**Federal Reserve Bank of Dallas**
**Globalization and Monetary Policy Institute**
Working Paper No. 330
https://doi.org/10.24149/gwp330

# Geographic Inequality of Economic Well-being among U.S. Cities: Evidence from Micro Panel Data*

Chi-Young Choi
University of Texas at Arlington

Alexander Chudik
Federal Reserve Bank of Dallas

November 2017

**Abstract**

We analyze the geographic inequality of economic well-being among U.S. cities by utilizing a novel measure of quantity based product-level economic well-being, i.e., the number of goods and services that can be purchased by consumers with an average city wage. We find a considerable cross-city dispersion in the economic well-being and the geographic dispersion has been on the steady rise since the mid-1990s for most goods and services under study. Strong geographic correlations exist in the local economic well-being and our empirical analysis based on a Global VAR (GVAR) model suggests that national shocks are an important source behind it. On average, about 30-35% of the variance of local well-being is explained by common national shocks, but the impact of common national shocks varies considerably across products, albeit to a lesser extent across cities. Nationwide unemployment shock, for example, has a stronger effect in the products whose prices are adjusted more frequently and in the cities that have a larger fraction of high-skill workers. Taken together, our results indicate that the geographic inequality of economic well-being observed in the U.S. has proceeded over time mainly through the products with more flexible price adjustments and in the cities with higher concentration of skilled workers.

**JEL codes**: E21, E31, R12, R31

* Cy Choi, University of Texas at Arlington, Department of Economics, 701 S. West Street, Arlington, TX 76019. 817-272-3860. cychoi@uta.edu. Alexander Chudik, Federal Reserve Bank of Dallas, Research Department, 2200 N. Pearl Street, Dallas, TX 75201. 214-922-5769. alexander.chudik@dal.frb.org. We are grateful for helpful comments to the participants at 2017 Asian Meeting of Econometric Society (AMES) in Hong Kong, the 2017 Midwest Econometrics Group (MEG) Meeting at Texas A&M University, and the 2017 Conference on Health and Development at Academia Sinica in Taiwan. The views in this paper are those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Dallas or the Federal Reserve System.

# 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 is 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., forthcoming; to cite a few), insufficient attention has been paid to the issue on the geographic dimension. Previous literature attributes the surge in income inequality at the national level 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 non-negligible 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 likely that these factors have exerted different effects 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 instance, 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. Beraja et al. (2017) also claim that the Fed's expansionary monetary policy during the recent Great Recession has widened the disparities among regions in the United States. 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 economic well-being. If cities with systematically higher income levels have higher consumer prices as often postulated in popular theoretical models (e.g., the basic Rosen-Roback model), the geographic inequality in economic well-being may not be as serious as it looks because 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 magnitude and evolution of geographic dispersion of regional economic well-being. Moreover, far less is understood about the channels through which nominal income differences are transmitted to the regional disparities in economic well-being.

The current study aims at filling this void by addressing several important questions regarding the geographic inequality of economic well-being: (i) how widely economic well-being is dispersed among U.S. cities; (ii) how the geographic disparities have evolved over time; and (iii) what factors account for the fluctuations and evolution of the geographic disparities. While most previous studies in this direction look at cross-sectional patterns of inequality, our study focuses on the dynamic behavior of the inequality across U.S. metro areas over time. Temporal variations of the geographic disparities are expected to provide potentially useful intuition in understanding the key issues at hand. Answering these questions, however, is by nature challenging in the lack of an appropriate measure of economic well-being across locations over time. To deal with this issue, we construct a novel measure of product-level economic well-being by utilizing 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 United States. Specifically, our *quantity based measure* of economic well-being is computed by dividing city-level wages by retail prices of individual consumer products. This captures the number of product units that can be purchased with an average wage in each city. 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 thanks to the homogeneity of products across locations. Since the underlying observations are collected consistently, by a single organization, from a survey of consumers with a specific income level (the mid-level managers), the ACCRA data also helps alleviate the issue of '*non-homotheticity*' of consumers. As highlighted by Handbury (2012), cross-city price indexes vary widely across income groups and using homothetic cost-of-living indexes understates the relative price level across locations once non-homotheticity is allowed for in preferences. Another merit of the ACCRA dataset is that it permits us to implement a panel data analysis in which we can identify the location and product specific factors that are conducive to the geographic dispersion of local economic well-being. Specifically, our city-level well-being measures are regressed onto a set of location-specific explanatory variables, including local labor market conditions and housing prices, within the framework of Global VAR (GVAR) model originally proposed by Pesaran et al. (2004). This approach allows us to track the dynamic impacts of both national and local idiosyncratic shocks of explanatory variables, providing additional insight into the dynamic evolution of geographic dispersion of economic well-being and the underlying factors influencing the evolution.

This study is not the first to look into the regional economic well-being inequality in the United States. 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). But, most of these studies are directed to study the issue at cross-sectional variations with no explicit consideration on the cost-of-living differences across locations. Failure to correct for local prices is likely to misguide subnational income inequality as often pointed out in the literature. Indeed, it has long been recognized that a salient feature of the cost-of-living in the U.S. is the considerable dispersion across locations with highly heterogeneous dynamics of regional prices (e.g., Choi and Wang, 2015). Some notable exceptions in this regard include the recent work by Beraja et al. (2014), Handbury (2012), and Handbury and Weinstein (2015) who used micro price datasets (e.g., Nielsen's Database) to construct local or state-level price indices. Their analyses, however, focus on the regional differences of the cost-of-living *per se* without extending it to the context of well-being inequality or looking at their dynamic behavior over time.

We find a significant geographic dispersion in the local economic well-being among the U.S. cities, although the size of the geographic dispersion differs vastly across products. For example, the ratio of the most affordable city (where consumers can buy most products with the average wage) relative to the least affordable city (where consumers can buy least products with the average wage) is in the range of 1.52 and 2.38, implying that consumers in the most affordable city can purchase 52% to 138% more goods or services than those in the least affordable city. In light of the homogeneity of products across locations in terms of the brand names and the key features, this size of well-being gap among sub-national economies is surprising and does not run in accordance with the models based on *spatial equilibrium* which predict that utility levels are equalized across cities within a national border. The large and persistent cross-city welfare disparities found in our data, however, squares well with the more recent findings in the literature (e.g., Kennan and Walker, 2011; Yoon, 2017). We further find that the geographic disparities in economic well-being do not attenuate over time. This can be seen from Figure 1, which plots the evolution of the average economic well-being in the three most affluent cities (dotted line) and that in the least affluent cities (solid line) for each product. 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 the cross-city coefficient of variation (CV) of economic well-being for U.S. cities over the sample period. The geographical dispersion of well-being has been on the rise since the mid-1990s for the entire products (ALL) as well as for three sub-groups: nondurables (ND), durables (D), and services (S).

