ISSN 1936-5330

kcFED Research Working Papers

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June 2019
RWP 19-02
https://doi.org/10.18651/RWP2019-02

Federal Reserve Bank of Kansas City

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Abstract

Using a vector autoregression that allows for time-varying parameters and stochastic volatility, we show that U.S. core inflation became 75 percent less responsive to shocks in food prices since the late 1970s. The decline in the pass-through of food price shocks to inflation is a result of a decline in both volatility and the persistence of food price changes in inflation. This decline in pass-through coincides with a period of increasing concentration in the food supply chain, especially among U.S. grocery retailers and distributors. We find that 60 percent of the variation in pass-through over the last four decades can be explained by changes in food retailers and distributors market concentration. Controlling for the composition of the food basket and inflation expectations explains an additional 20 percent of the variation. Our results suggest that if the market concentration of food retailers and distributors continues to increase and inflation expectations remain well-anchored, the pass-through of food price shocks to inflation will likely remain subdued.

Keywords: food prices; inflation; time-varying parameters

JEL Classification Numbers: E31, E52, Q11

*We wish to think A. Lee Smith and Christiane Baumeister and seminar participants at FRBKC for helpful comments. The views expressed here are those of the authors and are not attributable to the Federal Reserve Bank of Kansas City or the Federal Reserve System.

1 Introduction

In the 1970s, food price shocks heavily influenced inflation (Blinder and Rudd, 2012). Many economists viewed increases in food prices as a result of temporary supply-side factors that would reverse (Lombra and Mehra, 1983). This view was supported by a cost-push theory of inflation in which raw agricultural commodities pass through to food prices (Lamm, 1979). Others argued that only considering supply-side factors had led some economists to underestimate food price inflation in the early 1970s and that aggregate demand policies also had a significant effect on food prices (Lombra and Mehra, 1983). The sharp rise in food prices in 1973 prompted researchers to investigate the role government policies might play in changing prices (Eckstein and Heien, 1978). Far less has been written on food inflation in the U.S. since this earlier work. One exception is Stock and Watson (2016), who show the reduced volatility of food prices relative to before the mid-1980s. Substantial changes to patterns of food consumption as well as the maturing of supply chains and increases in market concentration call into question whether shocks to food prices pass through to core inflation in the same manner they once did.

Given the uncertainty surrounding causes of food price shocks (supply vs. demand) and whether those shocks affect the underlying rate of inflation, others have looked across countries to offer some potential rationale. Gelos and Ustyugova (2017) investigate the inflationary impact of commodity price shocks and find that countries with better governance and central bank autonomy are able to better contain the effects of a commodity price shock. They also find that countries with higher food shares in CPI baskets are more prone to persistent inflationary effects of commodity price shocks. Similarly, Walsh (2011) finds that food price inflation is more volatile in lower income, developing countries in large part due to the larger weight of food in the consumer basket. The volatility is an important aspect of the pass-through story and has been investigated in relation to other macroeconomic variables.

More generally, there is growing evidence that the mean and volatility of macroeconomic variables change over time. For example, Clark and Terry (2010) show that inflation pass-through of energy prices in the U.S. has declined over time using a vector autoregression (VAR) with time-varying parameters, mostly due to declines in the volatility of the macroeconomic variables in their model. Their results build upon the work of others, such as Chen (2009) and De Gregorio et al. (2007), who find similar declines in the pass-through of oil prices into inflation. In contrast, there is far less literature pertaining to the potential change in the pass-through of food prices. De Winne and Peersman (2016) investigate the role of shocks in the supply of agricultural commodities on macroeconomic variables including measures of inflation. However, they do not investigate the potential time varying nature of food inflation pass-through to core inflation.

We help bridge this gap in the research by estimating time variation in food price pass-through into core inflation. Using the Bureau of Economic Analysis Personal Consumption Expenditure Price Index and the Bureau of Labor Statistics Consumer Price Index, we estimate a vector auto-regression of energy, food, and core inflation over the past 50 years that allows for time-varying parameters and stochastic volatility. We find that the volatility and persistence of food price changes have been declining since the 1980s. Using impulse response functions, we find that the rate of pass-through from food inflation shocks to core inflation has declined by 75 percent since its peak in the late 1970s.

The decline in the pass-through of food inflation occurred during a period of consolidation and increased market power in portions of the food supply chain, most notably among food distributors and grocery retailers. Large retailers often use contracts that afford them vertical market control across the supply chain. We find that 60 percent of the variation in pass-through over the last four decades can be explained by changes in food retailers and distributors market concentration. Controlling for the composition of the food basket and inflation expectations explains an additional 20 percent of the variation. Our results suggest that if the market concentration of food retailers and distributors continues to increase and inflation expectations remain well-anchored, the pass-through of food inflation to core inflation will likely remain subdued.

In the remainder of the paper, section 2 discusses trends in food prices. Section 3 outlines the Bayesian methodology used in the study. Section 4 discusses the three main statistical factors showing declines in food inflation pass-through and estimates how much of this is explained by market power. Section 5 concludes.

2 Trends in Food Prices

Consumers in the U.S. are increasingly eating processed or partially processed food, whether at home or elsewhere (Guthrie et al., 2002; Smith et al., 2013). While food at home contains more items which are perishable and tend to be more subject to price fluctuations, Figure 1 shows that food at home is a declining share of total food consumption. Moreover, food expenditures as a share of total expenditures in Bureau of Labor Statistics Consumer Price Index (CPI) have declined over time, falling from 16 percent in the late 1980s to about 13.5 percent in 2018 (Figure 1).

In order to investigate trends in food price inflation, we use a price index from the CPI that includes purchases of food at home and food away from home. The rate of inflation is calculated as the annualized month-to-month percentage change for the period January 1959 to December 2018. Figure 2 shows differences in observed rates of inflation over the past six decades. Most notably, large swings in food inflation were less prevalent from the 1990s onward. The reduction in fluctuations is a result of a decline in the volatility of the price level. Table 1 reports summary statistics of core, food, and energy inflation by decade.[1] With the exception of energy, both the mean and standard deviation across the inflation measures declined since the 1970s. Figure 3 shows a time series of volatility measures from 1959 to 2018, where the coefficients of variation are calculated over one-year rolling windows. The

[1] We use BLS CPI to construct measures of core and food inflation. Only BLS CPI has measures of food price indexes separable into at home and away categories. Although BLS CPI has an energy index, over half of the monthly observations in the first few years of the index were the same reading for consecutive months. This resulted in an excess number of zeros in the energy inflation measures early in the index. This was not the case in the Bureau of Economic Analysis Personal Consumption Expenditure energy price index. As a result, we chose to use BEA energy PCE Index to construct a measure of energy inflation.

top panel (Figure 3a) shows the coefficient of variation for food and energy price indexes. Food prices are less volatile compared to energy. Volatility in food prices was highest in the early 1970s as was previously mentioned. However, since the 1980s the volatility appears to be more stable. The general decline in food price volatility occurred in both "food at home" and "food away from home" components (Figure 3b). As expected, the food at home component was more volatile compared to food away from home. Over the past several years, volatility in food at home has been below that of food away.

Agricultural commodity price fluctuations, historically, were contributing factors to food price inflation as they represent inputs to food. Unlike the trends in food price volatility and outside of the early 1970s, volatility in prices received by producers of farm products has increased. Using the Producer Price Index for farm products, Figure 4 indicates that volatility in the "commodity" portion of food prices has likely risen due to the steady upward trend in the volatility of the farm products index since the early 1990s. However, the increased volatility in farm products most likely did not fully translate into volatility in food prices due the decline in the farmer (commodity) share of the food dollar. Figure 5 shows a nearly 50 percent decline in the agricultural producers' share of the food dollar from about \$0.27 in 1993 to \$0.13 in 2016. This same downward trend occurred in food at home with the farm producers share falling from \$0.37 to \$0.21.

A declining commodity share of the food dollar has important implications for food prices. When agricultural commodity prices increase, less of that increase is likely passed on to food prices. Given the shifts in food consumption to more processed food and the decline in food's share of total expenditures, it is possible to see how pass-through of food price inflation into core inflation may have changed over time.

3 Econometric Model

We wish to explore potential temporal variation in the relationship between food price and core inflation. Prior studies have shown that time series models which allow for time varying parameters (TVP) are helpful in this context (Stock and Watson, 2007; Clark and Terry, 2010; Clark and Ravazzolo, 2015). We implement the model put forth by Primiceri (2005) and Del Negro and Primiceri (2015), which is a vector auto-regressive (VAR) model containing regression coefficients and variance parameters that may evolve according to random walks. This combination is often referred to as a VAR with TVP and stochastic volatility. Primiceri (2005) originally motivated this structure citing changes in observed levels and volatility of U.S. unemployment and inflation times series.

The model can be expressed as:

$$y_t = c_t + B_{1,t}y_{t-1} + ... + B_{j,t}y_{t-p} + A_t^{-1}\Sigma_t\varepsilon_t, \tag{1}$$

where y_t is a VAR of endogenous variables, but with an additional feature that allows the coefficients to vary over time. Additionally, the structure of the composite error term $A_t^{-1}\Sigma_t\varepsilon_t$ indicates that the variance-covariance matrix may also vary over time. The full model is shown by the following equations:

$$y_t = X_t'B_t + A_t^{-1}\Sigma_t\varepsilon_t \tag{2}$$

$$B_t = B_{t-1} + \nu_t \tag{3}$$

$$\alpha_t = \alpha_{t-1} + \zeta_t \tag{4}$$

$$\log\sigma_t = \log\sigma_{t-1} + \eta_t, \tag{5}$$

where y_t is a $n \times 1$ vector of the variables at a given date, $X_t' = I_n \otimes [1, y_{t-1}, ..., y_{t-p}]$, B_t collects the parameters c_t and $\{B_{j,t}\}_{t=1}^{p}$ of equation 1, A_t is a lower triangular matrix whose free elements are stacked in the vector α_t, and Σ_t is a diagonal matrix with positive elements $\sigma_t = diag(\Sigma_t)$. Within the composite error term, ε_t is assumed to follow an n-variate standard normal distribution, with $\{\nu_t, \zeta_t, \eta_t\}$ being mean zero, homoskedastic and mutually independent Gaussian random vectors of appropriate dimensions.

