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Revisiting Metropolitan House Price-Income Relationships

Elias Oikarinen
University of Oulu, Aalto University, and University of Turku

Steven C. Bourassa
Florida Atlantic University

Martin Hoesli
University of Geneva, University of Aberdeen, and Swiss Finance Institute

Janne Engblom
University of Turku

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Elias Oikarinen
Oulu Business School, University of Oulu, Finland
Department of Built Environment, Aalto University, Aalto, Finland
School of Economics, University of Turku, Turku, Finland
elias.oikarinen@oulu.fi

Steven C. Bourassa
Department of Urban and Regional Planning, Florida Atlantic University, Boca Raton, FL USA
sbourassa@fau.edu

Martin Hoesli
Geneva School of Economics and Management and Swiss Finance Institute, University of Geneva, Geneva, Switzerland
School of Business, University of Aberdeen, Aberdeen, UK
martin.hoesli@unige.ch

Janne Engblom
School of Economics, University of Turku, Turku, Finland
janne.engblom@utu.fi

Abstract

We explore long-term patterns of the house price-income relationship across the 70 largest U.S. metropolitan areas. In line with a standard spatial equilibrium model, our empirical findings indicate that house price-income ratios are typically not stable even over the long run. In contrast, panel regression models that relate house prices to aggregate personal income and allow for regional heterogeneity yield stationary long-term relationships in most areas. The relationship between house prices and income varies significantly across locations, underscoring the importance of using estimation techniques that allow for spatial heterogeneity. The substantial differences across metropolitan areas are closely related to the price elasticity of housing supply.

Keywords: House prices; Personal income; Spatial equilibrium; Regional heterogeneity; Supply elasticity

JEL codes: C33, R10, R31

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1. Introduction

The relationship between house prices and income is important for the economy for several reasons. The income elasticity of house prices affects housing affordability, and spatial differences in the elasticity influence regional growth: the larger the long-term elasticity of prices with respect to income, the greater the counterforce posed by rising house prices on regional growth. Moreover, the relationship between house prices and income is expected to influence household consumption, savings, and consumption inequality (Cooper 2013, Paiella and Pistaferri 2017, Etheridge 2019). On the other hand, the evolution of the house price-income relationship can affect trends in wealth-income ratios (Knoll, Schularik and Steger 2017). If house prices and incomes have stable long-term relationships, then deviations of prices from this relationship can be used to assess whether prices are under or over their long-term equilibrium levels. As house price dynamics influence credit and macroeconomic cycles, the house price-income relationship and its regional heterogeneity are of importance not only for regional policy makers, but also for central authorities aiming to stabilize macroeconomic cycles (Piazzesi and Schneider 2016).

We explore the long-term relationship between house prices and income by first considering the implications of a standard spatial equilibrium model for the stability of the price-income ratio, and provide a numerical illustration of the model using comparative static analysis. Then we test the predictions of the model empirically using data for the 70 largest U.S. metropolitan areas. Our focus is on regional house price-income relationships, as it is well established that house price dynamics vary across markets (Glaeser, Gyourko and Saiz 2008, Glaeser *et al.* 2014, Oikarinen *et al.* 2018). For numerous agents, including households, construction companies, investors, and credit institutions, local developments are of great importance.

Empirical investigations of house prices and income have often entailed quite restrictive assumptions. These include: (1) the assumption of a one-to-one relationship between price and income growth implied by price-income ratios; (2) the assumption of a linear stationary relationship between prices and per capita personal incomes in regression analyses based on the latter; and (3) the assumption of a homogeneous relationship between prices and income across locations in studies that use pooled regional or national data. Empirical findings regarding the relationship between prices and income vary, perhaps because of these methodological issues. That is, the actual nature of the relationship remains unclear.

Studies of house price bubbles have sometimes relied on price-income ratios, implicitly assuming that the long-term coefficient on income would be one in a stationary regression model explaining house prices. There are good reasons to expect that this is not the case, including the variations in supply elasticities across locations (Saiz 2010) that are closely related to income elasticities (Hilber and Vermeulen 2016, Oikarinen *et al.* 2018).

Some research implicitly assumes a linear stationary relationship between house prices and per capita income without testing whether this assumption holds true empirically. Other studies examine whether the data support the existence of such a relationship. In a panel study of U.S. metropolitan areas, Malpezzi (1999) finds cointegration between prices and per capita income. Gallin (2006), using different panel tests that allow for cross-correlations across cities (Pedroni 1999), 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, Pesaran and Yamagata (2010) control for spatial dependence in their regression models in addition to unit root tests. They do so by applying panel estimation techniques developed by Pesaran (2006) to U.S. state level data and conclude that the hypothesis of a unit root can be rejected in both the price-income ratio and a regression between house prices and per capita income. However, rejection in such unit root tests does not necessarily imply that the price-income relationship is stationary in all or even most regions.

Finally, there is the problematic assumption that the relationship between income and prices is homogeneous across locations. Harter-Dreiman (2004) finds a stationary vector between prices and aggregate personal income in U.S. metropolitan areas separately in panels of supply-constrained and unconstrained cities using conventional pooled panel estimators. In contrast, the panel estimator used by Holly, Pesaran and Yamagata (2010) allows slope coefficients to be heterogeneous across U.S. states, and they report notable spatial differences in the coefficients. Hilber and Vermeulen (2016) allow for spatial variation in the income elasticity of house prices in England through interaction effects with measures of local supply constraints. They show that income elasticity is positively influenced by supply restrictions.

To our knowledge, ours is the first study in which the house price-income relationship is considered using a spatial equilibrium framework. The model demonstrates why local house price-income ratios generally are not expected to be stable over the long run. In the empirical analysis, we apply panel econometric tools – including estimators and tests that have not been applied to housing price-income relation analyses before – that allow us to explore the implications of the spatial equilibrium model.

A further novelty is that, in addition to the price-income ratio, we study cointegration of regional house prices and income using both per capita and aggregate personal income and test formally for a one-to-one relation between house prices and these income measures. We also relax the assumption of similar slope coefficients across locations, permitting income elasticity to be heterogeneous across cities, and control for spatial dependence in the unit root and cointegration tests. As other contributions, we test for spatial heterogeneity in the price-income relations and investigate the association between local house price-income ratio trends and supply elasticities. In addition to housing affordability and regional growth, our findings are relevant to the analysis of house price bubbles because a stable (i.e. stationary) long-term relationship between income and prices is needed to measure deviations from equilibrium.

Consistent with the predictions of the spatial equilibrium model, our empirical results indicate that long-term stability of local house price-income ratios is the exception rather than the rule and that the income elasticity of house prices varies considerably across cities. As expected, city-specific price-income ratio trends and income elasticities are strongly correlated with supply elasticities. In line with the theoretical predictions, a panel regression model that allows for regional variation in the coefficient on aggregate personal income demonstrates a stationary long-term relationship with house prices in many more metropolitan areas than does the ratio of price to per capita income. We also show that the overall panel unit root test statistics may be misleading because they do not say anything about the proportion of MSAs with stable relationships between prices and incomes – an issue not considered previously in the related literature.

We are interested in whether *income variables alone* form a long-term trend for house prices, and hence do not include other possible fundamentals as control variables in the empirical analysis. If we added other variables, we would no longer be studying the stationarity of pure price-income relationships. In other words, a stationary relation is not an indication of a stable price-income relationship if that finding necessitates the inclusion of some other (non-stationary) variable(s) in the model. Furthermore, as our focus is on long-term relations rather than short-term dynamics, we do not investigate the causes of shorter-term deviations of house prices from their long-term trends.

The next section of the paper considers a standard spatial equilibrium framework for understanding the relationship between house prices, incomes, and population in the context of a system of cities or regions. It includes a simple numerical illustration based on comparative statics. Section three discusses our data, including analysis of the variables' time series properties. Section four contains the empirical analysis. A final section concludes.

2. Spatial equilibrium and the house price-income relationship

Understanding the factors affecting the house price-income relationship and its development over time in a given city requires 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 because housing costs, wages, city populations, and their growth rates are jointly determined and, therefore, population and income are endogenous to house prices (Glaeser and Gottlieb 2009, Moretti 2011).

We consider a general spatial equilibrium model with the typical assumption that welfare is equalized across space (Glaeser and Gottlieb 2009) and is assumed to be determined by three factors: wages, housing costs, and the quality of amenities. Our framework is a derivation of the standard Rosen (1979) and Roback (1982) model with spatial equilibrium and is largely based on the model presented in Moretti (2011). Carlino and Saiz (2019), for instance, provide empirical evidence consistent with such a model. The model is designed to explore *long-term* changes in the price-income relationship because, in the short run, there are frictions that can restrain labor and firm mobility and the adjustment of housing prices and supply toward equilibrium (Moretti 2011, Anenberg 2016). We are not aware of earlier studies using the spatial equilibrium concept to analyze the house price-income ratio.

