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 extension of agricultural price passthroughs to food prices in the United States after 2008. 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 weather instruments that shift supply of farm production but are excluded from demand. Our results suggest that understanding food inflation can benefit from focusing on factors affecting downstream segments of the supply chain.

JEL Codes: Q10, E31

Keywords: food inflation, passthrough, agricultural prices

1 Introduction

This paper measures the passthough of changes in agricultural commodity prices to food inflation in the United States. 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). Core inflation, which excludes food and energy components, remains an important tool for interpreting movements in headline inflation, as it helps policymakers assess underlying trends and forecast future headline inflation (Powell, 2024; Waller, 2024).

The modern literature recognizes that food inflation is the result of multiple forces, not merely weather shocks, and these other factors may weigh more heavily on food inflation. Changes in food prices are the outcome of shocks on supply, demand, and market structure (Tegene, 2009).[1] Supply shocks historically rationalize much of the food price movement in the United States, although large movements in demand have become more important post-pandemic (Adjemian et al., 2023). On the supply side, estimates of the passthrough from agricultural inputs to the retail prices can vary widely depending on the methods and time frame used. Leibtag (2009) shows farm to food retail passthoughs of between 2-18% in a semi-structural 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). 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

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[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.

and Kilian, 2014), but global shocks in commodity production tend to impact macroeconomic variables in non-food producing areas (Peersman, 2022). In general, however, papers that try to quantify the extent of these passthroughs use strong assumptions on the timing of the shocks on commodity prices, which are regarded as unrealistic (Ramey, 2016; Stock and Watson, 2018; Nakamura and Steinsson, 2018).

The literature has been mixed on the extent of the passthrough from agricultural price shocks to food prices, and this lack of consensus hinders our ability to understand the dynamics of food inflation. It is well understood that agricultural commodities make up a small fraction of food costs (USDA, 2024b). 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. Policymakers interested in curbing food inflation need to be armed with evidence that shows how different parts of the supply chain impact the *general* price of food under modern supply chains. In this paper, we offer a clear identification strategy to evaluate passthrough from farm prices to food retail prices in the United States.

Our paper uses external instruments in a SVAR-IV to identify the extent of the passthrough of changes in agricultural prices to food prices. Similar to Dice and Rodziewicz (2020) and Rodziewicz et al. (2023), we construct commodity-specific drought shocks that would impact food inflation only through changes in agricultural commodity prices. We use simple models derived from first principles to justify the necessity of instrumental variables. 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 justify the use of row crops for our analysis on the fact that row crops represent most of the caloric content of the food supply chain and are used widely as feed grains for livestock production (Roberts and Schlenker, 2013; USDA, 2024a). We also estimate the 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 CPI. 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 the prices of row crops in the United States leads to a small,

but generally imprecisely-estimated, increase in food-at-home prices. Shocks in agricultural prices, then, are unlikely to lead to significant increases in food prices in the United States. Furthermore, 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. In general, our results reinforce the previous literature that argues that the low cost share of agricultural goods on food inherently limits the passthrough of agricultural price shocks. However, our study contradicts previous evidence and case studies that point to high and statistically significant effects of changes in commodity prices on food inflation. On the contrary, we do not find strong evidence that increases in row crop prices lead to systematic higher food prices at retailers.

Our analysis on commodity price passthrough to food inflation provides important evidence that agriculture commodity prices may have a limited impact on food inflation, particularly in complex food supply chains or with heavily processed foods. 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, and rents for storefronts 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 the factors underpinning U.S. food inflation.

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 the limited passthrough from agriculture commodity prices to U.S. food inflation. Section 5 concludes.

2 Theoretical Decomposition of Food Inflation

We use first principles to argue for the necessity of an external instrumental variable 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. We also show that a model of dynamic firm-level pricing deepens the argument.

