Regional Inequality in the U.S.: Evidence from City-level Purchasing Power

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Abstract

This paper investigates the empirical facts and the drivers of regional inequality in the U.S. using a micro panel dataset of city-level purchasing power for 43 products in 41 cities over the period 1990.Q1-2015.Q4. We focus on two questions: (i) how widely is purchasing power dispersed among U.S. cities and how has the geographic dispersion evolved over time; and (ii) what factors are associated with the fluctuations in the purchasing power and with the evolution of the geographic disparities. We find a large cross-city dispersion in the purchasing power and the geographic dispersion has been on the rise for the sample period. Our analysis based on a Global VAR (GVAR) representation reveals that common national shocks account for about 30-35% of the variance of fluctuations in local purchasing power. The impulse responses to national shocks show differing magnitudes depending on the product and city characteristics, with greater effects in high-skilled cities and for products that have more flexible pricing. For the growing geographic disparities of purchasing power, we find some main macroeconomic variables, such as national GDP or total factor productivity (TFP), have predictive power on the rise in regional inequality. The predictability of macroeconomic variables, however, varies significantly with the characteristics of products and cities. Our subsample analysis suggests the regional inequality observed in the data might have proceeded in the cities with higher concentration of skilled workers and higher income over time primarily through the products with more flexible price adjustments.

Keywords: Regional inequality, Purchasing power, U.S. cities, GVAR model, National shocks.

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1 Introduction

Over the past few decades, income inequality in the U.S. has received a great deal of interest and inquiry from both researchers and policymakers. While there exists voluminous research on the topic (e.g., Acemoglu, 2002; Attanasio et al., 2012; Autor et al., 2008; Iacoviello, 2008; Piketty and Saez, 2003; Piketty et al., 2017; to cite a few), relatively insufficient attention has been paid to the issue on the geographic dimension. At the national level, previous literature often attributes the surge in income inequality to several factors, including the skill-biased technology progress, the impact of globalization and international trade, and the change in the labor market institutions such as unionization and minimum wage. In light of the nontrivial differences in the regional economic environments and heterogeneous regional shocks (e.g, Beraja et al., 2017; Carlino and DeFina, 1998; Hurst et al., 2016; Yoon, 2017), it is unlikely these factors have similar impacts on regional economies, as evidenced by the widening gap in income and wages across U.S. cities (e.g., Hsieh and Moretti, 2015; Moretti, 2013; Peri et al., 2015). For example, localized skill-biased technological progress is known to have taken place predominantly in the so-called information-economy cities like San Francisco and Boston that have experienced faster income growth than the national average. Since economic welfare is typically defined over consumption goods rather than income, however, it remains unclear whether this spatial inequality of incomes or wages has actually translated into an uneven geographic distribution of purchasing power. If cities with systematically higher income levels have higher consumer prices as often postulated in popular theoretical models (e.g., the classic Rosen-Roback model), the geographic inequality may not be as serious as it looks when high income levels are offset by high cost of living. Yet, in the dearth of an appropriate measurement for the cost of living across space, little is known about the extent and evolution of the regional inequality in the U.S. and far less is understood about the channels through which the observed nominal income differences are transmitted to the regional disparities in purchasing power. In fact, more recent studies (e.g., Atkin and Donaldson, 2015; DellaVigna and Gentzow, 2017; Jaravel, 2016) document that local retail prices are not necessarily higher in high-income areas due to lower trade costs, uniform pricing by retail chains, and higher rates of product innovation, that might have contributed to rising regional inequality.

The current study aims to fill this void by investigating the empirical facts and explanatory factors of regional inequality in the U.S. using a novel measure of real wage inequality, the purchasing power of wages (henceforth, purchasing power) at the city and product level. Constructed by dividing city-level wages by retail prices of individual consumer products, our measure of purchasing power captures the number of product units that can be purchased with an average wage in each city. Using this measure, we attempt to address the following questions: (i) how widely is purchasing power dispersed among U.S. cities and how has the geographic dispersion evolved over time; and (ii) what factors are associated with the fluctuations in the purchasing power and with the evolution of the geographic disparities. To this end, we utilize a quarterly retail price dataset from the American Chamber of Commerce Researchers Association (ACCRA) for a variety of goods and services purchased by consumers in the U.S. As the longest available dataset of absolute consumer prices for individual goods and services, the ACCRA dataset is well suited for the purpose of this study by virtue of the homogeneity of products across locations. Because the underlying observations are collected consistently, by a single organization, from a survey of consumers in a similar pool (the mid-level managers), the ACCRA data facilitates comparisons across locations. A broad coverage of this dataset in terms of product, city and time also permits us to conduct diverse econometric analyses to search for the sources of regional inequality across locations as well as across products. For example, we regress local purchasing power onto a set of location-specific explanatory variables within the framework of Global VAR (GVAR) model, which allows us to track the dynamic impacts of both national and local shocks.

Having said that, our paper is obviously not the first to study the regional inequality in the U.S. In fact, there is now a growing literature on the regional income or wage differences in the U.S. (e.g., Albouy, 2016; Diamond, 2016; Moretti, 2013, to cite a few). The current study, however, distinguishes itself from earlier contributions on a couple of grounds. First, we focus on the regional inequality of purchasing power of wage, instead of geographic differences in nominal income or wage. Second, our study focuses on the dynamic behavior of the inequality across U.S. metro areas over time in the belief that temporal variations of the geographic disparities can provide useful intuition in understanding the key issues at hand. Most previous studies in this direction look at cross-sectional variations of inequality with no explicit consideration on the cost-of-living differences across locations. As often pointed out in the literature, however, failure to correct for local prices is likely to misguide subnational income inequality. Indeed, it has long been recognized that a prominent feature of the cost-of-living in the U.S. is the considerable dispersion across locations with highly heterogeneous dynamics of regional prices. Some notable exceptions in this regard include the recent work by Beraja et al. (2014), DellaVigna and Gentzow (2017), Handbury (2012), and Handbury and Weinstein (2015) which employed micro price datasets (e.g., Nielsen or the IRI Database) to construct local- or state-level price indices. These studies, however, focus on the regional differences of the cost-of-living *per se* and hence neither extend it to the context of purchasing power inequality at the city level, nor look at the dynamic behavior of inequality over time.

Our analysis yields some interesting results. We find a large geographic dispersion in the purchasing power among the selected U.S. cities and the extent of the geographic dispersion differs broadly across products. For example, the ratio between the greatest purchasing power city (where consumers can buy the most amount of products with the average wage) relative to the least purchasing power city (where consumers can buy the least amount of products with the average wage) is in the range of 1.52 and 2.38, implying that consumers in the greatest purchasing power city can purchase 52% to 138% more goods or services than those in the least purchasing power city. In view of the homogeneity of products across locations in terms of the brand names and the key features, this size of purchasing power gap among sub-national economies is quite stunning. We further find that the geographic disparities in purchasing power do not attenuate over time. This can be seen from Figure 1, which plots the paths of the average purchasing power over the sample period in the top three cities (dotted line) and that in the bottom three cities (solid line) for various products. There is no sign of convergence over time between the two groups in all products considered. This finding is reinforced by Figure 2 which exhibits three different measures of the cross-city dispersion of purchasing power over the sample period: coefficient of variation (CV), 90-10 percentile ratio and 75-25 percentile ratio. The clear upward trends displayed in the plots, which are reminiscent of the time series plots of typical macroeconomics variables, indicates that the geographic dispersion of purchasing power has grown over time regardless of the measures of dispersion. This result squares well with the more recent findings in the literature (e.g., Kennan and Walker, 2011; Yoon, 2017) on the rising cross-city disparities in purchasing power.

Our regression analysis based on the GVAR model sheds some intuitive light on the transmission channels by which shocks influence the city-level purchasing power changes. National shocks play an important role in the fluctuations of purchasing power in most products under study. The cumulative effect of a nationwide unemployment shock, for instance, has a stronger effect on purchasing power in the vast majority of products considered, compared to local idiosyncratic shocks in the labor market. A surprise increase in the national unemployment rate hampers local purchasing power by lowering local wages more than consumer prices, which in turn reduces the number of goods and services available for city-level wages. These results seem at odds with a common belief, when a negative shock to income or wealth hits consumers in an area, the impact on purchasing power and hence welfare will be offset to some extent by reductions in local retail prices. That is, shocks that decrease local costs may not necessarily be reflected in lower consumer prices. We further find compelling evidence that the response of purchasing power to nationwide unemployment shocks is greater in high-skilled cities and for products that have more flexible pricing. At the city level, local purchasing power is more responsive to a national unemployment shock in cities which have a greater portion of high-skill workers holding at least a bachelor's degree. This outcome conforms to the widespread view that skill-biased geographic sorting may have contributed to the growing regional inequality in the purchasing power of U.S. cities. At the product level, the importance of national shocks is meaningfully associated with certain product characteristics such as the degree of price flexibility, i.e, local purchasing power is more responsive to national shocks in the products whose prices are adjusted more frequently.

For the growing regional inequality of local purchasing power, we find main macroeconomic variables have some predictive power of it. An increase in national macroeconomic variables such as real GDP and total factor productivity (TFP) precedes a greater geographic dispersion of local purchasing power, but not vice versa. The extent of their predictive power on the evolution of regional inequality again hinges on the characteristics of products and cities. Our empirical results from subgroup analysis uncover that the rise in regional inequality of local purchasing power after an increase in national macroeconomic variables takes place primarily in the products whose prices are adjusted more frequently and in the cities with a higher concentration of skilled workers, larger population and higher per capita income. This result can be interpreted as saying that the regional inequality in the U.S. might have had proceeded over the past two decades mainly in the cities with a higher concentration of skilled workers and higher per capital income through the products with more flexible price adjustments.

The remainder of this paper is organized as follows. The next section describes the data employed in the paper and provides a descriptive analysis for our measure of purchasing power. We also discuss the geographic distribution of purchasing power and its evolution over time. Section 3 lays out our empirical analysis based on a multitude of econometric tools to make quantitative assessments of the regional inequality of purchasing power before searching for the potential factors that account for the variation and evolution of regional inequality observed in the data. Section 4 concludes the paper. The Appendix contains a detailed description of the data and the technical notes on GVAR estimation.

2 Data and diagnostic analysis

2.1 The data

Our city-level purchasing power is constructed from micro-level data from two sources: (i) quarterly retail price data for selected U.S. cities from the American Chamber of Commerce Researchers Association (ACCRA); and (ii) city-level quarterly wage and unemployment rate data from the Bureau of Labor Statistics (BLS).

The panel dataset for individual retail prices comes from the ACCRA's quarterly retail price survey publication, *Cost of Living Index*, which has a broad coverage of consumer products for both goods and services. Prices in this dataset are quoted inclusive of all sales taxes levied on the products by state, county, and municipal governments. The selection of cities and products was governed by the requirement of having continuous data observations since 1990. Consequently, a balanced panel of prices for 43 products in 41 cities is obtained, resulting in the total number of time series of 1,753.[1] The sample covers a relatively long time span, 1990.Q1 to 2015.Q4, which is crucial for tracing out the dynamic behavior of geographic purchasing power distribution over time. Details about the data are provided in tabular form in Appendix A where summary descriptions of these price data are reported in Table A.1 along with the city-level information listed in Table A.2. As noted earlier, product homogeneity is an attractive feature of our price data in the comparison of purchasing power across different locations. The survey prices are absolute prices for specific goods and services collected in a consistent manner from a particular pool of consumers (mid-level managers) by a single agency and hence refer to almost the same product at different locations. To be specific, the definition of products is very specific and includes the brand name, weight, model, and other identifying information, such as *Steak* (one pound, USDA Choice), *Soft Drink* (two liters, Coca Cola), *Gasoline* (one gallon, regular unleaded), and *Beauty Salon* (woman's shampoo, trim, and blow dry).

With that said, the ACCRA data are not without drawbacks. Since the prices are collected in stores that offer different amenities and for products that are of different quality even within the same narrow product category, they may overstate cross-city price differences. Moreover, some products in our dataset may not be exactly identical across cities partly because specific information on brand names is missing for several goods and also because the quality of some services (e.g., medical services) is not necessarily homogeneous across different locations. In addition, the ACCRA data contains price quotes only without information about the quantities of each products purchased. This prevents us from constructing an overall price index in each city that would summarize price level differences across locations.[2] Next, the ACCRA survey price data is intended to reflect the purchasing pattern of "middle management" household with an income level typically in the top 20 percent of each city,

[1] Due to the unavailability of price data for the entire sample period, some major large cities like New York, Chicago and San Francisco are not included in our dataset.

[2] For this purpose, national level CPI expenditure weights could be used alternatively, but they are not suitable for our analysis because they do not vary frequently over time.

who might have different shopping behaviors from the median income level household (e.g., Argente and Lee, 2017). Despite these limitations, we stick to the dataset not just because it allows us to go beyond the supermarket related products typically used in the previous studies (e.g., Beraja et al., 2014; Handbury, 2012), but because its long data span is crucial for tracking the dynamic behavior of regional inequality.

