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ORIGINAL PAPER

Identifying the size and geographic scope of short-term rural cost-of-living increases in the United States

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Abstract

Difference in terms of cost-of-living between rural and urban areas is a frequent theoretical analysis in Regional Economics. Lack of routine measures in rural areas does not usually allow to observe changes in rural costs. We adapt the Big Mac index, typically used to measure purchasing power parity between countries, as a potential quick and inexpensive indicator of short-term local price variations. With a national random sample of McDonald's stores repeated in time, we find prices grew slightly faster in rural areas than in urban areas. Spatial transmission of prices seems to be limited to very localized effects, meaning that rural price increases are not due to urban spillover effects.

JEL Classification D22 · E31 · O18 · R11 · R12

1 Introduction

The US bases government food and other assistance to families in need on pan-territorial formal income thresholds. The income metric is a proxy for purchasing power because direct household data collection on food consumption, while important to collect periodically, is costly and challenging to manage (Kirlin and Denabaly 2017).

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As a local economy evolves, its cost-of-living may change in ways inconsistent with national trends. While a local boom can lift some out of poverty, it can also raise housing and service prices. If a household is unable to increase its income proportionally (due to age, disabilities, or lack of appropriate skills), the ability to purchase sufficient food is impacted. Despite billions in expenditures on poverty reduction efforts such as the Supplemental Nutrition Assistance Program (SNAP), up to 16% of households are food insecure in a given seven-day period (Kirlin and Denbaly 2017). Ways to efficiently identify appropriate regional support levels are needed. Disasters can also create temporary shortages and gouging behavior. Current price collection systems are ill-equipped to track the issue. The need is especially relevant in the current context, as COVID-19 related shortages and economic stimulus efforts translate into increased concern about a return to an era of high inflation (*The* Economist 2021).

Current price estimating systems use a basket approach and, in the US, are limited to twenty-three urbanized areas. It takes time to assemble the data, and there is no coverage of the rural regions, where roughly a quarter of the US population resides. People in rural areas can face excessive costs for nutritious foods (Kenny et al. 2018). Hence Davis et al. (2020) call for geographic adjustments to SNAP payments to address regional differences in food expenditure poverty. Clearly, rapid geographic methods for assessing local price changes could inform assistance programs in identifying emerging areas of need and setting appropriate aid levels. Geographically detailed price information could also help address the lack of food stores through demand or supply-side policies suggested by Cleary et al. (2018). Better regional price information could therefore make government programs more effective and efficient. Better regional price information could also inform private investment by identifying low-cost areas or identifying grades of integration through price convergence (Holmes et al. 2022). This article explores how Big Mac prices vary across time and space to help assess how they can help in understanding the magnitude and direction of localized price changes.

Rural–urban and geographical differences in cost-of-living or prices are often based on housing costs (e.g., Gnagey and Grijalva 2018; Gourley 2021; Cai et al. 2022; Otto and Schmid 2018 or Liu and Ma 2021) due to missing data for the other elements of a typical household's consumption basket—urban indices such as CPI-U use house rents in lieu of house purchase prices. The COVID-19 pandemic may have caused a substantial decoupling of housing costs and prices of different items, such as food, purchased by households. Acceleration of the national work-from-home trend under COVID-19 may help explain the recent increase in demand for rural housing (REDFIN 2021). To what extent do land rents reflect trends in the broader economy? Due to the lack of comparison data, there is also little analysis that represents urban and rural price differentials simultaneously. Better ways to measure convergence in price change between rural and urban areas would inform better food and rural development policy.

The pace of rural–urban price convergence is unexplored in the United States due to the aforementioned lack of data on rural prices. Land rents are typically cheaper outside of urban areas; so housing costs (a rural data point that is consistently available over time) may not be a good indicator of price convergence. Federal monetary goals influence house prices as changes in policy quickly work their way into mortgage rates, changing the amount of money consumers can afford to borrow for housing. To the extent that places vary in their churn level in the housing market, house prices in some areas may respond more quickly to changes in Federal rates than others. Also, housing suffers from a lack of homogeneity, across units (e.g., different floor plans) and time, as new owners make improvements or neglect maintenance and updates. The US Federal Reserve System is putting more emphasis on "trimmed" inflation estimates that strip out more volatile elements of the basket (The Economist 2021). Housing also exhibits a distinct pattern due to its nature as a non-tradable good. Primarily, demand for housing directly corresponds to migration flows which, when paired with an inelastic supply in the short run, results in market adjustments primarily through pricing. In essence, housing prices reflect inflationary dynamics more rapidly than homogeneous goods. Relying solely on rural housing prices is therefore problematic, and costs of other goods are readily measured, but Loveridge and Paredes (2018) produce several arguments against attempting to estimate prices for a rural basket of goods regularly. In rural areas, thin markets can increase inflation volatility, with supply depleted during a boom and flooded with offerings during a bust. Although a basket of goods is a robust approach to determining price changes (Volpe and Lavoie 2008), it still has shortcomings, namely, issues that arise when consumers substitute out of expensive goods (Paredes and Iturra 2011) or when an item in the basket becomes obsolete (Erikson and Pakes 2011). Similarly, one might consider wages as an appropriate variable. While wages are an important consideration in cost-of-living and convergence, the published data do not allow for very precise location of the transactions, whereas with the Big Mac, the analyst can determine the exact location of a frequently repeated transaction.

In this paper, we adapt the Big Mac Index approach as an interesting, low-cost technique for statistical offices to measure short-term changes in both prices and rural–urban price differences. Using two rounds of phone-collected Big Mac price observations from a national sample, we computed same-store price changes over a brief time span. In contrast to Loveridge and Paredes (2018), this article tries to understand the differences between rural and urban areas in terms of inflation, with the distance to the closest urban area as the key variable of interest. The methodological approach of this research considers common shocks in terms of inflation and spatial interactions. We use spatial models to explore price change patterns, including estimates of direct and indirect spatial impacts. We find spatial autocorrelation in price changes—controlling for local factors and common state effects—that rural prices rose faster than urban prices (albeit from a lower base) during the observation interval. Spatial relationships in prices seem to be limited to localized effects, meaning that rural price increases are not due to urban spillover effects. The method proposed in this article shows how a low-cost approach to documenting price changes can be a valuable complement to other methods to understand cost-of-living in rural and urban areas. To our knowledge, cost-of living-change at this level is rarely measured due to the lack of data. Consistent application of the technique over time could identify potential hot spots for a more detailed examination and adjustment of poverty-alleviation programs to ensure food security. While the example here is tailored to the US context, similar methods could be applied in other high or middle-income countries where high value-added, highly perishable standardized food items are sold.