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 $\{a_j^r\}$ to maximize profit equation 2 (for a similar setup, see Magnolfi et al. 2022), where p^r refers to prices, and q to quantity. Notice that this framework applies to firms different modes of competition (which would be translated into different values for markups, see Villas-Boas (2007) for examples), 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 $\sum_j \frac{\partial p_k gt}{\partial a_j gt} q_j + \sum_j (p_{jgt}^r - c_{jgt}^r)\frac{\partial q_{kgt}}{\partial a_{jgt}^r} = 0$ 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, 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:

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

where p^{r*} is equilibrium retailer prices, μ^r 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_{jgt}^{dist}, and wholesale prices, p_{jgt}^{w*} (Villas-Boas, 2007; Magnolfi et al., 2022). This leads to equation 4:

$$p_{jgt}^{r*} = \mu_{jgt}^r + c_{jt}^{dist} + p_{jgt}^{w*}, \tag{4}$$

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 $p_{jgt}^{w*} = \mu_{jgt}^w + c_{jgt}^w$.[2] We arrive at equation 12 by taking $c_{jgt}^w = c_{jgt}^{proc.} + p_{jt}^{farm}$:

$$p_{jgt}^{r*} = \mu_{jgt} + c_{jgt}^{dist} + \mu_{jgt}^w + c_{jgt}^{proc.} + p_{jt}^{farm}. \tag{5}$$

Equation 12 is the solution of a linear pricing strategy across the supply chain, where firms do not establish a vertical relationship,[3] 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 12), and across markets (which now suppresses index g).[4] Finally, one can weight (under some weight ω) and aggregate prices of food production a basket of consumption to form an index of food prices, as in equation 6:

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[2]One example of such behavior is when wholesalers choose action a_{jgt}^w knowing that retailer's action a_{jgt}^r is a function of a_{jgt}^w. The objective function of the wholesaler, then, becomes $p_{jgt}^w(a_{jgt}^w) - c_{jgt}^w)q_j(a_{jgt}^r(a_{jgt}^w))$

[3]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 12. 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.

[4]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 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.

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

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 strucutre of all these markets), marginal costs, and farm prices. A dynamic model shows that these measures are necessary, but not sufficient for the decomposition.

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 to purchase (x_t), and how much to consume (q_t) . Household budget for food (Z_J)[5] constraints household expenditures on the set of products available J. Food not consumed in period t builds inventory (I) for next period.

The complete solution of the household problem is not important for our argument and the full problem is in appendix A for the interested reader. What matters for our argument is that

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[5]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.

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.[6] Following the textbook models of sticky prices (e.g., Bils and Klenow, 2004; Cabral and Fishman, 2012; Galí, 2015), retailers set current prices p_{jt}^r 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_j^τ. The retailer problem, then, is given by equation 8 which states that firms maximize profits at time t for $t + \tau$ periods ahead, subject to quantity offered equals quantity demanded.

$$\max_{\{p_{jgt}^r\}} \quad \sum_{\tau=0}^{T} E_t \Big[\beta^\tau \sum_j^J \theta_j^\tau \Big(\big(p_{jgt}^r - c_{jgt+\tau|t}^r \big) y_{jgt+\tau|t} \Big) \Big] \tag{8}$$

$$\text{s.t.} \quad \mathbf{y_{gt+\tau|t}} = \mathbf{x_{gt+\tau|t}}(\mathbf{H_{gt+\tau|t}}),$$

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

$$\sum_{\tau=0}^{T} E_t \Big[\beta \theta_j^\tau \Big[x_{jgt+\tau|t} + (p_{jgt}^r - c_{jgt+\tau|t}^r) \frac{\partial x_{jgt+\tau|t}}{\partial p_{jgt}^r} \Big] + \sum_{k \neq j} \beta \theta_k^\tau (p_{kgt}^r - c_{kgt+\tau|t}^r) \frac{\partial x_{kgt+\tau|t}}{\partial p_{jgt}^r} \Big] = 0.$$

Under the assumption that $\frac{\partial x_{jgt+\tau|t}}{\partial p_{jgt}}$ and θ_j^τ is constant over $t + \tau$, one can stack the FOCs and solve for prices to obtain a closed-form solution as in equation 9.

$$\sum_{\tau=0}^{T} E_t[\beta_t(\mathbf{p_t^r} - \mathbf{c_{t+\tau|t}^r})] = \tilde{\mu}^{\mathbf{r}} = -\Big(\theta^\tau \odot \mathbf{\Omega^r} \odot \frac{\partial \mathbf{x_{t+\tau|t}}}{\partial \mathbf{p_t}} \Big)^{-1} \sum_{\tau}^{T} E_t \beta_t (\theta^\tau \odot \mathbf{x_{t+\tau|t}}), \tag{9}$$