The spatial equilibrium framework demonstrates that 1) the assumption of a constant price-income ratio is highly restrictive, 2) developments in other cities as well as shocks in the city in question affect the evolution of the ratio, and 3) the supply elasticity of housing has a major role regarding regional price-income ratio developments. 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 the model as simple and tractable as possible.[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. Similar to e.g. Moretti (2011) and Kline and Moretti (2014), the production function in city *i* takes the Cobb-Douglas form with constant returns to scale:

(1) $$Y_i = X_i N_i^h K_i^{1-h}, 0 < h < 1.$$

Here N_i represents the number of workers, 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. 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 homogeneous labor and that each worker provides one unit of labor. Hence, local labor supply is determined solely by the location decisions of workers. Following Glaeser and Gottlieb (2009), among others, we assume that the utility of workers in city *i* (U_i) is given by the Cobb-Douglas utility function

(2) $$U_i = M_i C_{H,i}^{\gamma} C_{O,i}^{1-\gamma}, 0 < \gamma < 1.$$

In (2), M_i is the quality of amenities in city *i*, C_H and C_O represent the consumption of housing and other goods, respectively, and γ is the share of expenditure on housing, which is assumed to be

[1] For instance, while tax rules can affect housing costs, our model abstracts from housing taxation. That is, the model shows that even if tax rules are constant over time and across space, the price-income ratio is expected to show temporal and regional variation.

similar over time and across cities.[2] Piazzesi, Schneider and Tuzel (2007), Davis and Ortalo-Magné (2011), and Piazzesi and Schneider (2016) provide support for this assumption, which is common in spatial equilibrium models. Similar to Glaeser and Gottlieb (2009) and Hsieh and Moretti (2015), the indirect utility (V_i) then equals[3]

(3) $$V_i = M_i W_i (P_i)^{-\gamma},$$

where W_i denotes the nominal wage level and P_i is the cost (or price) of housing in city *i*. In log form

(4) $$v_i = m_i + w_i - \gamma p_i,$$

where the lower-case letters denote natural logs. Utility is positively related to wage level and the quality of amenities, and negatively affected by higher housing costs. In spatial equilibrium, the utility levels are the same across cities; i.e., workers are indifferent between locations. Hence, in spatial equilibrium

(5) $$w_i - \gamma p_i + m_i = w_j - \gamma p_j + m_j$$

holds for every city *i* and *j*.

Given the utility function in (2), the Marshallian demand for housing of a household located in *i* (D_i^{hh}) is

(6) $$D_i^{hh} = \gamma W_i / P_i \; ; \; d_i^{hh} = \ln \gamma + w_i - p_i.$$

The market level demand in city *i* (d_i) then equals (in logs)

[2] Carlino and Saiz (2019) provide a recent review of literature supporting the role of amenities in households' location choices. Spatial variation in amenities can affect house values within cities as well (e.g., Lee et al. 2019, Letdin and Shim 2019). However, our focus is solely on the variations of local amenities *across* cities.

[3] As is typical, we abstract from the constant term that is assumed to be the same across cities.

(7) $$d_i = c_1 + w_i + n_i - p_i,$$

where c_1 (= $\ln \gamma$) is a constant term.

Housing supply (S), in turn, is provided by absentee landlords, and is positively related to the level of housing costs (which reflect the return on housing investment), with ω_i (> 0 for every i) denoting the price elasticity of housing supply:[4]

(8) $$S_i = C_{2i} P_i^{\omega_i} \; ; s_i = c_{2i} + \omega_i p_i; \; \omega_i > 0.$$

In the short and medium run, the elasticity of housing supply can vary depending on whether prices are decreasing or increasing (Glaeser and Gyourko 2005). This model focuses on *long-term* trends in the price-income relationship, however. Moreover, the demand for housing, measured as real aggregate income, trended upwards during the sample period (1979-2018) in all the metropolitan areas included in our empirical analysis. Therefore, we do not distinguish between upwards and downwards adjustment of housing supply.

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

(9) $$p_i = \alpha_i + \beta_{1i} w_i + \beta_{2i} n_i \; ; \alpha_i = \frac{c_1 - c_{2i}}{\omega_i + 1}, \; \beta_{1i} = \beta_{2i} = \frac{1}{\omega_i + 1} > 0.$$

Higher wages, greater population, and lower supply elasticity (smaller ω) due to topographic or regulatory constraints cause higher housing costs. If the number of households increases in a city but wages do not (i.e., population growth is induced by relative improvement in the quality of

[4] Although supply elasticity could be endogenous to city size (S), it is conventional in spatial equilibrium models to assume that it is exogenous (Moretti 2011, Kline and Moretti 2014, Hsieh and Moretti 2015). This assumption does not have any bearing on the conclusions we derive from the model and allowing supply elasticity to be endogenous would greatly diminish the model's tractability.

amenities), housing space per person must decrease in the city. The considerable spatial variation in ω_i (Saiz 2010) is expected to yield notable variation in β_{1i} and β_{2i} across cities. For simplicity, we assume that the constant term (α) in the price equation is the same across cities.

The cost of housing, p_i, can be interpreted as the rental level or the user cost of owner-occupied housing. By assuming a constant required rental yield for housing assets, similar to Glaeser and Gottlieb (2009), we can use p_i to analyze the temporal variation in the house price-income relationship, as the house price level is simply rent divided by the rental yield. This assumption should be realistic given that the city-level required rental yield (i.e., the inverse of the house price-to-rent ratio) can be assumed to be mean-reverting over the long run (Meese and Wallace 1994, Gallin 2008, Crone, Nakamura and Voith 2010, Baltagi and Li 2015). Moreover, the model abstracts from factors that determine the yield: interest rates, risk premia, and growth expectations.[5] Hence, we interpret p_i to reflect price levels 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 spatial equilibrium condition for the house price-income ratio. Given the spatial equilibrium condition, the inverse labor supply function in city *a* is:

$$w_a = w_b + \gamma(p_a - p_b) + (m_b - m_a). \tag{10}$$

Using equation (9) for p_a and p_b yields

$$w_a = [(1 - \gamma\beta_{1b})w_b + \gamma(\beta_{2a}n_a - \beta_{2b}n_b) + (m_b - m_a)]/(1 - \gamma\beta_{1a}). \tag{11}$$

[5] If the yield were non-stationary, it would provide another factor causing long-term instability (non-stationarity) in the price-income ratio. The model indicates that the ratio generally is not stable over the long run even if the yield is stationary.

Higher quality of amenities in city *a* induces larger local labor supply, i.e., a greater number of households and therefore higher house prices. In other words, the utility gain from higher amenities makes workers willing to live in a city even if their net wages after housing costs are lower. Given 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.

The total number of workers, N, is exogenous 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[6]

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

Labor market equilibrium is obtained by equating (11) and (12) for each city.

Productivity Shock and the House Price-Income Relationship

Next, we use this standard spatial equilibrium model to consider the influence of a labor demand shock on 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 $w_{a2} - w_{a1} = \Delta$

[6] 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.

(> 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 (11), we can write:[7]

$$\Delta = [\gamma\beta_{2a}(n_{a2} - n_{a1}) - \gamma\beta_{2b}(n_{b2} - n_{b1})]/(1 - \gamma\beta_{1a}). \quad (13)$$

Equation (13) 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:

$$n_{a2} - n_{a1} \approx (1 - \gamma\beta_{1a})/[\gamma(\beta_{2a} + \delta_{a1}\beta_{2b})] \times \Delta, \quad (14)$$

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 moderated by more inelastic housing supply in *a* (greater β_{1a} and β_{2a}) and in *b* (greater β_{2b}). 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*.[8] 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*.

Taking advantage of equations (9) and (10), the change in the house price-income ratio in city *a* due to the productivity shock is

[7] 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).

[8] In the short and medium term, when housing supply tends to be more inelastic downwards than upwards, the price level in city *b* would drop even more and population would decrease (increase) somewhat less in *b* (*a*). This would not affect the key conclusions of our model and, in any case, we are interested in the long-term dynamics.

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

where $d(p_a - w_a) = (p_{a2} - w_{a2}) - (p_{a1} - w_{a1})$. Using the above approximation for $n_{b2} - n_{b1}$ and equation (14), we can express $d(p_a - w_a)$ solely in terms of model parameters and the productivity increase:

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

where $\theta = \frac{(1-\gamma)\beta_{2a} - \delta_{a1}\gamma\beta_{2b}}{\gamma(\beta_{2a}+\delta_{a1}\beta_{2b})} = \frac{\beta_{2a}}{\gamma(\beta_{2a}+\delta_{a1}\beta_{2b})} - 1$. Based on (16), the price-income ratio remains constant after a productivity shock only in the special case where $\theta(1-\gamma\beta_{1a}) + (1-\gamma)\beta_{1a} = 0$.

