Rural-Urban Food Price Inflation Disparities in the United States

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Abstract

This paper shows that food price inflation varies across rural, urban, and metro counties in the United States. To quantify this disparity, we calculate food price indices using retail scanner data. Our indices suggest that between 2006 and 2020, rural areas had an overall higher food price inflation compared to urban and metro regions, with food price inflation averaging 0.7 percent lower in urban areas and 1.6 percent lower in metro areas. Additionally, we examine shifts in these disparities during key periods. We find that during the Great Recession, these differences were negligible, but in the post-Great Recession years, urban and metro areas consistently had lower food price inflation. However, the onset of the COVID-19 pandemic in 2020 led to a shift, with both urban and metro areas experiencing higher food price inflation, surpassing rural regions.

Keywords: Food price, price index, inflation, rural-urban disparity.

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Researcher's own analyses calculated (or derived) based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researcher and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

1. Introduction

In recent years, the United States has faced a significant surge in food price inflation, with rates in 2022 reaching its highest levels since 1979 (U.S. Bureau of Labor Statistics). This trend not only persisted but worsened into 2023, with the Consumer Price Index (CPI) for all food items climbing 0.3 percent from June to July 2023 alone, culminating in a 4.9 percent increase from July 2022, significantly outpacing the overall CPI's year-over-year rise of 3.2 percent. The escalation in food prices has been linked to various adverse consequences, including intensifying risks of food insecurity (Gregory and Coleman-Jensen, 2013) and deteriorating child health (Woldemichael et al., 2017; Kidane and Woldemichael, 2020). However, despite these alarming trends, the documentation of food price inflation across different regions in the United States remains inadequate.

The CPI is a widely used metric for gauging inflation, capturing price changes in consumer goods and services. However, it focuses solely on the spending habits of urban consumers and urban wage earners, overlooking rural, non-metropolitan areas (US Bureau of Labor Statistics, 2023). This limitation makes CPI a less reliable tool for assessing the economic and health impacts of inflation on rural communities, potentially leading to skewed results. Moreover, data on inflation in rural areas are scarce. These issues have caught the attention of researchers and policymakers, particularly in the wake of inflation spikes during the COVID-19 pandemic. For example, recent research from the Congressional Budget Office (Swagel 2022) and the Federal Reserve Bank of Richmond (George and O'Trakoun 2022) indicates that rural regions have faced higher inflation rates than their urban counterparts since the pandemic began.

In this paper, we document how food price inflation varies across rural, urban, and metro areas in the United States.[1] Different from Swagel (2022) and George and O'Trakoun (2022) who estimate inflation using imputation methods due to lack of price data, we leverage retail scanner data to construct price indices and compare food price inflation estimates. Our retail scanner data includes weekly price and volume for barcode-level items and provides comprehensive coverage of rural areas. To estimate food price inflation using retail scanner data, we construct temporal price indices using index number methods that have desirable properties when constructed with high-frequency, point-of-sale datasets. Specifically, we construct the Rolling Window GEKS (RWGEK) index, an extension of the widely adopted GEKS index (e.g., Çakır et al. 2018; Li and Çakır 2022).[2] The GEKS index has important advantages compared to conventional bilateral index methods such as Laspeyres, Fisher, and Törnqvist. One of its main advantages is its ability to incorporate information from all possible comparisons between different time periods. This approach is like the "chained indices", which update the base of comparison in each period to provide a more accurate reflection of changes over time. However, unlike chained indices, the GEKS method avoids "chain drift". Chain drift is a problem that can occur when the cumulative effect of small changes in the method of calculation leads to significant discrepancies over time. The GEKS index manages to use all available data to measure changes accurately without suffering from this drift, like the "direct indices", which compare all periods directly to a single base period but without their limitations.[3]

We find that between 2006 and 2020, the average food price inflation is higher in rural counties than urban and metro counties. Despite having a much smaller number of counties

[1] For simplicity, we use "metro" as shorthand for "metropolitan".
[2] The GEKS method is named after Gini (1931), Elteto and Koves (1964), and Szulc (1964).
[3] See de Haan and van der Grient (2011) and Ivancic et al. (2011) for an in-depth discussion of the GEKS method.

compared to urban and metro regions, rural areas exhibit a more pronounced variability in food price inflation. Our regression results quantify the disparities and show that food price inflation is, on average, 0.7 percent lower in urban areas and 1.6 percent lower in metro areas, compared to rural areas.