Following the convention in the literature, we consider explanatory variables for the regression analysis that may influence local purchasing power. Although theory offers a long list of factors that might explain cross-city differences in the purchasing power, city-level unemployment rates and house prices stand out as they are closely related to both consumer prices and wages that constitute local purchasing power (e.g., Case and Shiller, 2003). The data on city-level unemployment rates is the seasonally adjusted quarterly observations, which are collected from the BLS's *Local Area Unemployment Statistics (LAUS)* program (https://www.bls.gov/lau/). We take the data on city-level wages from the *Quarterly Census of Employment and Wages (QCEW)* dataset of the BLS (*https://www.bls.gov/cew/*). Compiled from the tabulation of employment and wages of all establishments reporting to the Unemployment Insurance (UI) program, the QCEW data are released by state governments for each quarter and are known to be the longest quarterly panel of wage data.[3]

We also consider local house prices as another control variable for local economic welfare. As a leading indicator for real economic activity as well as inflation (e.g., Stock and Watson, 2003), house prices are known to have significant direct and indirect effects on purchasing power, not just because they tend to move in line with changes in income, but also because spatial dispersion of house prices could lead to differences in the cost of living across locations (e.g, Hsieh and Moretti, 2015; Moretti, 2013; Stroebel and Vavra, 2015). It is often documented in the literature that differences in incomes across locations have been increasingly capitalized into house prices and thus patterns of consumer prices and house prices suggest a close relationship between the two over time and space (e.g., Gyourko et al., 2013; Moretti, 2013; Van Nieuwerburgh and Weill, 2010).[4] The city-level house price data are obtained from the ACCRA dataset as well.

We further consider several city characteristics that may affect local purchasing power, such as

[3] According to the BLS website (*https://www.bls.gov/cew/#faq*), *'the quarterly reports represent about 97% of all wage and salary civilian employment in the country. Wages include bonuses, stock options, severance pay, profit distributions, cash value of meals and lodging, tips and other gratuities, and, in some states, employer contributions to certain deferred compensation plans such as 401(k) plans. Covered employers in most states report total compensation paid during the calendar quarter, regardless of when the services were performed.'*

[4] Nieuwerburgh and Weill (2010) find house prices compensate for cross-sectional productivity differences reflected in the dispersion of wages. By contrast, Gyourko et al. (2013) maintain that a change in the house price induces a change in the local income distribution.

the ratio of high-skilled workers, city size measured by average population, and the average income level. These data are downloaded from the BEA website (*https : //www.bea.gov/*). The fraction of skilled workers is considered because skill-level is known to be an important driving force behind local productivity, income and hence purchasing power. Given the emphasis conventionally placed on human capital as a determinant of city productivity and prosperity, it is likely the share of high-skilled workers is a relevant factor for cross-city differences in the purchasing power. Furthermore, it is broadly agreed the cities with a higher share of college graduates not only experienced larger increases in wages, but also had larger increases in amenities. The skill-level of cities is measured by the proportion of city residents over 25 years old with at least a bachelor's degree.

2.2 Diagnostic analysis and cross-sectional dependence

Table 1 reports the summary statistics of average city-level purchasing power by products. Entries in the table denote the units of consumer products that can be purchased by a *daily* wage rate, except for 'Apartment rent' (using monthly wage). The first three columns present the cross-city mean, minimum and maximum values of the local purchasing power. Take 'Steak' for example, the mean value of 13.09 implies consumers in the 41 U.S. cities on average could buy about 13 pounds of USDA choice-grade steak beef with daily wage. Depending on where they live, however, the purchasing power of daily wages varies considerably from just over 10 pounds in the least affordable city to more than 18 pounds in the most affordable city. That is, consumers living in the most affordable city have almost 80 percent more purchasing power on steak beef than those in the least affordable city. A similarly large intercity gap is seen in other products. As reported in the fourth column of the table, the 'ratio' of purchasing power between the most affordable city to the least affordable city ranges from 1.52 for 'Movie ticket' to 2.38 for 'Appliance repair'. This size of purchasing power gaps among subnational economies is hardly attuned to the convergence of purchasing power across locations. Since the ratio is quite large for some products that are conventionally categorized as tradables like 'Bread', while it is relatively small for some nontradable products like 'Auto maintenance', tradeability of product may not serve as a potential explanation for the significant cross-product heterogeneity in the purchasing power. This argument can be readily supported by looking at three measures of cross-city dispersion of purchasing power presented in the last three columns of Table 1: the coefficient of variation (CV), 90-10 percentile ratio and 75-25 percentile ratio. The cross-city disparities of purchasing power vary considerably across products. Some products like 'Movies' and 'Gas' have relatively small dispersions across cities, indicating that purchasing power is not really geographically dispersed in those products, while the dispersions of other products such as Newspapers and Potatoes are quite large. Again, there seems to be no clear indication that the cross-city dispersion of purchasing power is meaningfully associated with the conventional product classification such as tradeability.

Since spatial relationships exist among subnational economies typically from geographic interactions of one city to another in the form of spillover of shocks or mobility of production factors, local purchasing power is liable to be geographically dependent to a certain extent. In the presence of factor mobility, for instance, spatial interdependence across cities may be prompted by interactions among cities when economic agents migrate from one region to another region in search of higher purchasing power. Alternatively, the geographic interdependence of purchasing power can arise from firms' exercising price discriminations across cities with different cost of living (e.g., Ngene et al. 2016). As pointed out by Vega and Elhorst (2016), regional economic activities like unemployment rates tend to be strongly correlated across space, parallel to the nation-wide economic conditions. This spatial dependence is not only informative for the dynamic behavior of local purchasing power, but also important for the econometric analysis of our panel data. In consequence, it is instructive to explore the pattern of geographic interdependences of purchasing power across cities by looking at its comovements over time. The literature (e.g., Chudik et al., 2011; Pesaran and Tosetti, 2011; Bailey et al. 2016a) emphasizes the distinction between strong cross-sectional dependence (CSD) which is often modeled by a factor model with strong factor loadings and weak CSD that is compatible with conventional spatial models in the literature.

To gauge cross-sectional dependence of local purchasing power, we employ several popular approaches: (i) average pair-wise correlation measure constructed by $\hat{\bar{\rho}} = 2N^{-1}(N-1)^{-1}\sum_{i=1}^{N}\sum_{j=i+1}^{N}\hat{\rho}_{ij}$ where $\hat{\rho}_{ij}$ denotes a pair-wise sample correlation between cities i and j; (ii) the cross-sectional dependence test developed by Pesaran (2004) defined by $CD = TN(N-1)\hat{\bar{\rho}}/2 \xrightarrow{d} N(0,1)$; and (iii) the exponent of CSD ($\hat{\alpha}$) proposed by Bailey et al. (2016b) which can be used to distinguish between the strong and weak CSDs.[5] Table 2 presents the summary statistics of the spatial correlation of purchasing power for each product. As presented in the left-hand panel of Table 2, there is a significant comovement and interdependence of purchasing power among U.S. cities in all products considered. The average pair-wise correlation ($\hat{\bar{\rho}}$) is positive for all products, with the wide range of 0.074 ('Tennis Balls') and 0.891 ('Gasoline'). Again, the cross-product variations in the spatial correlation do not seem to match the conventional categorizations of products based on tradeability. The Pesaran's

[5] The exponent of cross-sectional dependence ($\hat{\alpha}$) is defined by s.d.$(\bar{x}_t) = O(N^{\alpha-1})$, where $\bar{x}_t$ is the simple cross-section average of the variable x_{it}.

CD-test statistic is also consistently larger than the critical value of 1.96 at the 5% significance level for all products, suggesting that the local purchasing power is highly correlated across cities. To test whether the nature of the observed cross-sectional dependence is weak or strong, the exponent α-test of Bailey et al. (2016b) is also applied. This test statistic can take values on the interval 0 to 1; $\alpha \leq 0.5$ points to weak CSD and $\alpha = 1$ to strong CSD (see Bailey et al., 2016a, p.254). Given the estimates of the exponent of CSD ($\hat{\alpha}$) are consistently above 0.8 for all products and the null of $\alpha = 1$ cannot be rejected for most products, we conclude that the spatial correlation in the purchasing power among U.S. cities is strong for most products.

The strong cross-city comovement of purchasing power is likely driven by the factors common to various locations, such as the nationwide shocks or business cycle. Although it has been generally viewed that fully synchronized cycles are not the feature of regional business cycles in the U.S. due to heterogeneous regional shocks or differences in economic and non-economic environments, regional business cycles in the U.S. tend to take a similar profile to the national cycle identified by the NBER (e.g., Hamilton and Owyang, 2012; Owyang et al., 2005). The strong intercity dependence observed in the purchasing power could have been driven by this commonality of the regional business cycles or common national shocks. It is therefore important to account for this feature in carrying out econometric analysis.

3 Empirical analysis

Our analysis so far underscores that local purchasing power is widely dispersed across U.S. cities and the geographic dispersion has been on the rise as shown in Figure 2. What is less known is what factors are associated with the variations of purchasing power over space and time. The focus of this section will be addressing these questions via a multitude of regression analyses. We first carry out an econometric analysis based on the Global VAR (GVAR) model to study the driving forces behind the growth rates of purchasing power. Our focus here rests on the question of whether the cyclical movements in regional inequality are driven by nationwide shocks or local shocks. We then move to probe the factors that can account for the growing dispersion of purchasing power over time using various time series econometrics techniques. In view of the clear upward trend shown in Figure 2, cointegration techniques are useful for identifying such factors that share the same stochastic trend with the regional inequality pattern. Moreover, we implement the Granger causality test within the framework of a vector error correction model (VECM) to establish the direction of predictability between candidate macroeconomic variables and measures of regional inequality.

3.1 GVAR representation of the changes in regional purchasing power

Originally introduced by Pesaran et al. (2004) and subsequently extended by numerous contributions, the GVAR approach is a particularly useful tool on several grounds.[6] First, it can account for a rich pattern of dependence across space (cross-section units) and time. Specifically, it accounts for strong CSD found in the data by means of unobserved common factors, as well as weak CSD after conditioning on the unobserved common factors and their lags. Second, the GVAR model allows for sufficient heterogeneity across cities and products. This is an important feature because there seems to be no strong *a priori* reason to believe that any of the estimated slope coefficients are homogeneous.[7] Third, the GVAR model permits us to treat all variables as endogenous.

Let us define the following variables:

$$
\begin{array}{ll}
y_{mit} = \ln\left(\frac{W_{it}}{P_{mit}}\right) & \text{purchasing power of product } m \text{ in city } i \text{ at time } t, \\
ur_{it} & \text{unemployment rate in city } i \text{ at time } t, \\
hp_{it} = \ln\left(HP_{it}\right) & \text{house prices (in logs) in city } i \text{ at time } t,
\end{array}
$$

where $m = 1, 2, ..., M$, $i = 1, 2, ..., N$, and $t = 1, 2, ..., T$. y_{mit} represents the purchasing power in terms of product m, in city i, at time t, computed as the log of nominal wage (W_{it}) divided by the price of product m, in city i (P_{mit}); ur_{it} is the seasonally adjusted unemployment rate in city i, at time t; and hp_{it} denotes the log house price for city i at time t. Our sample covers $M = 43$ consumer products, $N = 41$ cities and $T = 104$ quarters spanning 1990.Q1 to 2015.Q4. We refer to the city dimension as the cross-section dimension, if not specified otherwise. We collect the first differences of these variables in the 3×1 vector $\mathbf{z}_{mit} = (\Delta y_{mit}, \Delta ur_{it}, \Delta hp_{it})'$. In addition, we define a 4×1 vector of national cross-section averages (aggregates)

$$
\bar{\mathbf{z}}_{mt} = \begin{pmatrix} \Delta \bar{y}_t \\ N^{-1} \sum_{i=1}^{N} \mathbf{z}_{mit} \end{pmatrix},
$$

featuring the double cross-city and cross-product average of purchasing power variables ($\Delta \bar{y}_t = \frac{1}{NM} \sum_{i=1}^{N} \sum_{m=1}^{M} \Delta y_{mit}$) as well as cross-city averages of $\mathbf{z}_{mit}$. The vector of granular averages $\bar{\mathbf{z}}_{mt}$ is used to approximate unobserved common factors (if present) as is now common in the literature

[6] For a further discussion on the GVAR model, the reader is referred to Chudik and Pesaran (2016).

[7] As noted by Pesaran and Smith (1995), a false imposition of homogeneity restriction in a dynamic setting will result in an inconsistent estimation.