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

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[6]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).

matrix of own- and cross-price elasticities.[7] Equation 9 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., $\mathbf{c}^{\mathbf{r}}_{\mathbf{gt}+\tau|\mathbf{t}} = \mathbf{c}^{\mathbf{dist}}_{\mathbf{gt}+\tau|\mathbf{t}} + \mathbf{p}^{\mathbf{w}}_{\mathbf{t}+\tau|\mathbf{t}}$. 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 10:

$$\max_{\{p^w_{gjt}\}} \quad \sum_{\tau=0}^{T} E_t\Big[\beta^\tau \sum_{j}^{J_f} \theta_j^\tau \Big(\big(p^w_{jgt} - c^{proc.}_{jgt+\tau|t} - p^{farm}_{jt+\tau|t}\big) x_{jgt+\tau|t}(\mathbf{H}_{\mathbf{gt}+\tau|\mathbf{t}}(p^w_{jgt})) \Big) \Big] \qquad (10)$$

By symmetry to the retailers' problem, processor choose wholesale prices to maximize their profits, and expected markup can be found under equation 11 for constant demand elasticities over time.

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

(11)

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 9, 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 12 represents the optimal solution for product j prices in retailer g, for time t in the dynamic model:

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[7]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.

$$p_{jgt}^{r*} = \tilde{\mu}_{jgt+\tau|t}^{r} + \tilde{c}_{jgt+\tau|t}^{dist} + \tilde{\mu}_{jgt+\tau|t}^{w} + \tilde{c}_{jgt+\tau|t}^{proc.} + \tilde{p}_{jt+\tau|t}^{farm}. \tag{12}$$

We aggregate across retailers, markets, and products (over some stable weight ω_j) to obtain the price level of food as in equation 13. 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.

$$p_{food}^{r*} = \sum_j (\omega_j \tilde{\mu}^r{}_j + \omega_j \tilde{c}_{jt}^{dist} + \omega_j \tilde{\mu}^w{}_{jt} + \omega_j \tilde{c}_{jt}^{proc.} + \omega_j \tilde{p}_{jt}^{farm}), \tag{13}$$

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.[8]

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

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[8]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.

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:

$$
\begin{aligned}
p_t^{farm} &= f(S_t^{farm,US}, q_t^{end-user}, S_t^{farm,ROW}, q^{ROW}, q^{energy}, \{p_{t-h}^{farm}\}) \\
c_t^{proc.} &= f(L^{upstream}, T_t^{upstream}, \{c_{t-h}^{proc}\}) \\
\mu_t^w &= f(\Omega^w, q^{end-user}, \{\mu_{t-h}^w\}) \\
c_t^{dist.} &= f(L^{downstream}, T_t^{downstream}, \{c_{t-h}^{dist}\}) \\
\mu_t^r &= f(\Omega^r, q^{end-user}, \{\mu_{t-h}^r\}) \\
p_t^{food} &= f(p_t^{farm}, c_t^{proc.}, \mu_t^w, c_t^{dist.}, \mu_t^r, \{p_{t-h}^{food}\}).
\end{aligned}
\tag{14}
$$

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}. 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. Thus, 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 14. 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, and particularly the chain for food at home, is more concentrated downstream (i.e., fewer retailers), more vertically coordinated across the chain, and more focused on packed and frozen products (USDA, 2024d,e). We are particularly interested in how modern food supply chains absorb these shocks. With these trends in mind, we discuss the data, sample, and the identification strategy.

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 United States. These commodities 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, 2024c).

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.[9]

SVAR-IV To estimate the passthrough of changes in agricultural commodity prices to food inflation, 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 Lusompa (2023). This methodology is robust to 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 2008 to 2023. We chose this span of time to match the period when data on the instrument is available, the period post Great Financial Crisis, and the period with two run ups in agricultural commodity prices– the periods of 2013 and 2021. We discuss the instrumental variable next.

External Instrument A valid instrument must be correlated with agricultural shifts 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. It also should not be anticipated by agents.