We also show that the disparity varies across notable time periods. In particular, we examine rural-urban food price inflation differences during the Great Recession (2007-2011), post-Great Recession (2011-2019), and the onset of COIVD-19 in 2020. Our results indicate that during the Great Recession, urban-rural differences in food price inflation are statistically insignificant. In the post-Great Recession era (2011-2019), urban and metro areas consistently display lower food price inflation compared to rural regions. Notably, with the advent of COVID-19 in 2020, this trend shifts. Both urban and metro areas begin to show higher food price inflation, outpacing those in rural areas.

Our study contributes to the literature on food price inflation by presenting distinct estimations for rural, urban, and metro regions in the United States. While there is a considerable number of studies on food price inflation, the spotlight predominantly shines on either the causes or consequences of such inflations. For example, Baek and Koo (2010) use all-food CPI data to examine factors affecting U.S. food price inflation. In a more recent study, Adjemian et al., (2023) use data from the personal consumption expenditure price (PCE) index to decompose food price inflation into demand and supply shocks. As for the ramifications, there is a large number of studies examining the impact of surging food prices on economically disadvantaged groups (e.g., Deaton, 1989; Ivanic et al., 2008).

Further, while regional variations in food prices are well-documented, the disparities in food price inflation—the rate at which these prices increase—remain less explored. While there are studies examining this phenomenon in other countries, such as Chong et al. (2011), which found that rural residents in China experience higher inflation rates than their urban counterparts, the focus within the U.S. context remains sparse. Leveraging granular data and index number methods, our study bridges this research void, showing disparities between rural and urban food price inflation.

The rest of the paper is organized as follows: Section 2 provides an overview of the data used. Section 3 outlines the methodology for constructing temporal price indices and for analyzing disparities in food price inflation. Section 4 presents the results of our analysis. Section 5 discusses potential factors underlying our findings. Section 6 concludes.

2. Data

To construct price indices, we utilize the NielsenIQ Retail Scanner data, spanning the years 2006 to 2020.[4] This dataset encompasses details on retail prices and sales from over 35,000 stores[5], accounting for approximately 50% of total sales volume from grocery and drug stores and 30% from mass merchandisers in the United States (Kilts Center for Marketing Data Center at the University of Chicago Booth School of Business, 2023). This data includes weekly prices and volume for products at the Universal Product Code (UPC) level, thereby providing novel opportunities to refine price change estimations using index number methods. The high-frequency details on price and quantity allow us to calculate weighted price indices at desired aggregation level. Our calculations are based on over 2 million UPCs of food products spanning more than 700 product modules from the scanner data.

[4] For additional information on this dataset, visit https://www.chicagobooth.edu/research/kilts/research-data/nielseniq.
[5] There were approximately 35,000 stores from 2006 to 2017. An additional 15,000 stores were added in 2018.

We obtain county demographic information, including household income and unemployment rate, from the American Community Survey (ACS). After merging the demographic data with the retail scanner data, we observe that our data contains at least one store in 83% of all U.S. counties and encompasses regions where 97% of the U.S. population lives. To classify these counties, we employ the USDA's 2013 Rural–Urban Continuum Codes (RUCC), designating each as either "Metro", "Urban", or "Rural".[6]

Table 1 presents the distribution of metro, urban, and rural counties in our sample across the contiguous U.S. states. There are 1,107 counties in metro areas of 1 million population or more (RUCC 1 to 3) in 50 states, 1,287 urban counties that are not part of a metropolitan area but have varying degrees of urban population (RUCC 4 to 7) in 46 states, and 366 counties in completely rural or less urbanized counties (RUCC 8 and 9) in 39 states. Although rural counties have lower average coverage (66%) compared to urban (98%) and metro areas (95%), the dataset still encompasses regions inhabited by over 72% of the U.S. rural population.

