.301***	1.000			
Δc	0.285***	0.137***	1.000		
Δr	0.102***	0.065***	0.424***	1.000	
Correlations between MSAs[b]					
Δp	0.426***				
Δy	0.817***				
Δc	0.982***				

The sample period is 1980Q1-2012Q4. Equality of means is tested by the Welch F-test (null hypothesis = equal means across MSAs). *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively. [a]Correlations for all of the data, i.e., all MSAs stacked together. [b]Means of quarterly between MSA correlations.

Table 2. Unit root test statistics

	0 lags	**1 lag**	**2 lags**	**3 lags**	**4 lags**
	CIPS panel unit root test statistics (H_0 = non-stationarity)				
With a linear trend					
p_{it}	5.916	4.799	3.689	1.138	-0.887
y_{it}	11.32	4.106	1.427	-0.016	1.540
c_{it}	-0.827	-2.405***	-5.258***	0.178	-0.154
Without a linear trend					
Δp_{it}	-32.97***	-27.50***	-20.08***	-15.03***	-12.03***
Δy_{it}	-26.45***	-17.18***	-13.30***	-14.70***	-10.50***
Δc_{it}	-30.12***	-23.88***	-25.27***	-21.60***	-16.31***
	ADF unit root test statistics (without a linear trend; H_0 = non-stationarity)				
r_t	-1.479	-0.927	-0.777	-0.973	-0.843
Δr_t	-15.91***	-10.45***	-6.845***	-6.559***	-5.942***
	Average residual cross-correlation of ADF regressions[a]				
p_{it}	0.410	0.397	0.423	0.426	0.425
y_{it}	0.784	0.796	0.810	0.814	0.808
c_{it}	0.943	0.954	0.955	0.956	0.955
Δp_{it}	0.397	0.422	0.425	0.424	0.424
Δy_{it}	0.798	0.812	0.815	0.808	0.806
Δc_{it}	0.953	0.954	0.955	0.954	0.955

The regression specification for the levels follows that in Holly et al. (2010). An intercept is included in all the regressions. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively. [a]With a linear trend for the levels and without a trend for the differences.

Table 3. Estimation results for the long-run equation

	[1] MG	[2] AMG	[3] FMOLS-MG	[4] FMOLS-AMG
	Mean-Group estimates (standard errors in parentheses)			
y_{it}	0.703***	0.863***	0.823***	0.853***
	(0.055)	(0.059)	(0.061)	(0.060)
c_{it}	0.416***	0.562***	0.291***	0.553***
	(0.073)	(0.077)	(0.078)	(0.074)
r_{it}	2.26***	-0.717**	3.608***	-0.508**
	(0.308)	(0.294)	(0.398)	(0.235)
	CIPS unit root test statistics (p-value)			
1 lag	0.000***	0.000***	0.000***	0.000***
2 lags	0.000***	0.000***	0.000***	0.000***
3 lags	0.000***	0.000***	0.000***	0.000***
4lags	0.000***	0.000***	0.000***	0.000***
Swamy test of slope homogeneity (p-value)	0.000***	0.000***		
F-test of slope homogeneity (p-value)			0.000***	0.000***
Average cross-correlation	0.599	0.007	0.619	0.010

Dependent variable = p_{it}. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively. The lag length in the Bartlett (Newey-West) window width in the FMOLS estimations is four. The lag length choice does not notably affect the results. The null hypothesis in the Swamy test and F-test is that of homogenous slope coefficients across MSAs. The CIPS statistics are based on regressions that include MSA-specific intercepts.

