Revisitando o Relacionamento Preço-Rendimento da Casa
(Revisitando la Relación Precio-Ingreso de la Casa)

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Abstrato

Este estudo realiza uma análise sistemática da relação entre os preços das casas e a renda pessoal, derivando um modelo de equilíbrio espacial simples e realizando uma análise empírica usando dados para as 50 maiores áreas estatísticas metropolitanas dos EUA (MSAs) para o período 1980-2014. Na análise empírica, aplicamos ferramentas de análise de dados de painel de última geração, definimos renda de múltiplas formas, permitem heterogeneidade regional e controle de dependência espacial e endogeneidade. Tanto as considerações teóricas como os achados empíricos nos levam a concluir que a relação preço-renda da casa não é um bom indicador para as bolhas dos preços das casas. Achamos que a relação preço-renda da casa não é estável a longo prazo para a maioria das cidades. Em contraste, os modelos de regressão de painel que permitem a heterogeneidade regional e o controle de endogeneidade produzem equações estacionárias para os preços das casas na maioria dos MSAs. Entre outras descobertas, mostramos que é importante permitir a heterogeneidade em locais ao analisar a relação entre preços de casas e renda. As descobertas também têm implicações para as tendências da relação renda-renda.

Keywords: Preços de casas, Renda pessoal, Dados do paneil, Dependência transversal, Heterogeneidade regional, Equilíbrio espacial

Revisiting the House Price-Income Relationship

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Revisiting the House Price-Income Relationship

Abstract

This study undertakes a systematic analysis of the relationship between house prices and personal income by deriving a simple spatial equilibrium model and conducting an empirical analysis using data for the 50 largest U.S. Metropolitan Statistical Areas (MSAs) for the period 1980-2014. In the empirical analysis, we apply state-of-the-art panel data analysis tools, define income in multiple ways, allow for regional heterogeneity, and control for spatial dependence and endogeneity. Both theoretical considerations and empirical findings lead us to conclude that the house price-income ratio is not a good indicator for house price bubbles. We find that the house price-income ratio is not stable in the long run for most cities. In contrast, panel regression models that allow for regional heterogeneity and control for endogeneity yield stationary equations for house prices in most MSAs. Among other findings, we show that it is important to allow for heterogeneity across locations when analyzing the relationship between house prices and income. The findings also have implications for trends in the wealth-income relationship.

Keywords: house prices, personal income, panel data, cross-sectional dependence, regional heterogeneity, spatial equilibrium

JEL codes: C33, R15, R31

1 Introduction

The long-term relationship between house prices and income is important for several reasons. For example, if house prices and income have a stable long-term relationship in terms of cointegration, then the deviation of prices from this relationship can be used to assess whether prices are under or over their long-term equilibrium levels. Furthermore, regional differences in this long-term relationship – in the elasticity of prices with respect to income in particular – are of significance for the prospects for regional growth: the larger the elasticity, the greater the counter-force that rising house prices pose for regional growth. The evolution of the house price-income relationship also can notably affect trends in wealth-income ratios (Knoll et al., 2017).

Empirical investigations of house prices and income generally entail quite restrictive assumptions regarding the nature of the relationship. These include: (1) the assumption of a one-to-one relationship between price and income growth implied by the use of price-income ratios; (2) the assumption that there is a linear stationary relationship between prices and per

capita personal income; and (3) the assumption of a homogeneous relationship between prices and incomes across locations. In addition to or perhaps as a result of these methodological issues, empirical findings regarding the relationship between prices and income vary.

Studies of house price bubbles have in some cases relied uncritically on price-income ratios (Case and Shiller, 2003; McCarthy and Peach, 2004; Wu et al., 2012). Price-income ratios implicitly assume that the long-term coefficient on income is one in a model explaining house prices. There are good reasons to expect that this is not necessarily the case, including the variations in supply elasticities across locations (Saiz, 2010) that are closely related to income elasticities (Oikarinen et al., 2016).

Some previous research implicitly assumes a linear stationary relationship between house prices and per capita income without testing whether this assumption holds true empirically (e.g., Lamont and Stein, 1999). Other studies examine whether the data support the existence of such a relationship. In a panel study of U.S. metropolitan areas, Malpezzi (1999) rejects the null hypothesis of no cointegration between prices and per capita income. Gallin (2006) argues that the unit root test used by Malpezzi overstates the likelihood of cointegration and requires independence across locations. Using different tests (based, for example, on Pedroni, 1999) that allow for cross-correlations across cities, he concludes that U.S. metropolitan area house prices are not cointegrated with per capita income and population. While Gallin (2006) is the first to control for spatial dependence in the context of unit root tests on the house price-income relationship, Holly et al. (2010) provide the only published analysis of the price-income relationship that controls for spatial dependence in the regressions models. They do so by applying panel estimation techniques developed by Pesaran (2006) for U.S. state level data.

Finally, there is the problematic assumption that the relationship between income and prices is the same across locations. As pointed out above, spatial variations in supply elasticities imply variations in income elasticities. Regional heterogeneity in price dynamics is not only of interest from the point of view of urban economics, but is also of importance for macroeconomic research: One major question in models considering the nexus between macroeconomics and housing is whether housing markets should be viewed at the country level or whether national housing markets should be treated as a “collection of small countries” defined as metropolitan areas or other regional units (Piazzesi and Schneider, 2016). Harter-Dreiman (2004), who finds a stationary vector between prices and aggregate personal income in her analysis of U.S. metropolitan area house prices, estimates separate panel models for “constrained” and “unconstrained” cities but does not use a panel estimator that would allow for heterogeneity in the elasticities across MSAs. In contrast, the estimator used by Holly et al. (2010) allows the slope coefficients to be heterogeneous across U.S. states. Based on the CIPS unit root test (Pesaran, 2007) that controls for cross-sectional dependence, they reject the hypothesis of a unit root in both a regression between house prices and per capita income and the price-income ratio. However, this does not necessarily

imply that the price-income relationship is stationary in all or even most locations. As we will show, this is the case for our sample of 50 MSAs.

In this paper, we focus on relaxing the restrictive assumptions of earlier studies of the house price-income relationship. We start by presenting a theoretical model that explains variations in the price-income relationship across locations. Then, using data for the 50 largest U.S. MSAs, we apply state-of-the-art panel analysis tools that allow us to shed more light on the long-term relationship between house prices and income. One contribution of this study is that we specify the price-income relationship in various ways. In particular, we study cointegration of house prices and income using per capita income, aggregate personal income, and per capita income together with population. We also relax the conventional restrictive assumption of similar slope coefficients across locations, permitting income elasticity to be heterogeneous, and control for spatial dependence in the unit root and cointegration tests. Results from panel regression models that consider cross-sectional dependence are also reported. Moreover, we explore MSA-level relationships, which theory suggests can vary significantly from panel-level measures.

The next section of the paper provides a theoretical framework for understanding the relationship between house prices, incomes, and population in the context of a system of metropolitan areas. Section three discusses our data, including analysis of the variables' time series properties. Section four contains the empirical analysis. A final section concludes.

2 A theoretical framework

In this section we present a simple spatial general equilibrium model to consider theoretically the stability of the house price-income ratio over time. To get a proper understanding of the factors affecting the house-price income relationship and its development over time in a given city, it is necessary to use a theoretical framework that considers the whole system of cities. Partial equilibrium models (i.e., models that consider a single city in isolation, such as the "closed city" model that assumes no migration and takes local population and income as exogenous) miss important effects that take place due to the fact that housing costs, wages, city populations, and their growth rates are jointly determined and thereby population and income are endogenous to house prices (Glaeser and Gottlieb, 2009; Moretti, 2011).

Our theoretical considerations are based on the typical assumption in general spatial equilibrium models that welfare is equalized across space (Glaeser and Gottlieb, 2009), where local welfare is assumed to be determined by three factors: wages, housing costs, and the quality of amenities. This approach offers a good starting point for a simple theoretical analysis of the relationship between housing costs, income, and population. We are not aware of earlier studies in which the spatial equilibrium concept would have been used to analyze the house price-income ratio.