We use agricultural commodity-specific exposure to extreme drought during planting, plant development, and harvesting as our instrumental variable. The instrument measures the share of production of a given agricultural commodity (e.g., corn, soybeans, wheat) under drought in a given month. The U.S. Drought Monitor (USDM) (USDM, 2024) offers this measure for several agricultural products and across drought intensities. Drought intensities
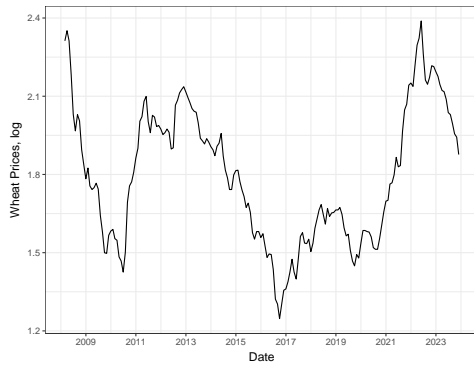
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[9]We show data as deviation from trend. We did not find evidence that commodity prices needed to be seasonally adjusted, but CPI data is seasonally adjusted by the BLS.
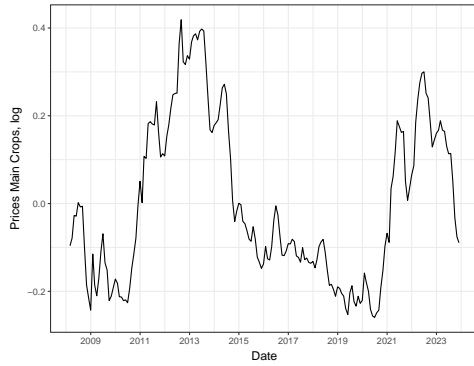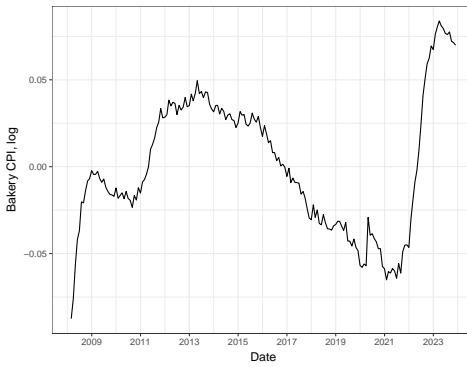
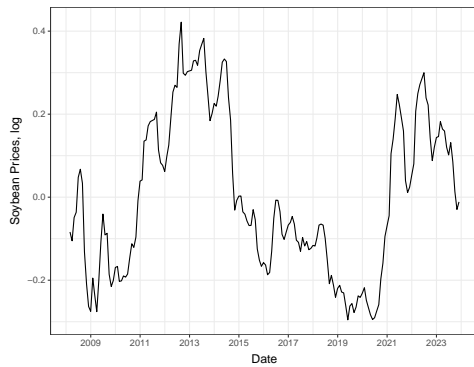(a) Prices row crops, index
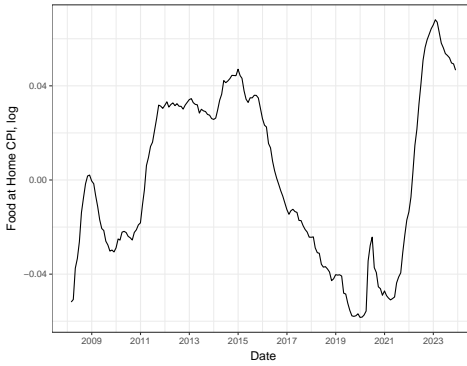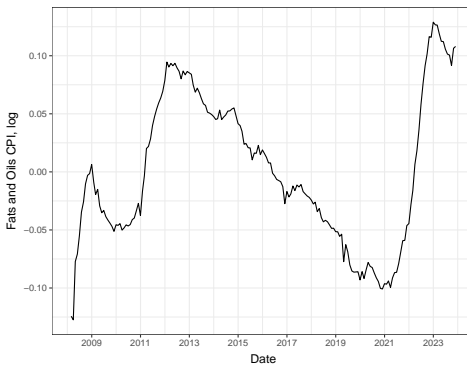
(b) Food at home CPI, index

