Pass-Through in Levels and the Incidence of Commodity Shocks

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Abstract

Empirical studies find that the pass-through of commodity price movements to downstream prices is incomplete: a 10 percent increase in upstream costs causes downstream prices to rise less than 10 percent, even at long horizons. Using microdata from gasoline and food products, we find that incomplete pass-through in percentages often disguises *complete pass-through in levels*: a $1/unit increase in commodity costs leads to $1/unit higher downstream prices. Pass-through appears incomplete in percentages due to a gap between prices and costs. This pass-through behavior, as well as other evidence on firm gross margins, operating margins, and entry rates, contrasts with workhorse models that feature fixed, multiplicative markups. An implication of complete pass-through in levels is that rising commodity costs lead to higher inflation rates for low-margin products in a category, though absolute price changes are similar across products. This generates cyclical inflation inequality. From 2020–2023, we estimate that this pass-through behavior is responsible for two-thirds of the gap in food-at-home inflation rates experienced by low- and high-income households.

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1 Introduction

Empirical work in macroeconomics and trade typically measures the pass-through of upstream cost changes to downstream prices in percentages. A large body of work studying the pass-through of commodity price movements in this way finds evidence of *incomplete pass-through*: when commodity prices increase 10 percent, downstream prices rise less than 10 percent (e.g., Peltzman 2000; Kim and Cotterill 2008; Leibtag 2009; Nakamura and Zerom 2010; Hong and Li 2017). Pass-through remains incomplete even at long horizons and after accounting for the cost share of commodity inputs.

In this paper, we instead measure the pass-through of commodity costs to downstream prices on an absolute (dollars-and-cents) basis. To do so, we study a set of markets, including retail gasoline and several food products, where the amount of the commodity input required to produce downstream goods can be measured precisely. We measure, for example, how much retail gas stations increase prices to customers when wholesale gasoline prices increase 10 cents per gallon.

In nearly all cases, we find that firms exhibit *complete pass-through in levels*. That is, a \$1/unit increase in commodity costs leads to a \$1/unit increase in downstream prices. Complete pass-through in levels explains why "log pass-through"—i.e., pass-through measured in percentage terms—appears incomplete: when price is greater than marginal cost, a \$1/unit increase is a smaller percentage change in price than in marginal cost.

Microdata from these markets suggests that complete pass-through in levels not only explains the fact that log pass-through is incomplete, but also explains cross-sectional heterogeneity in log pass-through across firms or products in a market. For example, in response to an increase in costs, products and firms with a larger gap between price and cost exhibit lower log pass-through, but no systematic difference in pass-through in levels.

Complete pass-through in levels contrasts with workhorse models in macroeconomics in which firms set price equal to marginal cost times a fixed percentage markup (e.g., the constant elasticity of substitution model of Dixit and Stiglitz 1977). When firms maintain a fixed multiplicative markup, pass-through in levels should equal the gross markup, a number greater than one. Moreover, firms with higher markups should exhibit larger pass-through in levels. In contrast, our estimates for pass-through in levels are consistently close to one, and pass-through appears uniform across firms with different markups.

Beyond pass-through, evidence from firms' margins and entry also casts doubt on the idea that firms set fixed, multiplicative markups. Multiplicative markups imply that when costs rise, the variable profits that firms earn on each unit sold increase. For example, if gas stations maintain a fixed 5 percent markup, an increase in the wholesale gasoline price from one to two dollars should double the profits earned per gallon sold. If aggregate industry demand is relatively inelastic—as it is for gasoline and the food products studied in this paper—these higher per-unit profits must appear as higher operating profits for existing firms or else be dissipated by the entry of new firms. In the data, we find no such signs that rising commodity costs lead to higher operating profits or entry by new firms. Rather, commodity costs have a strong negative correlation with gross margins (as a percent of sales), consistent with firms passing on input cost changes one-for-one.

One candidate explanation for complete pass-through in levels is perfect competition. If the gap between prices and commodity input costs is fully owed to other variable costs, then prices equal marginal costs, and changes in cost are reflected one-for-one in prices. Yet, we document that perfect competition is at odds with several other features of the data: sluggish price adjustment, price dispersion for identical products, finite firm-level demand elasticities, and substantial evidence of prices elevated over costs. In other words, while the *dynamics* of prices relative to costs resemble perfect competition, price *levels* do not.

Another possible explanation—and the prevailing explanation for incomplete log pass-through—relies on the curvature of demand. Complete pass-through in levels could result if changes in demand elasticity along the demand curve lead firms to adjust their multiplicative markups in a way that happens to coincide with constant unit margins. This is the case if the super-elasticity of demand curves is exactly equal to one (Bulow and Pfleiderer 1983; Weyl and Fabinger 2013; Mrázová and Neary 2017). In fact, logit demand systems used in the industrial organization literature have exactly this property, and yield complete pass-through in levels of aggregate cost shocks under some conditions. One reading of the evidence is that these demand systems better approximate pass-through behavior than the constant-elasticity demand systems used in macro models. Yet, we find that standard calibrations of these models (e.g., Nevo 2001, Nakamura and Zerom 2010) feature a range of super-elasticities and hence generate substantial dispersion in the pass-through of aggregate cost shocks across products in a market.[1] Moreover, direct estimates of the curvature of demand, measured using a technique developed by Burya and Mishra (2023), fall short of the magnitude required to explain pass-through in levels.

We briefly discuss other mechanisms that may explain complete pass-through in levels. Broadly, these explanations fall into four categories: they posit that firms mark up value added, but not intermediate, inputs; they attribute firm market power to consumer search

[1] Logit models without an outside option exhibit complete pass-through in levels of aggregate cost shocks, regardless of product-level super-elasticities. However, since standard calibrations include an outside option, the pass-through of aggregate cost shocks varies systematically with products' super-elasticities of demand, as we show in simulations of these demand systems in Section 6.2.

or transport costs that remain stable as commodity costs fluctuate; they posit that firms face kinked demand curves; or they emphasize heuristics used by firm managers when setting prices. The empirical evidence in this paper may be helpful in disciplining future variants of these models.

Complete pass-through in levels predicts the extent of commodity cost pass-through without requiring a rich model of demand. In the final section of the paper, we consider the implications of this pricing behavior for inflation inequality.

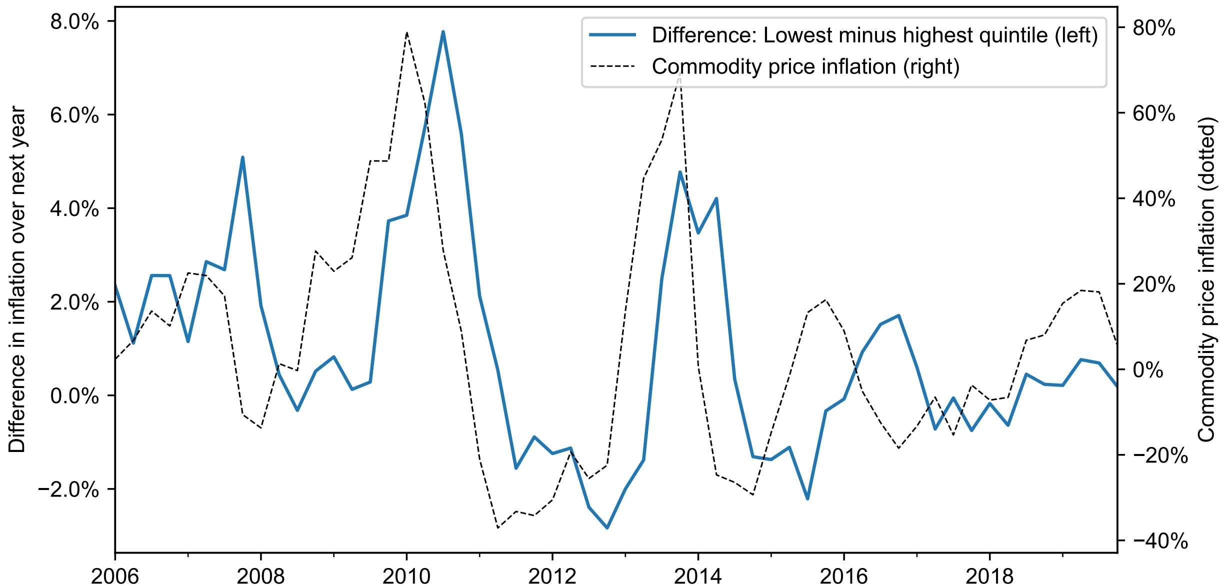
Specifically, we document a new, cyclical component of inflation inequality that arises due to complete pass-through in levels. When commodity costs rise, low-price products within a product category have higher inflation rates than high-price products, even though absolute price changes are similar across products. Since low-income households tend to purchase lower-priced products, rising commodity prices lead to higher inflation rates for low-income households even within narrow product categories. For example, as shown in Figure 1, the gap in coffee inflation rates experienced by low- and high-income households surges when coffee commodity prices are rising and falls, even becoming negative, when commodity prices are falling.

Aggregating over the food-at-home bundle, we find that food-at-home inflation rates for households in the lowest income quintile are both more sensitive to upstream price indices and more volatile than inflation rates for the highest income quintile. These cyclical fluctuations in inflation inequality stem from differences in the goods that households purchase within narrow product categories, and thus are absent in previous work that computes household price indices using basket shares across categories but assumes that households face identical inflation rates within each product category (e.g., Hobijn and Lagakos 2005; Klick and Stockburger 2021; Jaravel 2024).

Applying these estimates to the period from 2020–2023, we predict that prices of the cheapest decile of food-at-home products grew over twice as fast as prices of products in the most expensive decile. This gap emerges without retailers price-gouging a subset of customers or demand increasing disproportionately for bargain products. If upstream costs had not grown over this period, we estimate that the gap in inflation rates between the lowest and highest income quintiles would have been one-third the size.

Related literature. This paper relates to a large literature that studies theoretical and empirical determinants of pass-through (e.g., Bulow and Pfleiderer 1983; Nakamura and Zerom 2010; Weyl and Fabinger 2013; Hong and Li 2017; Minton and Wheaton 2022). We focus on the long-run pass-through of commodity shocks that shift costs for all firms in a market. Thus, we abstract from two topics that have generated large empirical literatures:

Figure 1: Within-category inflation inequality: Differences in coffee inflation for households in lowest vs. highest income quintiles track coffee commodity prices.



(1) asymmetry in the transmission of cost increases *vs.* decreases (e.g., Borenstein et al. 1997; Peltzman 2000; Benzarti et al. 2020) and (2) the pass-through of idiosyncratic shocks that only affect some firms in a market (as in much of the literature on exchange rate pass-through; e.g., Burstein and Gopinath 2014; Amiti et al. 2019). Some studies in this latter literature document patterns of heterogeneity in log pass-through. For example, the log pass-through of idiosyncratic shocks declines with firm size (e.g., Berman et al. 2012; Amiti et al. 2019; Gupta 2020) and with product quality (Chen and Juvenal 2016; Auer et al. 2018). Complete pass-through in levels could generate both patterns if markups increase with size and quality. We caution, however, that the evidence in the present paper concerns the pass-through of aggregate commodity cost shocks; whether firms also exhibit complete pass-through in levels in response to idiosyncratic cost shocks is a question for future work.[2]

While this paper is the first to propose complete pass-through in levels as a pattern spanning several markets, there are previous studies that measure pass-through in levels in specific contexts, especially in the industrial organization literature (see e.g., Dutta et al. 2002 in frozen orange juice concentrate; Fabra and Reguant 2014 in electricity markets; and Conlon and Rao (2020) in distilled spirits, among many others). Especially related

[2]Contemporaneous work by Alvarez et al. (2024) suggests this may be the case. Using data from a non-durables manufacturer, they find that complete pass-through in levels describes the manufacturer's response to both aggregate and idiosyncratic shocks.

is Nakamura and Zerom (2010), who find that retail coffee prices move one-for-one with coffee commodity prices in levels. However, the central exercise in Nakamura and Zerom (2010) seeks to account for incomplete pass-through in logs, attributing incomplete long-run log pass-through to non-commodity input costs and a positive super-elasticity of demand.[3] Studies of gasoline markets also typically measure pass-through in levels rather than in logs (e.g., Karrenbrock 1991; Borenstein et al. 1997; Deltas 2008). However, these studies do not explore why complete pass-through in levels is an appropriate benchmark.[4]

Most closely related to our study of pass-through in levels is Butters et al. (2022), who study how retail stores' prices respond to local cost shocks such as excise tax changes. Consistent with our evidence, Butters et al. (2022) find evidence of complete pass-through in levels of these cost changes. We add to this evidence by showing that complete pass-through in levels is not unique to retail stores, but holds along the chain of producers from commodity to retailer in the studied markets.

Finally, the application to inflation inequality builds on a rich literature exploring differences in inflation across households (e.g., Hobijn and Lagakos 2005; Kaplan and Schulhofer-Wohl 2017; Jaravel 2019, 2021, 2024; Argente and Lee 2021). Our findings point to a new source of inflation inequality that varies with upstream costs. This channel is relevant for understanding why inflation inequality can surge when commodity prices are rising. Since the first version of this paper was released, analyses of online price data by Cavallo and Kryvtsov (2024) and scanner data by Chen et al. (2024) have confirmed this paper's predictions on differential inflation for low-priced products over 2020–2023.

Layout. Section 2 describes the specifications used to measure pass-through in logs and in levels. Section 3 documents patterns of pass-through in retail gasoline, and Section 4 examines pass-through in food product markets. Section 5 compares the predictions of the multiplicative markup model with data on profits, margins, and entry. Section 6 explores explanations for pass-through in levels. Section 7 applies pass-through in levels to the incidence of commodity shocks across income groups, and Section 8 concludes.

[3]In Section 6.2, we simulate the pass-through of aggregate cost shocks in the Nakamura and Zerom (2010) demand system. Due to the presence of an outside option, products exhibit considerable variation in pass-through. The median super-elasticity of demand reported by Nakamura and Zerom (2010) is 4.64; products in the simulation with a comparable super-elasticity exhibit pass-through in levels around 0.7, below the pass-through in levels measured by both Nakamura and Zerom (2010) and the present paper.

[4]Borenstein (1991) notes, "Though standard economic theory indicates that the percentage markup over marginal cost is the correct measure of market power, the industry literature and analysis focuses on the retail/wholesale margin measured in cents." He suggests that this may be because retail gas stations' market power derives from consumers' time cost of visiting other stations, an explanation we return to in Section 6.

2 Framework and Empirical Specification

Pass-through in logs and levels. Consider a firm that produces an output good using a commodity input and other non-commodity inputs. We assume that the firm has a constant returns, Leontief production technology, so that the cost of producing y units of the output good is $C(y)$:[5]

$$C(y) = y(c + w),$$

where c is the price of the commodity input, w is the price of the bundle of non-commodity inputs, and units of each input required to produce one unit of the output good are normalized to one. Table 1 shows an example in which $c = \$1$ and $w = \$1$.

In many models, firms' desired prices p^* are equal to marginal cost times a fixed multiplicative markup, μ:

$$p^* = \mu(c + w). \tag{1}$$

In the example in Table 1, the markup is $\mu = 2$, resulting in an output price of $2(\$1+\$1) = \$4$.

How does an increase in the commodity price, Δc, affect the price set by the firm? Under the multiplicative pricing rule in (1), the change in the firm's desired price is

$$\Delta p^* = \mu \Delta c.$$

Thus, when a firm sets a fixed multiplicative markup over cost, the pass-through in levels of a commodity price change to the firm's desired price is equal to the markup μ. Typically, in markets with imperfect competition, $\mu > 1$, and so the pass-through in levels is greater than one.

Table 1 row (a) shows the pass-through of a \$0.20 increase in the commodity price under a fixed multiplicative markup rule. Since a \$0.20 increase in the commodity price increases marginal costs by 10 percent, the output price also rises by 10 percent, or \$0.40. The pass-through in levels is equal to the markup, $\mu = 2$. The "log pass-through"—i.e., the pass-through measured in percentage terms—is complete if measured with respect to marginal cost (10 percent / 10 percent = 1) or equal to the cost share if measured with respect to the commodity cost (10 percent / 20 percent = 0.5).

Suppose that the firm's desired price instead increases one-for-one with the change

[5]Constant returns, Leontief production seems appropriate for the markets we study: producing an ounce of ground coffee requires a fixed amount of coffee beans. Firms may be able to substitute between variants of the commodity, but as discussed by Nakamura and Zerom (2010) in the case of coffee, prices of variants of a commodity tend to be highly correlated. In Appendix B.2, we consider how pass-through changes if we relax Leontief production, constant returns to scale, or uncorrelated other variable costs. Each requires knife-edge conditions to deliver complete pass-through in levels.

Table 1: Example of pass-through in logs and levels.

	Initial		New	*% Change*	Pass-through Logs	Pass-through Levels
Commodity cost (c)	\$1	+\$0.20	\$1.20	*+20%*		
Other variable costs (w)	\$1	–	\$1.00			
Total marginal cost	\$2	+\$0.20	\$2.20	*+10%*		
Desired output price (p^*)						
(a) Fixed multiplicative markup	\$4	+\$0.40	\$4.40	*+10%*	1.0	2.0
(b) Fixed additive margin	\$4	+\$0.20	\$4.20	*+5%*	0.5	1.0

in the commodity cost. That is, the firm exhibits complete pass-through in levels, and $\Delta p^* = \Delta c$. As shown in row (b) of Table 1, when measured on a percentage basis, the change in the output price now appears incomplete relative to the change in marginal cost (5 percent *vs.* 10 percent). The percent change in the output price relative to the commodity price (5 percent / 20 percent = 0.25) is also incomplete relative to the commodity's initial cost share (0.5). In other words, complete pass-through in levels is disguised as incomplete log pass-through.

Empirical specification. Our empirical strategy aims to measure the pass-through of commodity cost movements to firms' desired prices p^*, both in logs and in levels. Of course, at short horizons, price rigidities may prevent a firm from setting its price p in accordance with its desired price p^*. Hence, we study the pass-through of persistent cost changes at long horizons where price rigidities should be overcome.

We follow the standard approach in measuring the long-run pass-through of cost changes to prices using a distributed lag regression (e.g., Campa and Goldberg 2005, Nakamura and Zerom 2010),

$$\Delta p_t = a + \sum_{k=0}^{K} b_k \Delta c_{t-k} + \epsilon_t, \tag{2}$$

where Δp_t is the change in the output price (in levels) from $t-1$ to t, Δc_{t-k} is the change in the commodity cost (in levels) from $t-k-1$ to $t-k$, and ϵ_t is a mean zero error term. The estimated coefficients b_k measure the change in the output price associated with a change in commodity costs k periods ago. Accordingly, the long-run pass-through of a change in the commodity cost Δc to prices is given by the sum of the coefficients, $\sum_{k=0}^{K} b_k$.

We estimate the long-run "log pass-through" using the analogous specification,

$$\Delta \log p_t = \alpha + \sum_{k=0}^{K} \beta_k \Delta \log c_{t-k} + \epsilon_t, \tag{3}$$

where the long-run log pass-through is $\sum_{k=0}^{K} \beta_k$.

Our use of specifications (2) and (3) is due to the fact that, as in Campa and Goldberg (2005) and Nakamura and Zerom (2010), our regressors are highly persistent. As we show in Appendix Table A1, autocorrelation coefficients for each of the commodity cost series we study are very close to one, and we are unable to reject the hypothesis of a unit root in commodity prices using an Augmented Dickey-Fuller test for all commodity prices except for orange juice solids.[6] While commodity prices are approximately unit root, they appear stationary in first-differences, enabling correct inference in (2).

We also check in Appendix Table A2 that the direction of causality runs from upstream commodity costs to downstream prices and not vice versa, using Granger causality tests. In all cases, we are unable to reject the null that downstream prices do not cause movements in upstream commodity prices.

3 Evidence from Retail Gasoline

Retail gasoline provides an ideal laboratory to study pass-through since there is rich data on firms' upstream costs and gasoline prices exhibit little rigidity. Our main analysis in this section uses data on the universe of retail gas stations in Perth, Australia, though at the end of the section we show that retail gasoline markets in the United States, Canada, and South Korea exhibit similar patterns.

This section documents four patterns. First, estimates of the pass-through in levels from wholesale prices to retail prices are statistically indistinguishable from one. Second, long-run log pass-through is incomplete even relative to the share of gasoline in stations' marginal costs. Third, there is little heterogeneity in pass-through in levels across stations in the sample, but substantial variation in log pass-through: stations with a larger gap between prices and costs have lower log pass-through. Using several instruments designed

[6]When commodity prices are unit root, if firms have fixed multiplicative markups, the long-run pass-through in levels estimated using (2) should approach the markup μ. Appendix Proposition B1 shows formally that in a model with time-dependent pricing frictions, the long-run pass-through $\sum_{k=1}^{K} b_k = \mu$ as K becomes large and the persistence of the commodity cost $\rho \to 1$. Even if commodity prices are not exactly unit root, under reasonable parameters (e.g., firms reset prices every 12 months, and $\rho = 0.96$, which is the minimum autocorrelation in Appendix Table A1), the bias in the measure of μ is small.

to isolate variation in stations' markups from stations' marginal costs, we find that stations with higher markups have lower log pass-through. Fourth, complete pass-through in levels and variation in stations' margins explain both cross-sectional heterogeneity in log pass-through and the overall level of incomplete log pass-through.

3.1 Station-Level Data from Perth, Australia

Station-level retail gasoline price data are from FuelWatch, a Western Australia government program that has monitored retail gasoline prices since January 2001. Alongside the introduction of the FuelWatch program in 2001, the Western Australian government banned intra-day price changes and required all retail gas stations to submit petrol prices by 2pm of the prior day. Since 2003, FuelWatch also provides daily data on the local spot price for wholesale gasoline, called the terminal gas price, across six terminals used by retail stations. Previous studies using these data include Wang (2009a) and Byrne and de Roos (2017, 2019, 2022).

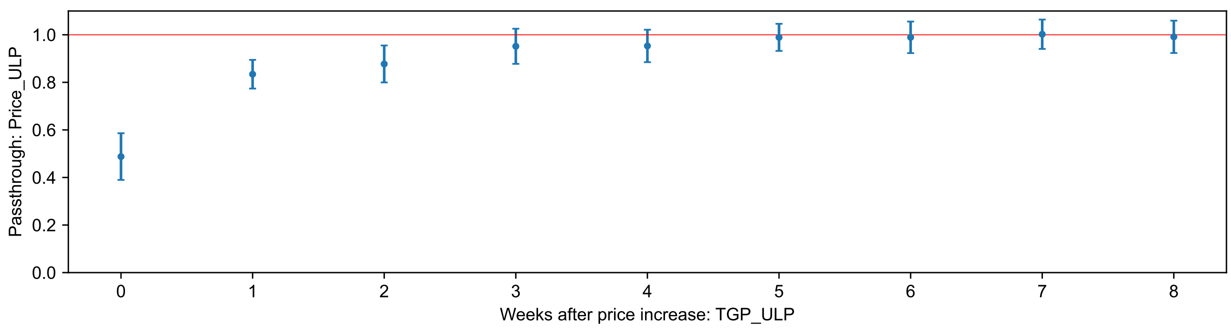
Following Byrne and de Roos (2019), we take the minimum terminal gas price offered by the six terminals each day as the input price for retail gas stations. Appendix Figure A1 shows the weekly average terminal gas price and the retail unleaded petrol (ULP) price for a single gas station from 2001 to 2022. The retail price is slightly above, but closely tracks, the terminal gas price. The gap between retail and wholesale prices visibly increases in 2010. Byrne and de Roos (2019) document that retail gas margins in Perth increased starting in 2010 due to the emergence of tacit collusion across stations, a feature of the market that we exploit later in the analysis.