3. Methods

3.1 Price Index Construction

The GEKS method is based on taking the geometric mean of the ratios of all bilateral indices between the two comparing periods, where each period (*l = 1, ..., T*) in the sample is taken as the base. The GEKS-Törnqvist index formula between periods *j* and *k* can be expressed as follows:

$$P_{GEKS}^{j,k} = \prod_{l=0}^{T} \left(P_T^{j,l} \times P_T^{l,k} \right)^{\frac{1}{T+1}}, \tag{1}$$

[6] Counties are categorized based on their RUCC codes as follows: those with a RUCC code of 8 or 9 are classified as 'Rural', those with a RUCC code between 4 and 7 are designated as 'Urban', and those with a RUCC code of 3 or less are labeled as 'Metro'.

where $P_T^{j,l}$ denotes the Törnqvist index between periods j and l given as:

$$P_T^{j,l} = \prod_{i=1}^{N} \left(\frac{p_i^l}{p_i^j} \right)^{\frac{s_i^j + s_i^l}{2}}, \quad (2)$$

where p_i^j is the price of item i in period j and s_i^j is the expenditure share of item i in period j.

We can continuously update the original GEKS index as more periods enter, extending the series further. Yet, as time progresses, earlier data in the sample diminish in relevance for subsequent comparisons. Thus, we adopt the RWGEKS method which employs a moving window, establishing chain links that constantly update the price series (Ivancic et al. 2011). As data from new periods emerge, there is no need to adjust parities from prior periods. We apply the mean splice method, which utilizes the geometric mean of the shifts between the final period and all other periods within the window, to extend the initial index to extend the series up to the final period in the data. Let P_{OLD} be the index computed over periods 1 to *w*, and let P_{NEW} be the index computed over the window rolled forward by one period, from periods 2 to *w* + 1. The index for the period *w* + 1 and beyond is computed using the following formula:

$$P_{GEKS}^{w+1} = P_{GEKS}^{w} \times \left(\prod_{t=1}^{w-1} \frac{P_{NEW}^{w+1}/P_{NEW}^{t+1}}{P_{OLD}^{w}/P_{OLD}^{t+1}}\right)^{\frac{1}{w-1}}. \quad (3)$$

The core idea entails shifting the window forward by one period and then calculating a new GEKS index based on this updated window. It is important to note that there will be periods that overlap between the original GEKS index and the newly computed GEKS index from the advanced window. Following Ivancic et al. (2011), we set the window length to 5 as we construct quarterly indices.

3.2 Estimation Strategy

To estimate the differences in food price inflation between rural, urban, and metro counties across the United States, we primary estimate the following regression specification:

$$P_{ijt} = \alpha + \beta Status_{ij} + \gamma_j + \boldsymbol{\theta_t} + \boldsymbol{X}_{it} + \varepsilon_{it}. \tag{4}$$

In the regression, i denotes counties, j denotes states, and t denotes time. Our primary independent variable, $Status_{ij}$, classifies county i in state j into one of the three urban statuses: rural, urban, or metro based on RUCC code. To account for the constant attributes of states in which counties are situated that could affect food prices, we include state-specific fixed effects denoted by γ_j. The vector $\boldsymbol{\theta_t}$ captures the fixed effects for both the quarter and the year, thereby adjusting for broader time-related fluctuations affecting food prices uniformly across all counties. Additionally, we control for economic variables that change over time within counties, specifically the yearly unemployment rates and household median income, represented in the $\boldsymbol{X}_{it}$ term.[7]