(c) Wheat prices, dollars per bushel

(d) Bakery CPI, index

(e) Soybean Prices, dollars per bushel

(f) Fat and oils CPI, index

Figure 1: Agricultural commodity and food prices, deviation from trend

vary from mild to extreme levels, classified from $D0$ (abnormally dry) to $D5$ (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).[10] 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 national cash receipts (γ) to aggregate across crops. Formally, our instrument is given by equation 15.
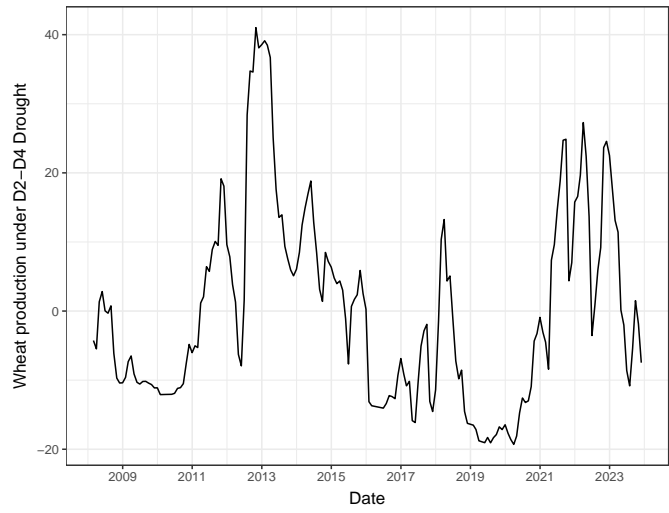
$$D_t = \sum_{c \in C} \left(1_{c,t \in T_c} \times \gamma_{c,year} \times \text{Share in Drought}_{ct} \right), \qquad (15)$$

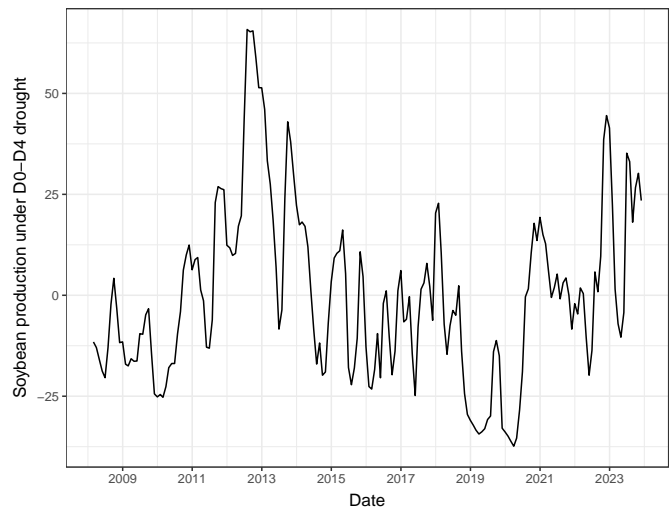Figure 2 shows the instrument for 3 sets of crops we use in this study.

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[10]Appendix B provides a full picture of this calendar for the crops we use in this study.
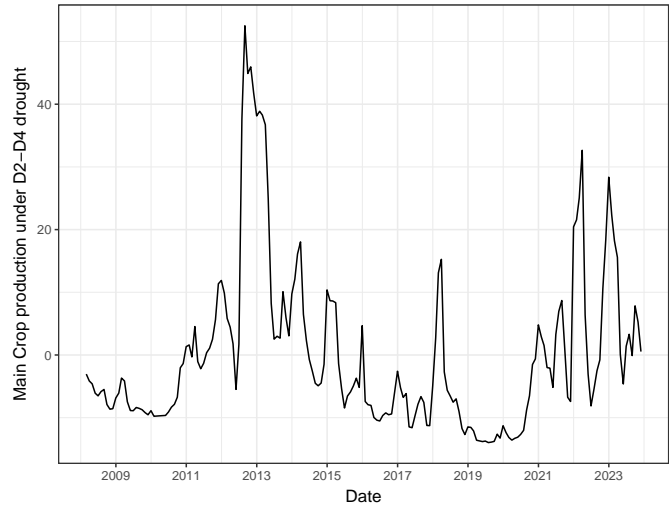
(a) Row crops

(b) Wheat

(c) Soybeans

Figure 2: Agricultural production under drought, deviation from trend

We claim that our instrument impacts food prices only through shifts in the structural shock for the supply of crops, which is 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. 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 may be persistent, so we include lags of the drought instrument to control for drought persistence. Finally, if expected prices differ from spot prices only through future i.i.d. shocks that cannot be predicted, the drought instrument is valid.