3.2 Empirical Results

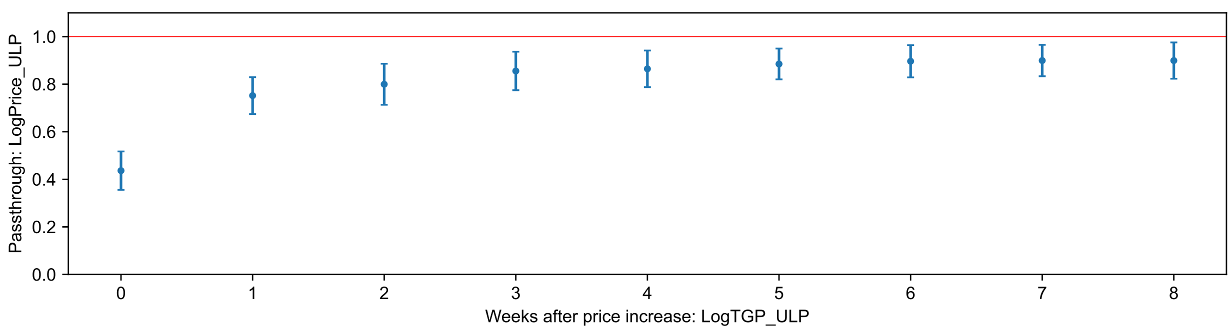
Pass-through is complete in levels and incomplete in logs. Figure 2 shows the estimated pass-through of changes in unleaded petrol (ULP) wholesale prices to station retail prices over a horizon of eight weeks. By three weeks, the pass-through in levels is statistically indistinguishable from one, and the point estimate for long-run pass-through at eight weeks is 0.991 (standard error 0.038). In contrast, the log pass-through at eight weeks is 0.899 (0.043) and is statistically different from one at a 1 percent level. Changing the horizon over which pass-through is estimated has little effect on the estimated long-run pass-throughs in logs and levels.

Estimates of the pass-through of premium unleaded (PULP) wholesale prices to retail prices (Appendix Figure A2) are similar: the long-run pass-through in levels is statistically

Figure 2: Unleaded petrol (ULP) pass-through in levels (top) and in logs (bottom).



(a) Pass-through in levels.



(b) Pass-through in logs.

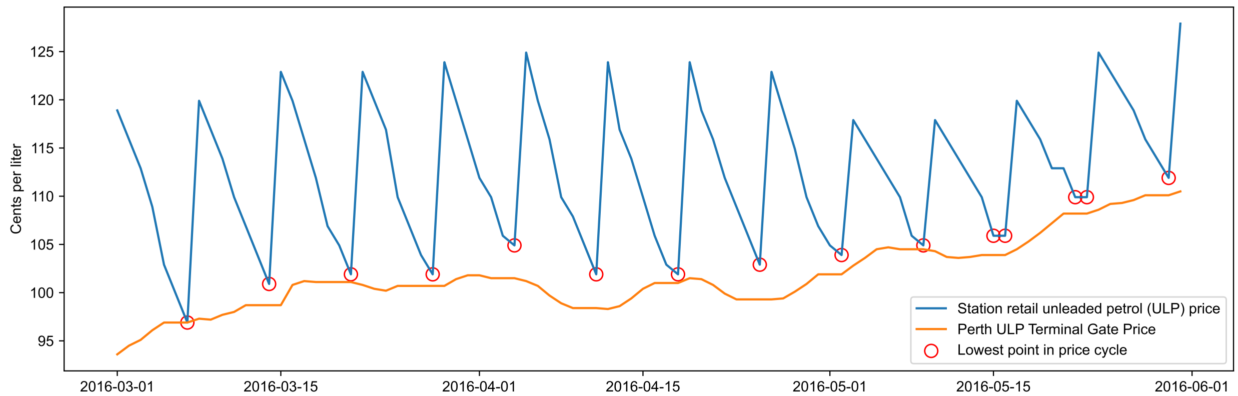
Note: Panels (a) and (b) show cumulative pass-through estimated from the specifications,

$$\Delta p_{i,t} = \sum_{k=0}^{k=8} b_k \Delta c_{i,t-k} + a_i + \varepsilon_{i,t}.$$

$$\Delta \log p_{i,t} = \sum_{k=0}^{k=8} \beta_k \Delta \log c_{i,t-k} + \alpha_i + \varepsilon_{i,t}.$$

Standard errors are two-way clustered by postcode and year, and standard errors for cumulative pass-through coefficients $\sum_{k=0}^{t} b_k$ and $\sum_{k=0}^{t} \beta_k$ are computed using the delta method.

Figure 3: Daily retail unleaded petrol price at a gas station in Kewdale, Perth in 2016, with lowest points in price cycle.



indistinguishable from one at 0.985 (0.036), while the long-run pass-through in logs is significantly below one at 0.887 (0.041).

Log pass-through is incomplete even accounting for cost share. If retail gas stations face other variable costs besides the cost of gasoline, and stations have fixed multiplicative markups, the log pass-through should be equal to the share of stations' marginal costs spent on gasoline. Luckily, the presence of price cycles in this setting allows us to estimate a lower bound for the cost share of gasoline and observe whether log pass-through is complete after accounting for the cost share. Figure 3 shows daily prices charged by a single gas station in the sample from March to June 2016. As previously documented by Byrne and de Roos (2019), the retail price follows weekly price cycles, jumping up on Tuesdays or Thursdays and then falling over the course of the week.

Under the assumption that gas stations never set prices below marginal cost,[7] we can use the days of the week at the lowest point of the price cycle to calculate an upper bound on the share of other variable costs in stations' marginal costs, and thus a lower bound for the cost share of gasoline. We find a lower bound for the cost share of gasoline of 0.98 for unleaded petrol and 0.96 for premium unleaded petrol. The estimated log pass-throughs, at 0.899 and 0.887, are significantly different from these cost shares at the 1 percent level. Thus, the estimated log pass-through of gasoline costs is incomplete, even after accounting for the share of gasoline in variable costs.[8]

[7]This is the case in the Maskin and Tirole (1988) model of price cycles.

[8]Could measured log pass-through be lower than the cost share due to higher order terms? In fact, higher order terms would likely *increase* measured log pass-through relative to the average cost share. To see why, suppose stations are perfectly competitive ($p = c + w$) and denote the gasoline cost share $\chi = c/(c + w)$. The change in log prices to a second order is $\Delta \log p \approx \chi(d \log c) + \chi(1 - \chi)(d \log c)^2$, and the estimated log pass-through is $\hat{\rho} = \mathbb{E}[\Delta \log p / d \log c] \approx \mathbb{E}[\chi] + \mathbb{E}[\chi(1 - \chi)(d \log c)]$. If the commodity price is a random walk

Exploiting variation in markups. While the point estimate for pass-through in levels (0.991) is very close to one, it is hard to reject low markups that would be plausible in this setting. We further test for multiplicative markups by exploiting cross-sectional and time series variation in markups. If stations follow a multiplicative markup pricing rule, and if some stations charge higher markups than others, then the pass-through in levels for high-markup stations should be higher than their low-markup counterparts.

We estimate the specification,

$$\Delta p_{it} = \alpha + \delta \Delta c_t + \gamma \text{Avg. Markup}_{it} + \beta(\Delta c_t \times \text{Avg. Markup}_{it}) + \varepsilon_{it}. \tag{4}$$

where Δp_{it} and Δc_t are changes in station i's price and the wholesale cost over the prior sixteen weeks, Avg. Markup_{it} is a measure of station markups, and ε_{it} is a mean-zero error.

The fixed multiplicative markup model predicts that the coefficient on the interaction term $\beta > 0$. For example, if some stations set a fixed 2 percent markup and other stations set a fixed 5 percent markup, pass-through in levels should be 1.05 for the high-markup stations compared to 1.02 for the low-markup stations. On the other hand, if all stations exhibit complete pass-through in levels, the interaction coefficient $\beta \approx 0$.

We use two proxies for Avg. Markup_{it}, along with instruments for both that are intended to isolate variation in markups from variation in non-gasoline input costs. The first measure exploits variation in markups across stations: Avg. Station Markup_i is the average retail price / wholesale cost charged by station i over all weeks in the sample. We also instrument for Avg. Station Markup_i with the average amplitude of price cycles of station i, that is, the difference between the maximum and minimum retail margin charged by i in each week, averaged over all weeks. While stations' retail prices / wholesale costs may also capture variation in non-gasoline variable costs, this instrument isolates variation in markups across stations coming from the intensity of stations' price cycles.

The second measure instead exploits variation in markups over time: in each quarter t, we construct the average retail price over wholesale cost for all gas stations in Perth, denoted Avg. Quarter Markup_t. To instrument for Avg. Quarter Markup_t, we take advantage of the fact that the emergence of coordinated price cycles in the Perth market was, according to Byrne and de Roos (2019), "unrelated to market primitives." Appendix Figure A3 shows that average gas station margins over the course of the sample co-move closely with the degree of coordination in price cycles, measured as the R^2 from a regression of daily margins on day-of-week fixed effects. (The most dramatic change over time is the increase in both coordination and margins around 2010, but there is also

with positive drift, the second order term increases measured log pass-through relative to the cost share.

Table 2: Complete pass-through in levels: No heterogeneity by station markup.

ΔPrice_{it}	(1) (OLS)	(2) (OLS)	(3) (IV1)	(4) (OLS)	(5) (IV2)
ΔCost_t	0.950**	0.989**	0.952**	0.987**	0.971**
	(0.021)	(0.037)	(0.044)	(0.034)	(0.043)
$\Delta\text{Cost}_t \times$ Avg. Station Markup_i (Net %)		-0.005	-0.000		
		(0.003)	(0.005)		
$\Delta\text{Cost}_t \times$ Avg. Quarter Markup_t (Net %)				-0.003	-0.002
				(0.003)	(0.004)
N	312215	312215	312215	312215	312215
R^2	0.89	0.89	0.89	0.89	0.89

Note: The table reports the coefficients γ and β estimated using specification (4). Changes in retail prices and wholesale costs are taken over 16 weeks. For readability, we include Avg. Markup_{it} on a net % basis (i.e., a markup of 1.1 is a 10% net markup). Column 3 (IV1) uses the average amplitude of stations' price cycles as an instrument for Avg. Station Markup_i. Column 5 (IV2) uses the quarterly R^2 of station margins on day-of-week dummies as an instrument for Avg. Quarter Markup_t. Standard errors two-way clustered by postcode and year.

subsequent variation in the strength of coordination and margins after 2010 owing to subsequent breakdowns in collusion.) We use this measure of price coordination over time—the quarterly R^2 of station margins on day-of-week dummies—as an instrument for Avg. Quarter Markup_t.

Table 2 reports the results. Column 1 omits the average markup and interaction term. A \$1 change in the wholesale cost of unleaded petrol (ULP) over 16 weeks is associated with a \$0.95 change in the retail station price over the same period. Columns 2–5 include the interaction of wholesale cost changes with markups, with columns 3 and 5 using the instruments discussed above. In all cases, $\beta \approx 0$, consistent with complete pass-through in levels rather than the fixed multiplicative markup model.

Pass-through in levels explains heterogenity in log pass-through. Table 3 reports estimates from an analogous specification that instead measures the pass-through of changes in log costs to changes in log prices,[9]

$$\Delta \log p_{it} = \alpha + \delta \Delta \log c_t + \gamma \text{Avg. Markup}_{it} + \beta(\Delta \log c_t \times \text{Avg. Markup}_{it}) + \varepsilon_{it}. \quad (5)$$

[9]Since Table 2 suggests that stations have additive margins, rather than multiplicative markups, it may be preferable to estimate specification (5) using a measure of additive margins rather than multiplicative markups. We find that doing so yields similar results.

Table 3: Incomplete log pass-through is explained by station markups.

Δ log(Price)$_{it}$	(1) (OLS)	(2) (OLS)	(3) (IV1)	(4) (OLS)	(5) (IV2)
Δ log(Cost)$_t$	0.870**	0.998**	0.968**	0.977**	0.967**
	(0.031)	(0.035)	(0.041)	(0.026)	(0.033)
Δ log(Cost)$_t$ $\times$ Avg. Station Markup$_i$ (Net %)		-0.015**	-0.011**		
		(0.003)	(0.004)		
Δ log(Cost)$_t$ $\times$ Avg. Quarter Markup$_t$ (Net %)				-0.010**	-0.010**
				(0.002)	(0.003)
N	312215	312215	312215	312215	312215
R^2	0.88	0.89	0.89	0.89	0.89

Note: The table reports the coefficients γ and β estimated using specification (5). Changes in log retail prices and log wholesale costs are taken over 16 weeks. For readability, we include Avg. Markup$_{it}$ on a net % basis (i.e., a markup of 1.1 is a 10% net markup). Column 3 (IV1) uses the average amplitude of stations' price cycles as an instrument for Avg. Station Markup$_i$. Column 5 (IV2) uses the quarterly R^2 of station margins on day-of-week dummies as an instrument for Avg. Quarter Markup$_t$. Standard errors two-way clustered by postcode and year.

Column 1 omits the average markup and interaction term and estimates that a 1 percent change in wholesale costs over 16 weeks leads to a 0.870% change in retail prices, significantly below the cost share of gasoline. Columns 2–5 include the average markup and interaction term, again exploiting cross-sectional variation in markups (columns 2–3) or time series variation in markups (columns 4–5). Two findings emerge. First, higher markups lead to more incomplete log pass-through.[10] Second, the gap between price and costs appears to fully account for incomplete pass-through: the coefficient on $\Delta \log c_t$ shows that as net markups approach zero, the log pass-through is tightly estimated around the cost share of 0.98.

Thus, Table 3 shows that incomplete log pass-through is rationalized by the combination of complete pass-through in levels (documented in Table 2) with a gap between stations' prices and marginal costs. Log pass-through is lower both for stations in the cross-section and periods in the time series with higher markups. The size of the gap between output price and commodity cost explains both the level of incomplete log pass-through and variation in log pass-through across stations.

[10]Complete pass-through in levels predicts that the interaction coefficient in the log specification $\beta \approx -0.01$. If stations set prices $p = c + w + \alpha$, where α is an additive unit margin, to a first order, $\Delta \log p \approx \chi\mu^{-1}\Delta \log c \approx \chi(1-0.01\mu^{\text{net},\%})\Delta \log c$, where $\chi = c/(c+w)$ is the cost share (0.96–0.98 in the data), $\mu = p/(c+w)$ is the markup, and $\mu^{\text{net},\%} = 100(\mu - 1)$.

Table 4: Pass-through estimates: Other geographies and Känzig (2021) instrument.

	Long-run pass-through (8 weeks)			
	Logs		Levels	
Description	Baseline	IV	Baseline	IV
Australia, station-level, 2001–2022				
Terminal to retail, Unleaded	0.899	0.805	0.991†	0.888†
	(0.043)	(0.118)	(0.038)	(0.132)
Terminal to retail, Premium Unleaded	0.887	0.812†	0.985†	0.901†
	(0.041)	(0.129)	(0.036)	(0.146)
Canada, city-level, 2007–2022				
Crude to wholesale	0.553	0.713	0.927†	1.086†
	(0.098)	(0.146)	(0.100)	(0.186)
Wholesale to retail (excl. taxes)	0.859	0.848	1.008†	0.994†
	(0.016)	(0.042)	(0.022)	(0.049)
South Korea, station-level, 2008–2022				
Refinery to retail, Unleaded	0.926	0.935†	0.997†	1.012†
	(0.044)	(0.097)	(0.052)	(0.108)
United States, national, 1990–2022				
NY Harbor spot price to retail	0.570	0.605	0.954†	0.955†
	(0.051)	(0.115)	(0.053)	(0.111)

Note: Long-run pass-through at eight weeks using data from Australia, Canada, South Korea, and the United States. Driscoll-Kraay standard errors (Newey-West for the U.S.) with eight lags in parentheses. The IV columns use OPEC announcement shocks from Känzig (2021) as an instrument for commodity price changes. † indicates estimates for which a pass-through of one is within the 90 percent confidence interval.

Evidence from other markets and oil supply shocks. Table 4 compares pass-through estimates from Perth to estimates from retail gasoline markets in Canada, South Korea, and the United States (Appendix D describes the data sources for each). Incomplete log pass-through and complete pass-through in levels appear across all the studied markets. The evidence from other geographies suggests that complete pass-through in levels is not a quirk of the Australian data, but rather describes price dynamics across a number of retail gasoline markets.

So far, we have assumed that commodity costs pass downstream to retail prices and not vice versa (this assumption is supported by the Granger causality tests in Appendix Table A2). As an additional check, Table 4 also estimates pass-through instrumenting for upstream commodity cost changes with OPEC announcement shocks from Känzig (2021). Estimates of long-run pass-through in levels and logs from the instrumented regressions are somewhat noisier, but qualitatively similar to the baseline results.

4 Evidence from Food Products

To investigate whether these empirical patterns hold in markets beyond retail gasoline, in this section we explore pass-through of commodity costs to retail prices in six staple food products (coffee, sugar, ground beef, white rice, all-purpose flour, and frozen orange juice concentrate). The pass-through in levels of these commodity costs to retail prices is a particularly strong test of the fixed multiplicative markup model, because it should detect if any firm along the chain of producers from commodity to retailer charges a gross markup greater than one.

For five out of the six products, the long-run pass-through of commodity costs in levels is statistically indistinguishable from one. Using product-level scanner data for three food products (rice, flour, and coffee), we find that products in the cross-section with higher unit prices have lower log pass-through, but have no systematic differences from low unit-price products in pass-through in levels. Like in the cross-section of retail gasoline stations, variation in log pass-through across products in a category can be rationalized by variation in non-commodity input costs and margins.

Finally, we document that these patterns in pass-through appear to extend to a broader set of fast-moving goods, by exploiting the fact that different retailers often set different prices for identical products (Kaplan and Menzio 2015; Kaplan et al. 2019). The behavior of prices of identical products across retailers conforms with complete pass-through in levels, rather than with the predictions of fixed multiplicative markup models.

4.1 Data on Food Retail and Commodity Prices

Retail prices. For retail prices of food products, we primarily rely on Average Price Data from the Bureau of Labor Statistics. While most BLS CPI series capture relative price changes, the Average Price Data track price levels for a select number of staple products. For each price series, the BLS chooses narrowly defined, homogeneous item categories (e.g., "Orange juice, frozen concentrate, 12 oz. can, per 16 oz.") to minimize input, quality, and package size differences between included items.

While the BLS Average Price Data allow us to study pass-through of commodity costs to retail prices over a long time series—many of the series record prices back to 1980—studying cross-sectional heterogeneity across products in a category requires richer data. For these investigations, we use NielsenIQ Retail Scanner data, which includes weekly barcode-level prices and quantities for products sold at participating stores from 2006 to 2020. These data are collected from point-of-sale systems in about 90 retail chains operating across the U.S., reflecting over $2 billion in annual sales.

Commodity costs. We match retail food prices with data on commodity costs from the IMF Primary Commodities Prices database. These commodity price series draw from statistics of specialized trade organizations or from commodity futures markets—for example, the U.S. sugar commodity price from the IMF uses the price of the nearest Sugar No. 16 futures contract. Appendix Table A3 provides a full list of the commodity price series used and the underlying data sources used by the IMF.

Measuring pass-through in levels requires carefully matching units from commodity prices to retail prices. For example, to measure pass-through of wheat commodity prices to retail flour prices requires knowing the quantity of wheat needed per pound of flour produced. To construct these mappings from commodity units to retail units, we rely on previous literature and on documentation from the USDA. Appendix Table A4 provides the conversion factors from commodity prices to retail prices for each series and delineates the sources and assumptions used to build each conversion factor.[11]

Matched products. Of the food products tracked by the BLS Average Price Data, six can be clearly matched to commodity input prices provided by the IMF. These are roasted ground coffee, sugar, ground beef, white rice, all-purpose flour, and frozen orange juice concentrate. Appendix Table A4 lists the corresponding Average Price Data Series IDs and reported units. For three of these products—rice, flour, and coffee—we also investigate cross-sectional pass-through patterns by matching the food product to a NielsenIQ product category.[12]

4.2 Empirical Results

Nearly all products exhibit complete pass-through in levels. Table 5 reports estimates of long-run pass-through in levels and logs (specifications (2) and (3)) for six food products. In five of the six products, long-run pass-through in levels is statistically indistinguishable from one. The exception is sugar, where the estimated pass-through in levels falls short of one. For all six products, the log pass-through is significantly below one.

Figure 4 shows an example of the price series and pass-through estimates for one of the studied food products, roasted ground coffee. As shown in panel (a), Arabica coffee

[11]This careful matching of units is why estimating pass-through in levels is difficult for highly differentiated products, where it is hard to estimate the amount of commodity inputs used for production. At the end of the section, we exploit the fact that retailers set different prices for identical products to test for pass-through in levels at the retail level across several other products in the data.

[12]The corresponding NielsenIQ product modules are "Rice - Packaged and bulk," "Flour - All purpose - White wheat,", and "Ground and whole bean coffee." Beef products are spread across several modules, and the "Sugar - granulated" and "Fruit juice - orange - frozen" modules have few unique products.

Table 5: Long-run pass-through of commodity costs to retail food prices.

Commodity (IMF)	Final Good (BLS)	Pass-through (12 mos.) Logs		Levels	
Arabica coffee	Coffee, 100%, ground roast	0.466	(0.051)	0.946†	(0.099)
Sugar, No. 16	Sugar, white	0.370	(0.035)	0.691	(0.072)
Beef	Ground beef, 100% beef	0.410	(0.068)	0.899†	(0.126)
Rice, Thailand	Rice, white, long grain, uncooked	0.307	(0.049)	0.882†	(0.169)
Wheat	Flour, white, all purpose	0.240	(0.048)	0.865†	(0.160)
Frozen orange juice	Orange juice, frozen concentrate	0.327	(0.040)	0.974†	(0.111)

Note: Long-run pass-through in levels and logs is $\sum_{k=0}^{K} b_k$ from specifications (2) and (3), using a horizon of $K = 12$ months. Newey-West standard errors in parentheses. † indicates estimates for which a pass-through of one is within the 90 percent confidence interval.

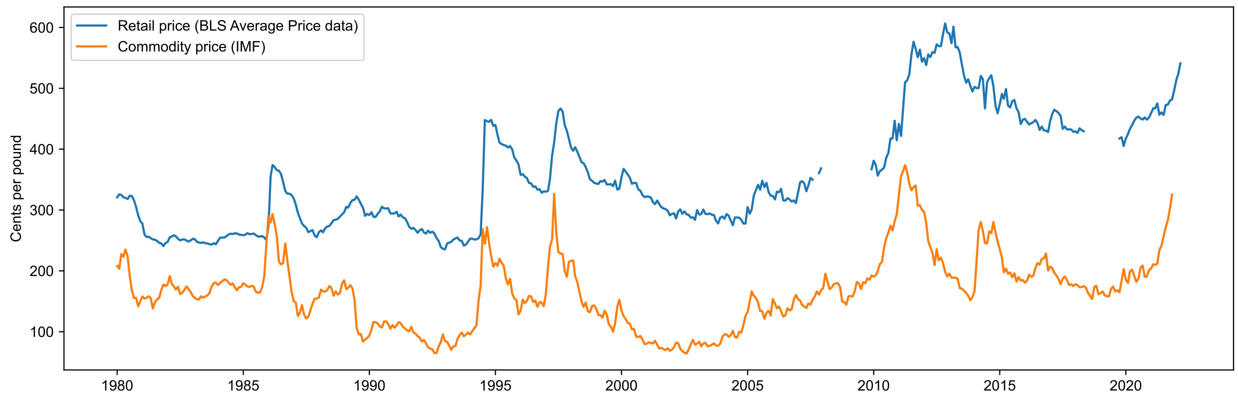
commodity prices exhibit substantial volatility over the period since 1980, with large spikes in 1986, 1994, 1997, 2011, and 2014 due largely to weather conditions in Brazil and Colombia.[13] These run-ups in commodity prices are followed by increases in the retail prices tracked by the BLS. Panel (b) shows the pass-through in levels from coffee commodity prices to retail prices occurs with lags, but approaches complete pass-through by eight months and stays around one thereafter. The log pass-through, in panel (c), instead plateaus around 0.5. These results are consistent with Nakamura and Zerom (2010), who estimate pass-through in the roasted ground coffee market from 2000–2005. Analogous figures for the other five food products are in Appendix A.