4. Results

4.1. Comparing Rural and Urban Food Price Inflation in the United States

We first construct quarterly food price indices for all counties in our sample from the first quarter of 2006 to the last quarter of 2020. Figure 1 shows the trend of average food price index values for rural, urban, and metro counties. The base period for the price index is set to a value of 100, serving as a reference point. Price index values for subsequent periods are calculated relative to this baseline. The trends outlined in Figure 1 illustrates a significant 23% increase in average food prices over a 15-year period, with rural areas having the highest food price index at the end of 2020, followed by urban areas, while metro areas had the lowest index values. Before 2009, both

[7] We include these control variables as low-income areas often have higher food prices (Kaufman, 1998) and there exists a correlation between unemployment and changes in food consumption patterns, which may also correlate with food price changes (Dave and Kelly, 2010).

urban and metro counties had similar food price indices, slightly exceeding those of rural counties. However, in 2009, urban and metro areas experienced a noticeable decline in their indices, whereas rural counties saw only a modest dip. After 2009, metro counties consistently maintained the lowest food price index values, while urban counties exhibited fluctuations but generally stayed below rural. Additionally, there was a significant spike in all indices in early 2020, potentially due to the impact of COVID-19.

Figure 1 highlights a notable disparity in food price inflation trends between rural, urban, and metro counties over the 2006 to 2020 period. However, it is worth noting that Figure 1 provides average index values, and there could be variations within each urban status. To further elucidate these distinctions, Figure 2 presents food price indices with data points at the 25th and 75th percentiles, as well as the 10th and 90th percentiles, offering a more comprehensive view of the trends and differences in food price inflation among these regions.

In Figure 2, the first panel illustrates the food price index trends for rural areas, the second panel depicts trends for urban areas, and the third panel represents trends for metro areas. Notably, despite having a much smaller number of counties compared to urban and metro regions, rural areas exhibit a notably higher degree of variability in food price inflation across their counties. Specifically, the disparity in food price inflation is quantified by an average difference of 6.5 percent in index values between rural counties at the 25th and 75th percentiles. In contrast, urban areas show a slightly less pronounced variability, with a 6.2 percent difference between the same percentiles, and metro counties exhibit an even tighter distribution, with a 4.9 percent difference, indicating more uniform inflation trends.

The figures offer a visual depiction of the variations in food price inflation among rural, urban, and metro regions. Subsequently, we conduct a formal examination of these differences by estimating equation (4), where we perform a regression of our food price indices on county categories. Table 2 displays the results of the regression analysis, with our calculated food price indices as the dependent variable. The coefficients estimated for the "Urban" and "Metro" categories denote the average disparities in food price inflation when compared to rural regions over the observed period. Column 1 presents the results without any control variables or fixed effects, column 2 includes results with only control variables but no fixed effects, column 3 presents results with fixed effects but no control variables, and column 4 provides results with both control variables and fixed effects included in the regression.

Table 2 shows that between 2006 and 2020, food price inflation rates are lower in urban and metro areas than in rural areas. Across different specifications, the estimated differences are both consistent and statistically significant. Our preferred specification, which incorporates both control variables and fixed effects, show that the food price inflation is, on average, 0.7 percent lower in urban areas and 1.6 percent lower in metro areas, compared to rural areas.

4.2. Rural-Urban Food Price Inflation Disparities Across Key Time Periods

In this section, we examine the disparities in food price inflation across three distinct time frames: during the Great Recession (2007-2011), post-Great Recession (2011-2019), and the start of COIVD-19 in 2020. By focusing on these distinct epochs, we aim to provide insight into the potential macroeconomic influences on rural-urban food price inflation disparities. Such nuances could have been overlooked in the previous section due to its broader time span.

Table 3 displays the findings based on samples from three distinct periods. Since temporal price indices track changes in price with respect to a reference period, we rebase our indices to the start of each period for our analyses. Furthermore, as we have fewer observations in our subsamples, we exclude the reference period to negate the impact of periods with uniform values.

From 2007 to 2011, during the Great Recession, with only fixed effects and no control variables (column 1), the difference in food price inflation rates between rural and urban areas is statistically insignificant. Yet, in metro areas, the rates are roughly 0.52 percent lower those in rural locales. Conversely, when control variables are added into the regression (column 2), the estimated difference between rural and urban areas, although still negative, is not statistically significant.