Drought shifts the farm supply structural shock down, and increases crop prices. Our instrument specifically targets area of production of specific commodities. These drought measures likely do not shift national preferences or spending for food. It is also unlikely these drought significant 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. While extensive periods of drought around major rivers (e.g., Mississippi river) can disrupt transportation through decline in rivers' depths, variation in our *commodity-specific* drought would have to systematically constrain transportation capacity to increase marginal costs nationally; 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 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 US supply and demand for several row crops. We project the measure of stocks (i.e., excess supply) to 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% increase in the production of wheat under drought is associated with a 0.26% decline in the stock-to-use ratio of wheat. A similar increase in soybeans production under drought is associated with a reduction in stocks-to-use ratio of oilseeds by 0.15%. 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 0.20%, of oilseeds of 0.12%, and total grains of 0.06%. These correlations have the expected sign as more drought associates with lower end stocks relative to demand.

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

	Wheat	Soybeans	Corn	Wheat	Soybeans	Corn
Drought Wheat (% production)	**−0.261**					
	(0.083)					
Drought Wheat (% production), 1 lag	0.051					
	(0.099)					
Drought Soybeans (% production)		**−0.155**				
		(0.052)				
Drought Soybean(% production), 1 lag		−0.012				
		(0.031)				
Drought Corn (% production)			−0.027			
			(0.029)			
Drought Corn (% production), 1 lag			**−0.058**			
			(0.020)			
Drought Row Crops (% production)				**−0.204**	**−0.120**	−0.014
				(0.060)	(0.052)	(0.024)
Drought Row Crops (% production), 1 lag				−0.011	−0.044	**−0.062**
				(0.054)	(0.042)	(0.020)

Notes: Bold numbers refer to 5% significant level. 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 systems of equations to assess the passthrough of agricultural commodity prices to food inflation. The first system includes the index of crop prices and food-at-home CPI, and 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 system of equations includes wheat prices and bakery CPI, and wheat under D2-D4 drought. The third system of equation includes soybean prices, fats and oils CPI, and the share of soybean production under D0-D4 drought. 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 8.6, and appendix C shows that this F-statistic drops to 7.5 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.
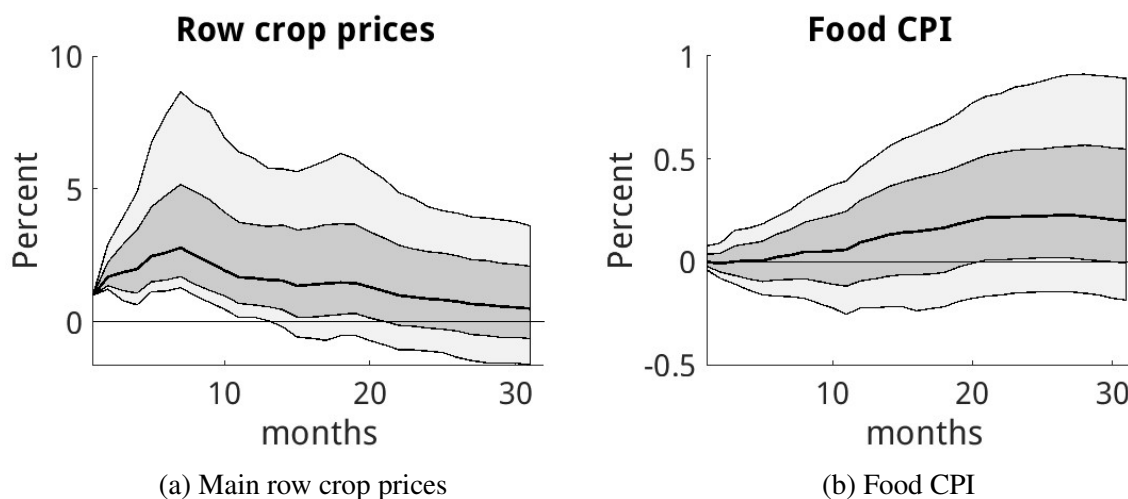
(a) Main row crop prices
(b) Food CPI

