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The Passthrough of Agricultural Commodity Prices to Food Prices*

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Abstract

Food inflation has been excluded from core measures of inflation under the reasoning that it is a phenomenon of the supply side of the economy, driven by stochastic supply shocks to agricultural production that can affect the availability of farm products and increase food price volatility. However, the share of food costs related to agricultural production has fallen over the years as food value chains have become more complex and food prices tied more closely to value added downstream in the supply chain. We calculate the magnitude and extent of agricultural price passthroughs to food prices in the United States after 2000. We leverage the results of simple models of food pricing under imperfect competition along the supply chain to identify possible sources of bias in the passthrough calculations. We argue that we can identify U.S. agricultural price passthrough to U.S. food prices in a structural vector autoregressive setting using a weather instrument (i.e., drought) that shifts supply of farm production but is excluded from demand. Our results suggest that the passthrough from row crops to food at home inflation is small and imprecisely estimated. These results reinforce the perspective that agriculture commodity prices are not a principle driving factor behind consumer food prices in the United States.

JEL Codes: Q10, E31

Keywords: food inflation, passthrough, agricultural prices

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1 Introduction

Consumers in the United States likely make decisions about food purchases more frequently than about any other product. As such, changes in food prices tend to be salient to consumers, affecting perceptions about inflation and inflation expectations (Armantier et al., 2013). Early economic literature described changes in food prices as largely stemming from stochastic supply shocks, such as weather disruptions to agricultural production (e.g., Gordon, 1975; Blinder and Rudd, 2013). Under this framework, food inflation represented transitory shocks to aggregate price indexes (i.e., headline inflation) rather than price changes that contributed to underlying “monetary inflation” – known as the core of overall prices in the economy (Bryan and Cecchetti, 1994; Wynne, 1999).

The modern literature recognizes that food inflation stems from multiple forces, not merely weather shocks, that may weigh more heavily on food inflation. Changes in food prices are the outcome of shocks to farm production and costs, processing costs, end-user demand, and market structure (Tegene, 2009).[1] It is well understood that agricultural commodities make up a small fraction of US food costs (USDA, 2024a), and that demand has played a larger role in explaining food inflation (Adjemian et al., 2023). However, shocks that constrain the availability of agricultural production and processing can have a large impact on the price that the end consumer pays for food. In this paper, we offer a clear identification strategy to evaluate passthrough from farm prices to food retail prices to answer the following question: what is the magnitude and duration of changes in agricultural prices to changes in food prices in the United States nowadays?

Overall, the academic literature has been mixed on the extent of passthrough from shocks in agricultural prices to food prices in the United States, and this lack of consensus hinders our ability to understand the dynamics of food inflation. Estimates of the passthrough from agricultural inputs to the retail prices can vary widely depending on the methods and time frame

[1] Cowley and Scott (2022) and Scott et al. (2023) stress the importance of off-farm costs (labor, transportation, and rent) to the formation of food prices. Industry-level changes and market concentration may also impact food inflation. Nuño-Ledesma and von Massow (2023) suggests, among several factors, the role of imbalanced bargaining power between grocers and suppliers as one possible cause of food inflation. Brown and Tousey (2019) argue that more concentrated food supply chains have softened the passthrough of changes in food prices to core inflation in the United States.

used. For example, Leibtag (2009) shows farm to food retail passthoughs of between 2-18% in a reduced-form time series model using US inflation data from 1972 to 2008, and input-output methods show passthrough from farm to retail prices of 12.5% in the surge of commodity prices from 2008 (Hobijn, 2008). Discrete choice models under imperfect competition point to passthroughs up to 79% for apples (Richards and Pofahl, 2009), and around 30% for coffee (Nakamura and Zerom, 2010). The literature has also argued that the passthrough from energy to food retail prices seem to be smaller than the passthrough from agricultural commodity prices (Hobijn, 2008; Leibtag, 2009; Baumeister and Kilian, 2014). However, global shocks in commodity production tend to impact macroeconomic variables in food-importer countries (Peersman, 2022), and there is evidence that shifts in agricultural futures prices can affect macroeconomic variables in food-producing countries (Adjemian and Jo, 2024). In general, however, papers that try to quantify the extent of these passthroughs use strong identification assumptions on the timing of the shocks on commodity prices, which can be regarded as unrealistic (Ramey, 2016; Stock and Watson, 2018; Nakamura and Steinsson, 2018).[2]

Our analysis applies a structural times series methodology to estimate the passthrough of agriculture commodity prices in aggregate to consumer food at home prices in the U.S. We implement drought instruments in a SVAR-IV to identify this passthrough. We justify the necessity of instrumental variables from a simple theoretical model that decomposes prices between marginal costs and markups, and we construct commodity-specific drought shocks that would impact food inflation only through changes in agricultural commodity prices in a similar vein to Dice and Rodziewicz (2020), Rodziewicz et al. (2023), and Peersman (2022). We then instrument agricultural prices with their commodity-specific drought exposure and estimate the passthrough of changes in prices of row crops to prices of food at home captured by the US Consumer Price Index (CPI).

We find that increases in the prices of row crops in the United States leads to a small, but generally imprecisely-estimated, increase in food-at-home prices. We also estimate the

[2] One exception to this in the context of food is Adjemian and Jo (2024) that uses news shocks on agricultural production that exogenously shift agricultural futures prices using data from 1992 to 2023. Despite differences in the time frame of the sample used in this study and ours, the magnitude and extent of Adjemian and Jo (2024) passthrough from agricultural prices to food inflation is similar to ours, although their estimates for passthrough present tighter standard errors and capture a more narrow period of price shocks within a month.

effect of changes in the price of wheat on the price of bakery goods CPI and the price of soybeans on the price of fats and oils. By doing so, we capture the general passthrough of row crop price changes to food-at-home inflation, but also the differential passthrough of specific commodities to components of food inflation. We find that increases in prices of wheat and soybeans also lead to imprecisely estimated passthroughs to bakery goods and fats and oils components of the CPI, respectively. We do not find evidence that increases in crop prices lead to increases in food prices in the United States.

In general, our results add credence to the literature that argues that the low cost share of agricultural commodities in food reflects market and technology structures that limit the passthrough of agricultural price shocks. The argument is important for policymakers' understanding of the dynamics of U.S. food inflation after the 2000s: food at home inflation is less volatile than in the past (Scott et al., 2025) and behaves much more like other goods in the economy as mentioned by recent policymaker's speeches (Schmid, 2025). However, our study contradicts previous evidence and case studies that point to high and statistically significant effects of changes in commodity prices to food at home inflation. We do not find strong evidence that increases in row crop prices lead to systematic higher food prices at retailers.

The remainder of the paper is structured as follows. Section 2 discusses the theoretical decomposition of food inflation. Section 3 outlines the empirical strategy for estimating agriculture commodity price passthrough to food inflation, describes our drought instrument, and discusses the data used in our analysis. Section 4 discusses empirical results. Section 5 concludes.

2 Decomposition of Food Inflation

It is well-understood that the passthrough of changes in marginal costs to retail prices depends on the curvature of demand and the nature of competition (Weyl and Fabinger, 2013). When supply chains are long and firms sell multiple products, changes in downstream prices affect profits and marginal costs for different firms across the production chain (Villas-Boas, 2007; Duarte et al., 2023). Thus, identification of a specific passthrough— e.g., changes in agricultural commodity prices to food prices— requires a structural shock that does not influence other structural aspects of the supply chain, which form the pricing equation at the retailer level (e.g., markups of processors or retailers). We use first principles to argue for the necessity of an instrumental variable approach to identify the passthroughs of agricultural commodity prices to food inflation. A static partial equilibrium model of firm-level pricing highlights the sources of omitted variable bias.

Static model. We let retail firm $r \in R$ (e.g., national grocery store), sell food product j defined as a brand-food combination (e.g., a certain brand of bread), at market g (e.g., a metropolitan area), and time t (i.e., any given month). Retail firms selling product $j \in J$ at market-time gt, finds the the equilibrium price for product j choosing a set of action $\{a_j^r\}$ (e.g., prices, quantities, qualities, among others) to maximize profit equation 2 (for a similar setup, see Magnolfi et al. 2022), where p^r refers to retail prices, and q to quantity sold. Notice that this framework applies to markets for differentiated products, and for single- or multiple-product firms.

$$\max_{\{a_{jgt}^r\}} \quad \sum_j (p_{jgt}^r(a_{jgt}^r) - c_{jgt}^r) q_{jgt}(a_{jgt}^r) \tag{1}$$

The first-order condition for this problem takes well-know form $\sum_j \frac{\partial p_{kgt}}{\partial a_{jgt}} q_j + \sum_j (p_{jgt}^r - c_{jgt}^r) \frac{\partial q_{kgt}}{\partial a_{jgt}^r} = 0$ for any $k, j \in J$, which we can stack across firms and markets (keeping track of which products belong to the same firm with a ownership matrix Ω^r), and solve for markup in matrix form, μ^r, as in equation 2:

$$(p^r - c^r) = \mu^r = -\left[\Omega^r \odot \left[\frac{\partial q}{\partial a}\right]'\right]^{-1} \left[\Omega^r \odot \left[\frac{\partial p}{\partial a}\right]'\right] q. \tag{2}$$