After the Great Recession period, from 2012 to 2019, we find that food price inflation rates are lower in urban and metro areas than in rural areas. The estimated differences are similar with and without control variables, yielding about 0.4 percent lower in urban and 0.9 percent lower in metro compared to rural.

Following the Great Recession, in the span of 2012 to 2019, results in columns 3 and 4 indicate that the average food price inflation rates are lower in both urban and metro regions compared to rural areas. The differences remain relatively consistent regardless of the inclusion or exclusion of control variables. Specifically, inflation rates are approximately 0.4 percent less in urban and 0.9 percent less in metro areas relative to rural ones.

To examine the disparities during the onset of COVID-19 in 2020, we set the last quarter of 2019 as the based period and include food price indices from all four quarter in 2020 for our analysis. Contrary to our previous results, the 2020 data indicates that food price inflation rates in urban and metro regions surpass those in rural areas. On average, the food price index values are 0.74 percent higher in urban and 0.78 percent higher in metro counties compared to the index values in rural counties.

5. Discussion

The overall higher food price inflation observed in rural markets relative to urban and metro areas from 2006 to 2020 suggests a more substantial percentage increase in food cost for rural households. This divergence can be attributed to supply-side factors such as input costs—including labor, energy, transportation, and farming supplies—as well as disruptions within the supply chain, which are key influencers of food price inflation (Adjemian et al., 2023a; Adjemian et al., 2023b). These elements are potential contributors to the disparity in food price inflation between rural and urban markets.

For example, fuel price fluctuations can disproportionately affect rural areas, where food distribution requires longer transit distances. This can result in amplified transportation costs that, when combined with the smaller-scale operations characteristic of rural transport, lead to heightened costs for food delivery (Kaufman, 1998). Consequently, these increased expenses can contribute to a more rapid increase in retail food prices in rural markets.

Rural markets may also confront greater vulnerability to or absorb more profound impacts from these supply-side shocks compared to urban and metro markets. In particular, Çakır et al., (2020) show that rural markets exhibit higher local market concentration, as measured by the Herfindahl-Hirschman Index (HHI), than urban and metro markets. The lack of competitive pressure allows retailers to transfer more of the inflationary costs to consumers without the risk of losing them to competitors, as might be the case in more densely populated urban areas where consumers have more shopping alternatives.

The fluctuation in the rural-urban disparity in food price inflation across the examined periods suggests these differences may be influenced by broader events. During the Great

Recession, the minimal difference in inflation rates suggests that the economic downturn could have impacted food prices uniformly across rural and urban areas, potentially due to a nationwide tightening of economic conditions that affected all markets similarly.

In the post-Great Recession era, the persistence of lower food price inflation in urban and metro areas compared to rural ones could be attributed to a quicker economic recovery in more densely populated areas (Bennett et al., 2018). Urban and metro areas often have more robust economic structures that can rebound more efficiently from economic shocks, benefit from more significant government intervention, and offer a greater variety of food supply chains, which could contribute to more stable food prices.

The reversal of this trend in 2020, with the advent of COVID-19, is particularly intriguing. The pandemic brought unprecedented challenges that may have disrupted the previously observed patterns. Urban and metro areas, which typically have more complex and interdependent supply chains, could have been more susceptible to the disruptions caused by lockdowns and restrictions on movement (Hobbs, 2020). The sudden shift in demand patterns, such as increased demand for delivery services and stockpiling behavior, along with the closure of restaurants and food services, may have led to a sharper rise in retail food prices in these areas. Conversely, rural areas might have been somewhat insulated from these effects due to their local supply chains and less dependence on food service outlets that were heavily impacted by the pandemic (Laborde et al., 2020).