Our regression analysis based on the GVAR models sheds some light on the transmission channels through which shocks influence the cross-city dispersion of economic well-being. National shocks play a nontrivial role in the variations of local economic well-being in most products under study. Interestingly, the importance of national shocks is meaningfully associated with the degree of price flexibility such that the economic well-being is more responsive to national shocks in the products whose prices are adjusted more frequently. Take the cumulative effect of unemployment shock for example, we uncover that economic well-being in the U.S. cities is more responsive to nationwide shocks than to local idiosyncratic shocks of labor market. In the vast majority of products, a surprise increase in the national unemployment rate hampers local economic well-being by reducing the number of goods and services available for city-level wages, which is consistent with wide-held belief. By contrast, in some other products whose prices are typically adjusted more frequently, the economic well-being actually improves rather than deteriorates after a national shock in unemployment. At the city level, we find moderate but intriguing evidence that economic well-being is more responsive to a national unemployment shock in the cities with greater portion of high-skill workers holding at least bachelor's degree. This lends credence to the view that skill-biased geographic sorting may have contributed to the growing disparities of economic well-being among U.S. cities.

We further find that the effect of nationwide unemployment shock on the geographic dispersion of well-being is asymmetrical. While the well-being of U.S. cities is geographically more dispersed after an increase in national unemployment rates, no significant change was found in the well-being dispersion when national unemployment rates fall. This result points to the possibility that the geographic dispersion of economic well-being in the U.S. might have been accelerated during the recent Global Financial Crisis when the national unemployment rate increased rapidly. We notice that the rise in the dispersion of well-being after a national unemployment shock occurred primarily in the products whose prices are adjusted more frequently. This stands in sharp contrast to the impact of national housing price changes which took place mainly in the products with sluggish 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 quantity-based economic well-being. We also discuss geographic distribution of economic well-being and its evolution over time. Section 3 lays out the regression analysis based on the GVAR model with the focus on the relative importance of national shocks, in particular unemployment shock, in explaining the volatility of local economic well-being. Here we attempt to parse out potential factors behind the widening geographic disparities of economic well-being among cities in the U.S. Section 4 concludes the paper. The Appendix contains a detailed description of the data and the technical notes on variance decomposition.

# 2 Data and diagnostic analysis

## 2.1 The data

We construct a quantity based measure city-level economic well-being using 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 choice 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. The sample covers a relatively long time span, 1990.Q1 to 2015.Q4, which is crucial for tracing out the dynamic behavior of geographic well-being distribution over time. Details about the data are provided in tabular form in Appendix A. Summary descriptions of these price data are reported in Table A.1 along with the city-level information listed in Table A.2.

As already noted, product homogeneity is a remarkable feature of our price data in the comparison of economic well-being across different locations. The survey prices are absolute prices for specific goods and services collected in a consistent manner by a single agency and thus refer to almost the same product at different locations. 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).[1] Recall that our price dataset is also robust to the non-homotheticity issue because the underlying observations are collected from a particular group of consumers (mid-level managers) at different locations.

Following the convention in the literature, we consider explanatory variables for the regression analysis that may influence local economic well-being. Although theory offers a long list of factors that might explain cross-city differences in the economic well-being, city-level unemployment rates and house prices stand out as they are closely related to both consumer prices and wages that constitute local economic well-being (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 U.S. Bureau of Labor Statistics (*https://www.bls.gov/cew/*). Compiled from all establishments reporting to the Unemployment Insurance (UI) program, the QCEW data are released by state governments for each

[1] That said, it is still possible that some products in our dataset may not be exactly identical across cities as there is no specific information on brand names.

quarter and are known to be the longest and most temporally granular panel of wage data.

We also consider local house prices as another control variable for local economic welfare. The house price data are obtained from the ACCRA dataset as well. 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 economic well-being, 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 cost of living across locations (e.g, Hsieh and Moretti 2015, Strobel 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 considerable relationship between the two over time and space (e.g., Gyourko et al., 2013; Moretti, 2013; Van Nieuwerburgh and Weill, 2010).[2]

We further consider several city characteristics that may affect local economic well-being, such as 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 area-level productivity, income and hence economic well-being. Given the emphasis conventionally placed on human capital as a determinant of city productivity and prosperity, it is likely that the share of high-skilled workers is a relevant factor for cross-city differences in the economic well-being. Furthermore, it is broadly agreed that the cities with 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 period average city-level economic well-being 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 quantity-based economic well-being measure. Take 'Steak' for example, the mean value of 13.09 implies that 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

[2] Nieuwerburgh and Weill (2010) find that house prices compensate for cross-sectional productivity differences reflected in the dispersion of wages. In a similar spirit, Moretti (2013) shows that local prices are highly influenced by local house prices. By contrast, Gyourko et al. (2013) maintain that a change in the house price induces a change in the local income distribution.

they live, however, the purchasing power of daily wages varies substantially 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 noticed in other products. As shown in the fourth column of the table, the 'ratio' of purchasing power of wage 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 well-being 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 satisfactory explanation for the significant cross-product heterogeneity in the economic well-being. This argument can be readily supported by looking at the cross-sectional coefficient of variation (CV), a scale-neutral measure of dispersion, presented in the last column of the table. The cross-city dispersion of economic well-being differs considerably across products. Some products like 'Movies' and 'Gas' have relatively small CVs, indicating that economic well-being is not much geographically dispersed in those products, while CVs of other products such as Newspaper and Potato are quite large. Again, there seems to be no clear indication that the cross-product difference in CV is meaningfully associated with the conventional product classification based on the tradeability.

Spatial relationships among subnational economies usually arise from geographic interactions of one city to another in the form of spillover of shocks or mobility of production factors. 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 economic well-being. Alternatively, the geographic interdependence of economic well-being 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. In this context, it is instructive to explore the pattern of geographic interdependences of economic well-being 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) that is often modeled by a factor model with strong factor loadings and weak dependence that is compatible with conventional spatial models in the literature. Since most panel datasets are subject to a combination of strong and weak CSDs, a methodology that is capable of identifying and dealing with both forms of CSD is needed.

To measure cross-sectional dependence of local economic well-being, 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.[3] Table 2 presents the summary statistics of the spatial correlation of economic well-being for each product. As presented in the left-hand panel of Table 2, there is a significant comovement and interdependence of economic well-being 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 support the conventional categorizations of products based on tradeability. The Pesaran's 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 economic well-being is highly correlated across cities. To test whether the nature of the observed cross-sectional dependence is weak or strong, the exponent $\alpha$-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 that 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 economic well-being among U.S. cities is strong for the vast majority of products.

The strong cross-city comovement of economic well-being 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 economic well-being 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] 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 $x_{it}$.