(e.g., Pesaran, 2006).[8] We also define the local or neighbor averages

$$\mathbf{z}_{mit}^{*} = \sum_{j=1}^{N} w_{ij}\mathbf{z}_{mjt},$$

where $\{w_{ij}\}$ is the local weights defining neighbors and their relative importance. Following standard practice in the literature and in the absence of any other prior knowledge, the weights are constructed based on the geographic contiguity proxied by state membership. The weights satisfy $w_{ii} = 0$ and are normalized without a loss of generality, such that $\sum_{j=1}^{N} w_{ij} = 1$ for each i. By including temporal lags of $\mathbf{z}_{mit}^{*}$, we allow for local neighborhood effects in the reduced-form VAR representation of the data, as defined by Chudik and Pesaran (2011).

We estimate the following cross-section augmented least square (CALS) regressions for each product m separately,

$$\mathbf{z}_{mit} = \sum_{\ell=1}^{p} \mathbf{\Phi}_{mi\ell}\mathbf{z}_{mi,t-\ell} + \sum_{\ell=0}^{p} \mathbf{B}_{mi\ell}\bar{\mathbf{z}}_{mt-\ell} + \sum_{\ell=1}^{p} \mathbf{\Psi}_{mi\ell}\mathbf{z}_{mi,t-\ell}^{*} + \mathbf{u}_{mit}, \tag{1}$$

for $i = 1, 2, ..., N$, where $\mathbf{\Phi}_{mi\ell}$ and $\mathbf{\Psi}_{mi\ell}$ are respectively 3×3 matrices of coefficients, $\mathbf{B}_{mi\ell}$ is 3×4 matrix of coefficients, and $\mathbf{u}_{mit}$ is the reduced form error vector which is orthogonal to unobserved factors approximated by $\bar{\mathbf{z}}_{mt}$. Unrestricted constant terms (fixed effects) are also added, but they are omitted from the exposition to simplify the notations. Sufficient conditions for consistency and asymptotic normality of the CALS regressions when the endogenous variables $\mathbf{z}_{mt} = (\mathbf{z}_{m1t}', \mathbf{z}_{m2t}', ..., \mathbf{z}_{mNt}')'$ is generated by a high-dimensional factor-augmented VAR model is formally established in Chudik and Pesaran (2011) under a joint asymptotics with N and T both being large. City-specific conditional model in (1), accompanied by a marginal model for $\bar{\mathbf{z}}_{mt}$, are then stacked together and solved in one reduced-form GVAR representation of $\mathbf{z}_{mt}$ featuring common (nation-wide) and idiosyncratic (local) shocks. As such, our focus on the use of the GVAR model is to decompose the changes of local purchasing power into contributions from national and local shocks. We also study the effects of surprise movements of national and local unemployment rates on the changes of purchasing power. A detailed description of the GVAR model and a brief discussion of the related literature are provided in Appendix B.

3.2 Estimation results of the GVAR model

We first look at the contribution of the national shocks ($\mathbf{v}_{mt}$ in (3) in Appendix B) to the changes in purchasing power. Because $E(\mathbf{v}_{mt}\mathbf{u}_{mt}) = 0$ by design with the sufficient number of lags (p),

[8] Our results are largely unaltered using principal components in place of cross-section averages.

it is possible to decompose the variance of Δy_{mit} into the contributions of national shocks ($\mathbf{v}_{mt}$) and idiosyncratic shocks ($\mathbf{u}_{mt}$). Since the two are orthogonal by construction, the corresponding contribution of national and idiosyncratic shocks will sum to 1 or 100%. A larger fraction of national shocks implies stronger response of local purchasing power to common national shocks, and thus stronger comovements of purchasing power across cities in those products. To remind, both types of shocks are reduced form shocks and we do not attempt to identify structural shocks. Details of the variance decomposition are provided in Appendix C.

Table 3 presents the estimated fractions of the national shocks in the variance of purchasing power changes by products (on the left-panel) as well as by cities (on the right panel). As reported in the left panel of Table 3, on average about 30-35% of the variance of local purchasing power change is explained by national shocks that commonly affect all cities. This implies that local purchasing power moves in tandem with the national level by about 30-35% on average, with the magnitude of a city's response to the national level varying across locations. Although not dominant, this size of the impact of the national shocks is consistent with our earlier findings on the strong cross-city correlation in local purchasing power. Again, we notice a large cross-product variation in the effect of national shock, ranging from 17.8% (Tennis balls) to 86.7% (Gasoline).

The national shocks also have nontrivial impacts on the changes of the purchasing power at the city level. As can be seen from the right panel of Table 3, the average share of the national shock is in a relatively narrow range between 25.6% (Salt Lake City) and 37.0% (Houston). Interestingly, the cross-city differences in the share of national shock do not seem to square well with the geographic locational feature of cities, such as coastal versus inland areas (Los Angeles vs. Louisville) or state borderline (Dallas vs. Houston). This renders us to turn to non-geographic city characteristics below as potential factors responsible for the cross-city differences in the impact of national shocks.

In view of the considerable cross-product differences observed in the relative importance of national shocks, it would be interesting to explore the product characteristics that can account for such a pattern. Obviously the product characteristics related to tradeability do not seem to be promising in this regard as mentioned earlier. Another potential source shown by recent contributions (e.g., Choi and O'Sullivan 2013) is the flexibility of price adjustment, i.e., how frequently (or flexibly) prices of products are adjusted, which is ultimately related to the degree of market power. Here we investigate whether and how the contribution of national shocks is associated with the degree of price flexibility of products. To this end, we utilize the data on product-level price flexibility employed by Choi and

O'Sullivan (2013).[9] The result of this exercise is exhibited in Figure 3 which plots the degree of price flexibility (on the horizontal axis) against the estimated contribution of national shocks to the variance of purchasing power (on the vertical axis) for the entire 43 products. As exhibited in the left panel of Figure 3, price flexibility bears a positive relationship with the share of national shocks. To rephrase, national shocks are likely to impart a greater impetus to the purchasing power in the products whose prices are adjusted more frequently. This is probably because national shocks are translated into local purchasing power mainly through price changes rather than through wage changes that are known to be adjusted more sluggishly in given locations. A largely similar story is told about the role of unemployment shocks in explaining the variance of the local purchasing power as displayed in the right panel of Figure 3.

We then investigate how a surprise in the unemployment rate translates into local purchasing power based on the generalized impulse response functions (GIRFs) in (5) in Appendix B. Intuitively, unemployment shocks are likely to hamper local purchasing power by lowering real wage rates. Table 4 presents the sensitivity of purchasing power with respect to national and idiosyncratic shocks of unemployment, both across products (on the left panel) and across cities (on the right panel), using a one-year cumulative effect of unemployment shocks on local purchasing power changes obtained from the median of the 20,000 bootstrap replications. Other variables included in the regressions are not reported in the table to conserve space.

The results in the left panel of Table 4 illustrate a couple of interesting points. First, in most products considered, nationwide shocks of unemployment dominates idiosyncratic counterparts in terms of the statistical significance and the magnitude of the impacts on purchasing power changes. Put alternatively, the changes in purchasing power in the U.S. cities are more responsive to the nationwide shocks in the labor market than to their local counterparts. Second, the one-year cumulative effect of national unemployment shock differs substantially across products, with the wide distribution from -0.0060 (Detergent) to 0.0093 (Gasoline). Note that the estimated cumulative effect has the expected negative signs in the vast majority of products (32 out of 43 products), implying that local purchasing power decreases after a surprise increase in the national unemployment rate. This outcome conforms broadly to our economic intuition that shocks in unemployment are likely to lower purchasing power by reducing the amount of goods or services available for city-level wages. In other products such as 'Gasoline' and 'Eggs', however, the national unemployment shock has an unanticipated positive

[9] Following Choi and O'Sullivan (2013), we obtain the data of price stickiness for our consumer products by utilizing the extensive dataset constructed by Nakamura and Steinsson (2008, Table 17) who document the duration of unchanged prices for non-shelter consumer prices for some 270 entry-level items (ELIs) for the period 1998-2005.

sign, i.e., a rise in national unemployment rate is likely to improve purchasing power in those products. Given that our purchasing power measure is constructed by dividing city-level wages by specific consumer prices, this seemingly counterintuitive outcome is plausible if a positive shock in national unemployment (or a rise in national unemployment rate) decreases both wages and consumer prices, but a faster reduction in consumer prices than in wage, which in turn increases the amount of products that can be purchased by the reduced wage. Taken together, whether national unemployment shocks increase or decrease local purchasing power depends on how fast the price of products adjusts relative to wage changes. During economic downturns when unemployment rate rises and wage declines, for example, purchasing power would decline in the products whose prices do not adjust as fast as wage decreases, while it goes up in the products where prices drop faster than wage decreases.

To substantiate this claim, we plot in Figure 4 the one-year cumulative effects of national unemployment shock (top-left) and local idiosyncratic shock (top-right) against the degree of price flexibility of the products. The upper-left panel of Figure 4 provides intriguing evidence of the positive relationship between price flexibility (on the horizontal axis) and the effect of a national unemployment shock on purchasing power (on the vertical axis), i.e., purchasing power increases more (or decreases less) in the products whose prices are adjusted more frequently after a national unemployment shock. This accords well with our prior intuition outlined above. The picture changes somewhat drastically when we turn to the effect of a local idiosyncratic shock of unemployment. As shown in the upper-right panel of Figure 4, there is no clear-cut relation between price flexibility and the effect of idiosyncratic unemployment shocks. Our results therefore suggest price flexibility as a potential factor behind the cross-product heterogeneity observed in the data. Price flexibility, however, matters for the local purchasing power mainly through national shocks rather than through local idiosyncratic shocks.

The right panel of Table 4 presents the cumulative effects of unemployment shocks on purchasing power at the city level. The overall impact of unemployment shock in each city is not much significant, regardless of whether the shock is national or idiosyncratic, probably due to the counterbalancing effects from different products. In the cities where they are significant, however, the unemployment shocks have expected positive signs, or hampering effects on purchasing power. To parse out the city characteristics conducive to the cross-city variations in the effect of unemployment shocks, we plot in the bottom two panels of Figure 4 the cumulative effects of national (left panel) and idiosyncratic (right panel) shocks of unemployment against the share of high-skill workers in each city. As recent evidence in the literature points to the importance of skills and ideas in determining city growth (e.g., Glaeser et al., 2011), human capital is a crucial source of local productivity and its growth. In fact, cities that added more bachelor's degree holders at high rates between 1990 and 2010 experienced greater employment growth per capita than their peers. The lower-left panel of Figure 4 indicates a moderate but positive association between the effect of a national unemployment shock and the ratio of high-skill workers in the city, i.e., the national unemployment shock has a stronger effect on the local purchasing power in the cities that have higher concentration of high-skill workers. As shown in the lower-right panel of Figure 4, however, no such relationship is detected in the effect of local idiosyncratic shock of unemployment. Again, it is not idiosyncratic shock but national shock that makes city characteristics relevant for local purchasing power changes.

3.3 Factors related to the upward trending regional inequality

We now search for the factors that are related to the upward trend observed in the regional inequality of purchasing power. Since there is no clear-cut guidance from theory about the source and nature of the trending behavior, we view identifying such factors as essentially an empirical question. Given that the factors need to not only closely track the upward trend but also be conceptually related to common national shocks which turn out to be an important source of the changes in local purchasing power, we consider national macroeconomic variables as natural and logical candidates. To be specific, we focus on major macroeconomic variables such as real GDP, the national unemployment rate, and national housing prices. In addition, we also consider total factor productivity (TFP) in light of the ample empirical evidence on the skill-biased economic growth in the U.S.[10]

We first implement a battery of popular unit-root tests, the ADF-test and the DF-GLS test, in order to determine whether the upward trend is characterized by a trend stationarity or a stochastic trend. As well established in the time series econometrics literature, distinction between the two is critical for empirical analysis. As reported in Table 5, both the ADF- and DF-GLS tests fail to reject the null hypothesis of unit-root for all the three measures of regional inequality, CV, 90-10 and 75-25 percentile ratios, indicating that the trending behavior of regional inequality is characterized by a stochastic trend rather than by a deterministic time trend. In turn, we apply a Hausman-type cointegration test developed by Choi et al. (2008) to identify variables that have a long-run cointegration relationship with the upward trending regional inequality. Under the null hypothesis

[10] In fact, we originally considered 257 macroeconomic variables from the FRED-QD database of the St. Louis Fed (*https://research.stlouisfed.org/econ/mccracken/fred-databases/*) discussed in McCracken and Ng (2016). Among them, our cointegration analysis suggests eleven macroeconomic variables (e.g., Personal Consumption Expenditure, All Employees, New Private Housing Permits) that are closely related to the main macroeconomic indicators considered here. These results are not reported here to conserve space, but will be available upon request. For the national TFP data, we use Fernald's (2014) quarterly utilization-adjusted total factor productivity (TFP) series obtained from the website of the San Francisco Fed (*https://www.frbsf.org/economic-research/indicators-data/*).

of cointegration, the Hausman-type cointegration test is known to have good finite sample properties especially when the time span is relatively small. As can be seen from the first column of Table 5, we find that except for national unemployment rates the selected main macroeconomic variables appear to have a long-run relationship with all three measures of regional inequality in our sample.