In our model, y_t is three-dimensional including monthly measures of energy, food, and core inflation. The measure of food inflation includes purchases at home and away from home.[2] Based on model selection criteria, we include two lags of energy, food and core inflation constructed as annualized month-to-month percentage changes in each of the three equations. The energy inflation equation is ordered first followed by food and core in the VAR. The parsimonious nature of our specification allows for better tractability of core inflation response from food price shocks, but controlling for energy inflation which could also influence food inflation.

We estimate the model with monthly data from January 1959 to December 2018 using Bayesian methods, specifically a Markov chain Monte Carlo (MCMC) Gibbs posterior sampler proposed by Del Negro and Primiceri (2015). The MCMC procedure is summarized as follows. Let B^T represent the full path of parameters $\{B_t\}_{t=1}^T$ and similarly for Σ^T and A^T. Let $\theta = [B^T, A^T, V]$, where $V = [Q, S, W]$ capture the variance covariance matrices of the i.i.d. shock components $[\nu_t, \zeta_t, \eta_t]$ using the Carter and Kohn (1994) (CK) algorithm. Initial priors for A^T, Σ^T, s^T, and V are taken from OLS estimation of each equation in 2. Next, B^T is sampled from $p(B^T|\theta^{-B^T}, \Sigma^T)$, using the CK algorithm. Samples for Q are taken from $p(Q|B^T)$, which is an inverse Wishart (IW) distribution. The matrix A^T is populated by sampling from $p(A^T|\theta^{-A^T}, \Sigma^T)$, also using the CK algorithm. A sample for S is then drawn from $p(S|\theta^{-S}, \Sigma^T)$, which contains several blocks that are IW distributed. A sample of the auxiliary discrete variables s^T are drawn from $p(s^T|\Sigma^T, \theta)$ for use in the Kim et al. (1998) algorithm, which handles the stochastic volatility. Draws for Σ^T are then taken from $p(\Sigma^T|\theta, s^T)$ using the CK algorithm. Next, a sample for W is drawn from $p(W|\Sigma^T)$, which

[2] Our results are robust to broader measures of food inflation that also include beverages.

is IW distributed. The MCMC Gibbs sampler then updates the priors and repeats the process by returning to draws on B^T until convergence is achieved. We implement the MCMC sampler by performing 5,000 burn-in draws, followed by an additional 50,000 draws. The training sample used to initialize the model is February 1959 to July 1962.

We identify shocks to each variable recursively through ordering energy inflation first in the VAR. This allows us to determine the response of core inflation from food price shocks conditional on energy inflation dynamics that could otherwise affect food inflation. Our approach is similar to those studies investigating energy price shocks, which order energy price inflation first (Davis and Haltiwanger, 2001; Leduc and Sill, 2004; Clark and Terry, 2010; Blanchard and Riggi, 2013). Identification of food price effects occurs by assuming shocks to food prices in the VAR are exogenous with respect to all other contemporaneous shocks.

Our estimates of impulse responses of core inflation to food price shocks takes into account the uncertainty surrounding parameter movements after the shock. We generate a sample of 5,000 impulse response estimates, of which we report the medians, inter-quartile range, and 90 percent credible sets. For each period t that we compute impulse responses, we simulate the future paths for 20 months. We estimate the impact of a one-unit shock in an element of ε_t, keeping the elements of $c_t, B_{j,t}, A_t$ and Σ_t fixed a their time t values. The error term variance-covariance matrix is orthogonalized via Cholesky decomposition at time point t. We use the time-varying parameter and stochastic volatility features of the VAR to evaluate the impulse response of core inflation to food price shocks every 10 years in our sample.

4 Declining Pass-Through of Food to Core Inflation

We document a decline in recent decades in the pass-through of food price inflation to core inflation based upon three main outputs from the TVP VAR model with stochastic volatility. We provide evidence of a reduction in the persistence of food price inflation from the sum of the reduced form coefficients on food inflation in the core inflation equation. Food prices became more stable as shown by the decline in the volatility of food price shocks over time. Finally, impulse responses of core inflation from the same size shock in food prices declined 75 percent between the late 1970s and mid-1990s. From the mid-1990s through the end of 2018, median estimates of pass-through gradually approach zero and are not statistically significant. We discuss each of these results in the subsections that follow.

4.1 Time Varying Parameters

A direct measure of the effect of food price changes on core inflation is the persistence of changes in food prices in subsequent periods. We construct such a measure by summing the reduced form coefficients of food inflation (i.e., two lags) in the core inflation equation. Our measure of persistence changes conditional on the changes in the time varying parameters. Figure 6 shows posterior medians, inter-quartile range, and the 90 percent credible sets of the persistence measures for food, food at home, and food away from home. In general, persistence is higher in measures of food away from home versus food at home.

Persistence of food price changes in core inflation initially increased until the late 1970s, then began to decline (Figure 6a). By March 1995, the posterior bands include zero indicating less precision in the estimates of persistence. There was a similar pattern in the persistence of food at home price changes in core inflation (Figure 6b). While persistence in the food away from home component showed a similar decline, the median estimate remained statistically significant through the end of the sample period (Figure 6c). Across food or the two separate components (food at home, food away), measures of persistence declined between 40 and 50 percent from peak levels. With evidence of the decline in the persistence of food price changes in core inflation, we turn to potential changes in volatility.

4.2 Changing Volatility

Previous research has shown evidence of declining volatility in innovations of U.S. macroeconomic variables starting in the early 1980s (Cogley and Sargent, 2005; Clark and Terry, 2010; Primiceri, 2005; Del Negro and Primiceri, 2015). Figure 7 shows the standard deviations of the orthogonalized innovations of the TVP VAR with stochastic volatility. The output of the model reveals large declines in the volatility of shocks to food price inflation and core inflation. We report the median, inter-quartile, and 90th percentile of the innovations in the food inflation (Figure 7a) and core inflation (Figure 7b) equations.

The large spike in food inflation innovations coincides with the large spike in food prices in 1973 as discussed earlier. Following the 1973 episode, innovations in the food inflation equation declined. This decline occurred in both median level of innovations as well as in the 90th percentile band, which became much tighter beginning in the mid- to late-1990s. Similarly, volatility in core inflation innovations declined over the sample period. Volatility from the 1960s through the early 1980s was much higher. Since the 1980s, volatility in core inflation was on a gradual decline leveling off somewhat following the Great Recession. With evidence of a decline in the persistence of food prices in core inflation and declining volatility in food and core inflation innovations, we turn to measures of pass-through.

4.3 Impulse Responses

We generate measures of pass-through via impulse response functions of core inflation from shocks to food inflation. Using the recursive identification strategy and posterior samples, we calculate impulse responses for a food inflation shock in the first month of a year for seven dates (1963, 1970, 1980, 1990, 2000, 2010, and 2018).[3] We normalize the size of the shock to be a one percent shock to food inflation; ensuring that each impulse response is generated

[3]Due to the training sample, the first date in which we can calculate an impulse response is August 1962. We wish to show the impulse responses for the same month in each year to avoid potential differences in responses throughout the year. As a result, we chose 1963 because it is the first date we can show the response in the first month of the year. We show in the appendix that our results are robust to selecting an alternative month in Figure A1.

from the same size shock. The normalization is constructed by dividing each impulse by the initial response of food inflation to a food inflation shock across each of the time periods evaluated.

The impulse responses for our food inflation measure that includes both food at home and food away are shown in Figure 8. We plot the median point estimates of the responses to both food and core inflation as well as the inter-quartile range and 90 percent credible sets. By 10 months after the initial food inflation shock, the food inflation response dies out. This same pattern is consistent across the seven decades as shown by the first column. The rate of pass-through is captured in the second column of Figure 8. The initial rate of food inflation pass-through was between 0.1 and 0.2 (10 to 20 percent of the food shock) in the same month of the shock during the decades of 1960 to 1990. Over those same decades, the impulse responses peaked one month after the initial shock and then slowly faded before dissipating around 10 months. However, looking across subsequent decades beginning in 2000, the impulse responses were flatter and the shocks faded more quickly. Between 2010 and 2018 there was no distinguishable pass through as the median impulse response was close to and indistinguishable from zero as shown by the 90 percent credible sets.

Given the differences in the trends of food at home versus food away discussed in section 2, we repeat the same exercise on those components separately. The impulse responses of core inflation from shocks to food at home (Figure 9) are different than shocks to food away (Figure 10). Shocks to food at home decline quickly in the subsequent responses in food at home inflation. Looking at the second column of Figure 9, the rate of pass-through from food at home to core peaks at 10 to 30 percent between the 1960s and 1990s. However, beginning in the 2000s, pass-through is no longer statistically significant at any time horizon.

Shocks to food away from home are much more persistent and have a higher rate of pass-through to core inflation. Between the 1960s and 1990s, the initial shock to food away continues to affect food away inflation 10 to 15 months later (Figure 10, first column). However, this effect declines in magnitude in later decades. In earlier decades, the second column in the figure shows that pass-through to core inflation peaked around 60 to 70 percent of the initial food away shock. The response to core remains significant throughout the forecast horizon through the decade of the 1990s. Beginning in 2000, the level of pass-through is smaller and by 2018, pass-through is no longer statistically significant after five months. The impulse responses across the separate food categories provide evidence that pass-through of food price inflation into core inflation has diminished appreciably in the U.S. economy. We rule out that our pass-through results are being driven by changes in the response to shocks of energy inflation passing through to food and then on to core. Figure A2 in the appendix shows that food inflation does not in an economically or statistically significant way respond to energy price shocks.