## 3 Empirical analysis

Our analysis so far underscores that economic well-being is widely dispersed across cities in the U.S. but with strong comovements, and the geographic dispersion varies substantially across products. What is less known is to what extent they vary and by which factors such variations across products and locations can be explained. To address these questions, in this section we carry out an econometric analysis based on a recent advances in the Global VAR (GVAR) model approach in the literature. Originally introduced by Pesaran et al. (2004) and subsequently extended by numerous contributions, the GVAR approach is particularly suitable for our analysis on several grounds. 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 a 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. As noted by Pesaran and Smith (1995), a false imposition of homogeneity restriction in a dynamic setting will result in inconsistent estimation. Third, the GVAR model permits us to treat all variables as endogenous.[4]

Here our model is closely related to the model estimated in Chudik and Pesaran (2011) for disaggregated consumer prices. In this section, we first describe the GVAR representation of our variables and then compare our approach with other alternative approaches popularly adopted in the empirical literature for studying similar datasets, prior to presenting the estimation results.

### 3.1 GVAR model of regional well-being

Let us define the following variables:

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

where $m = 1, 2, ..., M$, $i = 1, 2, ..., N$, and $t = 1, 2, ..., T$. $y_{mit}$ represents the economic well-being 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

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

dimension as the cross-section dimension, if not specified otherwise. We collect the first differences of these variables in the $3 \times 1$ vector $\mathbf{z}_{mit} = (\Delta y_{mit}, \Delta ur_{it}, \Delta hp_{it})'$. In addition, we define a $4 \times 1$ 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 all well-being 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 (e.g., Pesaran, 2006).[5] 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).

Following Chudik and Pesaran (2011), we estimate the following conditional models for each product $m$ separately,

$$\mathbf{z}_{mit} = \sum_{\ell=1}^{p} \mathbf{\Phi}_{mi\ell}\mathbf{z}_{mi,t-\ell} + \sum_{\ell=0}^{p} \mathbf{B}_{mi\ell}\bar{\mathbf{z}}_{mt-\ell} + \sum_{\ell=1}^{p} \mathbf{\Psi}_{mi\ell}\mathbf{z}^*_{mi,t-\ell} + \mathbf{u}_{mit}, \text{ for } i = 1, 2, ..., N, \tag{1}$$

where $\mathbf{\Phi}_{mi\ell}$ and $\mathbf{\Psi}_{mi\ell}$ are respectively $3 \times 3$ matrices of coefficients, $\mathbf{B}_{mi\ell}$ is $3 \times 4$ 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.

Following Chudik et al. (2016), we augment the conditional models in (1) with the following marginal model for the vector of national averages $\bar{\mathbf{z}}_{mt}$ and again constant terms are included but omitted from the exposition,

$$\bar{\mathbf{z}}_{mt} = \sum_{\ell=1}^{p} \mathbf{\Pi}_{m\ell}\bar{\mathbf{z}}_{m,t-\ell} + \mathbf{v}_{mt}, \tag{2}$$

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

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

We stack the conditional and marginal models in a single GVAR representation. Let $\mathbf{z}_{mt} = (\mathbf{z}'_{m1t}, \mathbf{z}'_{m2t}, ..., \mathbf{z}'_{mnt})'$, and define $\mathbf{x}_{mt} = (\mathbf{z}'_{mt}, \overline{\mathbf{z}}'_{mt})'$ where the dimension of $\mathbf{x}_{mt}$ is $3M + 4$. As a result, we obtain

$$\mathbf{A}_{m0}\mathbf{x}_{mt} = \sum_{\ell=1}^{p} \mathbf{A}_{m\ell}\mathbf{x}_{m,t-\ell} + \mathbf{e}_{mt}, \tag{3}$$

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 $\mathbf{I}_k$ is a $k \times k$ identity matrix, $\mathbf{B}_{m\ell} = (\mathbf{B}'_{m1\ell}, \mathbf{B}'_{m2\ell}, ..., \mathbf{B}'_{mn\ell})'$, 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 (3) by $\mathbf{A}_{m0}^{-1}$ from the left to obtain the following augmented GVAR representation for the product category $m$,

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

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 by estimating the GVAR model (4) for each product ($m$) separately.

Before moving on, it is informative to highlight the distinctive features of the GVAR approach in comparison with those popularly employed in the previous studies using similar datasets. Although the quantity based economic well-being measure ($y_{mit}$) has yet been 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).[6]

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

[6] 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.

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 slope coefficients, although we are aware that 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, the GVAR model in (4) is a reduced-form model where geographic origins of the shocks are not identified, and idiosyncratic shocks ($\mathbf{u}_{mit}$) are allowed to be arbitrarily weakly cross-sectionally correlated without a particular specification for spatial dependence.

### 3.2 Estimation results

We first look at the contribution of the national shocks ($\mathbf{v}_{mt}$ in (2)) to the changes in economic well-being. Because $E(\mathbf{v}_{mt}\mathbf{u}_{mt}) = 0$ by design with the sufficient number of lags $p$, it is possible to decompose the variance of $\Delta y_{mit}$ 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 shock will sum to 1 or 100%. A larger fraction of national shocks implies stronger response of local economic well-being to common national shocks. Thus, stronger comovements of economic well-being across cities in those products. Bear in mind that 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 B.

Table 3 presents the estimated fractions of the national shocks in the variance of economic well-being changes by products (on the left panel) as well as by cities (on the right panel). As presented in the left-panel of Table 3, on average around 30% of the variance of local economic well-being change is explained by national shocks that commonly affect all cities, possibly with different time profiles and magnitudes. This implies that economic well-being moves in tandem with the national level to a certain extent, 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 finding on the strong cross-city correlation in local economic well-being. Again, there is a large cross-product variation in the effect of national shock, ranging from 17.8% (Tennis balls) to 86.7% (Gasoline).

At the city level, the national shocks have nontrivial impacts on the fluctuations of the economic well-being. As can be seen from the right-hand panel of Table 3, the average share of the national shock is in a relatively narrow range from 25.6% (Salt Lake City) to 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 other 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 alone do not seem to be promising in this regard as discussed earlier. Another potential source that is 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. We look at 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).[7] 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 economic well-being (on the vertical axis) for the entire 43 products. As illustrated in the left panel of Figure 3, price flexibility bears a positive relationship to the share of national shocks. To rephrase, national shocks are likely to impart a greater impetus to the economic well-being in the products whose prices are adjusted more frequently. This is probably because national shocks are translated into local economic well-being mainly through price changes rather than through wage changes that are common to all the products in given locations. The right-panel of Figure 3 yields a largely similar story when we concentrate on the role of unemployment shocks in explaining the variance of the local economic well-being.