While the model presented here is, of course, a simplification of a complex reality, it captures central features in the relationships among the three variables. The model is designed to

explore long-term changes in the price-income relationship. This is because in the short run there are frictions that can restrain labor and firm mobility and the adjustment of housing supply; hence it is expected that the tendency of the system towards equilibrium operates fully only in the long run.

The theoretical model demonstrates that the assumption of a constant price-income ratio is highly restrictive. While we illustrate the influence of some shocks on the price-income ratio, we do not aim to investigate all potential sources of possible structural changes or trends in the ratio, and the aim is to keep to model as simple and tractable as possible.

2.1 The model

We start by assuming that each city is a competitive economy in a system of cities and produces a single output good *Y*. This good is traded in the "international" market so that its price is the same in all cities. The price of one unit of *Y* is set to be 1. The production function in city *i* takes the Cobb-Douglas form with constant returns to scale:

$$Y_i = X_i N_i^h K_i^{1-h}, \; 0 < h < 1. \tag{1}$$

N_i presents the number of workers and K_i is the amount of capital, in city *i*, and X_i is a city-specific productivity shifter. Firms and workers are mobile and locate where their profits and utility are maximized. Here, workers correspond to population, and we use these terms as synonyms: it is assumed that the number of workers determines the number of households and is perfectly correlated with population in each city.

For simplicity, we assume homogenous labor and abstract from labor supply decisions by assuming that each worker provides one unit of labor. Hence, local labor supply is determined solely by the location decisions of workers. We follow Hsieh and Moretti (2015) by assuming that the indirect utility of workers in city *i* (U_i) is given by the Cobb-Douglas utility function

$$U_i = M_i W_i (P_i Z)^{-\gamma}, \; 0 < \gamma < 1, \tag{2}$$

where W_i denotes the nominal wage level, M_i is a measure of local amenities, and P_i is the cost of occupying one square foot of housing, in city *i*. Z, in turn, is the size of a "standard" housing unit that is similar across locations. That is, $P_i Z$ represents the cost of occupying a "standard" housing unit in city *i*. Finally, γ is the share of expenditure on housing and is assumed to be similar across time and cities. This assumption, which is common in spatial equilibrium models, is supported by Piazzesi et al. (2007) and Davis and Ortalo-Magné (2011). In the log form

$$u_i = m_i + w_i - \gamma(p_i + z), \tag{3}$$

where the lower case letters denote natural logs. Utility is positively related to net income after "standard" housing costs, $w_i - \gamma(p_i + z)$, and the quality of amenities. In spatial

equilibrium, the utility levels are the same across cities; i.e., workers are indifferent between locations. Hence, in spatial equilibrium

$$w_i - \gamma(p_i + z) + m_i = w_j - \gamma(p_j + z) + m_j \tag{4}$$

holds for every city *i* and *j*. In the utility function, z is fixed to be the same everywhere for spatial equilibrium purposes, i.e., to have a fair comparison of utility levels across cities, especially regarding the influence of housing costs. Nevertheless, this does not imply that the actual housing space per person is assumed to be the same across cities. Households in cities where housing costs per square foot are higher (lower) relative to income, i.e., where $p_i - w_i$ is greater (smaller), have smaller (larger) homes so that the constant expenditure share assumption is not violated. The possible differences in housing space per household across cities do not matter for the spatial equilibrium condition in equation (4), because what matters there are the price levels for similar houses across cities.

Therefore, while we maintain the constant expenditure share assumption and the spatial equilibrium condition includes the housing costs of a standard unit that is comparable across cities, we let the demand for housing be dependent on wages in addition to income.[1] Although this somewhat lessens the tractability of the model, it is necessary to get a more realistic picture of the reaction of the local house price-income ratio to various shocks. Hence, the demand for housing (*D*) is assumed to be determined by *W*, *N*, and *P*:

$$D_i = C_{1i} W_i^{\omega_{1i}} N_i^{\omega_{2i}} P_i^{-\omega_{3i}};\ d_i = c_{1i} + \omega_{1i} w_i + \omega_{2i} n_i - \omega_{3i} p_i. \tag{5}$$

In (5), ω_1, ω_2, and ω_3 (all > 0) represent the elasticity of housing demand with respect to income level, population, and the level of housing costs, respectively, and c_i is a city-specific constant.

Housing supply (*S*), in turn, is provided by absentee landlords, and is the greater the higher is the level of housing costs (which reflect the return on housing investment), with ω_4 (> 0) denoting the price elasticity of housing supply:

$$S_i = C_{2i} P_i^{\omega_{4i}};\ s_i = c_{2i} + \omega_{4i} p_i. \tag{6}$$

To keep the framework tractable, we assume that housing production does not involve the use of local inputs. In equilibrium, housing supply equals housing demand; hence, the equilibrium price level is given by

$$p_i = \alpha_i + \beta_{1i} w_i + \beta_{2i} n_i;\ \alpha_i = \frac{c_{1i} - c_{2i}}{\omega_{3i} + \omega_{4i}},\ \beta_{1i} = \frac{\omega_{1i}}{\omega_{3i} + \omega_{4i}} > 0, \beta_{2i} = \frac{\omega_{2i}}{\omega_{3i} + \omega_{4i}} > 0. \tag{7}$$

[1] Note that the two typical assumptions in spatial equilibrium models – that all housing units are of similar size across space and time and that each household occupies exactly one unit of housing – lead to an assumption that housing demand is influenced directly only by the number of workers or households, not by income. This, together with assuming that housing costs account for a constant share of household expenditure, would imply a constant housing cost-income ratio.

Greater population, higher wages, and lower supply elasticity (smaller ω_4) due to topographic or regulatory constraints cause higher housing costs. The demand elasticities, too, affect the level of housing costs. For simplicity, we will assume that the constant term (α) in the price equation is the same across cities.

The cost of housing in the model, p_i, can be interpreted as the rental level or the user cost of owner-occupied housing. Nevertheless, we can use this concept to analyze the temporal and cross-sectional variation in the house price-income relationship. This is because the required rental return for housing assets can be assumed to be mean-reverting over the long run and, in any case, the model abstracts from interest rates and growth expectations that can affect the equilibrium price-rent relationship. Hence, we interpret p_i to reflect price levels for the standard housing unit and we call $p - w$ the house price-income ratio (instead of the housing cost-income ratio).

We follow Moretti (2011) and Kline and Moretti (2014) by assuming that there are two cities, *a* and *b*. This allows us to keep the model simple while still being able to illustrate the key implications of the spatial equilibrium condition on the house price-income ratio. Given the spatial equilibrium condition, the inverse labor supply function in city *a* is:

$$w_a = w_b + \gamma(p_a - p_b) + (m_b - m_a). \tag{8}$$

Using equation (7) for $p_a$and p_b yields

$$w_a = [(1 - \gamma\beta_{1b})w_b + \gamma(\beta_{2a}n_a - \beta_{2b}n_b) + (m_b - m_a)]/(1 - \gamma\beta_{1a}). \tag{9}$$

Higher quality of amenities in city *a* induces larger local labor supply and therefore lower wages. In other words, the utility gain from higher amenities makes workers willing to live in a city even if their net wages after standard housing costs are lower. Because of the upward sloping housing supply curve, the labor supply curve is also upward sloping: since greater n_i causes higher p_i, wages need to be higher to attract more workers in the city. Obviously, the parameters in (9) must be such that $w_a > 0$.

The total number of workers, N, is exogenously determined and divided between the two cities ($N = N_a + N_b$) so that the spatial equilibrium condition is fulfilled. The impact of a greater number of workers on local housing costs restricts city growth when wages increase (due to a positive productivity shock, for instance) or the quality of amenities improves relative to the other city.

Finally, the model is closed by the labor demand equation. We assume that firms are perfectly mobile and price takers, and labor is paid its marginal product. Hence, the (inverse) labor demand is[2]

$$W_i = hX_iN_i^{h-1}K_i^{1-h}; w_i = x_i + (h-1)n_i + (1-h)k_i + \ln h. \tag{10}$$

[2] It is assumed that there is an "international" capital market where capital is infinitely supplied at a given price, so that firms in each city can rent as much capital as is optimal at this price.