Comparative static predictions can be formulated with the following partial derivatives:

$$\frac{\partial[d(p_a - w_a)]}{\partial\beta_{1a}} = \frac{\delta_{a1}\beta_{2b}}{\beta_{2a} + \delta_{a1}\beta_{2b}} > 0$$

$$\frac{\partial[d(p_a - w_a)]}{\partial\beta_{2a}} = (1-\gamma\beta_{1a})\frac{\delta_{a1}\beta_{2b}}{\gamma(\beta_{2a} + \delta_{a1}\beta_{2b})^2} > 0$$

$$\frac{\partial[d(p_a - w_a)]}{\partial\beta_{2b}} = -(1-\gamma\beta_{1a})\frac{\delta_{a1}\beta_{2a}}{\gamma(\beta_{2a} + \delta_{a1}\beta_{2b})^2} < 0$$

Since higher income and population elasticities of house prices (β_{1a} and β_{2a}, respectively) in city *a* yield greater $d(p_a - w_a)$ as productivity in *a* increases, and β_1 and β_2 are positively dependent on supply elasticity, the model predicts that productivity increases lead to higher price-income ratios and thus greater growth in the ratio in more supply restricted cities. The decreasing influence of greater population elasticity (i.e., smaller supply elasticity) in city *b* on $d(p_a - w_a)$ is that fewer people will move from *b* to *a* after the productivity shock, since house prices drop more in *b* in response to declining population. Because fewer people move to *a*, house prices increase less.

A Simple Numerical Illustration

Consider two cities that are identical initially: N = 1 so that N_a and N_b reflect the population shares in the cities; the supply elasticity is 1.5 in both cities so that the elasticity of house prices with respect to income (β_1) and population (β_2) is 0.40; and the parameters in the production function are $X_{a1} = X_{b1} = 10$ and $h = 0.5$. Since $N_{a1} = N_{b1} = 0.5$, we get $W_a = W_b = 5$.[9] Finally, we set the share of expenditure on housing (γ) to 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 increases by 5%. As shown in Table 1 (column I), in the new equilibrium population is 22.5% greater and the house price level is 11% higher in city a than before the shock. Consequently, the house price-income ratio is 6% higher. In city b, in turn, the 22.5% population decline causes a 9% decrease in the price-income ratio; i.e., housing becomes more affordable.

Table 1 Numerical illustrations

Assumed supply elasticities and impacts of shocks	5% productivity increase in city *a*		5% productivity increase in both cities		5% increase in the value of amenities in city *a*	
City a	I	II	III	IV	V	VI
Assumed supply elasticity	1.500	0.600	1.500	0.600	1.500	0.600
Change in price-income ratio	0.060	0.084	–0.030	–0.026	0.100	0.122
Population change	0.225	0.165	0.000	–0.011	0.250	0.195
Price change	0.110	0.134	0.020	0.024	0.100	0.122
City b						
Assumed supply elasticity	1.500	1.500	1.500	1.500	1.500	1.500
Change in price-income ratio	–0.090	–0.066	–0.030	–0.026	–0.100	–0.078
Population change	–0.225	–0.165	0.000	0.011	–0.250	–0.195
Price change	–0.090	–0.066	0.020	0.024	–0.100	–0.078

Note: All examples are based on the following parameters before the shock: $N = 1$; $N_a = N_b = 0.5$; $\gamma = 0.25$; $X_a = X_b = 10$; $h = 0.5$. An exception is that, in the cases with 0.6 supply elasticity in city a (columns II, IV and VI), the productivity shifter in a, X_a, is initially 10.63.

[9] The assumed supply elasticity is close to the median for the 70 metropolitan areas investigated in this study.

To illustrate the role of supply elasticity, consider the same shock but with a different supply elasticity in city a. Column II in Table 1 shows the changes in price-income ratios when the supply is more inelastic in city a: the price-income ratio increase in a is greater and the decrease in b is milder; housing is more expensive in *both cities* than in the baseline case.[10] Given the assumption of equal city sizes before the shock, the more inelastic supply in a also means that initially the productivity shifter in city a, X_a, is 10.63: higher wages are needed to compensate for the more expensive housing (which is an outcome of the supply inelasticity).

Now assume that a similar productivity shock takes place in both cities, with both w_a and w_b rising by 5%. As there is a similar wage increase in both cities, there is no flow of workers between a and b in the baseline case (column III). The income increase induces house price growth of 2%. Thus, the price-income ratio decreases by 3%. Column IV reports the effects assuming an elasticity of 0.6 in a: because $\beta_{1a} > \beta_{1b}$, some households need to move from a to b so that the spatial equilibrium condition is maintained. Due to the inelastic supply in a, housing costs increase more in *both cities* than in the baseline case.

Finally, suppose that, instead of a productivity shock, there is a positive shock in the value of amenities in city a (column V). 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). The wage levels in the two cities are unaltered 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 so that the equilibrium condition is maintained: 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.[11] A lower supply elasticity in

[10] The 0.6 supply elasticity is the smallest among the 70 metropolitan areas that we consider.

[11] Regulatory restrictiveness – and thus supply elasticity – could be correlated with amenities (Hilber and Robert-Nicoud 2013): greater value of amenities can give rise to lower supply elasticity (through more regulation). This could

a (column VI) would yield greater price-income changes in *both cities* and less movement from *b* to *a*. The simultaneous influence of amenity shocks on populations and house prices and the role of supply elasticity in that process are consistent with the findings of Carlino and Saiz (2019).

In summary, comparative static analysis of the conventional spatial equilibrium model predicts that:

1) 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 the rule.
2) 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*.
3) The elasticity of housing supply is a key determinant of the influence of various shocks on the house price-income ratio, and *the elasticities in other cities*, too, affect the outcomes in a given city. Greater elasticity of supply is related to smaller growth trends in the price-income ratio.

Other implications regarding the relationships between house prices, incomes, and population are more familiar from the literature:

4) House prices, wages, and population are jointly determined.
5) House prices, wages, and population are spatially correlated.
6) The income elasticity of house prices is expected to vary across cities.

Our empirical analysis focuses on points 1 and 6. In addition, we investigate the extent of spatial correlations across MSAs (point 5) and relate income elasticities and trends in price-income ratios to supply elasticities (point 3).[12]

add another channel from an amenity shock to the price-income ratios. This potential channel does not alter the conclusions of the model.

[12] Clearly, the same implications that are presented for the price-income ratio apply to the rent-income ratio as well.

3. Data

Our empirical analysis is based on quarterly data for the 70 largest (as of 2018) U.S. Metropolitan Statistical Areas or Divisions (referred to below as MSAs) for the period 1979Q3 through 2018Q2. This period includes one or more prominent house price cycles in all 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).[13] The MSA per capita personal income (y) and aggregate personal income (ya) 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. While the quarter-to-quarter variations in the income variables do not affect the long-term estimates in cointegrating equations, the use of quarterly data provides us with a much greater number of observations and thereby more powerful tests. All variables are in real terms and in natural log form.[14] Table 2 provides summary statistics. Although not separately included in the regression models, we report statistics for MSA-level populations as well (also from the BEA).

As expected, there are considerable regional variations in the mean growth rates of house prices, incomes, and population. The mean real house price growth was negative between 1979 and 2018

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[13] We limit the sample to the 70 largest MSAs since smaller MSAs tend to exhibit too much implausible volatility in the FHFA house price indexes and many lack complete data. Due to extreme volatility (likely due to measurement error) in the early years of the price index, we also exclude Honolulu, which would have been ranked 69th with respect to population. In terms of short- and long-run house price dynamics, the FHFA data are similar to CoreLogic data (Oikarinen *et al.* 2018).

[14] All variables, including income, are deflated by the national urban CPI less shelter costs. If we were to deflate income by the CPI for all items (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 income and all other (non-housing) components of the CPI have remained constant. Therefore, housing demand growth would not only cause 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.

in six MSAs, of which all are inland. The highest price growth (annualized rate of 3.6%) was observed in San Francisco. In San Jose and Nassau-Suffolk, too, the figure was over 3%, while in Tulsa it was –0.4%. Population growth was very rapid in Las Vegas, 4.1% 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 Philadelphia; of these, Detroit had the largest rate of population loss (0.7% per year).

The mean real per capita and aggregate income growth rates were positive in all 70 MSAs. Across all the MSAs, the annual mean growth rates were 1.6% and 2.8%, respectively. In San Francisco, per capita income growth was 2.8% per year, while the growth rate was only 0.8% in Detroit and Riverside. Real aggregate income growth was highest in Austin (5.3%) and lowest in Detroit (0.1%).