We then investigate how a surprise in the unemployment rate translates into local economic well-being based on the generalized impulse response functions (GIRFs) in (4). Intuitively, unemployment

[7] 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.

shocks are likely to hamper local economic well-being by lowering real wage rates. Table 4 reports the results of such an exercise with one-year cumulative effect of unemployment shocks on local well-being changes, both across products (on the left panel) and across cities (on the right panel), obtained from the median of the 20,000 bootstrap replications. The left panel of Table 4 presents the estimated sensitivity of economic well-being by products with respect to national and idiosyncratic shocks of unemployment. Other variables included in the regressions are not reported in the table to conserve the space.

The results in the left panel of Table 4 illustrate a couple of interesting points. First, in almost all the products considered, national shocks of unemployment dominates idiosyncratic counterparts in terms of the statistical significance and the magnitude of the impacts on economic well-being. That is, the changes in economic well-being in the U.S. cities are more responsive to the nationwide shocks in the labor market than to the local idiosyncratic shocks. Second, the one-year cumulative effect of a one standard deviation shock to national unemployment differs substantially across products, with the wide dispersion of -0.0060 (Detergent) to 0.0093 (Gasoline). Note that the estimated effect has the expected negative signs in the vast majority of products (32 out of 43 products), implying that a local economic well-being or purchasing power of city wages is reduced 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 economic well-being 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 sign, i.e., a rise in national unemployment rate is likely to improve economic well-being in those products. Given that our economic well-being 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 rate in the reduction of consumer prices than in wage decrease. In consequence, the amount of products that can be purchased by the reduced wage actually increases. As such, whether national unemployment shocks increase or decrease local economic well-being seems to hinge on how fast the price of products adjusts relative to wage changes. During economic downturns when unemployment rate rises and wage declines, for example, economic well-being would decrease in the products whose prices do not adjust as fast as wage decreases, while it goes the other way around in the products where prices decline faster than wage decreases.

To substantiate this claim, we plot in Figure 4 the estimated cumulative effects of national unemployment shock (top-left) and local idiosyncratic shock (top-right) against the degree of price flexibility of products. The upper-left panel of Figure 4 provides supplementary evidence of the positive relationship between price flexibility (on the horizontal axis) and the effect of national unemployment shock on economic well-being (on the vertical axis), i.e., economic well-being increases more (or decreases less) in the products whose prices are adjusted more frequently after a national unemployment shock. This is in line with our intuition outlined above. By contrast, the picture changes somewhat substantially when it comes to the effect of local idiosyncratic shock of unemployment. As displayed in the upper-right panel of Figure 4, there is no clear-cut relation between price flexibility and the effect of idiosyncratic unemployment shock. Taken together, our results strongly suggest price flexibility as a potential factor behind the cross-product heterogeneity observed in the data. Price flexibility, however, matters for the local economic well-being mainly through national shocks rather than through local idiosyncratic shocks.

The right panel of Table 4 presents the cumulative effects of unemployment shocks on economic well-being 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 economic well-being. 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 fraction of high-skill workers in each city. Human capital is a very important source of productivity and its growth and recent evidence in the literature points to the importance of skills and ideas in determining city growth (e.g., Glaeser et al., 2011). As a matter of 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 national unemployment shock and the ratio of high-skill workers in the city, i.e., national unemployment shock has a stronger effect on economic well-being in the cities with 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.

Although intriguing, graphical representation may not provide detailed picture of the role of national shocks in explaining the growing geographic dispersion of well-being. To get a sense of magnitudes of their impacts on the cross-city dispersion of economic well-being in a more formal manner, we conduct another regression analysis based on the following model specification:

$$\Delta CV_t^m = \alpha_m + \theta_t + \beta_1 \Delta NUR_t^+ + \beta_2 \Delta NUR_t^- + \gamma \Delta NHP_t + \varepsilon_{it}^m, \tag{5}$$

where $CV_t^m$ denotes the coefficient of variation (CV) of economic well-being in product $m$, which is a scale-neutral measure of cross-city dispersion. $\alpha_m$ and $\theta_t$ respectively denote dummy variables for product and time. $NUR$ represents the seasonally adjusted national U.S. unemployment rates and $NHP$ is the seasonally adjusted S&P/Case-Shiller U.S. National Home Price Index. It should be noted that we explicitly include both increase ($\Delta NUR^+$) and decrease ($\Delta NUR^-$) in national unemployment rates as separate variables, along with the changes in national housing price ($\Delta NHP$). This is motivated by the fact that in the business cycle more could be learned by looking at different phases of business cycle separately rather than in combination. For example, it is widely documented in the literature (e.g., Neftci 1984, Rothman 1991) that business cycles have asymmetric effects on some key macroeconomic variables like unemployment rates.[8] In light of the asymmetric relationship between labor market indicators and aggregate outputs over the business cycle, it is possible that the effect of national unemployment rates on the local economic well-being also could be asymmetrical. Regression (5) formalizes this insight. Moreover, to take into account potential role of price flexibility in explaining the growing geographic dispersion of economic well-being in the U.S., we estimate this specification for two separate subgroups based on price flexibility as well as for the full sample, one with more flexibly priced products (FLEX) and the other with less flexibly priced products (RIGID) as presented in the fourth column of Table A.1. By so doing, we expect to detect the transmission channels through which labor market conditions affect local economic well-being.

The results are displayed in Table 5 where we only report the results for the variables of interest to keep the analysis focused. An overall assessment of our results is that the evidence appears to point to the existence of an asymmetric effect of national unemployment rates on the dispersion of economic well-being. As presented in the first column of the table, in the full sample case a rise in the national unemployment rate has a positive effect, but a decrease in the national unemployment rate has a negative effect on the dispersion of cross-city well-being. Put alternatively, local well-being of the U.S. cities is likely to be more (less) dispersed during economic downturns (upturns) when unemployment rate rises (declines), although they are statistically insignificant. National house price changes have a

[8] Neftci (1984) shows that several measures of U.S. unemployment display asymmetric adjustment over the course of the business cycle. Focusing on the asymmetric behavior of unemployment rates over the business cycle, Rothman (1991) also finds that the cyclical behavior of the unemployment rate in the manufacturing sector is the primary source of asymmetry.

positive and significant effect on the dispersion of well-being, i.e., economic well-being is geographically more (less) dispersed during the housing boom (bust) period. This can be interpreted as saying that the geographic dispersion of economic well-being might have accelerated during the recent recovery from the earlier housing market crash.