Product j's optimal price can be concisely written as equation 3. Optimal prices can be decomposed between marginal costs, and a markup term, which is a function of demand parameters and market structure; that is demand primitives and market structure fully rationalize the level of markups for product j. Therefore:

$$p_{jgt}^{r*} = \mu_{jgt}^r + c_{jgt}^r, \tag{3}$$

where p^{r*} is equilibrium retailer prices, μ^r_j refers to the markup for product j (itself a function of own-, cross-price elasticities, and the structure of competition), and c^r refers to marginal cost. The cost of offering an extra unit of product j at retailers comprises of cost of distribution, c^{dist}_{jgt}, and wholesale prices, p^{w*}_{jgt} (Villas-Boas, 2007; Magnolfi et al., 2022). This leads to equation 4:

$$p^{r*}_{jgt} = \mu^r_{jgt} + c^{dist}_{jt} + p^{w*}_{jgt}, \tag{4}$$

where p^{w*} refers to be equilibrium wholesale prices. Letting wholesale prices be determined by the profit maximization behavior of wholesalers facing residual demand from retailer r's product j, and we can decompose $p^{w*}_{jgt} = \mu^w_{jgt} + c^w_{jgt}$.[3] We arrive at equation 5 by taking $c^w_{jgt} = c^{proc.}_{jgt} + p^{farm}_{jt}$:

$$p^{r*}_{jgt} = \mu^r_{jgt} + c^{dist}_{jgt} + \mu^w_{jgt} + c^{proc.}_{jgt} + p^{farm}_{jt}. \tag{5}$$

Equation 5 is the solution of a linear pricing strategy across the supply chain, where firms do not establish a vertical relationship,[4] and it decomposes the price of product j into markups accrued by retailers and wholesalers in market t, the marginal costs of distributing and processing food, and the price of the farm input. We arrive at the price of product j by aggregating across retailers (which suppresses indexes r from equation 5), and across markets (which now suppresses index g). Finally, one can weight (under some weight ω)[5] and aggregate prices of food production a basket of consumption to form an index of food prices, as in equation 6:

[3]One example of such behavior is when wholesalers choose action a^w_{jgt} knowing that retailer's action a^r_{jgt} is a function of a^w_{jgt}. The objective function of the wholesaler, then, becomes $p^w_{jgt}(a^w_{jgt}) - c^w_{jgt})q_j(a^r_{jgt}(a^w_{jgt}))$

[4]Other supply conducts are fully compatible with this framework. For example, in a model of two-part tariff in which processors determine the price, retailer's markup would be set to 0 in equation 5. Similarly, for a two-part tariff where retailers set the price, processor's markup would be set to 0. In a perfect competitive market, both markups would turn 0, as prices equal marginal costs.

[5]The U.S. Bureau of Labor Statistics (BLS) updates CPI relative importance and weight information annually, based on the spending from the prior two years. For context on food inflation, all "Food" is roughly 13.5% of the consumption basket and "Food at Home" is 8.7% of total food consumption (i.e., 64% of total food). Important components of food at home relevant to our analysis include "Cereals and Bakery Products" and "Fats and Oils" which have relative importance weights of 1.2% and 0.3%, respectively (i.e., 14% and 3% of food at home) (BLS, 2024).

$$p^{r*}_{food,t} = \sum_j (\omega_j \mu^r_{jt} + \omega_j c^{dist}_{jt} + \omega_j \mu^w_{jt} + \omega_j c^{proc.}_{jt} + \omega_j p^{farm}_{jt}). \tag{6}$$

Under this framework, we arrive at food inflation, i.e., the change in food prices, by computing the sum of the weighted-change in markups, marginal costs, and farm inputs, across all products j in a basket of consumption, as in equation 7.

$$\Delta p^{r*}_{food,t} = \sum_j (\omega_j \Delta\mu^r_{jt} + \omega_j \Delta mc^{dist}_j + \omega_j \Delta\mu^w_j + \omega_j \Delta mc^{proc.}_j + \omega_j \Delta p^{farm}_t). \tag{7}$$

Equation 7 implies that one could directly decompose food inflation into costs of distribution and processing, farm inputs, and markups. Empirically, the decomposition could be estimated if researchers were able to identify markups (through identification of demand for all products j, and also through tracking market structure of all these markets), marginal costs, and farm prices.

The setting of optimal food prices in t can involve expectations about markups and marginal costs when consumers make intertemporal choices between consumption and storage (e.g., Hendel and Nevo 2006, 2013). It is, however, unlikely that these intertemporal choices span long time frames, as storage space for food is limited and stored food loses freshness. Under these assumptions, Appendix A shows that optimal prices can be decomposed between current markups and marginal costs along the supply chain and expectations of markups and marginal costs until in $t + \tau$ periods ahead, where τ is finite. This result resembles traditional models of sticky prices in the macroeconomic literature (Gali, 2002).

From theory to empirical application. Conditional on having information about the mode of conduct for firms producing food, changes in market structure, and retail, wholesale, and farm prices and quantities for food products, the models above provide a framework that could be taken to data. With this information, it would be possible to fully estimate a structural model of demand for bundles of products, identify markups for retailers and processors, and infer marginal costs from the first-order conditions of the models (Villas-Boas, 2007). In practice, detailed data of price and quantities across the supply chain is difficult to obtain, and we would need to make strong assumptions about modes of conduct and market structure because there would be too many markets to track.

However, we can still model the dynamic causal effects of a shock in agricultural prices on food inflation. The components that impact food prices are farm prices, marginal costs of processing and distributing food, and retail and processors' markups. At any given period t: 1) farm prices are a function of the balance between supply ($S^{farm,US}$) of US agricultural products (itself determined by yields, changes in input costs), supply of agricultural products from the rest of the world ($S^{farm,ROW}$), domestic demand ($q^{end-user}$) for these products, i.e., some share of demand from end consumers, demand from outside of the US, and demand to produce energy (q^{ROW}, q^{energy}); 2) marginal costs of processing are a function of input markets conditions (including labor) ($L^{upstream}$) at local processing areas and costs of transportation ($T^{upstream}$) from farm to processing plants; 3) marginal costs of retail distribution are a function of input markets conditions ($L^{downstream}$) at local retail markets and costs of transportation ($T^{upstream}$) from processing plants to retailers; 4) markups for retailers are a function of market structure (Ω^r) and end-user demand; and 5) markups for processors are a function of market structure (Ω^w), end-user demand, and elasticity of the retail price to wholesale prices. Empirically, we allow for some persistence in the data too and include h lags to the data generating process of these variables. We end up with the system of equations:

$$
\begin{aligned}
p_t^{farm} &= f(S_t^{farm,US}, q_t^{end-user}, S_t^{farm,ROW}, q^{ROW}, q^{energy}, \{p_{t-h}^{farm}\}) \\
c_t^{proc.} &= f(L^{upstream}, T_t^{upstream}, \{c_{t-h}^{proc}\}) \\
\mu_t^w &= f(\Omega^w, q^{end-user}, \{\mu_{t-h}^w\}) \\
c_t^{dist.} &= f(L^{downstream}, T_t^{downstream}, \{c_{t-h}^{dist}\}) \\
\mu_t^r &= f(\Omega^r, q^{end-user}, \{\mu_{t-h}^r\}) \\
p_t^{food} &= f(p_t^{farm}, c_t^{proc.}, \mu_t^w, c_t^{dist.}, \mu_t^r, \{p_{t-h}^{food}\}).
\end{aligned} \tag{8}
$$

Expectations about these variables as described in the dynamic structural model will depend on the distribution of structural shocks in the future.

Markups and marginal costs are unobserved and omitted from p_t^{food} for us. Thus, a shifts in the structural shocks of end-user $q^{end-user}$ shifts farm prices and also the omitted markups, rendering passthrough calculated from the the system passive of omitted variable bias. To identify the passthrough of agricultural prices to food prices, we need an instrument that shifts some other structural shock on the farm price equation. We will focus on an instrument that shifts farm supply in the U.S. as it is excluded from other equations in 8. As long as the instrument is not anticipated by agents and we can add instrument lags to uncover contemporaneous instrument shocks on current prices, foresight and farm price expectations should not hinder identification. See Ramey (2016) for a discussion of the problem of foresight.

Next, we discuss an empirical strategy to identify the passthrough of changes in commodity prices to food inflation.

3 Data and Methods

Broadly speaking, the modern food supply chain is more concentrated downstream (i.e., fewer retailers), more vertically coordinated across the chain, and more focused on packed and frozen products (Ellickson, 2016; USDA, 2024c,d). Intuitively, then, shocks that affect costs could be absorbed by different parts of the food supply chain rather than fully passthrough to end-user consumer. To empirically discuss these trends, we now present the data, sample, and the identification strategy that we use to investigate the passthroughs.

Data. National agricultural prices data comes from USDA and measure prices received by farmers. As most of the literature (e.g., Roberts and Schlenker, 2013; Hendricks et al., 2015; Peersman, 2022), we focus on row crops: corn, soybeans, wheat, and rice planted in the U.S. Using this products present two main advantages. They represent the bulk of calories in agricultural production and they also are widely used as inputs to many food products available in the diets of U.S. consumers (Desilver, 2016; USDA, 2024b)– in fact, these products may be inputs to virtually all products with some degree of processing offered in U.S. grocery stores, which are close to 90% of the food basket in the U.S. Moreover, strong and exogenous shifters are available to instrument for prices of these products, as it will become clear when we discuss our identification strategy.[6]

We are also interested in the differential passthrough of changes in prices of specific agricultural commodity to the prices of components of the food basket. We select wheat and soybeans as a case study and assess the passthrough to prices of bakery goods and fat and oils, respectively. We use three time series of interest in our exercises: an index of prices for row crops, prices of soybeans, and prices of wheat. The price index for row crops is a weighted-average of prices of corn, soybean, wheat, and rice. We weight each crop by their respective annual cash receipts provided by the USDA.