Pass-through in levels explains cross-sectional variation in log pass-through. The complete pass-through in levels documented in Table 5 has predictions for price changes in the cross-section of products. First, products that have higher margins and higher non-commodity input costs should exhibit lower log pass-through (as we saw in the cross-section of retail gas stations in Section 3). Second, pass-through in levels should be similar across products regardless of their margins and non-commodity input costs.

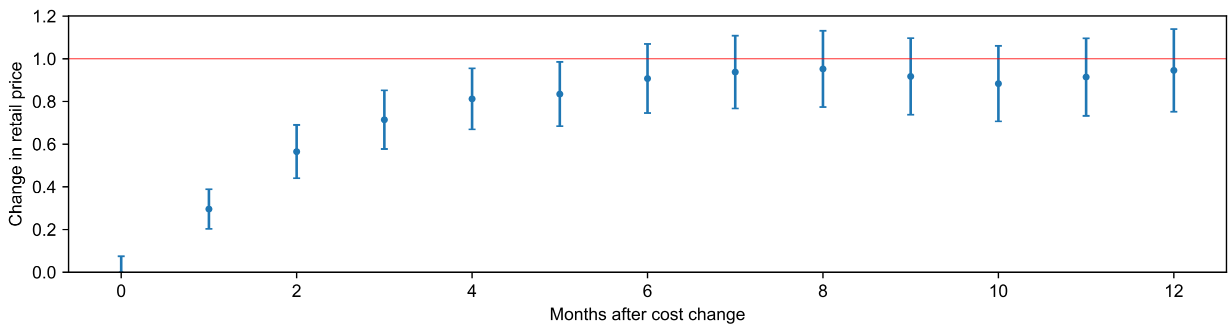
To test these predictions, we use NielsenIQ data on rice, flour, and coffee products from 2006 to 2020. We define a product as a specific UPC (universal product code, or product barcode) sold at a specific retail chain, since prices for a UPC tend to be fairly uniform within retail chains (DellaVigna and Gentzkow 2019). In each quarter t, we calculate the price p_{it} of product (i.e., UPC–retailer pair) i as the quantity-weighted average unit price

[13]See, e.g., New York Times: "*Coffee Hits a 20-Year High on Rumblings of a Shortage*" (1997) and New York Times: "*Heat Damages Colombia Coffee, Raising Prices*" (2011).

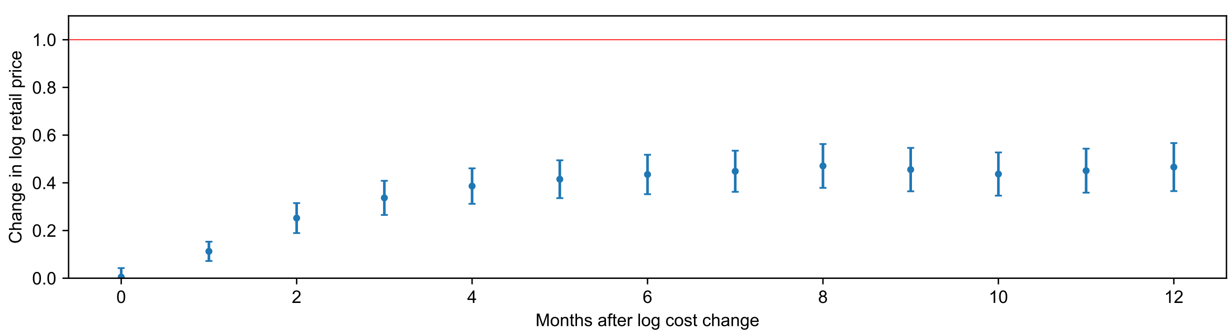
Figure 4: Passthrough of coffee commodity costs to retail prices.



(a) Arabica coffee commodity costs (IMF) and retail ground coffee prices (U.S. CPI).



(b) Pass-through in levels.



(c) Pass-through in logs.

Note: Panel (a) plots the time series of the commodity price from the IMF and the Average Price Data series from the BLS. The series are adjusted by the conversion factors in Appendix Table A4 so that the two series are in comparable units. Panels (b) and (c) plot the cumulative pass-through to month T, $\sum_{k=0}^{T} b_k$, from the specifications (2) and (3), using a total horizon of $K = 12$ months.

over all transactions. For each product in each quarter, we then measure the change in the product's price over the next year in levels (Δp_{it}) and in percentages ($\Delta \log p_{it}$) as

$$\Delta p_{it} = p_{it+4} - p_{i,t}, \qquad \Delta \log p_{it} = \log p_{it+4} - \log p_{it}.$$

Since these price changes are measured year over year, they avoid seasonality effects that may bias measures of price changes calculated over smaller time increments.[14]

We use the unit price (i.e., the price per ounce of rice or pound of flour) as a proxy for the extent of non-commodity variable costs and margins in the product's price. Thus, to test the above predictions for how pass-through in logs and levels varies with the level of non-commodity variable costs and margins, we group products in each product category by unit price in each quarter t. To ensure that these product groups capture persistent differences in unit price, we use products' average unit prices over the prior year.

As an example, Figure 5 plots average inflation rates and price changes in levels for these three groups of rice products. As shown in the top panel, a run-up in rice commodity prices into 2008 led to much higher inflation for rice products with lower unit prices—the average inflation rate for low unit price rice products reached nearly 70 percent in 2008, compared to under 25 percent for high unit price products.[15] These differences disappear when comparing the price changes in levels in the bottom panel: products in all unit price groups had roughly the same increase in absolute prices.

To formally test how pass-through in logs and levels varies in the cross-section of products, we estimate the following specifications,

$$\Delta \log p_{it} = \alpha_i + \beta_1 \Delta \log c_t + \sum_{g=2}^{3} \beta_g \left(1\{G(i,t) = g\} \times \Delta \log c_t\right) + \varepsilon_{it}, \tag{6}$$

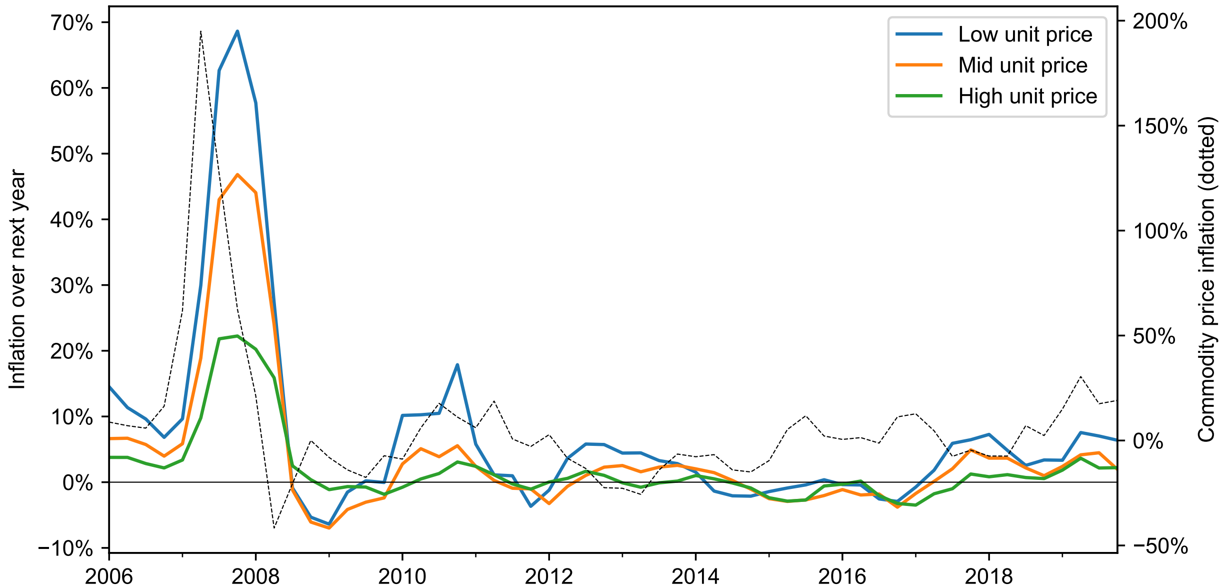
$$\Delta p_{it} = \alpha_i + \beta_1 \Delta c_t + \sum_{g=2}^{3} \beta_g \left(1\{G(i,t) = g\} \times \Delta c_t\right) + \varepsilon_{it}, \tag{7}$$

where $G(i,t) \in \{1,2,3\}$ is the unit price group of product i in quarter t, $\Delta \log c_t$ and Δc_t are changes in commodity prices over the next year in logs and levels, and α_i are product

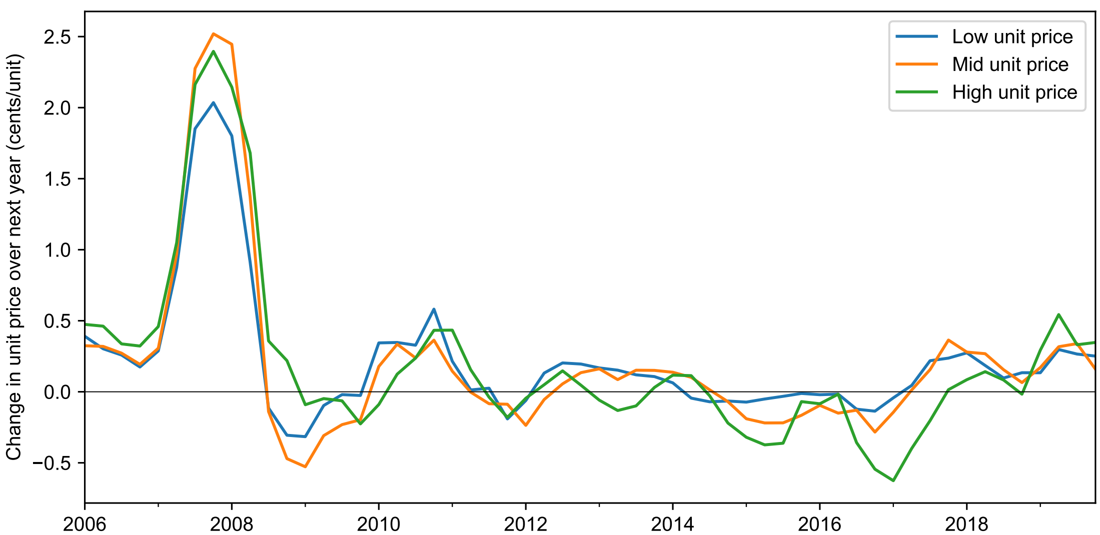
[14] Nakamura and Steinsson (2012) point out that using product-level data to measure pass-through may bias measurement when there is frequent product turnover. For these categories, over 75 percent of products in each quarter are observed in the following year, and turnover does not appear correlated with commodity inflation in a way that would downward bias measured pass-through: the correlation of commodity inflation with turnover is −0.03 for rice, −0.09 for flour, and −0.09 for coffee products.

[15] The run-up in rice prices was prompted by adverse weather shocks to wheat-growing areas from 2006–2008, and subsequent trade restrictions by Vietnam, India, and other major rice-exporting countries to ensure adequate rice supply for their domestic markets. See Childs and Kiawu (2009) for a detailed account.

Figure 5: Inflation and price changes of rice products by tercile of unit price.



(a) Inflation (in percentages)



(b) Price change (in levels)

Note: Both panels plot price changes for rice products in the NielsenIQ scanner data. In each quarter, products are separated into three groups with equal quarterly sales by average unit price over the prior year. Panel (a) plots the sales-weighted average inflation rate over the next year for products in each group, alongside commodity rice inflation. Panel (b) plots the sales-weighted average change in price levels over the next year for products in each group.

Table 6: Higher-priced products exhibit lower log pass-through, with no systematic difference in level pass-through.

Panel A: In percentages

	Retail price inflation		
	Rice	Flour	Coffee
Commodity Inflation × Mid Unit Price	−0.075**	−0.007	−0.064**
	(0.014)	(0.009)	(0.015)
Commodity Inflation × High Unit Price	−0.150**	−0.045**	−0.091**
	(0.022)	(0.009)	(0.017)
UPC FEs	Yes	Yes	Yes
N (thousands)	399.4	101.4	1570.0
R^2	0.15	0.05	0.14

Panel B: In levels

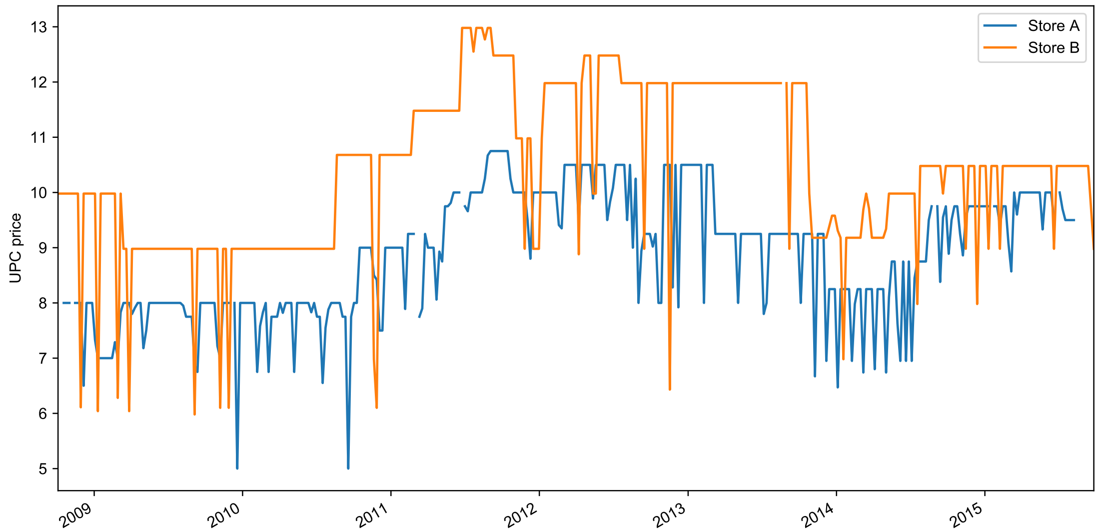
	Δ Retail price		
	Rice	Flour	Coffee
Δ Commodity Price × Mid Unit Price	0.059	0.027	−0.069
	(0.052)	(0.040)	(0.046)
Δ Commodity Price × High Unit Price	0.042	−0.067	−0.099*
	(0.100)	(0.044)	(0.058)
UPC FEs	Yes	Yes	Yes
N (thousands)	399.4	101.4	1570.0
R^2	0.07	0.05	0.14

Note: Panel A reports results from specification (6), and panel B reports results from specification (7). In each quarter, products are split into three groups with equal sales by average unit price over the past year; the Mid- and High Unit Price variables are indicators for the middle and highest-priced groups. Standard errors clustered by brand. * indicates significance at 10%, ** at 5%.

fixed effects.

Across product groups, panel A shows that the sensitivity of retail price inflation to commodity inflation systematically declines with unit price across all three product categories (rice, flour, and coffee). In contrast, panel B finds little evidence of systematic differences in the sensitivity of retail price changes to commodity price changes *in levels* across unit price groups, consistent with complete pass-through in levels across products explaining heterogeneity in log pass-through. Appendix Table A5 shows similar results if we instead split products into five unit price groups.

Figure 6: Price of a coffee UPC in two stores in same 3-digit ZIP in Philadelphia, PA.



Exploiting variation in identical products' prices across retailers. Heterogeneity in unit prices across products in a category can come from differences in markups or from differences in non-commodity input costs. Even when firms use multiplicative markup rules, log pass-through can decline with unit price if the heterogeneity in unit prices across products largely steps from differences in non-commodity input costs. (Of course, if firms use multiplicative markup rules and unit prices are positively correlated with markups, the pass-through in levels should still increase with unit price, which is rejected in Table 6.)

To narrow in on how heterogeneity in markups affects pass-through, we exploit the fact that different retailers often sell the same product at different prices. If differences in prices charged for the same product primarily reflect different retail markups rather than differences in costs, differences in pass-through for the same product across retailers will isolate the effect of markups on pass-through.

To fix ideas, consider two retail stores selling the same UPC, one with a low markup (store A) and one with a high markup (store B). Figure 6 shows, for example, the price of the same coffee UPC at two different stores in Philadelphia. Excluding some temporary sales, store A consistently charges a lower price than store B. If both stores A and B use fixed multiplicative markups, when the cost of the UPC rises, store B (the retailer with the higher markup) should increase its price by more in levels. On the other hand, if both stores exhibit complete pass-through in levels, when the cost of the UPC rises, the absolute price change in both store A and store B should be similar, and the price change in percentage terms for store B should be lower.

We test these predictions using the specification,

$$\Delta p_{irt} = \beta\left(\mu_{irt} \times \overline{\Delta p_{it}}\right) + \delta\mu_{irt} + \alpha_{it} + \varepsilon_{irt}. \quad (8)$$

where p_{irt} is the average price of UPC i at retailer r in quarter t, Δp_{irt} is the year-over-year change in the retailer's price for i starting in quarter t, $\overline{\Delta p_{it}}$ is the average year-over-year change in price charged by all retailers for UPC i, μ_{irt} is a measure of the markup charged by retailer r for UPC i, and α_{it} are UPC-quarter fixed effects (which absorb the average price change for UPC i across retailers). If retailers choose fixed multiplicative markups, then high-markup retailers should increase their prices more than other retailers when the cost of UPC i increases, and we should find $\beta > 0$. On the other hand, pass-through in levels would imply $\beta \approx 0$.

We do not observe retail markups directly, but under the assumption that differences in prices for the same product across retailers stem solely from variation in markups, we can use the deviation in the price that retailer r sets for UPC i relative to the average price of UPC i as a proxy for the retailer's relative markup:

$$\widehat{\mu}_{irt} = \log\left(p_{irt}/\bar{p}_{it}\right).$$

Columns 1–3 of Table 7 report results from (8) for rice, flour, and coffee products. For all three categories, the estimated coefficient β is slightly negative and indistinguishable from zero at the 5 percent level (columns 1–3). That is, retailers selling the same UPC with different markups exhibit similar price changes in levels.

Columns 4–6 report results from the analogous specification that instead measures price changes in percentages,

$$\Delta \log p_{irt} = \tilde{\beta}\left(\mu_{irt} \times \overline{\Delta \log p_{it}}\right) + \tilde{\delta}\mu_{irt} + \tilde{\alpha}_{it} + \varepsilon_{irt}. \quad (9)$$

In all cases, we estimate $\tilde{\beta} < 0$: retailers with higher markups increase prices by less in percentage terms than retailers with lower markups.[16] Thus, by exploiting variation in prices for the same product across retailers, we find that products have similar absolute price changes, which appears as lower log pass-through for high-markup products.

Since this approach does not require information on upstream commodity costs, we can extend this analysis to a broader set of product categories. We estimate specifications

[16]Pass-through in levels predicts that $\tilde{\beta} \approx -1$, which we find in columns 4–6 of Table 7. If the price of UPC i at retailer r is $p_{ir} = c_i + \alpha_{ir}$, in response to a change in c_i, the retailer's percentage price change is $d\log p_{ir} \approx c_i/(c_i + \alpha_{ir})d\log c_i$. The change in the average price $\bar{p}_i$ is approximately $d\log \bar{p}_i \approx (c_i/\bar{p}_i)d\log c_i$. Combining yields $d\log p_{ir} \approx (1 - \log(p_{ir}/\bar{p}_i))d\log \bar{p}_i$.

Table 7: Exploiting variation in markups for identical products across retailers.

	Δ UPC Price (Δp_{irt})			Δ Log UPC Price ($\Delta \log p_{irt}$)		
	Rice	Flour	Coffee	Rice	Flour	Coffee
	(1)	(2)	(3)	(4)	(5)	(6)
Avg Δ UPC Price $\times$ Markup$_{irt}$	−0.019	−0.200	−0.123			
	(0.111)	(0.216)	(0.352)			
Avg Δ Log UPC Price $\times$ Markup$_{irt}$				−0.988**	−0.879**	−1.386**
				(0.104)	(0.250)	(0.213)
UPC-Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
N (thousands)	399.4	101.4	1570.0	399.4	101.4	1570.0
R^2	0.51	0.50	0.55	0.64	0.60	0.58

Note: Columns 1–3 report results from specification (8), and columns 4–6 reports results from specification (9). Markup$_{irt}$ is measured as the log deviation in the price set by retailer r compared to the average price set by retailers, $\log(p_{irt}/\bar{p}_{it})$. Standard errors clustered by brand. ** indicates significance at 5%.

(8) and (9) for 616 other product modules in the NielsenIQ data (using all food product modules with at least 250 distinct observations). Appendix Table A6 shows that similar patterns to Table 7 emerge for the majority of product categories. In particular, the same product has similar price changes in levels across retailers for over half the modules in the data, and for over 85 percent of product modules, the same product has significantly lower log pass-through at retailers where it is sold at a higher markup.

5 Profits, Margins, and Entry

So far, we have seen that the pass-through of commodity costs to downstream prices appears inconsistent with standard models of fixed multiplicative markups. This section takes a different line of attack, starting with the observation that if firms charge a fixed markup over marginal cost, then as marginal costs increase, firms should make higher per-unit profits. For example, retail gas stations charging a fixed 5 percent markup would make five cents per gallon sold when the wholesale cost of gasoline is \$1/gallon and ten cents per gallon sold when the cost of gasoline increases to \$2/gallon.

If aggregate industry demand is relatively inelastic, then these higher per-unit profits must show up as higher profits of existing firms or be dissipated through the entry of new firms. In other words, a signature of multiplicative markups is that an increase in upstream costs should lead to higher operating margins, new firm entry, or both.

As we will see, both possible signs of higher per-unit profit margins are silent in the data. For retail gas stations and several manufacturing industries, we find that an increase in upstream commodity costs leads to no change in entry and, if anything, a decline in operating margins (as a percent of sales). Instead, rising upstream commodity costs lead to an erosion of gross margins, which would be constant in the standard model. These patterns are consistent with firms instead retaining fixed per-unit profits.[17]

5.1 Profits, Margins, and Entry in Workhorse Macro Models

To see how per-unit profits, margins, and entry respond to changes in costs in standard models, we introduce a workhorse model of monopolistic competition, following Dixit and Stiglitz (1977) and Melitz (2003). A mass N of symmetric firms produce with a constant returns production function with marginal cost c. Output is a CES aggregate of the output of individual firms, with an elasticity of substitution $\sigma > 1$.

Firms' optimal prices are given by the usual Lerner formula,

$$p = \frac{\sigma}{\sigma - 1} c.$$

Note that per-unit variable profits, $p - c = \frac{1}{\sigma-1} c$, are increasing in the marginal cost.

Aggregate industry demand is given by $Q = p^{-\theta}$. We assume that aggregate industry demand is inelastic ($\theta < 1$), which is the empirically relevant case for the industries studied in this paper.[18] Note that even though aggregate industry demand is inelastic, the residual demand curves for each individual firm have the higher elasticity $\sigma > 1$.