Table 2 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)	0.011	0.049	–0.004	0.036
Real per capita income growth (Δy)	0.016	0.021	0.008	0.028
Real aggregate income growth (Δya)	0.028	0.023	0.001	0.053
Population growth (Δn)	0.012	0.008	–0.007	0.041
Correlations	*p*	*y*	*ya*	*pop*
Real house price (*p*)	1.000			
Real per capita income (*y*)	0.630***	1.000		
Real aggregate income (*ya*)	0.392***	0.749***	1.000	
Population (*n*)	0.090***	0.323***	0.869***	1.000
	Δp	Δy	Δya	Δpop
Δp	1.000			
Δy	0.403***	1.000		
Δya	0.393***	0.945***	1.000	
Δn	0.073***	0.087***	0.407***	1.000
	p	*y*	*ya*	*pop*
Mean of cross-sectional correlations	0.581	0.956	0.963	0.693

Note: The sample period is 1979Q3-2018Q2. Correlations are reported for all MSA quarterly data 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.

Portland, OR offers an interesting illustration of how city-specific developments of the three variables, *p*, *y*, and *n*, 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, 1.9% (the mean across the MSAs is 1.1%) and 1.6% (1.2%), respectively, in terms of real per capita income growth Portland was ranked only 50th (1.4%). Based on 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 has substantially increased, thereby increasing the supply of labor (population) in the city (Miller 2014).

Table 2 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 theory, house prices are higher in larger cities with higher income levels. Also, in accordance with the theoretical model, cross-correlation across MSAs is strong for all the variables.

As a preliminary check, we conducted panel unit root tests to examine the stationarity of each variable used in the regression analysis. Since the residual series from conventional augmented Dickey-Fuller (ADF) regressions include significant cross-sectional correlation (Table 3) and hence the conventional panel ADF test statistics could be biased, we follow Holly, Pesaran and Yamagata (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. The results reported in Table 3 indicate that the variables should be treated as non-stationary in levels. For all the differenced variables, the test statistics indicate stationarity.

Table 3 CIPS unit root test statistics

Variable	p_{it}	y_{it}	ya_{it}	Δp_{it}	Δy_{it}	Δya_{it}
Test value	–2.477	–2.115	–2.300	-3.937^{***}	-4.906^{***}	-4.742^{***}
Lags	*Average residual cross-correlation of ADF regressions*					
0	.450	.837	.830	.447	.851	.842
1	.447	.849	.839	.487	.851	.839
2	.488	.849	.834	.493	.855	.855
3	.496	.854	.852	.478	.843	.850
4	.479	.842	.848	.484	.843	.850

Note: The sample period is 1979Q3-2018Q2. 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, Pesaran and Yamagata (2010). The number of lags in the CADF 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. In the unit root test statistics, *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. All the average residual cross-correlations of ADF regressions are statistically significant.

4. Empirical Analysis

In this section, we test some of the key implications of the spatial equilibrium model. In particular, we study the stationarity of the house price-income ratio and report regression results and cointegration tests based on several alternative estimators and model specifications. We also investigate the extent of heterogeneity across MSAs and relate this heterogeneity to the supply elasticity of housing.

The spatial equilibrium model predicts that the house price-income ratio is generally not stationary at the city level and therefore also point to complications with using the ratio to identify house price misalignments. In the regression models we relax the restrictive assumption – a coefficient of one on income – imposed implicitly by the ratio. The regression models are based on the house price equation (9) derived in the theory section,

$$p_i = \alpha_i + \beta_{1i} y_i + \beta_{2i} n_i, \; (\beta_{1i} = \beta_{2i} = \frac{1}{\omega_i + 1} > 0),$$

where income level in city *i* is denoted by y_i instead of w_i. The estimated models are:

(17a) Model 1: $p_{i,t} = \alpha_i + \beta_{y,i} y_{i,t} + \varepsilon_{i,t}$

(17b) Model 2: $p_{i,t} = \alpha_i + \beta_{ya,i} ya_{i,t} + \varepsilon_{i,t}$,

where ya_i is the natural log of aggregate income in city *i* (i.e., equals $y_i + n_i$), α_i are the MSA-specific fixed-effects, $\beta_{y,i}$ and $\beta_{ya,i}$ are MSA-specific slope coefficients, and ε_i are MSA-specific error terms. That is, we let the coefficients on *y* and *ya* vary across MSAs. Model 1 allows the coefficient on income per capita to differ from one but ignores the effects of population growth on housing demand. Hence, the residual component, ε_i, includes the effects of a city's own population growth in addition to other effects potentially affecting house price developments. Model 2 takes account of population developments by including aggregate instead of per capita income. Note that Model 2 corresponds to the price equation (9): since β_{1i} and β_{2i} should be similar, there is no need to include income and population in the regression model separately. This also circumvents the collinearity complication that is typically present in house price regressions when incomes and populations are separately included as explanatory variables.[15]

The price-income ratio can be presented in the same form as Model 1: $p_{i,t} - y_{i,t} = \alpha_i + \varepsilon_{i,t} \rightarrow$ $p_{i,t} = \alpha_i + \beta_{y,i} y_{i,t} + \varepsilon_{i,t}$, where $\beta_{y,i}$ = 1 for all cities i.

If $\varepsilon_{i,t}$ is stationary, then the (estimated) relationship can be regarded as a stable long-run relation, implying that factors other than $y_{i,t}$ or $ya_{i,t}$ have only temporary effects on house prices. In the case of the price-income ratio, stationarity of $\varepsilon_{i,t}$ would additionally suggest that $\beta_{y,i}$ = 1. In contrast, if $\varepsilon_{i,t}$ is non-stationary, the respective model does not imply a stable long-term relationship. Model 2

[15] Some studies of house price dynamics report negative coefficients on population when income and population enter the model separately.

should outperform both the price-income ratio and Model 1 in terms of producing stable long-run relationships, as it corresponds to (9).

The fully-modified OLS (FMOLS) estimator of Pedroni (2000, 2001) is a good starting point for our regressions given that the population component of aggregate income is likely to be endogenous and that there may be omitted variables that affect house prices.[16] While the estimators generally used in previous studies, such as conventional fixed-effects or random-effects OLS estimators, can exhibit endogeneity bias, the FMOLS estimator is consistent in the presence of endogenous regressors and endogeneity due to possible omitted variables (Pedroni 2001, 2007). We report results for both the pooled FMOLS (PFMOLS) estimator that allows regional heterogeneity only through city-specific fixed-effects and the FMOLS mean-group (FMOLS-MG) estimator that allows regional heterogeneity in all parameter estimates. The FMOLS estimators are also super-consistent in the presence of non-stationary but cointegrated data, which is not the case for the fixed-effects OLS estimator. For comparison purposes, we also report results from the basic pooled fixed-effects OLS (POLS) estimator.

A potential complication with the aforementioned estimators is that they do not control for spatial 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. Although these two estimators aim to remove the potential 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, due to the several additional variables that aim to remove cross-sectional dependence, the slope coefficient estimation may no longer be super-consistent. Hence, some of the attractive robustness features associated with super-consistent estimation under cointegration are potentially lost (Pedroni 2007). Indeed, it turns out that the (D)CCEMG estimators

[16] As noted previously, if we added other variables in the long-term equations, we would no longer be studying the stationarity of pure price-income relationships.

do not work well with our data, which could be due to these complications. Based on the properties of the estimator, FMOLS-MG is preferred.

Baseline Results

Consistent with Holly, Pesaran and Yamagata (2010), the CIPS unit root tests reported in Table 4 reject the hypothesis of a unit root in the price-income ratio. CIPS tests also reject the hypothesis of no-cointegration (i.e., of a unit root in $\varepsilon_{i,t}$) in all the regression models except for those based on the (D)CCEMG estimator.

Stationarity of $p - y$ would indicate that the long-run coefficient on y is one and homogenous across MSAs, which is in contrast with the theoretical predictions. However, based on the size-adjusted F-test for the FMOLS-MG model (Pedroni 2007) and the Swamy test of slope homogeneity for the (D)CCEMG models (Pesaran and Yamagata 2008), the hypothesis of homogeneous coefficients on y is clearly rejected. Moreover, Wald F-test statistics reject the hypothesis that the group mean or pooled coefficient on y equals one for all models. Hence, the regression results for Model 1 are in stark contrast with the concept of a stationary house price-income ratio. Consistent with theory, the test statistics for Model 2 (with aggregate personal income) also reject the hypothesis of $\beta = 1$ and indicate significant variations in the coefficient estimates across MSAs.

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

The preferred FMOLS-MG estimator yields mean group estimates of 0.75 on y and 0.48 on ya. The POLS and PFMOLS estimates differ somewhat from the FMOLS-MG ones, whereas the reported

CCEMG and DCCEMG estimates are substantially greater than the ones for the preferred estimator. The estimate of 0.48 in FMOLS-MG Model 2 is close to what the spatial equilibrium model would predict $[1/(\omega_i + 1) = 0.41]$ based on the median supply elasticity of 1.44 across MSAs.