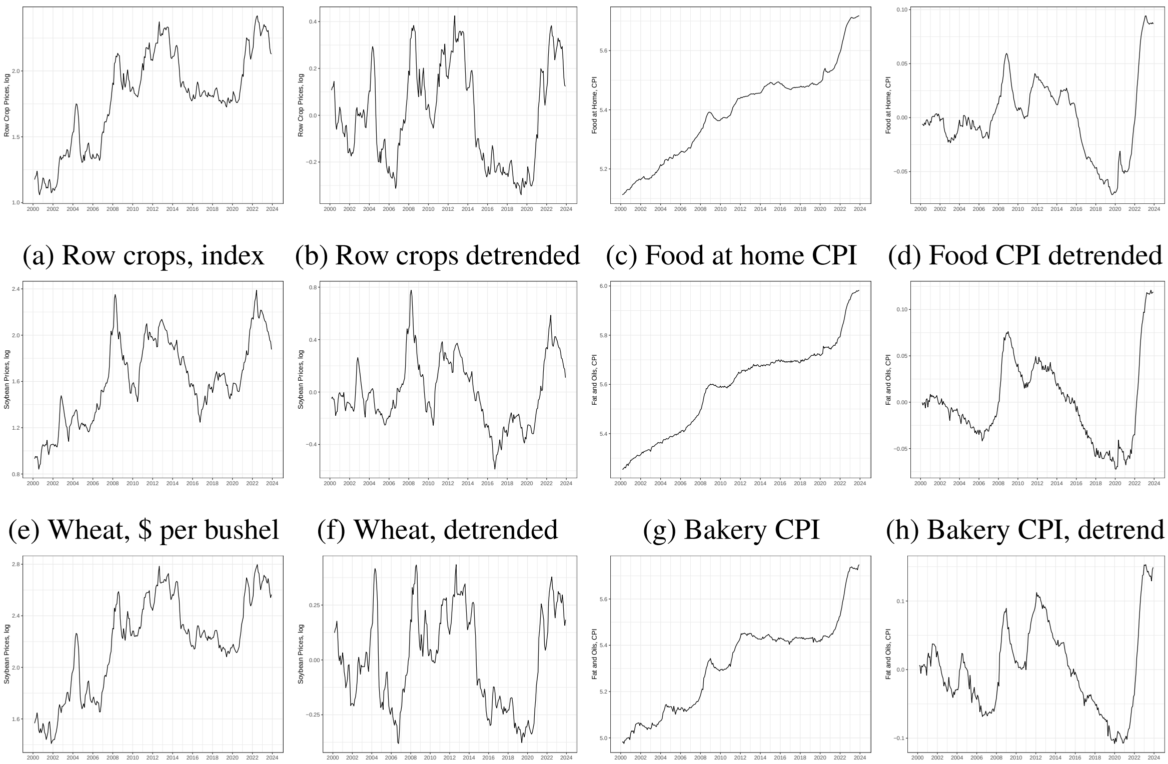
Food prices are captured by the the Consumer Price Index (CPI) from the the Bureau of Labor Statistics (BLS). We use 3 indexes from the CPI; the food-at-home price index, the index for bakery goods, and the index for fat and oils. In what follows, we estimate the passthrough of 1) the price of row crop prices to the food at home; 2) the price of wheat to bakery goods; and 3) the price of soybeans to fats and oils. While (1) captures the general passthrough of the main crops to food at home inflation inflation, estimating (2) and (3) allows us to capture differential passthrough of specific commodities to components of the food CPI. Figure 1 shows the time series.[7]

SVAR-IV. To estimate the passthrough of changes in agricultural commodity prices to food inflation,[8] we use instrumental variable approach adapted to time series. For an extensive treatment of identification in VARs and Local Projections using external instruments, see Stock and Watson (2018) and Plagborg-Møller and Wolf (2022). We use the SVAR-IV bootstrap methodology discussed in the appendix of Lusompa (2023). This methodology is robust to

[6]While the row crops in our analysis are important components in the U.S. food basket, the value of agriculture commodities is relatively small component of each dollar spent on food at home (less than 10% for most food categories). See Appendix B for further details the food dollar breakdown (USDA, 2024a) and how it relates to passthorugh calculations.

[7]We show data as deviation from trend. We did not find evidence that commodity prices needed to be seasonally adjusted, but CPI data is seasonally adjusted by the BLS.

[8]We should be clear about the concept of passthrough in this paper. Most of the industrial organization literature defines passthrough as $\frac{dp}{dx}$, i.e., a measure of change in variable p, generally prices, after a change in some variable x, generally marginal costs (Villas-Boas, 2007; Weyl and Fabinger, 2013; Conlon and Rao, 2020; Magnolfi et al., 2022). The macroeconomics and trade literatures tend to produce a slightly different statistic for passthrough as $\frac{dl\log(p)}{dl\log(x)}$ (Gopinath et al., 2010; Nakamura and Zerom, 2010). Our time series specification estimates Impulse Response Functions that are the dynamic version of the latter (i.e., we estimate our VARs in log-log form), as it will become clear in the *Result* section, in line with the macroeconomic literature. A broader discussion about these differences is in Appendix B.



(a) Row crops, index (b) Row crops detrended (c) Food at home CPI (d) Food CPI detrended

(e) Wheat, $ per bushel (f) Wheat, detrended (g) Bakery CPI (h) Bakery CPI, detrend

(i) Soybean, $ per bushel (j) Soybean, detrended (k) Fat and oils CPI (l) Fat & oils CPI detren.

Figure 1: Agricultural commodity and food prices

omitted variables and can handle conditional heteroskedasticity.

We use use a VAR instead of Local Projections to avoid losing observations in our relative short time series. The time series of monthly data spans from 2000 to 2023. We chose this span of time to match the period when data on the instrument is available, and the period with two run ups in agricultural commodity prices– the periods of 2013 and 2021. We discuss the instrumental variable next.

Instrument. A valid instrument must be correlated with structural shocks of commodity prices but uncorrelated with other shocks that move food prices. The theoretical model outlines these other factors. The instrument cannot shift structural shocks of marginal costs of processing food, marginal costs of distributing food, and markups across the supply chain. Agents also should not be able to anticipate the exogenous structural shift of the instrument.

We use agricultural *commodity-specific* exposure to extreme drought during planting, plant development, and harvesting as our instrumental variable. The U.S. Drought Monitor (USDM) (USDM, 2024) offers this measure for several agricultural products and across drought intensities. Specifically, our instrument measures the share of production of a given agricultural commodity (e.g., corn, soybeans, wheat, rice) under drought in a given month. Drought intensities vary from mild to extreme levels, classified from $D0$ (abnormally dry) to $D4$ (exceptional drought).

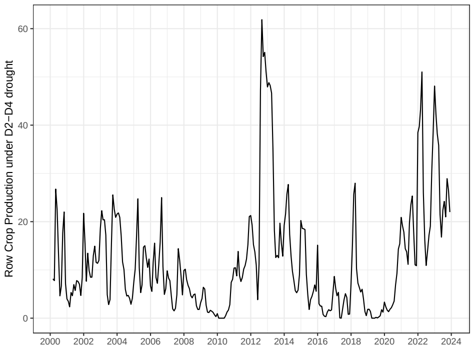
The drought monitor tracks crop specific areas under drought by overlaying drought maps on U.S. agricultural census data on agricultural production. USDM then calculates crop-specific production under drought by dividing crop production under drought by total production. The area of production given the Census of Agriculture is measured on a yearly basis, whereas drought maps are weekly. Therefore, the weekly crop-specific drought measures are reported by the USDM even if there is no crop in the ground. Although soil depletion from drought may impact future yields, drought will mainly affect yields when plants are in the ground.

We avoid spurious correlation between the instrument and agricultural commodity prices in periods when crops are not in the ground by following the methodology inspired by Peersman (2022). We adjust the share of a crop under drought by an indicator variable that tracks whether the crop is in the ground or not in a month. We consider a crop by being in the ground if the crop is being planted (planting phase), planted and growing (development phase), or being harvested (harvesting phase).[9] We let the month for which crop c is in the ground to be part of the set T. USDM data provides share of crop production under drought weekly and we average those to the monthly frequency. We weight-average these values by each crop yearly planted area(γ) to aggregate across crops. Formally, our instrument is given by equation 9.

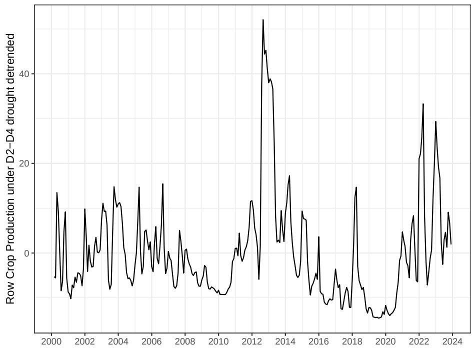
$$D_t = \sum_{c \in C} \left(1_{c,t \in T_c} \times \gamma_{c,year} \times \text{Share in Drought}_{ct} \right), \tag{9}$$

Figure 2 shows the instrument for 3 sets of crops we use in this study.

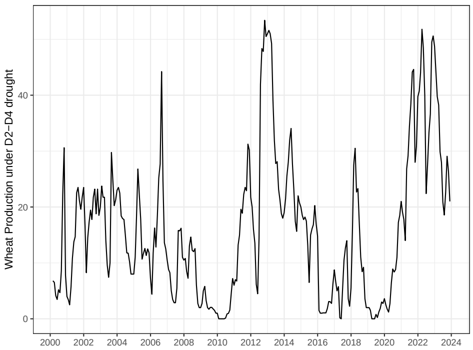
[9] Appendix C provides a full picture of this calendar for the crops we use in this study.