6. Conclusion

Food prices in the United States are currently escalating more rapidly than at any time in the past four decades. Despite this significant trend, there is a notable gap in academic research, particularly concerning the exploration and quantification of food price inflation disparities among different markets. In this paper, we show that there exist disparities in food price inflation across rural, urban, and metro counties in the United States. In particular, our findings illustrate that rural counties consistently experience higher average food price inflation than their urban and metro counterparts. Despite encompassing a smaller number of counties, rural regions exhibit more pronounced variability in inflation trends. Our regression analyses further quantify these disparities, revealing that, on average, food price inflation is 0.7 percent lower in urban areas and 1.6 percent lower in metro areas when contrasted with rural locales. This variation becomes even more evident when observing specific time frames, such as the Great Recession and the onset of the COVID-19 pandemic.

Our findings have implications for both policymakers and future research. The higher food price inflation in rural counties underscores the potential for exacerbating economic inequalities and food insecurities in these areas. Given that rural communities often face infrastructural and economic challenges, persistent inflation could lead to reduced purchasing power for essential commodities, which can have cascading effects on the overall quality of life. Furthermore, the inflation disparity could deter new businesses or industries from entering rural markets, thereby limiting economic diversification and growth opportunities. On the policy front, our results advocate for a more nuanced approach to price control and subsidy distribution, ensuring that interventions are region-specific and address the unique challenges faced by rural, urban, and metro counties. For future studies, our study sheds light on an under-explored domain, opening avenues for further exploration into the underlying causes and long-term consequences of these inflation disparities.

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Table 1: Sample Coverage

	Counties in Sample			Number of Counties			Sample Coverage		
State	Rural	Urban	Metro	Rural	Urban	Metro	Rural	Urban	Metro
AL	11	27	29	11	27	29	100%	100%	100%
AR	11	42	19	13	42	20	85%	100%	95%
AZ		7	8		7	8		100%	100%
CA	1	17	37	4	17	37	25%	100%	100%
CO	13	27	16	20	27	17	65%	100%	94%
CT		1	7		1	7		100%	100%
DC			1			1			100%
DE			3			3			100%
FL	2	21	44	2	21	44	100%	100%	100%
GA	15	63	72	22	63	74	68%	100%	97%
IA	16	57	21	20	58	21	80%	98%	100%
ID	7	20	11	10	22	12	70%	91%	92%
IL	1	50	36	10	52	40	10%	96%	90%
IN	4	43	41	5	43	44	80%	100%	93%
KS	12	40	14	42	44	19	29%	91%	74%
KY	31	49	32	36	49	35	86%	100%	91%
LA	5	24	35	5	24	35	100%	100%	100%
MA		3	11		3	11		100%	100%
MD		5	19		5	19		100%	100%
ME	2	9	5	2	9	5	100%	100%	100%
MI	14	43	26	14	43	26	100%	100%	100%
MN	11	40	26	19	41	27	58%	98%	96%
MO	15	46	30	30	51	34	50%	90%	88%
MS	18	44	16	21	44	17	86%	100%	94%
MT	10	21	4	29	22	5	34%	95%	80%
NC	14	38	46	16	38	46	88%	100%	100%
ND	15	10	5	37	10	6	41%	100%	83%
NE	9	27	10	51	29	13	18%	93%	77%
NH		7	3		7	3		100%	100%
NJ			21			21			100%
NM	4	20	7	6	20	7	67%	100%	100%
NV	2	9	3	4	9	4	50%	100%	75%
NY		23	38	1	23	38	0%	100%	100%
OH	2	48	38	2	48	38	100%	100%	100%
OK	10	40	16	16	43	18	63%	93%	89%
OR	2	17	13	5	18	13	40%	94%	100%
PA	3	26	37	4	26	37	75%	100%	100%