Labor market equilibrium is obtained by equating (9) and (10) for each city.[3]

2.2 *The influence of productivity and amenity shocks*

Next, we use this spatial equilibrium model to consider the influence of a labor demand shock on the house price-income ratios. Following Moretti (2011), we assume that the two cities are identical initially, after which total factor productivity increases in city *a* due to a shock in the local productivity shifter. That is, there is a small shock in x_a, causing a wage increase $w_{a2} - w_{a1} = \Delta$ (> 0) in city *a*, where subscripts 1 and 2 indicate time periods before and after the shock, respectively, and Δ equals the productivity increase. Using (9), we can write:[4]

$$\Delta = [\gamma\beta_{2a}(n_{a2} - n_{a1}) - \gamma\beta_{2b}(n_{b2} - n_{b1})]/(1 - \gamma\beta_{1a}). \tag{11}$$

Equation (11) cannot readily be used to compute the effect of the shock on the number of workers in *a*, as the number of workers in *b* is dependent on that in *a*. To circumvent this complication, we utilize the fact that $N_b = N - N_a$. Assuming that the cities are identical before the shock, $n_{b2} - n_{b1} = -(n_{a2} - n_{a1})$. However, if $n_{a1} \neq n_{b1}$, for a *small* change in N_b (corresponding to a *small* change in x_a and thereby a *small* Δ):
$n_{b2} - n_{b1} \approx -N_{a1}/(N - N_{a1}) \times (n_{a2} - n_{a1})$. Using this approximation to achieve greater generality, we get the population change in *a* due to the shock:[5]

$$n_{a2} - n_{a1} \approx (1 - \gamma\beta_{1a})/[\gamma(\beta_{2a} + \delta_{a1}\beta_{2b})] \times \Delta, \tag{12}$$

where δ_{a1} (= 1 in the case of identical cities) is the initial number of workers located in city *a* relative to workers located in *b* [$N_{a1}/(N - N_{a1})$]. The growth of city *a* after the productivity shock is decreased by more inelastic housing supply in *a* (greater β_{1a} and β_{2a}) and in *b* (greater β_{2b}), and by greater income elasticity of housing demand in *a* (greater β_{1a}). The elasticity of housing supply in *b* affects the growth rate of *a,* because less elastic supply in city *b* leads to a greater drop in housing costs in the city as workers move to city *a*.[6] This greater housing cost decline yields greater growth in income net of housing costs in *b*, which lessens the movement of workers from *b* to *a*.

Our interest lies in the development of the house price-income ratio, in particular. Taking advantage of equations (7) and (8), the change in the house price-income ratio in city *a* due to the productivity shock is

$$d(p_a - w_a) = (1 - \gamma)\beta_{2a}(n_{a2} - n_{a1}) + \gamma\beta_{2b}(n_{b2} - n_{b1}) + (1 - \gamma)\beta_{1a}\Delta, \tag{13}$$

[3] Although beyond the scope of this paper, the model could be extended to consider factors such as heterogeneous labor or agglomeration economies.
[4] Note that the wage level in city *b* does not change, since the amount of capital used by firms in *b* offsets the effect of the change in n_b (Moretti, 2011).
[5] It is required that $\gamma\beta_{1a}$ < 1. Given that $\gamma \approx 0.25$ (Davis and Ortalo-Magné, 2011), this should clearly hold in practice.
[6] In the relatively short run, the elasticity of housing supply can be different when prices decrease from when they increase. This model is aimed at considering long-term trends in the price-income relationship, however.

where $d(p_a - w_a)$ [= $(p_{a2} - w_{a2}) - (p_{a1} - w_{a1})$] is the change in the ratio. Using the above presented approximation for $n_{b2} - n_{b1}$ and equation (12), we can express $d(p_a - w_a)$ solely in terms of model parameters and the productivity increase:

$$d(p_a - w_a) = [\theta(1 - \gamma\beta_{1a}) + (1 - \gamma)\beta_{1a}] \times \Delta, \tag{14}$$

where

$$\theta = \frac{[(1 - \gamma)\beta_{2a} - \delta_{a1}\gamma\beta_{2b}]}{\gamma(\beta_{2a} + \delta_{a1}\beta_{2b})}.$$

We can use equation (14) to demonstrate numerically that the house price-income ratio can decrease or increase – depending on the parameter values – after a productivity shock and is thus not necessarily constant over time. Consider the example of two cities that are identical initially: N = 1 so that N_a and N_b reflect the population shares in the cities; the elasticity of housing costs with respect to income (β_1) and population (β_2) are 1.1 and 0.6, respectively;[7] and the parameters in the production function are $X_{a1} = X_{b1} = 1$ and $h = 0.5$. Since $N_{a1} = N_{b1} = 0.5$, we get $W_a = W_b = 0.5$. Finally, we set $\gamma = 0.25$ based on the findings reported in Davis and Ortalo-Magné (2011) for U.S. cities.

Suppose there is a total factor productivity shock in city *a* so that w_a given in (9) increases by 5%. In the new equilibrium after the shock, population is 12.1% greater and the house price level is 12.8% higher in city *a* than before the shock. Consequently, the house price-income ratio is 7.8% higher and income net of housing costs has increased by 1.8%. In city *b*, in turn, there is a 12.1% decrease in population and 7.3% decline in house prices, causing a net (of housing costs) income increase of 1.8% – so that the spatial equilibrium holds – and a decrease of almost just over 7% in $p - w$. That is, the productivity shock in *a* yields higher income net of housing costs [$w_i - \gamma(p_i + z)$] in both cities, while the price-income ratio moves in opposite directions in *a* and *b*. Note also that the ratio of house prices to aggregate income [$p_i - (w_i + n_i)$] is 4.3% lower in *a* and 4.8% higher in *b* after the shock. This ratio would remain constant in both cities if β_1 = β_2 = 1.

Now assume that a similar productivity shock takes place in both cities; i.e., both w_a and w_b rise by 5%. As the wage increase and model parameters are the same in both cities, there is no flow of workers between *a* and *b*. The income increase induces house price growth of 5.5%. Thus the price-income (and price-to-aggregate income) ratio decreases by 0.5%, while net income growth is 3.6%. In the special case where the income elasticity of house prices was equal to 1, $p - w$ would not be altered by the shock.

As another example, suppose that, instead of a productivity shock, there is a positive shock in the value of amenities in city *a*. This shock could take place due to a change in workers' preferences for various amenities (e.g., quality of public transportation or climate) or a change in the amenities themselves (e.g., better services, less crime, or cleaner environment).

[7] The choice of these values in this illustrative example is based on the corresponding parameter values estimated for Portland, OR in the empirical analysis in section 4.

The wage levels in the two cities remain similar as there is no change in productivity. Hence, the spatial equilibrium condition requires that some workers move from *b* to *a*, causing housing costs to adjust to fulfill the equilibrium condition. That is, the price level increases in *a* and decreases in *b* thereby causing a higher house price-income ratio in *a* and a lower ratio in *b*. The price-income ratio is expected to remain constant only in the special case where the elasticity of housing demand with respect to population (ω_2) is zero, which does not seem a plausible scenario. The price-to-aggregate income ratio is unaltered if β_2 = 1.

Obviously, the model parameters can significantly affect the outcomes. The elasticity of housing supply (ω_4), in particular, has been shown to vary substantially across cities (Saiz, 2010). As shown by equation (7), such variations can cause notable differences in the elasticity of house prices with respect to income and population. As a simple example, consider a case where, due to smaller constraints on housing supply in city *a*, β_{1a} is 0.7 and β_{2a} is 0.4 (instead of 1.1 and 0.6), respectively. In this case the influence of the 5% productivity increase in *a* causes a 5.1% increase in $p_a - w_a$ (compared with 7.8% in the baseline case), a 9.9% drop in $p_b - w_b$ (7.3%), and a 2.5% increase in incomes after standard housing costs (1.8%). Moreover, if β_{1a} and β_{2a} were sufficiently small (relatively elastic housing supply) and β_{1b} and β_{2b} sufficiently large (relatively inelastic housing supply), then the productivity increase would lead to a smaller $p - w$ in city *a*.