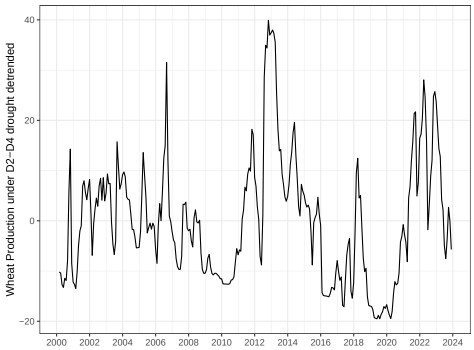
(a) Row crops



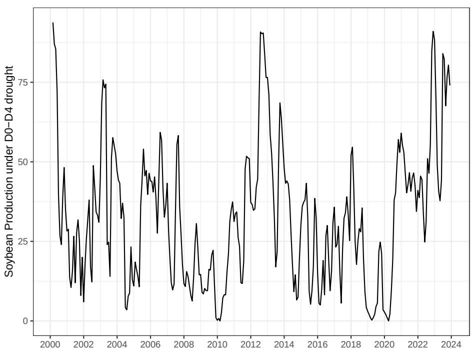
(b) Row crops detrended



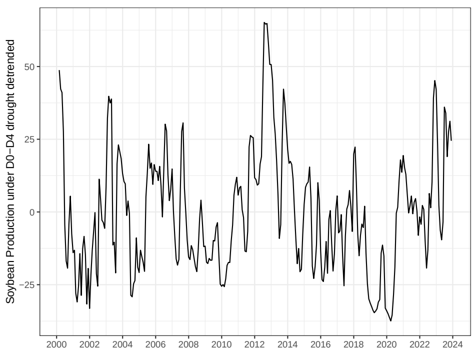
(c) Wheat



(d) Wheat detrended



(e) Soybeans



(f) Soybeans detrended

Figure 2: Agricultural production under drought

We claim that our instrument impacts food prices only through structural shifts in the structural shocks for the supply of crops, which are included only in the food price equation. In practice, a drought shock impacts prospects of good yields at the end of the season, declining end-of-season supplies (Kuwayama et al., 2019). In fact, there is a well-established tradition of using weather shocks as exogenous supply shifters that is unrelated to the demand of agricultural products (Wright, 1928; Roberts and Schlenker, 2013; Hendricks et al., 2015). Drought can be persistent (Zhang et al., 2025), so we include lags of the drought instrument to control for drought persistence. Finally, if expected prices systematically differ from spot prices only through future i.i.d. shocks that cannot be predicted, the drought instrument is valid.

Drought shocks shifts the farm supply structural shock down and increase crop prices. Our instrument specifically targets area of production for specific commodities. These drought measures likely do not shift national preferences or spending for food. It is also unlikely droughts significantly alter market structure. Therefore, without a major change in demand elasticities and market structure, markup across the supply chain should not be systematically altered by commodity-specific droughts. Extensive periods of drought around major rivers (e.g., Mississippi river) can disrupt transportation through decline in rivers' depths. Transportation constraints during these acute drought episodes are typically short-lived, local in nature, can lower *regional* crop prices, and the effects vary with distance to water transportation thoroughfares (Mitchell and Biram, 2025). Overall, these episodes are generally brief and variation in our *commodity-specific* drought would have to systematically constrain transportation capacity *nationally* to pose threats to identification. Again, an unlikely event as the variation in drought measures may be coming from different parts of the country.

The link between changes in drought and agricultural commodity prices. Drought can impact the balance between supply and demand for crops. Extensive drought can decrease crop yields which, in turn, can curb production and supply of crops in a year. Crop yields, however, are only observed after harvest and are unavailable on a monthly frequency limiting their use in empirical investigations of food inflation. However, the USDA provide monthly estimates of supply and demand for a few crops on the World Agricultural Supply and Demand

Estimates (WASDE) that can be used to assess the impact of drought on the expected balance of supply and demand of crops. WASDE is a accounting-based measure of supply and demand for agricultural products that uses surveys data, some modeling and private information collected from fields.

Our measure of drought moves the WASDE-implied balance between U.S. supply and demand for several row crops. We project the measure of U.S. stocks (i.e., excess supply) to U.S. use (i.e., total demand) implied by the WASDE report on our drought measures, year and month fixed effects. Table 1 shows that a 1 percentage point increase in the production of wheat under drought is associated with a 0.15 decline in the stock-to-use ratio of wheat in the current month. A similar increase in soybeans production under drought is associated with a reduction in stocks-to-use ratio of oilseeds 0.03 for the current month and 0.10 for the subsequent month. Finally, a increase in area under drought for the main row crops is associated with a move in stock-to-use ratio for wheat of 0.125, for oilseeds of 0.064, and total grains of 0.014 for the current month, and 0.061, 0.123, and 0.051 for the next month, respectively. These correlations have the expected sign as greater drought exposure is associated with lower end stocks relative to demand.

Table 1: Effect of drought on WASDE-implied U.S. stock-to-use ratio for several commodities

	Wheat	Soybeans	Corn	Wheat	Soybeans	Corn
Drought Wheat (% production)	**−0.151**					
	(0.068)					
Drought Wheat (% production), 1 lag	−0.032					
	(0.059)					
Drought Soybeans (% production)		−0.030				
		(0.067)				
Drought Soybean(% production), 1 lag		**−0.107**				
		(0.049)				
Drought Corn (% production)			−0.003			
			(0.027)			
Drought Corn (% production), 1 lag			**−0.052**			
			(0.025)			
Drought Row Crops (% production)				**−0.125**	−0.064	−0.014
				(0.043)	(0.055)	(0.020)
Drought Row Crops (% production), 1 lag				−0.061	**−0.123**	**−0.051**
				(0.042)	(0.047)	(0.019)

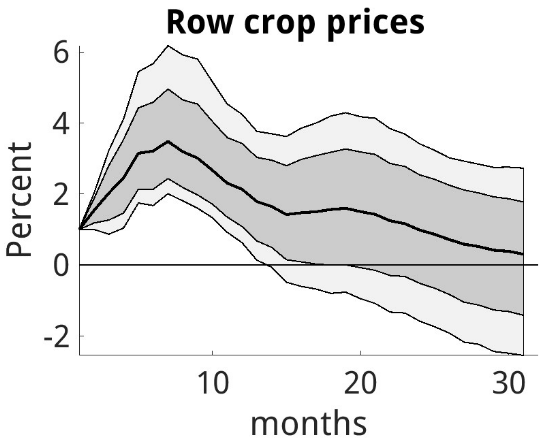
Notes: Bold numbers refer to 5% significant level. Drought refers to D2-D4 drought. Month and year fixed effects included in all specifications. Heteroskedasticity- and autocorrelation-consistent (HAC) standard errors in parenthesis.

Overall, Table 1 suggests that movements in drought intensity move alongside WASDE-implied balances between demand and supply. We move from correlations to a causal interpretation of changes in prices to food inflation under the SVAR-IV estimation.

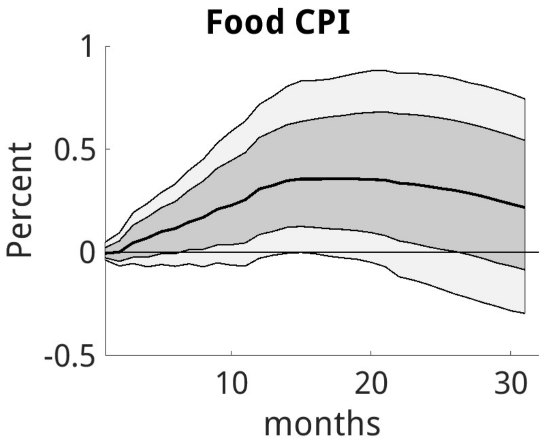
4 Results

We estimate three sets of SVARs to assess the passthrough of agricultural commodity prices to food inflation. The first set analyse the passthrough of the index of crop prices to food-at-home CPI, where the instrument used is the share of row crops production under D2 to D4 drought — the strongest instrument among the drought intensity instruments available. The drought instrument is ordered first in the system. We also log transform and detrend the prices indexes using a quadratic trend, but results are qualitatively similar using a linear trend, or keeping things in log levels, or growth rates. We use 12 lags in the estimation. The second set includes wheat prices and bakery CPI, and wheat under D2-D4 drought. The third set includes soybean prices, fats and oils CPI, and the share of soybean production under D0-D4 drought, again the strongest set of instruments for these variables. The equation specification and lag structure remain the same for the three estimations.

The passthrough of row crop prices to food at home CPI is positive, small, and imprecisely estimated, as shown by the impulse response functions of the system in Figure 3. The bootstrap F-statistic for the drought instrument is approximately 16.10, and Appendix D shows that this F-statistic drops to 14.1 depending on the block size used in the bootstrap for inference. The impulse response function of row crop prices on itself is positive, and dissipates after one year. Point estimates of the impulse response functions for food at home CPI starts to increase after one year, and about 2 years to ease. However, the wide confidence intervals around those estimates implies that any given shock in row crop prices are not guaranteed to passthrough positively to food inflation, meaning that the estimates are imprecise.



(a) Main row crop prices

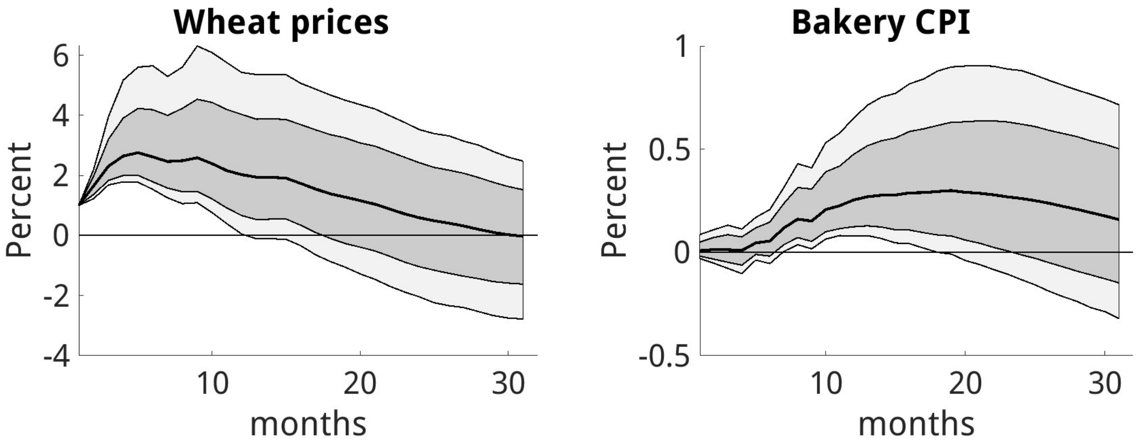


(b) Food CPI

Figure 3: Impulse response function of a 1% increase in row crop prices.