While the impulse responses across decades show the decline in pass-through, the decline is much more visible in the cumulative response. We construct cumulative measures of the pass-through by summing the response of core inflation to food price shocks over the 20 month horizon. Figure 11 shows the time varying cumulative impulse responses for food, food at home, and food away from home inflation shocks. The median cumulative pass-through peaked between 1977 and 1978. The median estimates of cumulative pass-through of food and food at home shocks contain zero in the interval beginning in 1994 and 1992, respectively. Using only the 90th percentile of the credible sets not containing zero, the cumulative amount of pass-through from food and food at home to core inflation declined by 75 percent from their peak levels. The cumulative response from food away remained significant through the end of the sample period. By 2018, the median estimate of the cumulative amount of pass-through from food away to core inflation declined 80 percent from its peak.

4.4 Market Concentration and Food Inflation Pass-Through

To the best of our knowledge, we are the first to document the decline in U.S. food price inflation pass-through to core inflation. Previous research has shown the decline in energy inflation pass-through to core. However, less is known on the potential causes for declining food inflation pass-through. Some have attributed it to adoption of energy-saving technology (Hooker, 2002; Bachmeier and Cha, 2011). Others have suggested a change in monetary policy response (Blinder and Rudd, 2012). Potentially most salient to food inflation is the mechanism suggested by Conflitti and Luciani (2017), who found that disaggregate prices have increasingly been driven by idiosyncratic dynamics in certain industries.

One of the idiosyncrasies potentially impacting food price volatility and inflation is market power and the role of supply chains more broadly. Increasing concentration in the agricultural supply chain is well documented (Sexton and Xia, 2018). One prime example of this consolidation has occurred in U.S. grocery retailers. Figure 12 shows shares of U.S. grocery sales by the largest firms. The share held by the largest eight firms increased from around 30 to 50 percent over the past three decades. Large retailers often use marketing contracts that allow them to exercise considerable vertical market control over upstream suppliers in terms of varieties of products, inputs utilized and production schedules (Ellickson, 2007). Despite this trend, little is known about grocery retailers, or retailers more broadly, pricing and promotion strategies or how these strategies affect both the level and variability of prices consumers face. Market concentration in supply chains may have contributed to the reduction of volatility in food prices. Large firms are in a better position to smooth out temporary or local price spikes or demand shocks more broadly via the contracts they put in place and their supply chains. The reduction in volatility from supply chains developed by large retailers combined with rising market concentration in food distribution are plausible factors explaining declines in pass-through of food price shocks into core inflation.

We consider the potential effect of firm concentration on the declines in pass-through by constructing measures of market concentration in both grocery retail sales and food distribution sales. We make use of quarterly firm-level sales from S&P Global Market Intelligence's Compustat data on U.S. publicly traded firms.[4] Sales are an individual firm's gross sales

[4]U.S. publicly traded firms are identified as companies incorporated in the United States. All Compustat data are copyright © 2018, S&P Global Market Intelligence. Reproduction of any information, data or

– the amount of actual billings for regular sales less cash discounts, trade discounts, and returned sales and allowances – over the previous four quarters, measured in million nominal U.S. dollars (S&P Global Market Intelligence, 2018). Compustat also includes the Global Industry Classification Standard (GICS) codes to identify industries, which we use to construct food-related industry Herfindahl–Hirschman Indexes (HHI) based on firm sales. The first industry we identify is "Food Distributors," which are distributors of food products to other companies and not directly to consumers, i.e. companies like Sysco Corp. (Morgan Stanley Capital International, 2018). The other industry we identify is "Food Retail," which are operators of primarily food retail stores, such as Kroger Co.[5] Figure 13 shows the trend in the HHI for each of these industries since the first quarter in 1980. Both of these industries have trended upwards since the late 1990s, mostly driven the by the exit of smaller firms, resulting in a rise in the share of sales coming from the largest companies. Concentration among food distributors declined in 2013, before leveling out in 2015, as a result of increased competition from a higher number of larger firms entering the market and smaller firms exiting.

We use the concentration measures in food retail and food distribution to test the link between higher concentration and declines in pass-through from food price shocks into core inflation. To do this, we use a similar approach as Boivin et al. (2009) who look at monetary policy shocks affect on changes in prices across various sectors in the economy. We model the impulse responses (IRF) of food price shocks as:

$$IRF_{i,t} = \alpha + \beta_1 HHI_t^r + \beta_2 HHI_t^d + \beta_3 Basket_t + \beta_4 E[\pi_t] + \varepsilon_{i,t}, \tag{6}$$

where i indexes pass-through from food, food at home, or food away from home, HHI^r and

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[5] The corresponding GICS codes for these industries are 30101020 and 30101030, respectively.

HHI^d are the natural logs of market concentration measures for grocery retail sales (r) and food distributor sales (d) in quarter t. We also control for the relative composition of the food basket by the ratio of food expenditures away versus at home ($Basket$) and inflation expectations ($E[\pi]$). Measures of inflation expectations were taken from the University of Michigan Survey.[6] They measure what on average consumers expect inflation to be at a point in time. They also capture the anchoring of inflation via the monetary policy channel (Beechey et al., 2011). Inflation expectations should be positively correlated with higher rates of pass-through from food to core. The dependent variable in equation 6 is the cumulative impulse response over a 20 month period of core inflation from a 1 percent shock to food (food at home, food away) price inflation.

Table 2 reports the results estimated from 1980:q1 to 2018:q4 for food, food at home and food away from home, separately. The model explains close to 80 percent of the variation in pass-through to core inflation. The market concentration measures by themselves are able to account for 60 percent of the variation in pass-through. Both coefficients on the market concentration measures are negative and statistically significant. For pass-through to core inflation from food price shocks, a 1 percent increase in food retail or food distributors market concentration implies a reduction in pass-through of food price shocks to core by 0.2 to 0.6 percentage points. The results for food at home (second column in Table 2) are similar. However, the market concentration coefficients are larger for food away from home (column 3). A 1 percent increase in food retail and distributors market concentration are associated with a 0.3 and 1.7 percent decline in the pass-through from shocks to core inflation, respectively. The coefficient on the composition of the food basket indicates shifting purchases towards more food away from home is correlated with higher rates of pass-through to core, but this correlation is not statistically significant. Lastly, inflation expectations are positively correlated with higher pass-through of food price shocks to core inflation. Our results suggest that if similar trends persist in increased market concentration of food retail

[6] http://www.sca.isr.umich.edu/

and distributors and well-anchored inflation expectations, food inflation pass-through will likely remain subdued.

5 Conclusion

We contribute to the growing literature exploring changes in macroeconomic relationships over time; particularly inflation dynamics. While others have previously highlighted the decline in energy price shocks into core inflation, prior research has not documented the decline in pass-through of food price shocks into core inflation in the U.S. economy or attempted to directly measure the most influential factors explaining the decline. Using a time varying parameter vector auto-regression with stochastic volatility we provide evidence of a decline in the persistence of food prices in core inflation, a decline in the volatility of both food and core inflation innovations, and a 75 percent decline in the rate of pass-through of food price shocks into core inflation. The decline in pass-through occurred in both food at home and food away from home, with the later continuing to grow as a larger share of total U.S. food consumption.

The decline in food inflation pass-through coincides with increasing concentration in the food supply chain, especially among U.S. grocery retailers and food distributors. Previously, little was known how this increasing concentration has impacted pass-through of food inflation. Over the past 40 years, 80 percent of the variation in food inflation pass-through can be explained by the composition of the food basket, inflation expectations, and changes in food retailers and distributors market concentration.

Our results have important implications for understanding inflation dynamics in other industries that are also experiencing increases in market concentration. A potentially fruitful area of future research would be to gain a better understanding of how supply chains of large firms affect price changes across various portions of the economy. Another area of interest would be to explore how international supply chains transmit shocks to U.S. import prices and the potential pass through to core inflation.