In any case, the main point is that the price-income ratio cannot be assumed to be stable in the long run in each city – rather, such long-term stability of $p - w$ is a "special case". The key implications regarding the relationship between house prices, income, and city population are summarized below:

1) House prices, wages, and population are jointly determined.
2) House prices, wages, and population are cross-sectionally dependent.
3) The equilibrium house price-income ratio is not necessarily stable over the long run – in fact, long-term stability of the ratio is expected to be a "special case" rather than a rule.
4) The price-income ratio can be altered by various shocks, such as a shock in productivity or in perceived quality of amenities, in the city itself or in other cities.
5) The elasticities of housing supply and demand are key determinants for the influence of various shocks on the house price-income ratio, and also the elasticities in other cities affect the outcomes in a given city.
6) The income elasticity of house prices is expected to vary considerably across cities.

3 Data

Our empirical analysis is based on quarterly data for the 50 largest (as of 2012) U.S. MSAs for the period 1980Q1 through 2014Q2. The sample period includes one or more prominent house price cycles in all of the MSAs. These cycles take place especially during the 2000s but also in the late 1980s through early 1990s. For house prices, we use the quarterly Federal

Housing Finance Agency (FHFA) all transactions house price indexes (*p*).[8] The MSA per capita personal income (*y*), aggregate personal income (*ya*), and population (*pop*) series are from the Bureau of Economic Analysis (BEA). As the income series are annual, we interpolate quarterly values of per capita income based on changes in the national GDP, which is also from the BEA. All the variables are specified in real terms, deflated by the national urban CPI less shelter costs.[9] All the series are in natural log form. Table 1 provides summary statistics.

[Table 1 here]

As expected, there are considerable regional variations in the mean growth rates of house prices, income, and population. The mean real house price growth was negative between 1980 and 2014 in 14 MSAs, of which all but two (Houston and New Orleans) are inland. The highest price growth (annualized rate of 2.7%) was observed in San Jose. In San Francisco, Boston, and New York, too, the figure was over 2%, while in Oklahoma City it was –0.9%. Population growth was very rapid in Las Vegas, 4.3% per year on average, and the growth rate reached 3% in a couple of other MSAs as well. The highest house price growth rates were not in any of the MSAs with the highest population growth rates. There were five MSAs with contracting population, four of them in the Great Lakes region and the other being New Orleans; of these, Pittsburgh had the largest rate of population loss (0.3% per year).

The mean real per capita and aggregate income growth rates were positive in all the MSAs. Across all 50 MSAs, the annual mean growth rates were 1.3% and 2.7%, respectively. In Boston, per capita income growth was 2.1% per year, while the growth rate was only 0.3% in Riverside. Finally, the real aggregate income growth rate was the highest in Austin (5.1%) and the lowest in Detroit (0.9%).

Portland, OR offers an interesting illustration of how city-specific developments of the three variables, *p*, *y* and *pop*, can differ relative to the average developments across cities: while Portland's annual real house price and population growth rates were relatively large during the sample period, 1.2% (the mean across the MSAs is 0.5%) and 1.6% (1.3%), respectively, real per capita income growth has been among the smallest across the MSAs at 1.1% (ranked 45th). In terms of the theoretical framework, these patterns could be explained by growth in the perceived quality of amenities in the city: higher quality of amenities leads to lower required income net of housing costs, inducing greater population and thereby higher prices relative to income. Indeed, Portland is perceived as a city in which the quality of amenities

[8] In cases where the FHFA indexes were for MSA divisions rather than the MSAs themselves, we created MSA indexes by combining population-weighted MSA division indexes.

[9] If we were to deflate income by the all items CPI (including shelter), house price growth would affect the deflated income series. Although house prices are not included in the CPI, rents are included, and house prices and rents are essentially measuring the same thing in the long run. For example, if housing demand grows substantially inducing greater house prices and rents while other prices stay constant, then the all items CPI would increase. This would lower our real income measure even though the income and all other components of the CPI have remained constant. Therefore, housing demand growth not only causes higher real house prices but also lower real incomes, meaning that house price growth would have a disproportionate impact on the relationship between prices and incomes.

has substantially increased, thereby increasing the supply of labor (population) in the city (see, e.g., Miller, 2014).

Table 1 further shows that all correlations between the variables are positive both in levels and in differences and the mean of cross-sectional correlations across MSAs is large in all cases. That is, in line with the theoretical considerations, house prices are higher in bigger cities with higher income levels.

As a preliminary check, we conducted panel unit root tests to examine the stationarity of each variable. Since the residual series from conventional augmented Dickey-Fuller (ADF) regressions include significant cross-sectional correlation (see Table 2) and hence the conventional panel ADF test statistics would be biased, we follow Holly et al. (2010) and report the cross-sectional augmented IPS (CIPS) panel unit root test (Pesaran, 2007). The CIPS test is based on ADF regressions that are augmented with cross-sectional averages of the variables (CADF) and is thereby not biased by spatial dependence in the data. The test also allows for regional heterogeneity, as CADF regressions are estimated separately for each MSA, and the number of lags in these regressions is allowed to vary across cities. For each MSA, the lag length is based on the general-to-specific method, using a threshold significance level of 5% and a maximum lag length of four. The results reported in Table 2 indicate that the variables should be treated as non-stationary in levels. An exception is population, for which the CIPS test rejects the null hypothesis of non-stationarity; this result is surprising and may be explained by the complications with panel unit root tests discussed in more detail in section 4.2. For all the differenced variables, the test statistics indicate stationarity.

[Table 2 here]

4 Empirical analysis

In this section we study the stationarity of the house price-income ratio and report cointegration tests and regression results based on several alternative estimators and model specifications. Given that the theoretical considerations point to substantial potential complications with using the house price-income relationship to identify house price misalignments, in the regression models we relax the restrictive assumption – a coefficient of one on income – implicitly imposed by the price-income ratio. Model 1 allows the coefficient on income per capita to differ from one. Model 2 then also takes account of population developments by including aggregate instead of per capita income. Aggregate income is often used in empirical applications due to complications caused by the typically high collinearity between income per capita and population. A downside of Model 2 is that it assumes that the coefficients on income and population are similar. Model 3 relaxes this assumption, too, by including income per capita and population separately as explanatory variables and thereby allowing their coefficients to differ from each other. We also let the coefficients on *y*, *ya*, and *pop* to vary across MSAs, since theory indicates that there may be substantial heterogeneity in these coefficients. The models can be expressed as:

Model 1: $p_{i,t} = \beta_{0,i} + \beta_{y,i} y_{i,t} + \varepsilon_{i,t}$

Model 2: $p_{i,t} = \beta_{0,i} + \beta_{ya,i} ya_{i,t} + \varepsilon_{i,t}$

Model 3: $p_{i,t} = \beta_{0,i} + \beta_{y,i} y_{i,t} + \beta_{pop,i} pop_{i,t} + \varepsilon_{i,t}$,

where $\beta_{0,i}$ are the MSA-specific fixed-effects, $\beta_{y,i}$ and $\beta_{ya,i}$ and $\beta_{pop,i}$ are MSA-specific slope coefficients, and ε_i are MSA-specific error terms.

Given that at least population is expected to be endogenous with respect to house prices, the Panel Fully-Modified OLS estimator of Pedroni (2000, 2001) is a good starting point for the panel regressions. While the estimators generally used in previous studies, such as the conventional fixed-effects or random-effects OLS estimator, can exhibit endogeneity bias, the FMOLS estimator is consistent even in the presence of endogenous regressors (Pedroni, 2001, 2007). We report regression results for both the pooled FMOLS estimator (PFMOLS) that allows regional heterogeneity only through city-specific fixed effects and the FMOLS mean-group estimator (FMOLS-MG) that allows regional heterogeneity in all parameter estimates. The FMOLS estimators are also consistent in the presence of nonstationary but cointegrated data, which is not generally the case for the fixed-effects OLS estimator. For comparison purposes, we also report results based on the basic pooled fixed-effects OLS estimator (POLS) that assumes homogeneous slope coefficients across MSAs.