2 Literature review

A well-established body of work related to spatial prices focuses on price transmission and movement of commodities (e.g., Fackler and Goodwin 2001; Burke and Myers 2014; Vitale and Bessler 2006), land rents (e.g., Capozza and Helsley 1989), or price discrimination (e.g., Guo and Lai 2014). Less well studied is the spatial dynamics of the cost-of-living or price indices. In the United States, the consumer price index is based on a basket of goods, which is measured only in urban areas. Therefore, regional price convergence studies tend to focus only on urban CPI and price movements only (e.g., Burridge et al. 2015 or more recently, Holmes et al. 2022).

Price/cost comparisons are problematic across countries due to the vagaries of exchange rates and government efforts to intervene, leading *The Economist* to propose using Big Mac prices as a fast and inexpensive way of measuring purchasing power parity (The Economist 2020). The Big Mac is a higher value-added food product best consumed within minutes of production, so spatial arbitrage is less feasible than it would be with an easily stored commodity such as maize. The lack of spatial arbitrage opportunities makes the Big Mac more appropriate for studying local costs than other standardized products. Since the inception of the Big Max Index, authors of over forty refereed journal articles used the index to explore a variety of price comparison issues in the international context; some recent studies include O'Brien and Vargas (2016); Cavallo and Rigobon (2016); Vo (2017); Gharehgozli and Atal (2019; 2020); Stadtmann, et al. (2020); and Tur-Sinai et al. (2020). As noted by Cerasa and Buscaglia (2017), the Big Mac Index incorporates the cost of services, not simply variation in ingredient prices. The index is also used as a control to explore issues such as international differences in obesity (Alston, et al. 2008).

Less studied is how Big Mac prices vary between places *within* a country. There are two contributing factors. First, in some countries, such as Chile, prices appear to be set at the corporate level rather than by individual location managers, as is done in the US (Ater and Rigbi 2015). Second, while the company operates over 30,000 locations in more than 100 countries, in many parts of the world, McDonald's restaurants are found only in large metropolitan areas (McDonald's Corporation 2016). Hence regional analysis of price changes in many countries would be hindered by a lack of ability to obtain observations outside of major cities. An exception to the lack of academic products related to the regional variation in the price of Big Mac is the study by Loveridge and Paredes (2018) that explored the static regional variation in the price levels of Big Mac. A component of analysis missing in Loveridge and Paredes (2018), addressed in the present work, is applying the technique's promise in learning how prices change over time and the role of spatial relationships in price changes. In addition, while Loveridge and Paredes (2018) focused on core metro counties differences, this paper tries to deeply understand the whole spatial pattern from urban to rural areas—using distances as the key factor. Even more importantly, exploring this type of spatial process also allows a better understanding of how potential economic shocks spread across time. Understanding spatial price spillovers could help determine the cost-of-living impacts of localized shocks, such as new activities to extract mineral deposits, or supply disruptions due to disasters.

3 Method

To explore whether the approach can capture price changes over a brief period, price change data is collected by means of a representative interviewed sample of McDonald's locations. In particular, the same-store Big Mac price change between mid-2014 and March 2015 is used as a variable of interest to demonstrate how the method estimates trends in the urban–rural price differential in the United States. In addition to the ease of data collection, the Big Mac index has a significant advantage. The Big Mac data allow us to evaluate relationships on a disaggregated scale and compare rural and urban areas. Through this data it is possible to explore price gradients across stores located at varying distances from the city center. The shape of this function can provide insight into understanding the incentives of the population to work or live in a specific area. Few other data sources are available at this level of spatial disaggregation.

With this advantage in mind, this research and its associated methods highlight Big Mac prices as a powerful way to observe how spatial price differences change, even over brief time periods. We use a set of control variables to consider the characteristics of each sampled restaurant's location and the distance from the closest urban area to the store. This strategy recovers the effect of the price index through the marginal impact associated with the variable of the urban distance. While the reliance on a single item makes the index subject to changes in consumer preferences, according to the USDA Economic Research Service (2023) demand for the key ingredient in the Big Mac—beef—has been very stable, trending upwards only gradually on a per capita basis in recent years (retail boneless weight was 51.8 pounds in 2014, 51.6 pounds in 2015, 53.1 pounds in 2016, and 56.5 pounds in 2022). The precision of this approach relies on the exogeneity of the control variables and the absence of selection bias or any other source of endogeneity. We built our identification strategy by analyzing a collected stratified random sample of Big Mac prices in McDonald's restaurants across the United States. The sample was stratified to match the proportion of McDonald's restaurants in each state to ensure the geographic diversity of the observations. The homogeneity of the Big Mac and services provided by McDonald's restaurants helps avoid problems with the econometric specification. We include control variables to consider location factors affecting the stores.

While the price of a Big Mac is set by the local manager (Ater and Rigbi 2015), the spatial econometrics literature provides several reasons to expect spatial correlation in price changes among restaurants. First, we can expect scale and agglomeration economies in large urban areas. When similar businesses are near each other, there are increments in productivity through the spillover interaction of knowledge and through better match between supply and demand in larger labor markets (see Rosenthal and Strange 2004; Combes 2000; Ciccone 2002; Combes et al. 2008; or Artis et al. 2012). The productivity improvement can be within the industry, namely location economies, or between sectors, also known as urbanization economies. In both cases, agglomeration economies would increase firm productivity, support higher wages, and perhaps also affect local prices of nearby stores. New agglomeration economies due to urban immigration could spill over into nearby rural locations as a change in cost. On the contrary, lack of agglomeration could lead to thin markets in rural areas, which, in turn, might mean a lack of capacity to meet new demand on a short-term basis. Thus, rural prices might fluctuate more than in large, more diverse local economies, where demand may be more predictable.