Table 4. Estimation results for short-term dynamics

	[1] OLS	[2] RE	[3] MG	[4] AMG	[5] CCEMG	[6] DCCEMG
$\Delta p_{i,t-1}$	0.318***	0.294***	0.294***	0.099**	0.134***	0.146***
	(0.013)	(0.040)	(0.038)	(0.032)	(0.040)	(0.044)
$\Delta y_{i,t-1}$	0.152***	0.119**	0.092*	0.036	0.573***	0.490***
	(0.029)	(0.037)	(0.041)	(0.039)	(0.099)	(0.083)
$\Delta c_{i,t-1}$	-0.034	-0.023	-0.024	-0.242***	0.190	0.165
	(0.032)	(0.040)	(0.036)	(0.038)	(0.122)	(0.143)
$\Delta r_{i,t-1}$	0.001**	0.001**	0.001**	0.005***	-0.000	0.002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)
$(p - p^*)_{i,t-1}$	-0.024***	-0.029***	-0.034***	-0.143***	-0.079***	-0.070***
	(0.003)	(0.003)	(0.004)	(0.011)	(0.009)	(0.010)
R^2	0.130	0.227	0.245	0.486	0.607	0.770
Swamy test of slope homogeneity (p-value)			0.000***	0.000***	0.000***	0.000***
Average cross-correlation	0.391	0.403	0.403	0.119	-0.007	-0.006

Dependent variable = $\Delta p_{i,t}$. Standard errors in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively. We also tested for the need for seasonal dummies in the models and found that such dummies are not needed. The null hypothesis in the Swamy test is that of homogenous slope coefficients across MSAs.

Table 5. Price elasticity of income, price elasticity of supply, maximum overvaluation and duration of bubble during 2000s, and population rank

MSA	Price elasticity of income	Price elasticity of supply (Saiz, 2010)	Maximum overvaluation (%)	Bubble duration (quarters)	Population rank
MSAs with smaller than average supply elasticity and >20% overvaluation during the 2000s					
Detroit, MI	2.01	1.24	21	3	14
Los Angeles, CA	1.64	0.63	39	14	2
Boston, MA	1.48	0.86	27	10	10
Providence, RI	1.45	1.61	32	9	38
San Francisco, CA	1.42	0.66	29	8	11
San Jose, CA	1.42	0.76	35	9	34
Miami, FL	1.36	0.60	37	16	8
New Orleans, LA	1.36	0.81	20	1	45
San Diego, CA	1.30	0.67	39	14	17
Chicago, IL	1.21	0.81	23	1	3
Seattle, WA	1.21	0.88	21	2	15
Tampa, FL	1.07	1.00	35	13	18
Riverside, CA	0.99	0.94	50	17	12
Minneapolis, MN	0.97	1.45	24	8	16
Jacksonville, FL	0.91	1.06	27	12	40
Baltimore, MD	0.89	1.23	28	8	20
Washington, D~~,~~C~~,~~	0.88	1.61	35	11	7
New York, NY	0.84	0.76	29	8	1
Phoenix, AZ	0.76	1.61	39	12	13
Orlando, FL	0.70	1.12	39	12	26
Philadelphia, PA	0.48	1.65	23	1	6
Las Vegas, NV	0.48	1.39	51	17	31
MSAs with smaller than average supply elasticity but no overvaluation >20% during the 2000s					
Portland, OR	1.34	1.07	20	–	24
Cleveland, OH	1.34	1.02	14	–	29
Milwaukee, WI	1.15	1.03	15	–	39
Salt Lake City, UT	0.98	0.75	16	–	50
Hartford, CT	0.97	1.50	16	–	46
Denver, CO	0.93	1.53	18	–	21
Virginia Beach, VA	0.77	0.82	20	–	37
Pittsburgh, PA	0.68	1.20	9	–	22

Table 5. Price elasticity of income, price elasticity of supply, maximum overvaluation and duration of bubble during 2000s, and population rank, cont'd

MSA	Price elasticity of income	Price elasticity of supply (Saiz, 2010)	Maximum overvaluation (%)	Bubble duration (quarters)	Population rank
		MSAs with greater than average supply elasticity			
Buffalo, NY	0.86	1.83	13	–	49
Louisville, KY	0.82	2.34	7	–	42
St. Louis, MO	0.66	2.34	14	–	19
Richmond, VA	0.62	2.60	16	–	44
Columbus, OH	0.61	2.71	11	–	32
Cincinnati, OH	0.61	2.46	10	–	28
Birmingham, AL	0.55	2.14	9	–	48
Kansas City, MO	0.53	3.19	13	–	30
Atlanta, GA	0.45	2.55	13	–	9
Nashville, TN	0.45	2.24	9	–	36
Austin, TX	0.43	3.00	17	–	35
Oklahoma City, OK	0.43	3.29	14	–	43
Indianapolis, IN	0.42	4.00	8	–	33
Charlotte, NC	0.41	3.09	11	–	23
Houston, TX	0.35	2.30	16	–	5
Memphis, TN	0.34	1.76	10	–	41
Raleigh, NC	0.27	2.11	7	–	47
San Antonio, TX	0.19	2.98	12	–	25
Dallas, TX	0.14	2.18	14	–	4
		Supply elasticity value missing			
Sacramento, CA	1.05	–	46	15	27