A potential complication with the aforementioned estimators is that they do not control for cross-sectional dependence. Hence, we also report results based on the Pesaran (2006) common correlated effects mean group (CCEMG) estimator and the Chudik and Pesaran (2015) Dynamic CCEMG (DCCEMG) estimator. While these two estimators aim to remove the biasing impact of spatial dependence by including the cross-sectional averages of the dependent and independent variables as additional regressors while allowing for regional heterogeneity, they can exhibit bias due to endogeneity. Moreover, in order for these estimators to be applicable in a cointegrated panel context, cointegration among the variables must arise only through a common non-stationary component (Pedroni, 2007). This property of the (D)CCE estimators is potentially problematic in our analysis, since it implies that the MSA-specific slope coefficient estimation is no longer super-consistent (in contrast with the FMOLS estimations). Indeed, it turns out that the (D)CCEMG estimators do not work well with our data, which could be due to these complications. Therefore, FMOLS-MG is our preferred estimator.

4.1 *Baseline results*

Unit root test results along with coefficient estimates for the regression models are presented in Table 3. Except for POLS and PFMOLS, the reported regression coefficients represent the mean group estimates, i.e., the means of $\beta_{y,i}$, $\beta_{ya,i}$ and $\beta_{pop,i}$ across all MSAs. The reported standard errors for the mean group estimates are computed following Pesaran and Smith (1995). Regarding the regression models, inability to reject the null hypothesis of non-stationarity of the residual series, $\hat{\varepsilon}_{i,t}$, would indicate that the estimated relationship is not

stable over the long run and thus cannot be interpreted as a long-term equilibrium equation. Again, the number of lags in the CADF equations is allowed to vary across cities. We do not include intercepts in the CADF equations for the residuals from the regressions or from the price-income ratios, since residuals from stable long-term relations should not be trending.[10]

[Table 3 here]

The CIPS unit root test rejects the hypothesis of a unit root in the price-income ratio ($p - y$), which is in line with Holly et al. (2010), and that of no-cointegration in most of the regression models. Stationarity of $p - y$ would indicate that the long-run coefficient on y is one and homogenous across MSAs. However, based on the size-adjusted F-test proposed by Pedroni (2007) for the FMOLS models (not for PFMOLS, which does not allow for heterogeneity) and the Swamy test of slope homogeneity of Pesaran and Yamagata (2008) for the (D)CCEMG models, the hypothesis of homogeneous coefficients on y is clearly rejected (Model 1). Moreover, Wald F-test statistics reject the hypothesis that the group mean, or pooled in the case of POLS and PFMOLS, coefficient on y equals one. Hence, the regressions are in stark contrast with the concept of a stationary house price-income relationship. We take a closer look at the reasons behind this discrepancy below.

The test statistics reject the hypothesis of $\beta_{y(a)} = 1$ and indicate significant variations in the coefficient estimates across individual MSAs in Models 2 and 3 as well. This is in line with expectations: long-term house price elasticities with respect to demand fundamentals show considerable differences across cities and even the mean elasticity across MSAs with respect to income can differ notably from one. The pooled OLS and FMOLS estimates in Model 3 provide exceptions to the general rule, as in these models the hypothesis is accepted that the group mean coefficient on income equals one. Even in this model, the MSA-specific coefficient estimates show substantial heterogeneity and are in many cases far from one.

As expected, the two estimators that aim to control for cross-sectional dependence CCEMG and DCCEMG are able to remove practically all cross-sectional correlation from the model residuals: the remaining correlation in these models is less than 0.01. However, these estimators do not work well in our data, as the residual unit root hypothesis cannot be rejected in Models 1 and 2, and the city-specific residual series are trending for practically all MSAs in these models. These complications are not totally unexpected given the properties of the (D)CCE estimators discussed above.

The preferred FMOLS-MG estimator yields mean group estimates of 0.85 on y and 0.48 on ya. These estimates somewhat differ from P(FM)OLS ones. All of the reported CCEMG estimates are substantially greater than the FMOLS-MG ones. In Model 3, the FMOLS-MG coefficient on *pop* is negative, contradicting what theory predicts, and the coefficient on y is as large as 1.5. Given the high correlation between y and *pop* and the consequent potential for complications due to multicollinearity, the negative sign on *pop* is not totally unexpected. Indeed, many

[10] The dependent variable in the CADF equations is the differenced residual. If the mean of differenced residual series was not zero (i.e., an intercept was needed in the regression), then the residual series would be trending.

studies of house price dynamics report similar negative coefficients when income and population enter the model separately (e.g., Gallin, 2006). Also, due to multicollinearity the coefficient estimate on *y* is likely overstated.

4.2 *A closer look at the unit root and cointegration results*

A complication with the panel unit root test statistics is the alternative hypothesis. While the null hypothesis is that of a unit root in each series, the alternative hypothesis is more complex especially in heterogeneous panels. In particular, rejecting the null does not necessarily mean that all or even most individual series are stationary (Pesaran, 2012). This has not been considered in previous literature on the house price-income relationship. The null hypothesis (H_0) and the alternative hypothesis (H_1) in our cointegration tests can be summarized as:

> H_0 : each of the residual series is nonstationary (i.e., none of the MSA-specific equations is cointegrated)
>
> H_1 : one or more residual series are stationary (i.e., one or more MSA-specific equations are cointegrated)

That is, rejection of the null hypothesis can be interpreted to provide evidence of the stationarity of a non-zero fraction of the series. Pesaran (2012) suggests that the rejection of the panel unit root null hypothesis should be interpreted as evidence of statistically significant fraction of the individual series being stationary. However, a rejection of the null hypothesis in Table 3 does not necessarily mean that the respective relationship is stationary for all or even most cities – only a relatively small group of MSAs with stationary relations can cause the panel unit root test to reject the null hypothesis.

A plot of the demeaned price-income ratios indicates that many of these ratios have notable trends, implying that in many MSAs the ratio is not stable over the long run (Figure 1). Therefore, we consider the city-specific CADF equations in order to reach more reliable conclusions regarding the nature of the various price-income relationships.

[Figure 1 here]

In line with the visual inspection of the residuals from $p - y$, the unit root in the residuals can be rejected in only 7 of the 50 MSAs (at the 5% level of significance) based on individual CADF statistics. Given the power problems with the individual (C)ADF test, the 10% level of significance may be a more reasonable threshold, but even at the 10% level the unit root is rejected in only 11 MSAs.[11] Clearly, the fact that the CIPS test rejects the null hypothesis concerning the price-income ratio cannot be used as evidence of stationarity of the ratio in all the MSAs; thus it would be misleading to conclude that the house price-income ratio generally is stationary and could be used as a reliable indicator of house price disequilibrium.

[11] While the ADF test is shown to have power problems (Type II error), it should also be noted that, in a set of 50 individual (C)ADF equations, it is quite probable that one or some rejections of the null are false (Type I error).

Given the potential power problems with individual CADF tests, we also apply the more powerful panel CIPS test on the 39 MSAs for which the individual MSA-level CADF test does not reject the null hypothesis (at the 10% level). The CIPS test does not reject the null hypothesis of non-stationarity, as the test value (-1.27) is not close to being significant even at the 10% level. By implying that the ratio is stationary in none (or at least not in a significant fraction) of the 39 MSAs, the CIPS test provides additional support for the argument that the ratio is non-stationary in a large majority of the MSAs.

If we regress the panel of price-income ratios on an intercept and a time trend using the Pesaran et al. (1999) mean group estimator that allows for regional heterogeneity in the coefficients, we find statistically significant trends in a large number of MSAs. Interestingly, the MSA-specific trends in the price-income relationship are significantly associated with the MSA-level price elasticity of housing supply reported in Saiz (2010). Figure 2 illustrates that generally the slope of the trend in the observed $p - y$ relationship is larger the more inelastic housing supply is; in other words, house prices have tended to increase more relative to income in areas with relatively inelastic supply. This is in line with theoretical predictions. Clearly, the most common trend in $p - y$ is decline, suggesting that housing affordability has increased in a major fraction of the MSAs. In line with the price-income trends, the MSA-specific FMOLS-MG estimates on y and ya (the income elasticities of house prices) are highly negatively correlated with the supply elasticity: the correlations are –.68 (Model 1) and –.66 (Model 2).