A second reason to expect spatial autocorrelation is the role played by functional areas instead of administrative divisions (Bellandi 2002; Dei Ottati 2002; Boix and Galleto 2008). An administrative division, for example, a county line, does not necessarily fit with the underlying economic forces shaping the economic interaction between spatial units. For example, core-periphery structures could generate significant externalities—see Lambert et al. (2014)—which do not follow administrative divisions. This implies that we could observe a weaker price change correlation among counties than might be present among functional areas.

Due to these spatial considerations, we complement the Ordinary Least Squares (OLS) estimation with spatial econometrics to improve the efficiency and consistency of the estimates (Anselin 1988; LeSage and Pace 2009). Estimates are produced using a Spatial Autoregressive Model (SAR), a Spatial Error Model (SEM) and a Spatial Autoregressive Model with Autoregressive Disturbances (SARAR). While a SAR model assumes spatial autocorrelation in the dependent variable as in Eq. (1), the SEM includes the spatial effect in the error (Eq. 5). The SARAR approach incorporates a spatial lag in the error term in addition to the spatially lagged dependent variable (Eq. 7).

Therefore, the SAR model specifies a spatial lag of price changes as in:

$$\begin{aligned} y &= \beta X + \rho W y + \varepsilon \\ \varepsilon &\sim N\left(0, \sigma^2 I\right), \end{aligned} \tag{1}$$

where, $\boldsymbol{y}$ is a $nx1$ vector with the dependent variable observed for n stores, $\boldsymbol{X}$ is defined as a nxk matrix with k explanatory variables (with a constant term), $\boldsymbol{\beta}$ es a $kx1$ vector of parameters, $\boldsymbol{\varepsilon}$ is a $nx1$ vector of standard errors with zero means and a constant diagonal variance–covariance matrix $\boldsymbol{\sigma}^2\boldsymbol{I}$.

The $n \times n$ spatial matrix $\boldsymbol{W}$ is made with w_{ij} weights, depicting the spatial relationship between territories (see a detailed explanation in LeSage and Pace 2009). Hence, the spatial lag $\boldsymbol{Wy}$ is an average-linear combination of the values of the variable of interest in all the j neighbors and ρ is the spatial autoregressive parameter.

The marginal effect in the spatial model differs from OLS estimates. When the model is fitted with an OLS estimation procedure, the coefficient of the variable is equal to the marginal impact of the variable. However, in the SAR model, an increase in an independent variable in an area could lead to an increase in the dependent variable in the neighbors. Following Lesage and Pace (2009) or Elhorst (2014), this process can be written in the reduced form as follows:

$$\begin{aligned} y &= (I - \rho W)^{-1}\beta X + (I - \rho W)^{-1}\varepsilon \\ \varepsilon &\sim N\left(0, \sigma^2 I\right). \end{aligned} \tag{2}$$

As indicated in LeSage and Pace (2009), SAR model can be estimated optimizing the Likelihood function in Eq. (3). The inverse of $(\boldsymbol{I} - \boldsymbol{\rho W})$ of Eq. (2) must exist to solve the optimization problem in Eq. (3). All the optimizations in this publication were obtained through Stata packages spmat and spreg as described in Drukker et al. (2013) with the well-known Newton Raphson (NR) optimization algorithm. Variance–covariance matrix of the parameters can be retrieved through the inverse of the Hessian matrix in the last iteration.

$$LnL = -\frac{n}{2}ln2\pi - \frac{n}{2}ln\sigma^2 - \frac{1}{2\sigma^2}\varepsilon'\varepsilon + ln|I - \rho W|. \tag{3}$$

In this model, an increase in the independent variable affects neighboring territories through endless but decreasing rounds. Hence, an increase in the r_{th} variable $(\boldsymbol{I} - \boldsymbol{\rho W})^{-1}\boldsymbol{\beta_r}$ generates two types of effects: direct and indirect impacts. The direct impact is the effect of the dependent variable on the territory due to a marginal increase in the independent variable on that same territory. However, the indirect impact would be the effect over the dependent variable in a particular area caused by the increase in the independent variable in the neighboring regions. If we decompose both effects, then we can measure spatial price change transmission among stores. As in LeSage and Pace (2009) or Elhorst (2014), we estimate both effects obtained through Eq. (4), while the standard deviation must be obtained through Monte Carlo Simulation of these expressions considering the standard deviations of the parameters.

$$\begin{aligned} &\text{Average Total Impact (ATI)}_r = \beta_r/(1 - \rho) \\ &\text{Average Direct Impact (ADI)}_r = n^{-1}tr\left[\beta_r(I - \rho W)^{-1}\right] \\ &\text{Average Indirect Impact}_r = ATI_r - ADI_r. \end{aligned} \tag{4}$$

On the other hand, as Eq. (5) shows, the SEM includes a spatial lag in the error term u instead of the dependent variable.

$$\begin{aligned} y &= \beta X + u \\ u &= \lambda W u + \varepsilon \\ \varepsilon &\sim N\left(0, \sigma^2 I\right). \end{aligned} \tag{5}$$

This model can be estimated by maximizing the Likelihood function in:

$$\begin{aligned} LnL &= -\frac{n}{2}\ln\left(\pi\sigma^2\right) - \frac{1}{2\sigma^2}e'e + \ln|I - \lambda W| \\ e &= (I - \lambda W)(y - X\beta). \end{aligned} \tag{6}$$

In a SEM, we assume that the omission of the spatial interactions is just a problem of efficiency because the spatial autocorrelation would exist only on unobservable factors. In this setup, autocorrelation does not change the interpretation of the coefficients of the variables. However, we need to consider that the standard deviations may change the significance of these coefficients.

Finally, SARAR includes a spatial lag of the dependent variable and error. The specification of the SARAR can be expressed as follows:

$$\begin{aligned} y &= \beta X + \rho W y + u \\ u &= \lambda W u + \varepsilon \\ \varepsilon &\sim N\left(0, \sigma^2 I\right). \end{aligned} \tag{7}$$

In this case, the Likelihood function of the SARAR model is defined as:

$$\begin{aligned} LnL &= -\frac{n}{2}\ln\left(\pi\sigma^2\right) + \ln|A| + \ln|B| - \frac{1}{2\sigma^2}e'e \\ A &= I - \rho W; B = I - \lambda W \\ e &= B(Ay - X\beta). \end{aligned} \tag{8}$$

As explained by LeSage and Pace (2009), this model is a nested version of the SEM and the SAR models, and it can be used when there is no statistical difference between them. Marginal effects of the SARAR model can also be calculated through Eq. (4), as in the SAR model.