As in Melitz (2003), in addition to variable costs of production, firms incur overhead costs given by f_o. Denote firms' variable profits and operating profits by π^{gross} and π^{op}:

$$\pi^{\text{gross}} = \frac{1}{\sigma - 1} c \frac{Q}{N}, \qquad \text{and} \qquad \pi^{\text{op}} = \pi^{\text{gross}} - f_o,$$

where we use the symmetry of firms to express quantity sold by each firm as total industry demand over the mass of firms, Q/N. Industry gross and operating margins (as a percent of sales) are given by

$$m^{\text{gross}} = \frac{\pi^{\text{gross}} N}{pQ}, \qquad \text{and} \qquad m^{\text{op}} = \frac{\pi^{\text{op}} N}{pQ}.$$

Finally, the model is closed by specifying how the mass of firms evolves. Two common

[17] An analog in exchange rate pass-through is how distribution margins respond to exchange rate fluctuations. Hellerstein (2008) and Campa and Goldberg (2010) find that distribution margins as a percent of sales fall when import prices rise (though Berger et al. 2012, in contrast, find limited evidence of responsiveness).

[18] For example, the USDA estimates the elasticities of aggregate demand for flour, rice, and coffee to be 0.07, −0.07, and −0.12, respectively (Okrent and Alston 2012).

approaches are to either assume a fixed mass of firms or to assume free entry. We choose a general condition that nests both as special cases:

$$N = N_0(\pi^{\text{op}} - f_e)^{\zeta},$$

where f_e is the entry cost and $\zeta \geq 0$ is the elasticity of the mass of firms to per-firm profits. When $\zeta = 0$, the mass of firms is fixed at $N = N_0$. As ζ approaches infinity, there is free entry, and firms make zero profits net of the entry cost. Values of $\zeta \in (0, \infty)$ correspond to intermediate cases where entry responds to changes in operating profits, but not enough to keep operating profits in line with the entry cost.

With this standard setup in place, we can consider how gross margins, operating margins, and the mass of firms in the industry respond to changes in firms' costs.

Proposition 1 (Gross margins, operating margins, and entry in workhorse macro models)**.** *In response to an increase in costs ($d\log c > 0$),*

(i) If $\zeta = 0$, operating margins rise ($dm^{op} > 0$) and the mass of firms is constant ($d\log N = 0$).

(ii) If $\zeta \in (0, \infty)$, both operating margins and the mass of firms increase ($dm^{op}, d\log N > 0$).

(iii) In the limit as $\zeta \to \infty$, operating margins are constant ($dm^{op} = 0$) and the mass of firms increases ($d\log N > 0$).

For all ζ, gross margins remain constant ($dm^{gross} = 0$).

When marginal costs rise, firms charging a fixed multiplicative markup make a higher profit per unit sold ($\frac{1}{\sigma-1}c$). Proposition 1 shows that these additional profits must accrue to firms' operating profits, new firm entry, or both. In the case where the mass of firms is fixed ($\zeta = 0$), firms' variable profits increase relative to overhead costs, resulting in a higher operating margins. On the other hand, when there is free entry ($\zeta \to \infty$), increases in profits per unit sold are entirely dissipated by entry of new firms, so that per-firm profits and operating margins remain constant. For any intermediate $\zeta \in (0, \infty)$, both operating margins and new firm entry respond positively to changes in costs.

5.2 Margins and Entry in the Data

We now evaluate the predictions of the standard model in Proposition 1 using data on margins and entry rates for retail gas stations and for a number of manufacturing industries. As we will see, the signatures of fixed multiplicative markups—rising commodity costs leading to higher operating margins, heightened firm entry, or both—are absent in the data. Instead, gross margins (as a percent of sales), which would be constant if firms set fixed multiplicative markups, respond negatively to rising commodity costs.

Retail gas stations. We use gross and operating margins for retail gas stations from the Census Annual Retail Trade Survey (ARTS). Gross margins as a percent of sales are available annually starting in 1983, and operating expenses are available every five years starting in 1992 and annually from 2006. As a complementary measure of retail gas stations' gross and operating margins, we also draw on income statements of retail gasoline station sole proprietorships from the IRS Statistics of Income (SOI) program starting in 1996.[19,20] Data on the number of retail gas station firms and establishments in each year comes from two sources: the Census Business Dynamics Statistics (BDS) starting in 1983 and the Census Statistics of U.S. Businesses (SUSB) starting in 1998.

Figure 7 shows the time series for gross margins, operating margins, and establishment growth rates. In contrast to Proposition 1, gross margins are not fixed and instead appear to covary negatively with upstream commodity costs (the correlations between gross margins from the Census ARTS and IRS SOI with the wholesale gasoline price are −0.94 and −0.74). Meanwhile, firm entry appears unresponsive to commodity costs, and operating margins are flat or slightly decline when commodity costs increase.

We test the relationship between industry outcome y_t and commodity costs c_t using the first-differences specification:

$$\Delta y_t = \alpha + \beta \Delta c_t + \varepsilon_t. \tag{10}$$

Table 8 reports results from specification (10) using gross margins, operating margins, and entry as outcome variables and using the wholesale gasoline price, deflated to 2017 USD, as the measure of commodity costs.[21] Neither operating margins nor entry increase when commodity costs rise, as the workhorse model would predict. In other words, rising commodity costs do not appear to increase per-unit profits, which would have to appear in either operating margins or new firm entry. Instead, rising commodity costs are associated with a decline in gross margins, consistent with constant per-unit profits.[22]

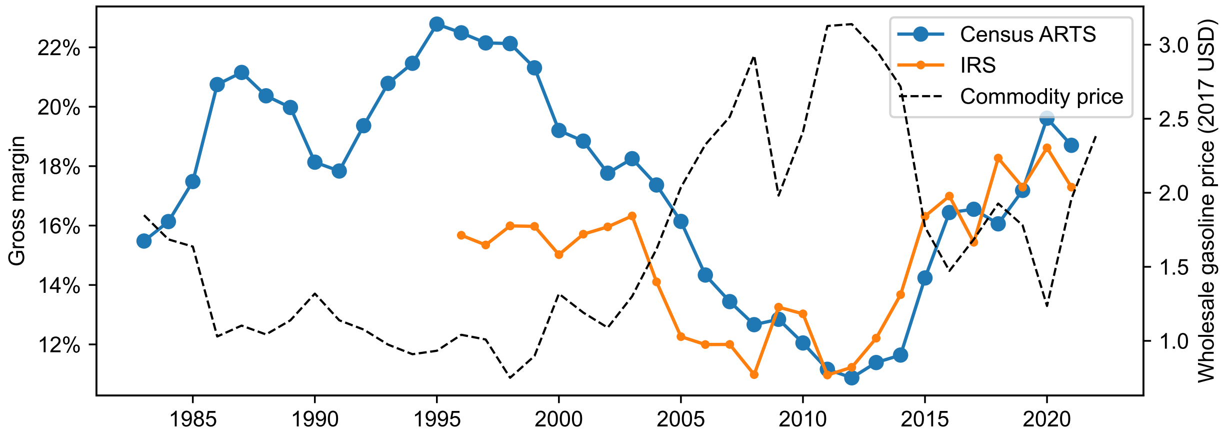
[19] In 2016, sole proprietorships accounted for 20% of retail gas station firms in the Census BDS.

[20] We calculate gross margins in the IRS SOI as income from sales and operations minus cost of sales, as a percent of sales. Following standard definitions, we calculate operating margins as net income plus taxes paid, payments of mortgage interest and other interest on debt, minus income from sources other than sales and operations, as a percent of sales. Results are similar if we use total receipts rather than income from sales and operations for either measure.

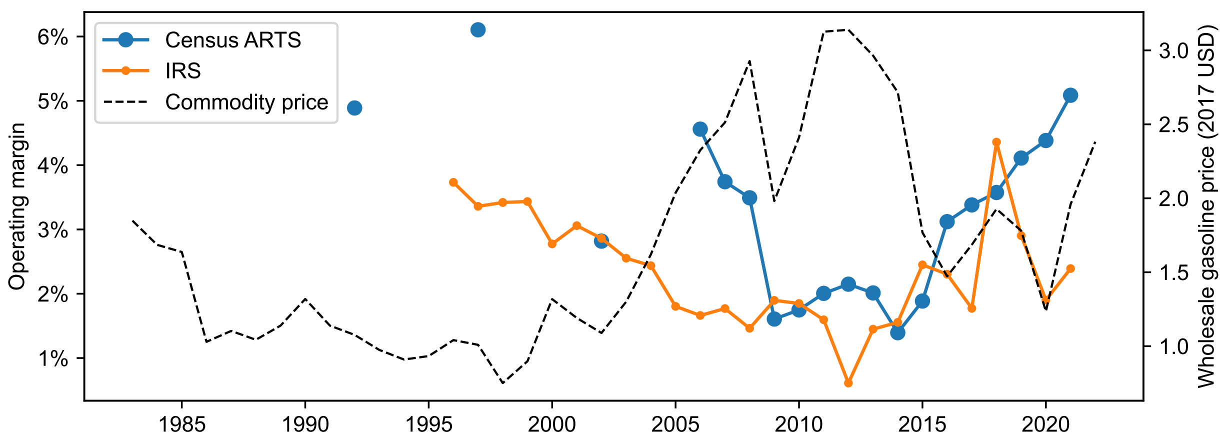
[21] Similar results obtain using the crude oil spot price or nominal rather than deflated wholesale prices.

[22] We could alternatively estimate the relationship between the outcome variables and commodity costs in levels, instead of in first-differences (10). Appendix Table A7 reports results from the level specification, $y_t = \alpha + \beta c_t + \gamma t + \varepsilon_t$, where γt absorbs linear trends in the outcome variable over time. Higher commodity costs are again associated with a significant reduction in gross margins. There is no evidence that higher commodity costs are associated with increased operating margins or entry; in fact, higher commodity costs are associated with lower operating margins.

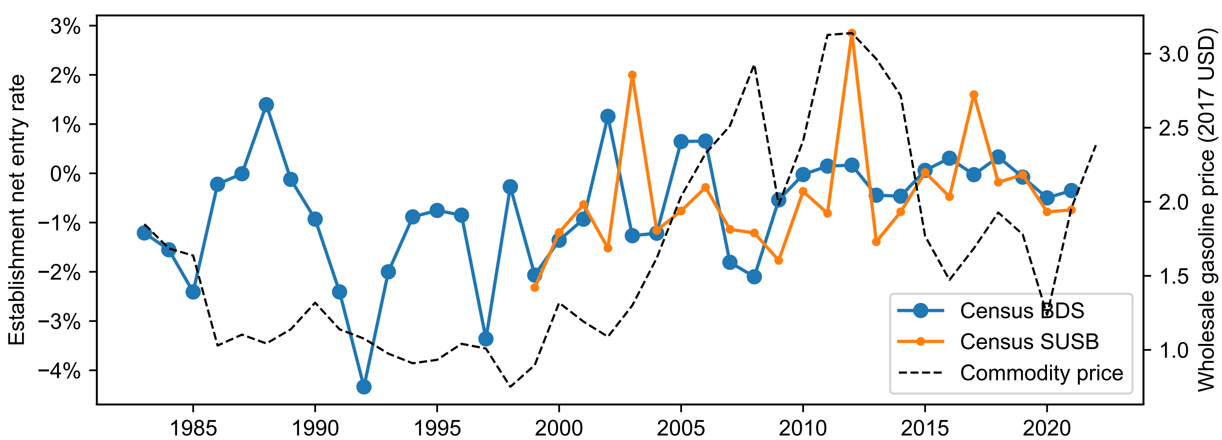
Figure 7: Gross margins, operating margins, and entry for retail gas stations.



(a) Gross margin.

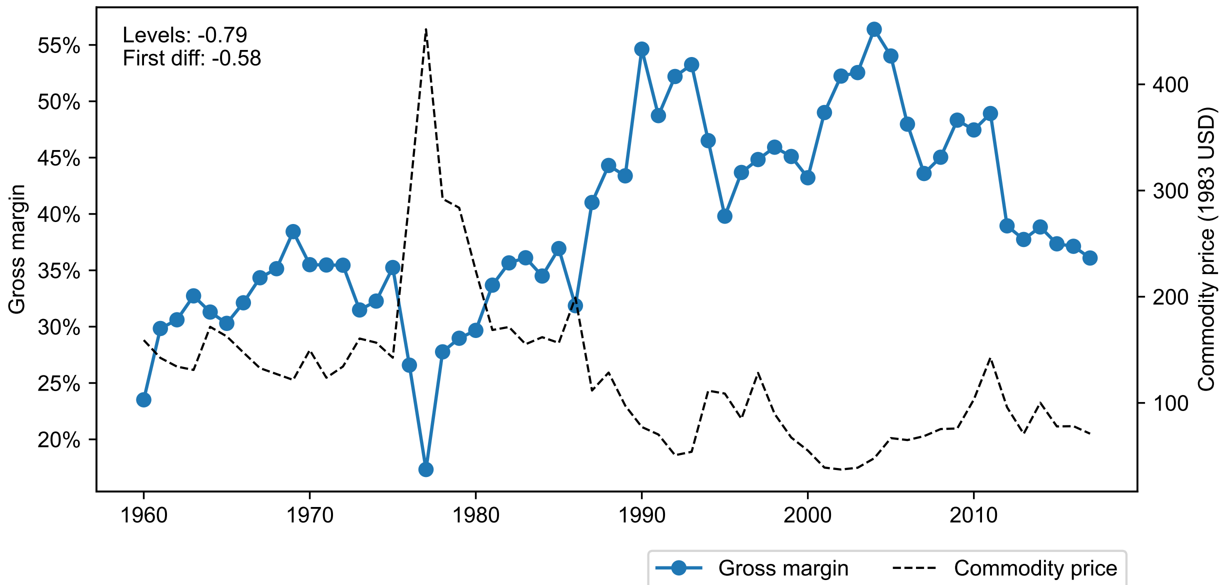


(b) Operating margin.

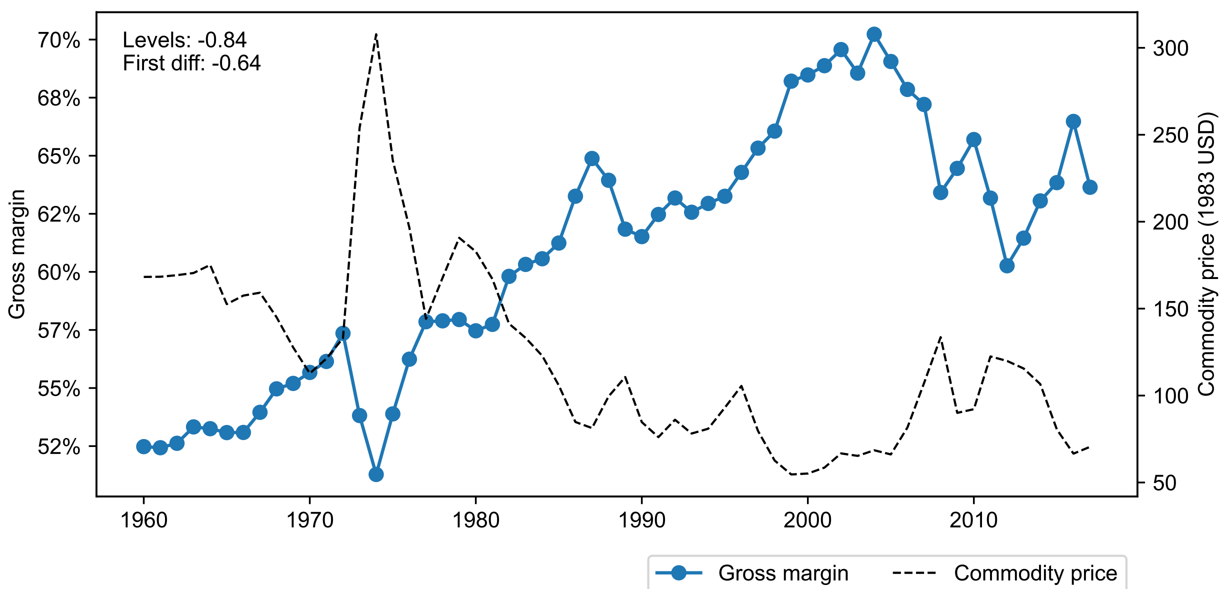


(c) Entry.

Figure 8: Commodity costs and downstream gross margins for two industries.



(a) Roasted coffee manufacturing, with coffee commodity prices.



(b) Bread, cake, and related products manufacturing, with wheat commodity prices.

Note: Gross margins are total sales minus costs of goods sold as a share of sales, from the NBER-CES manufacturing database. Annual wheat and coffee commodity prices are from UNCTADSTAT, deflated to 1983 dollars using CPI excluding food and energy.

Table 8: Changes in gross margins, operating margins, and entry.

Dep var:	Δ *Gross Margin*		Δ *Operating Margin*		Δ *Log Num. Estabs*	
Source:	ARTS	IRS	ARTS	IRS	BDS	SUSB
	(1)	(2)	(3)	(4)	(5)	(6)
Δ log Wholesale Price	-4.337**	-4.124**	0.668	-0.150	-0.002	0.001
	(0.703)	(0.731)	(0.824)	(0.749)	(0.006)	(0.007)
N	39	26	15	26	39	24
R^2	0.53	0.49	0.05	0.00	0.00	0.00

Note: The wholesale gasoline price is from the EIA and is deflated to 2017 USD. ARTS is the Census Annual Retail Trade Survey, IRS are income statement statistics for sole proprietorships, BDS is the Census Business Dynamics Statistics and SUSB is the Census Statistics of US Businesses.

Food and other manufacturing industries. Similar patterns appear in manufacturing industries for coffee, rice, flour, and other products downstream of commodity inputs. To calculate gross margins and operating margins for these industries, we draw on sales and cost data from the NBER-CES Manufacturing Industry database for 1958–2018 (Becker et al. 2021). Data on the number of firms and establishments in each industry comes from the Census Business Dynamics Statistics (BDS) starting in 1983 (for NAICS-4 industries) and the Census Statistics of U.S. Businesses (SUSB) starting in 1998 (for more granular NAICS-6 industries).

Figure 8 plots industry gross margins against commodity costs for two manufacturing industries that use coffee and wheat as commodity inputs. In contrast to Proposition 1, gross margins are not constant and instead are strongly negatively correlated with upstream commodity costs. Appendix Table A8 shows that, for fourteen manufacturing industries in the NBER-CES Manufacturing Industry database that can be matched with an upstream commodity, in nearly all cases industry gross margins exhibit a strong negative correlation with upstream commodity costs both in levels and in first differences.

On the other hand, both possible indicators of the positive correlation between commodity costs and per-unit profits described in Proposition 1—either an increase in operating margins or in entry—are silent in the data. Entry appears to have no systematic correlation with commodity costs, and operating margins like gross margins tend to fall, rather than increase, when commodity costs rise.[23]

[23]Counts of firms and establishments may be noisy indicators of entry and exit, since entry and exit can occur on the intensive margin by multi-product firms withdrawing a subset of products or foregoing certain sales channels. In Appendix Figure A9, we plot market share of the leading brands in rice, flour, and coffee categories from 2006–2019. If increases in commodity costs are associated with new entry, the market share of top brands should erode when commodity costs rise; instead, we find market shares are relatively stable.

Interpretation. This evidence on margins and entry appears inconsistent with fixed multiplicative markups. Admittedly, pass-through in levels is not the sole mechanism that could explain this gap between model and data: for example, one could rationalize the negative response of gross margins to upstream costs by adding sufficiently large price rigidities, arguing that costs of goods sold in the data omit a portion of variable costs, or arguing that within-industry firm heterogeneity generates the aggregate patterns. However, when paired with the micro evidence on complete pass-through in levels, a broader picture emerges that both firm prices and industry aggregates move in a way that is consistent with stable per-unit profits rather than the fixed multiplicative markups common in workhorse macro models.

6 Explaining Pass-Through in Levels

Why do firms in the studied industries exhibit complete pass-through in levels? Two candidate explanations—perfect competition and non-isoelastic demand—could in principle explain complete pass-through in levels. However, both models generate predictions that are at odds with other features of the data. At the close of the section, we briefly discuss other mechanisms that may explain the observed pass-through behavior.

6.1 Is Complete Pass-Through in Levels Due to Perfect Competition?

One explanation for complete pass-through in levels is that firms in the studied industries set prices equal to marginal cost. If this is the case, then changes in costs are reflected in prices one-for-one.

However, other features of the data are difficult to square with two central requirements of perfect competition: that the residual demand curves facing firms are perfectly horizontal and that firms price at marginal cost. In the case of retail gasoline, the presence of substantial price dispersion within narrow geographic areas casts doubt on the assumption of perfectly horizontal demand curves. Moreover, Wang (2009b), who collects sales data from seven gas stations in Perth, estimates station-level demand elasticities between 6–19. Price cycles in the Perth gasoline market also cast doubt on the idea that prices are equal to marginal cost: there are no similar cycles in wholesale costs over the course of the week, and cycles in firms' other variable costs like labor and rent over the course of the week are unlikely (see also the discussion in Wang 2009a). For the food products studied in Section 4, elasticities of demand estimated using Hausman (1996) instruments are small and finite (see Appendix Table E1). Previous studies of the coffee (Nakamura and Zerom

2010) and rice (Park 2013) markets also find that prices are substantially elevated over marginal costs, estimating markups around 1.6.

6.2 Is Complete Pass-Through in Levels Due to Demand Curvature?

The prevailing explanation of incomplete log pass-through attributes pass-through to the shape of demand curves. If demand curves are log-concave, then an increase in costs places firms on a more elastic portion of their demand curve, leading firms to reduce their markups and absorb part of the cost increase. To generate complete pass-through in levels, one could choose a curvature of demand so that the adjustment in firms' percentage markups happens to coincide with a fixed additive margin. This is the case if the elasticity of the demand elasticity with respect to price (i.e., the "super-elasticity") is exactly equal to one (Bulow and Pfleiderer 1983; Weyl and Fabinger 2013; Mrázová and Neary 2017).

Many models of variable markups used in the macro literature, such as nested CES (Atkeson and Burstein 2008) or Kimball preferences (e.g., Klenow and Willis 2016, Amiti et al. 2019), do not satisfy this property with respect to aggregate cost shocks. Those models are homothetic, so that when an aggregate cost shock increases costs identically for all firms in a sector, elasticities remain constant, firms retain the same markups, and the pass-through in levels is equal to firms' markups.

However, logit models of demand used in the industrial organization literature are non-homothetic and feature exactly this property. In fact, in logit models without an outside option (including heterogeneous coefficient models), the pass-through in levels of aggregate cost shocks is equal to one. One reading of the empirical evidence is that logit demand systems more closely approximate empirical patterns of pass-through compared to CES or other homothetic demand systems typically used in macroeconomic models.

Nevertheless, two data points suggest that the curvature of demand remains an unsatisfactory explanation for complete pass-through in levels. First, we show that calibrated logit models—which typically include an outside option—no longer predict uniform pass-through across products in response to an aggregate cost shock. Instead, calibrated demand models exhibit substantial heterogeneity in pass-through in levels, with firm market shares being an especially important predictor of pass-through. We find limited evidence of such a systematic relationship between pass-through and market share in the data. Second, we find that reduced-form estimates of the super-elasticity of demand, measured using a technique developed by Burya and Mishra (2023), are not sufficient to generate complete pass-through in levels.

Pass-through in calibrated logit models. Standard calibrations of logit models feature an outside option that is not exposed to industry cost shocks, making the shape of firms' residual demand curves matter for the extent of pass-through. We demonstrate this by simulating the pass-through of coffee commodity shocks using the demand system estimated for the roasted ground coffee market in Nakamura and Zerom (2010). Since market data for the years they study (2000–2004) are not available, we simulate their demand system using price and market share data from 2006–2019 from NielsenIQ. Appendix C provides a detailed description of how we assemble the data for this simulation.