Note: Impulse response functions estimated with log-log specification and production of main crops under D2-D4 drought as instrument. Dark grey area represent 68% confidence interval, and light grey area represents the 95% confidence interval.

The passthrough of wheat prices to bakery CPI is positive, but also imprecisely estimated, as seen in Figure 4. The drought instrument is strong in this specification with bootstrap F-statistic for this system around 13.1. A 1% increase in wheat prices takes less than 20 months to dissipate, and the point estimate of the impulse response shows that the shock takes less than 10 months to meaningfully impact Bakery CPI.



(a) Wheat prices (b) Bakery CPI

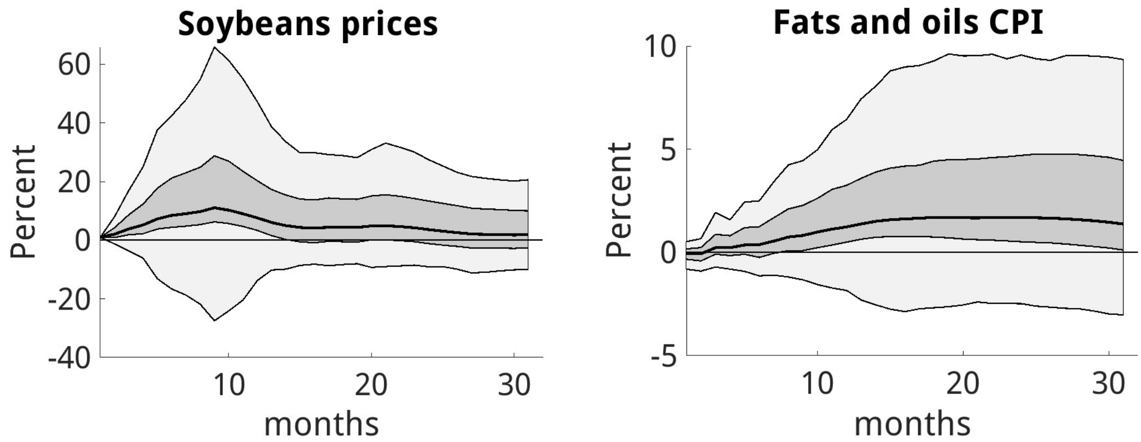
Figure 4: Impulse response function of a 1% increase in wheat prices.

Note: Impulse response functions estimated with log-log specification and production of wheat under D2-D4 drought as instrument. Dark grey area represent 68% confidence interval, and light grey area represents the 95% confidence interval.

The passthrough of soybean prices to fat and oils CPI produces a similar patterns of passthrough as row crop and wheat prices shocks, as shown in Figure 5. However, the drought instrument for soybean prices is much weaker with F-statistic for this system close to 4.[10] The weaker instrument produces wider confidence bands to an already relatively large impact of soybeans prices on itself. The passthrough to fat and oils CPI is imprecisely estimated, and point estimates show that the impact ease after 2 years.

These estimations survive a few robustness checks. Detrending the data series with a linear trend produces qualitatively identical results for the impulse response functions and instruments with comparable strength, as shown in Appendix D. We also show that major changes in U.S. agricultural energy policy that stem from the passage of the Renewable Fuel Standard program in 2007 does not affect our results: controlling for the new row crop price regime after the introduction of the Renewable Fuel Standard program in our SVAR still produces imprecisely estimated passthroughs. Finally, one may be concerned that our SVAR may not

[10]There are many potential explanations for the weaker F-statistic for soybean prices. Better irrigation technology, seed technology, and better cultivation practices may lead markets to discount the effect of droughts on soybean availability, weaking first-stage strength. Changes in demand for soybeans (export or domestic) are unlikely to make this F-statistic weaker unless one believes that the random weather shocks are always contemporaneously offset with unpredictable changes in demand for soybeans in the domestic or external market.



(a) Soybeans prices (b) Fat and Oils CPI

Figure 5: Impulse response function of a 1% increase in row crop prices.

Note: Impulse response functions estimated with log-log specification and production of soybean prices under D2-D4 drought as instrument. Dark grey area represent 68% confidence interval, and light grey area represents the 95% confidence interval.

be fully capturing the effects of expectations in row crop prices. To mitigate these concerns, we include futures prices in the SVAR and results remain qualitatively the same.

Overall, the passthrough of changes in agricultural commodity prices to food inflation tend to be small, and imprecisely estimated. The results hold for passthrough estimated with instruments of different strengths and across products. Our results support the idea that the low cost share of agricultural commodities in food prices results from structural configurations in the food supply chain that limits the extent to which shocks in agricultural prices passthrough to retail food prices. These findings highlight the importance of examining costs and demand-related factors, particularly those downstream in the supply chain, when analyzing potential drivers of food inflation.

5 Conclusion

Food is an important basic need, and food prices have historically been linked to agricultural commodity prices. This paper adds to a growing literature on food inflation by evaluating the passthrough of agricultural prices to U.S. food prices after 2000. We show that variation in crop prices have a limited effect on variations of food prices– i.e., the passthrough from row crops to food at home inflation is small and imprecisely estimated. We apply a time series methodology and weather instruments (i.e., drought) in a SVAR setting to compute these passthroughs. Results from simple theoretical models that decompose food prices into markups, marginal costs, and farm prices along the supply chain guide our empirical strategy. Since markups and marginal costs are unobserved in our setting, we require an instrument that shifts farm prices only. We use variation in crop-specific drought shocks that shift farm production to compute three measures of passthroughs: row crop prices to food at home CPI, wheat prices to bakery CPI, and soybean prices to oils and fats CPI.

Our analysis on commodity price passthrough to food inflation provides important evidence that agriculture commodity prices may have a limited impact on food inflation. This is especially true in the context of complex food supply chains, like the United States, where expenditures on food skew towards the consumption of more processed products. These results are an important consideration for those trying to better understand the driving forces behind food inflation dynamics. Many other factors weigh on the cost of retail food prices in complex food supply chains. Food manufacturing wages, capital equipment costs, packaging, transportation, storefront rents, and marketing, all contribute to retail food prices. While agriculture commodity prices matter substantially for farmers and the farm economy, our research contrasts with the commonly held perception that crop commodity prices are a principle driving force behind consumer food inflation in the U.S. for certain food categories. These findings may prove useful for policymakers (monetary and otherwise), market participants, consumers, and food industry professionals, as they better understand and communicate the factors underpinning U.S. food inflation.

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A Dynamic Model

Dynamics matter for inflation when households and firms have to make intertemporal trade-offs. We follow the literature on intertemporal consumption (e.g., Hendel and Nevo 2006, 2013) closely here. We assume that households can either consume food immediately or store it for a brief period of time. Consumption increases consumers' utility, but storage is costly because space for storage is limited and stored food eventually loses freshness. We let a consumer maximize their discounted utility by choosing how much food to purchase ($\mathbf{x_t}$), and how much to consume ($\mathbf{q_t}$) . Household budget for food (Z_J)[11] constraints household expenditures on the set of products available J. Food not consumed in period t builds inventory (I) for next period. The problem is stated in equation 10, where e refers to food products that get spoiled.

$$
\begin{aligned}
\max_{\{\mathbf{q_t}\},\{\mathbf{x_t}\}} \quad & E_t \sum_{t}^{T} \Big(u(\mathbf{q_t}) - C\big(\sum_{j}^{J} I_{jt}\big)\Big) \\
\text{s.t.} \quad & \sum_{j}^{J} p_{jt} x_{jt} \leq Z_{Jt}, \\
& \sum_{j}^{J} I_{jt} = \sum_{j}^{J} I_{jt} + \sum_{j}^{J} (x_{jt} - q_{jt} - e_{jt}),
\end{aligned} \tag{10}
$$

Traditional methods for solving dynamic problems yield the optimal path for intertemporal consumer choice, and, important for this paper, the demand for product j at any given grocery store $x_j(\mathbf{H_t})$. Demand for the product is given by prices of all products in time t, and also the history of prices up to time t (which governs the level of stored products, and the necessity to buy food at time t), given by H.

The complete solution of the household problem is not important for our argument. What matters for our argument is that the demand for product j at any given grocery store depends on the the history of prices up to time t (which governs the level of stored products, and the necessity to buy food at time t), given by $x_j(\mathbf{H_t})$, where H is a matrix of current and past prices for the set of products available. Armed with this definition, we set the problem for the retailer and processor next.

We assume that retailers define the price for the set J of products they have on store in t.[12] Following the textbook models of sticky prices (e.g., Bils and Klenow, 2004; Cabral and Fishman, 2012; Galí, 2015), retailers set current prices p^{r}_{jt} over some timespam $t \in [0, T]$ to maximize the stream of profits generated while that price remain effective. The likelihood of not being granted an opportunity to reprice product j over τ periods ahead of t is θ^{τ}_{j}. The retailer problem, then, is given by equation 11 which states that firms maximize profits at time

[11] We assume that households have a fixed budget for food. One could also introduce a more general budget constraint that would allow for more rich patterns of substitution and include a numeraire good in the utility function.