4 Application to big mac prices

4.1 Random sample

Empirical analysis uses the price change collected and other data from a stratified random sample of McDonald's restaurants. The sample includes 3,440 restaurants drawn from approximately 14,000 stores in the 48 contiguous US states and Washington DC. The stratified sample over-represents rural areas. From US Census information, estimated population shares built a weighted probability for urban and rural counties. These weights should affect only the standard errors, not the size of our estimated coefficients. As a result, this sample is designed to accurately measure rural–urban differences. Figure 1 shows the spatial distribution of the selected restaurants.

Repeated data collection from the same store captures the time variation. The first-round survey ran from late July to early September 2014, while the second round, covering the same sampled restaurants, was in March 2015. Data collection achieved a 93% completion rate for the two observations. Data from two periods make it possible to track the price change for each restaurant in the sample. As expected, when these prices are compared with Regional Price Parity (RPP) by state available in the Bureau of Economic Analysis, there is a clear positive correlation. A

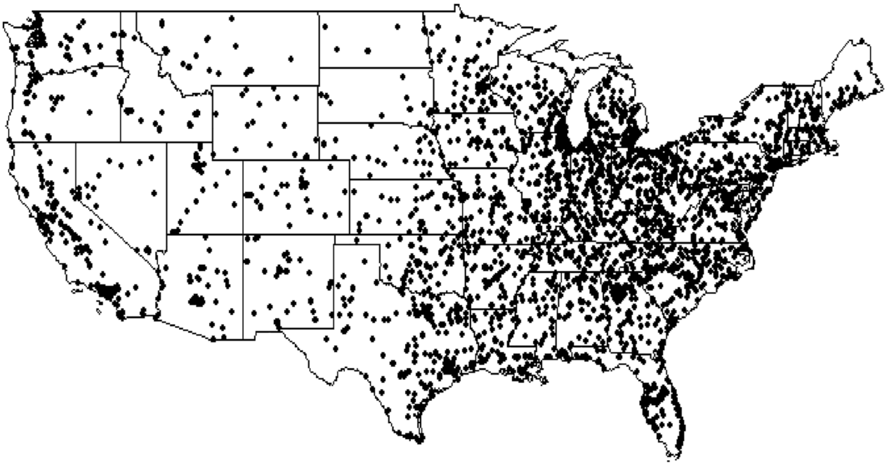

Fig. 1 McDonald's in the Sample. *Source:* Own projection. Alaska, Hawaii, Puerto Rico, Guam, Virgin Islands, American Samoa are excluded

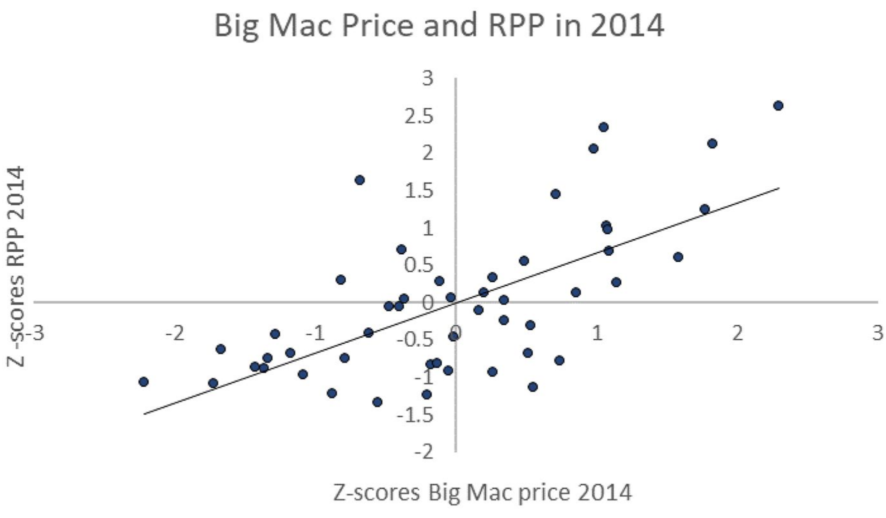

Fig. 2 State Average Big Mac Price vs State Regional Price Parity (RPP). *Source:* Own computation with BEA RPP data. BEA data retrieved from: https:/www.bea.gov/data/prices-inflation/regional-price-parities-state-and-metro-area

scatter plot of the standardized values of both variables (Z-scores[1]) is seen in Fig. 2. Of course, we also expect some differences because, according to the published methodology (BEA 2022a, b) the RPP is a statewide figure based in part on the CPI

[1] Z-scores are obtained subtracting the sample mean and dividing by the sample standard deviation.

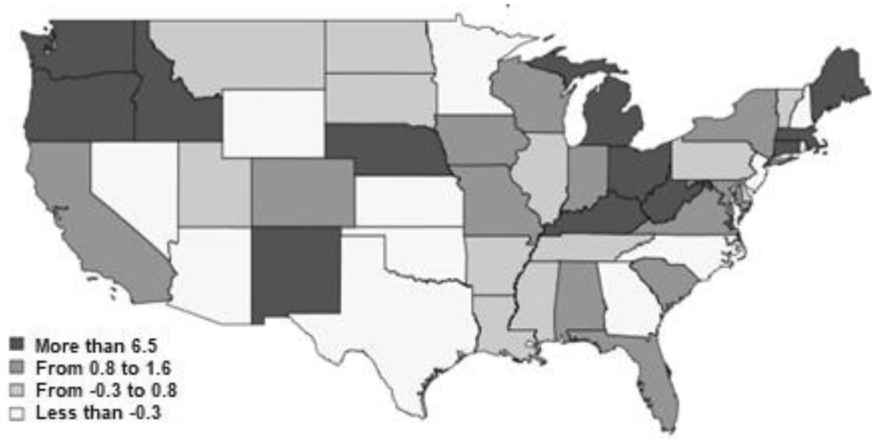

Fig. 3 McDonald's Big Mac mean price change by state (%). *Source:* Own computation. Alaska, Hawaii, Puerto Rico, Guam, Virgin Islands, American Samoa are excluded

(collected in 32 urban areas only), while the Big Mac prices are the simple state average from both rural and urban places.