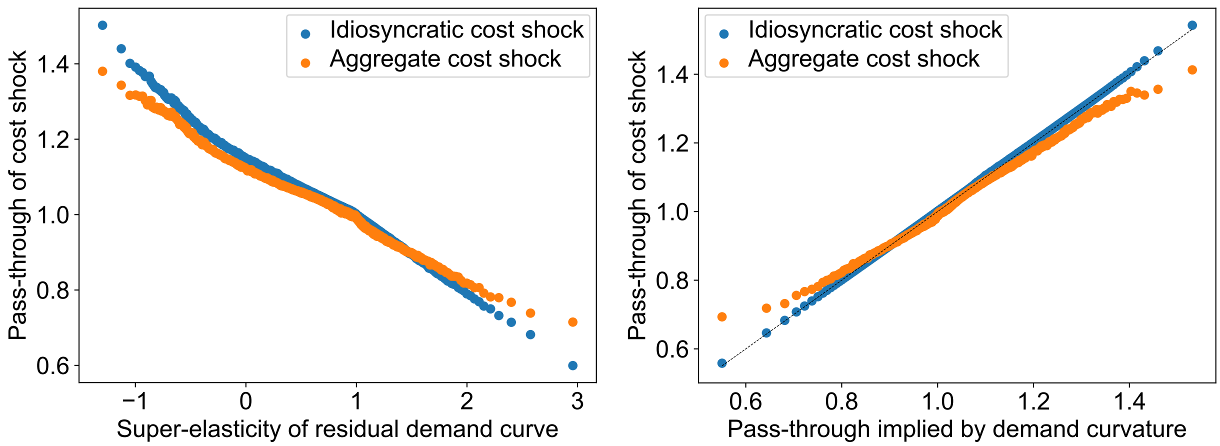
Figure 9 shows the pass-through in levels of idiosyncratic and aggregate cost shocks for coffee products. While the pass-through of aggregate cost shocks is centered around one and is more condensed than the pass-through of idiosyncratic cost shocks, it nevertheless varies considerably across products. The super-elasticity of a product's residual demand curve and the pass-through implied by the product's residual demand curve are systematic predictors for the pass-through of aggregate cost shocks: products with a super-elasticity of demand below one tend to pass through both idiosyncratic and aggregate cost shocks more than one-for-one, while products with a super-elasticity above one tend to pass through both types of shocks less than one-for-one. In other words, the logit model does not guarantee complete pass-through in levels of aggregate cost shocks unless the super-elasticity of demand is close to one.

Nakamura and Zerom (2010) report that the median super-elasticity of demand for products in their data is 4.64. As a point of comparison, for products in this simulation where the super-elasticity of demand is above 3.0, the average pass-through of aggregate cost shocks is 0.71 (std. 0.12), substantially below the complete pass-through in levels that both Nakamura and Zerom (2010) and we find in the data.[24]

Both the variation in the pass-through of aggregate cost shocks across products and the relationship between the curvature of demand and pass-through are not specific to Nakamura and Zerom (2010). Appendix C shows similar patterns also emerge in the demand system for breakfast cereal from Nevo (2001). Additionally, in both the Nakamura and Zerom (2010) and Nevo (2001) demand systems, market share is an important predictor of the super-elasticity of demand and hence the pass-through of aggregate cost shocks (see Appendix Table C2). Appendix Table A9 finds little evidence that pass-through systematically declines with product, brand, or retailer market shares in the data, however.

[24]Super-elasticities of demand in the simulation using 2006–2019 data are substantially lower than the median super-elasticity of 4.64 reported by Nakamura and Zerom (2010). This appears to be due to changes in market structure over time. Nakamura and Zerom (2010) describe the market in 2000–2004 as a near duopoly between Maxwell House and Folgers. In the NielsenIQ data from 2006, the market is less concentrated due to increased penetration by higher-end brands like Starbucks and Peets Coffee.

Figure 9: Pass-through of aggregate and idiosyncratic cost shocks in simulations of Nakamura and Zerom (2010) demand system.



(a) Super-elasticity of demand. **(b)** Pass-through implied by demand curvature.

Note: Each plot shows a binscatter with 1,000 bins. The pass-through of idiosyncratic shocks is calculated as the response (in levels) of firms' optimal prices for a product to an infinitesimal change in the product's cost. The pass-through of aggregate shocks is calculated as the response of firms' optimal prices to an infinitesimal change in all products' costs within the market, excluding the outside option. The pass-through implied by the demand curvature in panel (b) is given by $\rho_i^{\text{implied}} = \sigma_i/(\sigma_i + \varepsilon_i - 1)$, where σ_i and ε_i are the elasticity and super-elasticity of the product's residual demand curve.

Direct estimates of the super-elasticity. An alternative approach is to measure the super-elasticity of demand directly in the data without calibrating a full model of demand. Burya and Mishra (2023) develop a technique to estimate the super-elasticity of demand using the specification,[25]

$$\log q_{ist} = \eta \log p_{ist} + \kappa(\log p_{ist})^2 + \gamma X_{ist} + \varepsilon_{ist}, \tag{11}$$

where q_{ist} is the quantity of product i sold at store s in period t, p_{ist} is its price, and X_{ist} is a vector of controls. As they show, the ratio κ/η measures the super-elasticity of the firm's residual demand curve, since it captures how the elasticity of demand changes with price.

For each product category (coffee, rice, and flour), we select the top fifty UPCs by sales from 2006–2020 and estimate (11) individually for each UPC in each store.[26] To deal with the simultaneity of supply and demand, we use Hausman (1996) instruments to

[25] Pless and Benthem (2019) use a similar specification to measure the curvature of demand for residential solar power. They also find a super-elasticity below one (in fact, their estimated super-elasticity is negative).

[26] Burya and Mishra (2023) pool data across product categories and stores by assuming that all products lie on the same demand curve. If products do not lie on the same demand curve, then η and κ are weighted averages of demand primitives across products, and the ratio κ/η is no longer a consistent measure of the super-elasticity. Since DellaVigna and Gentzkow (2019) find that demand curves vary substantially across stores, we follow their approach in estimating demand curves individually at the product-store level.

Table 9: Share of products in category with super-elasticity estimates below one.

Percent of store-UPC pairs	Coffee	Rice	Flour
Super-elasticity point estimate below one	98.3%	99.9%	88.5%
Super-elasticity above one rejected at $p = 0.05$	52.9%	90.6%	51.7%

Note: A product is defined as a UPC at an individual store. Super-elasticities are estimated as the ratio of κ/η from the specification (11). See Appendix E for estimation details.

identify changes in prices that are plausibly exogenous to local demand conditions. In particular, as an instrument for the price of UPC i in store s at week t, we use the average price of UPC i at all stores in the same retail chain as s outside of s's designated market. This instrument exploits retailers' uniform pricing practices, as discussed by DellaVigna and Gentzkow (2019). Appendix E provides a detailed description of the sample and estimation procedure.

Table 9 reports that the vast majority of products (i.e., store-UPC pairs) in each product category have an estimated super-elasticity of demand below one. Super-elasticities of demand at or above one are rejected at the five percent level for over half of the products in the data. These estimates suggest that demand curves in the data are not sufficiently concave to generate pass-through in levels.

In Appendix Table E2, we use a similar approach to measure how the elasticity of demand facing a product changes as the average price in its store or its geographic market changes. Across these robustness exercises, we again find little evidence that changes in the elasticity of demand are sufficient to generate complete pass-through in levels.

6.3 Other Explanations

We briefly survey other models that may rationalize complete pass-through in levels. These broadly fall into four (non-exhaustive) categories: models where firms mark up value added, but not intermediate, inputs; models where firms' market power derives from consumers' switching costs; models where the demand curves facing firms are kinked due to competitive conduct or the threat of entry; and models that ascribe pricing behavior to manager heuristics or objectives other than profit-maximization.

One possibility is that firms apply markups only to value added costs and not intermediate input costs. Okun (1981) speculates a "special role for material costs," suggesting that costs of purchased materials may be passed through to customers one-for-one while labor costs are passed through with a percentage markup. Such a model of pricing would affect the standard intuition that chains of producers lead to double marginalization.

While this explanation is appealing for its simplicity, it is difficult to rationalize why firms would treat some components of marginal cost differently than others when setting prices. Models of exchange rate pass-through where imported goods are bundled with local distribution services (e.g., Burstein et al. 2003, Corsetti and Dedola 2005, Burstein et al. 2006) could in principle rationalize this pricing behavior if goods markets and the bundling of goods with distribution services are perfectly competitive.

A second possibility is that firms' market power derives from the opportunity costs that consumer face when switching to alternative providers. These opportunity costs customers face could be due to explicit differences in price offered by the firm and its competitors, as in models of limit pricing (e.g. Peters 2020), or could be due to other costs incurred by consumers such as search or transport costs (see e.g. Hotelling 1929; Stigler 1961; Salop 1979; Salop and Stiglitz 1982; as well as recent work by Menzio 2024 and Barro 2024). For example, in Barro (2024), firms choose an additive margin that scales with consumers' transportation costs and the maximum distance of customer served, despite facing isoelastic demand from existing customers. If consumers' switching costs are independent of firms' marginal costs, then firms may choose additive unit margins that do not vary as commodity costs fluctuate, leading to complete pass-through in levels.

The conduct of competition can also generate kinked demand curves that lead firms to maintain fixed margins. For example, Maskin and Tirole (1988) show that equilibrium strategies in a duopoly can generate kinked demand curves or price cycles. Several studies propose models in which the threat of entry prevents firms from increasing prices above a level that compensates them for overall costs (e.g., Bain 1949; Modigliani 1958; Bils and Chang 2000). Okun (1981) speculates that prices are constrained by implicit contracts between firms and their customers, leading firms to only increase prices when costs visibly increase (for related ideas on fairness and cost visibility, see Rotemberg 2005; Busse et al. 2006; and Westphal 2024).

A final set of explanations emerges from interviews with price-setters at firms, which suggest that managers tend to employ heuristics such as "full cost pricing" or "target returns pricing" (Hall and Hitch 1939; Lanzillotti 1958; Blinder 1994).[27] Such heuristics, or managers' other objectives (e.g., Baumol's 1959 conjecture that managers seek to maximize revenue subject to a profit constraint), may distort firms' prices from the multiplicative markups that would be optimal if demand is isoelastic.

[27]In our informal conversations with firm managers (largely retailers), some mention pricing rules (both additive and multiplicative), and others mention targeting constant operating or gross margins. Survey responses in Hall and Hitch (1939) also exhibit this mix of rules. Despite some managers mentioning multiplicative markup rules, few accept the premise that rising costs lead to higher per-unit profits, as multiplicative markups would predict (see Section 5).

7 The Unequal Incidence of Commodity Shocks

This section explores the implications of complete pass-through in levels for inflation inequality. As we have seen, increases in upstream costs result in greater inflation rates for low-markup products within a category, even though absolute price changes are similar across products. Since low-income households disproportionately purchase low-price and low-markup products (Sangani 2022), inflation rates faced by low-income households will be more sensitive to upstream commodity prices even within narrow product categories.

Section 7.1 shows that inflation rates faced by low-income households are indeed more sensitive to commodity costs in categories like coffee, rice, and flour. Section 7.2 then extends the analysis to the entire food-at-home bundle and applies the findings to inflation from 2020–2023.

7.1 Within-Category Inflation Inequality

We calculate the inflation rate π_{jct} faced by households in income quintile j in product category c and quarter t as

$$\pi_{jct} = \frac{\sum_{i \in \mathcal{I}(c)} \lambda_{ijt} \pi_{it}}{\sum_{i \in \mathcal{I}(c)} \lambda_{ijt}}, \tag{12}$$

where $\mathcal{I}(c)$ are the set of products in product category c, λ_{ijt} are the total expenditures on product i by households in quintile j in quarter t, and π_{it} is the inflation rate of product i over the next year from quarter t to quarter $t + 4$.

These category inflation rates use expenditure shares in the initial quarter t, and hence are not contaminated by how households substitute across products in response to price changes (i.e., π_{jct} is the inflation rate on a Laspeyres price index). Note also that by using year-over-year inflation rates, (12) avoids seasonality effects that may bias inflation measured over shorter increments.

Our measures of expenditures λ_{ijt} and product-level inflation rates π_{it} are from the NielsenIQ Homescan and NielsenIQ Retail Scanner datasets. We define a product i as a UPC sold at a specific retail chain and calculate the inflation rate π_{it} as the percent change in the quantity-weighted average price of product i from quarter t to $t + 4$.[28] We sort

[28]We have also constructed similar estimates defining each UPC as a product. The advantage of the finer, retailer-UPC level of disaggregation is that the same UPC is often priced differently across retailers, and households across the income distribution source their purchases from different retailers. On the other hand, taking the UPC as the lowest level of disaggregation increases the share of expenditures in the NielsenIQ Homescan data that we are able to match to the Retail Scanner data, as we report in Appendix Table A10. Nevertheless, we find similar results at both levels of disaggregation, with slightly larger cyclical differences in inflation across income quintiles when we define products at the retailer-UPC level.

households in the NielsenIQ Homescan data into income quintiles using the provided projection weights, and measure λ_{ijt} as total expenditures by households in quintile j in quarter t on product i for the subset of products that we match to the NielsenIQ Retail Scanner Data.

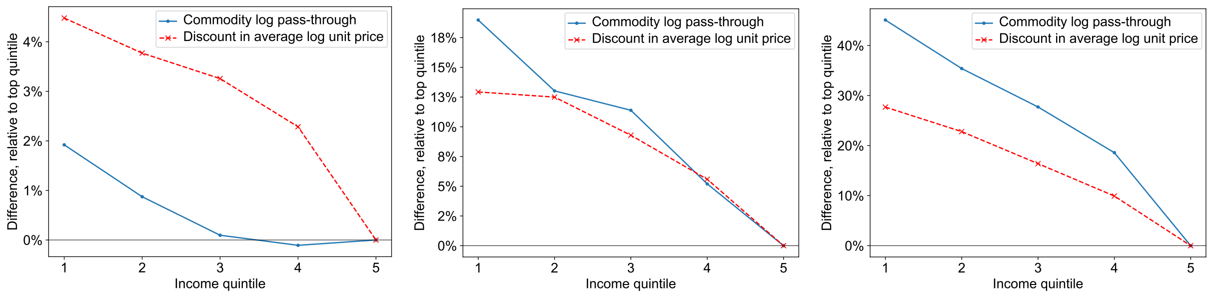
As an example, Figure 1 (in the Introduction) plots the difference between the inflation rate for coffee products for households in the lowest income quintile and the highest income quintile. There are large swings in the extent of the within-category inflation rates, with spikes in 2011 and 2014 coinciding with increases in coffee commodity costs. The inflation gap is positive on average, consistent with the secular drivers of inflation inequality documented by Jaravel (2019, 2021), but also features cyclical variation predicted by complete pass-through in levels—even becoming negative in periods of commodity price deflation, such as in 2012–2013.

Figure 10 shows the log pass-through of commodity costs to inflation rates faced by each income quintile in flour, rice, and coffee. Intuitively, differences in log pass-through across income groups depend on the extent to which low-income households purchase lower priced and lower margin products than high-income households. For example, there are only minor differences in the average prices paid by households for flour products, and thus differences in the long-run log pass-through of commodity costs to flour prices paid by different income groups are relatively small. On the other hand, the unit price paid by households in the lowest income quintile for coffee products is nearly 30 percent lower than that paid by households in the highest income quintile, and thus there are large differences in the log pass-through of coffee commodity costs to the prices faced by different income groups.

7.2 Food-at-Home Inflation Inequality

We now consider overall food-at-home inflation rates faced by households of different income groups. Rather than attempt to match specific commodities to each food item consumed by households, in this section we explore the log pass-through of two upstream price indices—producer price indices for Farm Products and Food Manufacturing—to downstream prices faced by consumers. Complete pass-through in levels predicts that log pass-through of these price indices to retail prices should decline as we consider higher-priced product varieties and the baskets of higher-income households. As we will see, both predictions are borne out in the data.

Figure 10: Log pass-through of commodity costs by income quintile.



(a) Flour. **(b)** Rice. **(c)** Coffee.

Note: Discount in average log unit price shows the percent difference in the average, posted unit price of products consumed by households in the income group relative to the highest income group (e.g., households in the lowest income quintile buy flour products that have a 4.3% lower unit price on average than flour products bought by households in the highest income quintile). Commodity log pass-through shows the percentage difference in the long-run log pass-through of commodity costs to retail prices for households in the income group vs. the highest income group.

Disaggregating food-at-home inflation by relative price. Beraja et al. (2019) show that price indices constructed from NielsenIQ Retail Scanner data can closely match consumer price indices released by the Bureau of Labor Statistics (BLS). We undertake a similar exercise, constructing the food-at-home inflation rate for all food products in the NielsenIQ data as

$$\pi_t^{\text{Retail Scanner}} = \frac{\sum_i \lambda_{it}\pi_{it}}{\sum_i \lambda_{it}},$$

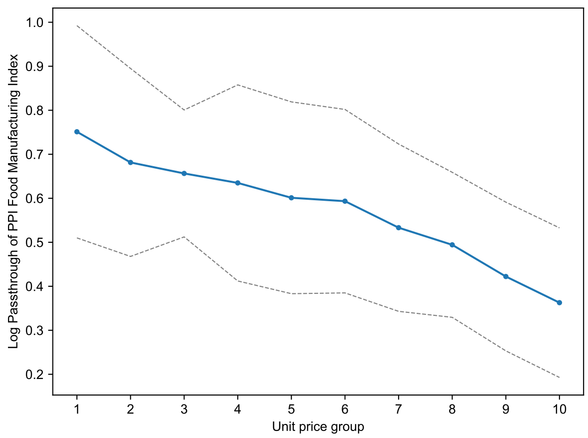
where π_{it} is the year-over-year growth in the quantity-weighted average price of product i from quarter t to quarter $t+4$ and λ_{it} is the total sales of product i in quarter t. Our inflation rates co-move closely with the BLS food-at-home consumer price index, as shown in Appendix Figure A10; the correlation between the inflation rates we construct in the retailer scanner data with BLS food-at-home inflation rates is over 0.96.

We can now further disaggregate food-at-home inflation by the relative price of products. In each quarter, we rank all products within each product category by average unit price over the prior year. We then split products in each product category into ten groups with equal sales and measure the inflation rate for products in the q-th unit price decile as

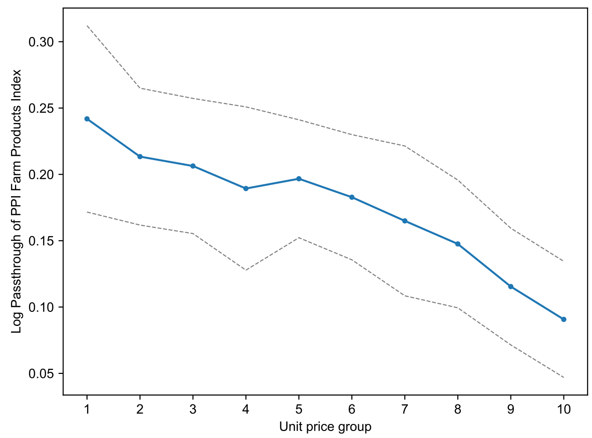
$$\pi_{qt}^{\text{Retail Scanner}} = \frac{\sum_{i\in\mathcal{I}(q)} \lambda_{it}\pi_{it}}{\sum_{i\in\mathcal{I}(q)} \lambda_{it}},$$

where $\mathcal{I}(q)$ is the set of products in the q-th decile of unit price within their product category in quarter t. Note that each group has an identical composition of sales across

Figure 11: Low unit price products have higher log pass-through of upstream prices.



(a) Food Manufacturing PPI.



(b) Farm Products PPI.

Note: Dotted lines indicate 95 percent confidence intervals using Driscoll-Kraay standard errors.

product categories, so that differences in inflation across groups are exclusively driven by differences in the inflation rates that low-priced products have relative to high-priced products within each category, rather than differences in weights across product categories. Appendix Figure A11 plots the inflation rates constructed for various deciles: inflation rates for lower unit price deciles are significantly more volatile than for high deciles, with the gap between inflation rates of low- and high-priced products expanding dramatically when overall food-at-home inflation is high.

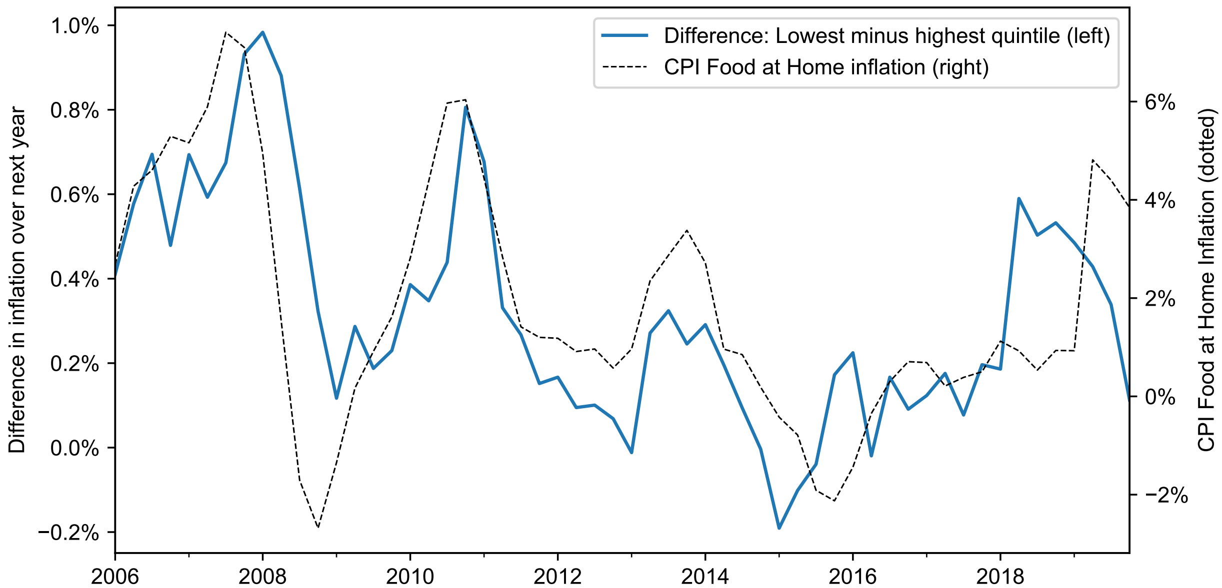
We test our prediction that log pass-through of upstream costs declines with relative price using the specification,

$$\Delta \log p_{qt}^{\text{Retail Scanner}} = a^q + \sum_{k=0}^{K} b_k^q \Delta \log \text{PPI}_{t-k} + \varepsilon_{qt}, \tag{13}$$

where $\Delta \log p_{qt}^{\text{Retail Scanner}}$ is the change in the price index for decile q, $\Delta \log \text{PPI}_t$ is the change in the upstream PPI (Farm Products or Food Manufacturing), and $\sum_{k=0}^{K} b_k^q$ measures the log pass-through of upstream PPI changes to retail price changes for decile q. We set $K = 3$ for a horizon of one year.

As predicted, log pass-through of both upstream PPIs to retail prices declines systematically with unit price, as shown in Figure 11. The magnitudes of this decline are large: the log pass-through of Food Manufacturing price changes to products in the lowest-priced decile is 0.75, compared to 0.39 for products in the highest-priced decile. Note that these differences in log pass-through are independent of secular differences in inflation across

Figure 12: Gap in food-at-home inflation rates: Households in lowest vs. highest income quintile.