We then perform the Granger causality test within the framework of VECM. A notable feature of VECM approach is that it allows us to examine long-run and short-run relationships among variables while imposing little structural restriction. Consisting of an endogenous system of equations with lagged endogenous variables, the basic idea of VECM is similar to vector autoregression (VAR) model except that it includes an error correction term to capture deviation from the long-run relationship between variables. Here we consider the following bivariate VECM,

$$\begin{bmatrix} \Delta y_t \\ \Delta x_t \end{bmatrix} = \begin{bmatrix} a^y \\ a^x \end{bmatrix} + \begin{bmatrix} \rho^y \\ \rho^x \end{bmatrix} (y_{t-1} - \beta x_{t-1}) + \sum_{j=1}^{k} \begin{bmatrix} \gamma_{11,j} & \gamma_{12,j} \\ \gamma_{21,j} & \gamma_{22,j} \end{bmatrix} \begin{bmatrix} \Delta y_{t-j} \\ \Delta x_{t-j} \end{bmatrix} + \begin{bmatrix} e_t^y \\ e_t^x \end{bmatrix}, \quad (2)$$

where y_t represents regional inequality measure, x_t is the macroeconomic variable and a^y and a^x are their fixed effects. $(y_{t-1} - \hat{\beta} x_{t-1})$ denotes the error correction term and ρ^y and ρ^x are the convergence speeds of each variable to their long-run equilibrium. If there is any deviation from the long-run relationship between regional inequality (y) and the macroeconomic variable (x), then either y or x or both should adjust to correct for the deviation. In eq.(2), we can conduct the Granger-causality test by looking at whether or not the lags of one variable are significant in predicting the current value of the other variable. This is equivalent to testing the following null hypothesis, x does not Granger cause y ($x \nRightarrow y$), or x does not help predict y, with a standard F-test,

$$H_0 : \rho^y = \gamma_{12,j} = 0 \quad \text{for } j = 1, ..., k.$$

Similarly, the null hypothesis y does not Granger cause x ($y \nRightarrow x$) can be represented as $H_0 : \rho^x = \gamma_{21,j} = 0$ for $j = 1, ..., k$. Originally developed by Granger (1969) to analyze dynamic relationships between time series, the Granger causality tests provide evidence on the presence of causality (predicatability), but not quantitative strength of the causality. Rejecting the null hypothesis of non-causality simply suggests those macroeconomic variables help in forecasting the regional inequality without providing any assessment on the strength of the improvement in the forecast.

As can be seen from Table 6, there is strong evidence of the Granger causality of macroeconomic variables (x) to regional inequality (y) as the null hypothesis of no Granger causality ($x \nRightarrow y$) can be rejected even at the one percent significance level in most cases considered. This exercise illustrates one-way Granger causality (predicatability) running from the selected main macroeconomic variables to regional inequality, but not the other way around. We also find evidence of asymmetry in the speed of adjustment, or $\rho^y \neq \rho^x$. While $\hat{\rho}^x$ is positive but close to zero and statistically insignificant, $\hat{\rho}^y$ is negative and statistically significant in most cases, indicating that the deviation from long-run relationship is mainly adjusted by regional inequality (y) rather than by the macroeconomic variable (x). This is in line with the Granger causality test results that macroeconomic variables are a predictor of regional inequality, but not vice versa. Among the four macroeconomic variables under study, real GDP and TFP have consistent predictive power for all three measures of regional inequality.

3.4 A subsample analysis

Our empirical results so far point to the predictability of main macroeconomic variables on the evolution of the regional inequality in purchasing power. Since the conclusion was reached from using aggregated measures of regional inequality which might obscure important variation across products and cities, it is unclear about whether those macroeconomic variables still have the predictive power on the trending behavior of the regional inequality at the disaggregated level. If the predictability of the macroeconomic variables is found in some subgroups but not in others, it is fair to posit that regional inequality in purchasing power might have moved on mainly in those subgroups. In fact, our results in the preceding sections highlight the usefulness for distinguishing between flexible price products and rigid price products at the disaggregated level. Disaggregating to the city level also would improve our understanding of the sources of the trending behavior of regional inequality.

This leads us to conduct a subsample analysis for various subgroups based on product and city characteristics such as 'flexible price products' versus 'rigid price products' and 'high-skilled cities' versus 'low-skilled cities'. The purpose of this exercise is to identify the subsets of our data in which shocks to the macroeconomic variables affect the regional inequality of purchasing power. For the simplicity of analysis, we focus on the effect of TFP on the 90-10 percentile ratio as a representative case of our exercise. The VECM regression in (2) is run on separate subsamples as well as on the full sample to investigate potential heterogeneity across different groups of cities and products.

The regression results are displayed in Table 7 by the product groups: the entire products (top panel), the flexible price product group (middle panel), and the product group whose prices are adjusted more sluggishly (bottom panel). In each product group, we look at various subgroups based on city characteristics. We find pervasive evidence of a one-way Granger causality (predicatability) running from TFP to regional inequality in all cases considered where the null hypothesis of no Granger causality ($x \nRightarrow y$) is soundly rejected at the usual significance levels, but not vice versa. Moreover, the deviation from long-run relationship is adjusted mainly by regional inequality (y) judging from the asymmetric speed of adjustment. As reported in the last column of the table, there is some evidence that TFP has a positive long-run effect (predicatability) on the regional inequality for the entire products. This suggests a gain in national TFP predicts a rise in the regional inequality, echoing the notion of skill-biased economic growth.

The story changes somewhat drastically when it comes to the subgroup analysis. In the flexible price product (FLEX) group, there exists clear evidence on the significant positive long-run effect (predicatability) of TFP on the cross-city inequality of purchasing power. By contrast, we fail to find any evidence from the less flexibly priced product group (RIGID).[11] This indicates that TFP has predictive power in the evolution of regional inequality mainly through the products whose prices are more frequently adjusted. This mirrors our finding from the GVAR analysis that price flexibility is an important factor behind the cross-product heterogeneity in the growth rates of local purchasing power. Even in the flexible price product group, however, the significance of the long-run effect of TFP varies vastly across city groups. TFP has a statistically significant long-run effect on the regional inequality in the cities with a higher concentration of skilled workers, higher per capita income, and larger populations. By contrast, no significance of TFP can be found in the cities with a lower fraction of skilled workers, lower per capita income, and smaller population. Combined together, our subgroup analysis convincingly suggests that regional inequality of purchasing power in the U.S. might have proceeded over time mainly in the cities with a higher concentration of skilled workers, higher income and larger populations through the products with more flexible price adjustments.

4 Concluding remarks

Recent years have seen a surge in research interest in income inequality. Despite substantial investigation of the issue, the debate surrounding it has predominantly focused on the national level and thus far less attention has been paid to its implications at the regional level. This is particularly the case for the subnational economies, like cities in the U.S. sharing almost identical institutional environments with a high mobility of technology and resources. In fact, there exists mounting evidence that nominal wages or income systematically vary across sub-regions in the U.S., but little is known about the extent to which the geographic wage or income inequality observed in the data is translated into actual inequality of purchasing power. Far less is known about how such regional inequality in

[11] See the fourth column of Table A.1 for the products belonging to each product group.

the purchasing power has evolved over time. To gain further insight on these issues, we constructed a novel quantity based measure of purchasing power among U.S. cities utilizing a micro panel dataset of actual consumer prices.

By analyzing the city-level purchasing power data over time across products, we draw several main conclusions. First, there has been a large and persistent dispersion of the purchasing power among the U.S. cities. The geographic dispersion of purchasing power is substantial in all products under study and it has been on a steady rise since the mid-1990s, possibly due to the reduced factor mobility across subnational economies (e.g., Kennan and Walker, 2011). The persistent and large cross-city dispersion of purchasing power found in the data certainly poses an important challenge to policymakers.

Second, national shocks which are common to all cities turn out to be quite influential to the changes in local purchasing power. Common national shocks contribute a nontrivial fraction of the variation of local purchasing power, with the fraction varying considerably across products. Interestingly, the channels by which shocks affect the inter-city dispersion of purchasing power differs significantly across the source and nature of the shocks. At the city level, we found cities with systematically higher portion of skilled workers tend to have a greater impact of national unemployment shocks on the local purchasing power. On the product front, the effect of a national unemployment shock is meaningfully associated with the differences in the flexibility of price adjustments across products. In general, the impact of national shocks is stronger for the products whose prices are adjusted more frequently, compared to the products whose prices are adjusted sluggishly.

Last but not least, we find compelling evidence that major macroeconomic variables have predictive power on the evolution of regional inequality, but not the other way around. This finding is in line with the established literature that macroeconomic shocks such as a national productivity shock have a disproportionate influence on the local economy. For example, Beraja et al. (2017) document that the Fed's expansionary monetary policy during the recent Great Recession has widened the disparities among regions in the U.S. The significance of macroeconomic variables in predicting the evolution of regional inequality, however, hinges on the characteristics of the product and city. A gain in national TFP, for instance, precedes a greater geographic dispersion of purchasing power, mainly in the products whose prices are adjusted more frequently and in the cities that have a higher concentration of skilled workers, larger populations, and higher per capita income. These results can be viewed as suggesting that the regional inequality of purchasing power in the U.S. might have proceeded over time primarily in the cities that have a higher concentration of skilled workers and higher income and larger populations through the products with more flexible price adjustments.

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Table 1: Summary statistics of local purchasing power by products

Product	mean	min	max	max-min ratio	dispersion measure: 90-10 ratio	75-25 ratio	CV
Steak	13.09	10.10	18.13	1.79	1.50	1.26	0.17
Ground beef	47.05	34.92	58.79	1.68	1.57	1.27	0.18
Whole chicken	96.34	69.35	134.11	1.93	1.61	1.28	0.19
Canned tuna	128.57	100.44	180.89	1.80	1.53	1.25	0.17
Milk	53.65	41.10	69.98	1.70	1.54	1.28	0.17
Eggs	82.11	57.58	105.08	1.82	1.54	1.26	0.17
Margarine	123.02	82.72	178.50	2.16	1.68	1.31	0.20
Cheese	26.69	20.98	35.26	1.68	1.54	1.25	0.16
Potatoes	35.14	22.45	53.22	2.37	1.87	1.38	0.25
Bananas	187.93	152.88	275.50	1.80	1.51	1.25	0.17
Lettuce	86.87	60.55	115.79	1.91	1.66	1.32	0.20
Bread	96.24	73.88	149.82	2.03	1.66	1.31	0.22
Coffee	30.82	24.69	42.38	1.72	1.48	1.25	0.16
Sugar	53.47	42.10	74.50	1.77	1.48	1.24	0.16
Corn flakes	35.83	27.83	51.92	1.87	1.54	1.26	0.17
Canned peas	122.32	93.85	168.49	1.80	1.52	1.26	0.16
Canned peaches	54.97	41.59	74.23	1.78	1.51	1.26	0.17
Tissue	66.63	49.55	86.96	1.75	1.50	1.24	0.16
Detergent	25.44	19.95	34.20	1.71	1.48	1.24	0.15
Shortening	31.91	23.37	44.25	1.89	1.49	1.23	0.16
Frozen corn	90.75	68.75	123.62	1.80	1.61	1.30	0.18
Soft drink	75.30	55.98	99.42	1.78	1.62	1.27	0.18
Apartment rent*	4.30	2.83	5.68	2.00	1.47	1.22	0.16
Telephone	4.24	2.94	5.54	1.89	1.73	1.31	0.21
Auto maintenance	10.82	8.68	13.33	1.54	1.49	1.24	0.15
Gas	55.79	44.63	71.46	1.60	1.42	1.19	0.13
Doctor visit	1.51	1.21	1.93	1.60	1.48	1.23	0.16
Dentist visit	1.39	1.12	1.73	1.55	1.48	1.25	0.15
McDonald's	38.42	30.01	49.12	1.64	1.39	1.21	0.13
Pizza	10.45	8.28	14.66	1.77	1.50	1.25	0.16
Fried chicken	35.45	26.42	47.91	1.81	1.61	1.26	0.18
Man's haircut	8.86	5.88	11.06	1.88	1.45	1.23	0.15
Beauty salon	3.58	2.75	4.62	1.68	1.65	1.30	0.19
Toothpaste	43.90	34.44	59.72	1.73	1.55	1.26	0.17
Dry cleaning	11.73	8.90	18.54	2.08	1.60	1.26	0.19
Man's shirt	3.82	2.64	5.00	1.89	1.69	1.35	0.20
Appliance repair	2.17	1.57	3.74	2.38	1.63	1.31	0.22
Newspaper	6.89	5.01	10.62	2.12	1.79	1.36	0.25
Movie	12.81	10.47	15.88	1.52	1.37	1.19	0.12
Bowling	31.77	25.49	42.57	1.67	1.53	1.25	0.18
Tennis balls	41.96	25.80	57.36	2.22	1.63	1.28	0.18
Beer	15.43	10.76	19.66	1.83	1.47	1.24	0.15
Wine	15.71	10.19	22.81	2.24	1.76	1.35	0.22

Note: Entries represent the cross-city mean, minimum, and maximum values of the period average units of consumer products that can be purchased by daily wage rate, except for 'Apartment rent' (using monthly wage). 'max/min' denotes the ratio of the city with the highest value to the city with the lowest value for each product and '90-10 ratio' represents the price ratio of the 90^{th}-percentile city to the 10^{th}-percentile city.