Figure 3 illustrates the spatial distribution of the mean percentage change in the Big Mac price. The spatial distribution shows that price changes in the northeast and northwest tend to be higher than in other regions.

The short-term variability of the Big Mac Index is low, with most state averages changing by less than two percent over the study interval. This is an expected result, as we are using just one good of the same brand and the national change in the CPI was low over the studied period. As a result, consumers do not expect drastic differences in prices within the same brand from one place to another, which may function as a check on increases. But management decisions about the Big Mac price are not homogeneous (Ater and Rigbi 2015).

We control for local characteristics to address the possibility of different effects across outlets. In addition to state dummies, these variables are chosen to proxy demand characteristics and changes at county level, given the short-term perspective of the analysis. Although they are not the main variables of the analysis, they are used to mitigate possible bias due to omitted variables. The information comes from the Bureau of Economic Analysis (BEA) for all the control variables except for the percentage of the population with a college degree, which is collected from the American Community Survey (ACS), 5-year estimates. Variable selection is based on covariates commonly found in the literature, as in Gourinchas and Parker (2002).

Education attainment of the population is measured as the percentage of the population with college degree within the county in 2014. As indicated in Gourinchas and Parker (2002) educational attainment could easily modify preferences of consumption of individuals.

Another variable possibly influencing Big Mac consumption is the employment rate. Certainty in employment could modify consumption patterns when uncertainty of households is lower—see Gourinchas and Parker (2002). It is measured in this

Table 1 Summary statistics

Variable	Definition	Source	Obs	Mean	Std. Dev
Price increase	Percentage Big Mac price increase	Surveyed	3194	1.227	11.099
Graduation rate	Population with college degree (%)	ACS	3194	79.54	11.471
Growth income	Growth of income (%)	BEA	3194	3.617	3.529
Growth density	Growth of population density (%)	BEA	3194	0.361	1.074
Employment rate	Employed population (%)	BEA	3194	55.736	13.956
Urban distance	Distance to the nearest urban city in km (RUCC < 3)	Surveyed	3194	60.715	71.551
Contributions per worker	Contributions for government social insurance per worker (thousands of dollars)	BEA	3194	5.38	1.115

analysis as the percentage of occupied population out of the population of in the county in 2014.

Most of the tax structure, such as indirect taxes or tax pressure should already be covered by the state dummies. However, given that tax-income can easily generate inflation (see Blinder 1973), we also included contributions to government social insurance per worker in thousands of dollars with a log transformation.

Growth of the Total Personal Income attributed to the county is included as the percentage increase between 2014 and 2015. This variable represents changes in the total purchase capacity of the county in that period. A sudden change in the total income of a county could lead to a demand surplus creating upward price pressure.

Growth of density in the county is considered as the percentage increase between 2014 and 2015. Although sudden changes in population are not expected, the coefficient of this variable would indicate the *ceteris paribus* effect of increasing the density of population in a location, *ceteris paribus* the total income of the county and other control variables. It would indicate a first rural–urban differential effect in this analysis.

Growth of density could be considered as one of the main variables to measure the *ceteris paribus* differences between rural and urban areas. However, a clearer effect should be observed when we compare stores with the same characteristics, but with a different location. This spatial pattern is represented with the distance to the closest city center of an urban area. The rurality of each location is based on the USDA Economic Research Service 2013 Rural–Urban Continuum Classification (RUCC) code. The RUCC code is a commonly used grouping variable in urban research (Rickman and Wang 2015; Porter and Howell 2016). We consider a county urban if its RUCC code is less than 3. Through these categories, the urban–rural effect is computed as the distance to the closest urban city center. Coordinates of city centers in urban areas and stores are evaluated according to the Google API database. Then, distance in kilometers from each store to urban is calculated through Euclidean distance to choose the closest one.

We provide a set of summary statistics for all the variables in Table 1. It is worth mentioning that, nationally, the average Big Mac price increased about 1.2% during

Table 2 AIC optimization—model specification and weight matrix

	OLS	SAR	SEM	SARAR	OLS	SAR	SEM	SARAR
State dummies	NO	NO	NO	NO	Yes	Yes	Yes	Yes
Inverse of quadratic distance	***24,412.7***	***24,335.1***	***24,335.8***	***24,333.4***	***24,387.2***	***24,339.2***	24,337.6	***24,337.2***
Inverse of distance	24,412.7	24,367.0	24,365.4	24,359.1	24,387.2	24,372.7	24,369.8	24,369.1
K-nearest neighbors (25)	24,412.7	24,341.6	24,345.5	24,342.5	24,387.2	24,370.9	24,373.7	24,349.0
K-nearest neighbors (100)	24,412.7	24,352.2	24,355.5	24,354.1	24,387.2	24,381.9	24,381.6	24,381.4
K-nearest neighbors (150)	24,412.7	24,373.3	24,374.6	24,374.6	24,387.2	24,389.4	24,388.7	24,376.7
K-nearest neighbors (200)	24,412.7	24,387.7	24,389.4	24,389.5	24,387.2	24,391.2	24,391.1	24,393.1
K-nearest neighbors (500)	24,412.7	24,413.0	24,413.7	24,411.5	24,387.2	24,377.3	24,357.6	24,359.4
Cut-off distance (10 km)	24,412.7	24,362.9	24,360.8	24,359.7	24,387.2	24,348.2	***24,336.9***	24,338.7
Cut-off distance (50 km)	24,412.7	24,361.7	24,363.6	24,363.4	24,387.2	24,369.0	24,370.6	24,370.9
Cut-off distance (100 km)	24,412.7	24,363.3	24,366.1	24,357.0	24,387.2	24,377.3	24,380.2	24,373.7

Spatial matrices have been row-standardized. Non-standardized matrices have also been evaluated without finding more suitable matrices in terms of the AIC

the months between data collection periods. The reported Big Mac price range (including both periods) was between \$1.19 and \$6.00. In addition, it shows a mean distance to an urban area of 60.7 km in the sample.

Given the possible relationships between our control variables, a possible problem of multicollinearity may arise. Apart from avoiding choosing variables with only subtle differences, we tried to provide a sample as large as possible to minimize this problem. In addition, the stratification of the sample is specially designed to measure rural–urban differences. Finally, as can be seen in Table 7 of the appendix, Variation Inflation Factors (VIFs)[2] seem to be within reasonable levels—see Wooldridge (2020). Nonetheless, estimated coefficients should be carefully interpreted as *ceteris paribus* effects.