[Figure 2 here]

The price-income trends are also in line with the argument by Glaeser and Gottlieb (2009) that the rise of "Sunbelt cities" seems to be related to abundant housing supply rather than possibly rising amenity values. If amenity values drove the growth of Sunbelt cities, then we would expect the price-income trends to be increasing in these cities. However, with the exception of the Californian MSAs and Miami, all of which are supply constrained, the price-income ratio has trended downwards in the Sunbelt cities (i.e., in 16 out of 17 cities outside California). Moreover, the price-income trends are not correlated with the MSA-specific average January temperatures.

Table 4 shows the MSA-level unit root statistics for the price-income ratio and each of the FMOLS-MG models. If the assumption of a coefficient of one on per capita income in all MSAs (imposed by the price-income ratio) is relaxed by allowing it to differ from one and furthermore to be heterogeneous across cities (Model 1), the number of MSAs for which the unit root can be rejected at the 10% level in individual CADF tests increases from 11 to 27. However, the model with aggregate income (Model 2) works better, since it is stationary in 31 cities (at the 10% level of significance) based on the MSA-specific tests.[12] The number of "stationary MSAs" further increases to 34 when the coefficient on population is allowed to

[12] This is in line with Bourassa et al. (2016), who report that a regression model with aggregate income works as a better indicator for housing price bubbles than a model with per capita income.

differ from that on per capita income (Model 3). This provides evidence of the relationship being stationary in more and more cities when the restrictive assumptions regarding its form are further relaxed.

[Table 4 here]

Finding that the relationship gets stationary in more MSAs when the population is included in the regression indicates that population, as predicted by theory, affects the equilibrium house price level and should thus be included in regressions in order to make more reliable conclusions regarding possible disequilibria in house price levels. A complication with the MSA-specific equations and mean coefficient estimates in Model 3 is that – presumably due to multicollinearity problems – the parameter estimate for population is negative in the majority of MSAs. Although many of these city-specific equations produce stationary residuals, the interpretation of the equations is complicated.

Thus, while Model 2, with aggregate income as the sole explanatory variable, is stationary in slightly fewer MSAs than Model 3, it generally seems to be the most useful for examining house price cycles relative to long-term fundamental levels. Importantly, the residuals from Model 2 do not exhibit clear trends in any of the MSAs. This is in stark contrast with the simple price-income relationship, as shown in Figure 3. Nevertheless, the inability to detect cointegration in approximately one third of the MSA-specific equations in Model 2 may indicate that other fundamentals, too, should be included in regression models aiming to capture long-term trends in house prices in a number of cities, or that there have been structural changes in the price elasticities over time.

[Figure 3 here]

In contrast with the city-specific residual series based on the FMOLS-MG equations, POLS and PFMOLS equations – that assume homogenous slope coefficient across MSAs – yield clearly trending residuals in a large number of MSAs. This, too, suggests that the homogeneity assumption is too restrictive and heterogeneity across cities should be allowed in order to get more reliable assessments of house price elasticities and misalignments.

5 Conclusions

This study undertakes a systematic analysis of the relationship between house prices and personal income by deriving a simple spatial equilibrium model and conducting an empirical analysis using a panel of the 50 largest U.S. MSAs. Our main message is that the often used assumption of a constant house price-income ratio is not in line with either theoretical considerations or empirical facts. Instead, long-term stability of the price-income ratio in a given city is expected to be a “special case” rather than a rule, and evaluations of house price deviations from their long-term fundamental levels should be based on less restrictive assumptions, allowing for an income elasticity of house prices that is different from one and

heterogeneous across cities. In addition, population growth should be considered when assessing house price levels.

Among other findings, we show that it is important to allow for heterogeneity across locations when analyzing the relationship between house prices and income. While both theoretical considerations and empirical findings lead us to conclude that the house price-income ratio is not a good indicator for house price bubbles, panel regression models that allow for regional heterogeneity and control for endogeneity yield stationary equations for house prices in most MSAs. A regression model with aggregate income as the sole explanatory variable is stationary for most of the MSAs, and the residuals from the model do not exhibit clear trends in any of the MSAs. This is in stark contrast with the simple price-income relationship. However, the inability to detect cointegration in approximately one third of the MSA-specific equations may indicate that other fundamentals, too, should be included in regression models aiming to capture long-term trends in house prices, or that there have been structural changes in the price elasticities over time.

Piazzesi and Schneider (2016) point out that a major question regarding the nexus between macroeconomics and housing is whether housing markets should be viewed at the country level or whether national housing markets should be treated as a "collection of small countries" defined by metropolitan areas or other regional units. Our results suggest that it could often be worthwhile in macroeconomic studies to consider the heterogeneity across local housing markets.

Finally, our findings also entail implications regarding trends in the wealth-income relationship – trends that have been under extensive discussion especially after the publication of Piketty (2014). The findings of Piketty and Zucman (2014) suggest that capital gains on housing explain a large part of the rise of wealth-income ratios in several countries, including the U.S., since 1970 and Knoll et al. (2017) report a substantial rise in house prices relative to GDP across a number of developed countries. However, the downward trending price-income ratios that we report for many MSAs imply that such increases in the wealth-income ratios have not taken place due to house price trends since 1980 and are not inevitable in the future, at least within the U.S. Generally, the price-income ratio has increased less in MSAs with greater supply elasticities. The price-income trends are also in line with the argument by Glaeser and Gottlieb (2009) that the rise of "Sunbelt cities" seems to be related to abundant housing supply rather than possibly rising amenity values.

Table 1. Summary statistics

Variable	**Mean across all MSAs (annualized)**	**Standard deviation of MSA-specific means (annualized)**	**Lowest mean across MSAs (annualized)**	**Highest mean across MSAs (annualized)**
Real house price growth (Δp)	0.005	0.048	–0.009	0.027
Real per capita income growth (Δy)	0.013	0.021	0.004	0.021
Real aggregate income growth (Δya)	0.027	0.023	0.009	0.051
Population growth (Δpop)	0.014	0.008	–0.003	0.043
Correlations	*p*	*y*	*ya*	*pop*
p	1.000			
y	0.592***	1.000		
ya	0.391***	0.747***	1.000	
pop	0.148***	0.371***	0.895***	1.000
	Δp	Δy	Δya	Δpop
Δp	1.000			
Δy	0.395***	1.000		
Δya	0.391***	0.935***	1.000	
Δpop	0.099***	0.095***	0.443***	1.000
	p	*y*	*ya*	*pop*
Mean of cross-sectional correlations	0.590	0.953	0.981	0.705

The sample period is 1980Q1-2014Q2. Correlations are reported for all of the data, i.e., all MSAs stacked together. For the correlations, *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. The mean of cross-sectional correlations is the average of cross-sectional correlations between all MSA-pairs.

Table 2. CIPS unit root test statistics

Variable	p_{it}	y_{it}	ya_{it}	pop_{it}	Δp_{it}	Δy_{it}	Δya_{it}	Δpop_{it}
Test value	–2.403	–2.006	–2.220	–3.160***	–4.235***	–4.660***	–4.533***	–3.304***
Lags			*Average residual cross-correlation of ADF regressions*					
0	.450	.837	.830	.447	.447	.851	.842	.414
1	.447	.849	.839	.487	.487	.851	.839	.452
2	.488	.849	.834	.493	.493	.855	.855	.487
3	.496	.854	.852	.478	.478	.843	.850	.479
4	.479	.842	.848	.484	.484	.843	.850	.487

The CIPS test values are based on city-specific CADF regressions. An intercept is included in all the CADF and ADF regressions. The regressions in the tests for levels include a linear trend following Holly et al. (2010). In the unit root test statistics, *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 3. Cointegration tests and regression results