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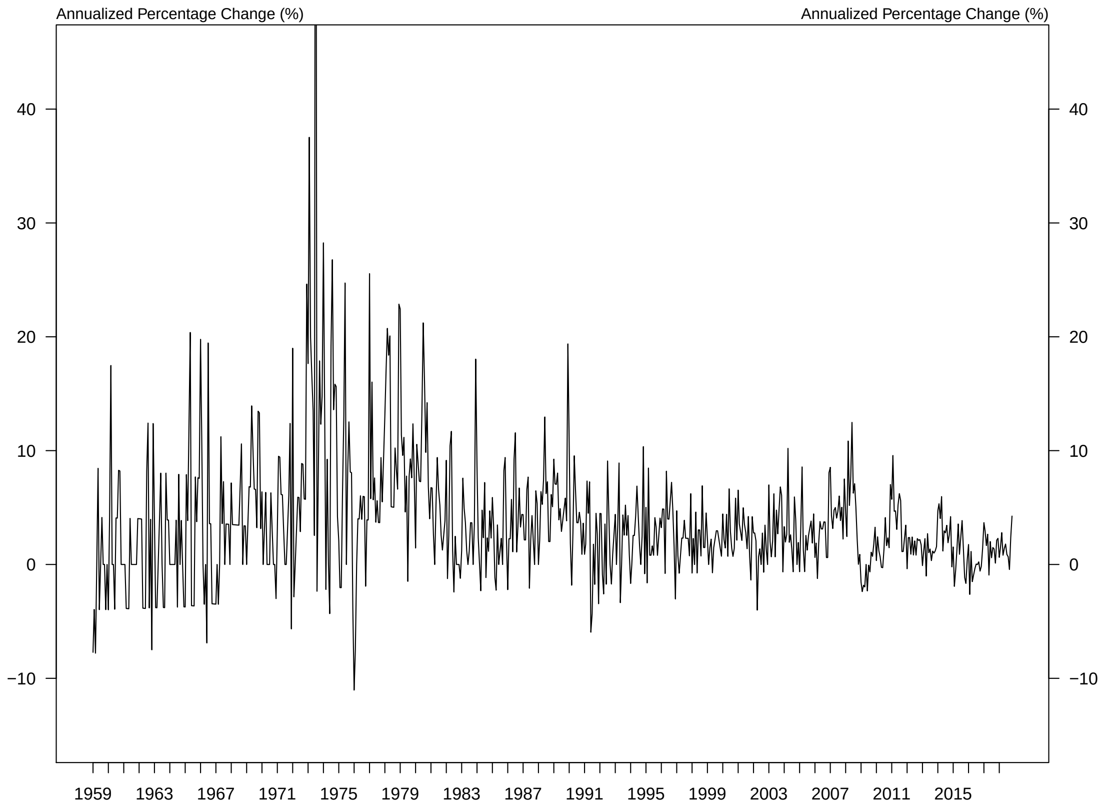
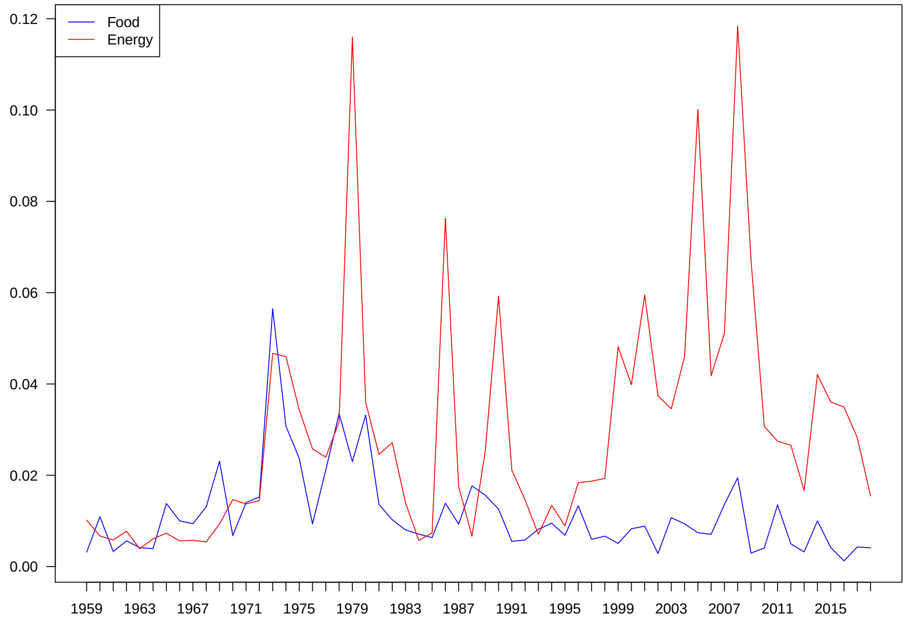
Source: Bureau of Labor Statistics, authors.

Figure 1: Food Expenditures Share of Total CPI Expenditures

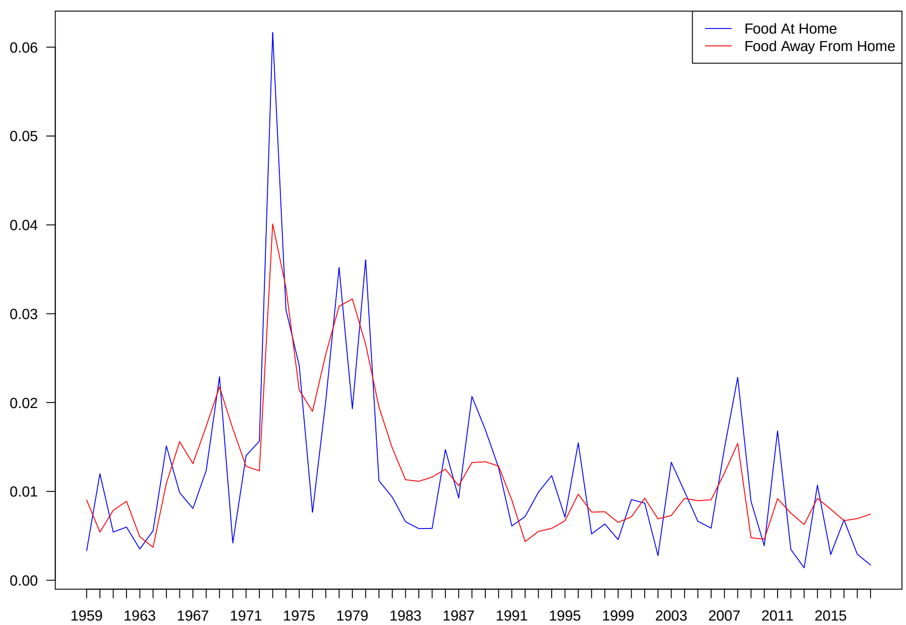


Source: Bureau of Labor Statistics, authors.

Figure 2: Annualized Rate of Month-to-Month Food Price Inflation (%)



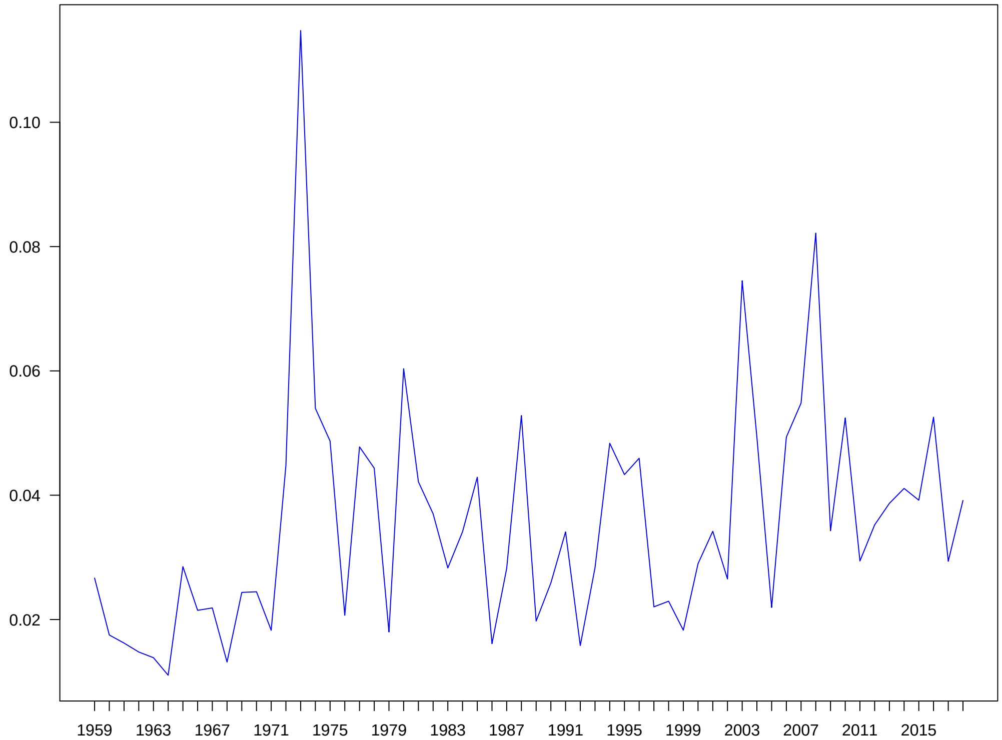
(a) Food and Energy Price Coefficients of Variation



(b) Food at Home and Food Away From Home Coefficients of Variation

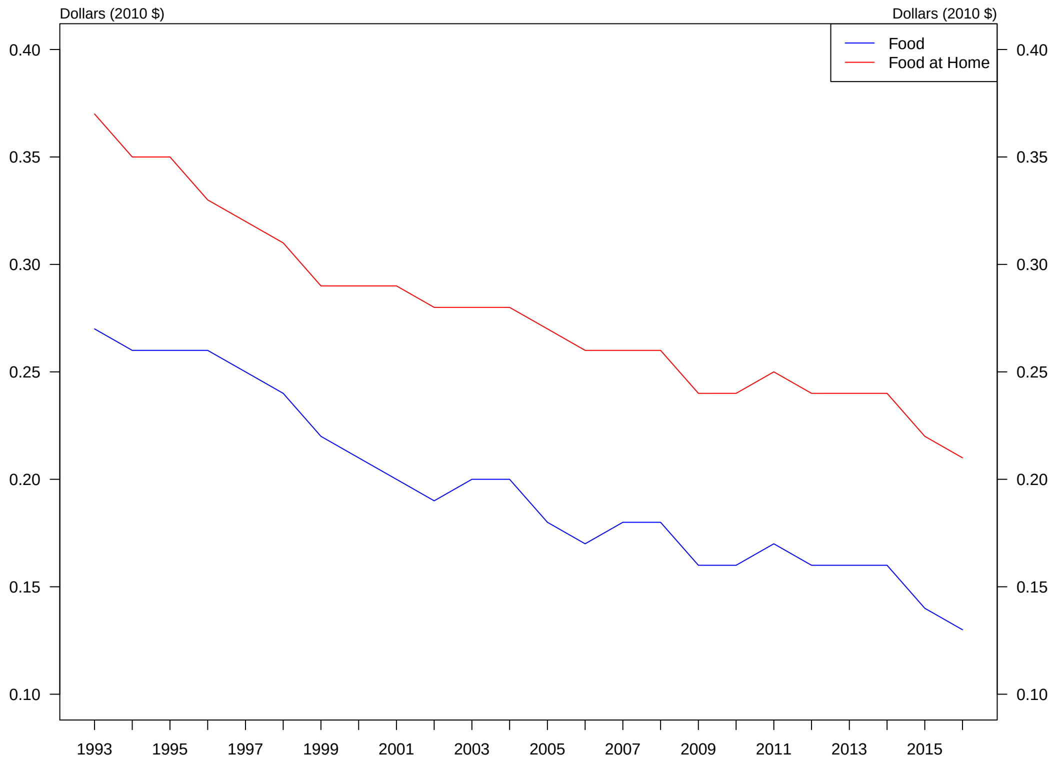
Note: Coefficients of variation were calculated over one-year rolling windows.