RI			5			5			100%
SC	1	19	26	1	19	26	100%	100%	100%
SD	16	15	7	42	16	8	38%	94%	88%
TN	15	37	42	16	37	42	94%	100%	100%
TX	27	120	77	49	123	82	55%	98%	94%
UT	2	14	10	5	14	10	40%	100%	100%
VA	16	27	70	21	32	81	76%	84%	86%
VT	2	8	2	3	8	3	67%	100%	67%
WA	1	11	19	5	13	21	20%	85%	90%
WI	13	33	26	13	33	26	100%	100%	100%
WV	10	22	21	11	23	21	91%	96%	100%
WY	3	17	2	4	17	2	75%	100%	100%

Notes: The table outlines the representation of metro, urban, and rural areas in our sample across the contiguous U.S. states. “Counties in Sample” indicates the number of counties for which we have data, “Number of Counties” shows the total number of counties in each state, and “Sample Coverage” provides the percentage of counties in each state included in our sample. A blank cell signifies there in no county in the specified urban status for that state (e.g., Rhode Island (RI) has neither urban nor rural counties according to the 2013 RUCC). AL: Alabama; AZ: Arizona; AR: Arkansas; CA: California; CO: Colorado; CT: Connecticut; DE: Delaware; DC: District of Columbia; FL: Florida; GA: Georgia; ID: Idaho; IL: Illinois; IN: Indiana; IA: Iowa; KS: Kansas; KY: Kentucky; LA: Louisiana; ME: Maine; MD: Maryland; MA: Massachusetts; MI: Michigan; MN: Minnesota; MS: Mississippi; MO: Missouri; MT: Montana; NE: Nebraska; NV: Nevada; NH: New Hampshire; NJ: New Jersey; NM: New Mexico; NY: New York; NC: North Carolina; ND: North Dakota; OH: Ohio; OK: Oklahoma; OR: Oregon; PA: Pennsylvania; RI: Rhode Island; SC: South Carolina; SD: South Dakota; TN: Tennessee; TX: Texas; UT: Utah; VT: Vermont; VA: Virginia; WA: Washington; WV: West Virginia; WI: Wisconsin; WY: Wyoming.

Table 2
Food Price Inflation Differences by County Classification

	(1)	(2)	(3)	(4)
Urban Status				
Urban	-0.894***	-1.383***	-0.844***	-0.712**
	(0.324)	(0.325)	(0.296)	(0.297)
Metro	-2.301***	-4.075***	-2.211***	-1.593***
	(0.320)	(0.344)	(0.292)	(0.304)
Controls	No	Yes	No	Yes
Fixed Effects	No	No	Yes	Yes
Observations	157,422	157,394	157,422	157,394

Notes: This table reports estimates from regressions based on equation (4). The dependent variable is the food price index. The reference group for the urban status variable is "Rural". Control variables include unemployment rates and median household income, while fixed effects account for state, quarter, and year. Standard errors are clustered at the county level. Stars indicate significance at 10% (*), 5% (**), and 1% (***) levels.

Table 3

Food Price Inflation Differences across Notable Time Periods

	(1)	(2)	(3)	(4)	(5)	(6)
Urban Status						
Urban	0.115	0.177	-0.441*	-0.404*	0.718***	0.735***
	(0.218)	(0.220)	(0.230)	(0.230)	(0.220)	(0.221)
Metro	-0.519**	-0.242	-1.032***	-0.884***	0.708***	0.778***
	(0.216)	(0.224)	(0.232)	(0.243)	(0.220)	(0.227)
Controls	No	Yes	No	Yes	No	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Period	2007 to 2011	2007 to 2011	2012 to 2019	2012 to 2019	2020	2020
Observations	49,489	49,489	80,601	80,601	9,763	9,763

Notes: This table reports estimates from regressions based on equation (4) but for varying time periods. The dependent variable is the food price index, rebased to 100 for the starting period of each analyzed time frame. The reference group for the urban status variable is "Rural". Control variables include unemployment rates and median household income, while fixed effects account for state, quarter, and year. Standard errors are clustered at the county level. Stars indicate significance at 10% (*), 5% (**), and 1% (***) levels.