Table 4 Cointegration tests and regression results

	FMOLS-MG	POLS	PFMOLS	CCEMG	DCCEMG
CIPS cointegration test statistics					
$p - y$: -1.774^{***}					
Model (1)	-2.156^{***}	-2.081^{**}	-2.052^{***}	-1.329	-1.332
Model (2)	-2.549^{***}	-2.076^{***}	-2.007^{***}	$-.674$	$-.714$
Coefficient estimates and test statistics					
	Model 1				
y_{it}	$.745^{***}$	$.844^{***}$	0.771^{***}	1.776^{***}	1.744^{***}
	(.042)	(.008)	(.044)	(.177)	(.190)
Average residual cross-correlation	.340	.347	.341	–.008	–.009
F-test of homogeneity (p-value)	$.000^{***}$				
Swamy test (p-value)				$.000^{***}$	$.000^{***}$
Wald F-test on $\beta_y = 1$ (p-value)	$.000^{***}$	$.000^{***}$	$.000^{***}$	$.000^{***}$	$.001^{***}$
	Model 2				
ya_{it}	$.479^{***}$	$.412^{***}$	$.351^{***}$	1.650^{***}	1.642^{***}
	(.023)	(.005)	(.028)	(.142)	(.146)
Average residual cross-correlation	.338	.332	.343	–.002	–.003
F-test of homogeneity (p-value)	$.000^{***}$				
Swamy test (p-value)				$.000^{***}$	$.000^{***}$
Wald F-test on $\beta_{ya} = 1$ (p-value)	$.000^{***}$	$.000^{***}$	$.000^{***}$	$.000^{***}$	$.000^{***}$

Note: The sample period is 1979Q3-2018Q2. $p - y$ is the log house price-income ratio. 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 estimates across all MSAs. The standard errors for the mean group estimates are computed following Pesaran and Smith (1995). 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, since residuals from stable long-term relationships should not be trending. The number of lags in the CADF 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. Critical values in the CIPS test are –1.45, –1.53 and –1.65 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.

A Closer Look at the Results

The interpretation of the unit root test results from panel level analysis is complicated due to the nature of 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: rejecting the null does not necessarily mean that all or even most individual series are stationary; this point has not been considered in the related literature. The null hypothesis (H_0) and the alternative hypothesis (H_1) in our panel cointegration tests are:

H_0: *Each* of the residual series is non-stationary (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).

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

In accordance with theory, Figure 1 shows that many of the (demeaned) price-income ratios have notable trends, implying that in many MSAs the ratio is not stable even over the long run. In line with the visual inspection, a unit root in the residuals from $p - y$ can be rejected in only 11 of the 70 MSAs (at the 5% level of significance) based on individual CADF statistics. Given the power problems with individual ADF-type tests, the 10% level of significance may be a more reasonable threshold, but even at the 10% level the unit root is rejected in only 17 MSAs.[17] Hence, the fact that

[17] While ADF tests have power problems (Type II error), it should be noted that, in a set of 70 individual equations, it is likely that one or some rejections of the null are false (Type I error).

the CIPS test rejects the null hypothesis of a unit root in $p - y$ cannot be used as evidence of stationarity of the price-income ratio in all, or even most of, the MSAs.

If we regress the panel of price-income ratios on an intercept and a time trend using the Pesaran, Shin and Smith (1999) mean group estimator that allows for regional heterogeneity in the coefficients, we find statistically significant trends in 57 MSAs (approximately 80%). The MSA-specific trends are significantly associated with the price elasticities 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, i.e., house prices have increased more relative to income, in cities with relatively inelastic supply. For example, the two MSAs with the least elastic supply – Boston and Miami – both have positive price-income trends. In contrast, Indianapolis has the highest supply elasticity and one of the lowest price-income slopes. Consistent with its perceived increase in the quality of amenities, Portland is the MSA with the highest price-income slope; it has a relatively low (although slightly greater than one) supply elasticity. Tulsa OK has the lowest price-income slope and the second highest supply elasticity.

In fact, the most common trend in $p - y$ is negative, suggesting that housing affordability has increased in a majority of the MSAs. Figure 3 shows that the $p - y$ trends tend to be positive on the east and west coasts and negative elsewhere. In line with the price-income trends and theoretical considerations, the MSA-specific FMOLS-MG estimates on y and ya (the income elasticities of house prices) are highly negatively correlated with supply elasticities: the correlations are -.63 (Model 1) and -.44 (Model 2).[18]

[18] This is consistent with the results of Hilber and Vermeulen (2016) based on micro data for the English market.

Figure 1 Residuals from (log of) house price-income ratios (demeaned)