[12] One can easily replace the choice variable for firms by any a action that impacts quantities, prices, or both, as in the static model. We choose prices for easiness in exposition and to parallel our exposition with traditional models in macroeconomics as in Galí (2015).

t for $t + \tau$ periods ahead, subject to quantity offered equals quantity demanded.

$$\begin{aligned} \max_{\{p^r_{jgt}\}} \quad & \sum_{\tau=0}^{T} E_t\Big[\beta^\tau \sum_{j}^{J} \theta^\tau_j \Big((p^r_{jgt} - c^r_{jgt+\tau|t}) y_{jgt+\tau|t} \Big) \Big] \\ \text{s.t.} \quad & \mathbf{y_{gt+\tau|t}} = \mathbf{x_{gt+\tau|t}}(\mathbf{H_{gt+\tau|t}}), \end{aligned} \tag{11}$$

The FOC for a given product j offered by retailer r takes the form

$$\sum_{\tau=0}^{T} E_t\big[\beta\theta^\tau_j \Big[x_{jgt+\tau|t} + (p^r_{jgt} - c^r_{jgt+\tau|t})\frac{\partial x_{jgt+\tau|t}}{\partial p^r_{jgt}}\Big] + \sum_{k\neq j} \beta\theta^\tau_k (p^r_{kgt} - c^r_{kgt+\tau|t})\frac{\partial x_{kgt+\tau|t}}{\partial p^r_{jgt}}\big] = 0.$$

Under the assumption that $\frac{\partial x_{jgt+\tau|t}}{\partial p_{jgt}}$ and θ^τ_j is constant over $t + \tau$, one can stack the FOCs and solve for prices to obtain a closed-form solution as in equation 12.

$$\sum_{\tau=0}^{T} E_t[\beta_t(\mathbf{p^r_t} - \mathbf{c^r_{t+\tau|t}})] = \tilde{\mu^{\mathbf{r}}} = -\Big(\theta^\tau \odot \mathbf{\Omega^r} \odot \frac{\partial \mathbf{x_{t+\tau|t}}}{\partial \mathbf{p_t}}\Big)^{-\mathbf{1}} \sum_{\tau}^{T} E_t\beta_t(\theta^\tau \odot \mathbf{x_{t+\tau|t}}), \tag{12}$$

where Ω^r is an ownership matrix that tracks products being offered by a retailer in a given market, θ^τ is a matrix of probabilities of product being stuck at the price at t, $\frac{\partial x_{gt+\tau|t}}{\partial p}$ is a matrix of own- and cross-price elasticities.[13] Equation 12 states that the stream of discounted markups is a function of demand elasticities, expected demand, and market structure.

As in the static model, we let retailers' marginal cost be the sum of distribution costs and wholesale prices., i.e., $\mathbf{c^r_{gt+\tau|t}} = \mathbf{c^{dist}_{gt+\tau|t}} + \mathbf{p^w_{t+\tau|t}}$. Assume now that the processor has some degree of market power over the subset of J_f products it supplies to the retailer. We assume that the processor's problem s similar to the retailers' in the sense that they compete in imperfect markets, face the same residual demand for product j as retailers, and the same likelihood of not being able to reprice. Formally, the processor's problem is given by equation 13:

$$\max_{\{p^w_{gjt}\}} \quad \sum_{\tau=0}^{T} E_t\Big[\beta^\tau \sum_{j}^{J_f} \theta^\tau_j \Big((p^w_{jgt} - c^{proc.}_{jgt+\tau|t} - p^{farm}_{jt+\tau|t}) x_{jgt+\tau|t}(\mathbf{H_{gt+\tau|t}}(p^w_{jgt})) \Big) \Big] \tag{13}$$

By symmetry to the retailers' problem, processor choose wholesale prices to maximize their profits, and expected markup can be found under equation 14 for constant demand elasticities over time.

[13]Note that constant price elasticities and θ are strong assumptions for long T. A constant path of own-and cross-price elasticities and a single draw of θ are only likely over small T. Small T is indeed more likely for firms re-optimizing over food products as opposed to durable goods, where intertemporal trade-offs for consumers tend to be more salient given the size of durable goods expenditures and the small frequency of purchases for these goods.

$$\sum_{\tau=0}^{T} E_t[\beta_t(\mathbf{p^w_t} - \mathbf{c^w_{t+\tau|t}} - \mathbf{p^{farm}_{t+\tau|t}})] = \tilde{\mu^{\mathbf{w}}} = -\Big(\theta^\tau \odot \mathbf{\Omega^w} \odot \frac{\partial \mathbf{\tilde{x}_{t+\tau|t}}}{\partial \mathbf{p^w}}\Big)^{-1} \sum_{\tau}^{T} E_t(\theta^\tau \odot \mathbf{x_{t+\tau|t}}), \tag{14}$$

where entry (j, k) is the matrix is given by $\frac{\partial x_{kgt+\tau|t}}{\partial p^r_{jgt}} \frac{dp^r_{jgt}}{dp^w_{jgt}} = \frac{\partial \tilde{x}_{kgt+\tau|t}}{\partial p^w_{jgt}}$

Then, we follow the same steps of the static problem: we stack the FOC for the wholesale problem, substitute wholesale prices in equation 12, and note that marginal costs for the retailer can be decomposed into expected discounted costs of processing ($\tilde{c}^{proc}$), and expected discounted agricultural commodity prices ($\tilde{p}^{farm}$). Equation 15 represents the optimal solution for product j prices in retailer g, for time t in the dynamic model:

$$p^{r*}_{jgt} = \tilde{\mu}^r_{jgt+\tau|t} + \tilde{c}^{dist}_{jgt+\tau|t} + \tilde{\mu}^w_{jgt+\tau|t} + \tilde{c}^{proc.}_{jgt+\tau|t} + \tilde{p}^{farm}_{jt+\tau|t}. \tag{15}$$

We aggregate across retailers, markets, and products (over some stable weight ω_j) to obtain the price level of food as in equation 16. Inflation is the first difference across time. Differently from the static mode, firms here are forward looking, and expectations about costs and markups directly enter food inflation formula.

$$p^{r*}_{food} = \sum_j (\omega_j \tilde{\mu^r}_j + \omega_j \tilde{c}^{dist}_{jt} + \omega_j \tilde{\mu^w}_{jt} + \omega_j \tilde{c}^{proc.}_{jt} + \omega_j \tilde{p}^{farm}_{jt}), \tag{16}$$

The static and dynamic models show that food inflation depends on measures of markup, and marginal costs across the supply chain. Thus, accounting measures of markup and marginal costs could empirically rationalize changes in food inflation. The dynamic model, however, shows that the full rationalization of food inflation requires measures of expected on markups, marginal costs, and farm prices.[14]

[14]Measures of output gap and inflation expectations can substitute for economy-wide measures of expected marginal costs (Neiss and Nelson, 2001; Woodford, 2001; Gali, 2002). Of course, our interest is to compute the magnitude and extent of changes in agricultural prices to food inflation. Therefore, such substitution is impossible for our purposes.

B Definitions of Passthrough and the Food Dollar

Passthrough is a well-defined economic concept that relays how much of a change in a variable x changes variable y. A common use of the concept of passthrough across economics is the passthrough of increases in marginal costs (mc) to prices (p) (Magnolfi et al., 2022; Nakamura and Zerom, 2010). We will stick with the price-marginal cost example for this section.

The mathematical definition of passthrough, however, differs in the economic profession. Generally, papers in the tradition of industrial organization state passthrough as purely the change in price levels resulting from a change in the level of marginal costs, $\frac{dp}{dmc}$ (Weyl and Fabinger, 2013; Conlon et al., 2023). As such, a passthrough of 1 implies that same magnitude of change in mc and in p. This is particularly useful when authors discuss increases of marginal cost to price in perfect competitive markets, where $p = mc$, and thus passthrough is, by definition, 1. Macroeconomists and trade economists often define passthrough as $\frac{d\log(p)}{d\log(mc)}$ (Nakamura and Zerom, 2010). Differently from the industrial organization literature, a passthrough of 1 implies that $\log(mc)$ and $\log(p)$ changed in the same magnitude, a slightly different interpretation of the passthrough object. Both definitions are equaly valid as long as readers understand the difference in what is being estimated and discussed in papers of different economic sub-fields.

However, comparing results across literatures can become challenging when authors describe passthroughs in terms of magnitude (e.g., "small"). Table B1 below show a numerical example of how confusion can manifest. Take a market where prices and marginal costs are \$9 and \$10, respectively, in equilibrium. An increase of marginal cost from \$9 in $t = 1$ to \$10 in $t = 2$ that leads to an increase of \$1 in the final price of a good, from \$10 to \$11, leads to a passthrough of 1 under $\frac{dp}{dmc}$, and a passthrough of 0.91 under $\frac{d\log(p)}{d\log(mc)}$. Even though results may be qualitatively similar, passthrough under changes in log are smaller. This implies that comparing passthrough estimations that use two different definitions can lead to different results, even with the same data.