Figure 3: Price Volatility Over Time, 1957–2018



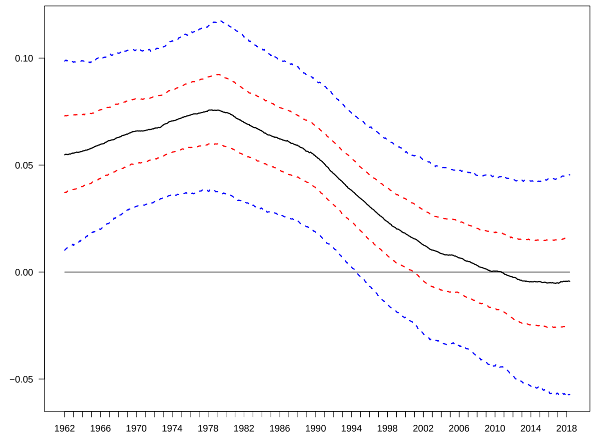
Source: Bureau of Labor Statistics, Producer Price Index, authors.

Figure 4: Farm Products Price Received Coefficients of Variation

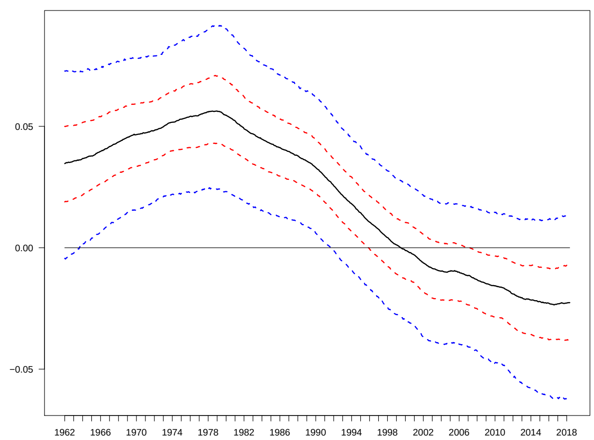


Source: USDA ERS, authors.

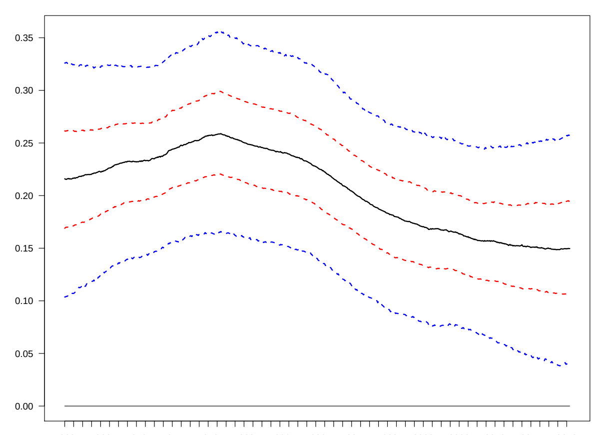
Figure 5: Farm Producers Share of Food Dollar



(a) Food



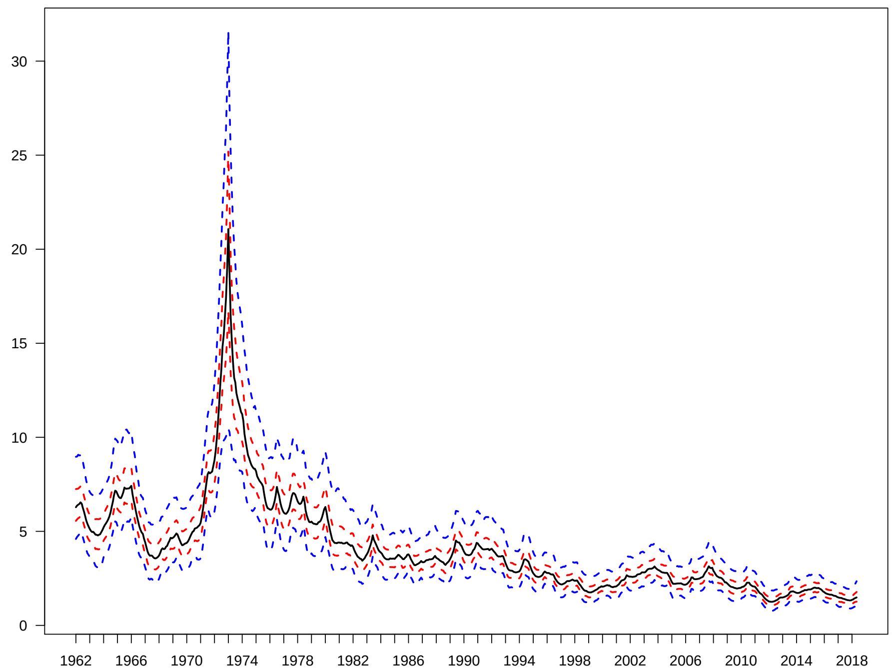
(b) Food at Home



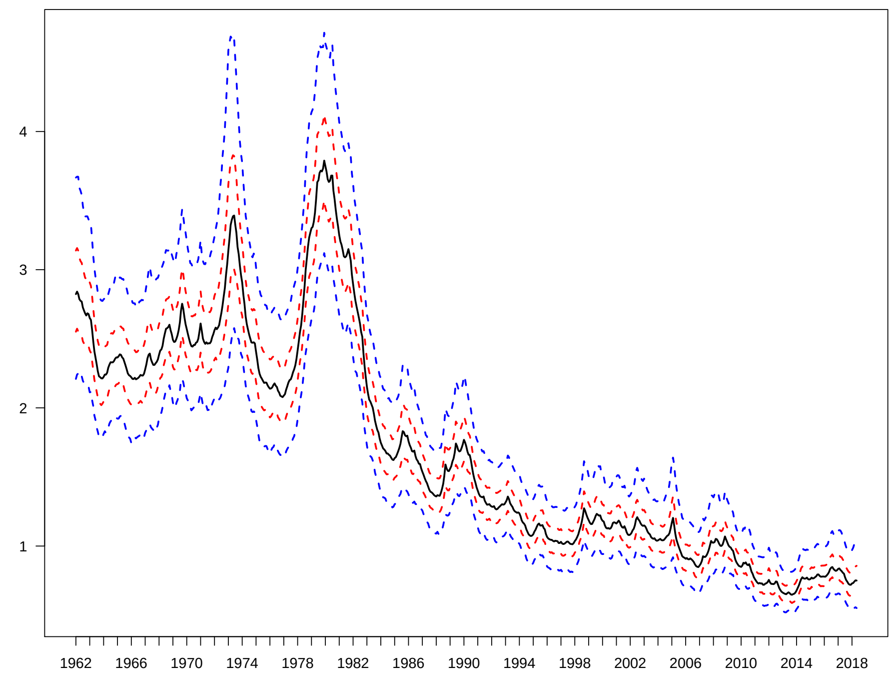
(c) Food Away from Home

Notes: The black line represents the median of 5,000 draws. The blue and red dashed lines represent the 90th percentile and inter-quartile region of the posterior distribution.

Figure 6: Time Varying Sum of Coefficients of Food Inflation in the Core Inflation Equation