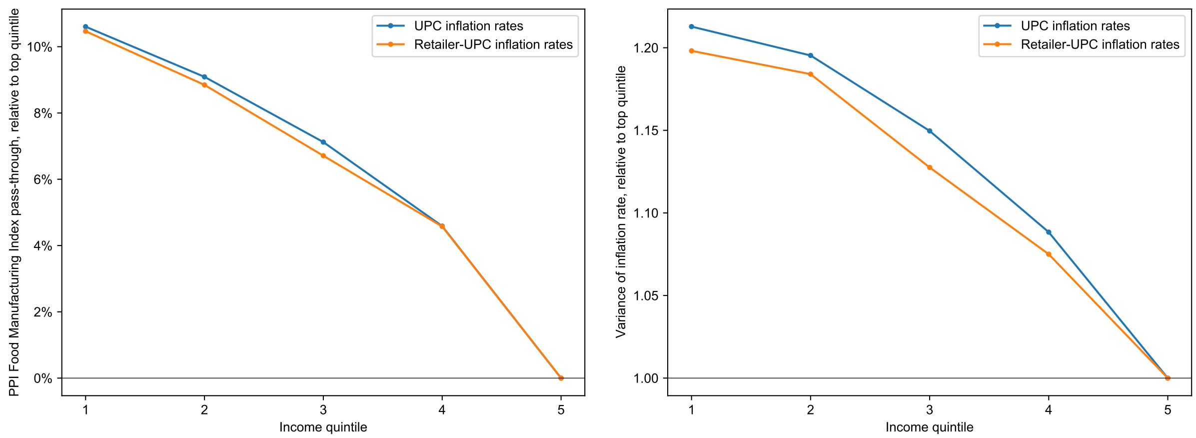


unit price groups, which are instead captured by the intercept coefficients a^q. (Appendix Figure A12 shows that the estimated intercept coefficients also decrease with unit price, consistent with the secular drivers of inflation differences documented by Jaravel 2019.)

Differences across income groups. How large are these effects for differences in food-at-home inflation faced by different income groups? We construct food-at-home price indices for each household income quintile using (12), now using the expenditures of households in NielsenIQ Homescan data across all food products.

Figure 12 plots the gap in food-at-home inflation rates experienced by the lowest and highest income quintiles since 2006. As documented by Jaravel (2019), this gap tends to be positive. However, there is significant cyclical variation in the level of inflation inequality that co-moves with the level of food-at-home inflation. In particular, inflation inequality grows when overall price levels are rising. As shown in Figure 13a, the log pass-through of upstream producer prices (the Food Manufacturing PPI) to prices faced by the lowest income quintile is 10 percent higher than that of the highest income quintile. This heightened sensitivity to upstream prices also translates into more volatile food-at-home inflation rates: Figure 13b shows that the variance of food-at-home inflation rates for the lowest income quintile is 20 percent higher than that of the highest income quintile.

Figure 13: Food-at-home inflation for low-income more sensitive to upstream prices and higher variance.



(a) Pass-through of Food Manufacturing PPI.

(b) Variance of inflation rates.

Implications for food-at-home inflation, 2020–2023. At the time of conducting this exercise, the most recent NielsenIQ data available ended in December 2020. We construct back-of-the-envelope estimates for inflation inequality over the post-pandemic period based on the evolution of upstream price indices. These estimates suggest sizable differences in inflation rates across income groups from January 2020 to January 2023, in part due to large increases in upstream costs over this period.

To estimate the price growth of a price index i from 2020 to 2023, we use fitted values for the intercept and long-run pass-through from (13) to calculate

$$\Delta \log(\text{PriceIndex}_{qt}) \approx \underbrace{\alpha^q t}_{\text{Due to secular inflation rate}} + \underbrace{\rho_q^{\text{PPI}}(\Delta \log \text{PPI}_t)}_{\text{Due to pass-through}}, \tag{14}$$

where t is the number of quarters since January 2020, α^q is the intercept from the pass-through specification (13), and $\rho_q^{\text{PPI}} = \sum_{k=0}^{K} b_k^q$ is the long-run log pass-through of changes in the upstream PPI to price index q. The two terms in (14) capture two distinct channels that contribute to growth in the price index: secular trends in prices and how changes in upstream costs contribute to price growth.

Table 10 reports the predicted growth in price indices using this approach, with the Food Manufacturing PPI as the measure of upstream costs. The prices of products in the lowest-priced decile are predicted to have grown by 11pp more than products in the highest-priced decile. Over 60 percent of this difference is due to differences in the pass-through of upstream costs. The food-at-home price index for households in the lowest

Table 10: Unequal price growth predicted from January 2020 to January 2023.

	Predicted growth in price index		
	Total	Due to pass-through of upstream costs	Due to intercept
Products in unit price decile 1	20.7pp	16.0pp	4.7pp
Products in unit price decile 10	9.3pp	8.9pp	0.3pp
Difference	**11.4pp**	**7.1pp**	**4.3pp**
Lowest income quintile	15.6pp	12.7pp	2.8pp
Highest income quintile	13.7pp	11.5pp	2.2pp
Difference	**1.8pp**	**1.2pp**	**0.6pp**

income quintile is predicted to have grown 15.6pp, compared to 13.7pp for households in the highest income quintile. Had upstream producer prices instead been flat during this period, we estimate that the gap in price growth across high- and low-income households would have been 0.6pp, rather than 1.8pp.

8 Conclusion

Incomplete log pass-through and markup adjustment may be better understood in terms of complete pass-through in levels and a lack of adjustment in additive unit margins. In the retail gasoline and food markets studied in this paper, complete pass-through in levels explains both the extent of and cross-sectional variation in log pass-through, and empirical exercises suggest that similar patterns appear across a broader array of food-at-home products purchased by households. More broadly, complete pass-through in levels offers an explanation for cyclical variation in inflation inequality and the disproportionate inflation faced by low-income households in the post-pandemic period.

This pass-through behavior, as well as accompanying evidence on firms' gross margins, operating margins, and new firm entry, casts doubt on theories of fixed, multiplicative markups, which are a staple of models in macroeconomics and trade. Previous work, in seeking to accommodate evidence of incomplete log pass-through, has extended these models to allow for non-isoelastic demand and variable markups. However, the fact that complete pass-through in levels emerges across markets and appears quite uniform across products within a market suggests that such explanations that rely on the curvature of demand alone remain unsatisfactory. Future work is needed to reconcile macroeconomic models of pricing with these patterns of pass-through. It also remains to be seen whether the patterns of commodity cost pass-through documented in this paper extend to more differentiated products, beyond the relatively homogeneous categories studied here, and whether they also explain the pass-through of idiosyncratic shocks.

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Online Appendix

(Not for publication)

Appendix A Additional Tables and Figures

Table A1: Unit root tests for commodity series.

	Levels			First differences		
	Auto-correlation (β)	Standard error	ADF test p-value	Auto-correlation (γ)	Standard error	ADF test p-value
Terminal ULP	0.996	(0.007)	0.731	0.449	(0.058)	0.000
Terminal PULP	0.995	(0.006)	0.665	0.442	(0.058)	0.000
Coffee	0.983	(0.010)	0.322	0.229	(0.052)	0.000
Sugar	0.975	(0.018)	0.242	0.199	(0.083)	0.000
Beef	0.997	(0.008)	0.939	0.238	(0.042)	0.000
Rice	0.987	(0.010)	0.165	0.347	(0.078)	0.000
Flour	0.984	(0.011)	0.343	0.213	(0.047)	0.000
Orange	0.967	(0.013)	0.028	0.238	(0.045)	0.000

Note: Columns 1 and 4 report coefficients estimated from the specifications,

$$c_t = \beta c_{t-1} + \varepsilon_t,$$
$$\Delta c_t = \gamma \Delta c_{t-1} + \hat{\varepsilon}_t.$$

Columns 2 and 5 report Newey-West standard errors with four lags. Columns 3 and 6 report the p-value from Augmented Dickey-Fuller tests for unit roots, where the null hypothesis is that the series is a unit root process. Terminal ULP and PULP refer to wholesale prices of regular and premium unleaded gasoline from Perth, Australia terminals.

Table A2: Granger causality tests for commodity and retail prices.

	Granger causality test p-value	
	Δc causes Δp	Δp causes Δc
Retail gasoline market in Perth, Australia		
Terminal ULP to Station Price ULP	0.000	0.209
Terminal PULP to Station Price PULP	0.000	0.508
Food products		
Coffee Commodity (IMF) to Retail (CPI)	0.000	0.334
Sugar Commodity (IMF) to Retail (CPI)	0.003	0.652
Beef Commodity (IMF) to Retail (CPI)	0.688	0.956
Rice Commodity (IMF) to Retail (CPI)	0.353	0.877
Flour Commodity (IMF) to Retail (CPI)	0.700	0.931
Orange Commodity (IMF) to Retail (CPI)	0.053	0.979

Note: Granger causality tests for whether changes in upstream prices, Δc, Granger-cause changes in downstream prices, Δp, and vice versa. Column 1 reports p-values for the null hypothesis that changes in upstream prices do not cause downstream prices, and column 2 reports p-values for the null hypothesis that changes in downstream prices do not cause upstream prices. All tests use four lags. For the Perth, Australia retail gasoline market, we run Granger causality tests using the fifty stations in the data with the highest number of weekly observations.

Table A3: IMF primary commodity prices and sources.

Commodity series	IMF Series ID	Description
Global price of Coffee, Other Mild Arabica	PCOFFOTMUSDM	Coffee, Other Mild Arabicas, International Coffee Organization New York cash price, ex-dock New York
Global price of Sugar, No. 16, US	PSUGAUSAUSDM	Sugar, U.S. import price, contract no. 16 futures position
Global price of Beef	PBEEFUSDM	Beef, Australian and New Zealand 85% lean fores, CIF U.S. import price
Global price of Rice, Thailand	PRICENPQUSDM	Rice, 5 percent broken milled white rice, Thailand nominal price quote
Global price of Wheat	PWHEAMTUSDM	Wheat, No. 1. Hard Red Winter, ordinary protein, Kansas City
Global price of Orange	PORANGUSDM	Generic 1st 'JO' Future

Table A4: Food products commodity and retail price series with unit conversion factors.

Commodity series	IMF Series ID	Units	BLS Average Price Data series	Series ID[29]	Unit conversion factor
Global price of Coffee, Other Mild Arabica	PCOFFOTMUSDM	Cents per Pound	Coffee, 100 percent, ground roast, per lb.	717311, 717312	1.235 (19% weight lost in roasting process[30])
Global price of Sugar, No. 16, US	PSUGAUSAUSDM	Cents per Pound	Sugar, white, per lb.	715211, 715212	1
Global price of Beef	PBEEFUSDM	Cents per Pound	Ground beef, 100% beef, per lb. (453.6 gm)	703112	1
Global price of Rice, Thailand	PRICENPQUSDM	Dollars per Metric Ton	Rice, white, long grain, uncooked, per lb. (453.6 gm)	701312	0.0454 (100 dollars per cent / 2204.62 lbs per metric ton)
Global price of Wheat	PWHEAMTUSDM	Dollars per Metric Ton	Flour, white, all purpose, per lb. (453.6 gm)	701111	0.0613 (100 dollars per cent / 2204.62 lbs per metric ton wheat / 44.40 lbs flour per 60 lbs (1 bushel) wheat[31])
Global price of Orange	PORANGUSDM	Dollars per Pound	Orange juice, frozen concentrate, 12 oz. can, per 16 oz. (473.2 mL)	713111	51.7 (100 dollars per cent $\times$ 4.133 lbs orange solids / gallon concentrate $\times$ (1/8) gallon per 16 fl oz.[32])

[29] For some products, multiple series are available which track different package sizes.
[30] Nakamura and Zerom (2010).
[31] USDA Conversion Table (p.41) for pounds white flour per bushel of wheat.
[32] USDA Conversion Table (p.34) for orange solids per gallon of retail concentrate (41.8 retail brix from Dutta et al. 2002).

Table A5: Higher-priced products exhibit lower log pass-through, with no systematic difference in level pass-through: Five groups.

Panel A: In percentages

	Retail price inflation		
	Rice	Flour	Coffee
Commodity Inflation × Unit Price Group 2	−0.070**	−0.001	−0.034
	(0.017)	(0.019)	(0.022)
Commodity Inflation × Unit Price Group 3	−0.095**	−0.006	−0.088**
	(0.015)	(0.006)	(0.021)
Commodity Inflation × Unit Price Group 4	−0.127**	−0.044**	−0.102**
	(0.018)	(0.010)	(0.019)
Commodity Inflation × Unit Price Group 5	−0.197**	−0.054**	−0.105**
	(0.021)	(0.009)	(0.015)
UPC FEs	Yes	Yes	Yes
N (thousands)	399.4	101.4	1570.0
R^2	0.16	0.06	0.15

Panel B: In levels

	Δ Retail price		
	Rice	Flour	Coffee
Δ Commodity Price × Unit Price Group 2	0.007	0.048	−0.003
	(0.069)	(0.029)	(0.040)
Δ Commodity Price × Unit Price Group 3	0.084	0.048**	−0.100
	(0.056)	(0.021)	(0.063)
Δ Commodity Price × Unit Price Group 4	0.052	−0.051	−0.120*
	(0.070)	(0.063)	(0.070)
Δ Commodity Price × Unit Price Group 5	0.050	−0.084**	−0.090*
	(0.133)	(0.037)	(0.046)
UPC FEs	Yes	Yes	Yes
N (thousands)	399.4	101.4	1570.0
R^2	0.07	0.05	0.15

Note: Panel A reports results from specification (6), and panel B reports results from specification (7). In each quarter, products are split into five groups with equal sales by average unit price over the past year, ordered from lowest (1) to highest unit price (5). Standard errors clustered by brand. * indicates significance at 10%, ** at 5%.

Table A6: Exploiting variation in markups for identical products across retailers: Summary of results across all product modules.

Share of modules	Unweighted	Observations-weighted	Sales-weighted
Panel A: In levels			
Positive coefficient	9.7	5.6	7.2
Not significant	63.2	54.1	54.0
Negative coefficient	27.1	40.3	38.8
Panel B: In logs			
Positive coefficient	0.6	0.0	0.0
Not significant	13.7	3.6	3.6
Negative coefficient	85.7	96.4	96.4

Note: Summary of results from specifications (8) (for panel A) and (9) (for panel B) estimated across 616 product modules. Each cell reports the fraction of product modules for which the estimated interaction between the average UPC price change (in levels or logs) and the relative price of the product at the retailer is significant at a 5% level.

Table A7: Relationship of retail gas station gross margins, operating margins, and entry with commodity price.

Dep var:	*Gross margin*		*Operating margin*		*Log Num. Estabs*	
Source:	ARTS	IRS	ARTS	IRS	BDS	SUSB
	(1)	(2)	(3)	(4)	(5)	(6)
Log Wholesale Price	-8.246**	-5.971**	-1.986**	-1.597**	0.007	-0.028**
	(0.483)	(0.406)	(0.688)	(0.216)	(0.020)	(0.006)
Year	0.004	0.236**	-0.013	0.006	-0.008**	-0.003**
	(0.025)	(0.017)	(0.037)	(0.017)	(0.001)	(0.000)
N	40	27	19	27	40	25
R^2	0.89	0.88	0.33	0.59	0.88	0.89

Note: The spot price is the WTI Crude Oil price, deflated to 2017 USD. ARTS is the Census Annual Retail Trade Survey, IRS are income statement statistics for sole proprietorships, BDS is the Census Business Dynamics Statistics and SUSB is the Census Statistics of US Businesses.

Table A8: Correlation between commodity costs and downstream gross margins, operating margins, and entry.

	SIC industry		Correlation					
			Gross Margin		Oper. Margin		Entry	
Commodity	Description	SIC	Lvl.	Diff.	Lvl.	Diff.	Lvl.	Diff.
Sugar	Candy and other confectionery products	2064	−0.58**	−0.37**	−0.49**	−0.16	0.04	0.06
Beef	Sausages and other prepared meats	2013	−0.82**	−0.39**	−0.81**	−0.27**	−0.24	−0.04
Wheat	Flour and other grain mill products	2041	−0.80**	−0.55**	−0.70**	−0.43**	−0.05	0.16
Wheat	Prepared flour mixes and doughs	2045	−0.80**	−0.57**	−0.78**	−0.46**	0.09	−0.13
Wheat	Bread, cake, and related products	2051	−0.84**	−0.64**	−0.76**	−0.49**	0.09	−0.13
Rice	Rice milling	2044	−0.70**	−0.17	−0.57**	−0.06	0.02	0.44**
Coffee	Roasted coffee	2095	−0.79**	−0.58**	−0.75**	−0.54**	−0.33**	0.05
Cocoa beans	Chocolate and cocoa products	2066	−0.36**	−0.07	−0.35**	−0.03	0.08	−0.27
Cotton	Broadwoven fabric mills, cotton	2211	0.02	−0.42**	−0.61**	−0.37**	0.50**	0.37**
Milk	Cheese; natural and processed	2022	−0.66**	−0.61**	−0.53**	−0.46**	0.28	0.34*
Milk	Dry, condensed, evaporated products	2023	−0.52**	−0.58**	−0.52**	−0.50**	0.28	0.34*
Aluminum	Aluminum sheet, plate, and foil	3353	−0.73**	−0.41**	−0.70**	−0.26	0.24	0.15
Aluminum	Aluminum die-castings	3363	−0.63**	−0.57**	−0.61**	−0.12	0.39**	0.26
Orange juice	Frozen fruits and vegetables	2037	−0.63**	−0.18	−0.70**	−0.14	−0.17	−0.12

Note: Industry data from NBER-CES manufacturing database (1958–2018). Variable costs defined as material costs. Operating costs are defined as the sum of material, energy, and labor costs. Entry rates are net establishment entry rates from the Census Business Dynamics Statistics (BDS) (1983–2018). Commodity prices are from UNCTADSTAT (1960–2017), except milk, aluminum, and frozen orange juice, which are from the IMF Commodities database (1980–2018). Commodity prices deflated using core CPI. * indicates significance at 10%, ** at 5%.

Table A9: Relationship between pass-through and measures of sales share.

	Δ Retail price								
	Rice			Flour			Coffee		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ Commodity Price $\times$ UPC Sales Share	0.013			-0.001			0.014**		
	(0.014)			(0.007)			(0.004)		
Δ Commodity Price $\times$ Brand Sales Share		-0.034			-0.050**			0.074**	
		(0.027)			(0.019)			(0.014)	
Δ Commodity Price $\times$ Retailer Sales Share			-0.003			0.013			0.000
			(0.018)			(0.010)			(0.006)
Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N (thousands)	399.4	399.4	399.4	101.4	101.4	101.4	1570.0	1570.0	1570.0
R^2	0.10	0.10	0.10	0.28	0.28	0.28	0.12	0.12	0.12

Note: UPC, brand, and retailer sales shares are standardized, so that estimates correspond to the effect of a one standard deviation increase in market share. Standard errors clustered by brand. * indicates significance at 10%, ** at 5%.

Table A10: Percent of expenditures matched to retail scanner and inflation data, by income group.

Income quintile	Matched to UPC		Matched to retailer-UPC	
	Total	With infl.	Total	With infl.
1	60.2	52.7	22.5	18.5
2	59.9	52.6	23.1	19.0
3	60.2	53.5	24.0	20.1
4	60.7	54.5	25.7	21.7
5	59.7	52.6	27.2	22.7

Figure A1: Weekly average retail unleaded petrol (ULP) price and terminal gas price for a station in Kewdale (Perth suburb).

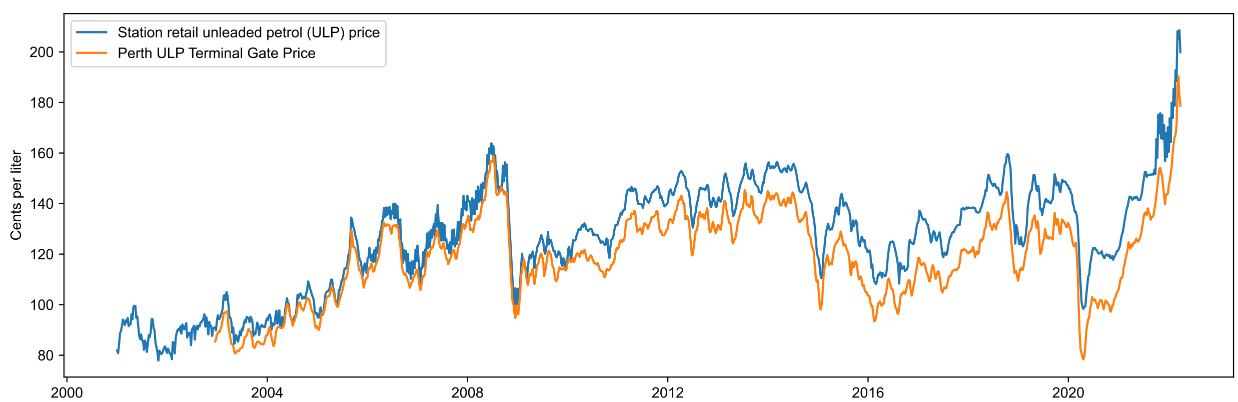
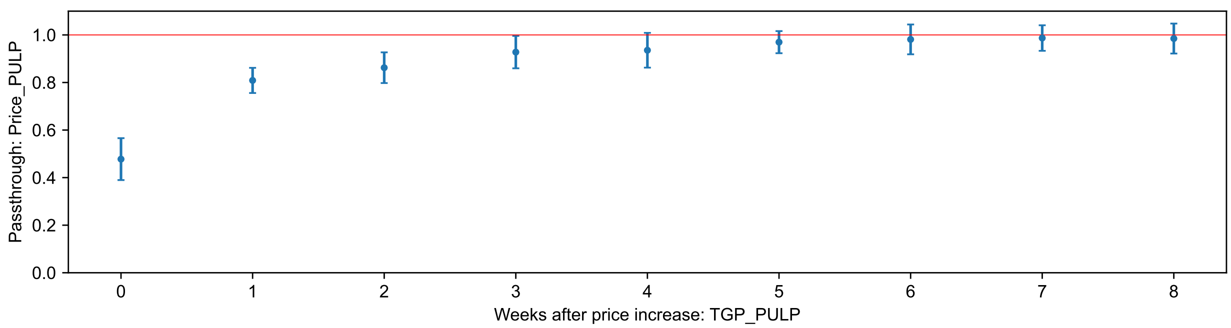
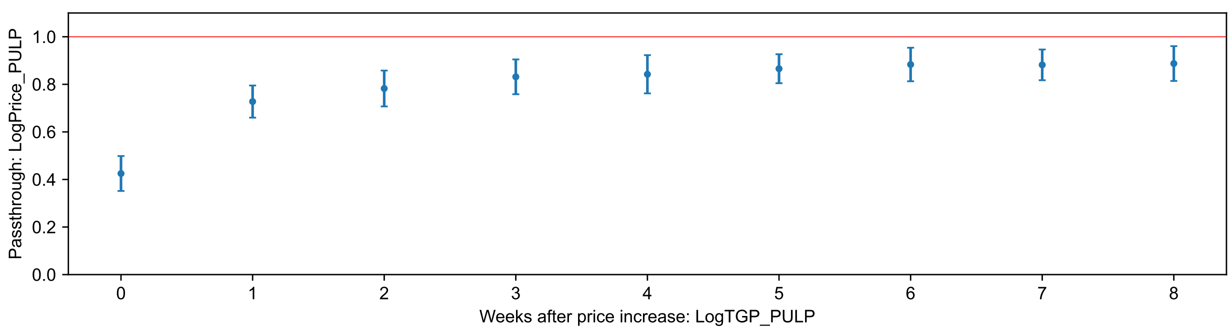


Figure A2: Premium unleaded petrol price (PULP) pass-through in levels (top) and in logs (bottom).



(a) Pass-through in levels.



(b) Pass-through in logs.