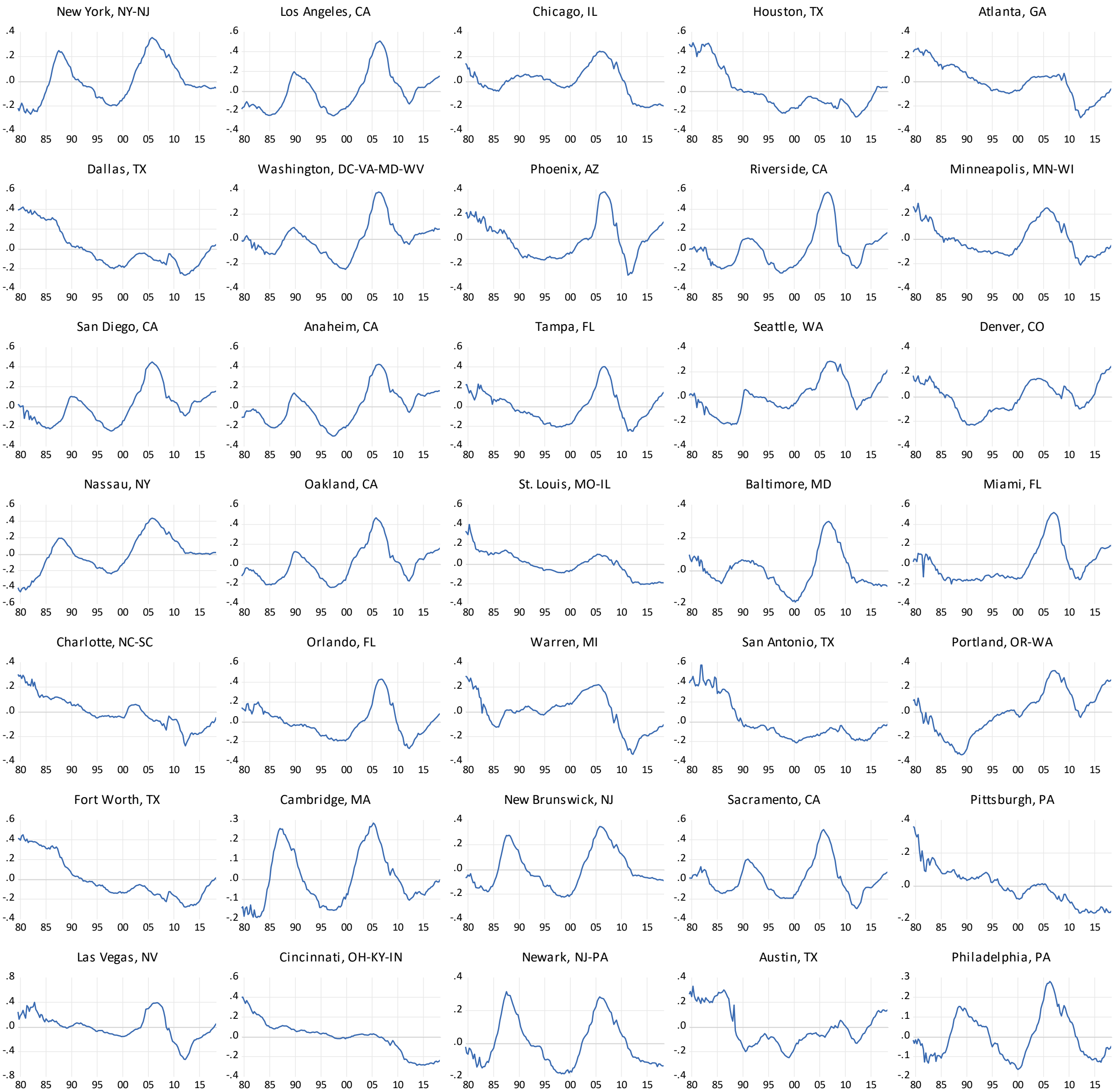


Figure 1 Residuals from (log of) house price-income ratios (demeaned), cont’d

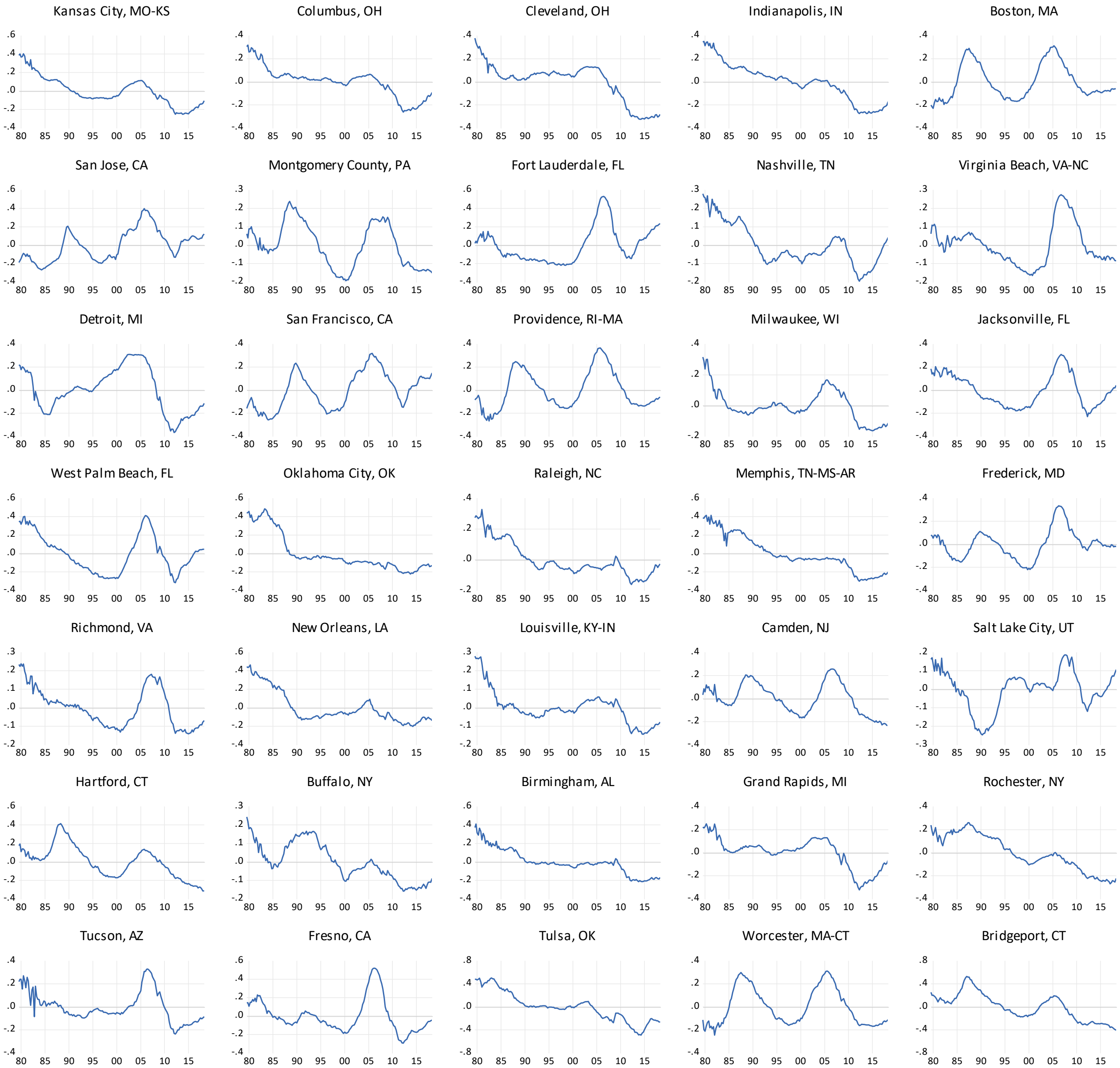


Figure 2 Annualized trends in house price-income ratio and the supply elasticity of housing

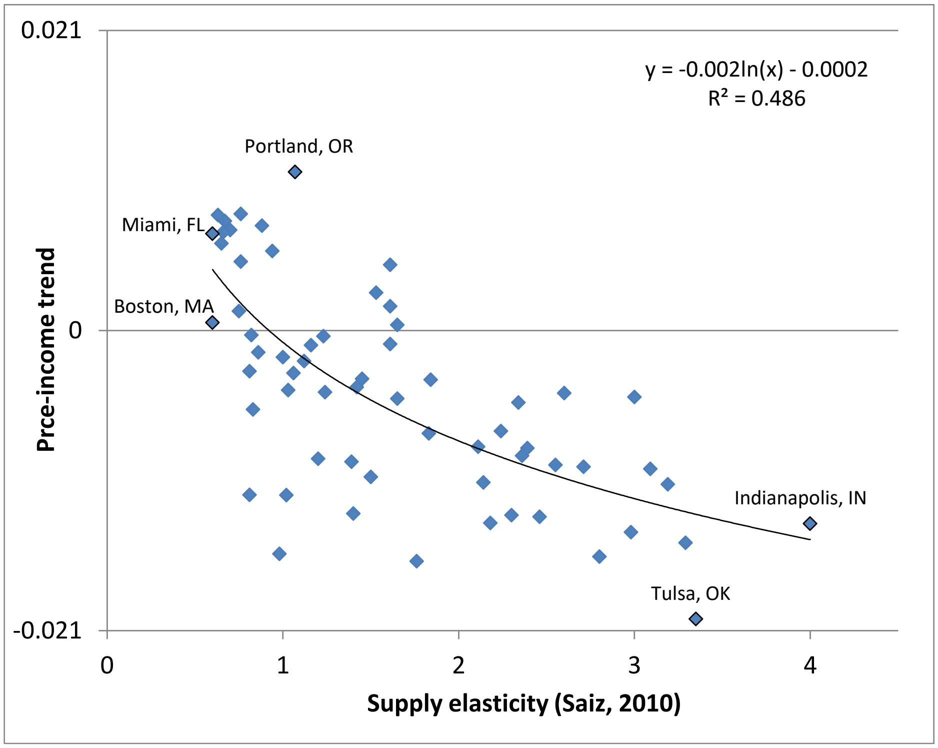
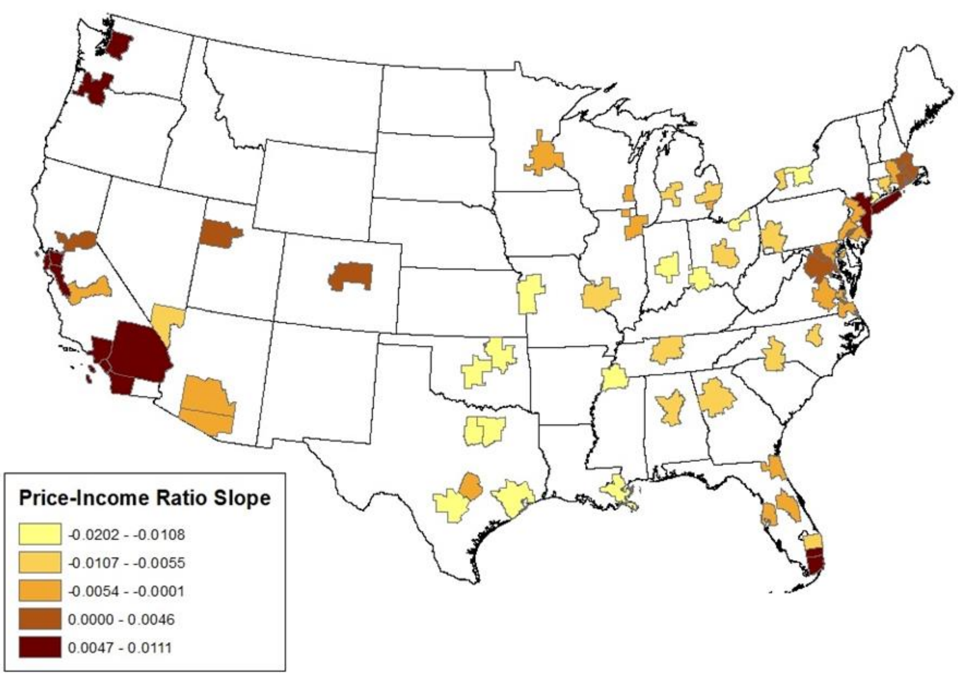


Figure 3 Geographic distribution of annualized price-income ratio slopes



The developments in house price-income ratios are relevant to trends in the wealth-income relationship. 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, Schularik and Steger (2017) report a substantial rise in house prices relative to GDP across a number of developed countries. However, the price-income developments at the country level can hide heterogeneous developments across regions within a country. Indeed, our data provide evidence of downward trending price-income ratios in a large number of MSAs, suggesting that increases in the wealth-income ratios due to house price trends have not occurred in these cities since 1979 and are not inevitable in the future. On the other hand, these downward trends translate into improved affordability. Our observed time paths are in line with Sinai (2010), who reports that most metropolitan areas did not experience much, if any, deterioration in housing affordability during 1950-2000 based on developments in local house prices vs. national level income.

The price-income trends also are in line with Glaeser and Gottlieb (2009), who argue that the rise of Sunbelt cities is related to abundant housing supply rather than 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 most California MSAs and Miami and Fort Lauderdale in Florida, all of which are supply constrained, the price-income ratio has trended downwards in the Sunbelt metropolitan areas (in 15 out of 17 such areas outside California). Moreover, the price-income trends are not significantly correlated with the MSA-specific average January temperatures.