Spatial weight matrices were chosen using the Akaike Information Criteria (AIC). We compared inverse-distance and inverse quadratic distance, k-nearest neighbors (25,100, 150, 200 and 500) and a cut-off distance of (10, 50 and 100 km)—see Table 2. As can be seen in the results, the inverse quadratic distance obtained the lowest AIC value in all the specifications, except for the SEM model with state dummies, where a 10 km cut-off-distance matrix was applied.

[2] VIFs are obtained as $1/(1-R_r^2)$ where R_r^2 if the R-square of a regression of the r_{th} variable over the rest of the variables.

Table 3 OLS, SAR, SEM and SARAR Big Mac price change model estimates

	OLS	SAR	SEM	SARAR
Income growth	0.14** (0.056)	0.119** (0.059)	0.134** (0.066)	0.126** (0.063)
Contributions per worker (in logs)	3.957*** (1.49)	3.48*** (1.247)	3.859*** (1.417)	3.668*** (1.337)
Employment rate	−0.051*** (0.019)	−0.045*** (0.017)	−0.05*** (0.019)	−0.047*** (0.018)
Graduation rate	−0.022* (0.012)	−0.02 (0.017)	−0.021 (0.018)	−0.02 (0.018)
Density growth	−0.713*** (0.234)	−0.593*** (0.195)	−0.664*** (0.226)	−0.629*** (0.212)
Urban distance (in logs)	0.651*** (0.17)	0.6*** (0.203)	0.71*** (0.237)	0.652*** (0.222)
Constant	−3.388 (2.242)	−3.169 (2.554)	−3.606 (2.864)	−3.39 (2.716)
ρ		0.242*** (0.026)		0.135** (0.064)
λ			0.242*** (0.026)	0.125* (0.064)
State effects	No	No	No	No
Log likelihood	−12,199.34	−12,158.57	−12,158.88	−12,156.68
AIC	24,412.67	24,335.13	24,335.75	24,333.36
Moran'I on residuals	0.102***	0.0096	0.0097	0.005

Numbers in parentheses are standard errors. *, ** and *** represent estimates significantly different from zero at 10%, 5% and 1%, respectively. SAR, SEM and SARAR estimations were obtained through Maximum Likelihood optimization. Weight matrix has been chosen using AIC, resulting in the Quadratic inverse matrix (row-standardized) for all the models

Following LeSage and Pace (2009) all the spatial matrices in this analysis were row-standardized.[3] Thanks to this transformation, $\boldsymbol{Wy}$ and $\boldsymbol{Wu}$ represent the weighted mean the dependent variable and the error in the neighbors, making the interpretation of the spatial parameters ρ and λ easier. The total number of neighbors should be considered otherwise.

4.2 Results

Table 3 compares the OLS estimates of a linear regression ($\rho = \lambda = 0$) together with the maximum likelihood estimations of SAR, SEM, and SARAR models, to evaluate potential bias and efficiency problems of a non-spatial model.

Control variables in the analysis indicate that income growth has a significant and positive effect on price increases. This increment is also higher in counties with

[3] Non-standardized versions of the matrices were also tested, without finding better results in terms of the AIC.

more social insurance contributions per worker. These effects have the expected sign, and they introduce differences in demand of the different counties.

The *ceteris paribus* effect of control variables closely related to urbanization of the economy are very interesting in this period.[4] The employment rate, graduation rate, and density growth indicate a negative and significant effect. This urbanization effect is clearly confirmed when we observe the effect of distance to an urban area. The distance coefficient to an urban area is positive and significant. Therefore, the OLS estimator suggests that rural and peripheral areas—with the same values in the other variables—had higher price increases than urban areas throughout the study period.

Turning to the other spatial dependence specifications reported in Table 3, the SAR and SEM models produce slightly different price changes for urban areas, but the conclusions are not substantially different from OLS model. The estimated price change elasticity index for urban distance ranges from 0.6 to 0.71. However, significant estimated λ and ρ coefficients in the models identify a spatial process in the price mechanism. It seems that stores are clearly influenced by price increases and reductions in surrounding stores.

It can easily be observed that the performance of the models in terms of the Log likelihood as well as the AIC are quite similar. The SAR model obtains a small improvement, but it is a small change compared to the SEM model values. To avoid possible misspecification in either spatial model, the last column shows the results of the nested version of both models, the SARAR estimator. SARAR estimates obtain the lowest AIC value among all models. As in the other two models, the distance from an urban location indicates a positive and significant effect on price increases.

Given that the adjustments of prices could vary across geographic areas, assuming that price adjustments are not affected by specific, state-level conditions could be unreasonable. Table 4 shows the estimated model with state-level effects.

Although the AIC do not indicate an improvement with these models, there are a few details worth mentioning. The results, far from indicating a possible reduction in the urban effect, seem to point toward a greater significance when state-level heterogeneity is introduced in the model. In fact, this variable and the spatial interactions seem to be the main significant variables in these models. In this case, the SEM model appears to be the best specification, as the ρ parameter is not significant in the SARAR model while the AIC value is almost identical. Despite the introduction of these effects, it can easily be seen that the conclusions are quite robust to changes in the specification.

Given the AIC values of the models with dummies, the rest of the analysis focus on models from Table 3. In these models, Eq. (4) can be followed to identify marginal effects. The estimated average direct, indirect, and total impacts for the SAR and SARAR models are shown in Table 5.

The estimates of the marginal effects help us to evaluate this question and compare the elasticities of SARAR and SAR models with SEM or OLS. As

[4] We tested proximity to competitor stores and did not find a significant relationship, so those results are not reported.

