The Missing Internal Devaluation: Regional Adjustment in the US Great Recession*

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Abstract

Adjustment in relative prices and wages in response to asymmetric shocks---"internal devaluation"---is a key rebalancing mechanism to ensure employment and macroeconomic stability across regions sharing the same currency. We carry out a systematic analysis of the price, wage and employment adjustment across US Metropolitan Statistical Areas (MSAs) in response to the house price cycle during the Great Recession. Relative to the literature, we study heterogeneity in the real exchange rate adjustment by sector, distinguishing goods, services, distribution and construction, at the disaggregated MSA level. For each sector, we analyze how relative prices adjust to relative wages (cost) and employment (slack) dynamics across MSAs. We document that, while relative prices responds negatively to sectoral unemployment, they adjust in opposite directions across goods and services in response to negative asymmetric shocks to house prices. We find evidence of decreasing competitiveness and relative increase in markups in services that may help explain this pattern. Overall, real exchange rates do not depreciate in the worst-hit MSAs, despite the large differential response in local employment.

1 Introduction

According to standard theory, adjustment in relative prices and wages is a key rebalancing mechanism in response to asymmetric supply and demand shocks in a currency area. If adjustment via nominal exchange rate flexibility is not an option, “internal devaluation” can nonetheless uphold employment and economic activity across states, regions and sub regional areas. Not surprisingly, the topic has become a core issue in the policy debate in the euro area, whereas insufficient relative price (i.e. real exchange rate) adjustment has been singled out as a primary cause for persistent unemployment and macroeconomic underperformance in some countries. But internal devaluation is not just of interest for academic and policy studies of monetary unions. From a theoretical perspective, the mechanism rests on the tenet that there exists a stable link between wage and price inflation and measures of slack in labor and product markets. In other words, there are well-defined wage and price Phillips curves not only at aggregate level, but also at disaggregated, state and regional, level. In this sense, understanding internal devaluation can provide valuable insight on a defining issue in macroeconomics.

Several recent contributions have argued that regional business cycles can shed new light on the amplification forces of aggregate fluctuations (see, e.g., Nakamura and Steinsson (2014) on fiscal multipliers, Beraja, Hurst and Ospina (2016) on wage Phillips curves, going back to the seminal paper by Blanchard and Katz (1992)). Boom and bust episodes are natural candidates for empirical work on the issue. Mian, Rao and Sufi (2013), Mian and Sufi (2014), Kaplan, Mitman and Violante (2016), among others, have shown that the local house price bust in the US over the period 2007-2011 has been associated with asymmetric fluctuations in household demand and employment. A number of contributions have provided evidence on wages and prices in the wake of large and asymmetric housing shocks, studying adjustment in overall regional nominal wages (Mian and Sufi (2014) and Beraja et al. (2016)), or tracing the response of local store-level sale prices (see, e.g., Kaplan et al. (2016) and Stroebl and Vavra (2018)).

In this paper, we contribute to this literature by carrying out a systematic analysis of the evidence on adjustment in prices, costs and economic activity across US jurisdictions in response to the house price cycle during the Great Recession. Relative to previous contributions, first, we offer a rich decomposition of real exchange rate adjustment across US areas, looking not only at the relative price of overall consumption, but also at sectoral heterogeneity in relative price adjustment, distinguishing between goods and services. Second, we relate sectoral relative price adjustment to its determinants in terms of relative sectoral costs and activity dynamics. To do so, we use the BLS CPI research database to construct MSA-specific CPI indexes and combine these data with regional measures of sectoral costs and activity. We focus our analysis on the geographical disaggregation of US Metropolitan Statistical Areas (henceforth MSAs). These areas can be thought of as very small open economies, fully integrated in the US national goods and financial markets. Given that trading frictions in these markets are relatively contained, MSAs provide an ideal laboratory to look at the adjustment mechanism through relative wages and prices in an integrated currency area.

We set the stage for our analysis by plotting, in Figure 1, the annual rate of inflation in goods and services against the change in the price of housing at MSA level between 2007 and 2011—for the 27 largest MSAs for which the BLS publishes data. Using the same data, in Figure 2, we plot the cumulative inflation in goods and services together with the house price dynamics, contrasting the MSAs that experienced the largest and the smallest contraction in house prices. The main takeaway from the two Figures 1 and 2 is straightforward: there is no apparent relation between inflation at MSA level and the intensity of the housing bust. The correlation, pronounced for rents, is only mildly positive for goods and actually negative for services once we exclude rents.

The econometric work that we discuss in the rest of the paper for an extended sample of MSAs corroborates the same message. We show that, based on comprehensive measures of relative prices, there is no evidence of internal devaluation (i.e., a relative fall in the overall price level) in the areas suffering the deepest contraction in demand, as measured by the deepest fall in house prices. Specifically, we find that, when house prices fall, the relative price of goods falls somewhat, but not significantly so; the relative price of services actually tend to rise, i.e., they move in the "wrong" direction. Vis-à-vis these results, we document that local differential responses in employment are large in the service and distribution sectors, but not in goods producing industries (essentially manufacturing). Similarly to Mian and Sufi (2014), we find that a local housing bust only depresses the demands for local goods, and thus employment in services and distribution.[1] Because manufacturing is highly tradable, there is no differential local demand effect on employment in this sector.[2]

Our evidence could be reconciled with textbook macroeconomic models of the Phillips curve, if we could show that marginal costs and/or markups adjust in different directions across sectors. In our sectoral measures of wages, however, adjustment is positive—insignificantly so in manufacturing, small in services, and economically sizeable in the construction service. Our results are thus consistent with established evidence at regional level, whereas most studies find a positive (but in some cases limited) wage response to shocks (e.g. Mian and Sufi (2014) and Beraja et al. 2016). In light of these results, wage adjustment cannot per se account for the divergent pattern of price response we document at sectoral level. Conversely, we find evidence in line with an interpretation attributing heterogeneity in the sectoral price response to heterogeneity in sectoral markup adjustment, arguably reflecting the effects of the contraction in demand on competitiveness. In our findings, the number of firms (and establishments) falls with house prices in most sectors—implying, at least in principle, a drop in competition during the housing bust. The notable exception is the grocery retail sector, where the housing bust was associated with both a net increase in the number of establishments and a fall in relative prices. In addition, we find that the labor and intermediates shares (inversely related to markups) respond to house prices with the correct (positive) sign, although the result is not always statistically significant. Remarkably, the response is statistically significant for the restaurant sector, whose relative price is negatively correlated with house price shocks in the Great Recession.

Taken together, the pieces of evidence documented in this paper point to a "missing

[1] In this respect, it is worth stressing that the local demand for goods falls on a composite of (nationally traded) manufacturing goods and (locally produced) distribution services (in the retail and wholesale trade sectors).

[2] While, consistent with the literature, we focus on a demand channel, there could be other channels by which a fall in house prices affects the economy. An important one is a tightening in firms' borrowing constraints through a fall in their collateral value, also causing a cut in employment demand, but possibly translating into higher marginal costs. This channel thus tend to attenuate (or can even overturn) the effects of a fall in prices via the demand channel. It is far from clear whether and why the two channels should operate with a different intensity across sectors. We are not aware of any evidence linking the intensity of collateral constraints with the tradability of output. Moreover, Mian and Sufi (2014) shows that the correlation between house prices and employment reflects the behavior of large firms, which are less likely to be constrained.

internal devaluation puzzle": in facilitating adjustment to local demand shocks, the role played by relative prices appears to be tenuous at best at the level of the overall price of consumption. The puzzle is especially pronounced in the service sector. This is a sector in which, due to a relatively high share of nontradable production, internal devaluation should be prominent. As is well understood, the production of nontradable goods and services exclusively serves local demand—suppliers are unlikely to level their price across locations. In comparison to tradables, local economic conditions can be expected to have a much stronger effects on the supply and relative price of nontradables. Indeed, different vintages of classical open economy models emphasize movements in the supply and relative price of these goods, as a key adjustment mechanism to cushion activity and employment against demand shocks (see the traditional and modern textbook treatment by Dornbusch (1990) and Schmidt Grohe and Uribe (2012)). In our findings, the relative price of this sector does respond to unemployment with the correct sign—higher sectoral unemployment causes prices to fall. But, even after controlling for measures of wages, slack and incidence of financial frictions, the contraction of demand associated with a fall in house prices still drive sectoral prices up, rather than down. If anything, relative to standard theory, our evidence suggests that price adjustment in services may have actually worked the wrong way.

In light of these considerations, our findings add a regional dimension to the so-called missing disinflation puzzle, the apparent lack of a connection between the high level of slack and subdued wage and price inflation in the US (and many advanced countries) during the Great Recession of 2008 (see e.g. Williams (2010), IMF (2013) and Ball and Mazumer (2011)).[3] During the Great Recession, the lack of connection between slack and price dynamics is pervasive not only over time, but also across US locations.

We proceed as follows. To establish our main results, in line with Stroebel and Vavra (2018), we run OLS and IV regressions at the MSA level, regressing the cumulative inflation between 2007 and 2011 of local prices and activity on local house prices. In the IV specification, we use as an instruments the housing supply elasticities from Saiz (2010). As for the

[3]"The surprise [about inflation] is that it's fallen so little, given the depth and duration of the recent downturn. Based on the experience of past severe recessions, I would have expected inflation to fall by twice as much as it has" (John Williams, 2010."Sailing into Headwinds: The Uncertain Outlook for the U.S. Economy').

inflation data, when possible, we use publicly available data at the MSA level—this is the case for most subindexes for the largest 27 MSAs. Otherwise we construct CPI indexes by using the BLS CPI research database (for the remaining MSAs in the BLS sample). In the end, we can rely on a dataset of CPI indexes MSA-specific, distinguishing in sub-items for goods and services excluding rents (which are not included in the BLS CPI research database).

This paper is organized as follows. In section 2 we will draw on a simple multi-sector model and open-economy macro to derive a theoretical framework linking internal devaluation to Phillips Curves theory. In sections 3 and 4, we present our empirical model and describe our data in detail. In section 5 we present and discuss our main results. Section 6 concludes deriving some implications for policy and further research.

2 Internal devaluation and relative Phillips Curves

To shed light on the economics and drivers of internal devaluation, in this section we discuss the theoretical underpinning of the real exchange rate across states and regions sharing the same currency. Our starting point is the definition of the real exchange rate across two locations l as the relative price of consumption in the two locations. Since the consumption bundle includes both tradables and nontradables, or, from a different perspective, goods and services, it is natural to decompose further the real exchange rate using the corresponding price indexes. To wit, the following is a decomposition of the (log) real exchange rate (ex-rents) for location l as a function of the relative price of goods $(p^l_{G,t} - p_{G,t})$ and services $(p^l_{S,t} - p_{S,t})$ relative to the overall currency area:

$$q^l_t = (1 - \alpha_S) \left(p^l_{G,t} - p_{G,t}\right) + \alpha_S \left(p^l_{S,t} - p_{S,t}\right), \tag{1}$$

where α_S is the share of services, for simplicity assumed to be the same for all l. The price of goods at consumer level can be further decomposed as a combination of the price of (tradable) manufacturing $p^l_{T,t}$, and the price of (nontradable) distribution services, $p^l_{NT,t}$, required to bring the goods to consumers (see Burstein, Neves and Rebelo (2003); Corsetti and Dedola

(2005)), namely:

$$p^l_{G,t} = (1-\delta)\, p^l_{T,t} + \delta p^l_{NT,t}, \tag{2}$$

where δ is the distribution share. For future reference, define the relative price of goods, tradable manufacturing, services and distribution as, respectively, $\widehat{\mathcal{T}}^l_{G,t} = \left(p^l_{G,t} - p_{G,t}\right)$, $\widehat{\mathcal{T}}^l_{T,t} = \left(p^l_{T,t} - p_{T,t}\right)$, $\widehat{\mathcal{T}}^l_{S,t} = \left(p^l_{S,t} - p_{S,t}\right)$ and $\widehat{\mathcal{T}}^l_{N,t} = \left(p^l_{NT,t} - p_{NT,t}\right)$.

2.1 The transmission mechanism

In order to investigate the link between house prices and demand, on the one hand, and relative prices on the other, we draw on standard international macroeconomic theory and New Keynesian Phillips Curve theory (see, e.g., Schmidt-Grohe and Uribe (2016), and Gali (2014), respectively). A key prediction of classical open-macro theory is that the bulk of adjustment to region-specific demand shocks should fall on sectors with the largest incidence of nontradability in production (and thus the lowest incidence of exports). In line with this prediction, it has been shown that, given the effects of house prices on local demand (Campbell and Cocco (2007) and Mian et al. (2014)), the employment effects are concentrated in the nontradables industries (Mian-Sufi (2014)).

To clarify the standard mechanism, consider the case of flexible prices: after a region-specific decline in demand, the price of nontradables falls more than that of tradables. In line with the falling local demand, this adjustment in relative prices leads firms to produce less nontradables, while inducing a production switch towards traded goods for the external markets. So, while output and employment decline in the nontraded sector, they fall less than domestic demand, or even rise, in the tradable sector. Analytically, focus on the market clearing conditions for production of nontraded goods (i.e., services), equating their log-linear demand and supply in l:

$$y^l_S = -\alpha_s \eta_{NT} \cdot \left(p^l_{S,t} - p^l_{G,t}\right) + c^l$$

The demand for nontradables depends positively on local consumption c^l but negatively on their relative price. In particular a fall in c^l can be cushioned by a fall in $p^l_{S,t} - p^l_{G,t}$, which in turn depends on local nominal marginal costs (i.e., wages and labor demand, see below).

Other things equal, this fall would translate into real exchange rate depreciation:

$$q_t^l = (1-\alpha_S)\left(p_{G,t}^l - p_{G,t}\right) + \alpha_S\left(p_{S,t}^l - p_{S,t}\right) = \left(p_{G,t}^l - p_{G,t}\right) + \alpha_S\left[\left(p_{S,t}^l - p_{G,t}^l\right) - \left(p_{S,t} - p_{G,t}\right)\right].$$

Conversely, the demand for locally-produced traded goods depends to a large extent on overall national consumption, and is likely to be very elastic with respect to its relative price, $\widehat{\mathcal{T}}_{T,t}^l = \left(p_{T,t}^l - p_{T,t}\right)$. This price (or more precisely, the price of the tradable components of final goods and services) is thus unlikely to vary significantly (if at all) across locations.

The adjustment mechanism is similar in the presence of nominal rigidities, although obviously slower, and with more nuanced implications for markups and marginal costs. Accounting for these rigidities, inflation in sector $j = T, N, S$ in location l, $\pi_{j,t}^l = p_{j,t}^l - p_{j,t-1}^l$ can be written as a function of expected inflation and current *real* marginal costs (in terms of the aggregate price level p_t) $\widehat{mc}_{j,t}^l$:

$$\pi_{j,t}^l = \beta E_t \pi_{j,t+1}^l + \kappa_j^l\left[\widehat{mc}_{j,t}^l - \left(p_{j,t}^l - p_t\right) + \widehat{\mu}_{j,t}^l\right], \tag{3}$$

where $\widehat{\mu}_{j,t}^l$ is an unobservable component in markup or marginal cost. For each sector j, we then express local inflation as the differential from the Phillips Curve for aggregate inflation in the same sector $\pi_{j,t}$

$$\begin{aligned}\pi_{j,t}^l - \pi_{j,t} = \beta E_t\left(\pi_{j,t+1}^l - \pi_{j,t+1}\right) + \kappa_j^l\left[\widehat{mc}_{j,t}^l - \widehat{\mathcal{T}}_{j,t}^l - \widehat{mc}_{j,t} + \widehat{\mu}_{j,t}^l - \widehat{\mu}_{j,t}\right] + \\ \left(\kappa_j^l - \kappa_j\right)\left[\widehat{mc}_{j,t} + \widehat{\mu}_{j,t}\right].\end{aligned} \tag{4}$$

This expression establishes that, for each sector j, inflation differentials across locations are given by the discounted sum of (i) the expected differential in the real marginal cost in terms of the aggregate price level $\left(\widehat{mc}_{j,t+s}^l - \widehat{\mathcal{T}}_{j,t+s}^l - \widehat{mc}_{j,t+s}\right)$, (ii) the expected differential in the markups $\left(\widehat{\mu}_{j,t+s}^l - \widehat{\mu}_{j,t+s}\right)$, and (iii) the differential in the slope of the Phillips curve

$\left(\kappa_j^l - \kappa_j\right)(\widehat{mc}_{j,t+s} + \widehat{\mu}_{j,t+s})$:

$$\pi_{j,t}^l - \pi_{j,t} = \kappa_j^l \sum_{s=0}^{\infty} \beta^s E_t \left[\left(\widehat{mc}_{j,t+s}^l - \widehat{\mathcal{T}}_{j,t+s}^l - \widehat{mc}_{j,t+s} \right) + \left(\widehat{\mu}_{j,t+s}^l - \widehat{\mu}_{j,t+s} \right) \right] + \left(\kappa_j^l - \kappa_j\right) \sum_{s=0}^{\infty} \beta^s E_t \left[\widehat{mc}_{j,t+s} + \widehat{\mu}_{j,t+s} \right]. \quad (5)$$

For a given slope of the curve, conditional on a fall in demand (e.g., driven by house prices), a negative inflation differential (causing real depreciation) would result from either lower relative marginal costs or higher markups over time.