Table 5 summarizes the MSA-level unit root statistics for the price-income ratio and both FMOLS-MG models. If the assumption of a coefficient of one on per capita income (imposed by the price-income ratio) is relaxed, and the coefficient is allowed to vary 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 17 to 35. The model with aggregate income (Model 2) works even better, with stationary relationships in 43 cities. Thus, the relationship is stationary in more and more cities when the restrictive assumptions – that are not consistent with the theoretical considerations – are progressively relaxed. The results therefore indicate that population should be included in regressions (by using aggregate instead of per capita income) to better capture price dynamics and to reach more reliable conclusions regarding possible disequilibria in house price levels.

Hence, Model 2 is the most useful for examining house price cycles relative to long-term fundamental levels. Importantly, the residuals from Model 2 do not exhibit evident trends in any of the MSAs. This is in stark contrast with the simple price-income ratio, as shown in Figure 4. However, the inability to detect cointegration in Model 2 in over one third of the MSA-specific equations may indicate that other fundamentals should be included in models aiming to capture long-term trends in house prices in some cities or that there have been structural changes in the price elasticities over time.[19] We do not include such variables in the analysis since our aim is to study whether there are stable long-term relationships between house prices and incomes, and not to investigate the reasons for the lack of such relationships in some MSAs. As noted, if finding a stationary relationship necessitated the inclusion of some other (non-stationary) variable(s) in the equation, this would not provide an indication of a stable long-term price-income relationship.

[19] Bourassa, Hoesli and Oikarinen (2019) report that a parsimonious regression model with only aggregate income on the right-hand side works as a better indicator for house price bubbles than a model that also includes other explanatory variables.

Table 5 MSA-specific CADF unit root test statistics for house price-income ratio and FMOLS-MG models (MSAs ordered by 2018 population)

			Regression model					Regression model	
		$p–y$	1	2			$p–y$	1	2
1	New York, NY-NJ (MSAD)	**	**	***	36	Kansas City, MO-KS			
2	Los Angeles, CA (MSAD)		**	**	37	Columbus, OH			
3	Chicago, IL (MSAD)				38	Cleveland, OH			
4	Houston, TX				39	Indianapolis, IN			
5	Atlanta, GA		**	***	40	Boston, MA (MSAD)	***	**	**
6	Dallas, TX (MSAD)				41	San Jose, CA		**	**
7	Washington, DC-VA-MD-WV (MSAD)			***	42	Montgomery, PA (MSAD)			
8	Phoenix, AZ			**	43	Fort Lauderdale, FL (MSAD)		*	**
9	Riverside, CA	*		***	44	Nashville, TN	*		
10	Minneapolis, MN-WI				45	Virginia Beach, VA-NC		**	*
11	San Diego, CA		*	***	46	Detroit, MI (MSAD)		*	***
12	Anaheim, CA (MSAD)			**	47	San Francisco, CA (MSAD)		*	*
13	Tampa, FL				48	Providence, RI-MA		*	*
14	Seattle, WA (MSAD)		**	**	49	Milwaukee, WI	*	*	**
15	Denver, CO			*	50	Jacksonville, FL			*
16	Nassau, NY (MSAD)	***	***	**	51	West Palm Beach, FL (MSAD)		*	*
17	Oakland, CA (MSAD)		**	***	52	Oklahoma City, OK	**		
18	St. Louis, MO-IL		**	***	53	Raleigh, NC	*		
19	Baltimore, MD				54	Memphis, TN-MS-AR		*	*
20	Miami, FL (MSAD)		*		55	Frederick, MD (MSAD)		*	**
21	Charlotte, NC-SC	*		**	56	Richmond, VA	***	**	
22	Orlando, FL		**	***	57	New Orleans, LA			*
23	Warren, MI (MSAD)				58	Louisville, KY-IN	**		*
24	San Antonio, TX				59	Camden, NJ (MSAD)			
25	Portland, OR-WA			*	60	Salt Lake City, UT		*	*
26	Fort Worth, TX (MSAD)				61	Hartford, CT		***	***
27	Cambridge, MA (MSAD)	***	***	***	62	Buffalo, NY			
28	New Brunswick, NJ (MSAD)		**	**	63	Birmingham, AL	**	*	**
29	Sacramento, CA	**	*	***	64	Grand Rapids, MI			
30	Pittsburgh, PA	*	**	***	65	Rochester, NY		*	*
31	Las Vegas, NV		**	**	66	Tucson, AZ			
32	Cincinnati, OH-KY-IN				67	Fresno, CA	***	**	***
33	Newark, NJ-PA (MSAD)		**	**	68	Tulsa, OK			**
34	Austin, TX				69	Worcester, MA-CT	***	**	**
35	Philadelphia, PA (MSAD)				70	Bridgeport, CT		*	

Note: *, **, 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. MSAD refers to areas that are metropolitan divisions.

Figure 4 Residuals from regression Model 2 (continuous blue) and from price-income ratio (dashed red)

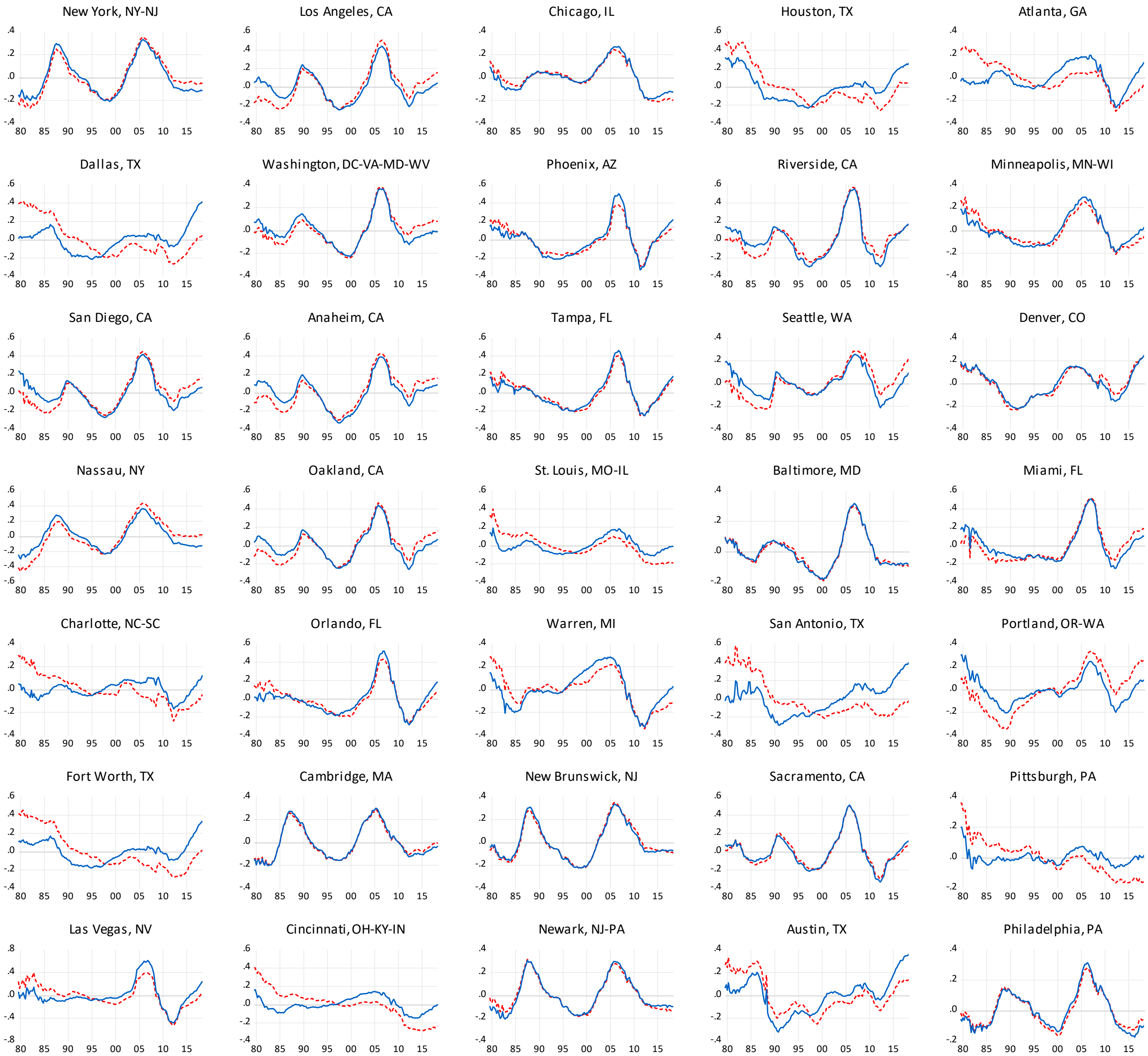


Figure 4 Residuals from regression Model 2 (continuous blue) and from price-income ratio (dashed red), cont'd