Table 2: Cross-sectional dependence (CD) of purchasing power

Product	$\hat{\bar{\rho}}$	CD-stat	$\hat{\alpha}$ [5%,95%]
Steak	0.174	35.6	0.994 [0.966,1.021]
Ground beef	0.128	22.3	0.954 [0.903,1.005]
Whole chicken	0.085	9.9	0.804 [0.779,0.830]
Canned tuna	0.152	29.3	0.981 [0.929,1.032]
Milk	0.308	74.1	1.001 [0.942,1.060]
Eggs	0.513	133.3	1.001 [0.962,1.040]
Margarine	0.125	21.6	0.924 [0.876,0.972]
Cheese	0.257	59.6	1.001 [0.908,1.094]
Potatoes	0.377	94.2	1.001 [0.931,1.072]
Bananas	0.257	59.6	0.986 [0.925,1.047]
Lettuce	0.500	129.5	1.001 [0.915,1.087]
Bread	0.088	10.9	0.884 [0.831,0.937]
Coffee	0.398	100.1	1.001 [0.918,1.085]
Sugar	0.196	42.0	0.991 [0.932,1.049]
Corn flakes	0.117	19.3	0.942 [0.903,0.981]
Canned peas	0.199	42.7	1.000 [0.980,1.020]
Canned peaches	0.137	25.1	0.951 [0.895,1.007]
Tissue	0.204	44.2	1.000 [0.931,1.069]
Detergent	0.373	92.9	1.001 [0.914,1.089]
Shortening	0.386	96.6	1.001 [0.854,1.148]
Frozen corn	0.155	30.1	0.971 [0.856,1.086]
Soft drink	0.105	15.6	0.907 [0.859,0.954]
Apartment rent	0.219	48.6	0.985 [0.933,1.036]
Telephone	0.141	26.1	0.934 [0.885,0.983]
Auto maintenance	0.797	214.9	1.001 [0.805,1.198]
Gas	0.891	242.1	1.001 [0.920,1.083]
Doctor visit	0.138	25.1	0.949 [0.895,1.003]
Dentist visit	0.245	56.1	0.973 [0.835,1.110]
McDonald's	0.232	52.3	0.995 [0.927,1.063]
Pizza	0.175	36.0	0.956 [0.862,1.051]
Fried chicken	0.093	12.4	0.846 [0.796,0.897]
Man's haircut	0.130	23.0	0.944 [0.882,1.006]
Beauty salon	0.098	13.7	0.875 [0.828,0.921]
Toothpaste	0.087	10.5	0.829 [0.776,0.883]
Dry cleaning	0.184	38.5	0.958 [0.913,1.004]
Man's shirt	0.153	29.7	0.978 [0.881,1.074]
Appliance repair	0.110	17.1	0.924 [0.862,0.986]
Newspaper	0.101	14.5	0.858 [0.808,0.909]
Movie	0.242	55.2	1.001 [0.949,1.052]
Bowling	0.130	22.9	0.895 [0.834,0.956]
Tennis balls	0.074	6.9	0.818 [0.762,0.875]
Beer	0.528	137.4	1.001 [0.846,1.157]

Note: Entries represent the averages of pair-wise correlations of cities which is constructed by $\hat{\bar{\rho}} = \frac{2}{N(N-1)} \sum_{i=1}^{N} \sum_{j=i+1}^{N} \hat{\rho}_{ij}$ where $\hat{\rho}_{ij}$ denotes the pair-wise correlation coefficient between cities i and j. Entries inside the parenthesis represent cross-sectional dependence (CD) statistics of Pesaran (2015) that are defined by $CD = \left[\frac{TN(N-1)}{2}\right] \hat{\bar{\rho}}$ and $CD \xrightarrow{d} N(0,1)$. $\hat{\alpha}$ denotes the estimates of the exponent of cross-sectional dependence developed by Bailey et al. (2016b).

Table 3: Average share of common national shocks in the variance of purchasing power

By product		By city	
Product	share	CITY	share
Steak	0.272	AMARILLO	0.321
Ground beef	0.222	ATLANTA	0.305
Whole chicken	0.184	CEDAR RAPIDS	0.365
Canned tuna	0.256	CHARLOTTE	0.324
Milk	0.392	CHATTANOOGA	0.317
Eggs	0.567	CLEVELAND	0.333
Margarine	0.221	COLORADO SPRINGS	0.308
Cheese	0.311	COLUMBIA, MO	0.329
Potatoes	0.437	COLUMBIA, SC	0.295
Bananas	0.348	DALLAS	0.305
Lettuce	0.544	DENVER	0.301
Bread	0.203	DOVER	0.267
Coffee	0.445	HOUSTON	0.370
Sugar	0.268	HUNTSVILLE	0.326
Corn flakes	0.199	JONESBORO	0.320
Canned peas	0.296	JOPLIN	0.298
Canned peaches	0.216	KNOXVILLE	0.334
Tissue	0.291	LEXINGTON	0.328
Detergent	0.435	LOS ANGELES	0.272
Shortening	0.462	LOUISVILLE	0.267
Frozen corn	0.244	LUBBOCK	0.336
Soft drink	0.189	MEMPHIS	0.289
Apartment rent	0.210	MONTGOMERY	0.293
Telephone	0.189	ODESSA	0.303
Auto maintenance	0.781	OKLAHOMA CITY	0.327
Gas	0.867	OMAHA	0.367
Doctor visit	0.184	PHILADELPHIA	0.271
Dentist visit	0.362	PHOENIX	0.307
McDonald's	0.249	PORTLAND	0.291
Pizza	0.256	RALEIGH	0.329
Fried chicken	0.193	RENO-SPARKS	0.271
Man's haircut	0.185	SALT LAKE CITY	0.256
Beauty salon	0.186	SAN ANTONIO	0.262
Toothpaste	0.210	SOUTH BEND	0.315
Dry cleaning	0.218	SPRINGFIELD	0.269
Man's shirt	0.261	ST. CLOUD	0.333
Appliance repair	0.179	ST. LOUIS	0.291
Newspaper	0.203	TACOMA	0.292
Movie	0.274	TUCSON	0.292
Bowling	0.223	WACO	0.294
Tennis balls	0.178	YORK	0.319
Beer	0.518		
Wine	0.274		

Note: Entries represent the portion of the variance of purchasing power changes (Δy_{mit}) that is explained by national shocks common to all cities ($\mathbf{v}_{mt}$ in (3)).

Table 4: The response of local purchasing power to national and local unemployment shocks (1-year IRF-based cumulative effects)

By product			By city		
Product	national	local-idio	CITY	national	local-idio
Steak	0.0015‡	0.0001	AMARILLO	-0.0004	-0.0004
Ground beef	0.0012‡	-0.0002	ATLANTA	0.0002	0.0001
Whole chicken	0.0008*	-0.0003	CEDAR RAPIDS	-0.0014†	-0.0006‡
Canned tuna	-0.0032‡	0.0002	CHARLOTTE	-0.0004	-0.0001
Milk	0.0041‡	0.0003	CHATTANOOGA	-0.0002	0.0001
Eggs	0.0077‡	0.0000	CLEVELAND	-0.0018‡	-0.0001
Margarine	-0.0027‡	0.0002	COLORADO SPRINGS	0.0002	0.0001
Cheese	-0.0026‡	0.0000	COLUMBIA, MO	0.0004	-0.0001
Potatoes	-0.0017‡	0.0001	COLUMBIA, SC	0.0002	0.0003
Bananas	-0.0014‡	-0.0005‡	DALLAS	-0.0003	0.0003*
Lettuce	-0.0021‡	-0.0001	DENVER	0.0005	-0.0001
Bread	-0.0008	-0.0002	DOVER	0.0014†	0.0003
Coffee	0.0034‡	-0.0002	HOUSTON	-0.0002	-0.0001
Sugar	-0.0021‡	0.0000	HUNTSVILLE	0.0007	0.0002
Corn flakes	0.0000	-0.0001	JONESBORO	0.0001	-0.0002
Canned peas	-0.0030‡	-0.0001	JOPLIN	-0.0015‡	0.0005*
Canned peaches	-0.0017‡	-0.0002	KNOXVILLE	0.0001	-0.0004†
Tissue	-0.0021‡	0.0003	LEXINGTON	0.0007	-0.0001
Detergent	-0.0060‡	-0.0002	LOS ANGELES	-0.0003	0.0000
Shortening	0.0069‡	0.0001	LOUISVILLE	0.0005	-0.0004
Frozen corn	-0.0003	-0.0003	LUBBOCK	0.0001	0.0000
Soft drink	-0.0015‡	0.0001	MEMPHIS	-0.0004	-0.0008‡
Apartment rent	-0.0002	-0.0001	MONTGOMERY	-0.0003	-0.0003‡
Telephone	-0.0012‡	-0.0002	ODESSA	-0.0019‡	-0.0006‡
Auto maintenance	0.0048‡	0.0000	OKLAHOMA CITY	-0.0013†	-0.0003‡
Gas	0.0093‡	0.0000	OMAHA	-0.0001	0.0001
Doctor visit	-0.0010‡	0.0002	PHILADELPHIA	-0.0012‡	-0.0003
Dentist visit	-0.0011‡	-0.0002	PHOENIX	0.0001	0.0002
McDonald's	-0.0016‡	-0.0002	PORTLAND	-0.0015‡	0.0004
Pizza	-0.0013‡	-0.0002‡	RALEIGH	-0.0010*	-0.0005‡
Fried chicken	-0.0013‡	0.0000	RENO-SPARKS	0.0005	0.0000
Man's haircut	-0.0005*	0.0004*	SALT LAKE CITY	-0.0001	0.0007‡
Beauty salon	-0.0009‡	-0.0003	SAN ANTONIO	-0.0002	0.0002
Toothpaste	-0.0007*	-0.0003	SOUTH BEND	-0.0002	0.0001
Dry cleaning	-0.0011‡	0.0001	SPRINGFIELD	0.0001	-0.0003
Man's shirt	0.0015‡	0.0002	ST. CLOUD	-0.0001	-0.0002
Appliance repair	-0.0012‡	0.0000	ST. LOUIS	-0.0005	0.0000
Newspaper	-0.0009*	0.0000	TACOMA	0.0005	0.0006‡
Movie	-0.0013‡	-0.0002*	TUCSON	0.0003	-0.0005‡
Bowling	-0.0009‡	-0.0004*	WACO	0.0004	0.0005*
Tennis balls	0.0003	0.0000	YORK	0.0003	0.0002
Beer	-0.0020‡	0.0003‡			
Wine	-0.0014‡	0.0002			

Note: Entries represent the one-year mean response of purchasing power to a one-standard-deviation increase in the national and local unemployment shocks, which are estimated from the high-dimensional reduced form global VAR model given by eq.(5).

Table 5: Unit-root test results on different measures of cross-city dispersion of purchasing power

Dispersion measures	ADF test	DF-GLS test
CV	-2.523	-1.205
90-10 ratio	-2.459	-1.417
75-25 ratio	-2.782	-2.456

Note: The critical values of the ADF- and DF-GLS tests for the constant and trend case are -3.15 (10%), -3.45 (5%), -4.04 (1%) and -3.13 (10%), -3.41 (5%), -3.96 (1%), respectively.

Table 6: Cointegration test, Granger Causality and VECM model estimation

Dispersion measures	Macroeconomic variables	Hausman Stat	Granger Causality (p-value) $H_0 : x \not\Rightarrow y$	Granger Causality (p-value) $H_0 : y \not\Rightarrow x$	VECM estimation $\hat{\rho}_y$	VECM estimation $\hat{\rho}_x$
CV	Real GDP	0.000	0.000	0.383	-0.216‡	0.000
	TFP	0.000	0.000	0.390	-0.196‡	0.001
	Unemployment rate	11.66‡	-	-	-	-
	House Price	0.294	0.000	0.538	-0.021	0.009
90-10 ratio	Real GDP	0.000	0.000	0.408	-0.342‡	0.006
	TFP	0.000	0.000	0.700	-0.340‡	0.010
	Unemployment rate	0.000	0.000	0.001	-0.177‡	0.036
	House Price	0.047	0.000	0.000	-0.188‡	0.010
75-25 ratio	Real GDP	0.000	0.000	0.229	-0.487*	0.009
	TFP	0.173	0.000	0.290	-0.512‡	0.072
	Unemployment rate	4.112†	-	-	-	-
	House Price	0.736	0.000	0.138	-0.500‡	0.053

Note: The critical values of the Hausman-type cointegration test ($\chi^2(1)$) are 2.706 (10%), 3.841 (5%) and 6.635 (1%). ‡, † and asterisk (*) respectively indicate the statistical significance at the 1%, 5% and 10% significance levels with the corresponding t-values inside parentheses. The lag length (k) in the VECM model was selected by the BIC rule and the standard errors were obtained from 10,000 residual-based bootstrap simulations.