To gain insight on *internal devaluation*, we solve directly for the relative price $\widehat{\mathcal{T}}_{j,t}^l$:

$$\widehat{\mathcal{T}}_{j,t}^l - \widehat{\mathcal{T}}_{j,t-1}^l = \beta E_t \left(\widehat{\mathcal{T}}_{j,t+1}^l - \widehat{\mathcal{T}}_{j,t}^l \right) + \kappa_j^l \left[\widehat{mc}_{j,t}^l - \widehat{\mathcal{T}}_{j,t}^l - \widehat{mc}_{j,t} + \widehat{\mu}_{j,t}^l - \widehat{\mu}_t \right] + \left(\kappa_j^l - \kappa_j\right) \left[\widehat{mc}_t + \widehat{\mu}_t \right];$$

this is an expectational second order difference equation in the price level:

$$\beta E_t \left(\widehat{\mathcal{T}}_{j,t+1}^l - \widehat{\mathcal{T}}_{j,t}^l \right) - \left(\widehat{\mathcal{T}}_{j,t}^l - \widehat{\mathcal{T}}_{j,t-1}^l \right) - \kappa_j^l \widehat{\mathcal{T}}_{j,t}^l = -\kappa_j^l \left[\widehat{MC}_{j,t}^l - \widehat{MC}_{j,t} + \widehat{\mu}_{j,t}^l - \widehat{\mu}_t \right] - \left(\kappa_j^l - \kappa_j\right) \left[\widehat{mc}_t + \widehat{\mu}_t \right],$$

where now $\widehat{MC}_{j,t}^l - \widehat{MC}_{j,t}$ is the marginal cost differential in *nominal* terms. The above equation has the following general solution:

$$\widehat{\mathcal{T}}_{j,t}^l = \nu_1 \widehat{\mathcal{T}}_{j,t-1}^l + \kappa_j^l \sum_{s=0}^{\infty} \nu_2^{-s-1} E_t \left[\left(\widehat{MC}_{j,t+s}^l - \widehat{MC}_{j,t+s} \right) + \left(\widehat{\mu}_{j,t+s}^l - \widehat{\mu}_{j,t+s} \right) \right] + \left(\kappa_j^l - \kappa_j\right) \sum_{s=0}^{\infty} \nu_{j,2}^{-s-1} E_t \left[\widehat{mc}_{j,t+s} + \widehat{\mu}_{j,t+s} \right] \quad (6)$$

where $0 < \nu_1 < 1 < \beta^{-1} < \nu_2$ solve the standard characteristic equation:

$$\beta \nu^2 - \left[1 + \beta + \kappa_j^l \right] \nu + 1 = 0,$$

namely:

$$\nu_{1,2}=\frac{1+\beta+\kappa_j^l\pm\sqrt{\left[1+\beta+\kappa_j^l\right]^2-4\beta}}{2\beta}.$$

The equation for $\widehat{\mathcal{T}}_{j,t}^l$ is at the heart of the adjustment mechanism via *internal devaluation*. Asymmetric shocks affecting relative *nominal* marginal costs will be absorbed through movements in relative prices, with a speed inversely related to the slope of the local and sector specific Phillips curve κ_j^l (the larger κ_j^l the closer ν_1 to zero). For our purposes, an asymmetric bust in house prices that leads (via demand effects) to lower relative nominal marginal costs and/or markups, also results in a depreciation in the relative price $\widehat{\mathcal{T}}_{j,t}^l$. Observe that the PC *slope* differential may/may not be correlated with house prices across jurisdictions. If it is, it would be reasonable to expect a steeper curve $\left(\kappa_j^l>\kappa_j\right)$, i.e., more price responsiveness, in areas where the recessionary shock is larger. This effect would reinforce the hypothesis that local shocks should be associated with re-equilibrating relative price adjustment, as relative prices would become more sensitive to local costs and markups.

Assuming that nominal wages are a good proxy for nominal marginal costs, a testable hypothesis is that movements in the relative price $\widehat{\mathcal{T}}_{j,t}^l=\left(p_{j,t}^l-p_{j,t}\right)$ result from expected changes in relative nominal wages in the same direction. Indeed, the bulk of the literature on the NKPC assumes that nominal marginal costs are equal to nominal wages ($w_{j,t}^l$) adjusted by the nominal marginal product of labor ($MPL_{j,t}^l$):

$$\widehat{MC}_{j,t}^l=w_{j,t}^l-MPL_{j,t}^l.$$

In turn, the latter is assumed to be a function of measures of the "employment gap", namely, deviations of employment from its flexible-price (potential) level; the exact relation can also account for the presence of nominal wage rigidities (see e.g., Gali textbook and Beraja et al. 2016 for a regional application). For instance, if labor is the only input in production, i.e., $H_j^l,\ Y_j^l=A_j^l\left(H_j^l\right)^{\alpha_j}$, we can derive the following expression for nominal marginal costs as a function of wages and labor demand:

$$\widehat{MC}_{j,t}^l=w_{j,t}^l-\frac{1}{\alpha_j}a_{j,t}^l+\frac{1-\alpha_j}{\alpha_j}y_{j,t}^l=w_{j,t}^l-\left(y_{j,t}^l-h_{j,t}^l\right),$$

where the last term on the right hand side is the real unit labor costs in sector j. Provided that the production function is the same across jurisdictions l, the differential in nominal marginal costs can then be expressed as the differential in unit labor costs (as a function of local wages and labor demand):

$$\widehat{MC}_{j,t}^{l} - \widehat{MC}_{j,t} = \left(w_{j,t}^{l} + h_{j,t}^{l} - y_{j,t}^{l}\right) - \left(w_{j,t} + h_{j,t} - y_{j,t}\right).$$

It is worth stressing that the same expression also holds when the production function includes intermediate inputs (X_j^l) in the form i.e., $Y_j^l = A_j^l \left(H_j^l\right)^{\alpha_j} \left(X_j^l\right)^{1-\alpha_j}$, provided that these inputs enter production in the same proportion and with the same price P^X across locations.

Under the same prior assumptions, we also note that the inverse of overall markups are proportional to sectoral labor and intermediates shares:

$$Markup_j^l = \frac{P_j^l}{W_j^l / \left(\alpha_j Y_j^l / H_j^l\right)} = \alpha_j \left(\frac{W_j^l H_j^l}{P_j^l Y_j^l}\right)^{-1} = (1-\alpha_j)\left(\frac{X_j^l P^X}{P_j^l Y_j^l}\right)^{-1}.$$

In other words, relative labor shares provide evidence on markup adjustment. Under sticky prices, relative markups should be countercyclical in response to local demand fluctuations driven by house prices. This observation will come in handy since, while in our empirical study we lack data on real sectoral GDP and sectoral unit labor costs, we do have sectoral data on nominal GDP and labor compensation, hence we can compute labor shares at sectoral level.

In the above framework, local house prices affect marginal costs by impinging on the demand for goods and services, in turn determining the demand for local labor and wages. However, further transmission channels may be active. A relevant instance is the channel working through the effects of house prices on the value of collateral—a channel which may be especially relevant for small, more opaque firms (see, e.g., Gertler and Gilchrist (1994), Kashyap, Stein and Wilcox (1993)). If a fall in the value of collateral exacerbates information asymmetries among borrowers and lenders, a fall in house prices can be expected to raise the cost of borrowing for firms. To the extent that firms borrow in order to finance working capital, this in turn translates into higher marginal costs (see, e.g., Jerman and Quadrini

(2012) and Liu, Wang, Zha (2013)). Marginal costs may actually rise so much, that firms' prices increase, instead of falling, with a house price bust (see the model simulations by Gertler, Schoenle, Sim and Zakraijsek (2016)). Empirical evidence on the relevance of this channel in driving employment in small firms across US counties is provided by Adelino, Schoar and Severino (2014). The findings by these authors suggest that the channel is strong during the housing boom period, between 2002 and 2007, although seems to be much less significant during the subsequent bust, which is the focus of our study.

2.2 From theory to the empirical framework

Under the assumption that the slope of the Phillips curve is the same across all locations, $\kappa_j^l = \kappa_j$,[4] the equilibrium solution for the relative price $\widehat{\mathcal{T}}_{j,t}^l$ simplifies as follows,

$$\widehat{\mathcal{T}}_{j,t}^l = \nu_{j1}\widehat{\mathcal{T}}_{j,t-1}^l + \kappa_j \left[\overline{\mathcal{MC}}_{j,t}^l + \overline{\mu}_{j,t}^l\right]$$

where we have defined

$$\overline{\mathcal{MC}}_{j,t}^l = \sum_{s=0}^{\infty} \nu_{j2}^{-s-1} E_t \left(\widehat{MC}_{j,t+s}^l - \widehat{MC}_{j,t+s}\right)$$
$$\overline{\mu}_{j,t}^l = \sum_{s=0}^{\infty} \nu_{j2}^{-s-1} E_t \left(\widehat{\mu}_{j,t+s}^l - \widehat{\mu}_{j,t+s}\right),$$

and now the coefficients ν_{j1}, ν_{j2} are explicitly recognized as sector specific. While this equation naturally lends itself to panel estimation, the literature on regional effects of the Great Recession in the US has mainly relied on model specifications based on cumulated growth rates over a few years (see Mian and Sufi (2014) and Stroebl and Vavra (2018)). It is straightforward to show that the log difference of relative prices between t+s and t, $\widehat{\mathcal{T}}_{j,t+s}^l - \widehat{\mathcal{T}}_{j,t}^l$, for $s \geq 0$ is given by the following expression:

$$\widehat{\mathcal{T}}_{j,t+s}^l - \widehat{\mathcal{T}}_{j,t}^l = \left(\nu_{j1}^s - 1\right)\nu_{j1}\widehat{\mathcal{T}}_{j,t-1}^l + \kappa_j \left\{\sum_{h=0}^{s} \nu_{j1}^{s-h}\left[\overline{\mathcal{MC}}_{j,t+h}^l + \overline{\mu}_{j,t+h}^l\right] - \left[\overline{\mathcal{MC}}_{j,t}^l + \overline{\mu}_{j,t}^l\right]\right\}$$

[4]Unfortunately the limited time series dimension of our dataset forces us to impose homogeneous slope coefficients across MSAs in our panel estimates.

Neither the equation for the (log) level of the relative price $\widehat{\mathcal{T}}^l_{j,t}$, nor the one for the cumulated growth rate $\widehat{\mathcal{T}}^l_{j,t+s} - \widehat{\mathcal{T}}^l_{j,t}$ can be directly estimated, since the terms $\left[\overline{\mathcal{MC}}^l_{j,t+h} + \overline{\mu}^l_{j,t+h}\right]$ are not observable. However, a regression model can be derived under the assumption that the summation term on the right-hand side is a linear function of some state variables s_{t-1} and of cumulated structural shocks between $\sum_{h=0}^{s} \varepsilon_{t+h}$:

$$\sum_{h=0}^{s} \nu_{j1}^{s-h} \left[\overline{\mathcal{MC}}^l_{j,t+h} + \overline{\mu}^l_{j,t+h}\right] - \left[\overline{\mathcal{MC}}^l_{j,t} + \overline{\mu}^l_{j,t}\right] = \phi_0^l + \phi_1^{l\prime} s_{t-1} + \phi_2' \sum_{h=0}^{s} \varepsilon_{t+h}$$

where ε_{t+h} includes the demand shock ε^d_{t+h}, and that the cumulated demand shocks are related to house prices:

$$\sum_{h=0}^{s} \varepsilon^d_{t+h} = \delta^l_{j,0} + \delta_{j,1} \left(hp^l_{t+h} - hp^l_t\right) + u_{jt+h},$$

where $\delta_{j,1} \neq 0$, and by definition $E\left(u_{jt} \,\middle|\, \left(hp^l_{t+h} - hp^l_t\right)\right) = 0$. Under these maintained assumptions, the regression model at MSA level, linking the sectoral change in the relative price $\widehat{\mathcal{T}}^l_{j,t+s} - \widehat{\mathcal{T}}^l_{j,t}$ to the (log) level of house prices in location l is as follows:

$$\widehat{\mathcal{T}}^l_{j,t+s} - \widehat{\mathcal{T}}^l_{j,t} = \left(\nu^s_{j1} - 1\right) \nu_{j1} \widehat{\mathcal{T}}^l_{j,t-1} + \widetilde{\phi}_0 + \widetilde{\phi}_1 \left(hp^l_{t+h} - hp^l_t\right) + \eta_t$$

This cross-sectional regression can yield a consistent estimate of the sector specific parameter $\widetilde{\phi}_1$ across locations if we have a set of MSA-specific instruments z^l_t for $\left(hp^l_{t+h} - hp^l_t\right)$, uncorrelated with the (omitted) term $\left(\nu^s_{j1} - 1\right) \nu_{j1} \widehat{\mathcal{T}}^l_{j,t-1} + \eta_t$, where η_t is a function of all the other shocks which potentially affect also house prices (and of s_{t-1}). In the next section, we draw from the literature and propose instruments based on the housing supply elasticities from Saiz (2010).

3 Model specification

In our empirical investigation, we estimate the elasticity of local sectoral relative prices, costs, employment and activity to shocks to local house prices. Our empirical model follows closely Mian, Rao and Sufi (2013), Mian and Sufi (2014) and Stroebl and Vavra (2018). All regressions are run at the MSA level of geographical disaggregation. We run an ordinary least squares (OLS) specification and an instrumental variable (IV) one. Our baseline strategy consists of regressing the cumulated log-differences of the dependent variable on the cumulated log-differences of local house prices, controlling for a number of MSA observables. All regressions cover the period 2007-2011, that is, the period during the Great Recession over which house prices were consistently falling on average.

3.1 OLS specification

The OLS regression specification is as follows:

$$\Delta log\,(y_l) = \alpha + \beta \cdot \Delta log\,(hp_l) + \theta X_l + \varepsilon_l, \tag{7}$$

where, for each MSA "l", y_l is the dependent variable of interest, hp_l is the house price in the MSA, X_l is a matrix of MSA-specific controls, and ε_l is an error term (α is a constant common across MSAs). The main dependent variables of interest are, in turn, the MSA consumer price levels in each sector j, with $j = G, S, NT$, whereas G stands for the Good Sector, S for Services (S), and NT for Nontradables; nominal wages again for each sector, sectoral employment, total number of firms (and establishments), and labor and intermediates shares. We also look at additional dependent variable, such as population, unemployment, unit labor costs, and we use our data to reproduce the estimates in Mian and Sufi (2014), for the same sectoral aggregations. The coefficient of interest β yields the elasticity of y_l to hp_l. By way of example, when the dependent variable is the j-sector consumer price level p_j^l, β can be interpreted as the elasticity of the relative price $\widehat{\mathcal{T}}_{j,t}^l = \left(p_{j,t}^l - p_{j,t}\right)$ to $hp_l - hp$, or as an estimate of $\widetilde{\phi}_1$. As for X_l, the matrix of MSA-specific controls, all regressions include the following variables: the change in total population, the change in the share of people with college degree, the change in the share of population above 14 years old, and the change in the share of population above 65 years old. In addition, in the regression specifications for consumer prices, following Stroebl and Vavra (2018), we control for wages and unemployment; in the specifications for employment, wages and markups, following Mian and Sufi

(2014), we control for the change in the relevant sectoral employment shares (construction, goods, services, distribution, tradable and non-tradable respectively; controls are detailed in the notes to the Tables 3 through 12).