Table 6. Cross-sectional OLS regressions for bubble size and duration in the 2000s

	Dependent variable				
	Bubble size	**Bubble size**	**Bubble duration**	**Bubble duration**	**Bubble duration[a]**
Constant	0.347***	0.234***	10.16***	4.991**	3.807
	(0.029)	(0.035)	(1.558)	(1.952)	(3.184)
Supply elasticity	-0.079***	-0.087***	-3.589***	-3.953***	-3.358
	(0.016)	(0.013)	(0.835)	(0.745)	(2.451)
Growth of *y*		0.275***		12.57***	18.89***
		(0.059)		(3.356)	(4.654)
R^2	0.352	0.558	0.282	0.450	0.469
Observations	49	49	49	49	22

Standard errors in parenthesis. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively. The duration is the number of continuous quarters during which at least 20% overvaluation is observed. [a]The regression includes only those MSAs with at least one bubble period. The estimations exclude Sacramento.

Figure 1. Real house price indexes

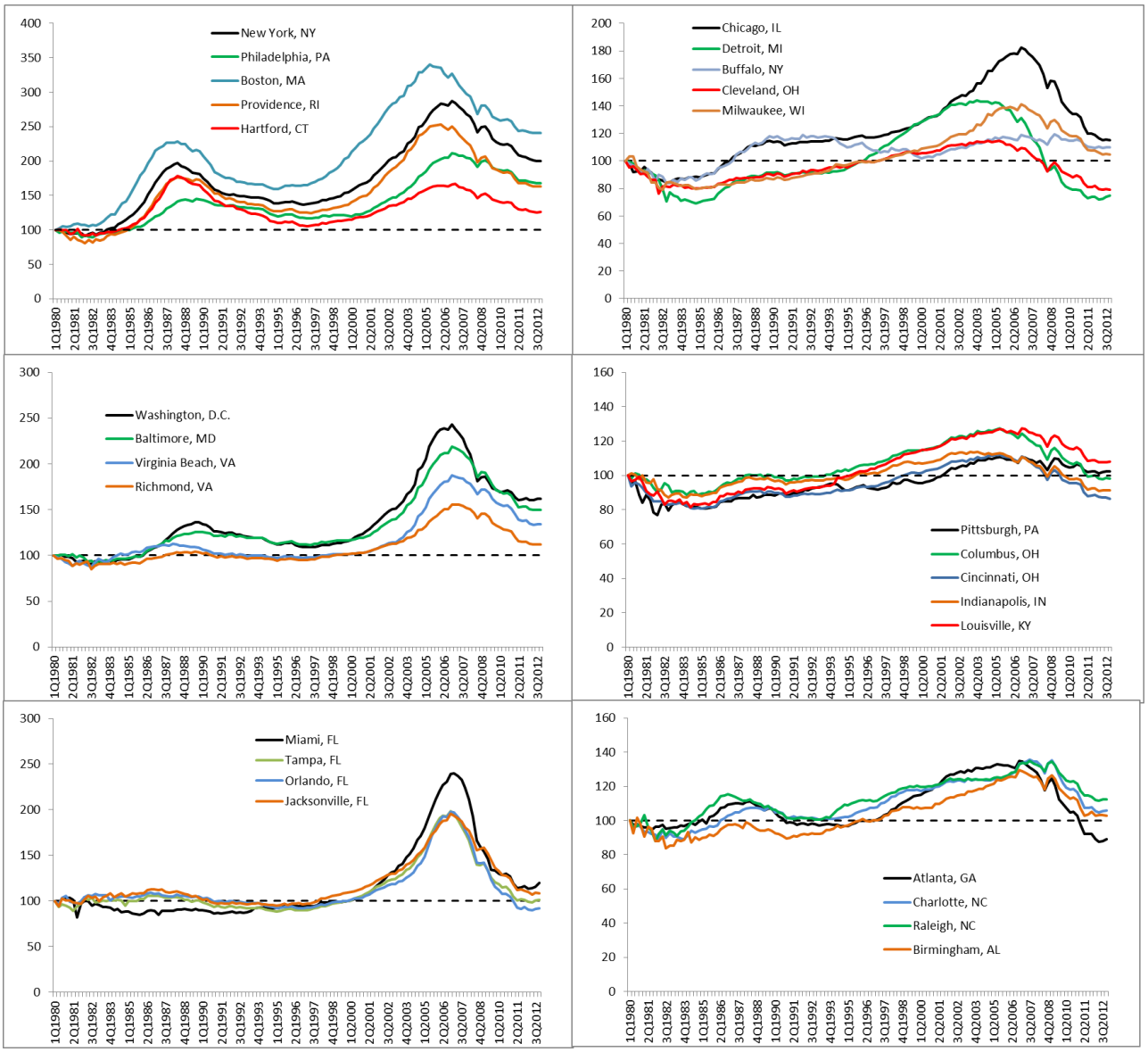

Figure 1. Real house price indexes, cont'd

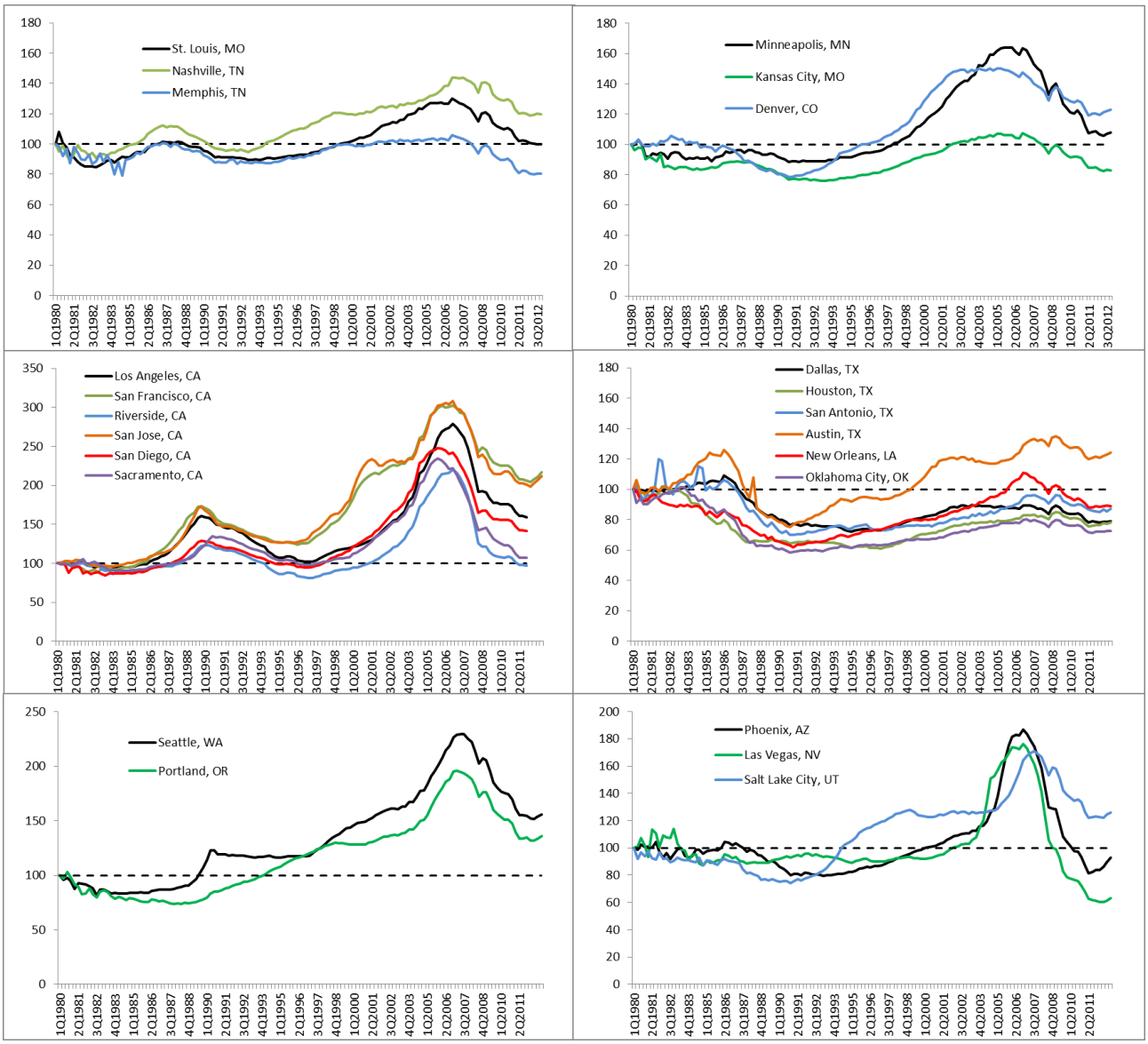

Figure 2. Relationship between income elasticity of house prices and price elasticity of housing supply