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 estimation with bootstrap F-statistic for this system around 16.8. A 1% shock on 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. Interestingly, the passthrough of wheat prices to bakery CPI is qualitatively similar to the passthough of row crop prices to food at home CPI, even though the instruments for wheat prices are much stronger.
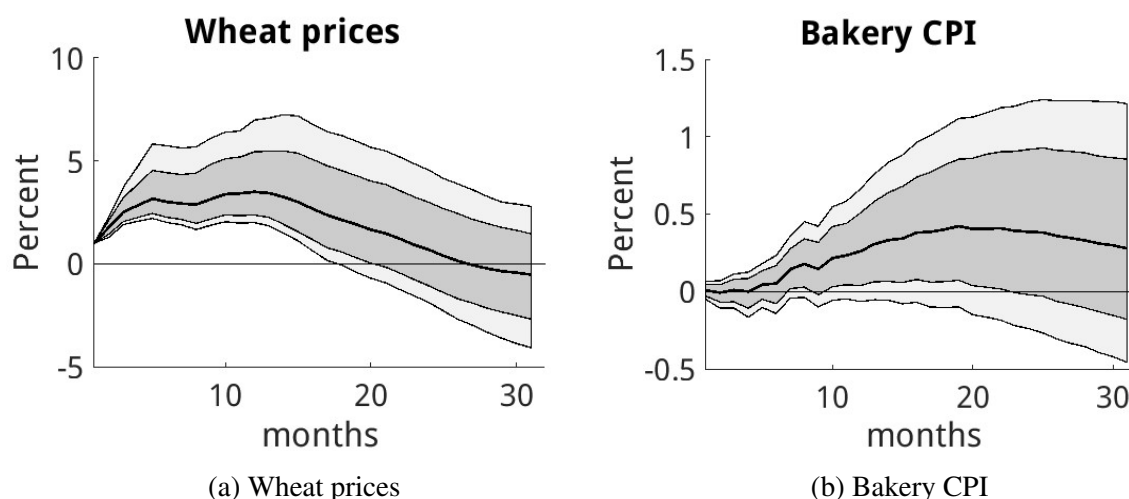
| (a) Wheat prices | (b) Bakery CPI |

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 produce similar patterns of the passthrough calculated for 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 5.5. 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.

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 goods in food prices 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.

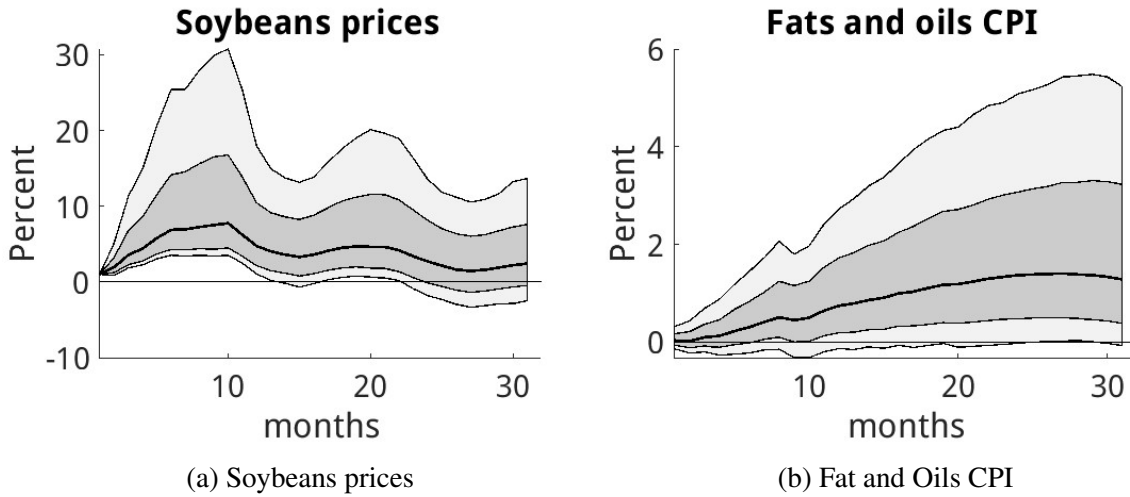(a) Soybeans prices   (b) Fat and Oils CPI

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.