	FMOLS-MG	POLS	PFMOLS	CCEMG	DCCEMG
CIPS cointegration test statistics					
$p - y$: –1.545**					
Model (1)	–2.426***	–2.027***	–1.993***	–.424	–.866
Model (2)	–2.510***	–1.806***	–1.788***	–1.365	–.631
Model (3)	–2.547***	–2.054***	–1.972**	–2.219***	–1.079
Coefficient estimates and test statistics					
	Model 1				
y_{it}	.846***	.933***	1.161***	1.881***	1.827***
	(.017)	(.015)	(.059)	(.216)	(.244)
Average residual cross-correlation	.498	.386	.456	–.008	–.009
F-test of homogeneity (p-value)	.000***				
Swamy test (p-value)				.000***	.000***
F-test on $\beta_y = 1$ (p-value)	.000***	.000***	.007***	.000***	.001***
	Model 2				
ya_{it}	.478***	.296***	.333***	1.995***	1.945***
	(.011)	(.008)	(.039)	(.176)	(.179)
Average residual cross-correlation	.530	.377	.365	–.006	–.007
F-test of homogeneity (p-value)	.000***				
Swamy test (p-value)				.000***	.000***
F-test on $\beta_{ya} = 1$ (p-value)	.000***	.000***	.000***	.000***	.000***
	Model 3				
y_{it}	1.529***	.981***	1.053***	1.922***	1.698***
	(.046)	(.016)	(.065)	(.226)	(.242)
pop_{it}	–.661***	–.087***	–.266***	3.424***	3.679***
	(.055)	(.011)	(.060)	(.371)	(.412)
Average residual cross-correlation	.465	.357	.349	.006	.011
F-test of homogeneity (p-value)	.000***				
Swamy test (p-value)				.000***	.000***
F-test on $\beta_y = 1$ (p-value)	.000***	.238	.416	.000***	.004***
F-test on $\beta_y = \beta_{pop}$ (p-value)	.000***	.000***	.000***	.000***	.000***
F-test on $\beta_y = \beta_{pop} = 1$ (p-value)	.000***	.000***	.000***	.000***	.000***

Dependent variable = $p_{i,t}$. The intercepts are not reported. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Except for POLS and PFMOLS, the reported regression coefficients represent the mean group estimates, i.e., the mean of $\beta_{y/ya/pop,i}$ across all MSAs. All the models include MSA-specific intercepts (fixed-effects). The null hypothesis in the Swamy test and F-test on homogeneity is that of homogeneous slope coefficients across MSAs. The CIPS statistics are based on CADF regressions that do not include intercepts. Critical values in the CIPS test are –1.46, –1.54 and –1.68 at the 10%, 5% and 1% level of significance, 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.

Table 4. MSA-specific CADF unit root test statistics for house price-income ratio and FMOLS-MG models (MSAs ordered by 2012 population)

			Regression model						Regression model		
		p – y	**1**	**2**	**3**			***p – y***	**1**	**2**	**3**
1	New York, NY		**	**		26	Orlando, FL		***	***	***
2	Los Angeles, CA			*		27	Sacramento, CA	***	***	***	***
3	Chicago, IL					28	Cincinnati, OH				**
4	Dallas, TX	*		**	*	29	Cleveland, OH				
5	Houston, TX					30	Kansas City, MO			*	
6	Philadelphia, PA					31	Las Vegas, NV	**	**	***	*
7	Washington, DC		**	**		32	Columbus, OH				
8	Miami, FL					33	Indianapolis, IN				*
9	Atlanta, GA		**	**		34	San Jose, CA		*	**	**
10	Boston, MA		**	***		35	Austin, TX	**	*	*	*
11	San Francisco, CA		**	**		36	Nashville, TN	*	**	**	**
12	Riverside, CA		**	***		37	Virginia Beach, VA				
13	Phoenix, AZ	**	**	**	**	38	Providence, RI	**	***	***	**
14	Detroit, MI					39	Milwaukee, WI		***	***	*
15	Seattle, WA			*		40	Jacksonville, FL		***	***	***
16	Minneapolis, MN					41	Memphis, TN				
17	San Diego, CA	*	***	***	*	42	Louisville, KY		**	*	*
18	Tampa, FL		***	***		43	Oklahoma City, OK				**
19	St. Louis, MO		***	***		44	Richmond, VA	**			***
20	Baltimore, MD					45	New Orleans, LA			*	
21	Denver, CO		*			46	Hartford, CT		**	**	**
22	Pittsburgh, PA		***	***		47	Raleigh, NC		*		*
23	Charlotte, NC		**	*		48	Birmingham, AL		**	**	**
24	Portland, OR			*		49	Buffalo, NY				
25	San Antonio, TX	*			*	50	Salt Lake City, UT	**	***	***	**

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Critical values at the 10%, 5% and 1% level of significance are: -2.26, -2.60, and -3.30. *p – y* is the log house price-income ratio.

Figure 1. Residuals from house price-income relations (demeaned)

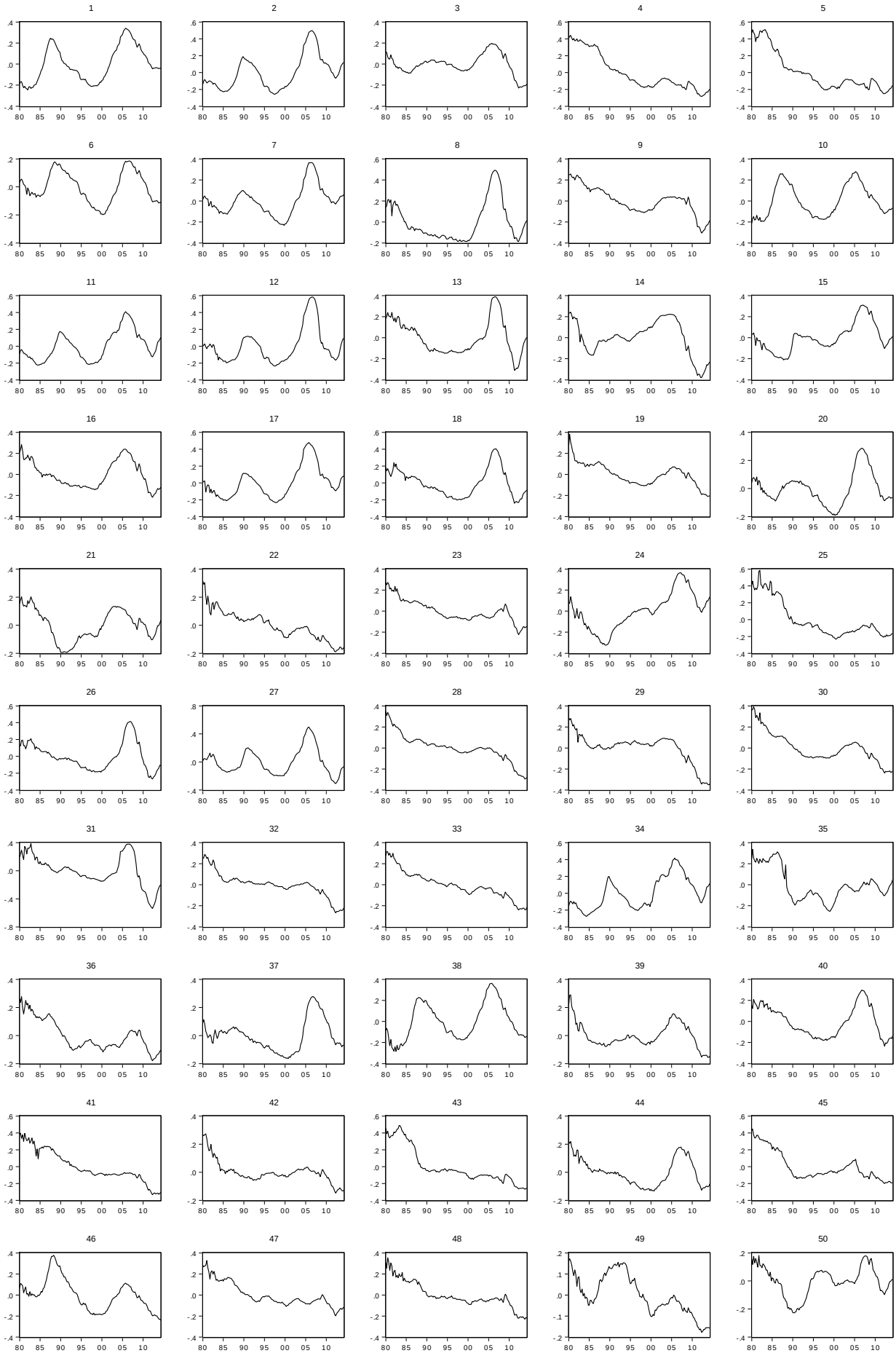


Figure 2. Trends in house price-income ratio and the supply elasticity of housing