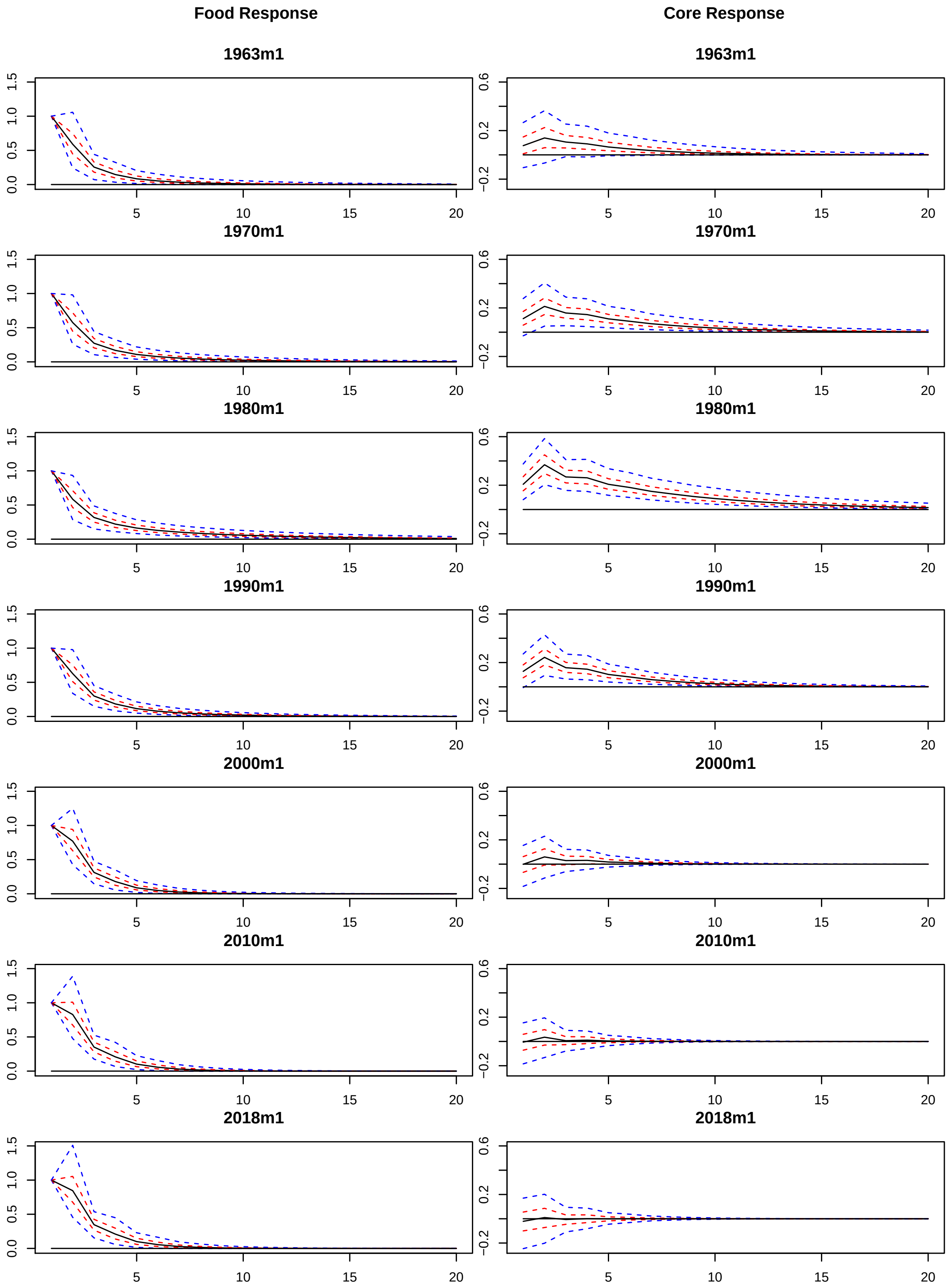
(a) Food Equation



(b) Core Equation

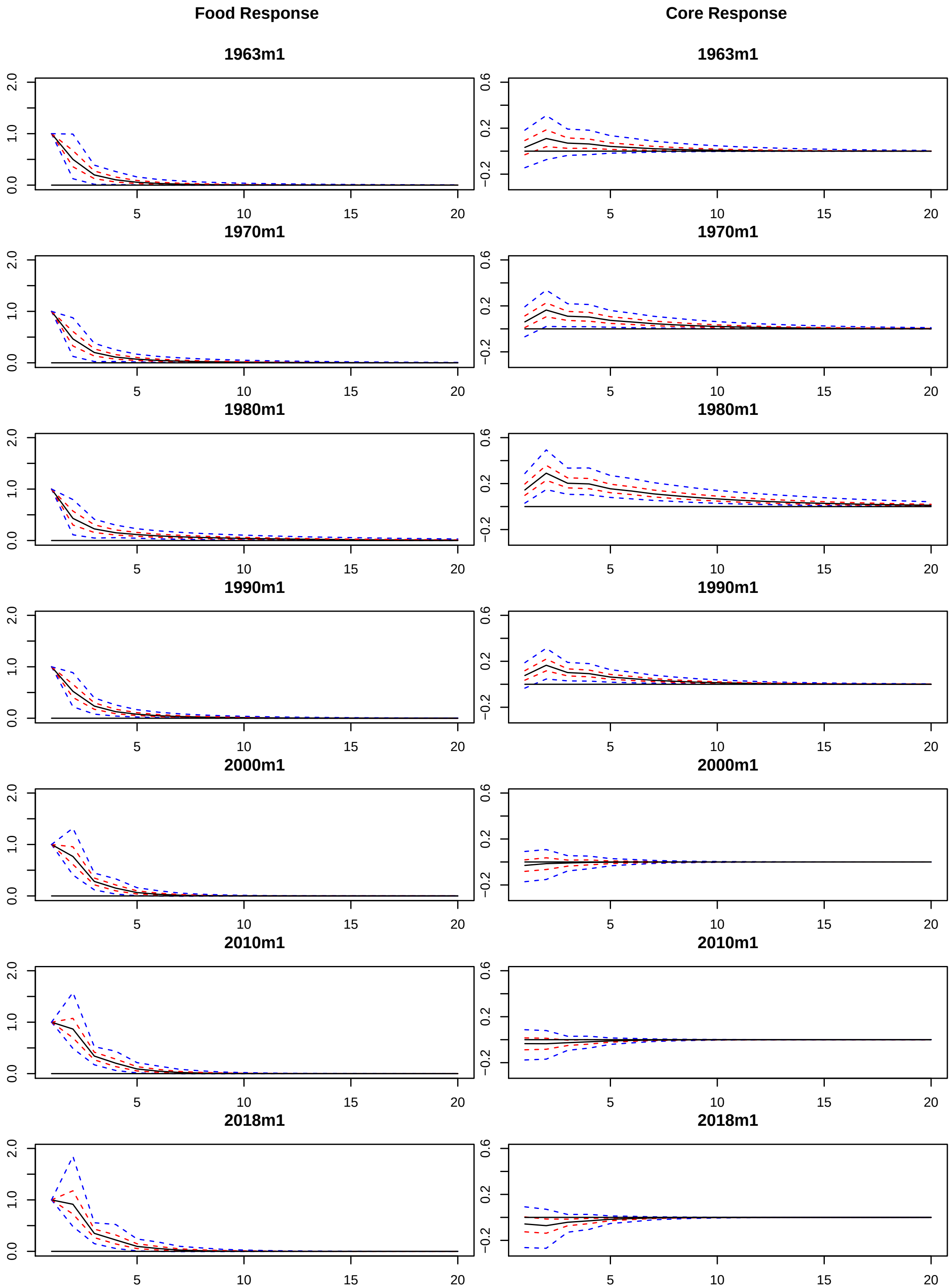
Note: The black line represents the median of 5,000 draws. The blue and red dashed lines represent the 90th percentile and inter-quartile region of the simulations.

Figure 7: Residual Standard Deviations from Time-Varying Parameter VAR with Stochastic Volatility



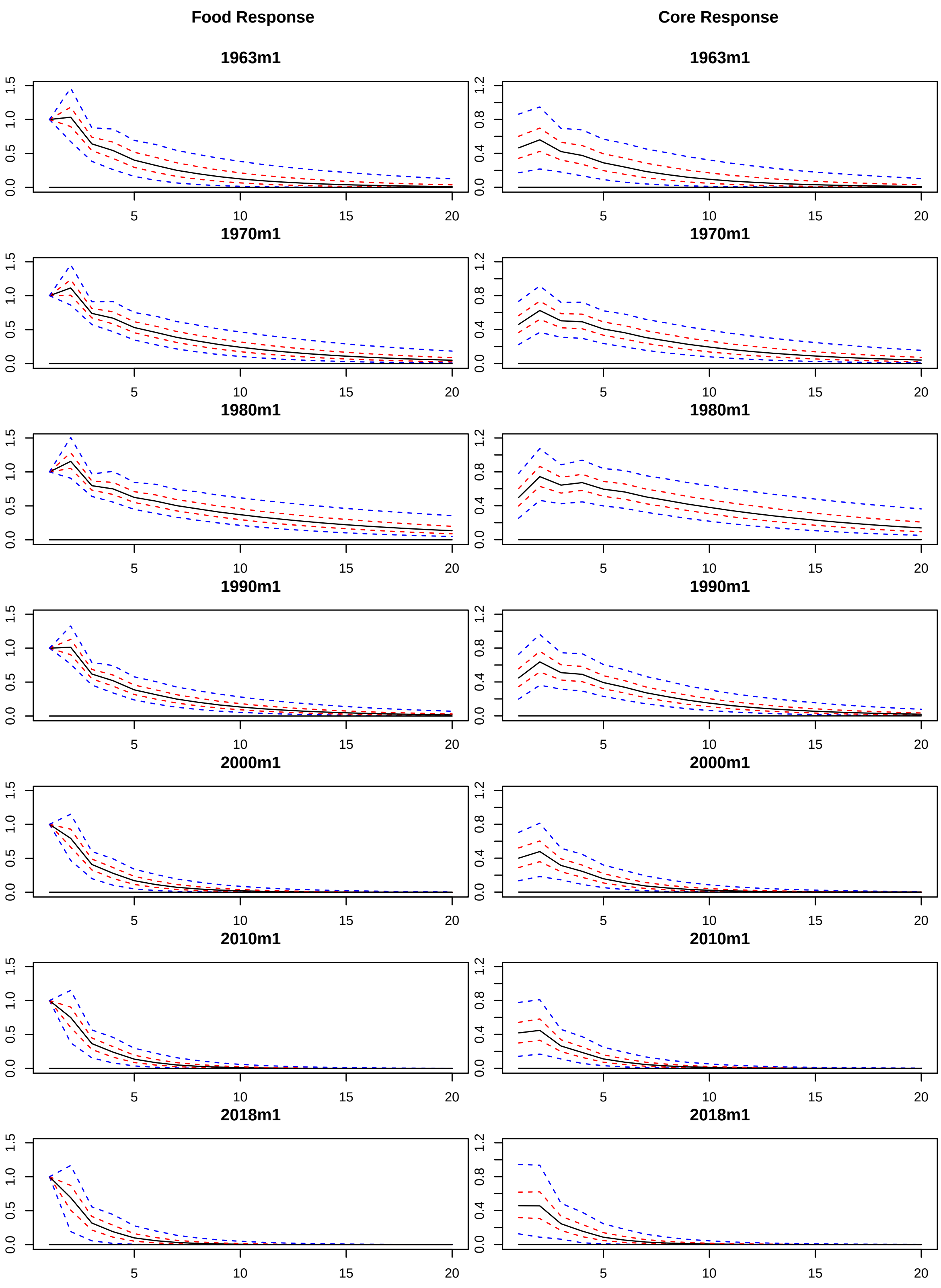
Notes: The black line represents the median of 5,000 draws. The blue and red dashed lines represent the 90th percentile and inter-quartile region of the simulations.