3.2 The Instrumental Variable (IV) approach

Despite the inclusion of the matrix of controls X_l in equation (7), the estimate of β would not establish causality from local house prices to the variable of interest if the right-hand side and the left-hand side variables were simultaneously affected by some unobserved variable, such as productivity differentials across MSAs. If this were the case, the estimate of β obtained running OLS would be biased. In order to address possible endogeneity issues, we rely on an instrumental variable approach, closely following several previous contributions (Mian and Sufi (2011), Mian and Sufi (2014), Adelino, Schoar and Severino (2013), Brown, Stein Zafar (2013), Bhutta and Keys (2014), and Stroebl and Vavra (2018)). As discussed by these authors, house prices can be expected to respond to both demand and supply shocks—to the extent that housing supply shocks also affect our variables of interest, they confound the transmission of housing demand movements (see a formal derivation in Stroebl and Vavra (2018)).

Our approach therefore consists of instrumenting hp_l using the estimates of housing supply elasticities, denoted with hse_l, from Saiz (2010).[5] The first and second stages of the IV regression are given by the following equations:

$$\Delta log\left(hp_l\right) = \alpha_1 + \rho hse_l + \gamma X_l + \epsilon_l \tag{8}$$

$$\Delta log\left(y_l\right) = \alpha_2 + \beta \Delta log\left(\widehat{hp}_l\right) + \theta X_l + \varepsilon_l. \tag{9}$$

The underlying idea is that for a given housing demand shock during the boom, house prices should react more in areas where housing supply is less elastic and this would tend to

[5]Saiz (2010) uses satellite-generated data on terrain elevation and presence of water bodies to precisely estimate the amount of developable land in U.S. metropolitan areas. The index assigns a high elasticity to areas with a flat topology without many water bodies (such as lakes and oceans).

generate increases in local demand in these areas (Stroebl and Vavra (2018)). Consequently, during the following bust, the areas where house prices rose the most would experience the largest declines in house prices and demand (Glaeser (2013)). Identification thus relies on the (untestable) exclusion restriction that the instrument is not correlated with MSA-level variables of interest, such as relative prices, for reasons other than house price growth. The Saiz (2010) instrument is available at the MSA level, but not necessarily for every MSA. For consistency, we report our OLS and IV estimates for the same set of MSAs, the one covered by Saiz (2010). Our OLS results are nonetheless insensitive to extending the sample to all MSAs.

It is worth stressing that the exclusion restriction requires the housing supply elasticity to affect the dependent variable (such as CPI consumer prices) only through house prices. In this respect, as in Stroebl and Vavra (2018), we find no correlation between housing supply elasticities and income growth in the Great Recession period. Like these authors, we also include wages in our regressions as control, to take care of any possible correlation between wages and the Saiz elasticity reflecting strong demand in areas with amenities and high growth. Moreover, we also find that the Saiz elasticity is not correlated with pre-crisis wage growth and inflation in goods and services.[6]

4 Data

Our dataset covers 253 Metropolitan Statistical Areas across the United States. All data used for regression analysis have been collected (or elaborated) at annual frequency. The period of interest is 2007-2011 (when on average house prices were contracting) but for some series we have collected data going back as far as 1986. Because the definition of an MSA (that is, whether a geographic area is "metropolitan" or not and what counties are

[6]Previous studies (Mian and Sufi (2014)) show that wage growth did not behave differentially in elastic and inelastic areas during the boom period. Also, Mian and Sufi (2014) show that the instrument is not statistically correlated with the pre-crisis employment share in construction, construction employment growth, and population growth.Davidoff (2015) criticizes the use as of the Saiz (2010) elasticities as an instrument for house prices over samples before the Great Recession, since the elasticities would be correlated with secular trends in productivity and housing demand. This criticism seems less relevant for our 2007-2011 sample, in which it is not obvious that MSA-specific productivity growth was correlated with housing supply elasticities.

included) changes over time, we have used the 2015 Census MSA definitions and constructed an historical crosswalk to match the current definition to the past. When available, we have collected data at the county level and aggregated them using the 2015 Census definition of each MSA. We have built our dataset using both publicly available data and by constructing MSA-specific CPI price indexes using the BLS CPI research database. In this section, we describe the data contained in our dataset. We start by explaining how we constructed the dataset using publicly available data (Section 4.1). Then, we explain how we used the BLS CPI research database to construct MSA-specific CPI indexes (Section 4.2). Descriptive statistics of the regression sample are shown in Table 1.

In the Appendix, we report the relevant complementary information and tables. Specifically, Appendix A shows the CPI aggregation tree we have used to construct the CPI indexes. Appendix B contains detailed information about the regression sample, including: (i) a BLS PSU to Census CBSA MSA correspondence table (Table B.1), (ii) a table showing the geographical (counties) coverage of BLS PSU sampling (Table B.2), and (iii) a map of the regression sample (Figure B.1). Appendix C shows the distribution (Table C.1) of observations per PSU in the BLS CPI research database. NAICS industry classification at the two-digit level is shown in Appendix D. Data sources can be found in Appendix E.

4.1 Publicly available data

Using publicly available databases we have collected the following data:

- **Employment and payroll.** Sectoral employment and sectoral payroll figures are from U.S. Census Statistics of US Business (SUSB). Payroll and employment data are tabulated from administrative records for single-unit enterprises and a combination of administrative records and survey-collected data for multi-unit enterprises. Payroll includes all forms of compensation, such as salaries, wages, commissions, dismissal pay, bonuses, vacation allowances, sick-leave pay, and employee contributions to qualified pension plans paid during the year to all employees.[7]

[7] See https://www.census.gov/programs-surveys/susb/about/glossary.html for more details.

- **Firms' observables.** Number, size, and industry of firms and establishments are also from U.S. Census Statistics of US Business (SUSB). According to the SUBS classification, an establishment is "a single physical location where business transactions take place and for which payroll and employment records are kept". Groups of one or more establishments under common ownership or control are enterprises. In our analysis, we use SUSB data at the two-digit NAICS classification industry level. We classify industries using four categories (goods, services, distribution, and construction) that ensure comparability with the prices data. Following the spirit of Mian and Sufi (2014) we have also placed each of the two-digit industries into one of the four categories: non-tradable, tradable, construction, and other. Table D.1 in Appendix D shows the classification we have used for each NAICS industry at the two-digit level.

- **Unemployment.** Using the BLS Local Area Unemployment Statistics (LAUS) we have collected data on MSA unemployment rates. The LAUS program is a hierarchy of non-survey methodologies for producing monthly estimates of civilian labor force, employment, unemployment, and the unemployment rate for approximately 7,500 sub-national areas.

- **Demographics.** Demographics data are from Census.

- **House prices.** House prices data at the zip code level come from CoreLogic. We then constructed a crosswalk from zip-codes to MSA using the 2015 MSA Census definition.

- **Home ownership rates.** Home ownership rates are from the Census Housing Vacancies and Homeownership (CPS/HVS) database.

- **Instruments.** In our econometric framework, our main instrument is the housing supply elasticities from Saiz (2010).[8] The Saiz (2010) housing supply elasticity index is calculated for 269 MSAs (using the 2000-circa Census definitions and excluding U.S.

[8] As robustness we also redo our analysis using the Warton regulatory index. The Warton regulatory index is provided by Gyourko et al. (2008), available at: http://real.wharton.upenn.edu/~gyourko/landusesurvey.html.

territories) covering all 50 states plus the District of Columbia. Using the 2015 Census MSAs definitions, the instrument covers 253 MSAs.[9]

- **Nominal GDP.** Nominal GDP figures are from the regional database of the BEA. Gross domestic product (GDP) by metropolitan area is the measure of the market value of all final goods and services produced within a metropolitan area in a particular period of time. An industry's GDP by metropolitan area, referred to as the MSA "value added" is equivalent to its gross output (sales or receipts and other operating income, commodity taxes, and inventory change) minus its intermediate inputs (consumption of goods and services purchased from other U.S. industries or imported).

- **RPPs.** As a robustness check we collected the BEA Regional Price Parities (RPPs) data (for details about the BEA RPPs see Appendix F). The BEA RPPs are regional price levels expressed as a percentage of the overall national price level for a given year. Regional prices are provided disaggregating the Personal Consumption Expenditure categories in three items: goods, services excluding rents, and services rents. Goods refer to durable and nondurable consumption goods, including apparel, education, food and beverages, housing, medical goods, recreation, transportation, and other goods. Services excluding rents categories include education, food away from home, housing services (excluding rents), medical, recreation, transportation, and other services. Notably, rents RPPs are estimated only for observed tenants' rents and do not include imputed owner-occupied rent values such as in the CPI index. The RPP dataset covers

[9]The missing MSAs are: Fort Lauderdale, FL (now included in MSA 33100 "Miami-Fort Lauderdale-West Palm Beach, FL"), Fort Worth-Arlington, TX (now included in MSA 19100 "Dallas-Fort Worth-Arlington, TX"), Galveston-Texas City, TX (PMSA) (now included in MSA 26420 "Houston-The Woodlands-Sugar Land, TX"), Gary, IN (now included in MSA 16980 "Chicago-Naperville-Elgin, IL-IN-WI"), Hamilton-Middletown, OH (now included in MSA 17140 "Cincinnati, OH-KY-IN"), Jamestown, NY (now classified as "micropolitan statistical area" (μSA)), Jersey City, NJ (now included in MSA 35620 "New York-Newark-Jersey City, NY-NJ-PA"), Kenosha, WI (now included in MSA 16980 "Chicago-Naperville-Elgin, IL-IN-WI"), Newark, NJ (now included in MSA 35620 "New York-Newark-Jersey City, NY-NJ-PA"), Oakland, CA (now included in MSA 41860 "San Francisco-Oakland-Hayward, CA"), Poughkeepsie-Newburgh-Middletown, NY (now included in MSA 35620 "New York-Newark-Jersey City, NY-NJ-PA"), Sharon, PA (now included in MSA 37980 "Philadelphia-Camden-Wilmington, PA-NJ-DE-MD"), Tacoma, WA (now included in MSA 42660 "Seattle-Tacoma-Bellevue, WA"), West Palm Beach-Boca Raton, FL (now included in MSA 33100 "Miami-Fort Lauderdale-West Palm Beach, FL"), Wilmington-Newark, DE-MD (now included in MSA 37980 "Philadelphia-Camden-Wilmington, PA-NJ-DE-MD").

381 MSAs over the period 2008-2014.

4.2 Constructing the MSA-specific CPI indexes

Using the BLS CPI research database we have constructed MSA-specific CPI indexes. The BLS CPI research database is a confidential dataset that contains each single price recorded by the BLS used to compute the US all-cities CPI index. The database covers all goods and services other then shelter. The BLS categorizes the records into about 300 Entry Level Items, or "ELIs".[10] The database identifies products at an extremely detailed level. In general, two products are considered different products in the database if they have different bar codes (therefore, the same product at two different stores has two different entries in the database). An example of a product in the database is a two-liter bottle of Sprite sold at a particular supermarket in Washington, D.C.. The frequency of the data collection depends on the specific ELI and geographical region. For the three largest MSAs (New York, Los Angeles and Chicago), the BLS collects prices for all goods on a monthly basis. For all the other areas, the BLS collects prices for food and fuel products on a monthly basis, and prices for the remaining products on a bi-monthly basis. The CPI research database contains around 80,000 entries in each month (see Appendix C for details) for a total of a bit more than 1 million records per year. Data start in 1977—for the purpose of our paper we focus on the 2000-to present period. In our analysis we are interested in data at annual frequency and therefore we can disregard issues raised by seasonality.

Geographical coverage. The geographical sample covers 87 areas called "Primary Sampling Units" or "PSUs" (See Appendix B for a full list) located in 43 States and it is intended to represent the urban portion of the US population (around 90 percent of the total population). A PSU consists of counties (or parts thereof), groups of counties, or independent cities. For each PSU the BLS samples in more than one county, located in one

[10] A detailed description of the BLS methodology for sampling and constructing the CPI index can be found at: https://www.bls.gov/opub/hom/pdf/homch17.pdf. See Appendix 4 for the full list of ELIs.

or more states. For instance, for the PSU A102 ("Philadelphia, PA") the BLS samples in 14 counties located in 4 states: Delaware (1 county), New Jersey (7 counties), Maryland (1 county), and Pennsylvania (5 counties). The 8 states in which the BLS does not sample in any county are: Iowa, Mississippi, Montana, New Mexico, North Dakota, Rhode Island, South Dakota, and Wyoming.

Among the 87 PSUs included in the sample:

- 31 PSUs are Metropolitan Statistical Areas (MSAs) with a population of 1.5 million or greater. These PSUs are identified with a code starting with the letter "A".
- 46 PSUs are MSAs with a population less than 1.5 million. These PSUs are identified with a code starting with the letter "B".
- 10 PSUs, are nonmetropolitan areas. These PSUs are identified with a code starting with the letter "C".[11] Because we run our analysis at the MSA level of geographical aggregation, we cannot include the data collected in these PSUs in our dataset. This constraint reduces the number of PSUs from 87 to 77.

Matching PSUs to MSAs. Unfortunately, there is not a unique/perfect match between a PSU and a (corresponding) MSA.[12] In this dimension, two issues arise. First, there are 7 cases in which the BLS splits the Census(CBSA)-defined MSA territory in two or more primary sampling units. Put it differently, two (or more) PSUs are associated to the same MSA. Specifically:

- PSU A419 ("Los Angeles, CA") and PSU A420 ("Los Angeles Suburbs") can be associated to Census-defined MSA 31080 ("Los Angeles-Long Beach-Anaheim, CA").

[11] See Appendix C - 1998 revision geographical dimension of the "CPI-RDB: the CPI research database" documentation provided by the BLS. The list of PSU "urban non-metropolitan areas" (that is, those with an identifier that begins with the letter "C") is reported in Appendix B.

[12] See BLS (https://www.bls.gov/ore/pdf/st020060.pdf) for additional details about the PSUs selected for the CPI sampling.

- PSUs A109 ("New York City, NY"), A110 ("New York Suburbs"), and A111 ("New Jersey Suburbs") can be associated to Census-defined MSA 35620 ("New York-Newark-Jersey City, NY-NJ-PA").
- PSU B112 ("Sharon, PA") and PSU B232 ("Youngstown, OH") can be associated to Census-defined MSA 49660 ("Youngstown-Warren-Boardman, OH-PA").

In these cases, we pool together all data sampled across PSUs in the same MSA and use them to construct a single MSA-specific CPI index. This reduces the number of PUSs from 77 to 73 and ensures a unique match between a PSU and a corresponding MSA. The second issue arises because, for other PSUs (typically "B" PSUs), the BLS samples only in some of the counties included in the Census MSA definition (See Table B.2 in Appendix B). For these PSUs we assume a one-to-one correspondence PSU/MSA and assume the same inflation rate in the remaining counties. Table C.1 in Appendix C shows the sampling distribution across PSUs. As previously mentioned, the BLS CPI research database contains around 1 million observations per year. On average, an "A" PSU is sampled a bit less than 20 thousand times each year, while a "B" PSU is sampled a bit more than 7 thousand times. Figure B.1 in Appendix B shows a map of the MSA regression sample.

Constructing the MSA-specific CPI indexes. After we have identified a unique geographical match between PSUs and the corresponding MSAs, we constructed the PSU/MSA-specific yearly CPI index for the 73 PSUs/MSAs. In order to do so, we have followed closely chapter 17 of the "BLS Handbook of methods" and computed the Laspeyres CPI index for a set of sub-items (see Appendix A for the CPI aggregation tree we have used to construct the CPI sub-items indexes), as well as for total CPI excluding rents (which are not included in the BLS research database).[13] Following the BLS, we assume the same CPI sub-items weights across PSUs. We use the 2008 weights. Because the BLS publishes MSA-specific indexes for the largest 27 MSAs, we can compare the indexes that we have calculated using the BLS research database with the publicly available ones in order to check whether our

[13]See https://www.bls.gov/opub/hom/pdf/homch17.pdf for details.

methodology produces reliable results.[14] Figure 3 plots the comparison between publicly available BLS data and the indexes we have calculated for some selected MSAs and sub-indexes. The main take-away from Figure 3 is that our procedure seems to reproduce the BLS indexes remarkably well. Anyway, for the 73 MSA with a PSU/MSA match, we will use publicly available data when possible (for the largest 27 MSAs)—and use our constructed CPI indexes otherwise (for the remaining 46 MSAs). For all MSAs, we will also use our constructed indexes for sub-items that are not published by the BLS.