5   Conclusion

Food is an important basic need, and food prices have historically been linked to agricultural commodity prices. This paper evaluates the passthrough of agricultural prices to U.S. food prices after 2008. We find evidence that, despite being a key source of input for foods, agricultural commodities prices have a small and uncertain impact in changes in food prices.

We use external instruments in a SVAR setting to compute passthroughs. Results of simple theoretical models that decompose food prices into markups, marginal costs, and farm prices along the supply chain guide our empirical strategy. We argue that structural shocks related to U.S. food demand shifts markups and farm prices. Since markups are unobserved in our setting, we require an instrument that shifts farm prices only. We use crop-specific drought variations that shift farm production structural shocks to compute three measures of passthroughs: row crop prices to food CPI, wheat prices to bakery CPI, and soybean prices to oils and fats CPI.

We find that passthroughs are positive but imprecisely estimated, regardless of the instrument strength in our empirical setting. Our results suggest that addressing food inflation can benefit from a closer examination of costs and markups downstream in the food supply chain.

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A Dynamic model

We describe a model of consumer demand that allows for intertemporal choice of food products by consumers. 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 16, where e refers to food products that get spoiled.
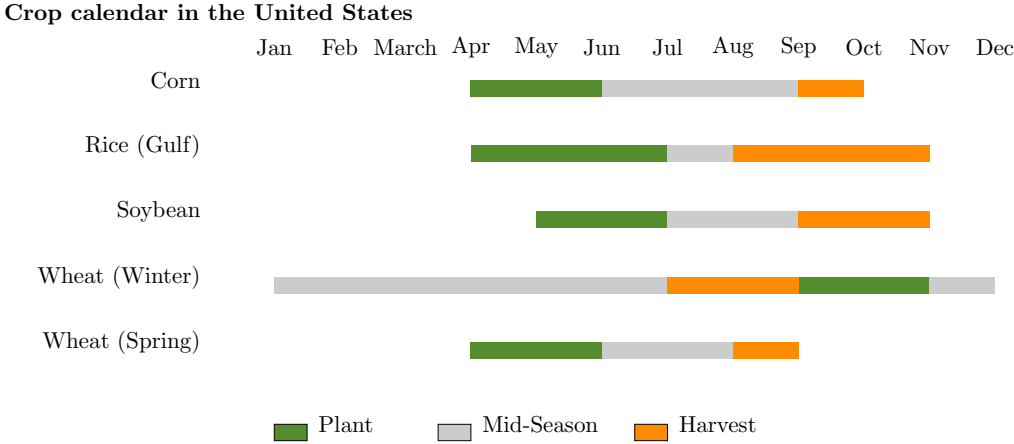
$$
\max_{\{\mathbf{q_t}\},\{\mathbf{x_t}\}} \quad E_t \sum_t^T \left(u(\mathbf{q_t}) - C\Big(\sum_j^J I_{jt}\Big) \right)
$$

$$
\text{s.t.} \quad \sum_j^J p_{jt} x_{jt} \leq Z_{Jt}, \tag{16}
$$

$$
\sum_j^J I_{jt} = \sum_j^J I_{jt} + \sum_j^J (x_{jt} - q_{jt} - e_{jt}),
$$

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.

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[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.

B   USDA crop calendar

Figure A1: Crop Calendar

Crop calendar in the United States

	Jan	Feb	March	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec

Corn

Rice (Gulf)

Soybean

Wheat (Winter)

Wheat (Spring)

■ Plant   ■ Mid-Season   ■ Harvest

C   F-stats other products

Table A1: F-stats

Model	Block size 1	Block size 3
Main Crops, no trend	8.58	4.20
Main Crops, linear	7.38	6.92
Main Crops, 2nd order polynomial trend	8.59	7.46
Wheat on Bakery, no trend	16.01	15.04
Wheat on Bakery, linear trend	15.50	14.29
Wheat on Bakery, 2nd-order polynomial trend	16.78	14.73
Soybeans on Fat and Oils, no trend	4.26	4.92
Soybeans on Fat and Oils, linear	4.34	5.02
Soybeans on Fat and Oils, 2nd-order polynomial trend	5.32	5.48

F-statistics calculated from block bootstrap with 5001 draws as described in Lusompa (2023).