Figure 8: Impulse Response Functions of Food Inflation Shocks



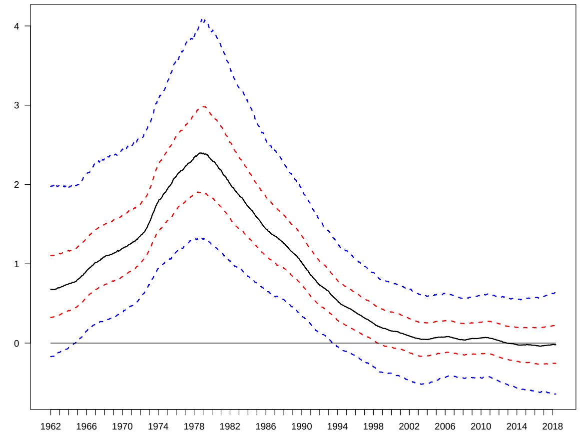
Notes: The black line represents the median of 5,000 draws. The blue and red dashed lines represent the 90th percentile and inter-quartile region of the simulations.

Figure 9: Impulse Response Functions of Food at Home Inflation Shocks

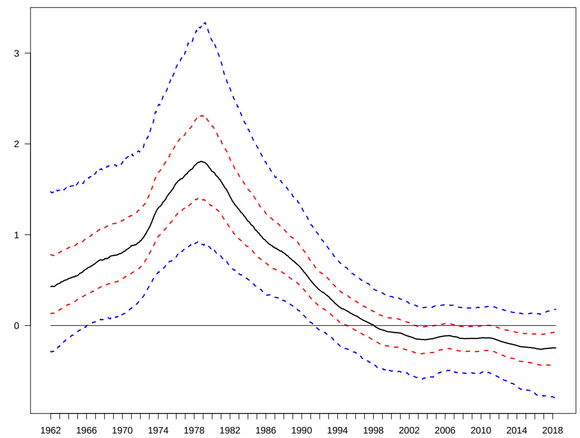


Notes: The black line represents the median of 5,000 draws. The blue and red dashed lines represent the 90th percentile and inter-quartile region of the simulations.

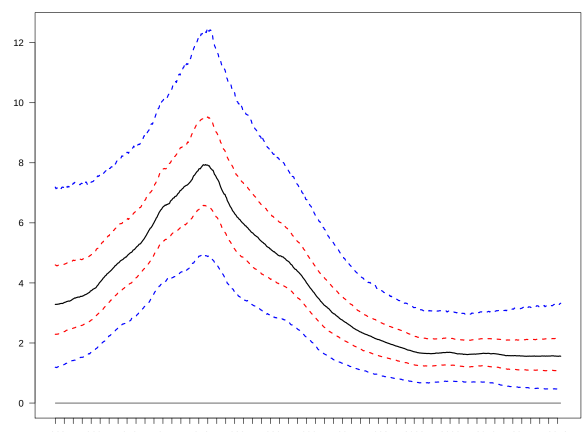
Figure 10: Impulse Response Functions of of Food Away from Home Inflation Shocks



(a) Food



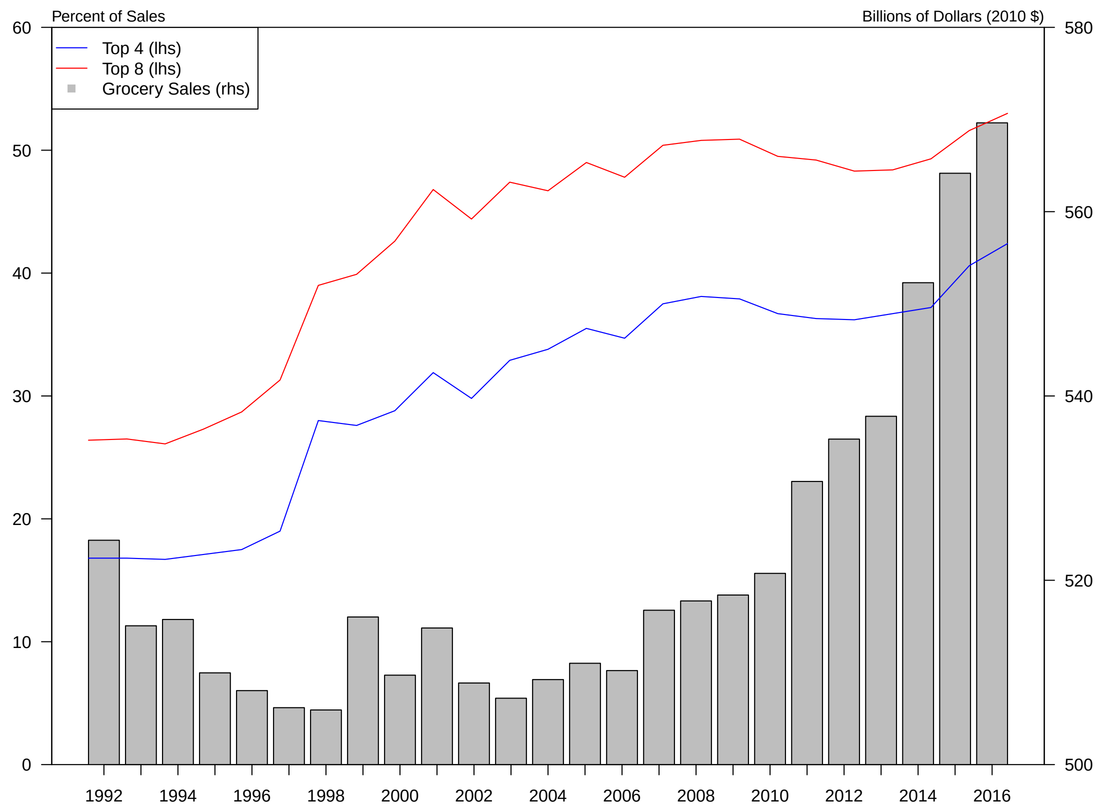
(b) Food at Home



(c) Food Away from Home

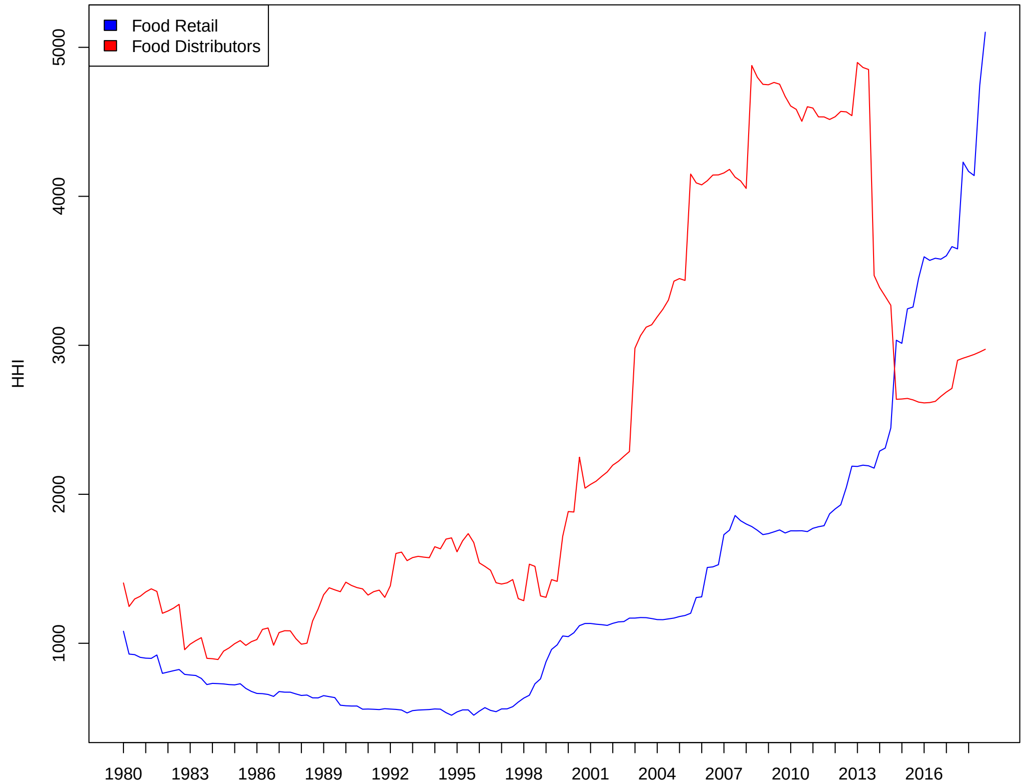
Notes: The black line represents the median of 5,000 draws. The blue and red dashed lines represent the 90th percentile and inter-quartile region of the posterior distribution.

Figure 11: Time Varying Cumulative Response of Core Inflation to a Food Inflation Shock



Source: USDA ERS, authors.

Figure 12: Top Four and Eight Firms' Share of U.S. Grocery Stores



Source: Compustat, authors.