Table 7: Results of subsample analysis using 75-25 percentile ratio (y) and TFP (x)

Product Group	City group	Granger Causality		VECM estimation		
		$H_0 : x \nRightarrow y$	$H_0 : y \nRightarrow x$	$\hat{\rho}_y$	$\hat{\rho}_x$	LRE ($\hat{\beta}$)
All	All cities	0.00	0.29	-0.51‡	0.07	0.089* [0.050]
	High-skill	0.00	0.75	-0.76‡	0.03	0.097* [0.050]
	Low-skill	0.00	0.36	-0.30*	-0.06	0.104 [0.075]
	Large pop.	0.00	0.06	-0.42*	-0.13	0.112 [0.077]
	Small pop.	0.00	0.52	-0.29*	-0.05	0.009 [0.054]
	High income	0.00	0.10	-0.58‡	0.15	0.146†[0.071]
	Low income	0.00	0.61	-0.25*	-0.03	0.039 [0.084]
Flexible price	All cities	0.00	0.21	-0.89‡	0.30	0.085* [0.050]
	High-skill	0.00	0.22	-0.80‡	0.19	0.120†[0.059]
	Low-skill	0.00	0.01	-0.56‡	-0.09	0.093 [0.065]
	Large pop.	0.00	0.22	-0.56‡	0.20	0.208‡[0.085]
	Small pop.	0.00	0.11	-0.17‡	0.07	0.042 [0.090]
	High income	0.00	0.99	-0.70‡	0.00	0.112* [0.067]
	Low income	0.00	0.14	-0.16‡	0.06	0.090 [0.137]
Rigid price	All cities	0.00	0.05	-0.36‡	-0.15	0.124 [0.078]
	High-skill	0.00	0.28	-0.66‡	-0.10	0.062 [0.062]
	Low-skill	0.00	0.07	-0.20	-0.09	0.136 [0.106]
	Large pop.	0.00	0.01	-0.56‡	-0.17	0.033 [0.117]
	Small pop.	0.00	0.12	-0.90	-0.19	0.010 [0.049]
	High income	0.00	0.00	-0.30‡	0.02	0.093 [0.169]
	Low income	0.00	0.06	-0.65	-0.14	0.009 [0.069]

Note: Entries represent the bivariate VECM result in eq.(2) in which y denotes the regional inequality based on 75-25 percentile ratio and x denotes U.S. real GDP. 'LRE ($\hat{\beta}$)' denotes the estimated long-run effect of x onto y. Refer to the notes in Table 6 for further details.

Appendix

A Data description

Table A.1: Data Description (by product)

Number	Item	Group	Flex	Descriptions
1	Steak	ND	H	Pound, USDA Choice
2	Ground beef	ND	H	Pound, lowest price
3	Whole chicken	ND	H	Pound, whole fryer
4	Canned tuna	D	H	Starkist or Chicken of the Sea; 6.5 oz.(85.1-91.3),6.125 oz.(91.4-95.3), 6-6.125 oz.(95.3-99.4), 6.0 oz. (00.1-09.4)
5	Milk	ND	H	1/2 gal. carton
6	Eggs	ND	H	One Dozen, Grade A, Large
7	Margarine	ND	H	One Pound, Blue Bonnet or Parkay
8	Cheese	ND	H	Parmesan, grated 8 oz. canister, Kraft
9	Potatoes	ND	H	10 lbs. white or red
10	Bananas	ND	H	One pound
11	Lettuce	ND	H	Head, approximately 1.25 pounds
12	Bread	ND	L	24 oz loaf
13	Coffee	D	H	Can, Maxwell House, Hills Brothers, or Folgers; 1 lb. (85.1-88.3); 13 oz. (88.4-99.4); 11.5 oz. (00.1-09.4)
14	Sugar	D	L	Cane or beet; 5 lbs. (85.1-92.3); 4 lbs. (92.4-09.4)
15	Corn flakes	D	H	18 oz, Kellog's or Post Toasties
16	Canned peas	D	-	Can, Del Monte or Green Giant; 17 oz can, 15-17 oz. (85.1-85.4), 17 oz. (86.1-91.4), 15-15.25 oz. (92.1-09.4)
17	Canned peaches	D	L	1/2 can approx. 29 oz.; Hunt's, Del Monte, or Libby's or Lady Alberta
18	Tissue	D	L	175-count box (85.1-02.3), 200-count box (02.4-09.4); Kleenex brand
19	Detergent	D	L	42 oz, Tide, Bold, or Cheer (85.1-96.3); 50 oz. (96.4-00.4), 60 oz (01.1-02.3), 75 oz (02.4-09.4), Cascade dishwashing powder
20	Shortening	D	H	3 lbs. can, all-vegetable, Crisco brand
21	Frozen corn	D	L	10 oz. (85.1-95.3), 16 oz. (95.4-09.4); Whole Kernel
22	Soft drink	D	H	2 liter Coca Cola
23	Apartment rent	S	H	Two-Bedroom, unfurnished, excluding all utilities except water, 1.2 or 2 baths, approx. 950 sqft
24	Home price	S	-	1,800 sqft, new house, 8,000 sqft lot, (85.1-99.4); 2,400 sqft, new house, 8,000 sqft lot, 4 bedrooms, 2 baths (00.1-09.4)
25	Telephone	S	L	Private residential line, basic monthly rate, fees and taxes
26	Auto maintenance	S	L	average price to balance one front wheel (85.1-88.3); average price to computer or spin balance one front wheel (88.4-09.4)
27	Gas	D	H	One gallon regular unleaded, national brand, including all taxes
28	Doctor visit	S	L	General practitioner's routine examination of established patient
29	Dentist visit	S	L	Adult teeth cleaning and periodic oral examination (85.1-04.4); Adult teeth cleaning (05.1-09.1)
30	McDonald's	ND	L	McDonald's Quarter-Pounder with Cheese
31	Pizza	ND	L	12"-13" (85.1-94.3), 11"-12" (94.4-09.4) thin crust cheese pizza, Pizza Hut or Pizza Inn from 1990Q1 to 1994Q3
32	Fried chicken	ND	L	Thigh and Drumstick, KFC or Church's where available
33	Man's haircut	S	-	Man's barber shop haircut, no styling
34	Beauty salon	S	L	Woman's shampoo, trim, and blow dry
35	Toothpaste	D	L	6 to 7 oz. tube (85.1-06.2), 6 oz-6.4oz tube (06.3-09.4); Crest, or Colgate
36	Dry cleaning	S	L	Man's two-piece suit
37	Man's shirt	D	H	Arrow, Enro, Van Huesen, or JC Penny's Stafford, White, cotton/polyester blend (at least 55% cotton) long sleeves (85.1-94.3); 100% cotton pinpoint Oxford, Long sleeves (94.4-99.4)Cotton/Polyester, pinpoint weave, long sleeves (00.1-09.4)
38	Appliance repair	S	L	Home service call, washing machine, excluding parts
39	Newspaper	S	L	Daily and Sunday home delivery, large-city newspaper, monthly rate
40	Movie	S	L	First-run, indoor, evening, no discount
41	Bowling	S	L	Price per line, evening rate (85.1-98.2); Saturday evening non-league rate (98.3-09.4)
42	Tennis balls	D	L	Can of three extra duty, yellow, Wilson or Penn Brand
43	Beer	D	L	6-pack, 12 oz containers, excluding deposit; Budweiser or Miller Lite, (85.1-99.4), Heineken's (00.1-09.4)
44	Wine	D	L	1.5-liter bottle; Paul Masson Chablis (85.1-90.3); Gallo sauvignon blanc (90.4-91.3); Gallo chablis blanc (91.4-97.3); Livingston Cellars or Gallo chablis blanc (97.1-00.1); Livingston Cellars or Gallo chablis or Chenin blanc (00.2-09.4)

Note: 'Group' represents product groups for Non-durables (ND), durables (D) and service (S). 'Flex' represents the flexibility of price adjustment for highly flexible products (H) and less flexible products (L).

Table A.2: Summary statistics at the city level (period average: 1985-2015)

	City name (CODE)	Per capita income ($)	Weekly wage ($)	Population (1,000 people)	% of bachelor higher degree	Home price ($1,000)
1	AMARILLO (AMA)	24,933 (L)	551.85	225.7 (L)	21.9 (L)	166.9
2	ATLANTA (ATL)	29,895 (H)	725.99	4,124.2 (H)	34.0 (H)	189.0
3	CEDAR RAPIDS (CID)	28,688 (H)	627.70	234.0 (L)	26.6 (L)	174.4
4	CHARLOTTE (CLT)	28,281 (H)	689.81	1,720.9 (H)	31.7 (H)	175.2
5	CHATTANOOGA (CHA)	25,707 (L)	568.90	476.7 (L)	22.4 (L)	170.6
6	CLEVELAND (CLE)	30,168 (H)	669.55	2,116.9 (H)	26.3 (L)	186.4
7	COLORADO SPRINGS (COS)	28,253 (H)	606.75	525.7 (L)	34.8 (H)	190.3
8	COLUMBIA, MO (COU)	26,777 (L)	522.88	135.4 (L)	43.3 (H)	173.0
9	COLUMBIA, SC (CAE)	25,843 (L)	559.08	646.1 (L)	29.9 (H)	164.9
10	DALLAS (DAL)	30,870 (H)	746.67	5,122.2 (H)	30.1 (H)	157.7
11	DENVER (DEN)	34,063 (H)	755.54	2,099.7 (H)	37.1 (H)	231.4
12	DOVER (DOV)	24,721 (L)	540.38	131.6 (L)	19.4 (L)	184.2
13	HOUSTON (HOU)	31,677 (H)	791.38	4,724.4 (H)	28.1 (H)	155.6
14	HUNTSVILLE (HSV)	27,952 (L)	712.31	346.3 (L)	34.1 (H)	164.3
15	JONESBORO (JBR)	21,746 (L)	478.09	106.2 (L)	19.6 (L)	156.7
16	JOPLIN (JLN)	22,405 (L)	488.40	154.4 (L)	18.1 (L)	156.8
17	KNOXVILLE (KNX*)	25,157 (L)	590.00	741.9 (L)	27.8 (L)	163.9
18	LEXINGTON (LEX)	28,076 (H)	596.10	405.3 (L)	33.4 (H)	174.2
19	LOS ANGELES (LAX)	31,459 (H)	768.22	12,057.1 (H)	30.0 (H)	409.3
20	LOUISVILLE (LOU*)	27,928 (L)	609.10	1,121.3 (H)	23.8 (L)	162.5
21	LUBBOCK (LBB)	24,009 (L)	513.25	260.4 (L)	26.3 (L)	156.2
22	MEMPHIS (MEM)	27,632 (L)	639.77	1,195.0 (H)	24.4 (L)	153.5
23	MONTGOMERY (MGM)	26,111 (L)	556.48	340.4 (L)	26.2 (L)	182.9
24	ODESSA (ODS*)	23,000 (L)	620.24	126.9 (L)	13.0 (L)	167.4
25	OKLAHOMA CITY (OKC)	27,121 (L)	579.05	1,101.9 (H)	27.0 (L)	159.2
26	OMAHA (OMA)	30,860 (H)	593.40	766.7 (L)	31.3 (H)	163.7
27	PHILADELPHIA (PHL)	33,571 (H)	758.68	5,678.2 (H)	31.8 (H)	270.2
28	PHOENIX (PHX)	27,280 (L)	653.52	3,163.3 (H)	27.3 (L)	189.5
29	PORTLAND (POR*)	29,594 (H)	680.71	1,869.5 (H)	32.9 (H)	244.5
30	RALEIGH (RDU)	30,653 (H)	645.46	799.9 (L)	41.3 (H)	186.3
31	RENO-SPARKS (RNO)	33,645 (H)	621.32	336.6 (L)	26.3 (L)	214.2
32	SALT LAKE CITY (SLC)	26,507 (L)	616.31	918.9 (L)	29.8 (H)	190.6
33	SAN ANTONIO (SAT)	25,538 (L)	575.58	1,729.8 (H)	24.5 (L)	163.8
34	SOUTH BEND (SBN)	25,736 (L)	568.57	309.8 (L)	24.1 (L)	169.8
35	SPRINGFIELD (SPI)	29,162 (H)	661.14	200.8 (L)	29.6 (H)	172.3
36	ST. CLOUD (STC)	24,374 (L)	527.69	166.8 (L)	22.4 (L)	169.2
37	ST. LOUIS (STL)	30,428 (H)	664.89	2,667.5 (H)	28.5 (H)	161.9
38	TACOMA (SEA)	35,396 (H)	773.51	2,966.6 (H)	36.7 (H)	206.5
39	TUCSON (TUS)	24,845 (L)	572.94	819.9 (L)	29.0 (H)	179.7
40	WACO (WAC*)	22,662 (L)	535.64	228.9 (L)	20.4 (L)	155.6
41	YORK (YRK*)	27,903 (L)	598.73	381.8 (L)	21.0 (L)	196.4
	Average	27,820	623.31	1,542.6	28.0	184.4

Note: 'H' and 'L' respectively denote 'high' and 'low' groups with the threshold levels of $28,000 for income, 1 million people for population, and 28% of the share of bachelor's degree holders for skill level. City codes are the airport codes of the corresponding cities except for those asterisked.