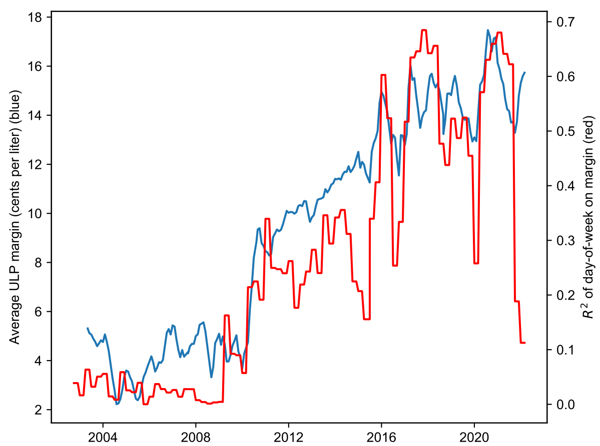
Note: Panels (a) and (b) show cumulative pass-through estimated from the specifications,

$$\Delta p_{i,t} = \sum_{k=0}^{k=8} b_k \Delta c_{i,t-k} + a_i + \varepsilon_{i,t}.$$

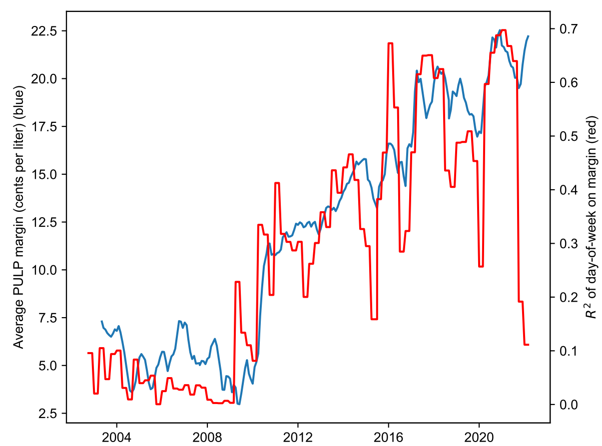
$$\Delta \log p_{i,t} = \sum_{k=0}^{k=8} \beta_k \Delta \log c_{i,t-k} + \alpha_i + \varepsilon_{i,t}.$$

Standard errors are two-way clustered by postcode and year (Driscoll-Kraay panel standard errors are similar), and standard errors for cumulative pass-through coefficients $\sum_{k=0}^{t} b_k$ and $\sum_{k=0}^{t} \beta_k$ are computed using the delta method.

Figure A3: Comovement of retail gas margins with strength of weekly price cycles.



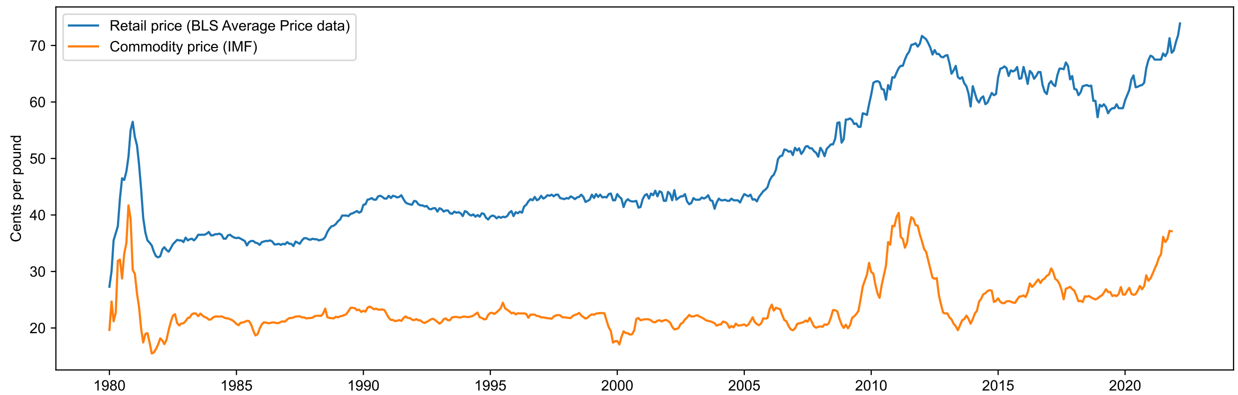
(a) Unleaded petrol (ULP).



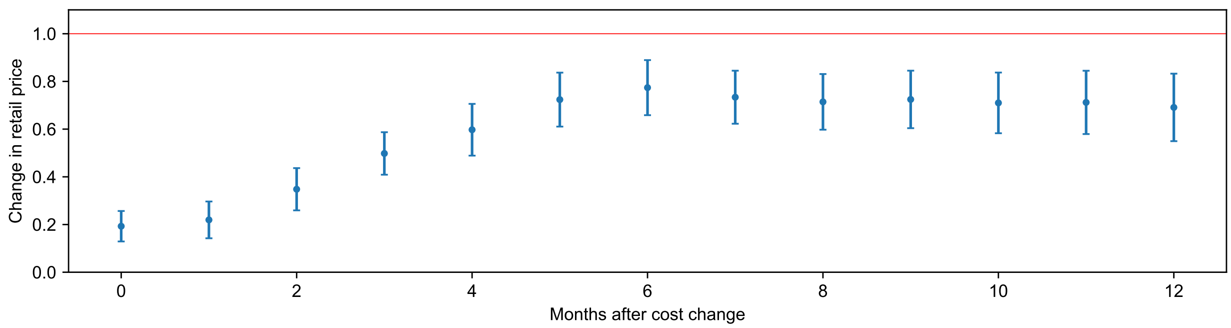
(b) Premium unleaded petrol (PULP).

Note: In each panel, the blue line (left axis) plots the six-month moving average of margins across all stations. The red line (right axis) plots the R^2 from a regression of gas station margins of day-of-week dummies for each quarter.

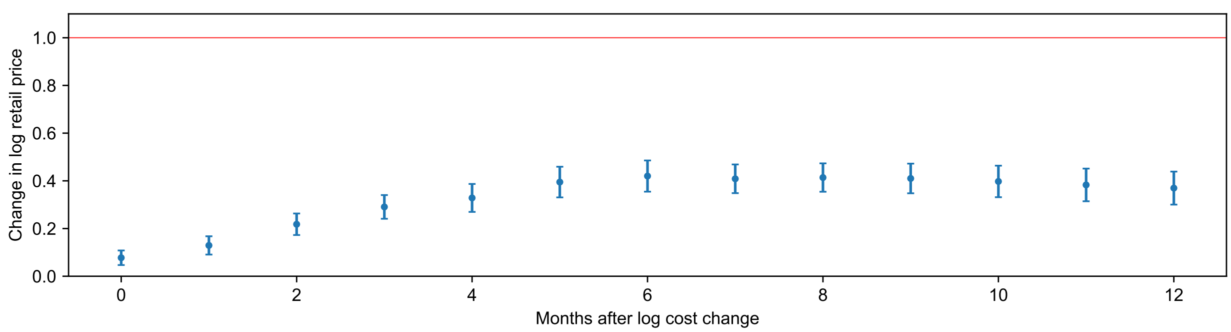
Figure A4: Passthrough of sugar commodity costs to retail prices.



(a) Sugar No. 16 commodity costs (IMF) and retail white granulated sugar prices (U.S. CPI).



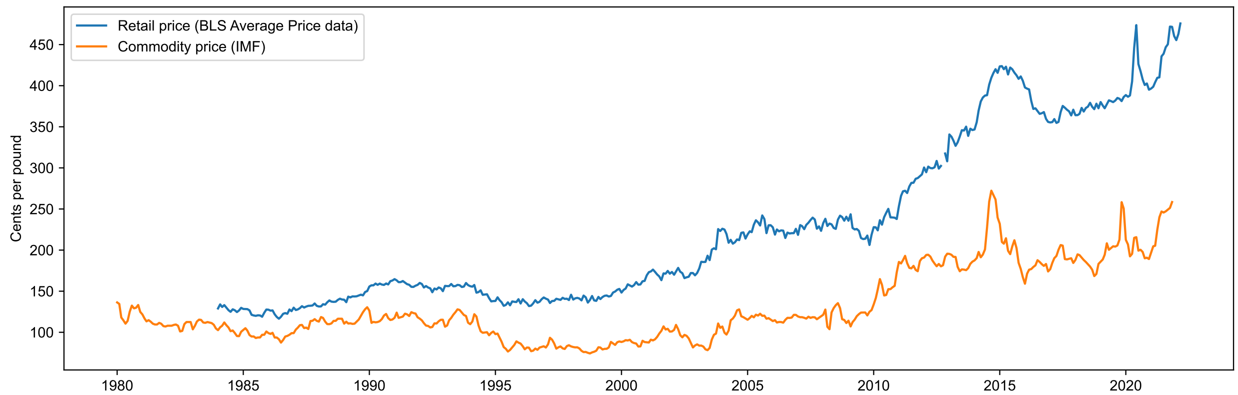
(b) Pass-through in levels.



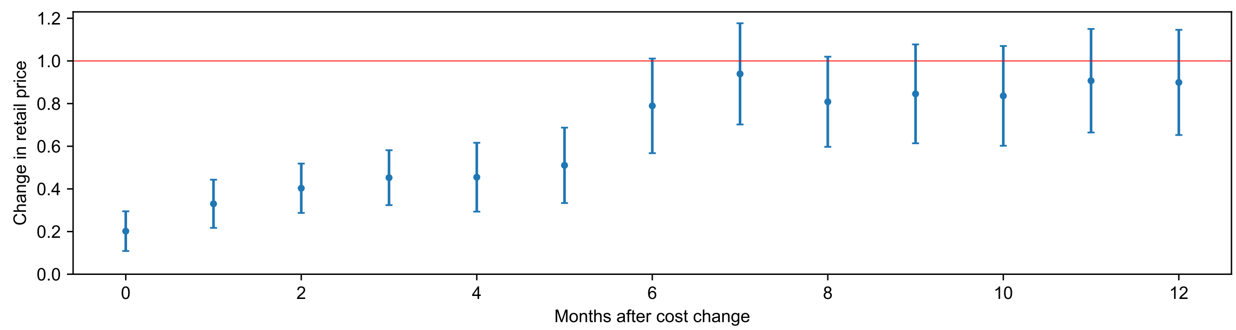
(c) Pass-through in logs.

Note: Panel (a) plots the time series of the commodity price from the IMF and the Average Price Data series from the BLS. The series are adjusted by the conversion factors in Appendix Table A4 so that the two series are in comparable units. Panels (b) and (c) plot the cumulative pass-through to month T, $\sum_{k=0}^{T} b_k$, from the specifications (2) and (3), using a total horizon of $K = 12$ months.

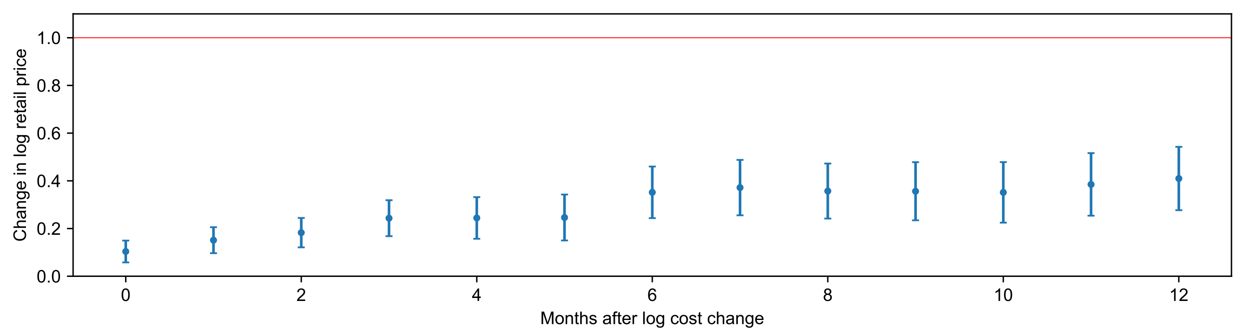
Figure A5: Passthrough of beef commodity costs to retail prices.



(a) Beef commodity costs (IMF) and retail ground beef prices (U.S. CPI).



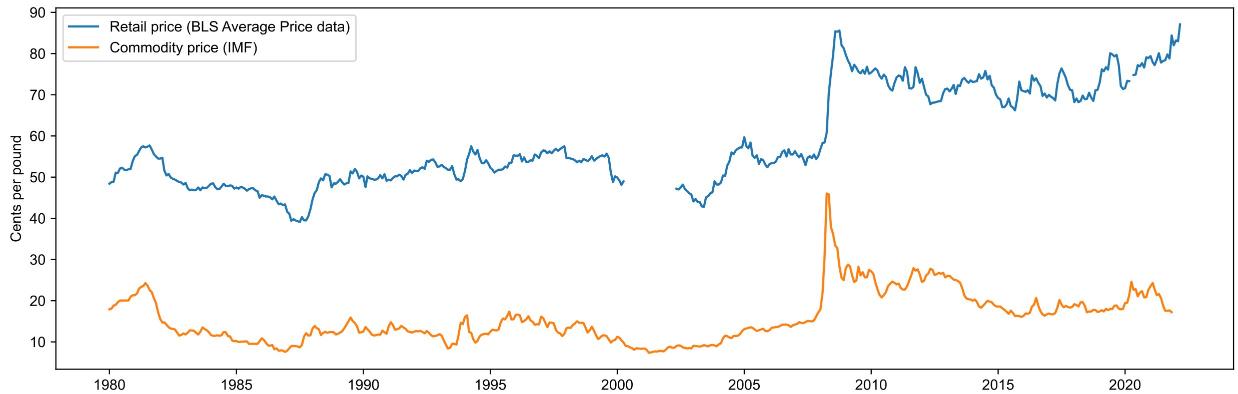
(b) Pass-through in levels.



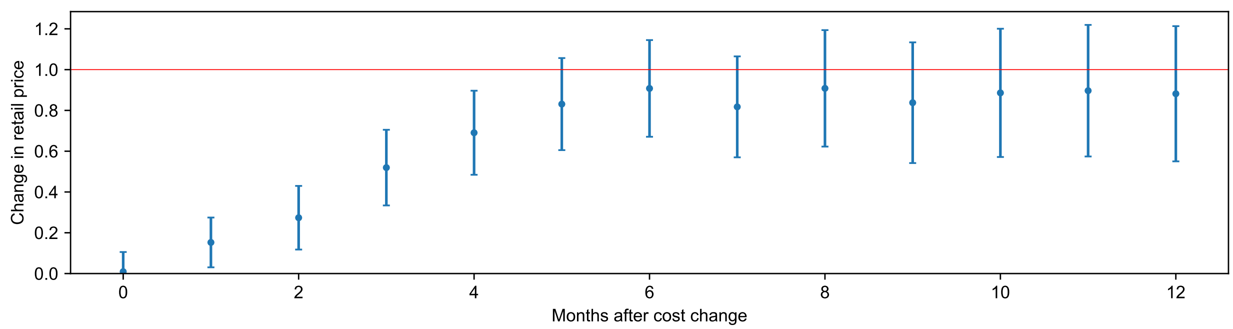
(c) Pass-through in logs.

Note: Panel (a) plots the time series of the commodity price from the IMF and the Average Price Data series from the BLS. The series are adjusted by the conversion factors in Appendix Table A4 so that the two series are in comparable units. Panels (b) and (c) plot the cumulative pass-through to month T, $\sum_{k=0}^{T} b_k$, from the specifications (2) and (3), using a total horizon of $K = 12$ months.

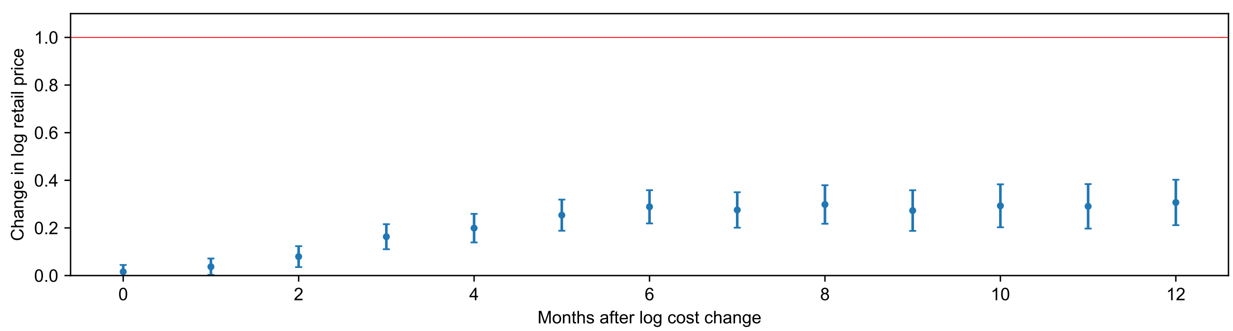
Figure A6: Passthrough of rice commodity costs to retail prices.



(a) Thailand rice commodity costs (IMF) and retail long-grain white rice prices (U.S. CPI).



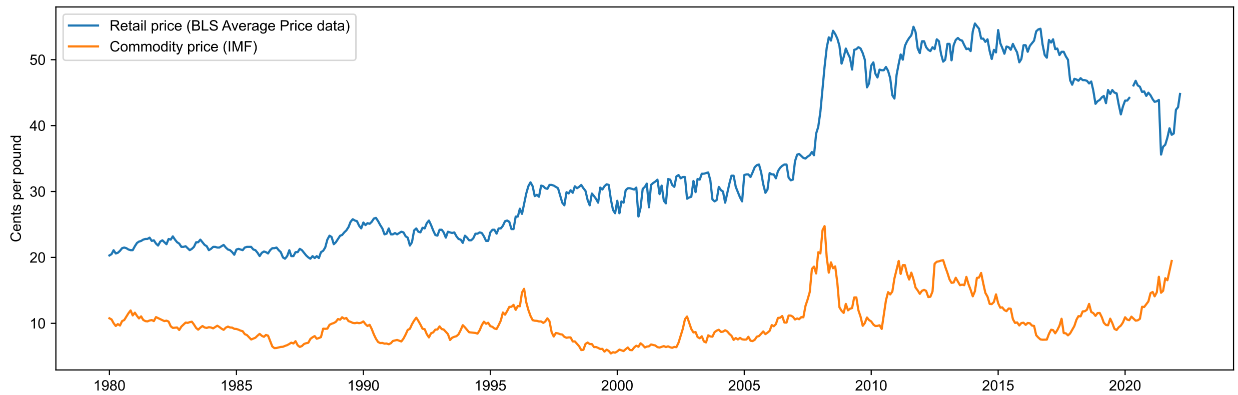
(b) Pass-through in levels.



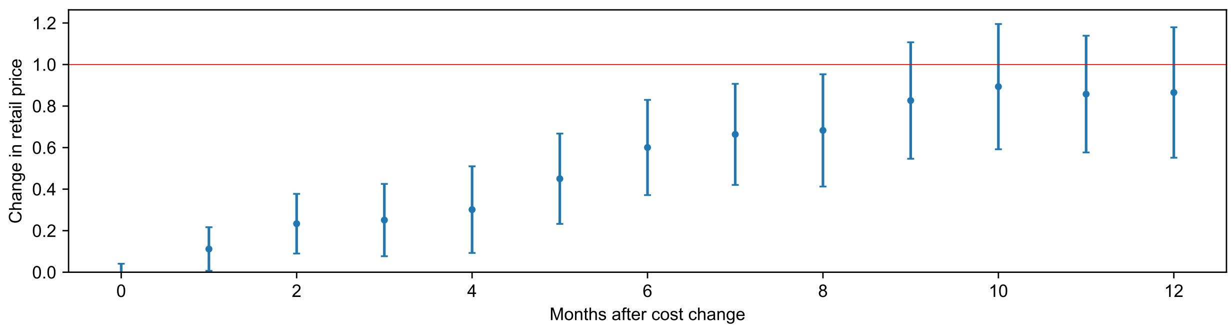
(c) Pass-through in logs.

Note: Panel (a) plots the time series of the commodity price from the IMF and the Average Price Data series from the BLS. The series are adjusted by the conversion factors in Appendix Table A4 so that the two series are in comparable units. Panels (b) and (c) plot the cumulative pass-through to month T, $\sum_{k=0}^{T} b_k$, from the specifications (2) and (3), using a total horizon of $K = 12$ months.

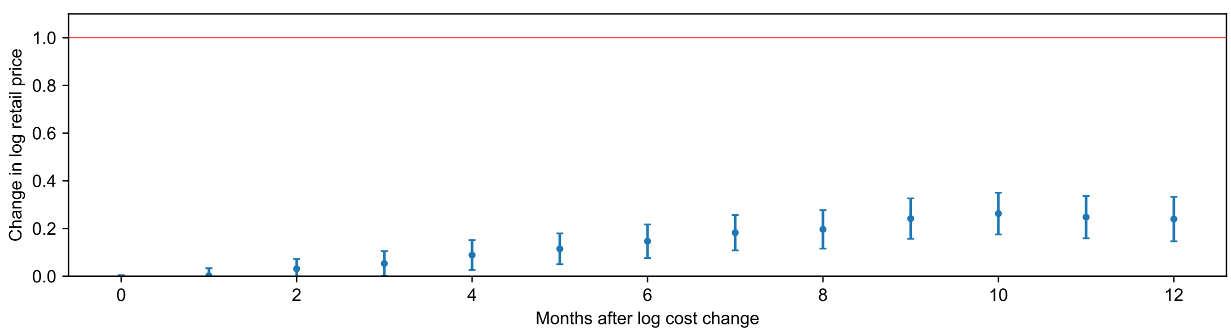
Figure A7: Passthrough of flour commodity costs to retail prices.



(a) Wheat commodity costs (IMF) and retail all-purpose flour prices (U.S. CPI).



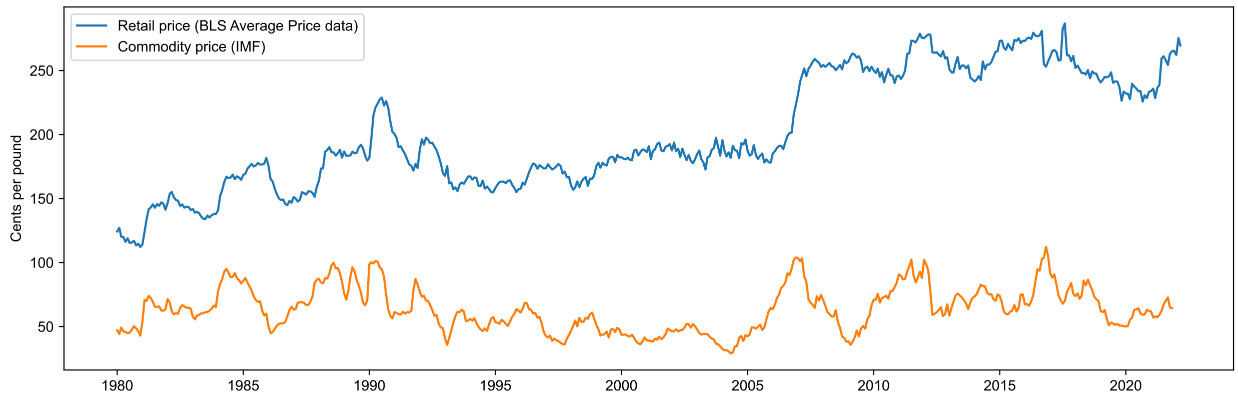
(b) Pass-through in levels.