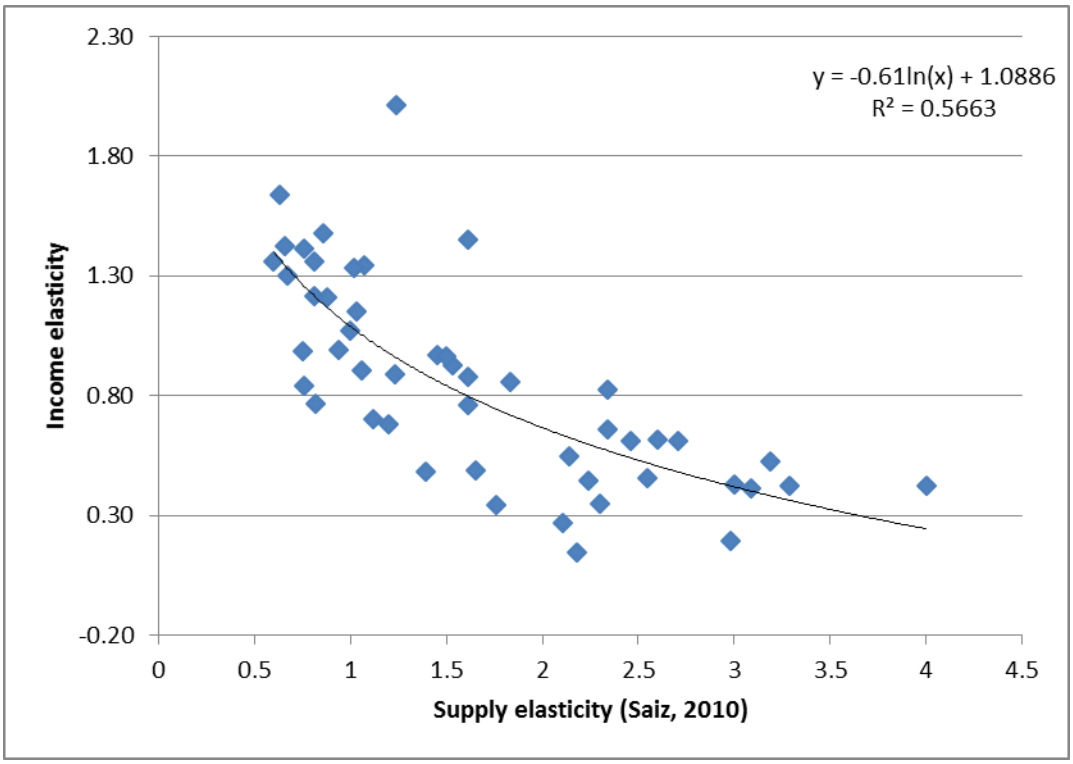

Figure 3. House price deviations from the long-term fundamental level