The story changes somewhat drastically when it comes to the subgroup analysis. In the flexible price product (FLEX) group, there exists strong evidence on the asymmetric effect of unemployment rates, clearly demonstrating the explanatory power of $\Delta NUR^{+}$ but not of $\Delta NUR^{-}$. Interestingly, the effect of national house price changes is no longer significant in this subgroup. By contrast, in the sluggish price product (RIGID) group reported in the last column, national house price changes have a positive and significant effect on the economic well-being dispersion, while the changes in national unemployment rates have unexpected signs with no statistical significance. In sum, our results can be viewed as indicating that the channels through which national economic shocks influence the geographic dispersion of economic well-being of the U.S. cities hinges on the product characteristics. While national unemployment rate changes affect the geographic well-being dispersion primarily through the products with flexible price adjustments, national house price changes do so mainly via the products whose prices are less flexibly adjusted.

## 4 Concluding remarks

Recent years have seen a surge in research interest in income inequality. Despite substantial investigation of the issue, the debate surrounding the income inequality in the U.S. has mainly concentrated on the national level and thus far less attention has been paid to its implications at the regional level. A large and persistent dispersion of economic well-being across locations within a national border implies distortions in efficient resource allocations. This is particularly the case for the subnational economies, like cities in the U.S. that share 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 that the geographic wage or income inequality observed in the data is translated to actual inequality in economic well-being. Far less is known about how such geographic inequality in the economic well-being has evolved over time. To gain further insight on these issues, we utilized a micro panel dataset of actual consumer prices and constructed a novel quantity based measure of economic well-being among U.S. cities.

Using the city-level economic well-being we reach several main conclusions. First, there has been a large and persistent dispersion of the economic well-being in the United States. The geographic dispersion of economic well-being is substantial in all products under study and it has been on a steady rise since the mid-1990s. The persistent cross-city dispersion of economic well-being found in the data is difficult to compromise with some theoretical models which predict that utility levels are equalized across cities in the presence of factor mobility.

Second, the movements of local economic well-being are quite responsive to national shocks which are common to all cities, possibly due to the reduced factor mobility across subnational economies (e.g., Kennan and Walker, 2011; Yoon, 2017). Common national shocks contribute a nontrivial fraction of the variation of local economic well-being, with the fraction varying considerably across products. Interestingly, the cross-product heterogeneity in the effect of national unemployment shock is meaningfully associated with the cross-product differences in the flexibility of price adjustments. 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. While local economic well-being tends to deteriorate after an unanticipated increase in national unemployment rate in the sluggish price products, it is likely to improve in the flexible price products. When it comes to the cross-city variations, it was found that cities with systematically higher portion of skilled workers are prone to have greater impact of national unemployment shocks on the economic well-being.

Last but not the least, national unemployment rates have an asymmetric effect on the geographic dispersion of well-being such that economic well-being gets more dispersed across the U.S. cities after a rise in unemployment rate, but no significant change was noted after its decline. Moreover, such an increase in the geographic dispersion takes place mainly in the products whose prices are adjusted more frequently. By contrast, an increase in national house prices leads to a greater geographic dispersion of well-being, primarily in the products where prices are adjusted sluggishly. As such, the channels through which shocks affect the inter-city dispersion of economic well-being differs across the source and nature of the shocks.

Combined together, our analysis yields some intuition on the channels through which nationwide shocks are transmitted to the geographic dispersion of economic well-being among U.S. cities. Our results indicate that the geographic inequality of economic well-being in the U.S. might have proceeded over time mainly through the products with more flexible price adjustments and in the cities with higher concentration of skilled workers.

## References


[1] Acemoglu, Daron, 2002, Technical Change, Inequality, and the Labor Market. Journal of Economic Literature, 40(1), 7–72.

[2] Albouy, David, 2016, What Are Cities Worth? Land Rents, Local Productivity, and the Total Value of Amenities. Review of Economics and Statistics, 98(3), 477–487.

[3] Attanasio, Attanasio, Erik Hurst and Luigi Pistaferri, 2012, The Evolution of Income, Consumption, and Leisure Inequality in The US, 1980-2010, NBER Working Paper No. 17982.

[4] Autor, David H., Lawrence F. Katz and Melissa S. Kearney, 2008, Trends in U.S. Wage Inequality: Revising the Revisionists. Review of Economics and Statistics, 90(2), 300–23.

[5] Bailey, Natalia, Sean Holly and M. Hashem Pesaran, 2016a, A Two-stage Approach to Spatio-temporal Analysis with Strong and Weak Cross-sectional Dependence. Journal of Applied Econometrics, 31, 249–280.

[6] Bailey, Natalia, George Kapetanios and M. Hashem Pesaran, 2016b, Exponent of Cross-sectional Dependence: Estimation and Inference. Journal of Applied Econometrics, 31, 929-1196.

[7] Beraja, Martin, Andreas Fuster, Erik Hurst and Joseph Vavra, 2017, Regional Heterogeneity and Monetary Policy. NBER Working Paper No. 23270.

[8] Beraja, Martin, Erik Hurst and Juan Ospina, 2014, The Regional Evolution of Prices and Wages During the Great Recession. mimeo, University of Chicago.

[9] Brady, Ryan R., 2011, Measuring the Diffusion of Housing Prices across Space and over Time. Journal of Applied Econometrics, 26, 213–231.

[10] Carlino, Gerald A. and Robert F. DeFina, 1998, The Differential Regional Effects of Monetary Policy. Review of Economics and Statistics, 80, 572–587.

[11] Case, Karl E. and Robert J. Shiller, 2003, Is There a Bubble in the Housing Market? Brookings Papers on Economic Activity, No 2, 299–342.

[12] Choi, C.Y. and Róisín O'Sullivan, 2013, Heterogeneous Response of Disaggregate Inflation to Monetary Policy Regime Change: The Role of Price stickiness. Journal of Economic Dynamics and Control, 37(9), 1814–1832.

[13] Choi, C.Y. and Xiaojun Wang, 2015, Discontinuity of Output Convergence within the U.S.: Why Has the Cource Changed? Economic Inquiry, 53(1), 49–71.

[14] Chudik, Alexander and M. Hashem Pesaran, 2011, Infinite-dimensional VARs and Factor Models. Journal of Econometrics, 163, 4–22.

[15] Chudik, Alexander, Elisa Tosetti, and M. Hashem Pesaran, 2011, Weak and Strong Cross Section Dependence and Estimation of Large Panels. Econometrics Journal, 14, C45–C90.

[16] Chudik, Alexander and M. Hashem Pesaran, 2016, Theory and Practice of GVAR Modeling. Journal of Economic Surveys, 30, 165–197.

[17] Chudik, Alexander, Valerie Grossman and M. Hashem Pesaran, 2016, A Multi-Country Approach to Forecasting Output Growth Using PMIs. Journal of Econometrics, 192, 349–365.

[18] Combes, Pierre-Philippe, Gilles Duranton, and Laurent Gobillon, 2008, Spatial wage disparities: Sorting matters!, Journal of Urban Economics, 63(2), 723–742.