Table 4 OLS, SEM, SAR and SARAR Big Mac price change model estimates with state effects

	OLS	SAR	SEM	SARAR
Income growth	0.078 (0.063)	0.069 (0.07)	0.062 (0.075)	0.067 (0.074)
Contributions per worker (in logs)	2.783 (1.612)	2.534* (1.462)	2.832* (1.559)	2.521 (1.538)
Employment rate	−0.035 (0.022)	−0.032* (0.019)	−0.037*(0.02)	−0.327 (0.02)
Density growth	−0.328 (0.254)	−0.287 (0.244)	−0.302* (0.26)	−0.302 (0.258)
Graduation rate	−0.018 (0.014)	−0.018 (0.02)	−0.017 (0.02)	−0.018 (0.02)
Urban distance (in logs)	0.816*** (0.224)	0.763*** (0.245)	0.871*** (0.263)	0.818*** (0.262)
Constant	−3.511 (2.671)	−3.278 (3.113)	−3.86 (3.297)	−3.423 (3.273)
ρ		0.197*** (0.027)		0.094 (0.061)
λ			0.173*** (0.023)	0.122** (0.061)
State effects	YES	YES	YES	YES
Log likelihood	−12,139.62	−12,113.58	−12,112.46	−12,111.61
AIC	24,387.24	24,339.17	24,336.9	24,337.23
Moran'I on residuals	0.081***	0.01	0.02	0.005

Numbers in parentheses are standard errors. *, ** and *** represent estimates significantly different from zero at 10%, 5% and 1%, respectively. SAR, SEM and SARAR estimations were obtained through Maximum Likelihood optimization. Weight matrix has been chosen using AIC, resulting in the Quadratic inverse matrix (row-standardized) except for the SEM model, with 10 km cut-off distance matrix (row-standardized)

Table 5 shows, the total distance elasticity increases to 0.754 and 0.792 in the SARAR and SAR models when we include the spillover effects. As a result, these marginal effects indicate that a percent increase in the distance toward an urban center modifies the variation of prices in 0.792 percentage points. Figure 4 illustrates this variability in the predicted price increase (SARAR) over the distance to an urban area.

Depending on the assumptions, a higher proportion of these effects are caused by the indirect effects (SAR) or direct effects—as in the SARAR model. Consequently, SARAR, as well as SAR, SEM or OLS results reveal Big Mac prices

Table 5 Marginal urban effects—SAR and SARAR model, quadratic inverse matrix (row-standardized)

	SAR			SARAR		
	Total	Direct	Indirect	Total	Direct	Indirect
Income growth	0.156** (0.078)	0.12** (0.06)	0.036* (0.019)	0.146* (0.075)	0.127** (0.063)	0.019 (0.017)
Contributions per worker (in logs)	4.592*** (1.671)	3.526*** (1.27)	1.065** (0.428)	4.239*** (1.619)	3.682*** (1.35)	0.557 (0.426)
Employment rate	−0.059*** (0.022)	−0.045*** (0.017)	−0.014** (0.006)	−0.054** (0.021)	−0.047*** (0.018)	−0.007 (0.006)
Graduation rate	−0.026 (0.022)	−0.02 (0.017)	−0.006 (0.005)	−0.024 (0.021)	−0.02 (0.018)	−0.003 (0.004)
Density growth	−0.782*** (0.26)	−0.601*** (0.198)	−0.182*** (0.068)	−0.727*** (0.256)	−0.631*** (0.214)	−0.096 (0.074)
Urban distance (in logs)	0.792*** (0.273)	0.608*** (0.207)	0.184*** (0.07)	0.754*** (0.275)	0.655*** (0.229)	0.099 (0.074)

P values computed based on Montecarlo simulations with 500 iterations

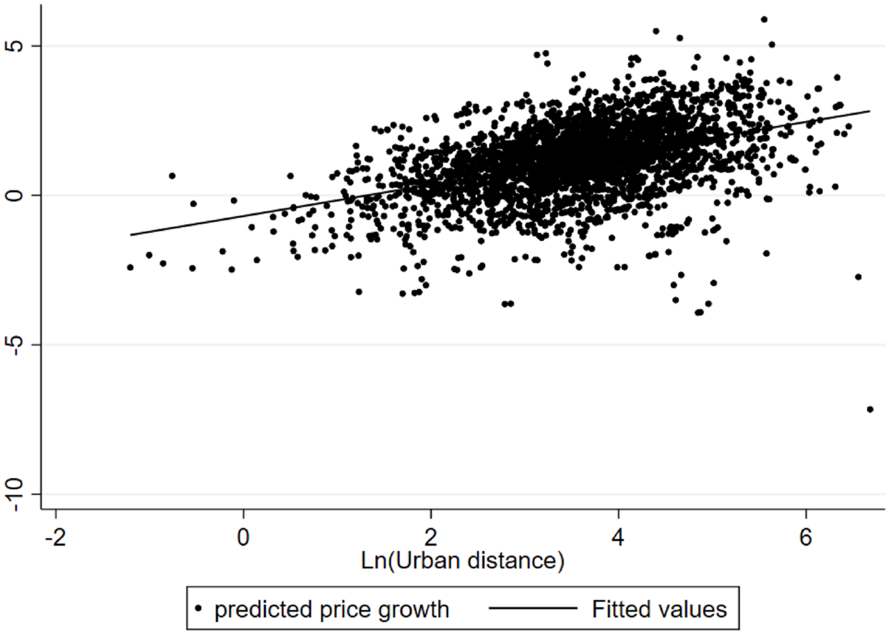

Fig. 4 Predicted price growth against distance to urban centers—SARAR model. *Source:* Own computation

grew significantly faster in rural areas than in urban areas. The high proportion of the direct effects in the SARAR model would indicate a localized effect of distance, where spatial idiosyncratic effects—represented by the spatial structure of the errors—transmit the rest of the spatial correlation.

Lastly, we evaluated whether this spatial pattern holds in rural and isolated areas. Table 6 estimates the SARAR model from Table 3 in two sub-samples depending on the RUCC—from 1 to 5 and from 6 to 9.

In this case, the coefficient of income growth becomes non-significant in these areas. However, it is not the same case for the spatial pattern. The coefficient of distance to an urban core remains significant. In fact, its value becomes even higher, from 0.652 to 1.071. Two possible implications may be interpreted from this result. Our hypothesis seems to hold in these areas, and it could even indicate a possible heterogeneity in the effect.