5 Evidence on regional adjustment and (the lack of) internal devaluation

In this section, we present and discuss our main findings. Based on the empirical model presented in Section 3, we document the effects of large house price movements—driving local demand—on relative prices across MSAs. In the next subsection, we look at the price of the overall consumption basket (net of rents), the MSA equivalent of the real exchange rate for a country, as well as at its disaggregated components by sector and/or type of goods. In a second subsection, we document the effects of local shocks to house prices on a number of sectoral variables of interest, including employment, wages and measures of firms market power at MSA level. In doing so, we will use first the BLS PSU sample and then the entire MSA samples,—as shown in Table 1, the two samples are quite similar in terms of key variables such as house price changes, employment shares, unemployment and so on (they mainly differ in terms of population).

Before turning to our main results, we show the first stage of our Instrumental Variable (IV) approach, explained above, in Table 2. The table reports the results for the whole sample (253 MSAs) and for the 69 MSAs in the BLS samples, for which we have the Saiz (2010) elasticity instrument. The instrument is strongly correlated with the growth rate of local

[14] See https://www.bls.gov/cpi/factsheets/available-cpi-data.htm for details about the publicly available BLS CPI data for the largest 27 MSAs.

house prices. As expected, the estimated coefficient of the Saiz (2010) elasticity is positive, meaning that declines in house prices have been smaller in areas with a higher housing supply elasticity (see also Stroebl and Vavra (2018)). The weak instrument statistics is well above the critical value (59.3 and 11.2 for the first and second column, respectively), rejecting the null of weak instruments at the 1% confidence level. Also, note that the coefficient estimated using the extended sample of 253 MSAs is very close to the one estimated using the BLS sample of 69 MSAs. Overall, the main takeaway from this table is that our IV regressions do not seem to suffer from a weak instrument issue. This allows us to rely on standard inferences, whereas we cluster standard errors at the MSA area level.

5.1 The Missing Internal Devaluation

Our key results on relative price adjustment across US areas in the Great Recession are shown in Table 3. The estimates in this table are obtained using the sample of 69 PSUs/MSAs for which instruments are available (for details and list, see Table B.1). The table highlights two key variables from the set of controls we include in the regressions. The first is unemployment (to detect a possible negative relation consistent with the Phillips Curve); the second is the share of employment share in firms with less than 20 employees (to proxy for the incidence of financial frictions, more pervasive for small firms, at local level). We report the inflation elasticity to unemployment for comparability with both Stroebl and Vavra (2018) and Beraja et al. (2016), especially in relation to question of whether one can detect a Phillips Curve relation at local level. As shown in the first two columns in the table, asymmetric shocks to house prices are uncorrelated with the relative price of consumption across MSAs. Both the OLS and IV coefficients are number actually negative, that is, they have the "wrong" sign—the point estimates of the IV coefficient even more so, although they are imprecisely estimated and insignificant. The coefficients of unemployment, instead, have the correct, negative sign, but are also very imprecisely estimated. Overall, there is little evidence of internal devaluation across US MSAs. As shown in the rest of the table, however, the lack of response in the overall relative price of consumption masks heterogeneous inflation responses at sectoral level. For the relative price of consumption goods (columns 3 and 4), the estimated elasticity to local housing shocks, while small and insignificant, is positive:

the OLS and IV estimates are equal to 0.03 and 0.11, respectively. Conversely, for the relative price of consumption services (ex-rent, columns 5 and 6), the effects of asymmetric housing shocks are negative—significantly so for our IV estimates. The elasticity from our IV estimates is equal to -0.31, implying that, over the period 2007-2011, a 50 percent divergence in the contraction of house prices (e.g., the difference between Phoenix and Cincinnati) was associated with a 15 percent positive differential in inflation rates in services. These findings are robust to the inclusion of a comprehensive set of controls, including wages and especially unemployment. A notable result from the table is that, for inflation in the services, the unemployment elasticity is negative and significant in the IV specification—complementing the analysis by Beraja et al (2016). This suggests that, in the Great Recession, the effects of house prices on inflation differentials was distinct (and opposite) from the traditional effects of unemployment, operating via a standard Phillips Curve. We will come back to this result in the following subsection.

The picture that emerges from the first six columns of the Table 3 is that the relative prices of goods and services appear to respond in different directions, possibly offsetting each other's effect on the overall real exchange rate.[15] As a result, the elasticity of the relative price of overall consumption (the MSA consumption real exchange rate) is small and insignificant, in both our OLS a and IV estimates. A starker result emerges when we focus on the relative price of services to goods across MSAs. Under the assumption that goods prices are broadly equalized across MSAs (which is consistent with their insignificant coefficients in the table), this relative price becomes the key driver of the real exchange rate. As shown in the last column of the table, its IV elasticity to house prices is negative and significantly so. This is evidence that the MSA experiencing the largest housing bust also experienced a push towards (relative) appreciation.

To dig deeper into the sectoral heterogeneity highlighted by our findings, we carry out an analysis of selected subindexes—results are shown in Table 4 and Table 5. In Table 4 we consider "core goods", that is, goods excluding food and energy commodities, and "core services", that is, services excluding food and energy services. These two sub-indices exclude

[15] Interestingly, the OLS bias seems to go in the opposite direction in the two sectors.

prices (of goods and services related to energy) that mainly reflect national and international factors—and thus are unlikely to be affected by local shocks. We also exclude food prices to study them separately (see below). Relative to the results shown in Table 3, when using "core" price indexes, the estimated (OLS and IV) elasticities of the good prices to housing shocks become larger, with the OLS coefficient being also statistically significant at the 5% level (the elasticity of unemployment remains imprecisely estimated). The estimated elasticities of the price of core services instead remain in line with Table 3, the IV estimates being negative and statistically significant. The lesson from this exercise is straightforward. Excluding energy goods and services (whose price is more likely to be administered and/or set nationally) exacerbates the sectoral heterogeneity in inflation, by restricting the composition of the index to good prices that are more sensitive to local economic conditions, and move in the opposite direction relative to the price of non-energy services.

We now turn our attention to three key sub-indices—results are shown in Table 5. The first two are "food at home", and "food away from home", which include goods and services prices that are well-measured *and* are very likely to be affected by local demand conditions, as shown for the former by Stroebl and Vavra (2019). The last one is "services excluding food, energy, and medical". Besides energy-related services, this sub-index also excludes also exclude service prices that are potentially not very well measured, such as health care and education.[16] They also exclude the prices of food services—that comprise a high share of nontradables—but note that we study these services as a separate sub-index.

The analysis of "food at home" is particularly important in relation to Stroebl and Vavra (2018). This index comprises the prices of food items purchased in supermarkets and other stores, with a substantial overlap with the store-level scanner data used by these two authors. A key finding by Stroebl and Vavra (2018) is that these prices did move together with local house prices in the Great Recession. In line with their findings, the first two column of Table 5 shows that, for "food at home", the IV estimates are positive and statistically significant (while the elasticity of unemploymentis is insignificant but has the wrong sign). This result suggests that, for the same categories of goods, the BLS price data display the same sensitivity to local housing shocks as prices from store-level scanner data. As apparent from the Table

[16] Eventually, one could also exclude financial services but the weight of such item in the CPI is extremely small (0.2 percent).

5, the results for "food at home" are strikingly different relatively to the other sub-indices, which confirm our findings for the overall price of services. For "food away from home" and "services excluding food, energy, and medical", the IV estimates of the elasticity of house prices are all negative and statistically significant. Again, these results are robust to including not only wages and unemployment, but also the employment share of small firms among the controls. Strikingly, the coefficient of unemployment, positive and insignificant in the IV estimates for "food at home", is again negative and significant for services, providing evidence in favor of sectoral Phillips Curve relations at local level.

We conclude this section by addressing the question of whether, in spite of lack of relative price adjustment in goods and services, the MSAs suffering the worst house price decline could nonetheless experience real depreciation because of a large fall in rents. Rents are a significant component of the US consumption basket but are not in the BLS Research Database. Hence, to address our question, we need to use a different dataset, the regional relative prices, or RPPs, compiled by BEA for all MSAs. The RPPs have well known severe limitations with respect to the BLS inflation data. For instance, for a large fraction of the MSAs, many components of the CPI are imputed. However, the RPPs also have a key advantage in that they include rent prices. Results from our econometric analysis using this dataset are shown in Table H.1. As apparent from the table, the lack of internal devaluation in the 2007 housing bust is also confirmed for rents. The elasticity of rents to house prices is significantly positive in the OLS estimates (with unemployment having the wrong sign), but becomes insignificant and negative in the IV estimates.

5.2 Evidence on regional adjustment in costs and markups

We now turn to exploring potential determinants of the lack of internal devaluation. In particular, we focus the analysis on the relation between housing shocks and a number of variables for which we have information at MSA level. In order to facilitate the comparison of our results with previous studies, such as the Mian and Sufi (2014), we use the entire sample of 253 MSAs.

The response of sectoral employment to house prices is shown in Table 6. In the upper panel of this table, we define sectors according to our definition, which matches closely the composition of the consumer price indices for goods and services. For comparative purposes, in the lower panel, we use the definitions adopted by Mian and Sufi (2014), based on sector output tradability (less inclusive than ours). Despite differences across the two exercises (in addition to using a different sectoral break down, Mian and Sufi 2014 study county-level data rather than MSA-level data), results are consistent. The elasticity of employment is high and statistically significant in the service and distribution sectors, as well as in the nontradable sector. In contrast, in the goods sector, both the OLS and the IV estimates are positive, but neither is significant, and the IV estimates are lower than their OLS counterparts. Not surprisingly, the largest elasticity is for the construction sector.

These results are best appreciated in light of the fact that, while employment in pure tradables mainly reflects nation-wide demand, employment in the service and distribution sectors mainly reflects local (MSA-specific) demand, falling on a composite of nationally traded goods and local services. Similarly to Mian and Sufi (2014), we find that a local house price bust mainly depresses demand for the local components of services and goods, and thus employment in services and distribution.

In Table 7 we provide evidence on the house price elasticity of total unemployment and overall population over the sample. The estimated elasticity between house prices and unemployment is negative and statistically significant, as expected, but total population appears to be uncorrelated with house prices. Together, these two pieces of evidence rule out labor supply adjustment via migration, a mechanism that in principle could have mitigated the unemployment effect of the fall in local labor demand associated with falling local house prices (see Blanchard and Katz (1992)).

Vis-à-vis the strong employment elasticity documented in Table 6, Table 8 provides evidence of a positive, although contained, correlation between shocks to house prices and wages. In particular, the table documents that the OLS estimates of the elasticity of wages are positive across all sectors exposed to local demand, especially construction, where both the OLS and the IV estimates are also significant. The bottom panels of these tables confirm and complement the results by Mian and Sufi (2014), using their definitions of tradables and non tradables (narrower than ours)—however, recall that these authors do not distinguish wage dynamics across sectors.

In line with the evidence of some wage adjustment at sectoral level, we find evidence of some adjustment also at MSA aggregate level. This is shown by Table 9, where we report the elasticity, with respect to house price shocks, of total nominal wages, unit labor costs (total compensation divided by real GDP), and the total labor share (compensation divided by nominal GDP) at MSA level. As apparent from the table, the overall measures of costs are not significantly related to house price dynamics. Nonetheless, wages displays a positive elasticity, driven by the construction and services sectors.[17]

A last and important adjustment margin to consider is markups, whose role is stressed in recent work by Stroebl and Vavra (2018) based on store-level sales prices. We conclude this section by presenting two pieces of evidence that can shed light on this margin. First, we look at the number of establishments and firms across sectors. A large reduction in this number, i.e., a large exit of firms from a sector, could be correlated to a decrease in competition and a relative increase in markups. In Table 10 and 11, we report the correlation of net entry with house prices, which is positive most sectors, with the notable exception of the grocery retail sector (NAICS 455) in Table 11—for which the evidence suggests that the housing bust was associated with a net increase in the number of establishments. A part from the grocery sector, however, OLS and IV point estimates tend to be similar and highly statistically significant. Now, a fall in the number of firms and hence in the intensity of competition during the housing bust can be expected to have a larger impact on the market power of local firms operating in the service sector, relative to firms operating in the manufacturing sector—given that tradables can be more easily substituted with imports. In light of this consideration, the results in the table (showing a comparable fall in the number of firms across goods and services) suggests that market power, hence markups, increased by more in services. Moreover, for the sector in which we find a pattern of adjustment in the number of firms that is opposite relative to the rest of the economy—pointing to stronger competition—, we also find a significant price response to the housing bust that has the right sign.

Second, we calculate the share of sectoral labor and intermediates in gross output, which (as discussed in Section 2) are inversely related to markups (under a unitary elasticity of

[17] The measure of wages we use may be not very responsive to cyclical conditions as it does not take into account the number of hours worked but only the number of workers, and the different composition in labor supply across age, gender and race (see Beraja et al. (2016)). Nevertheless, our results are still useful to the extent they provide a lower bound estimate of the elasticity of wages to house price shocks.

substitution between labor and other inputs). Intermediates shares as a fraction of gross output are calculated by subtracting nominal GDP from sales. As shown in Table 13 and 14, sectoral labor and intermediates shares are not strongly related to house prices: OLS and IV estimates are generally positive but insignificant. The notable exception is the restaurant sector (NAICS 722), where IV estimates are significant at the 10% level. This piece of evidence squares with the fall in the number of establishments suffered by the sector in the crisis years (see Table 11).

We take our results as evidence that, during the housing bust period, markups have increased in services, especially in the restaurant sector (consistent with the increase in their sectoral relative price). In the light of the findings by Stroebl and Vavra (2018), suggesting that markups fell in supermarkets (in line with our findings on the price response for "food at home"), our results point to heterogeneous markup adjustment across sectors as a key contributing factor explaining the lack of internal devaluation during the Great Recession.

6 Concluding remarks

In this paper we have shown evidence that, across regions in US, there has been virtually no internal real exchange rate adjustment during the 2007 Great Recession. Even when the housing bust in 2007-2011 created large local demand shocks, the relative price of consumption basket displays little movements at local level. The lack of overall real exchange rate adjustment results from heterogeneous and opposite movements in sectoral prices. Looking at the different components of this basket, adjustment tends to have the correct sign—a drop in demand causes relative prices to fall—for goods (although our estimates are mostly insignificant, with the notable exception of groceries as in Stroebl and Vavra (2019)), but not for services. Heterogeneity in the price response cannot be attributed to heterogeneity in the wage and unit labor cost response—we show evidence that wages actually tend to respond to housing shocks with the right sign in all sectors. By the same token, our evidence is not at odds with a standard, negative relation between unemployment and prices at both local and sectoral level. In our estimates, the coefficient on unemployment tend to have the right sign, and be significant in sectors most exposed to local demand conditions, in line with the research by Beraja et al/ 2016. As our controls include proxies capturing the incidence of financial frictions (such as, the incidence of small firms at MSA level), what is left as a plausible explanation for the divergent response of prices to the housing burst we find in the data, is heterogenous markup adjustment. A leading example is provided by the comparison of the prices response in "Food at Home" as opposed to "Food Away from Home"—fully consistent with the conclusions by Stroebl and Vavra (2018). For these two sectors, in particular, we have provided evidence that differences in prices and markup adjustment square well with a very different response of net firm entry to the negative demand shocks of the Great Recession.

The results from our econometric estimates are puzzling in light of macro and international theory, at both aggregate and disaggregated (by sector) level. According to conventional wisdom, the bulk of adjustment should fall in sectors with the largest incidence of nontradability in production. Consistently, we find that, besides construction, the elasticity of employment is highest in services and distribution. However, we also find that adjustment falls almost exclusively on employment. The relative price of services, if anything, exacerbates the adverse propagation of the shocks on the economic activity.

This evidence, however puzzling, raises important issues in this European debate. In a mature currency area like the US, lack of real exchange rate adjustment has prevented neither recovery at national level, nor rebalancing across states and regional convergence along the recovery. Conversely, in Europe, insufficient real exchange rate adjustment has been singled out as a major factor hampering recovery and keeping the countries in the periphery, worst hit by the crisis, in a persistent state of underemployment. Estimates of the real exchange rate depreciation required to restore full employment vary widely, often as high as 30 percent.

A key question is whether an adjustment mechanism that, as shown in this paper, does not seem crucial in correcting regional imbalances in a mature currency area like the US, could be expected to ever play a more significant role in the euro area—even after undertaking reforms in labor, goods and financial markets which are unlikely to bring the euro area close to the level of integration enjoyed across US jurisdictions.