Figure 1

Food Price Inflation Trends Across Rural, Urban, and Metro Counties

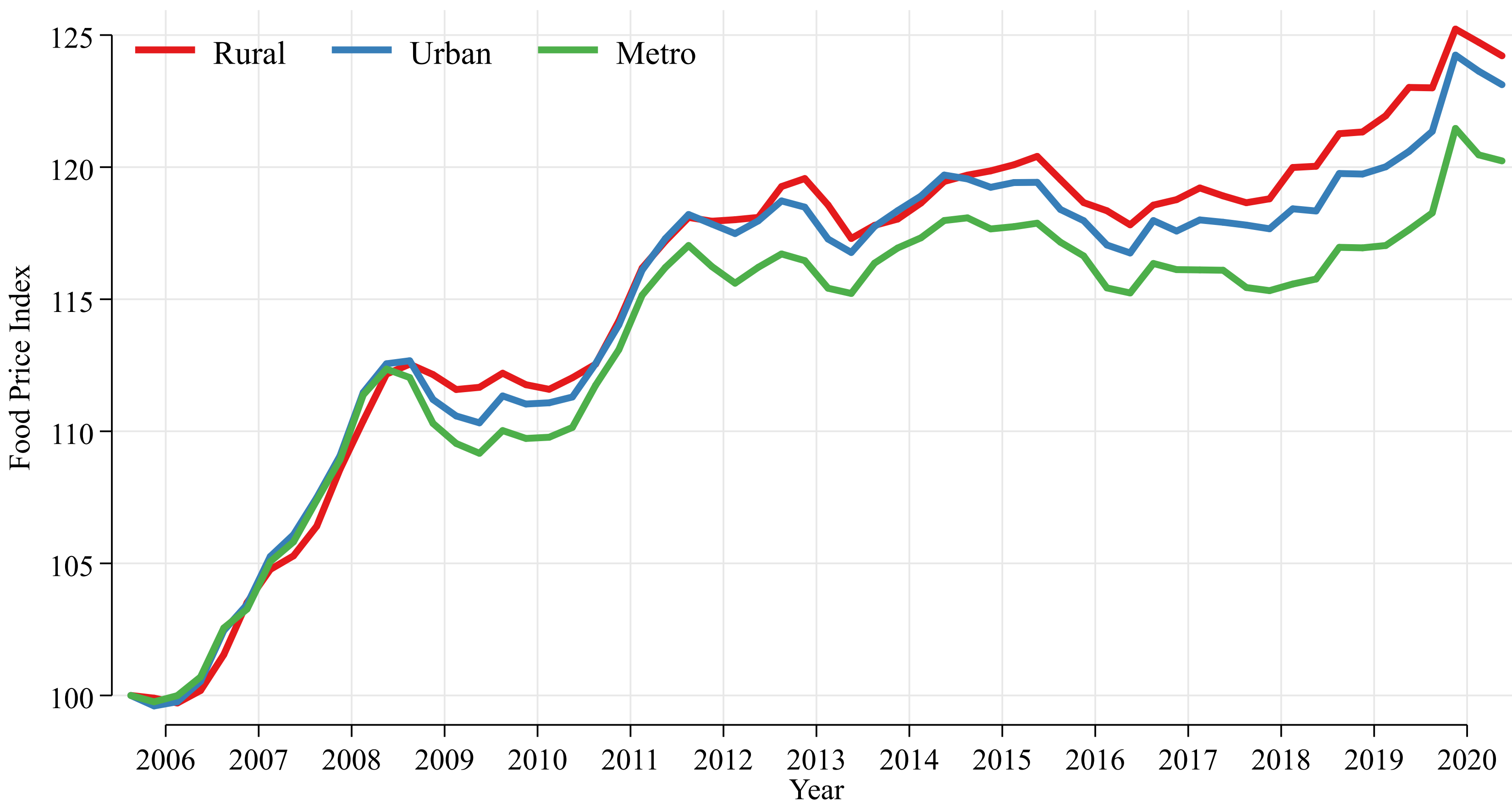

Figure 2

Food Price Index Trends and Distributions Across Rural, Urban, and Metro Counties