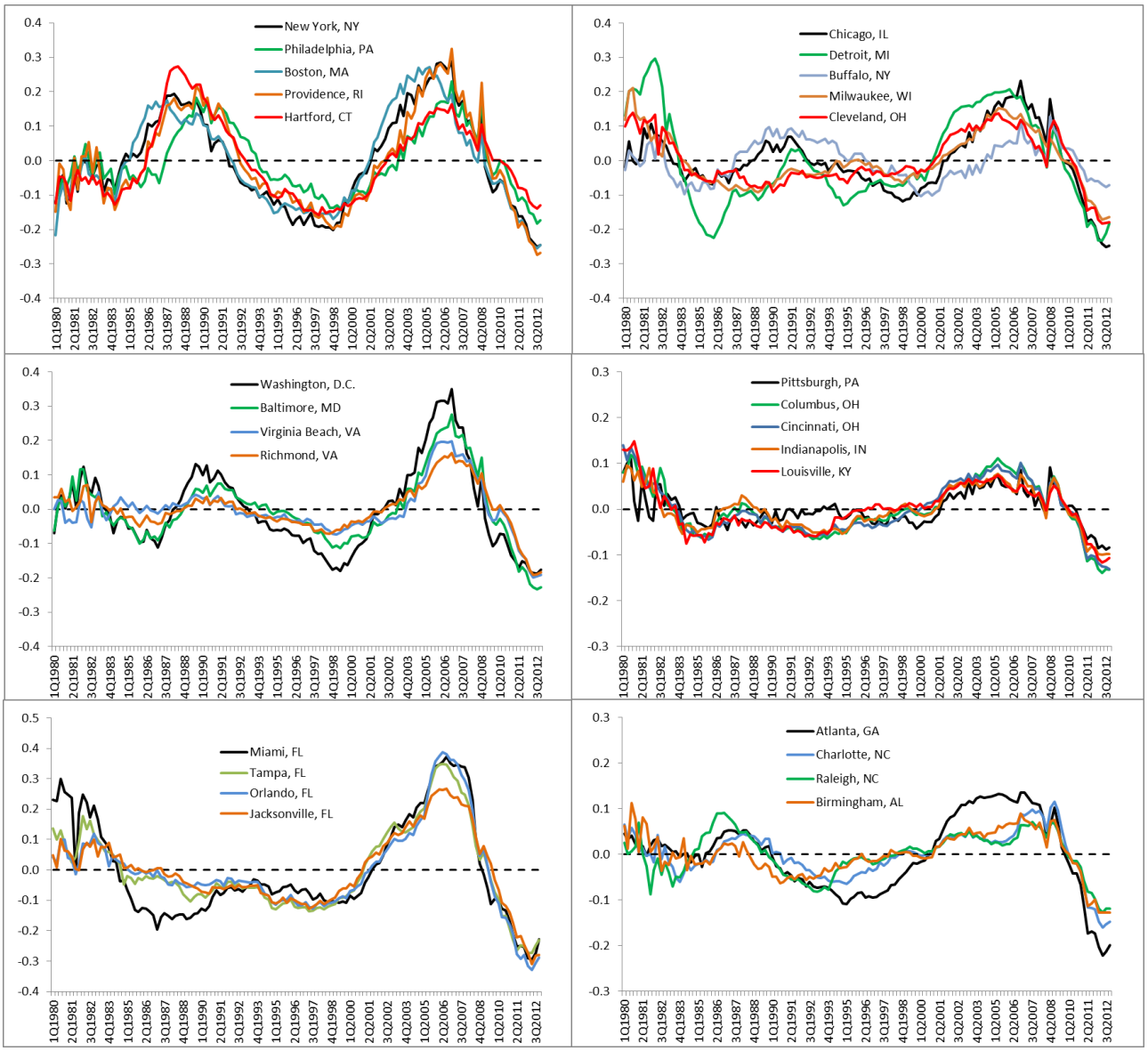

Figure 3. House price deviations from the long-term fundamental level, cont'd

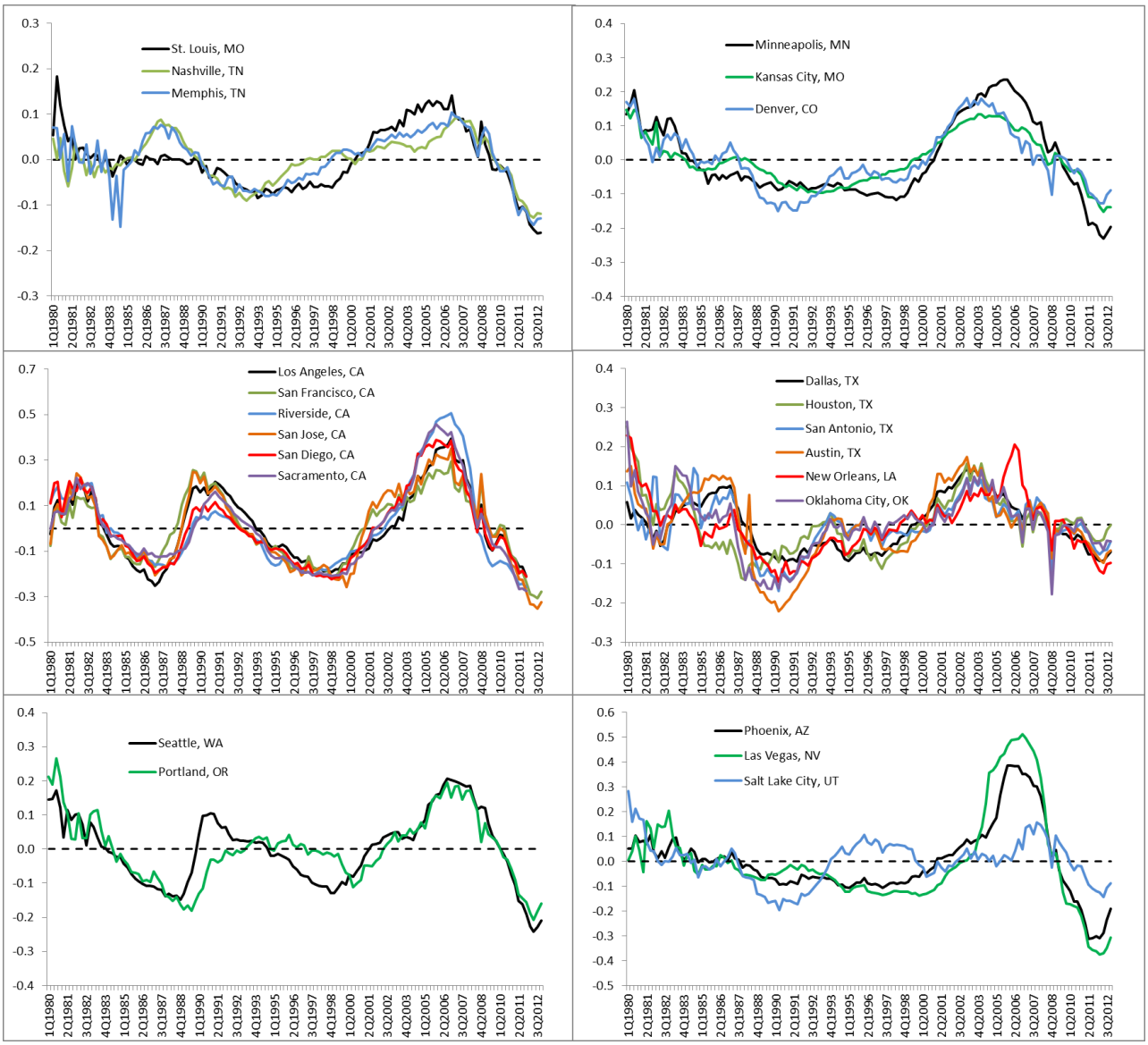

Figure 4. Relationship between the peak of price overshoot in the 2000s and price elasticity of housing supply