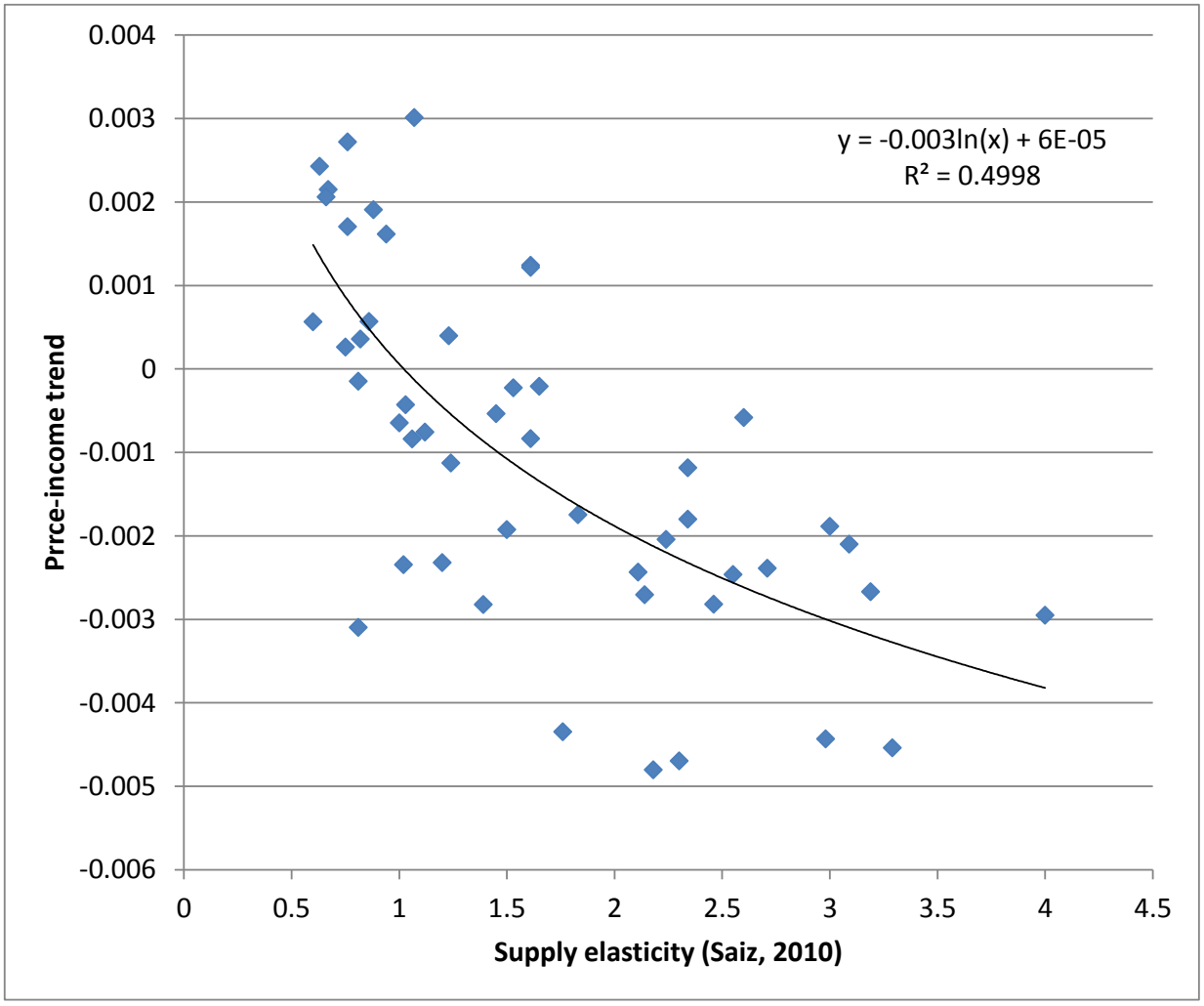
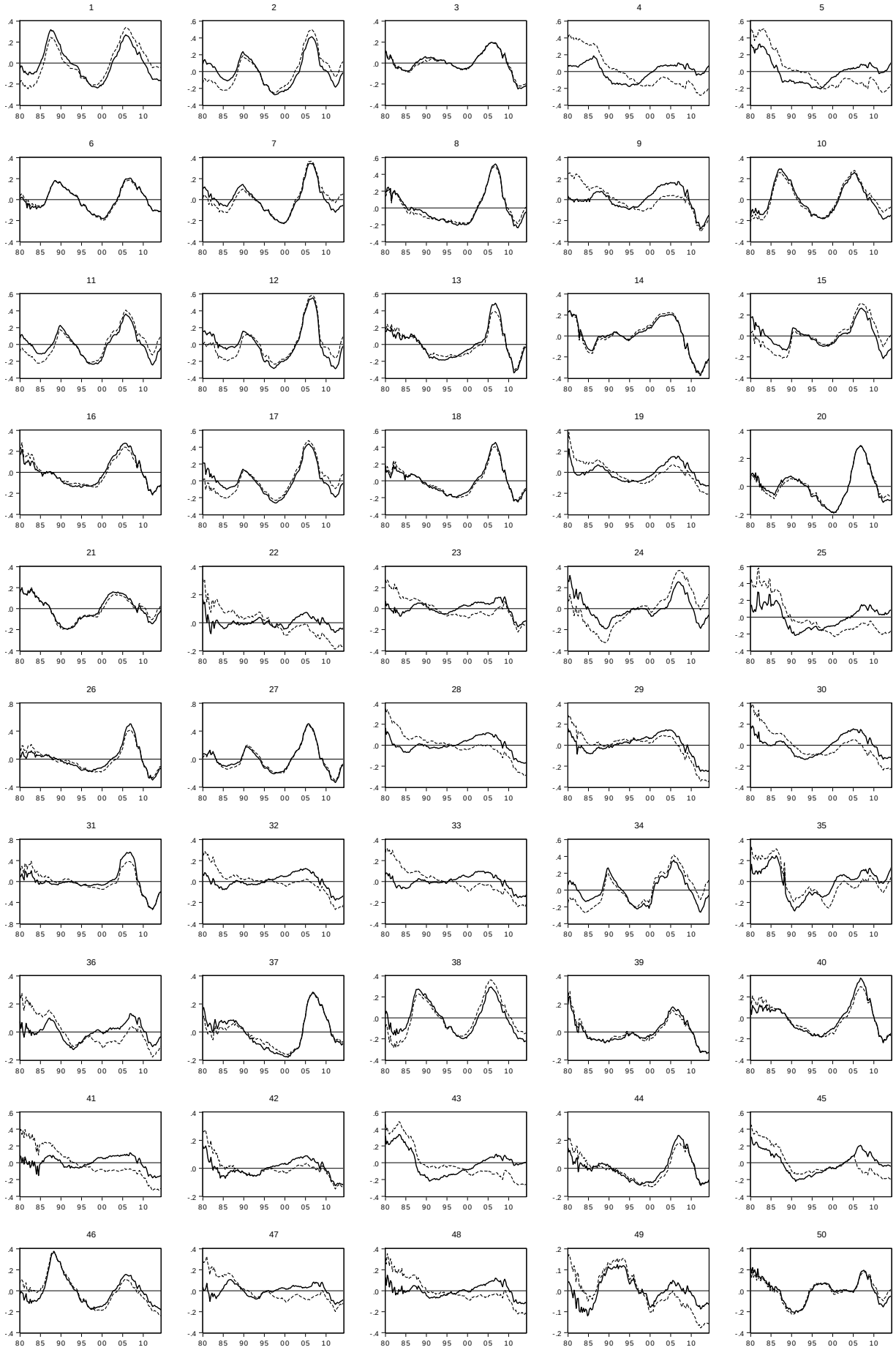


Figure 3. Residuals from Model 2 (continuous) and from price-income ratio (dashed)



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