[19] Diamond, Rebecca, 2016, The Determinants and Welfare Implications of US Workers' Diverging Location Choices by Skill: 1980–2000. American Economic Review, 106(3), 479–524.

[20] Glaeser, Edward L., Giacomo A.M. Ponzetto and Kristina Tobio, 2011, Cities, Skills, and Regional Change, NBER Working Paper No. 16934.

[21] Gyourko, Joseph, Christopher Mayer and Todd Sinai, 2013, Superstar Cities. American Economic Journal: Economic Policy, 5(4), 167–199.

[22] Hamilton, James D. and Michael T. Owyang, 2012, The Propagation of Regional Recessions. Review of Economics and Statistics, 94(4), 935–947.

[23] Handbury, Jessie, 2012, Are Poor Cities Cheap for Everyone? Non-Homotheticity and the Cost of Living Across U.S. Cities. mimeo, Columbia University.

[24] Handbury, Jessie and David E. Weinstein, 2015, Goods Prices and Availability in Cities. Review of Economic Studies, 82, 258–296.

[25] Hsieh, Chang-Tai and Enrico Moretti, 2015, Why Do Cities Matter? Local Growth and Aggregate Growth. NBER Working Papers No. 21154, National Bureau of Economic Research.

[26] Hurst, Erik, Benjamin J. Keys, Amit Seru, and Joseph Vavra, 2016, Regional Redistribution through the US Mortgage Market. American Economic Review, 106(10), 2982–3028.

[27] Iacoviello, Matteo, 2008, Household Debt and Income Inequality, 1963-2003. Journal of Money, Credit, and Banking, 40(5), 929–965.

[28] Kelejian, Harry H. and Gianfranco Piras, 2014, Estimation of spatial models with endogenous weighting matrices, and an application to a demand model for cigarettes. Regional Science and Urban Economics, 46, 140–149.

[29] Kelejian, Harry H. and Ingmar R. Prucha, 2004, Estimation of simultaneous systems of spatially interrelated cross sectional equations. Journal of Econometrics, 118, 27–50.

[30] Kennan, John and James R. Walker, 2011, The Effect of Expected Income on Individual Migration Decisions. Econometrica, 79(1), 211–251.

[31] Lee, Lung-fei and Jihai Yu, 2010, Estimation of spatial autoregressive panel data models with fixed effects. Journal of Econometrics, 154(2), 165–185.

[32] Moretti, Enrico, 2013, Real Wage Inequality. American Economic Journal: Applied Economics 5(1), 65–103.

[33] Nakamura, E., Steinsson, J., 2008, Five Facts about Prices: A Reevaluation of Menu Cost Models. Quarterly Journal of Economics 123, 1415–64.

[34] Neftci, Salih N., 1984, Are Economic Time Series Asymmetric over the Business Cycle? Journal of Political Economy, 92, 307–328.

[35] Ngene, Geoffrey M., Daniel P. Sohn and M. Kabir Hassan, 2016, Time-Varying and Spatial Herding Behavior in the US Housing Market: Evidence from Direct Housing Prices. Journal of Real Estate Finance and Economics, 53, 1-33.

[36] Owyang, Michael T., Piger, Jeremy, Wall, Howard J., 2005, Business cycle phases in US states. Review of Economics and Statistics 87, 604–616.

[37] Peri, Giovanni, Kevin Shih and Chad Sparber, 2015, STEM Workers, H-1B Visas, and Productivity in US Cities. Journal of Labor Economics, 33(S1), S225–S255.

[38] Pesaran, M. Hashem, 2004, General Diagnostic Tests for Cross Section Dependence in Panels. CESifo Working Paper 1229, IZA Discussion Paper 1240.

[39] Pesaran, M. Hashem, 2006, Estimation and Inference in Large Heterogeneous Panels with a Multifactor Error Structure. Econometrica, 74(4), 967–1012.

[40] Pesaran, M. Hashem, Til Schuermann and Scott M. Weiner, 2004, Modelling regional interdependencies using a global error-correcting macroeconometric model. Journal of Business and Economics Statistics, 22, 129–162.

[41] Pesaran, M. Hashem and R. P Smith, 1995, Estimating Long-Run Relationships from Dynamic Heterogeneous Panels. Journal of Econometrics, 68, 79–113.

[42] Pesaran, M. Hashem and Elisa Tosetti, 2011, Large Panels with Common Factors and Spatial Correlation. Journal of Econometrics, 161(2), 182–202.

[43] Piketty, Thomas and Emmanuel Saez, 2003, Income Inequality in the United States, 1913-1998. Quarterly Journal of Economics, 118(1), 1–39.

[44] Piketty, Thomas, Emmanuel Saez and Gabriel Zucman, 2017, Distributional National Accounts: Methods and Estimates for the United States. Quarterly Journal of Economics, forthcoming.

[45] Rothman, Philip, 1991, Further Evidence on the Asymmetric Behavior of Unemployment Rates over the Business Cycle. Journal of Macroeconomics, 13(2), 291–298.

[46] Stock, James H. and Mark W. Watson, 2003, Forecasting Output and Inflation: The Role of Asset Prices. Journal of Economic Literature, 41, 788–829.

[47] Stroebel, Johannes and Joseph Vavra, 2015, House Prices, Local Demand, and Retail Prices. Kilts Booth Marketing Series Paper No. 1-030, University of Chicago.

[48] Van Nieuwerburgh, Stijn and Pierre-Olivier Weill, 2010, Why Has House Price Dispersion Gone Up? Review of Economic Studies 77, 1567–1606.

[49] Vega, Solmaria H. and J. Paul Elhorst, 2016, A Regional Unemployment Model Simultaneously Accounting for Serial Dynamics, Spatial Dependence and Common Factors. Regional Science and Urban Economics 60, 85–95.

[50] Whittle, P., 1954, On stationary processes in the plane. Biometrica, 41, 434–449.

[51] Yoon, Chamna, 2017, Estimating Dynamic Spatial Equilibrium Model to Evaluate the Welfare Implications of Regional Adjustment Processes: The Decline of the Rust Belt. International Economic Review, 58(2), 473–497.

**Table 1**: Summary statistics of economic well-being

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

**Table 2**: Cross-sectional dependence (CD) of economic well-being

| 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 economic well-being

| 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 economic well-being changes ($\Delta y_{mit}$) that is explained by nation shocks common to all cities ($\mathbf{v}_{mt}$ in (2)).

**Table 4**: The response of local economic well-being 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 economic well-being to a one-standard-deviation increase in the national and local unemployment shocks, which is estimated from the high-dimensional reduced form global VAR model given by eq.(4).