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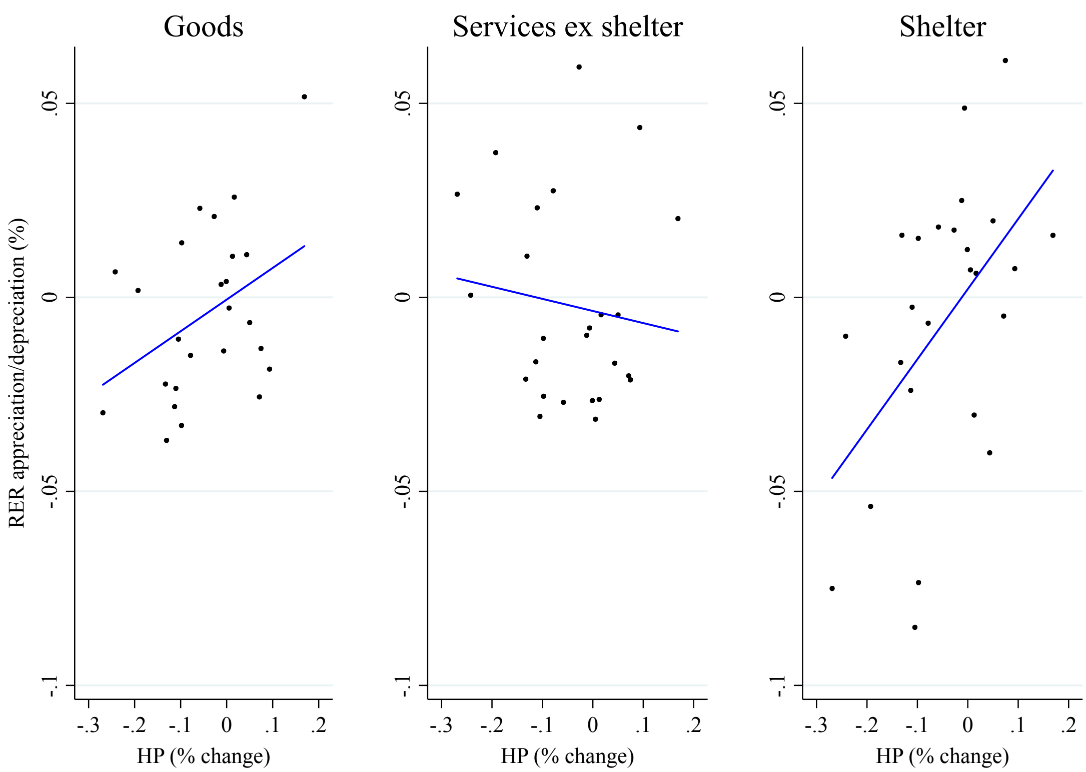
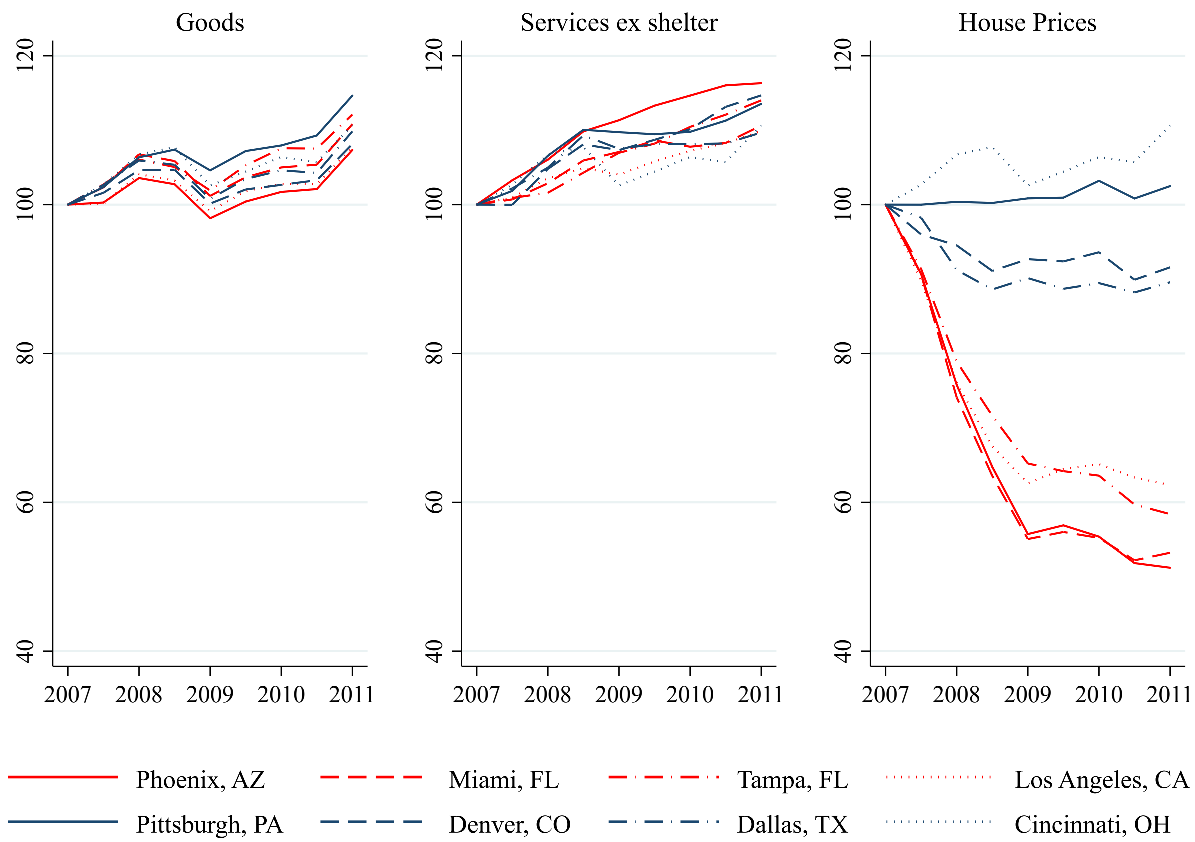
Figures and Tables

Figure 1: Change in house prices and RER appreciation/depreciation.



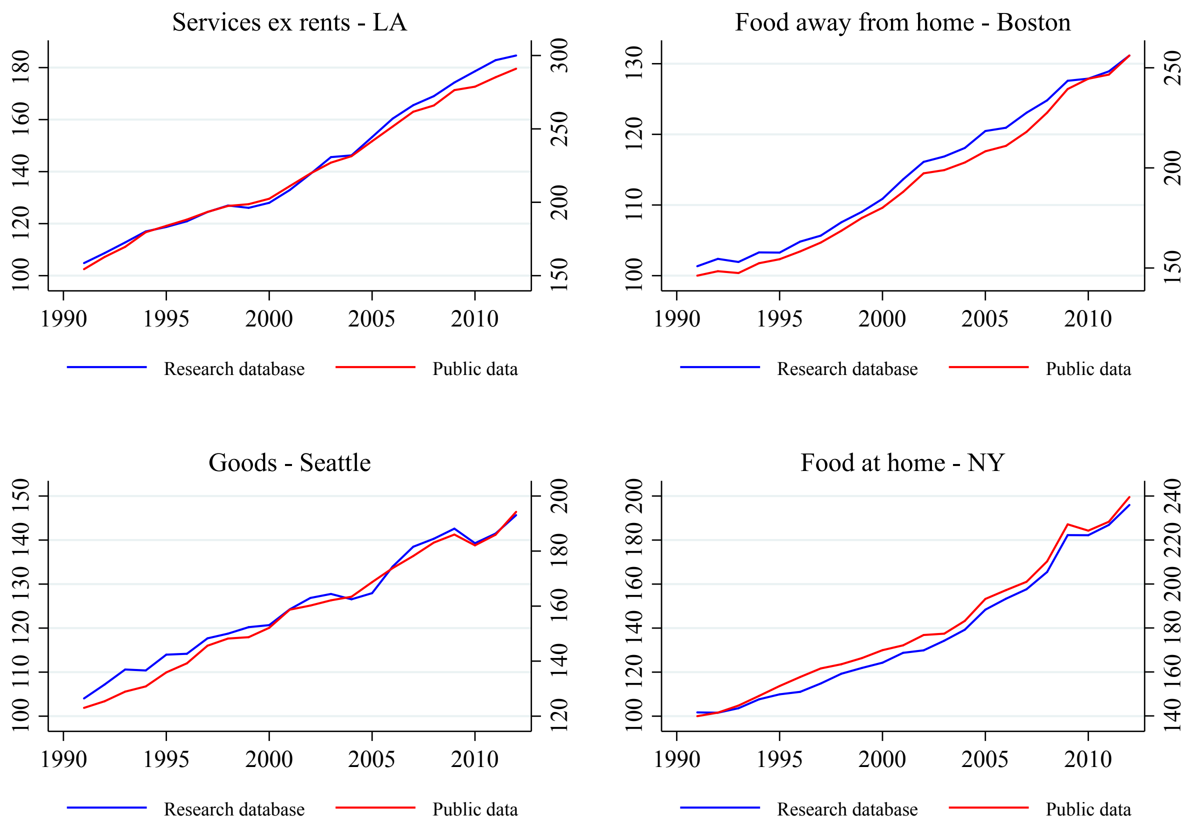
Note: The above figure shows the correlation between CPI inflation rates at the MSA level and the change in local house prices. Each dot on the chart is an MSA in a given year. The figure refers to the 27 largest metropolitan areas in the US between 2007m12 and 2011m12. The vertical axis plots the CPI inflation rate relative to the national aggregate (that is, the real exchange rate) for “Goods” (left panel) and “Services excluding shelter” (mid panel), and “Shelter” (right panel). The horizontal axis shows the percent change in house prices relative to the national aggregate. National aggregate is defined as simple average of the 27 areas in each year. The CPI index for “Goods” refers to the variable “Commodities” in the BLS database, while the CPI index for “Services excluding shelter” refers to the variable “services_norentshelter” in the BLS database. The figure excludes the MSAs for which the Saiz (2010) instrument was not calculated. **Source:** CPI indexes at MSA level are provided by the Bureau of Labor Statistics (available at: https://www.bls.gov/cex/csxmsa.htm). House prices data come from CoreLogic (available at: http://www.corelogic.com).

Figure 2: Cumulative CPI inflation and house price dynamics.



Note: The figure plots the cumulative CPI inflation and house price dynamics for 8 selected MSAs out of the 27 largest metropolitan areas in the US. The MSAs in red are those in which house prices contracted the most in between 2008 and 2011, while the MSAs in blu are those in which house prices contracted the least or did not contract at all. Services refers to “Services excluding shelter” (variable “services_norentshelter” in the BLS database). All indexes have been rebased 2008m6 = 100. **Source:** CPI indexes at MSA level are provided by the Bureau of Labor Statistics (available at: https://www.bls.gov/cex/csxmsa.htm). House prices data come from CoreLogic (available at: http://www.corelogic.com).

Figure 3: Comparison between publicly available CPI data and BLS research database constructed.



Note: The figure shows CPI-indexes for selected PSUs (MSAs) and sub-items. The blue line (left axis) refers to the indexes constructed using the BLS research micro database. The red line (right axis) refers to the publicly available CPI indexes. The top left panel refers to PSU "A421" corresponding to MSA "Los Angeles-Long Beach-Anaheim, CA". The top right panel refers to PSU "A103" corresponding to MSA "Boston-Cambridge-Newton, MA-NH". The bottom left panel refers to PSU "A423" corresponding to MSA "Seattle-Tacoma-Bellevue, WA". The bottom right panel refers to PSU "A101" corresponding to MSA "New York-Newark-Jersey City, NY-NJ-PA". **Source:** Bureau of Labor Statistics data (available at: https://www.bls.gov/cex/csxmsa.htm) and authors' calculation on Bureau of Labor Statistics research database data.

Table 1: Summary statistics, regression sample.

		Full sample				69 MSAs in BLS PSU sample			
Variable	Unit	*Mean*	*Median*	*25%*	*75%*	*Mean*	*Median*	*25%*	*75%*
Population	'000	908.7	358.6	182.5	761.1	2190.9	1123.7	377.6	2761.5
Share pop. above 14	%	19.0	19.0	17.2	20.5	19.3	19.2	17.4	20.8
Share pop. above 65	%	15.5	15.0	13.3	17.3	15.3	14.8	12.9	16.9
Share pop. college	%	19.2	19.1	15.7	21.5	20.3	20.2	16.4	23.8
Unemployment rate	%	6.0	5.5	4.3	7.2	6.2	5.5	4.4	7.3
Share employment goods	%	12.7	11.7	8.2	16.6	11.9	10.9	7.6	15.2
Share employment services	%	57.4	59.4	52.9	64.6	58.0	61.1	53.3	66.4
Share employment distribution	%	18.9	18.8	17.5	20.5	18.1	18.1	16.9	19.4
Share employment construction	%	6.9	6.7	5.4	8.2	7.2	6.9	5.5	8.5
Share firms below 20	%	81.8	79.5	76.8	82.2	81.7	81.6	78.5	84.1
Share employment below 20	%	18.6	17.8	16.1	20.3	17.7	17.1	15.6	19.1
△ CPI excluding rents	%	-	-	-	-	6.4	6.5	5.7	7.7
△ CPI goods	%	-	-	-	-	8.9	8.7	10.2	7.2
△ CPI services excluding rents	%	-	-	-	-	10.6	10.0	12.7	8.9
△ House Price	%	-19.2	-15.0	-28.0	-8.0	-22.4	-17.8	-31.5	-9.8
Number of MSAs		253				69			

Note: The table above shows the descriptive statistics of the regression sample: "full sample" of 253 MSAs and the 69 MSAs in which the BLS samples for constructing the all-cities US CPI index. "Δ CPI excluding rents" refers to the delta-log between 2007 and 2011 of CPI index net of shelters in the largest 27 MSAs for which the BLS provides public data. "Δ CPIgoods" refers to the delta-log between 2007 and 2011 of CPI of commodities in the largest 27 MSAs for which the BLS provides public data. "Δ CPI services excluding rents" refers to the delta-log between 2007 and 2011 of CPI index of services net of shelters in the largest 27 MSAs for which the BLS provides public data. "Δ House price" refers to the delta-log between 2007 and 2011 of house price index. **Source:** raw data are from Census, BLS, and CoreLogit.

Table 2: First stage of instrumental variables (IV) regressions.

	Full sample	Full sample
Housing supply elasticity	0.01	0.02
	[0.00]***	[0.01]***
Observations	253	69
R^2	0.70	0.77

Note: robust standard errors clustered by MSA in brackets. *** indicates significance at 1% level, **at 5% * at 10%. Regressions refer to the time period 2007-2011. The first two columns refer to the full sample (253 MSAs for which we have data), while the second two columns refer to the 69 MSAs (PSUs) in which the BLS samples in order to construct the "U.S. all-cities CPI index". The dependent variable is the delta-log of House Prices in each MSA between 2007 and 2011. All regressions include a set of demographic controls: change in (total) population, change in the share of population with a college degree, change in the share of population above 14 and 65 years old. The F-statistics (weak identification Cragg-Donald Wald test) is 59.312 for the first column and 45.108 for the second column; the statistics of the first and second columns reject the null of weak instruments at 1 percent level. Robust standard errors clustered by MSA in brackets. **Source:** House prices data come from CoreLogic (available at: http://www.corelogic.com). The housing supply elasticity instrument is provided by Saiz (2010).

Table 3: Effect of house price change on local prices: 2007-2011.

	All		Goods		Services		Rel.Pr Ser/Goods	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
House Prices	-0.01	-0.14	0.03	0.11	-0.03	-0.31	-0.06	-0.42
	[0.04]	[0.11]	[0.05]	[0.13]	[0.07]	[0.14]**	[0.09]	[0.16]**
Unemployment rate	-0.16	-0.70	0.17	0.49	-0.33	-1.46	-0.50	-1.95
	[0.22]	[0.44]	[0.45]	[0.65]	[0.37]	[0.54]**	[0.70]	[0.80]**
Share Emp Small	-0.30	-0.41	-0.68	-0.62	-0.00	-0.25	0.68	0.37
	[0.67]	[0.79]	[0.57]	[0.53]	[1.04]	[1.27]	[1.03]	[1.26]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	69	69	69	69	69	69	69	69
R^2	0.13	.	0.13	0.10	0.14	.	0.12	.