Table 6 Comparison of rural and isolated areas—SARAR model

	Full sample	RUCC 1—5	RUCC 6—9
Income growth	0.126** (0.063)	0.202** (0.084)	−0.013 (0.092)
Contributions per worker (in logs)	3.668*** (1.337)	1.246 (1.714)	6.474*** (2.478)
Employment rate	−0.047*** (0.018)	−0.013 (0.021)	−0.113*** (0.033)
Graduation rate	−0.02 (0.018)	−0.026 (0.026)	−0.009 (0.023)
Density growth	−0.629*** (0.212)	−0.551** (0.255)	−0.978** (0.414)
Urban distance (in logs)	0.652*** (0.222)	0.651*** (0.253)	1.071** (0.506)
Constant	−3.39 (2.716)	−1.027 (3.68)	−6.966 (4.441)
ρ	0.135** (0.064)	0.131** (0.063)	0.235* (0.138)
λ	0.125* (0.064)	0.129** (0.063)	−0.046 (0.15)
State effects	No	No	No

Numbers in parentheses are standard errors. *, ** and *** represent estimates significantly different from zero at 10%, 5% and 1%, respectively. SAR, SEM and SARAR estimations are obtained through Maximum Likelihood

5 Policy implications

This article illustrates the potential of using Big Mac prices as an indicator to study changes in price differences between rural and urban areas. This information could be an essential missing piece in the puzzle of how to deliver food or income assistance efficiently and equitably. The analysis documents how Big Mac prices changed and how that change differed between rural and urban areas over a few months and then explores the influence of localized processes on price changes. The different techniques suggest that prices are highly dependent on spatial distribution of the stores. Econometric analysis of the data from the Big Mac price survey revealed a significant positive effect of being in a rural area on the increase in prices. This considerable effect indicates that urban areas in the US experienced slower price increases relative to rural areas during the studied period. Estimated indirect effects suggest that most of the rural price change is likely due to localized effects.

Several factors could be behind the relative difference in change. First, transitory influences may have caused faster increases in rural prices. A commodity boom, for example, could affect rural areas more than urban areas. Rural areas have lower labor force participation than urban areas, but at the same time, rural markets are thin, as evidenced by the fact workers may travel great distances for high paying jobs, such as those found in the natural gas extraction industry during the time of our data collection (Brown 2014). On the other hand, urban cost structures may be becoming more efficient. Many urban areas were experiencing a renaissance during the data collection interval, and concomitant population increase could help restaurants spread their fixed costs over more customers or increase the spatial competition with other McDonald's locations or new non-McDonald's competitor restaurants. Finally, it is possible that high volume outlets simply innovate faster to reduce costs and stay competitive; in a study of Norway, Carlsen et al. (2016) find less-educated worker wages go up more quickly with tenure in urban areas than in rural areas. Perhaps similar effects are in play here.

The approach outlined here demonstrates the utility of using a single, standardized, widely available, but relatively complex item to collect price change information. The analysis provides insights into the structure of rural price transmission, showing that spillovers can be highly localized, at least in this item.

The Big Mac method is inexpensive relative to other ways of measuring rural price changes, and our analysis shows that it can detect regional differences in short-term price changes. Regularly collecting Big Mac and similar price data could document where prices are increasing for a variety of foods, and not just the artifact of other changes, such as new restaurant management, closure of a competitor, or reduced fixed costs (e.g., mortgage paid off). This analysis should be considered as an example of the potential of using this technique in Regional Economics. The limited period in our study does not allow a deep understanding of cost-of-living dynamics in the long run. Additional data beyond the two points in time presented here could reveal whether the relationships in this article are consistent or changing and is therefore worth exploring in future. For example, these relationships may vary during an economic crisis or during specific region shortages. As a result, a consistent database with this information may prove especially useful to easily identify those changes in the rural–urban relationships—something difficult to find in existing Cost-of-Living analyses.

As a low-cost method for identifying price changes, a Big Mac Index could help identifying candidate regions for region-specific adjustments to eligibility criteria and payments for food assistance programs such as SNAP. The method may reveal localities that should be considered for higher support levels, or possibly that current national support levels provide an incentive to remain in place rather than moving to higher cost but higher opportunity regions. An initial mapping of Big Mac price changes could identify possible price hotspots to be studied more intensively with a broader range of products in regions of concern.

Although the focus of data collection in this article is the US, the method could be employed in other places where Big Mac differences in prices are expected or the available information between rural and urban areas is limited. Some examples of using Big Mac prices in Europe are Parsley and Wei (2008), who evaluate inflation after creating the Euro currency, or Clementi et al. (2010), who assess the dispersion of prices in the Euro area. Other studies highlighted the differences in prices and cost-of-living across space in Europe, e.g., Lasarte-Navamuel et al. (2014) and Lasarte-Navamuel et al. (2019) found that city size creates a significant differential in Spanish food prices and cost-of-living. Vaona (2011) also found a remarkable heterogeneity in Italian long-run inflation rates. Despite this evidence, most national subsidies and indicators do not consider these differences. For example, the new Spanish minimum living income subsidy created to counteract the COVID-19 crisis is the same for the whole country.

With this type of data, the analysis could be extended to study spatial patterns of the price not only in terms of inflation, but also in the volatility of prices with models like the spatial ARCH model proposed by Otto et al. (2018). In this case, the study of conditional variances could uncover additional rural–urban patterns in the USA. Similarly, future work could seek additional covariates to more explicitly assess the magnitude of Marshall-Arrow-Romer externalities.

The method could also be extended to other high value, relatively perishable foods. For example, Subway has roughly 24,000 locations in the US and approximately 17,000 locations in 100 different countries (Statista 2020). Since it lacks large cooking systems and is typically smaller than McDonald's outlets in terms of square meters, a Subway outlet is probably less capital intensive than a McDonald's, and therefore may not be as representative of a range of local costs as McDonald's. Future work could explore whether highly perishable but standardized food products from other chains, such as Subway, could complement (or improve upon) the Big Mac Index, both in the US and in other countries. In other high or middle-income countries, international chains such as Nordsee, Telepizza, Wimpy, Pans & Company, or Pizza Hut could be explored as sources of local prices. These same chains could also be considered competitors in models of Big Mac price changes in assessing nutrition assistance program support levels or other poverty reduction strategies. Finally, results from Big Mac analyses could be compared to more traditional measures such as housing or wages.

Appendix

See Table 7.

Table 7 Variance inflation factors (VIFs) of the control variables

Control variables	Variance inflation factors (VIF)
Income growth	1.17
Contributions per worker (in logs)	1.61
Employment rate	1.47
Density growth	1.19
Graduation rate	1
Urban distance (in logs)	1.23
Mean VIF	**1.28**

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