**Table 5**: Sensitivity of the cross-city dispersion of well-being with respect to the changes in national unemployment rate and housing prices (subgroup analysis)

| Regressor | FULL | FLEX group | RIGID group |
|---|---|---|---|
| $\Delta U_t^+$ | 0.094 (0.102) | 0.378†(0.191) | -0.121 (0.092) |
| $\Delta U_t^-$ | -0.149 (0.162) | -0.143 (0.256) | 0.057 (0.161) |
| $\Delta HP_t$ | 0.354†(0.176) | 0.227 (0.243) | 0.498* (0.265) |

Note: 'FULL' denotes the entire 41 products under study and 'FLEX' and 'RIGID' respectively represent 18 flexible price products and 23 rigid price products shown in Table A.1. Regression equation is

$$\Delta CV_t^m = \alpha_m + \theta_t + \beta_1 \Delta NUR_t^+ + \beta_2 \Delta NUR_t^- + \gamma \Delta NHP_t + \varepsilon_{it}^m$$

where $CV_t^m$ denotes the cross-city dispersion of economic well-being in $m_{th}$ product, $\alpha_m$ and $\theta_t$ respectively represent product and time dummy variables, $\Delta NUR_t^+$ and $\Delta NUR_t^-$ respectively denote increase and decrease in seasonally adjusted national unemployment rates (NUR), and $\Delta NHP_t$ denotes the change in seasonally adjusted S&P/Case-Shiller U.S. National Home Price Index. † and asterisk (*) respectively indicate the statistical significance at the 5% and 10% error levels based on robust clustered standard errors (in parentheses).

# 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 degree holders for skill level. City codes are the airport codes of the corresponding cities except for those asterisked.

## B Variance decompositions

Reduced-form VAR model (3) 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.

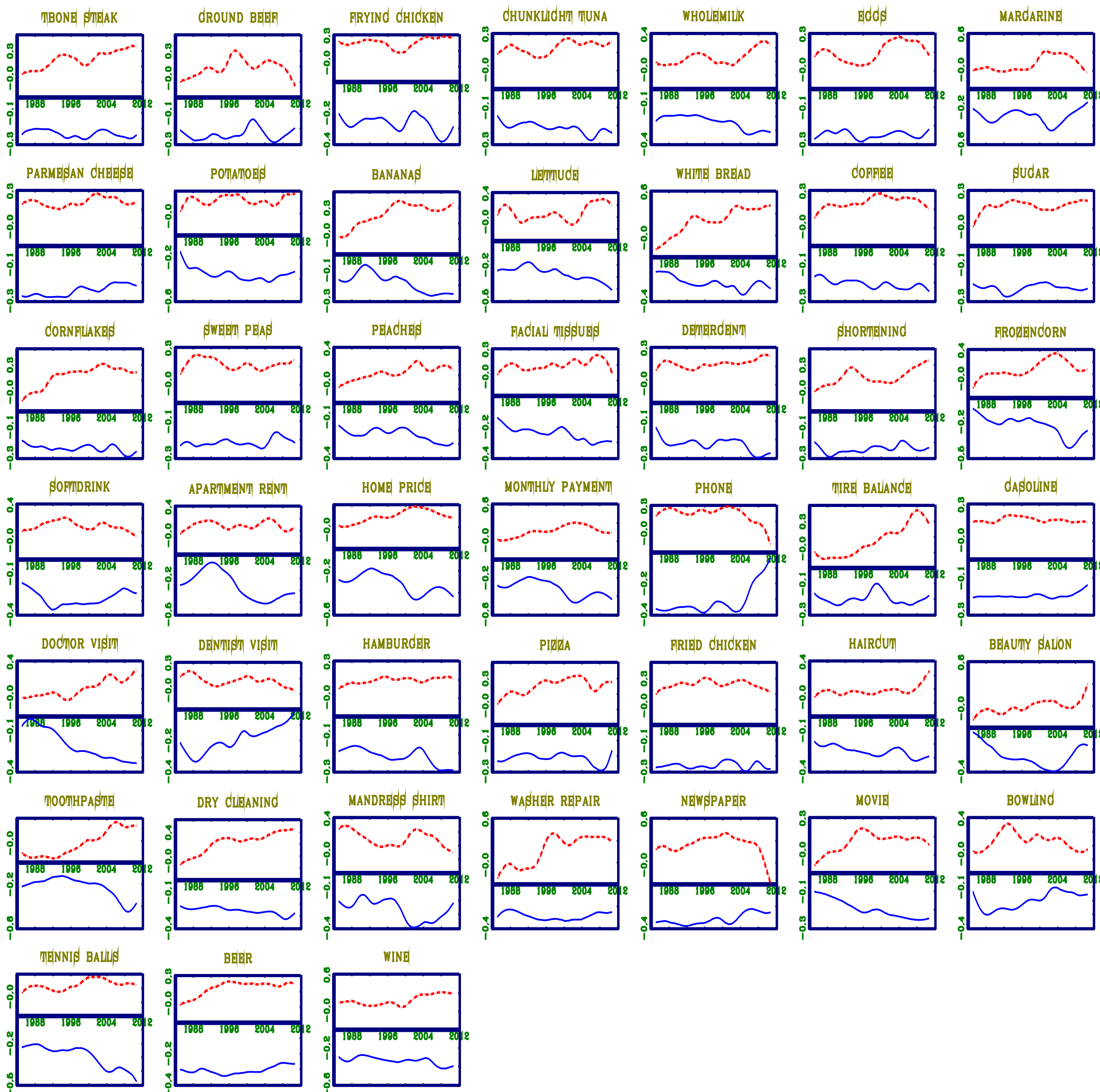



Figure 1: Average economic well-being of top three cities (dotted line) and bottom three cities (solid line)