B Construction of GVAR model of local purchasing power

Since there are three equations for three endogenous variables in (1), it is intuitive to estimate it for $i = 1, 2, ..., N$ first. Following the common practice in the GVAR literature, we then stack the resulting system of $3N$ equations to get a large VAR representation for the $3N \times 1$ vector of variables $\mathbf{z}_{mt}$. However, this strategy is justified only if the matrix

$$\mathbf{G}_0 = \mathbf{I}_{3N} - \mathbf{B}_{m0}\mathbf{W},$$

is invertible, where $\mathbf{I}_{3N}$ is $3N \times 3N$ identity matrix, $\mathbf{B}_{m0} = \left(\mathbf{B}'_{m,1,0}, \mathbf{B}'_{m,2,0}, ..., \mathbf{B}'_{m,N,0}\right)'$ contains stacked matrices $\mathbf{B}_{mi0}$ in (1), and $\mathbf{W}$ is the matrix of weights defining the vector of cross-section averages, namely $\bar{\mathbf{z}}_{mt} \equiv \mathbf{W}\mathbf{z}_{mt}$. Contrary to intuition, as shown by Chudik et al. (2016, Section 4.1-2), $\mathbf{G}_0$ becomes singular as $N \to \infty$ in the presence of unobserved common factors. Rank deficiency of $\mathbf{G}_0$ implies that the system of equations in (1) for $i = 1, 2, ..., N$, is undetermined and additional equations are required for $\mathbf{z}_{mt}$ to be uniquely determined. Chudik et al. (2016) establish the additional equations can be specified in the form of a marginal VAR model for cross-section averages,

$$\bar{\mathbf{z}}_{mt} = \sum_{\ell=1}^{p} \mathbf{\Pi}_{m\ell}\bar{\mathbf{z}}_{m,t-\ell} + \mathbf{v}_{mt}, \tag{3}$$

where $\mathbf{v}_{mt}$ is the vector of reduced-form national (common) shocks, which is orthogonal to the vector of reduced-form idiosyncratic shocks ($\mathbf{u}_{mit}$) in (1).

We stack the conditional and marginal models, (1) and (3), in a single GVAR representation. Let $\mathbf{x}_{mt} = (\mathbf{z}'_{mt}, \bar{\mathbf{z}}'_{mt})'$ where the dimension of $\mathbf{x}_{mt}$ is $3M + 4$. As a result, we obtain

$$\mathbf{A}_{m0}\mathbf{x}_{mt} = \sum_{\ell=1}^{p} \mathbf{A}_{m\ell}\mathbf{x}_{m,t-\ell} + \mathbf{e}_{mt}, \tag{4}$$

where $\mathbf{e}_{mt} = (\mathbf{u}'_{mt}, \mathbf{v}'_{mt})'$ with $\mathbf{u}_{mt} = (\mathbf{u}'_{m1t}, \mathbf{u}'_{m2t}, ..., \mathbf{u}'_{mnt})'$, and the coefficient matrices are given by

$$\mathbf{A}_{m0} = \begin{pmatrix} \mathbf{I}_{3M} & -\mathbf{B}_{m0} \\ \mathbf{0} & \mathbf{I}_4 \end{pmatrix} \text{ and } \mathbf{A}_{m\ell} = \begin{pmatrix} \mathbf{\Phi}_{m\ell}+\mathbf{\Psi}_{m\ell}\mathbf{W} & \mathbf{B}_{m\ell} \\ \mathbf{0} & \mathbf{\Pi}_{m\ell} \end{pmatrix} \text{ for } \ell = 1, 2, ..., p,$$

in which $\mathbf{B}_{m\ell} = (\mathbf{B}'_{m1\ell}, \mathbf{B}'_{m2\ell}, ..., \mathbf{B}'_{mn\ell})'$, and $\mathbf{\Phi}_{m\ell}$ and $\mathbf{\Psi}_{m\ell}$ are diagonal matrices with blocks $\mathbf{\Phi}_{mi\ell}$ and $\mathbf{\Psi}_{mi\ell}$ on the diagonal, respectively. Noting that $\mathbf{A}_{m0}$ is always invertible, we can multiply the representation (4) by $\mathbf{A}_{m0}^{-1}$ from the left to obtain the following augmented GVAR representation for the product category m,

$$\mathbf{x}_{mt} = \sum_{\ell=1}^{p} \mathbf{G}_{m\ell}\mathbf{x}_{m,t-\ell} + \mathbf{A}_{m0}^{-1}\mathbf{e}_{mt}, \tag{5}$$

in which $\mathbf{G}_{m\ell} = \mathbf{A}_{m,0}^{-1}\mathbf{A}_{m\ell}$ and

$$\mathbf{A}_{m,0}^{-1} = \begin{pmatrix} \mathbf{I}_{3M} & \mathbf{B}_{m,0} \\ \mathbf{0} & \mathbf{I}_4 \end{pmatrix}.$$

Our econometric analysis is conducted based on GVAR model in (5) for each product (m) separately.

It is informative to highlight the distinctive features of the GVAR approach in comparison with those popularly employed in the previous studies using similar panel datasets. Although the purchasing power measure (y_{mit}) has yet to be considered in the literature, there are numerous applications in this direction that focus on the behavior of disaggregated prices and/or wages. The majority of studies in this regard tend to rely on spatial econometric models (e.g., Kelejian and Prucha, 2004). Since pioneered by Whittle (1954), spatial econometrics has seen a rapid growth in terms of the depth and breadth. See Lee and Yu (2010) for a review on the developments in this field. From an econometric perspective, the spatial econometric tools can be grouped into two categories depending on the relative size of cross-sections and time dimensions of panel data. When time dimension (T) is limited (to only a few annual observations) and hence T is treated as fixed while the cross-section dimension (N) is large ($N \to \infty$), modeling dynamics is quite challenging. Studies in this strand either employ static specifications (e.g., Combes et al., 2008) or allow for dynamics in the form of lagged dependent variable(s) with homogeneous slope coefficients (e.g., Kelejian and Piras, 2014). With the increased availability of data observations for both time and cross-sections, however, the focus of the spatial econometric studies has shifted to the case with N and T both large ($N, T \to \infty$ jointly). This environment allows for more general specifications in which one can track the diffusion of the shocks of interest across both space and time (e.g., Brady, 2011). Nevertheless, most empirical studies based on the mainstream spatial models typically place homogeneity restrictions on the slope coefficients and rule out strong cross-sectional dependence in innovations. For this reason, it is fair to claim that the GVAR approach is more general by allowing for both strong cross-section dependence and heterogeneity in the slope coefficients, although it is important to note that a more recent contributions in spatial econometric literature have relaxed the slope homogeneity and accommodated strong cross-sectional correlation (e.g., the two-step approach proposed by Bailey et al., 2016a). In contrast to the spatial econometric approaches, however, the GVAR model in (1) is a reduced-form model where geographic origins of the idiosyncratic shocks ($\mathbf{u}_{mit}$) are left unidentified. Nevertheless, the estimated coefficients in (1) are consistent and asymptotically normal for any arbitrary spatial dependence of $\mathbf{u}_{mit}$ that results in a weak cross-sectional correlation.

C Variance decompositions

Reduced-form VAR model (4) has a large dimension, but once estimated, it can be used for variance decomposition in the standard way, recognizing that $E(\mathbf{v}_{mt}\mathbf{u}'_{mt}) = \mathbf{0}$.

Assuming $p = 1$ for simplicity of exposition, we have

$$\mathbf{x}_{mt} = \mathbf{G}_{m1}\mathbf{x}_{m,t-1} + \mathbf{A}_{m0}^{-1}\mathbf{e}_{mt},$$

which implies the following moving average representation,

$$\mathbf{x}_{mt} = \sum_{\ell=0}^{\infty} \mathbf{G}_{m1}^{\ell}\mathbf{A}_{m0}^{-1}\mathbf{e}_{m,t-\ell}.$$

Hence, the total variance is given by

$$\boldsymbol{\omega}_m = \sum_{\ell=0}^{\infty} \mathbf{G}_{m1}^{\ell}\mathbf{A}_{m0}^{-1}\boldsymbol{\Sigma}_e\mathbf{A}_{m0}^{-1\prime}\mathbf{G}_{m1}^{\ell\prime},$$

where (noting that $\mathbf{e}_{mt} = (\mathbf{u}'_{mt}, \mathbf{v}'_{mt})'$ and $E(\mathbf{v}_{mt}\mathbf{u}'_{mt}) = 0$)

$$\underset{k+4\times k+4}{\boldsymbol{\Sigma}_e} = E\left(\mathbf{e}_{mt}\mathbf{e}'_{mt}\right) = \begin{pmatrix} E(\mathbf{u}_{mt}\mathbf{u}'_{mt}) & \mathbf{0} \\ \mathbf{0} & E(\mathbf{v}_{mt}\mathbf{v}'_{mt}) \end{pmatrix}.$$

Let us define

$$\underset{k+4\times k+4}{\tilde{\boldsymbol{\Sigma}}_u} = \begin{pmatrix} E(\mathbf{u}_{mt}\mathbf{u}'_{mt}) & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \end{pmatrix} \text{ and } \underset{k+4\times k+4}{\tilde{\boldsymbol{\Sigma}}_v} = \begin{pmatrix} \mathbf{0} & \mathbf{0} \\ \mathbf{0} & E(\mathbf{v}_{mt}\mathbf{v}'_{mt}) \end{pmatrix},$$

so that $\boldsymbol{\Sigma}_e = \tilde{\boldsymbol{\Sigma}}_u + \tilde{\boldsymbol{\Sigma}}_v$. Variance explained by the national and idiosyncratic shocks is given by

$$\boldsymbol{\omega}_m^{nat} = \sum_{\ell=0}^{\infty} \mathbf{G}_{m1}^{\ell}\mathbf{A}_{m0}^{-1}\tilde{\boldsymbol{\Sigma}}_u\mathbf{A}_{m0}^{-1\prime}\mathbf{G}_{m1}^{\ell\prime},$$

and

$$\boldsymbol{\omega}_m^{id} = \sum_{\ell=0}^{\infty} \mathbf{G}_{m1}^{\ell}\mathbf{A}_{m0}^{-1}\tilde{\boldsymbol{\Sigma}}_v\mathbf{A}_{m0}^{-1\prime}\mathbf{G}_{m1}^{\ell\prime},$$

respectively. Formulas for VAR(p) model wiht $p > 1$, can be obtained using its corresponding companion VAR(1) representation.