Note: robust standard errors clustered by MSA in brackets. *** indicates significance at 1% level, **at 5% * at 10%. "OLS" refers to Ordinary Least Squares, and "IV" refers to Instrumental Variables. "All" refers to all-items excluding shelter. "Services" refer to services excluding shelter. All regressions refer to the period 2007-2011. In the IV the instrument is the estimates of housing supply elasticities from Saiz (2010). The dependent variable is the delta-log of CPI indexes. "House Prices" refers to the delta-log of house price index in each MSA. Controls include: the change in the share of employment in the construction sector as well as in the non-tradable sector, the change in the unemployment rate (shown in the table), the change (delta-log) of nominal wages, and the change in the share of employment in firms below 20 employees (shown in the table). All regressions include also a set of demographic controls: change in (total) population, change in the share of population with a college degree, change in the share of population above 14 and 65 years old. **Source:** CPI indexes at MSA level are provided by the Bureau of Labor Statistics (available at: https://www.bls.gov/cex/csxmsa.htm) for the largest 27 MSAs; for the remaining ones, authors' calculations on BLS CPI research database data. House prices data come from CoreLogic (available at: http://www.corelogic.com).

Table 4: Effect of house price change on local prices.

	Core goods		Core services	
	OLS	IV	OLS	IV
House Prices	0.15	0.21	-0.04	-0.26
	[0.07]**	[0.25]	[0.03]	[0.08]***
Unemployment rate	-0.15	0.10	0.14	-0.76
	[0.58]	[0.74]	[0.16]	[0.23]***
Share Emp Small	-0.97	-0.91	-0.66	-0.86
	[1.56]	[1.66]	[0.32]**	[0.58]
Controls	Yes	Yes	Yes	Yes
Observations	69	69	69	69
R^2	0.18	0.18	0.12	.

Note: robust standard errors clustered by MSA in brackets. *** indicates significance at 1% level, **at 5% * at 10%. "OLS" refers to Ordinary Least Squares, and "IV" refers to Instrumental Variables. "Core goods" refers to goods excluding food and energy. "Core services" refers to services excluding food and energy. All regressions refer to the period 2007-2011. In the IV the instrument is the estimates of housing supply elasticities from Saiz (2010). The dependent variable is the delta-log of CPI indexes. "House Prices" refers to the delta-log of house price index in each MSA. Controls include: the change in the share of employment in the construction sector as well as in the non-tradable sector, the change in the unemployment rate (shown in the table), the change (delta-log) of nominal wages, and the change in the share of employment in firms below 20 employees (shown in the table). All regressions include also a set of demographic controls: change in (total) population, change in the share of population with a college degree, change in the share of population above 14 and 65 years old. **Source:** CPI indexes at MSA level are provided by the Bureau of Labor Statistics (available at: https://www.bls.gov/cex/csxmsa.htm) for the largest 27 MSAs; for the remaining ones, authors' calculations on BLS CPI research database data. House prices data come from CoreLogic (available at: http://www.corelogic.com).

Table 5: Effect of house price change on local prices.

	Food at home		Food away home		Services ex efm	
	OLS	IV	OLS	IV	OLS	IV
House Prices	0.01	0.27	-0.06	-0.34	-0.05	-0.22
	[0.03]	[0.12]**	[0.04]	[0.13]**	[0.03]*	[0.09]**
Unemployment rate	-0.66	0.94	-0.43	-1.53	0.12	-0.54
	[0.43]	[1.06]	[0.26]	[0.60]**	[0.19]	[0.21]**
Share Emp Small	-1.52	-0.78	0.76	0.52	-0.87	-1.01
	[0.70]**	[0.61]	[0.68]	[0.80]	[0.36]**	[0.41]**
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	69	69	69	69	69	69
R^2	0.46	.	0.11	.	0.13	.

Note: robust standard errors clustered by MSA in brackets. *** indicates significance at 1% level, **at 5% * at 10%. "OLS" refers to Ordinary Least Squares, and "IV" refers to Instrumental Variables. "Services ex efm" refers to services excluding food, energy, and medical. "Services ex efme" refers to services excluding food, energy, medical, and education. All regressions refer to the period 2007-2011. In the IV the instrument is the estimates of housing supply elasticities from Saiz (2010). The dependent variable is the delta-log of CPI indexes. "House Prices" refers to the delta-log of house price index in each MSA. Controls include: the change in the share of employment in the construction sector as well as in the non-tradable sector, the change in the unemployment rate (shown in the table), the change (delta-log) of nominal wages, and the change in the share of employment in firms below 20 employees (shown in the table). All regressions include also a set of demographic controls: change in (total) population, change in the share of population with a college degree, change in the share of population above 14 and 65 years old. **Source:** CPI indexes at MSA level are provided by the Bureau of Labor Statistics (available at: https://www.bls.gov/cex/csxmsa.htm) for the largest 27 MSAs; for the remaining ones, authors' calculations on BLS CPI research database data. House prices data come from CoreLogic (available at: http://www.corelogic.com).

Table 6: Effect of house price change on change in local employment (2-digit level) .

	Goods		Services		Distribution		Construction	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
House Prices	0.26	0.13	0.14	0.17	0.16	0.12	0.85	0.93
	[0.16]	[0.16]	[0.02]***	[0.06]***	[0.01]***	[0.04]***	[0.06]***	[0.06]***
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	253	253	253	253	253	253	253	253
R^2	0.53	0.53	0.17	0.17	0.25	0.24	0.62	0.62

	Tradable		Non Tradable		Construction		Other	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
House Prices	0.11	0.63	0.16	0.12	0.85	0.93	0.11	0.14
	[0.07]	[0.47]	[0.02]***	[0.04]***	[0.06]***	[0.06]***	[0.02]***	[0.06]**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	253	253	253	253	253	253	253	253
R^2	0.05	0.03	0.23	0.22	0.62	0.62	0.13	0.12

Note: robust standard errors clustered by MSA in brackets. *** indicates significance at 1% level, **at 5% * at 10%. "OLS" refers to Ordinary Least Squares. "IV" refers to Instrumental Variables. The above regressions refer to the time period 2007-2011. The dependent variable is the delta-log of MSAs employment (at 2-digit NAICS level of disaggregation). "House Prices" refers to the delta-log of house price. All regressions include a set of demographic controls: change in (total) population, change in the share of population with a college degree, change in the share of population above 14 and 65 years old. Also, each column controls for the respective (pre-crisis) share of sectoral employment (at 2-digit NAICS level of classification). The IV instrument is based on housing supply elasticities from Saiz (2010). **Source:** employment data are from the Census County Business Patterns (available at: https://www.census.gov/programs-surveys/cbp.html). House prices data come from CoreLogic (available at: http://www.corelogic.com).

Table 7: Effect of house price change on total population and unemployment.

	Population		Unemployment	
	OLS	IV	OLS	IV
House Prices	-0.00	-0.01	-0.11	-0.08
	[0.01]	[0.02]	[0.03]***	[0.02]***
Controls	No	No	Yes	Yes
Observations	253	253	253	253
R^2	0.02	0.01	0.44	0.41

Note: robust standard errors clustered by MSA in brackets. *** indicates significance at 1% level, **at 5% * at 10%. "OLS" refers to Ordinary Least Squares. "IV" refers to Instrumental Variables. The above regressions refer to the time period 2007-2011. The dependent variable is the delta-log of total population (first two columns) or the unemployment rate (last two columns) in each MSA. "House Prices" refers to the delta-log of house price index in each MSA. All regressions include a set of demographic controls: change in (total) population (only in last two columns), change in the share of population with a college degree, change in the share of population above 14 and 65 years old. The IV instrument is based on housing supply elasticities from Saiz (2010). **Source:** population data come from US Census (available at: https://www.census.gov/). House prices data come from CoreLogic (available at: http://www.corelogic.com). Unemployment figures at MSA level are provided by the Bureau of Labor Statistics (available at: https://www.bls.gov/web/metro/laummtrk.htm).

Table 8: Effect of house price change on nominal wages (2-digit level).

	Goods		Services		Distribution		Construction	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
House Prices	0.03	-0.05	0.03	0.09	0.08	0.06	0.09	0.23
	[0.03]	[0.08]	[0.01]**	[0.07]	[0.02]***	[0.06]	[0.01]***	[0.09]**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	251	251	253	253	253	253	253	253
R^2	0.02	0.01	0.09	0.06	0.06	0.06	0.10	0.00

	Tradable		Non Tradable		Construction		Other	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
House Prices	0.07	0.27	0.03	0.07	0.09	0.23	0.05	0.09
	[0.07]	[0.25]	[0.03]	[0.04]*	[0.01]***	[0.09]**	[0.01]***	[0.05]*
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	251	251	253	253	253	253	253	253
R^2	0.05	0.04	0.07	0.05	0.10	0.00	0.10	0.08

Note: robust standard errors clustered by MSA in brackets. *** indicates significance at 1% level, **at 5% * at 10%. "OLS" refers to Ordinary Least Squares. "IV" refers to Instrumental Variables. The above regressions refer to the time period 2007-2011. The dependent variable is the delta-log of MSAs nominal payrolls (at 2-digit NAICS level of disaggregation). "House Prices" refers to the delta-log of house price. All regressions include a set of demographic controls: change in (total) population, change in the share of population with a college degree, change in the share of population above 14 and 65 years old. Also, each column controls for the respective (pre-crisis) share of sectoral employment (at 2-digit NAICS level of classification). The IV instrument is based on housing supply elasticities from Saiz (2010). **Source:** payroll data are from the Census County Business Patterns (available at: https://www.census.gov/programs-surveys/cbp.html). House prices data come from CoreLogic (available at: http://www.corelogic.com).

Table 9: Effect of house price change on wages, labor share, and unit labor cost.

	Wages		Labor Share		ULC	
	OLS	IV	OLS	IV	OLS	IV
House Prices	0.04	0.06	0.05	0.36	-0.02	-0.02
	[0.01]***	[0.03]*	[0.05]	[0.56]	[0.01]	[0.02]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	253	253	253	253	253	253
R^2	0.06	0.06	0.00	-0.00	0.02	0.02

Note: robust standard errors clustered by MSA in brackets. *** indicates significance at 1% level, **at 5% * at 10%. "OLS" refers to Ordinary Least Squares. "IV" refers to Instrumental Variables. The above regressions refer to the time period 2007-2011. "Unemployment" refers to the unemployment rate in each MSA. "Wage/employee" refers to the (delta-log of the) payroll per employee. "Labor share" refers to (delta of) total compensation divided by nominal GDP. "ULC" refers to (delta of) Unit Labor Cost, that is total compensation divided by real GDP. "House Prices" refers to the delta-log of house price index in each MSA. All regressions include a set of demographic controls: change in (total) population, change in the share of population with a college degree, change in the share of population above 14 and 65 years old. The IV instrument is based on housing supply elasticities from Saiz (2010). **Source:** payroll data are from the Census County Business Patterns (available at: https://www.census.gov/programs-surveys/cbp.html). GDP data are provided by the Regional Economics Account of the BEA. House prices data come from CoreLogic (available at: http://www.corelogic.com).

Table 10: Effect of house price change on number of establishments.

	Goods		Services		Distribution		Construction	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
House Prices	0.12	0.07	0.09	0.05	0.05	0.05	0.33	0.35
	[0.02]***	[0.03]**	[0.01]***	[0.02]*	[0.01]***	[0.03]	[0.05]***	[0.08]***
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	253	253	253	253	253	253	253	253
R^2	0.15	0.14	0.31	0.27	0.18	0.18	0.39	0.39

Table 11: Effect of house price change on number of firms.

	Goods		Services		Distribution		Construction	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
House Prices	0.12	0.08	0.12	0.09	0.07	0.06	0.40	0.46
	[0.02]***	[0.04]*	[0.01]***	[0.02]***	[0.01]***	[0.04]	[0.05]***	[0.07]***
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	253	253	253	253	253	253	253	253
R^2	0.15	0.14	0.41	0.40	0.18	0.19	0.47	0.46

Note: robust standard errors clustered by MSA in brackets. *** indicates significance at 1% level, **at 5% * at 10%. "OLS" refers to Ordinary Least Squares. "IV" refers to Instrumental Variables. The above regressions refer to the time period 2007-2011. The dependent variable is the delta-log of the number of establishments (or firms) in each MSA. "House Prices" refers to the delta-log of house price index in each MSA. All regressions include a set of demographic controls: change in (total) population, change in the share of population with a college degree, change in the share of population above 14 and 65 years old. Also, each column controls for the respective (pre-crisis) share of sectoral employment (at 2-digit NAICS level of classification). The IV instrument is based on housing supply elasticities from Saiz (2010). **Source:** sectoral number of firms and establishments are from the Census Statistics of US Business (SUSB) (available at: https://www.census.gov/programs-surveys/susb.html). House prices data come from CoreLogic (available at: http://www.corelogic.com).

Table 12: Effect of house price change on number of establishments.

	FoodBeverages		Restaurants		Restaurants (no outlier)
	OLS	IV	OLS	IV	IV
House Prices	-0.10	-0.20	0.07	0.07	0.09
	[0.02]***	[0.12]*	[0.03]**	[0.05]	[0.05]*
Controls	Yes	Yes	Yes	Yes	Yes
Observations	253	253	253	253	251
R^2	0.15	0.12	0.22	0.23	0.21

Note: robust standard errors clustered by MSA in brackets. *** indicates significance at 1% level, **at 5% * at 10%. "OLS" refers to Ordinary Least Squares. "IV" refers to Instrumental Variables. The above regressions refer to the time period 2007-2011. The dependent variable is the delta-log of the number of establishments (or firms) in each MSA. "House Prices" refers to the delta-log of house price index in each MSA. All regressions include a set of demographic controls: change in (total) population, change in the share of population with a college degree, change in the share of population above 14 and 65 years old. Also, each column controls for the respective (pre-crisis) share of sectoral employment (at 2-digit NAICS level of classification). The IV instrument is based on housing supply elasticities from Saiz (2010). **Source:** sectoral number of firms and establishments are from the Census Statistics of US Business (SUSB) (available at: https://www.census.gov/programs-surveys/susb.html). House prices data come from CoreLogic (available at: http://www.corelogic.com).

Table 13: Effect of house price change on labor shares.

	Goods		Services		Distribution		Construction	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
House Prices	0.06	0.25	0.14	0.67	0.02	0.16	0.02	0.20
	[0.04]	[0.20]	[0.16]	[0.83]	[0.05]	[0.14]	[0.05]	[0.11]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	221	221	243	243	245	245	234	234
R^2	0.09	0.06	0.01	.	0.01	.	0.02	.

Table 14: Effects of house price changes on intermediate shares

	Goods		Services		Distribution		Food away	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
House Prices	-0.04	0.16	0.54	2.67	0.03	0.12	-0.13	1.09
	[0.05]	[0.24]	[0.52]	[7.35]	[0.02]	[0.08]	[0.14]	[0.66]*
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	195	195	148	148	239	239	125	125
R^2	0.25	0.22	0.09	0.03	0.09	0.04	0.21	-0.20

Note: robust standard errors clustered by MSA in brackets. *** indicates significance at 1% level, **at 5% * at 10%. "OLS" refers to Ordinary Least Squares. "IV" refers to Instrumental Variables. The above regressions refer to the time period 2007-2011. The dependent variable are the delta of, respectively, labor and intermediate share in each MSA. "Labor share" refers to total compensation divided by nominal GDP. Intermediate shares refer to total sales minus nominal Value Added, divided by nominal GDP. Total Sales are from Economic Census Table. All regressions include a set of demographic controls: change in (total) population, change in the share of population with a college degree, change in the share of population above 14 and 65 years old. The IV instrument is based on housing supply elasticities from Saiz (2010). **Source:** payroll data are from the Census County Business Patterns (available at: https://www.census.gov/programs-surveys/cbp.html). GDP data are provided by the Regional Economics Account of the BEA. House prices data come from CoreLogic (available at: http://www.corelogic.com).