Figure 13: Concentration of Food Retail and Food Distributors Sales from Publicly Traded Companies

Table 1: Inflation Summary Statistics

Decade		π_{core}	π_{food}	$\pi_{food\ at\ home}$	$\pi_{food\ away}$	π_{energy}
1960	$\bar{x}$	2.631	2.843	2.657	3.745	1.347
	σ	2.807	5.701	6.735	3.036	6.528
1970	$\bar{x}$	6.805	8.429	8.644	8.297	12.598
	σ	3.529	11.568	15.076	4.285	18.018
1980	$\bar{x}$	5.752	4.520	4.356	5.060	4.363
	σ	3.812	4.250	5.979	2.441	20.246
1990	$\bar{x}$	3.117	2.674	2.810	2.539	3.813
	σ	1.477	3.401	5.353	1.218	21.435
2000	$\bar{x}$	2.147	2.828	2.694	3.039	17.989
	σ	1.046	2.847	4.544	1.450	55.502
2010-2018	$\bar{x}$	1.835	1.803	1.363	2.453	4.173
	σ	0.827	1.992	3.219	1.162	28.740

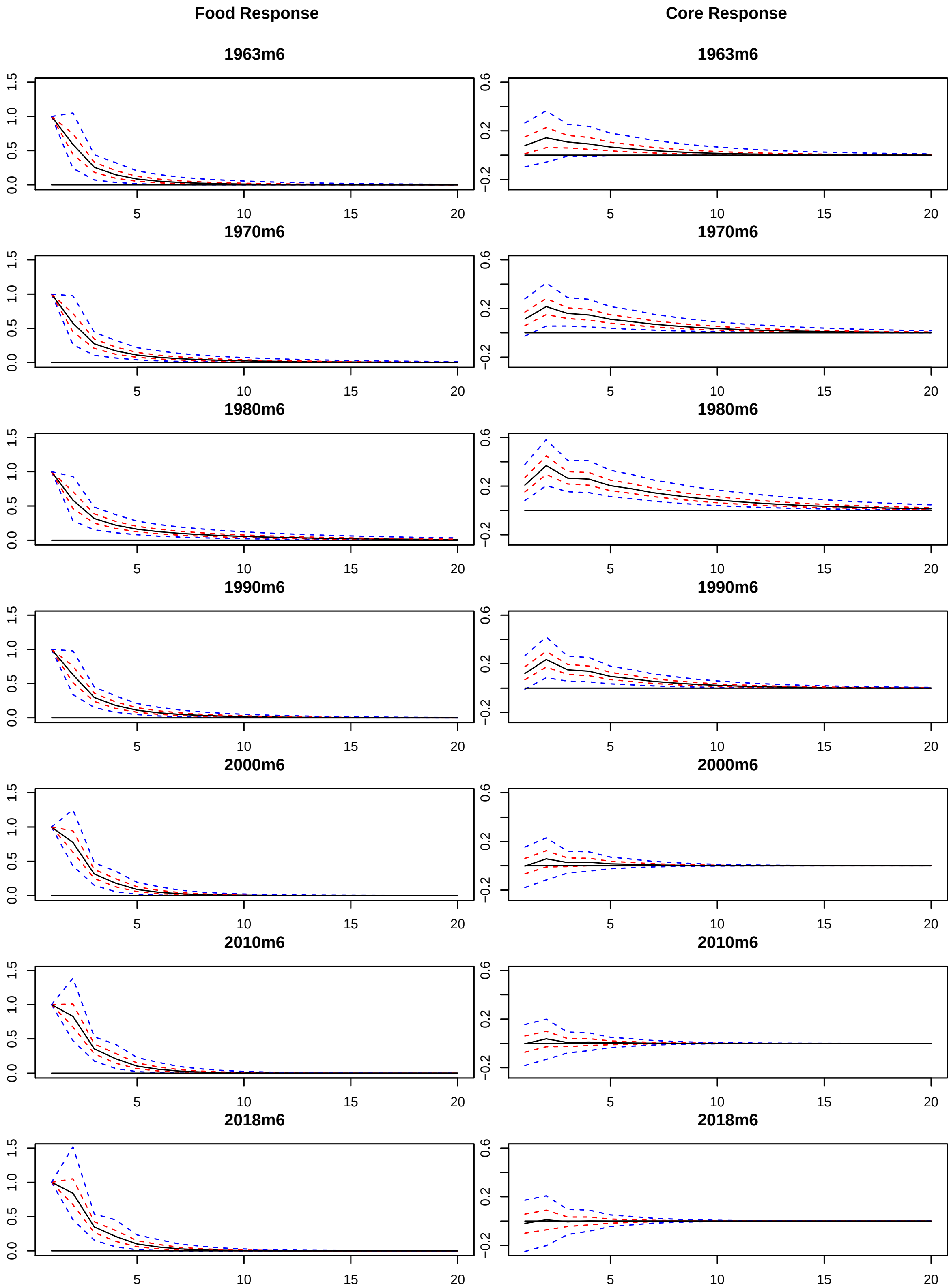
Source: Bureau of Labor Statistics, Bureau of Economic Analysis.

Note: Inflation numbers were calculated as annualized monthly percent change.

Table 2: Effect of Concentration on Pass-Through

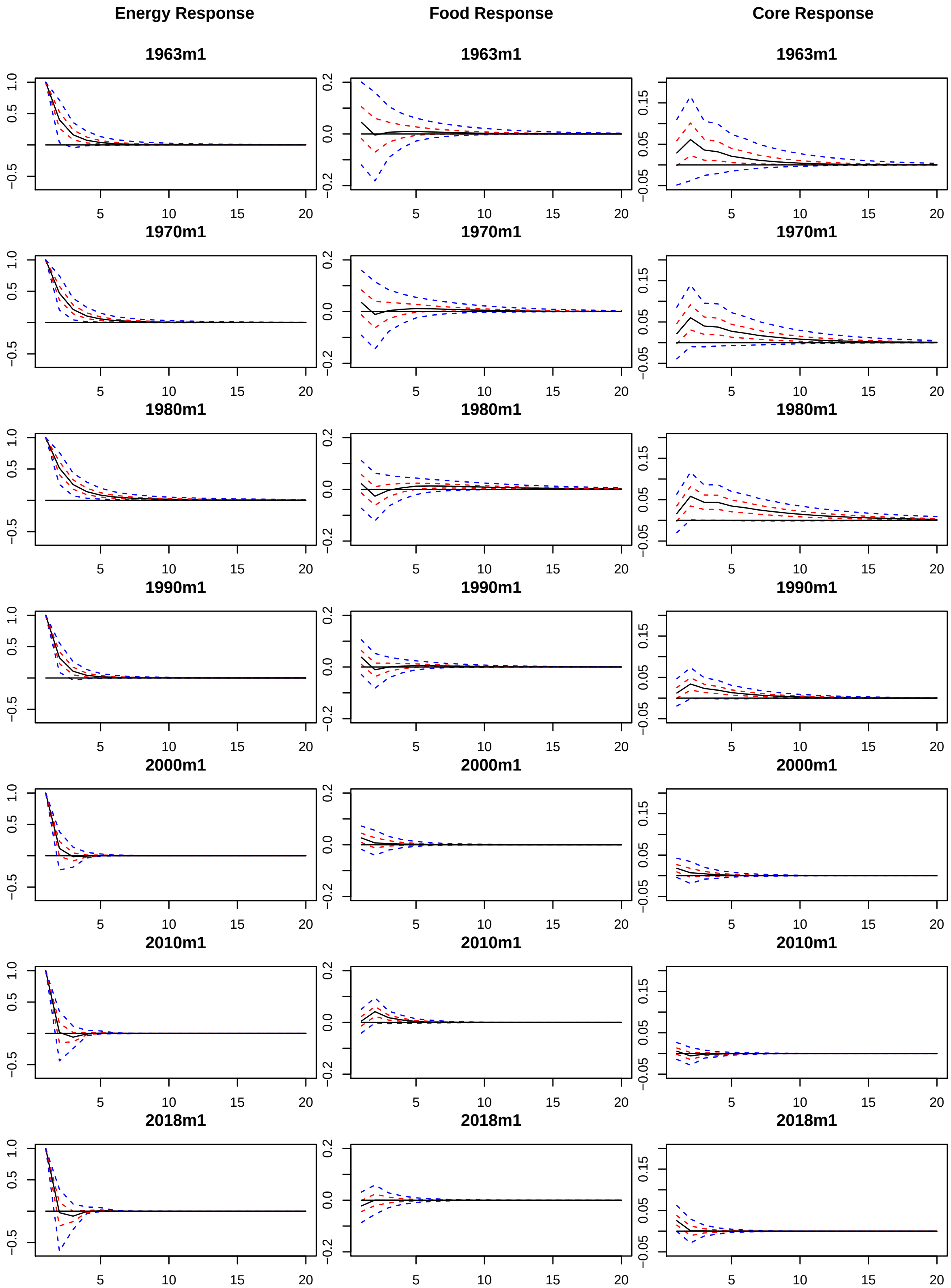
	Food	Food At Home	Food Away From Home
Log(Food Retail HHI)	-0.190^{***}	-0.176^{***}	-0.347^{**}
	(0.059)	(0.049)	(0.147)
Log(Food Distributors HHI)	-0.640^{***}	-0.475^{***}	-1.693^{***}
	(0.213)	(0.168)	(0.551)
Basket	1.383	1.089	3.522
	(1.015)	(0.798)	(2.585)
Inf. Exp.	0.260^{***}	0.210^{***}	0.667^{***}
	(0.093)	(0.074)	(0.241)
Constant	4.908^{***}	3.613^{***}	13.498^{***}
	(1.108)	(0.870)	(2.847)
Observations	128	128	128
Adjusted R^2	0.778	0.778	0.759

Notes: HAC robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01



Notes: The black line represents the median of 5,000 draws. The blue and red dashed lines represent the 90th percentile and inter-quartile region of the simulations.

Figure A1: Alternative Month for Impulse Response Functions of Food Inflation Shocks



Notes: The black line represents the median of 5,000 draws. The blue and red dashed lines represent the 90th percentile and inter-quartile region of the simulations.

Figure A2: Impulse Response Functions of Energy Inflation Shocks to Food and Core