Table B1: Example of different passthrough values

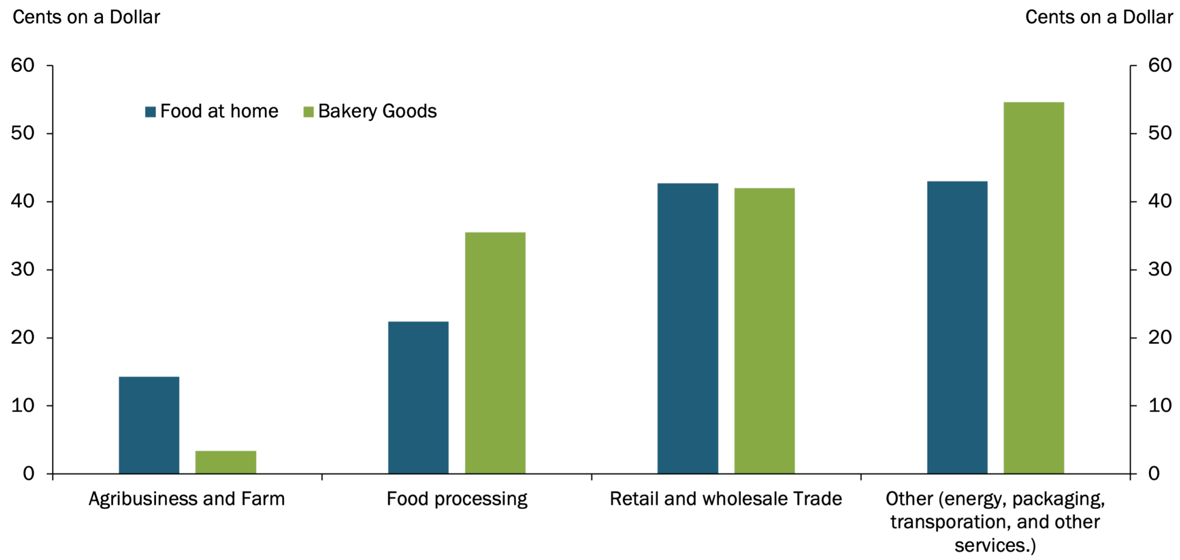
$t = 1$		$t = 2$		Passthrough	
mc	p	mc	p	$\Delta p/\Delta mc$	$\Delta\log(p)/\Delta\log(mc)$
9	10	10	11	$\frac{11-10}{10-9} = 1$	$\frac{\log(11)-\log(10)}{\log(10)-\log(9)} \approx 0.91$

Another challenge in interpreting passthrough values refers to the relationship between passthrough and cost share. It is well-understood that farm prices are a small percentage of the food value. For example, USDA's Food Dollar in figure B1 shows farm prices and agribusiness value-added represent 15 cents for each dollar of food in grocery stores. Similarly, farm prices and agribusiness value-added represent 3 cents for each dollar of bakery products. Both are very small in magnitude compared to retail and wholesale value-added.

The Food Dollar, however, is estimated from Input-Output analysis (Kelly et al., 2015), thus, from value-added tables and expenditure data, and do not necessarily capture how agricultural commodity prices enter into the marginal cost function of firms. Imagine, for example, that the marginal cost of the food supply chain is linearly parameterized as the sum of costs components x and agricultural commodity prices, p_{ag}, such that $mc_{i,food} = \beta_1 x_{i1} + \beta_2 x_{i2} +$

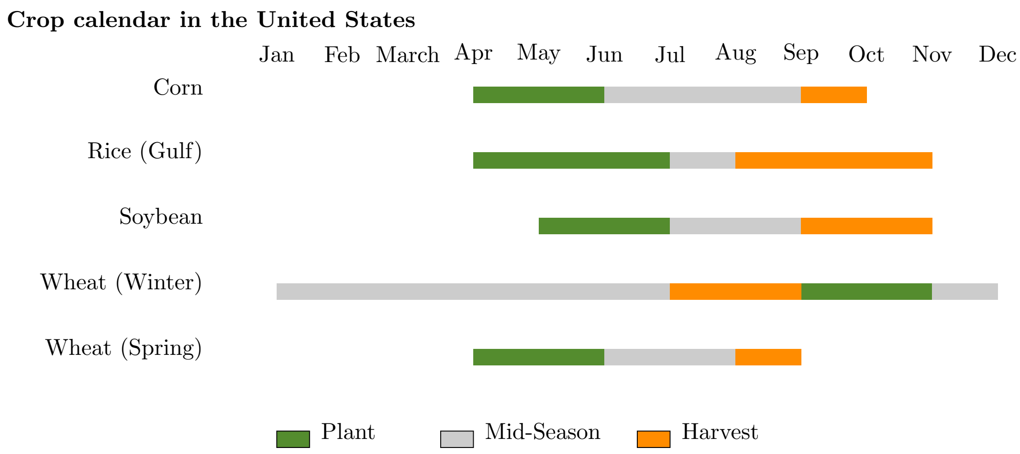
$\beta_{ag}p_{i,ag} + \epsilon$, for retailer i, a one-food product monopolist. Assume further, for the argument, that retail firms add a constant markup μ on top of marginal costs. Thus, food price at retail store i is $p_{i,food} = \mu + mc_{i,food} = \mu + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_{ag}p_{i,ag} + \epsilon$. A shock that increase $p_{i,ag}$ in 10%, all else constant, moves $p_{i,food}$ by $1.1 \times \beta_{ag}$. Thus, β_{ag} scales the shock and the magnitude of the food price change. But notice that β_{ag} arises from a decomposition on marginal cost (thus, the supply side of the firm), not on the value-added of the farm sector to the food dollar. In other words, β_{ag} can be relatively large compared to share of farm value on the food dollar if the marginal cost structure puts enough weight on agricultural prices. While both share of farm value on food prices and β_{ag} are related through technology, market structure, and the depth of the supply chain, they are also not the same object and should not be discussed the same way.

Figure B1: USDA Food Dollar for Food at Home and Bakery Goods, 2017.



C USDA crop calendar

Figure C1: Crop Calendar



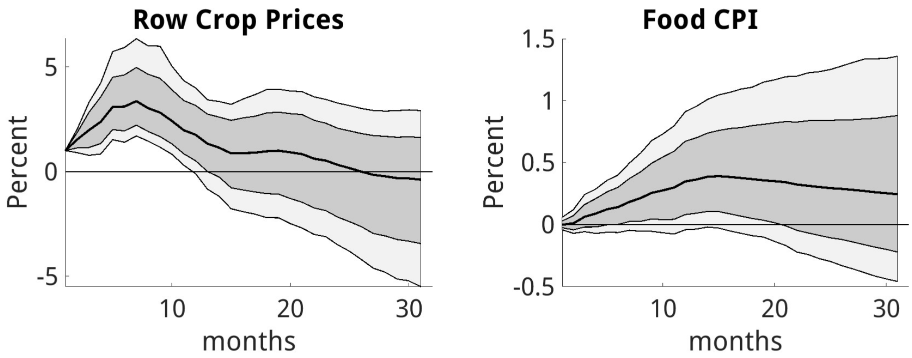
D Instrument Strength and Robustness Checks

We test for weak correlation between instruments and our endogenous variables across different regressions using the F-statistic calculated from block bootstraps as described in the appendix of Lusompa (2023). We use 5001 draws in all models. Overall, table D1 shows that instruments are generally strong for regressions where the endogenous variable is a price index for row crops and for wheat prices. Instruments for soybean prices are weak.

Table D1: F-statistics under different block sizes and models

Model	Block size 1	Block size 3	Block size 5
Main Crops, no trend	16.81	12.51	13.58
Main Crops, linear trend	16.97	13.28	13.74
Main Crops, 2nd-order polynomial trend	17.65	14.11	16.10
Main Crops, 2nd-order polynomial trend, control for RFS.	21.50	20.04	12.73
Main Crops, 2nd-order polynomial trend, futures incl.	9.66	9.62	8.35
Wheat on Bakery, no trend	15.54	14.01	12.39
Wheat on Bakery, linear trend	15.37	14.19	12.18
Wheat on Bakery, 2nd-order polynomial trend	17.26	14.87	13.11
Wheat on Bakery, 2nd-order polynomial trend, futures incl.	18.48	17.53	14.43
Wheat on Bakery, 2nd-order polynomial trend, control for RFS.	17.16	15.61	17.40
Soybeans on Fat and Oils, no trend	1.73	3.04	1.17
Soybeans on Fat and Oils, linear trend	4.24	3.77	4.50
Soybeans on Fat and Oils, 2nd-order polynomial trend	3.71	3.42	3.98
Soybeans on Fat and Oils, 2nd-order polynomial trend, futures incl.	3.61	3.04	4.30
Soybeans on Fat and Oils, 2nd-order polynomial trend, control for RFS.	3.87	3.51	3.99

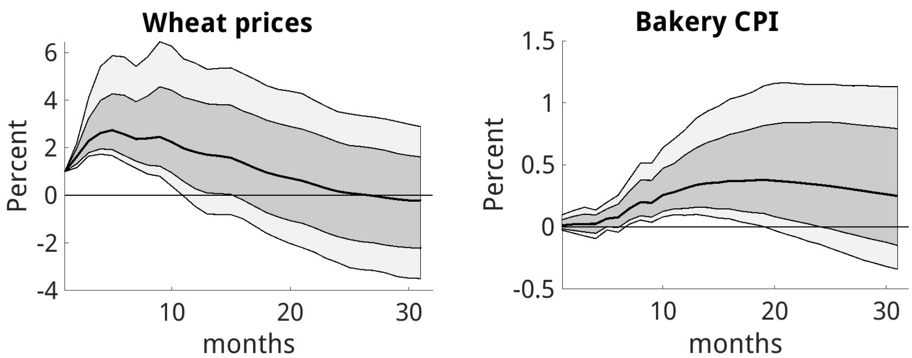
Linear trend: For this exercise, we check the robustness of our results by detrending data used in the SVAR using a linear time trend. Overall, the impulse response functions show identical patterns as our main results, as shown in figures D1, D2, and D3.



(a) Main row crop prices (b) Food CPI

Figure D1: Impulse response function of a 1% increase in row crop prices.

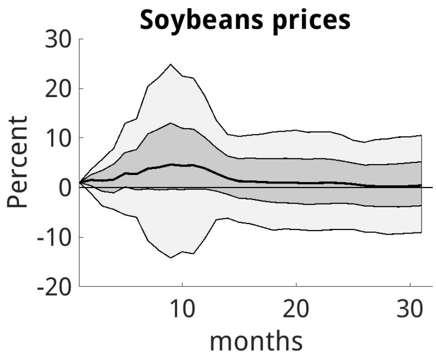
Note: Impulse response functions estimated with log-log specification and production of main crops under D2-D4 drought as instrument. Dark grey area represent 68% confidence interval, and light grey area represents the 95% confidence interval.