Appendix

Not intended for publication

A CPI aggregation tree

Table A.1: CPI aggregation tree

Expenditure category	Relative importance (as of March 2018)	Goods/Services	In BLS CPI research database?
All items	100.000		
Food and energy			
Food at home	7.327	Goods	YES
Food away from home	5.978	Services	YES
Energy commodities	4.254	Goods	YES
Energy services	3.433	Services	YES
Goods less food and energy			
Household furnishing and supplies	3.395	Goods	YES
Apparel	3.136	Goods	YES
New vehicles	3.775	Goods	YES
Used cars and trucks	2.407	Goods	YES
Medical care commodities	1.740	Goods	YES
Recreation commodities	1.849	Goods	YES
Education and comm. commodities	0.562	Goods	YES
Alcoholic beverages	0.970	Goods	YES
Other goods	1.569	Goods	YES
Services less food and energy			
Shelter	32.697	Services	**NO**
Water and sewer and trash collection	1.073	Services	YES
Household operations	0.869	Services	YES
Medical care services	6.939	Services	YES
Transportation services	5.987	Services	YES
Recreation services	3.867	Services	YES
Education and communication services	6.063	Services	YES
Other personal services	1.616	Services	YES

B Regression samples

Table B.1: BLS PSU to Census CBSA correspondence table

BLS name	PSU	PSU area	Census MSA name	CBSA	Saiz
Philadelphia, PA	A102	A102	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	37980	YES
Boston, MA	A103	A103	Boston-Cambridge-Newton, MA-NH	14460	YES
Pittsburgh, PA	A104	A104	Pittsburgh, PA	38300	YES
New York City, NY	A109	A101	New York-Newark-Jersey City, NY-NJ-PA	35620	YES
New York Suburbs	A110	A101	New York-Newark-Jersey City, NY-NJ-PA	35620	YES
New Jersey Suburbs	A111	A101	New York-Newark-Jersey City, NY-NJ-PA	35620	YES
Chicago, IL	A207	A207	Chicago-Naperville-Elgin, IL-IN-WI	16980	YES
Detroit, MI	A208	A208	Detroit-Warren-Dearborn, MI	19820	YES
St. Louis, MO	A209	A209	St. Louis, MO-IL	41180	YES
Cleveland, OH	A210	A210	Cleveland-Elyria, OH	17460	YES
Minneapolis, MN	A211	A211	Minneapolis-St. Paul-Bloomington, MN-WI	33460	YES
Milwaukee, WI	A212	A212	Milwaukee-Waukesha-West Allis, WI	33340	YES
Cincinnati, OH	A213	A213	Cincinnati, OH-KY-IN	17140	YES
Kansas City, MO	A214	A214	Kansas City, MO-KS	28140	YES
Washington, DC	A312	A312	Washington-Arlington-Alexandria, DC-VA-MD-WV	47900	YES
Baltimore, MD	A313	A313	Baltimore-Columbia-Towson, MD	12580	YES
Dallas, TX	A316	A316	Dallas-Fort Worth-Arlington, TX	19100	YES
Houston, TX	A318	A318	Houston-The Woodlands-Sugar Land, TX	26420	YES
Atlanta, GA	A319	A319	Atlanta-Sandy Springs-Roswell, GA	12060	YES
Miami, FL	A320	A320	Miami-Fort Lauderdale-West Palm Beach, FL	33100	YES
Tampa, FL	A321	A321	Tampa-St. Petersburg-Clearwater, FL	45300	YES
Los Angeles, CA	A419	A421	Los Angeles-Long Beach-Anaheim, CA	31080	YES
Los Angeles Suburbs	A420	A421	Los Angeles-Long Beach-Anaheim, CA	31080	YES
San Francisco, CA	A422	A422	San Francisco-Oakland-Hayward, CA	41860	YES
Seattle, WA	A423	A423	Seattle-Tacoma-Bellevue, WA	42660	YES
San Diego, CA	A424	A424	San Diego-Carlsbad, CA	41740	YES

BLS name	PSU	PSU area	Census MSA name	CBSA	Saiz
Portland, OR	A425	A425	Portland-Vancouver-Hillsboro, OR-WA	38900	YES
Honolulu, HI	A426	A426	Urban Honolulu, HI	46520	**NO**
Anchorage, AK	A427	A427	Anchorage, AK	11260	**NO**
Phoenix, AZ	A429	A429	Phoenix-Mesa-Scottsdale, AZ	38060	YES
Denver, CO	A433	A433	Denver-Aurora-Lakewood, CO	19740	YES
Reading, PA	B102	X100	Reading, PA	39740	YES
Syracuse, NY	B104	X100	Syracuse, NY	45060	YES
Buffalo, NY	B106	X100	Buffalo-Niagara Falls, NY	15380	YES
Hartford, CT	B108	X100	Hartford-West Hartford-East Hartford, CT	25540	YES
Burlington, VT	B110	X100	Burlington-South Burlington, VT	15540	YES
Sharon, PA	B112	X100	Youngstown-Warren-Boardman, OH-PA	49660	YES
Johnstown, PA	B114	X100	Johnstown, PA	27780	YES
Springfield, MA	B116	X100	Springfield, MA	44140	YES
Wausau, WI	B218	X200	Wausau, WI	48140	YES
Dayton, OH	B220	X200	Dayton, OH	19380	YES
Evansville, IN	B222	X200	Evansville, IN-KY	21780	YES
Columbus, OH	B224	X200	Columbus, OH	18140	YES
Saginaw, MI	B226	X200	Saginaw-Saginaw Township North, MI	40980	YES
Elkhart, IN	B228	X200	Elkhart-Goshen, IN	21140	YES
Decatur, IL	B230	X200	Decatur, IL	19500	YES
Youngstown, OH	B232	X200	Youngstown-Warren-Boardman, OH-PA	49660	YES
Madison, WI	B234	X200	Madison, WI	31540	YES
Lincoln, NE	B236	X200	Lincoln, NE	30700	YES
Chattanooga, TN	B338	X300	Chattanooga, TN-GA	16860	YES
Florence, SC	B340	X300	Florence, SC	22500	YES
Albany, GA	B342	X300	Albany, GA	10500	YES
Norfolk, VA	B344	X300	Virginia Beach-Norfolk-Newport News, VA-NC	47260	YES
Pine Bluff, AR	B346	X300	Pine Bluff, AR	38220	YES
Raleigh, NC	B348	X300	Raleigh-Cary, NC	39580	YES
Richmond, VA	B350	X300	Richmond, VA	40060	YES

BLS name	PSU	PSU area	Census MSA name	CBSA	Saiz
Beaumont, TX	B352	X300	Beaumont-Port Arthur, TX	13140	YES
Brownsville, TX	B354	X300	Brownsville-Harlingen, TX	15180	YES
Florence, AL	B356	X300	Florence-Muscle Shoals, AL	22520	**NO**
Greenville, SC	B358	X300	Greenville, SC	24860	YES
Ft. Myers, FL	B360	X300	Cape Coral-Fort Myers, FL	15980	YES
Birmingham, AL	B362	X300	Birmingham-Hoover, AL	13820	YES
Melbourne, FL	B364	X300	Palm Bay-Melbourne-Titusville, FL	37340	YES
Lafayette, LA	B366	X300	Lafayette, LA	29180	YES
Ocala, FL	B368	X300	Ocala, FL	36100	YES
Gainesville, FL	B370	X300	Gainesville, FL	23540	YES
Amarillo, TX	B372	X300	Amarillo, TX	11100	YES
San Antonio, TX	B374	X300	San Antonio, TX	41700	YES
Oklahoma City, OK	B376	X300	Oklahoma City, OK	36420	YES
Baton Rouge, LA	B378	X300	Baton Rouge, LA	12940	YES
Odessa, TX	B380	X300	Odessa, TX	36220	**NO**
Chico, CA	B482	X400	Chico, CA	17020	YES
Provo, UT	B484	X400	Provo-Orem, UT	39340	YES
Modesto, CA	B486	X400	Modesto, CA	33700	YES
Boise City, ID	B488	X400	Boise City-Nampa, ID	14260	YES
Las Vegas, NV	B490	X400	Las Vegas-Paradise, NV	29820	YES
Yuma, AZ	B492	X400	Yuma, AZ	49740	YES
Faribault, MN	C212	D200	-	-	**NO**
Chanute, KS	C216	D200	-	-	**NO**
Brookings, SD	C218	D200	-	-	**NO**
Mt. Vernon, IL	C222	D200	-	-	**NO**
Arcadia, FL	C328	D300	-	-	**NO**
Morristown, TN	C332	D300	-	-	**NO**
Picayune, MS	C334	D300	-	-	**NO**
Statesboro, GA	C344	D300	-	-	**NO**
Bend, OR	C450	D400	-	-	**NO**
Pullman, WA	C456	D400	-	-	**NO**

Table B.2: Geographical coverage of BLS PSU sampling.

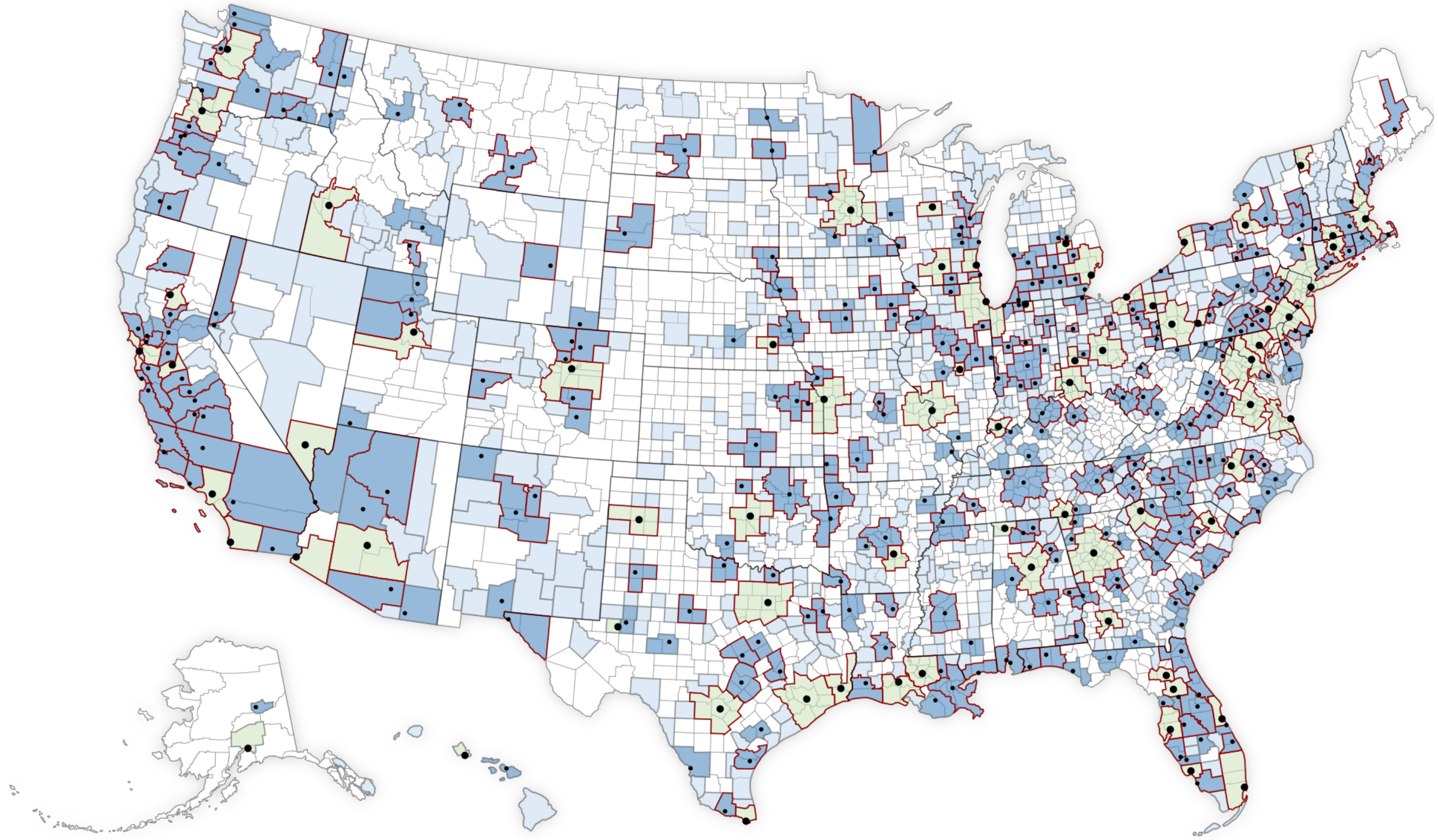
BLS name	PSU ID	Counties included in BLS sampling
Philadelphia, PA	A102	**Delaware:** New Castle.
		New Jersey: Atlantic, Burlington, Camden, Cape May, Cumberland, Gloucester, Salem.
		Maryland: Cecil.
		Pennsylvania: Bucks, Chester, Delaware, Montgomery, Philadelphia.
Boston, MA	A103	**Connecticut:** Windham*.
		Massachusetts: Bristol*, Essex, Hampden*, Middlesex, Norfolk, Plymouth, Suffolk, Worcester*.
		Maine: York*.
		New Hampshire: Hillsborough*, Merrimack*, Rockingham*, Strafford*.
Pittsburgh, PA	A104	**Pennsylvania:** Alleghany, Beaver, Butler, Fayette, Washington, Westmoreland.
New York City, NY	A109	**New York:** Bronx, Kings, New York, Queens, Richmond.
New York Suburbs	A110	**New York:** Dutchess, Nassau, Orange, Putnam, Rockland, Suffolk, Westchester;
		Connecticut: Fairfield, Litchfield*, Middlesex*, New Haven*.
New Jersey Suburbs	A111	**New Jersey:** Bergen, Essex, Hudson, Hunterdon, Mercer, Middlesex, Monmouth, Morris, Ocean, Passaic, Somerset, Sussex, Union, Warren.
		Pennsylvania: Pike.
Chicago, IL	A207	**Illinois:** Cook, DeKalb, DuPage, Grundy, Kane, Kankakee, Kendall, Lake, McHenry, Will.
		Indiana: Lake, Porter.
		Wisconsin: Kenosha.
Detroit, MI	A208	**Michigan:** Genesee, Lapeer, Lenawee, Livingston, Macomb, Monroe, Oakland, St. Clair, Washtenaw, Wayne.
St. Louis, MO	A209	**Illinois:** Clinton, Jersey, Madison, Monroe, St. Clair.
		Missouri: Crawford*, Franklin, Jefferson, Lincoln, St. Charles, St. Louis, Warren, St. Louis City.
Cleveland, OH	A210	**Ohio:** Ashtabula, Cuyahoga, Geauga, Lake, Lorain, Medina, Portage, Summit.
Minneapolis, MN	A211	**Minnesota:** Anoka, Carver, Chisago, Dakota, Hennepin, Isanti, Ramsey, Scott, Sherburne, Washington, Wright.
		Wisconsin: Pierce, St. Croix.
Milwaukee, WI	A212	**Wisconsin:** Milwaukee, Ozaukee, Racine, Washington, Waukesha.
Cincinnati, OH	A213	**Indiana:** Dearborn, Ohio.
		Kentucky: Boone, Campbell, Gallatin, Grant, Kenton, Pendleton.
		Ohio: Brown, Butler, Clermont, Hamilton, Warren.
Kansas City, MO	A214	**Kansas:** Johnson, Leavenworth, Miami, Wyandotte.
		Missouri: Cass, Clay, Clinton, Jackson, Lafayette, Platte, Ray.
Washington, DC	A312	District Of Columbia
		Maryland: Calvert, Charles, Frederick, Montgomery, Prince George's, Washington.
		Virginia: Arlington, Clarke, Culpepper, Fairfax, Fauquier, King George, Loudoun, Prince William, Spotsylvania, Stafford, Warren, Alexandria City, Fairfax City, Falls Church City, Fredericksburg City, Manassas City, Manassas Park City.
		West Virginia: Berkeley, Jefferson.
Baltimore, MD	A313	**Maryland:** Anne Arundel, Baltimore, Carroll, Harford, Howard, Queen Anne's, Baltimore City.

Note: an * indentifies an area that is only covered in part by the PSU.