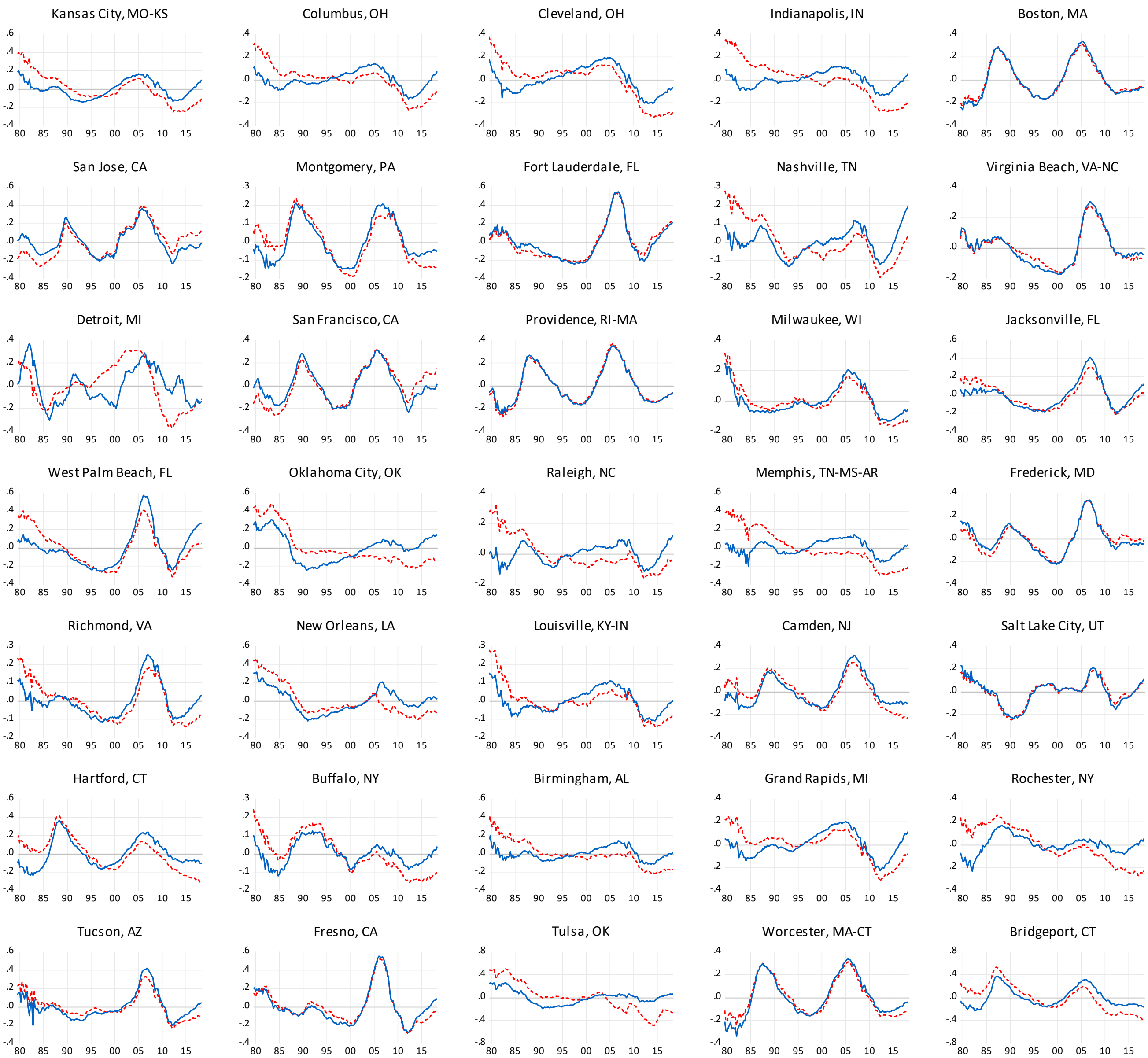


Figure 5 Geographic distribution of aggregate income coefficient estimates (Model 2)

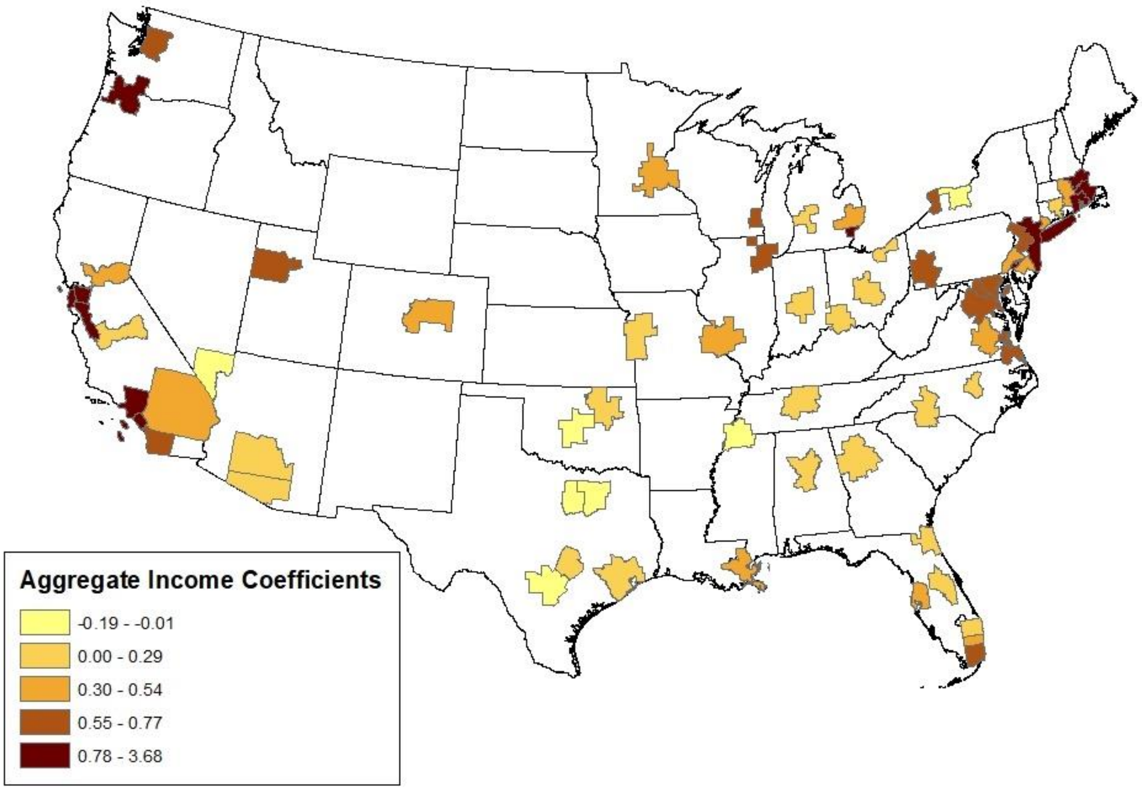


Figure 5 displays the geographic distribution of the aggregate income coefficients from Model 2. These tend to be higher in relatively supply inelastic coastal locations on the west coast and in the North, Mid-Atlantic, and Great Lakes regions.

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

5. Conclusions

This study contributes to the analysis of the relationship between house prices and personal income and regional heterogeneity in this relationship in several ways. We consider a standard spatial equilibrium model and conduct an empirical analysis that examines whether results using panel data from the 70 largest U.S. MSAs are in line with that model's predictions – which they are.

Our primary conclusion is that, at the city level, the assumption of a constant house price-income ratio over the long run is in line with neither theory nor empirical facts. Instead, long-term stability of the price-income ratio in a given city is expected to be a special case rather than the rule, and house price predictions as well as evaluations of house price deviations from their long-term fundamental levels should be based on less restrictive assumptions, allowing income elasticities of house prices to differ from one and vary across regions. In addition, population growth should be taken into account when assessing local house price levels and dynamics by using aggregate income measures.

Our analysis leads to several additional conclusions: (1) It supports the argument that supply constraints are related to greater increases in local house prices relative to incomes, thus generating a counterforce for regional growth through adverse effects on the affordability of housing (while on the other hand supporting wealth accumulation). (2) Panel level cointegration, or unit root, tests can lead to misleading conclusions regarding the nature of the house price-income relationship. (3) Consistent with variations in supply elasticities across locations, our results underscore the importance of allowing for spatial heterogeneity when modeling house price dynamics. (4) The spatial equilibrium model also indicates that the long-term equilibrium price-income ratio can increase or decrease when there is a positive regional productivity shock; the change in the ratio is dependent not only on the city's own supply elasticity but on the elasticity in other cities as well.

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c/o University of Geneva, Bd. Du Pont d'Arve 42, CH-1211 Geneva 4
T +41 22 379 84 71, rps@sfi.ch, www.sfi.ch