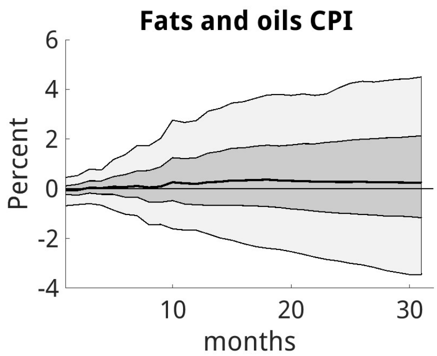
(a) Wheat prices (b) Bakery CPI

Figure D2: Impulse response function of a 1% increase in wheat prices.

Note: Impulse response functions estimated with log-log specification and production of wheat under D2-D4 drought as instrument. Dark grey area represent 68% confidence interval, and light grey area represents the 95% confidence interval.



(a) Soybean prices

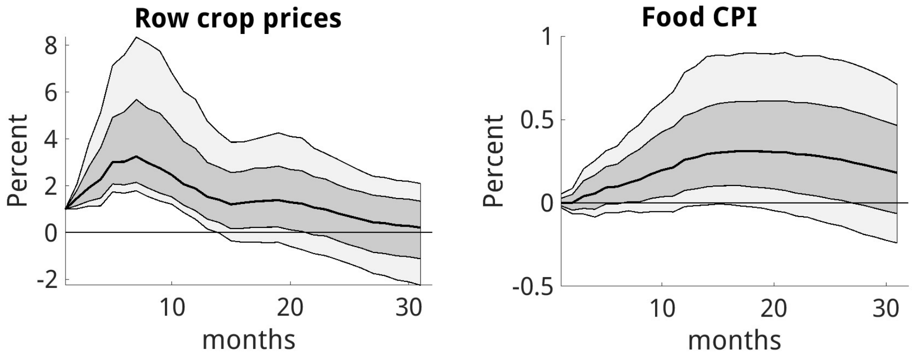


(b) Fat and Oils CPI

Figure D3: Impulse response function of a 1% increase in wheat prices.

Note: Impulse response functions estimated with log-log specification and production of soybeans crops under D0-D4 drought as instrument. Dark grey area represent 68% confidence interval, and light grey area represents the 95% confidence interval.

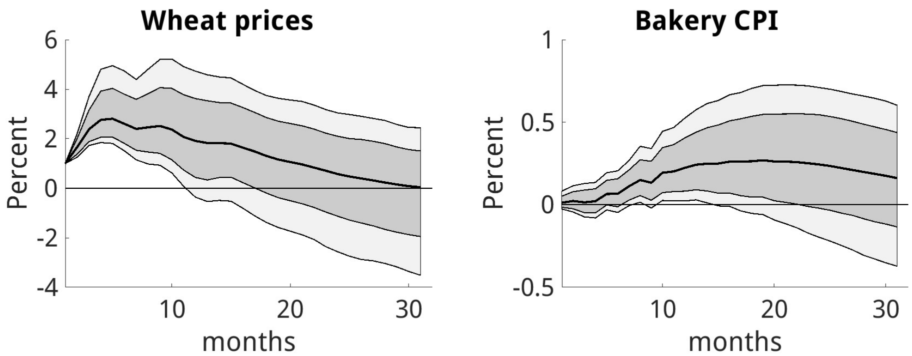
Control for period after Renewable Fuel Standard: We control for the post-2007 period that marks the expansion of the Renewable Fuel Standard. We residualize all price series after 2007 using a post-2007 dummy. We do so to account for the the different price regime that was established after the introduction of the program, particularly for corn (Lark et al., 2022). We find no difference from the main results, as we can see from figures D4, D5, and D6.



(a) Main row crop prices (b) Food CPI

Figure D4: Impulse response function of a 1% increase in row crop prices.

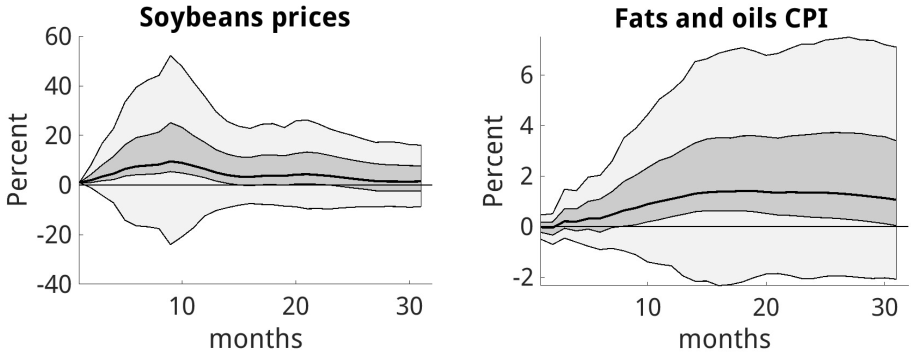
Note: Impulse response functions estimated with log-log specification and production of main crops under D2-D4 drought as instrument. Dark grey area represent 68% confidence interval, and light grey area represents the 95% confidence interval.



(a) Wheat prices (b) Bakery CPI

Figure D5: Impulse response function of a 1% increase in wheat prices.

Note: Impulse response functions estimated with log-log specification and production of wheat under D2-D4 drought as instrument. Dark grey area represent 68% confidence interval, and light grey area represents the 95% confidence interval.

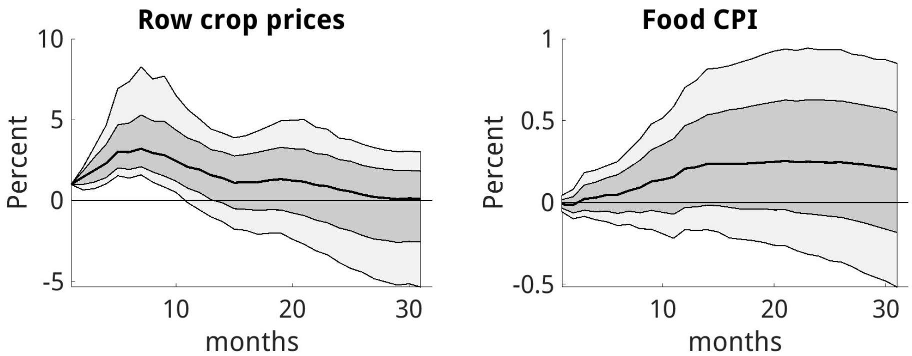


(a) Soybean prices (b) Fat and Oils CPI

Figure D6: Impulse response function of a 1% increase in wheat prices.

Note: Impulse response functions estimated with log-log specification and production of soybeans crops under D0-D4 drought as instrument. Dark grey area represent 68% confidence interval, and light grey area represents the 95% confidence interval.

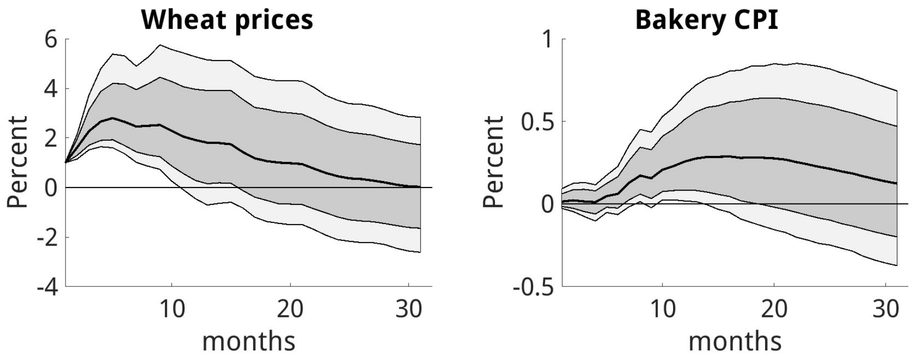
Inclusion of futures prices: We included futures prices in the SVAR as a way to account for expectations directly. We use the first expiring contract for corn, soybeans, rice, and wheat, and aggregate futures prices by planted area, similarly to the aggregation of spot prices described in the main text. Results remain qualitatively similar.



(a) Main row crop prices (b) Food CPI

Figure D7: Impulse response function of a 1% increase in row crop prices.

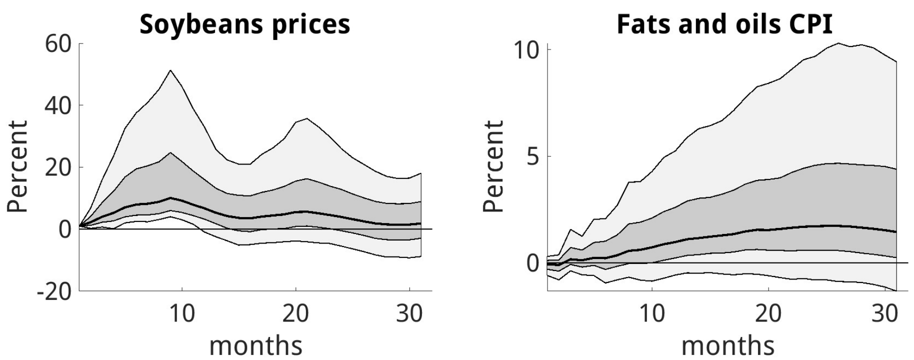
Note: Impulse response functions estimated with log-log specification and production of main crops under D2-D4 drought as instrument. Dark grey area represent 68% confidence interval, and light grey area represents the 95% confidence interval.



(a) Wheat prices (b) Bakery CPI

Figure D8: Impulse response function of a 1% increase in wheat prices.

Note: Impulse response functions estimated with log-log specification and production of main crops under D2-D4 drought as instrument. Dark grey area represent 68% confidence interval, and light grey area represents the 95% confidence interval.



(a) Soybean prices (b) Fat and Oils CPI

Figure D9: Impulse response function of a 1% increase in wheat prices.

Note: Impulse response functions estimated with log-log specification and production of main crops under D2-D4 drought as instrument. Dark grey area represent 68% confidence interval, and light grey area represents the 95% confidence interval.