BLS name	PSU ID	Counties included in BLS sampling
Dallas, TX	A316	**Texas:** Collin, Dallas, Denton, Ellis, Henderson, Hood, Hunt, Johnson, Kaufman, Parker, Rockwall, Tarrant.
Houston, TX	A318	**Texas:** Brazoria, Chambers, Fort Bend, Galveston, Harris, Liberty, Montgomery, Waller.
Atlanta, GA	A319	**Georgia:** Barrow, Bartow, Carroll, Cherokee, Clayton, Cobb, Coweta, DeKalb, Douglas, Fayette, Forsyth, Fulton, Gwinnett, Henry, Newton, Paulding, Pickens, Rockdale, Spalding, Walton.
Miami, FL	A320	**Florida:** Broward, Dade.
Tampa, FL	A321	**Florida:** Hernando, Hillsborough, Pasco, Pinellas.
Los Angeles, CA	A419	**California:** Los Angeles.
Los Angeles Suburbs	A420	**California:** Orange, Riverside, San Bernardino, Ventura.
San Francisco, CA	A422	**California:** Alameda, Contra Costa, Marin, Napa, San Francisco, San Mateo, Santa Clara, Santa Cruz, Solano, Sonoma.
Seattle, WA	A423	**Washington:** Island, King, Kitsap, Pierce, Snohomish, Thurston.
San Diego, CA	A424	**California:** San Diego.
Portland, OR	A425	**Oregon:** Clackamas, Columbia, Marion, Multnomah, Polk, Washington, Yamhill; Washington: Clark.
Honolulu, HI	A426	**Hawaii:** Honolulu.
Anchorage, AK	A427	**Alaska:** Anchorage.
Phoenix, AZ	A429	**Arizona:** Maricopa, Pinal.
Denver, CO	A433	**Colorado:** Adams, Arapahoe, Boulder, Denver, Douglas, Jefferson, Weld.
Reading, PA	B102	**Pennsylvania:** Berks.
Syracuse, NY	B104	**New York:** Cayuga, Madison, Onondaga, Oswego.
Buffalo, NY	B106	**New York:** Erie, Niagara.
Hartford, CT	B108	**Connecticut:** Hartford*, Litchfield*, Middlesex*, New London*, Tolland*, Windham*.
Burlington, VT	B110	**Vermont:** Chittenden*, Franklin*, Grand Isle*.
Sharon, PA	B112	**Pennsylvania:** Mercer.
Johnstown, PA	B114	**Pennsylvania:** Cambria, Somerset.
Springfield, MA	B116	**Massachussets:** Franklin*, Hampden*, Hampshire*.
Wausau, WI	B218	**Wisconsin:** Marathon.
Dayton, OH	B220	**Ohio:** Clark, Greene, Miami, Montgomery.
Evansville, IN	B222	**Indiana:** Posey, Vanderburgh, Warrick. **Kentucky:** Henderson.
Columbus, OH	B224	**Ohio:** Delaware, Fairfield, Franklin, Licking, Madison, Pickaway.
Saginaw, MI	B226	**Michigan:** Bay, Midland, Saginaw.
Elkhart, IN	B228	**Indiana:** Elkhart.
Decatur, IL	B230	**Illinois:** Macon.

BLS name	PSU ID	Counties included in BLS sampling
Youngstown, OH	B232	**Ohio:** Columbiana, Mahoning, Trumbull.
Madison, WI	B234	**Winsconsin:** Dane.
Lincoln, NE	B236	**New Hemspshire:** Lancaster.
Chattanooga, TN	B338	**Georgia:** Catoosa, Dade, Walker.
		Tennessee: Hamilton.
Florence, SC	B340	**South Carolina:** Florence.
Albany, GA	B342	**Georgia:** Dougherty, Lee.
Norfolk, VA	B344	**North Carolina:** Currituck.
		Virginia: Gloucester, Isle Of Wight, James City, Mathews, York, Chesapeake City,
		Hampton City, Newport News City, Norfolk City, Poquoson City,
		Portsmouth City, Suffolk City, Virginia Beach City, Williamsburg City.
Pine Bluff, AR	B346	**Arkansas:** Jefferson.
Raleigh, NC	B348	**North Carolina:** Chatham, Durham, Franklin, Johnstown, Orange, Wake.
Richmond, VA	B350	**Virginia:** Charles City, Chesterfield, Dinwiddie, Goochland, Hanover,
		Henrico, New Kent, Powhatan, Prince George, Colonial Heights City,
		Hopewell City, Petersburg City, Richmond City.
Beaumont, TX	B352	**Texas:** Hardin, Jefferson, Orange.
Brownsville, TX	B354	**Texas:** Cameron.
Florence, AL	B356	**Alabama:** Colbert, Lauderdale.
Greenville, SC	B358	**South Carolina:** Anderson, Cherokee, Greenville, Pickens, Spartanburg.
Ft. Myers, FL	B360	**Florida:** Lee.
Birmingham, AL	B362	**Alabama:** Blount, Jefferson, St. Clair, Shelby.
Melbourne, FL	B364	**Florida:** Brevard.
Lafayette, LA	B366	**Louisiana:** Acadia, Lafayette, St. Landry, St. Martin.
Ocala, FL	B368	**Florida:** Marion.
Gainesville, FL	B370	**Florida:** Alachua.
Amarillo, TX	B372	**Texas:** Potter, Randall.
San Antonio, TX	B374	**Texas:** Bexar, Comal, Guadalupe, Wilson.
Oklahoma City, OK	B376	**Oklahoma:** Canadian, Cleveland, Logan, McClain, Oklahoma, Pottawattamie.
Baton Rouge, LA	B378	**Louisiana:** East Baton Rouge, Livingston, West Baton Rouge
Odessa, TX	B380	**Texas:** Ector, Midland.
Chico, CA	B482	**California:** Butte.
Provo, UT	B484	**Utah:** Utah.
Modesto, CA	B486	**California:** Stanislaus.
Boise City, ID	B488	**Idaho:** Ada, Canyon.
Las Vegas, NV	B490	**Arizona:** Mohave.
		Nevada: Clark, Nye.
Yuma, AZ	B492	**Arizona:** Yuma.

Figure B.1: Map of regressions samples.



Note: The map shows the visual representation of the regressions samples. White territories indicates rural counties. Territories in light blue indicates micropolitan statistical areas (therefore, excluded from our analysis). Territories in blue represent Macropolitan Statistical Areas (MSAs) defined using the 2015 CBSA (Census) definitions. The green territories are MSAs in which the BLS samples to construct the all-cities CPI index. Therefore, the green territories are a subset of the blue ones. There are 73 green territories on the map and they correspond to the 77 "A"s and "B"s PSUs of the BLS CPI. A red boundary indicates an MSA for which the Saiz (2010) was calculated. Finally, a black dot indicates the geographical location of the most populated city in each MSA. Source: Country-level administrative areas shapes data are from DIVA-GIS (availabel at: http://www.diva-gis.org/Data). MSA shapes are from Census (available at: https://catalog.data.gov/dataset/tiger-line-shapefile-2015-nation-u-s-current-metropolitan-statistical-area-micropolitan-statist). CPI sampling areas are from BLS (available at: https://www.bls.gov/cpi/).

C The CPI Research Database

Table C.1: Number of observations - BLS research database.

PSU code	# PSUs	Variable	Mean	Std. Dev.	Min	Max
”A”	31	# observations	19,371	7,259	13,445	40,469
”B”	46	# observations	7,184	405	6,458	7,931
”C”	10	# observations	8,256	563	6,941	8,978

Note: The table shows descriptive statistics of the BLS CPI research micro dataset, by PSU. PSUs are categorized in 3 groups according to the population size (“A”, “B”, or “C”), see paragraphs above for details. Raw “# observations” refers to the total number of observations (that is, total number of individual item price) registered in each year, by PSU group. All figures are rounded to the closest integer. The total number of observations is around 1 million per year (for instance, in 2014 the database contains 1,035,606 observations). **Source:** authors’ calculation on BLS CPI research database data.

D NAICS industry classification

Table D.1: Two-digit NAICS industry classification.

NAICS code	Industry name		
11	Agriculture, forestry, fishing, and hunting	Other	Goods
21	Mining, quarrying, and oil and gas extraction	Tradable	Goods
22	Utilities	Other	Services
23	Construction	Construction	Construction
31-33	Manufacturing	Tradable	Goods
42	Wholesale trade	Other	Distribution
44-45	Retail trade	Non tradable	Distribution
48-49	Transportation and warehousing	Non tradable	Services
51	Information	Other	Services
52	Finance and insurance	Other	Services
53	Real estate and rental and leasing	Contruction	Services
54	Professional, scientific, and technical services	Other	Services
55	Management of companies and enterprises	Other	Services
56	Administrative and support and waste management and remediation services	Other	Services
61	Educational services	Other	Services
62	Health care and social assistance	Other	Services
71	Arts, entertainment, and recreation	Other	Services
72	Accommodation and food services	Non tradables	Services
81	Other services (except public administration)	Other	Services
92	Government and government enterprises	Not classified	Not classifed

E Data sources

Table E.1: Data sources

Data	Source	MSA classification
Employment data	Census County Business Patterns (CBP)	Census IDs
	https://www.census.gov/programs-surveys/cbp.html	
Payroll data	Census County Business Patterns (CBP)	Census IDs
	https://www.census.gov/programs-surveys/cbp.html	
Gross Domestic Product data	BEA Regional Accounts	OMB IDs
	https://www.bea.gov/regional/	
Number of firms	Census County Business Patterns (CBP)	Census IDs
	https://www.census.gov/programs-surveys/cbp.html	
Number of establishments	Census County Business Patterns (CBP)	Census IDs
	https://www.census.gov/programs-surveys/cbp.html	
RPPs	BEA Regional Accounts	OMB IDs
	https://www.bea.gov/regional/	
Micro CPI	BLS	PSUs
	https://www.bls.gov/cpi/	
House Prices	Zillow	Census IDs
Saiz instrument	Saiz (2010)	Saiz (2010) IDs
	https://urbaneconomics.mit.edu/albert-saiz	
Warton regulatory index	Gyourko et al. (2008)	Census IDs
	http://real.wharton.upenn.edu/~gyourko/landusesurvey.html	
Demographic data	American Community Survey	Census IDs
	https://usa.ipums.org/usa/acs.shtml	
Unemployment data	BLS Local Area Unemployment Statistics	Census IDs
	https://www.bls.gov/lau/	
Home ownership rates	Housing Vacancies and Homeownership (CPS/HVS)	Census IDs
	https://www.census.gov/housing/hvs/index.html	
Case-Shiller composite index	http://www.econ.yale.edu/~shiller/data.htm	-
U.S. 10-year interest rate	Bloomberg	-

F Regional Price Parities (RPPs)

The Bureau of Economic Analysis (BEA) provides estimates of Regional Price Parities (RPPs) for U.S. States and U.S. Metropolitan Statistical Areas. The RPPs dataset is part of the regional account datasets and it is freely available on the BEA website.[18] Here below we summarize the BEA methodology used to estimate the RPPs. Additional details are available on the BEA website.[19]

Definitions. RPPs are price indexes that measure geographic price level differences for one period in time within the United States. According to the BEA definition, an RPP is *"a weighted average of the price level of goods and services for the average consumer in one geographic region compared to all other regions in the U.S. BEA's estimates of real personal income consist of the current dollar estimates adjusted by the RPPs and converted to constant dollars using the U.S. PCE price index. The RPPs use only price and expenditure-related survey data that are collected by U.S. federal agencies. These include the BLS' CPI price survey and the Census Bureau's ACS housing survey. RPPs are based on the CPI sampling of 38 metropolitan and urban areas, represent about 89% of the total population. The 38 CPI index areas are designed to represent the U.S. urban and metropolitan population. Of the 38 areas, 31 represent large metropolitan areas, 4 represent small metropolitan regions, and 3 represent urban non metropolitan regions".*

Methodology. The methods and results involve a two-stage, rolling average estimation process. The first stage estimates annual multilateral price level indexes for CPI areas and for several consumption expenditure classes such as apparel, food and transportation. In the second stage, the price levels and expenditure weights are allocated from CPI areas to all counties in the United States. They are then recombined for regions, such as states and metropolitan areas, and merged with data on rents from the Census Bureau's American Community Survey (ACS). The ACS provides more detailed geographic coverage than the

[18] Regional data are available at: https://www.bea.gov/regional/.
[19] Full BEA methodology is available at: https://www.bea.gov/regional/pdf/RPP2016_methodology.pdf.

CPI areas, including county-level data, thus allowing us to augment the allocated CPI price levels with observed housing observations. The final RPPs are calculated by stacking five years of the first-stage results, plus the annual rent indexes, and calculating the multilateral aggregate price index for all goods and services and rents. For example, the 2010 RPP is a five-year average of the 2008-2012 CPI-derived price indexes for goods and services excepting rents, plus the 2010 rent indexes from the ACS.

Additional details. While the first stage of the BEA methodology is closely related to the BLS methodology to produce the aggregate CPI index for all U.S. cities, it seems worth giving additional details about the second stage. The second stage begins with the allocation of price levels and expenditure weights from CPI areas to counties. Price levels for each county are assumed to be those of the CPI sampling area in which the county is located. For example, counties in Pennsylvania are assigned price levels from either the Philadelphia or Pittsburgh areas or from the Northeast small metropolitan area. Rural counties are not included in any of the 38 urban areas for which stage one price levels are estimated, therefore these counties are assigned price levels of the urban area that (1) is located in the same region and (2) has the lowest population threshold. Expenditure weights in the second stage include CPI data for rural regions, and thus in combination with the 38 urban areas, cover all U.S. counties. Weights are allocated from each CPI area and rural region to the component counties in proportion to household income.

The county-level allocations undergo two adjustments. First, the distribution of rent weights is replaced with one based on directly observed rent expenditures from the 5-year ACS file plus imputed owner-equivalent rent expenditures. The second adjustment to the county level weights is to control the national shares of the 16 expenditure classes to BEA's personal consumption expenditure shares. This yields weights consistent with BEA's national accounts. The adjustment shifts the distribution of weights across expenditure classes, notably reducing the share of rents expenditures from total consumption in the United States from 30.2 percent to 20.6 percent. Once the county price levels and expenditure weights have been obtained for each class and for each year as outlined above, the BEA takes the weighted geometric mean of the price levels for states, state metropolitan and nonmetropolitan portions, and metropolitan areas. This weighted geometric mean is a five-year rolling average for goods and services other than rents.

Rent price levels are estimated directly from tenant rent observations in the ACS: annually for states, and across 3 years for metropolitan areas. No imputation of owner-occupied rents is used in the price levels, instead the BEA uses rent price levels for both renters and owners. The rent price level estimates are quality-adjusted using a hedonic model that controls for basic unit characteristics such as the type of structure, the number of bedrooms and the total number of rooms, when the structure was built, whether it resides in an urban or rural location, and if utilities are included in the monthly rent. In the second multilateral aggregation the BEA uses the five-year rolling average for the 15expenditure classes derived from the BLS CPI, together with the one-year state level rents and three-year metropolitan area rents from the Census ACS to estimate the final all items RPPs. For expenditure weights, the BEA uses one-year files for states and three-year files for metropolitan areas. The multi-year rolling averages imply that for 2010, for example, final state-level RPPs are composed of rent price levels in 2010 plus an average of the price levels for goods and services other than rents between 2008 and 2012.

Statistical areas. Since different agencies define Metropolitan Statistical Areas (MSAs) using different aggregation methods, it is worth mentioning that the BEA currently follows the definitions of the Office of Management and Budget in bulletin no. 15-01 issued July 15, 2015, and the definitions are updated as new information warrants. When OMB adds a new statistical area, BEA creates a time series for it starting in the earliest year in which data is available, even though it may not have had any urban area at the time. Similarly, when OMB changes the definition of a statistical area, BEA recreates the time series for that area, using the new definition for every year in the time series, published at the scheduled release date of the data set. (see https://www.bea.gov/regional/docs/msalist.cfm).

Results using RPPs

Table H.1: Effect of house price change on Regional Price Parities (RPP).

	Rents	
	OLS	IV
House Prices	0.10	-0.05
	[0.02]***	[0.12]
Unemployment rate	0.42	-0.23
	[0.19]**	[0.58]
Controls	Yes	Yes
Observations	253	253
R^2	0.27	0.18

Note: robust standard errors are clustered by State in brackets. "OLS" refers to Ordinary Least Squares. "IV" refers to Instrumental Variables. The above regressions refer to the time period 2008-2011. The upper panel refers to all MSAs in the BEA dataset while the bottom panel refers to all MSAs in the BEA dataset with non-repeated observations. "Services" refers to services excluding rents. "Rents" refer to actual rents, excluding owners equivalent rents. The dependent variable is the delta-log of Regional Price Parity (RPP) (for "All items", "Goods", "Services", and "Rents"). RPPs are calculated using PCE inflation definitions and weights. Regional price parities (RPPs) are regional price levels expressed as a percentage of the overall national price level for a given year. The price levels are determined by the average prices paid by consumers for the mix of goods and services consumed in each region. "House Prices" refers to the log of house price index in each MSA. All regressions include a set of demographic controls: change in (total) population, change in the share of population with a college degree, change in the share of population above 14 and 65 years old. In the IV the instrument is the estimates of housing supply elasticities from Saiz (2010). **Source:** RPPs data come from the BEA regional economic account dataset (available at: https://www.bea.gov/regional/). House prices data come from CoreLogic (available at: http://www.corelogic.com).