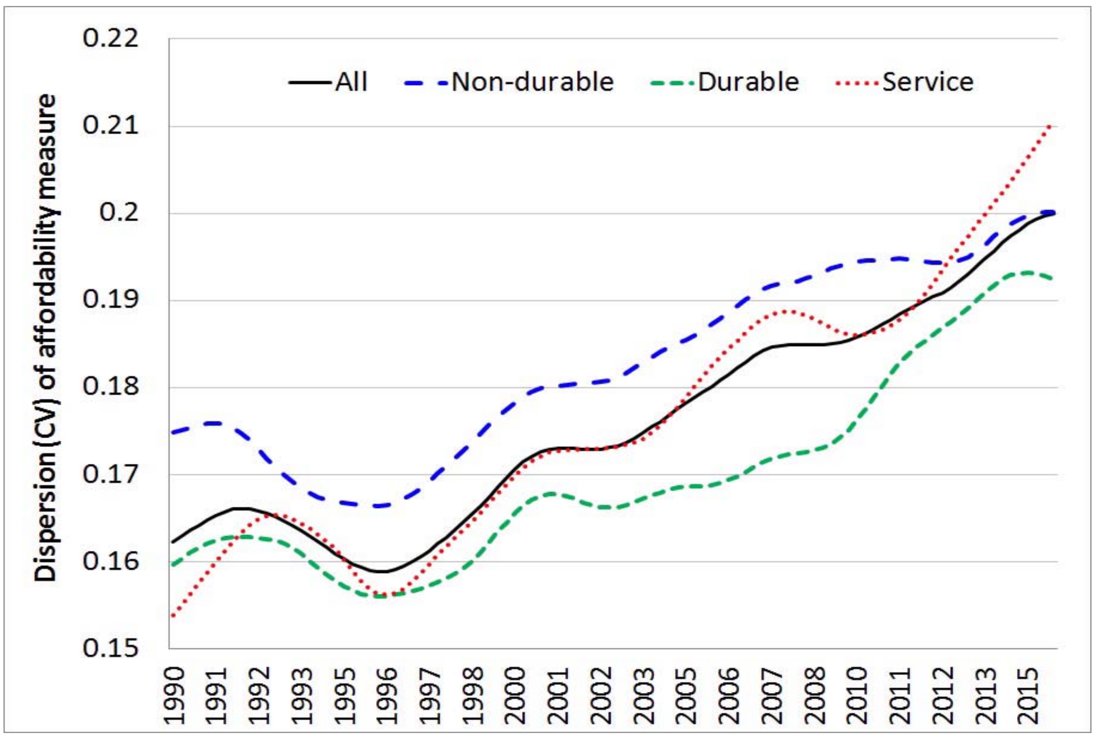
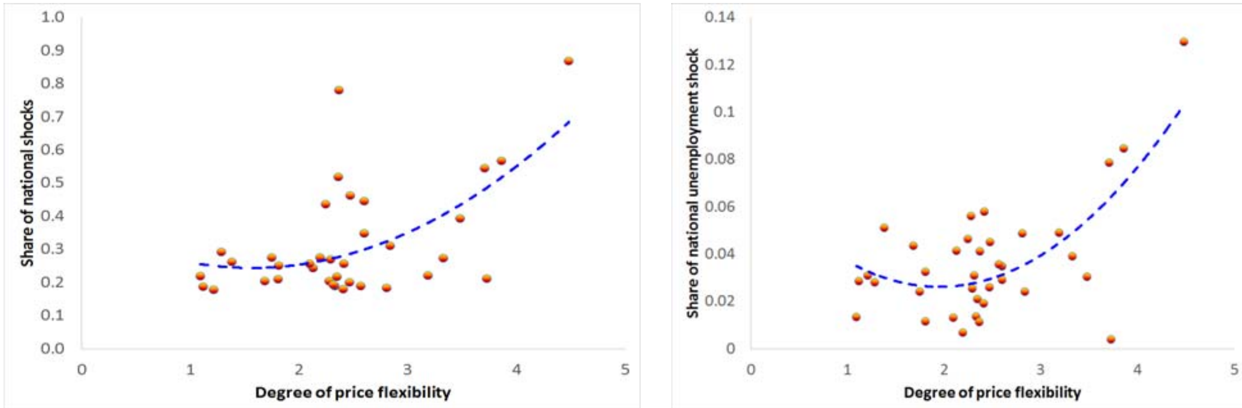
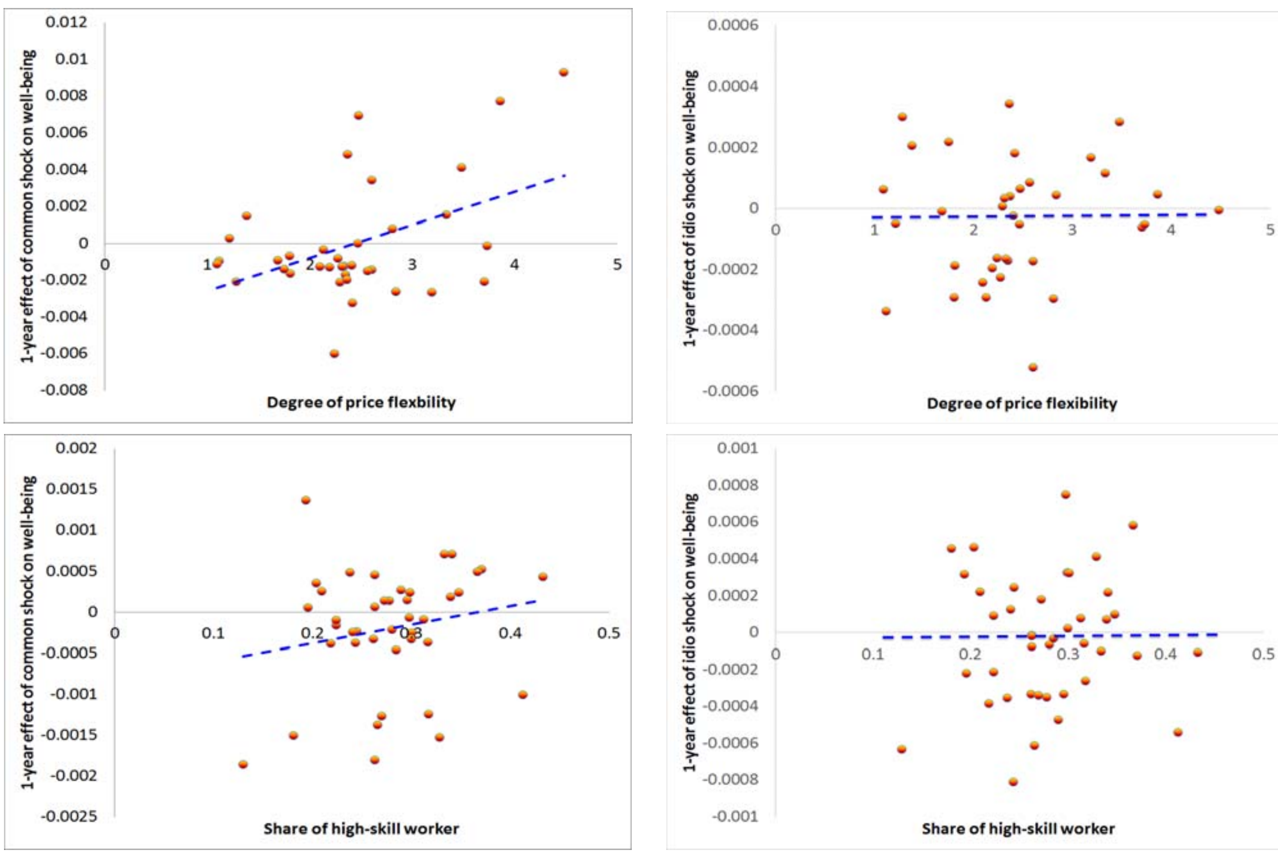



Figure 2: Evolution of cross-city dispersion of (CV) affordability measure by product groups




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