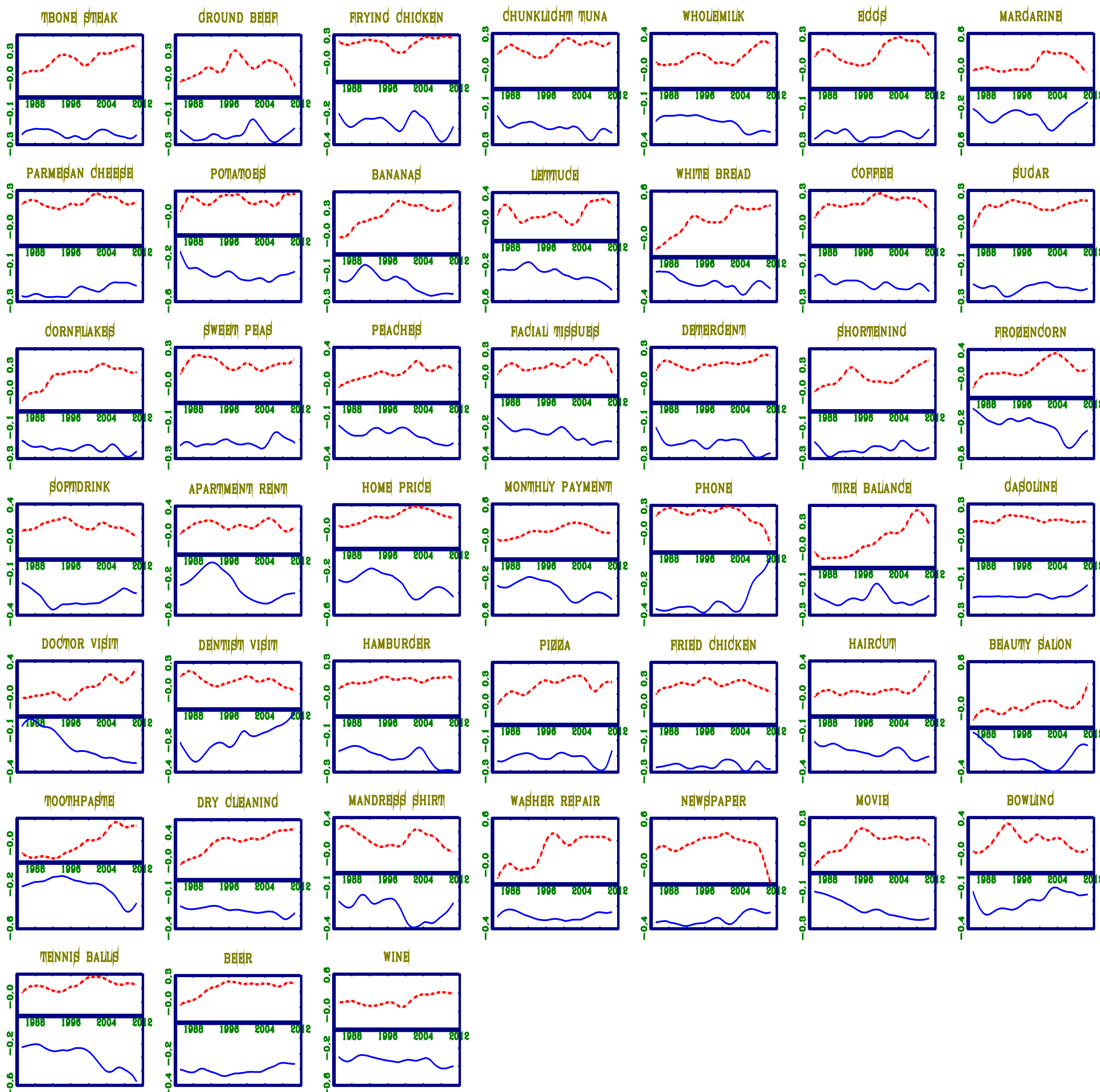
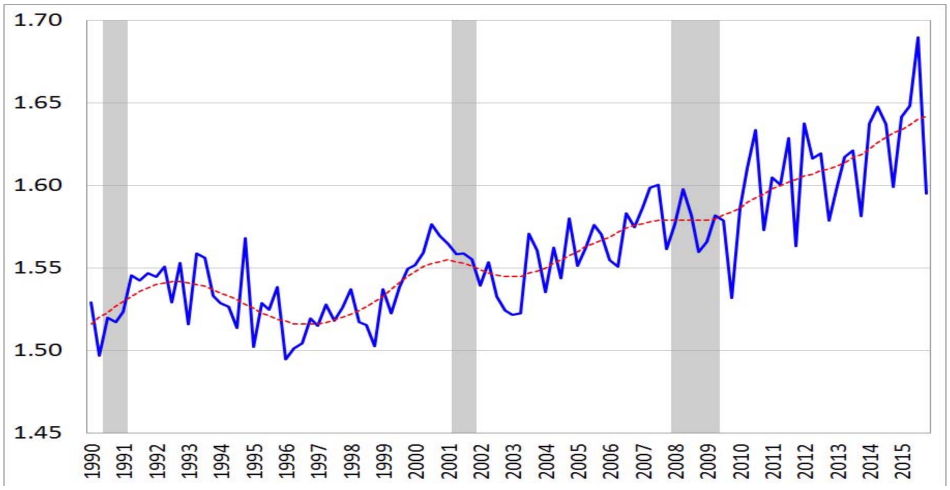
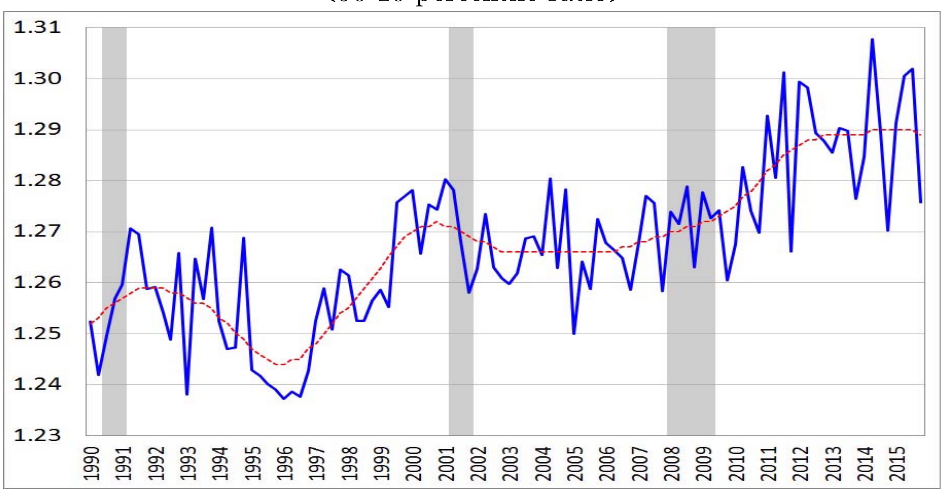


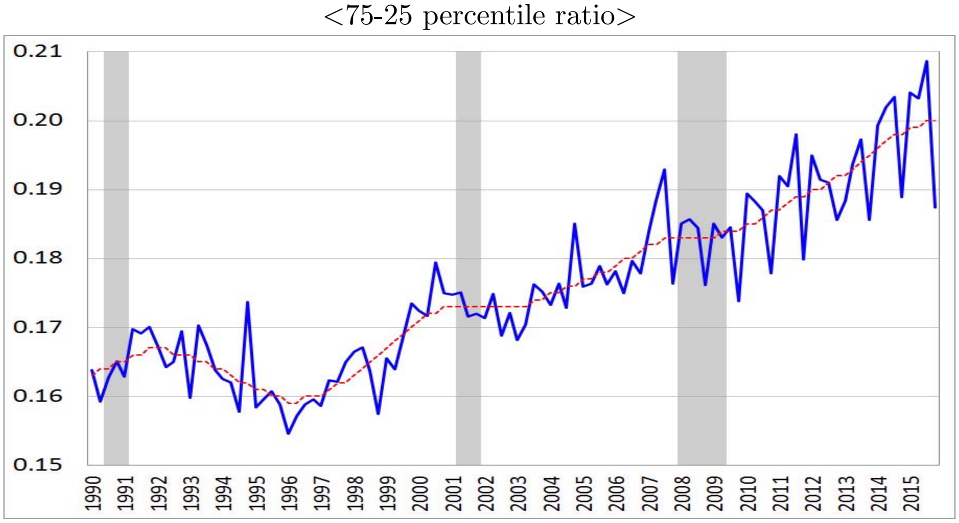
Figure 1: Average economic well-being of the top three cities (dotted line) and the bottom three cities (solid line)



<90-10 percentile ratio>

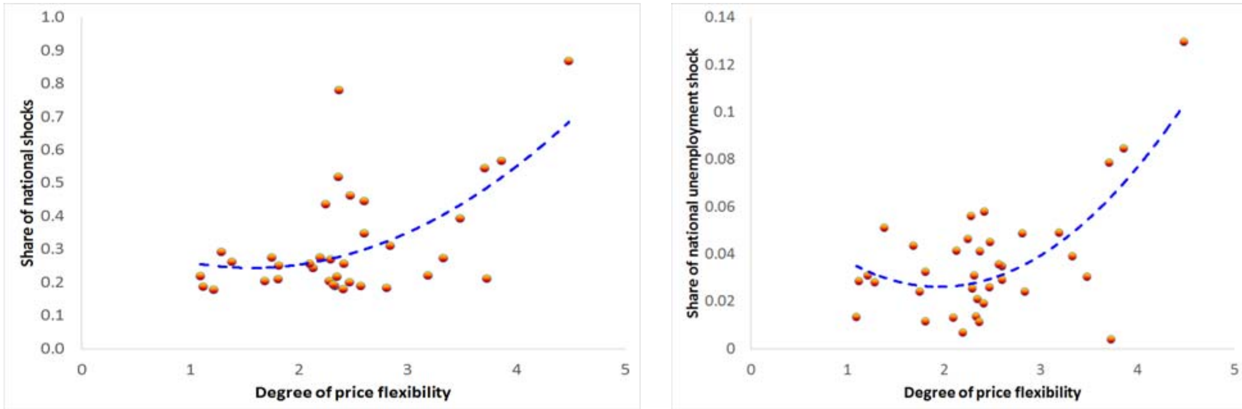


<75-25 percentile ratio>



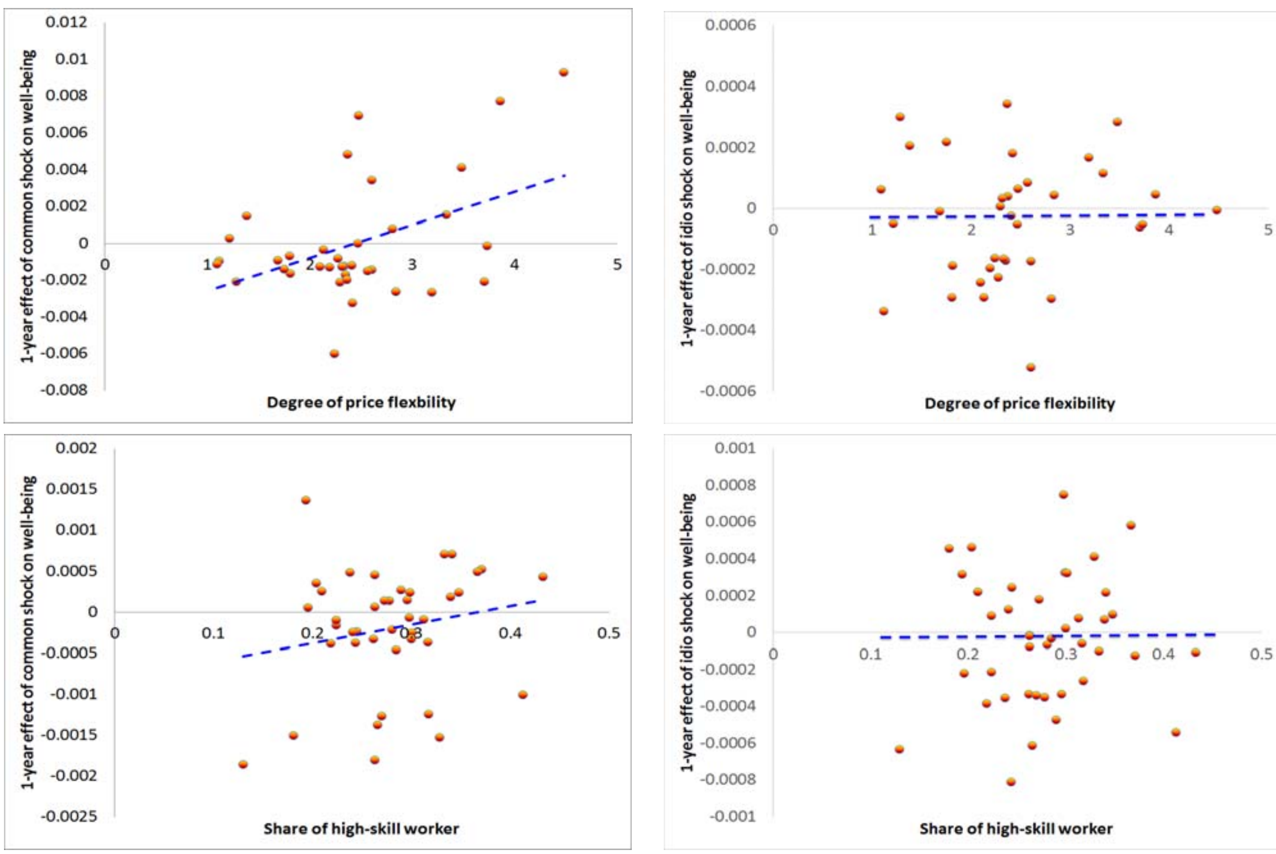
<Coefficient of Variations (CV)>

Figure 2: Evolution of aggregate cross-city dispersion of local purchasing power



All national shocks National unemployment shock

Figure 3: Price flexibility (horizontal axis) and the average share of well-being explained by all national shocks (left) and national unemployment shock (right)



Common UR shock Idiosyncratic UR shock

Figure 4: Product flexibility (top) and share of high-skill worker (bottom) against 1-year cumulative national (left) and idiosyncratic (right) shocks of unemployment rates on well-being