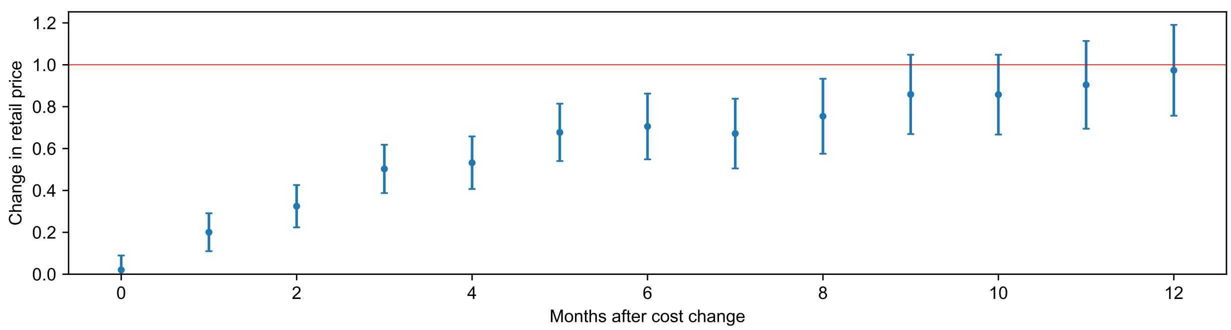
(c) Pass-through in logs.

Note: Panel (a) plots the time series of the commodity price from the IMF and the Average Price Data series from the BLS. The series are adjusted by the conversion factors in Appendix Table A4 so that the two series are in comparable units. Panels (b) and (c) plot the cumulative pass-through to month T, $\sum_{k=0}^{T} b_k$, from the specifications (2) and (3), using a total horizon of $K = 12$ months.

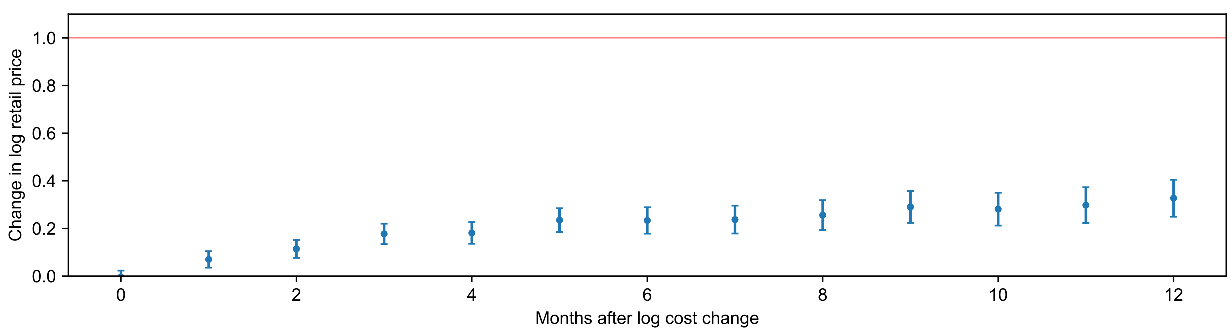
Figure A8: Passthrough of frozen orange juice commodity costs to retail prices.



(a) Frozen orange juice commodity costs (IMF) and retail orange concentrate prices (U.S. CPI).



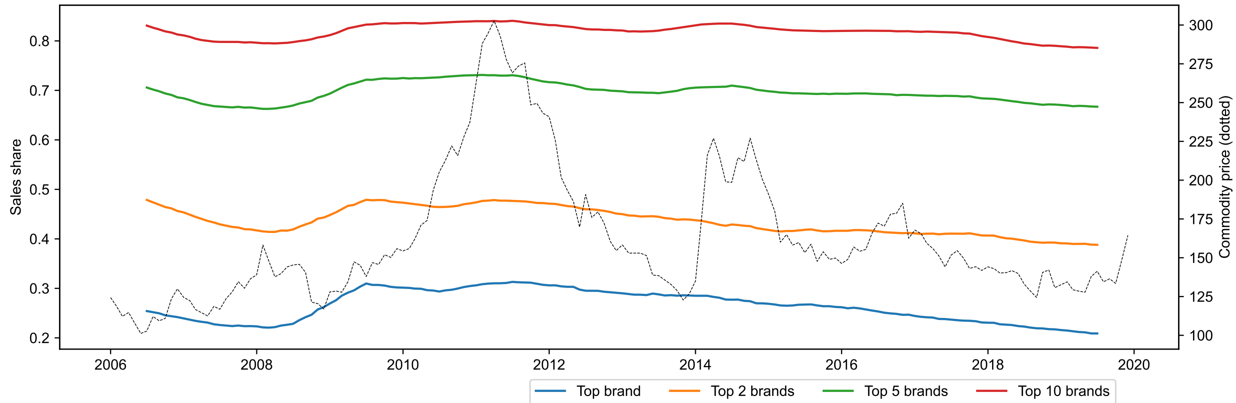
(b) Pass-through in levels.



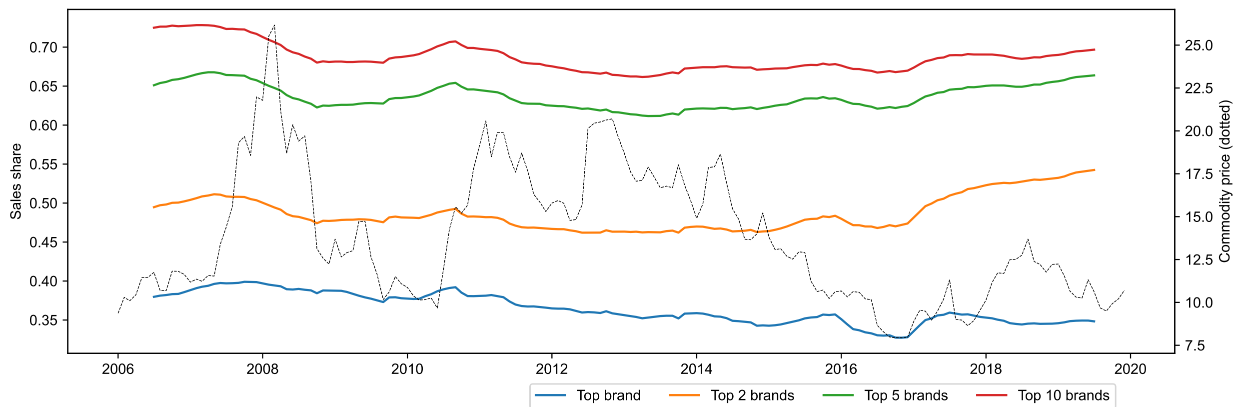
(c) Pass-through in logs.

Note: Panel (a) plots the time series of the commodity price from the IMF and the Average Price Data series from the BLS. The series are adjusted by the conversion factors in Appendix Table A4 so that the two series are in comparable units. Panels (b) and (c) plot the cumulative pass-through to month T, $\sum_{k=0}^{T} b_k$, from the specifications (2) and (3), using a total horizon of $K = 12$ months.

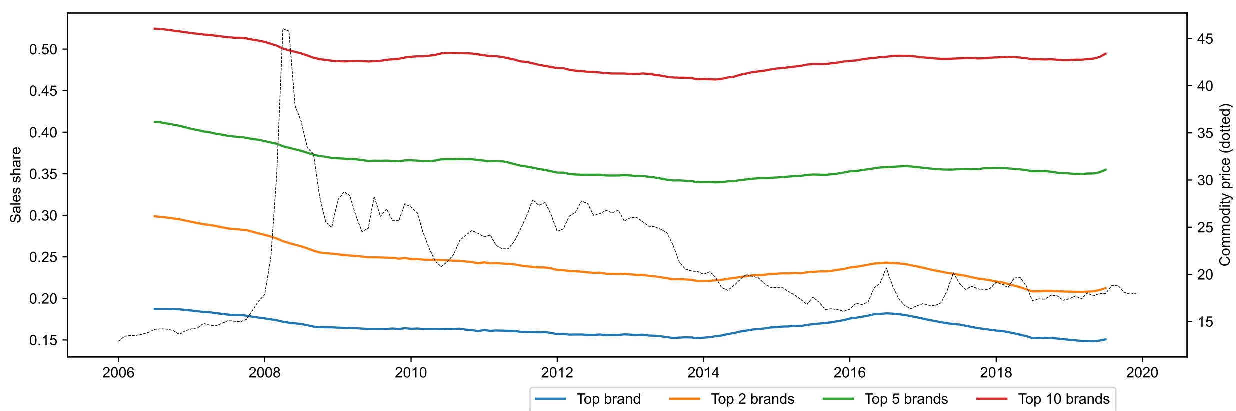
Figure A9: Commodity prices and market shares of top brands.



(a) Coffee.



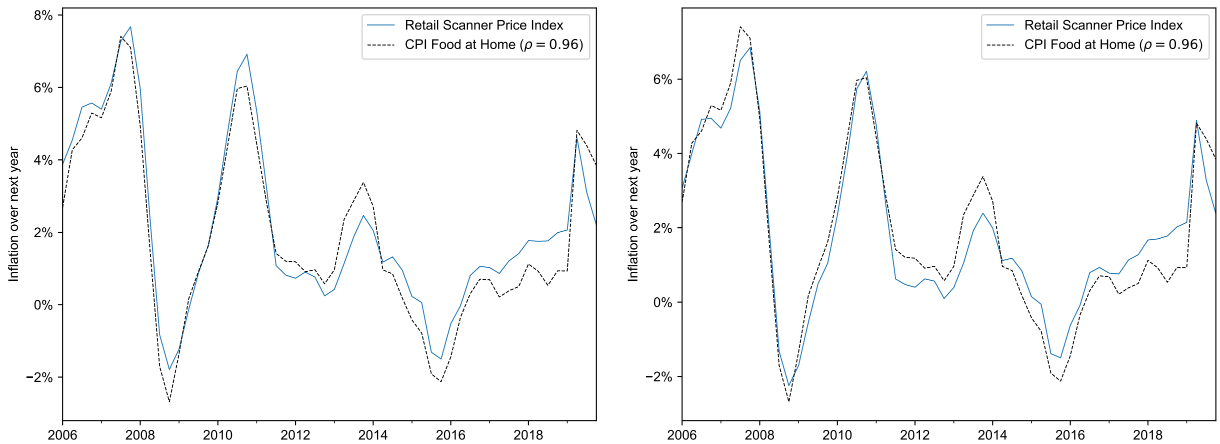
(b) Flour.



(c) Rice.

Note: Commodity prices are from the IMF. Brands are defined using unique brand identifiers provided by NielsenIQ. In each product module, brands are ranked by total sales over the full sample, and the share of sales by the top one, two, five, and ten brands is calculated as a six-month moving average of brand sales over total product module sales.

Figure A10: Inflation rates on food at home CPI and Retail Scanner price index.



(a) Level of aggregation: Retailer-UPC

(b) Level of aggregation: UPC

Figure A11: Retail scanner price inflation for products split by decile of unit price.

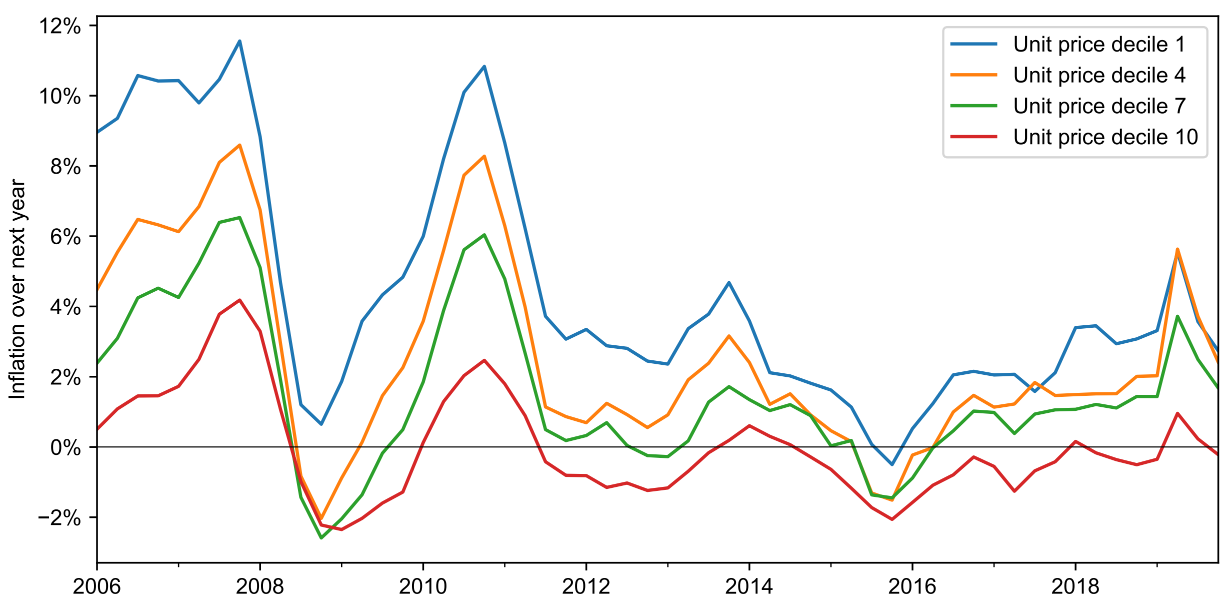
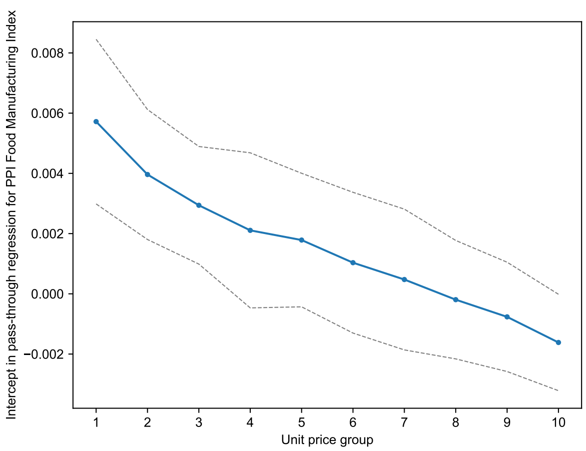
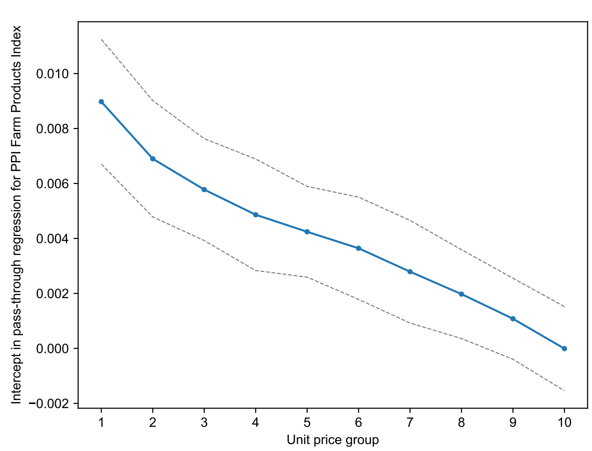


Figure A12: Intercept in log pass-through regressions of upstream producer price indices.



(a) Food Manufacturing PPI.



(b) Farm Products PPI.

Note: Dotted lines indicate 95 percent confidence intervals using Driscoll-Kraay standard errors.

Appendix B Proofs

B.1 Estimating Long-Run Pass-through

In this section, we consider a general time-dependent model of nominal rigidities and characterize the long-run pass-through estimated by a distributed lag regression in this environment.

Our representation of a general time-dependent model follows Werning (2022). We take as primitive a hazard function h_s, where h_s is the probability that a firm is able to reset its price $s+1$ periods since the previous reset. (I.e., the probability that a firm that reset its price last period is able to reset its price in the current period is h_0).

Using the hazard rate, we define the survival probability S_s as the probability that a price spell lasts at leasts s periods,

$$S_{s+1} = S_s(1 - h_s),$$

with $S_0 = 1$. We require that no price spells are infinitely lived, so that $\lim_{s\to\infty} S_s = 0$.

Firms' profit-maximizing prices in each period, which we denote p_t^*, are a function of a commodity cost, c_t. We make three assumptions about firms' profit-maximizing prices and costs: (1) that the profit-maximizing price is an affine function of costs, including a multiplicative markup over cost and an additive margin; (2) that commodity costs follow an AR(1) process; and (3) that a firms' losses from setting some price $p_t \neq p_t^*$ scale quadratically in the distance from the price to the profit-maximizing price.

Assumption 1 (Profit-maximizing prices)**.** Absent nominal rigidities, a firm's desired price in period t is

$$p_t^* = \mu(c_t + w) + \alpha,$$

where μ is a multiplicative markup, w is the (constant) cost of non-commodity inputs, and α is an additive unit margin.

Assumption 2 (Cost process)**.** The commodity cost process follows

$$c_t = \rho c_{t-1} + \nu_t,$$

where $\rho \leq 1$ is the persistence of the process and ν_t is a mean-zero shock.

Assumption 3. Firms' losses from setting price p_t are given by,

$$\mathcal{L} = -\frac{\omega}{2}\left(p_t - p_t^*\right)^2.$$

Given these assumptions, Proposition B1 shows that the long-run pass-through estimated using a distributed lag regression is equal to the multiplicative markup μ when the number of lags included in the regression is large and the commodity cost is unit root.

Proposition B1 (Estimating long-run pass-through)**.** *Suppose the commodity cost process is unit root (ρ = 1). Given the distributed lag regression,*

$$\Delta p_t = \sum_{k=0}^{K} b_t \Delta c_t + \varepsilon_t,$$

as $K \to \infty$, the estimated long-run pass-through $\sum_{k=0}^{K} b_t$ converges to the markup μ.

Proof. The proof proceeds in two parts. First, we show that firms' optimal reset prices each period are equal to a constant plus current commodity costs times the markup μ. Then, we show that the long-run pass-through from a distributed lag specification measures μ.

Firms' optimal reset prices solve the maximization problem,

$$p_t^{\text{reset}} = \text{argmax}_p \; \mathbb{E}_t \left[-\sum_{s=0}^{\infty} \beta^s S_s \frac{\omega}{2} \left(p - p_{t+s}^*\right)^2 \right].$$

The first order condition yields an an expression for the optimal reset price,

$$p_t^{\text{reset}} = \mu \frac{\sum_{s=0}^{\infty} \beta^s S_s \mathbb{E}\left[c_{t+s}\right]}{\sum_{s=0}^{\infty} \beta^s S_s} + (\mu w + \alpha) = \mu \frac{\sum_{s=0}^{\infty} \beta^s S_s \rho^s}{\sum_{s=0}^{\infty} \beta^s S_s} c_t + (\mu w + \alpha). \tag{15}$$

For convenience, define $\phi \equiv \frac{\sum_{s=0}^{\infty} \beta^s S_s \rho^s}{\sum_{s=0}^{\infty} \beta^s S_s}$. Note that $\lim_{\rho \to 1} \phi = 1$. Next, consider the distributed lag specification in Proposition B1. In expectation, the change in the price Δp_t is,

$$\mathbb{E}[\Delta p_t] = \sum_{k=0}^{\infty} \frac{S_k}{\sum_{s=0}^{\infty} S_s} h_k \left(p_t^{\text{reset}} - p_{t-k-1}^{\text{reset}}\right).$$

In this expression, $\frac{S_k}{\sum_{s=0}^{\infty} S_s}$ is the fraction of ongoing price spells with a length of k periods, h_k is the probability that those firms will reset their price in the current period, and $p_t^{\text{reset}} - p_{t-k-1}^{\text{reset}}$ is the change in price they will choose if they reset their price today. By substituting in the reset price (15), we find that

$$\mathbb{E}[\Delta p_t] = \mu \phi \sum_{k=0}^{\infty} \left(\sum_{j=k}^{\infty} \frac{h_j S_j}{\sum_{s=0}^{\infty} S_s} \right) \Delta c_{t-k}.$$

Given this expression, as the number of lags $K \to \infty$, we get that $b_k = \mu \phi \left(\sum_{j=k}^{\infty} \frac{h_j S_j}{\sum_{s=0}^{\infty} S_s} \right)$.

Finally, for the long-run pass-through $\sum_{k=0}^{\infty} b_k$, we find,

$$\sum_{k=0}^{\infty} b_k = \mu\phi\left(\frac{\sum_{k=0}^{\infty}\sum_{j=k}^{\infty} h_j S_j}{\sum_{s=0}^{\infty} S_s}\right) = \mu\phi\left(\frac{\sum_{k=0}^{\infty}\sum_{j=k}^{\infty}\left(S_j - S_{j+1}\right)}{\sum_{s=0}^{\infty} S_s}\right) = \mu\phi\left(\frac{\sum_{k=0}^{\infty} S_k}{\sum_{s=0}^{\infty} S_s}\right) = \mu\phi.$$

When $\rho = 1$ (i.e., the commodity price is unit root), $\phi = 1$, and hence $\sum_{k=0}^{\infty} b_k = \mu$. ■

Even when $\rho \neq 1$, ϕ is close to one for reasonable parameters. For example, suppose $\rho = 0.96$ (the minimum autocorrelation among commodity series in Table A1), $\beta = (0.96)^{1/12}$, and firms have Taylor pricing, resetting prices every 12 months. This yields a value of $\phi \approx 0.983$. If firms reset prices every 6 months, this rises to $\phi \approx 0.992$.

B.2 Pass-Through Under Relaxed Assumptions

This section explores how relaxing assumptions about production, demand, and correlations in input costs affect long-run pass-through in levels when firms use a multiplicative markup pricing rule. Suppose a firm's price is equal to a markup μ times marginal cost mc:

$$p = \mu\, mc.$$

Differentiating totally with respect to the commodity cost c yields:

$$\frac{dp}{dc} = \mu\left[\frac{d\log\mu}{d\log p}\frac{d\log p}{d\log mc} + 1\right]\frac{dmc}{dc} = \mu\left[1 - \frac{d\log\mu}{d\log p}\right]^{-1}\frac{dmc}{dc}.$$

Imposing that the markup is related to the price elasticity of demand using the Lerner rule, $\mu = \sigma/(\sigma - 1)$, we get:

$$\frac{dp}{dc} = \frac{\sigma}{\sigma - 1 + \frac{d\log\sigma}{d\log p}}\frac{dmc}{dc}. \tag{16}$$

We now consider if we can achieve complete pass-through in levels (i.e., $dp/dc = 1$) by allowing for non-isoelastic demand, relaxing Leontief production, allowing for decreasing returns to scale in the non-commodity input, and allowing the cost of the non-commodity input to be correlated with the commodity cost.

Non-isoelastic demand. It follows immediately from (16) that if $dm/dc = 1$ and the super-elasticity of demand $d\log\sigma/d\log p = 1$, then pass-through is complete in levels (see also Bulow and Pfleiderer 1983; Weyl and Fabinger 2013; Mrázová and Neary 2017). This case is discussed in detail in the main text in Section 6.2.

Relaxing Leontief production. Suppose production is given by

$$y = \left(\omega x^{\frac{\theta-1}{\theta}} + (1-\omega)\ell^{\frac{\theta-1}{\theta}}\right)^{\frac{\theta}{\theta-1}},$$

where y is total output, x is the commodity input with price c, ℓ is the non-commodity input with price w, θ is the elasticity of substitution between the commodity and non-commodity inputs, and ω are weights on the use of the two inputs. The main text assumes $\theta = 0$, i.e. production is Leontief.

For complete pass-through in levels $dp/dc = 1$, we must have:

$$1 = \mu \frac{dmc}{dc} = \mu \left(\frac{c}{\omega C}\right)^{-\theta} \qquad \Rightarrow \qquad \theta = \frac{\log \mu}{\log \frac{c}{\omega C}}.$$

Clearly, this cannot always hold, since when $\theta \neq 0$, c/C fluctuates with the level of the commodity cost.

Decreasing returns to scale in the non-commodity input. Suppose production is given by

$$y = \min\{x, \ell^{\alpha}\}.$$

With some algebra, we can show that increases in the commodity cost are partially offset, since as price increases the firm shrinks and hence the marginal cost of non-commodity inputs falls:

$$\frac{dmc}{dc} = 1 + w\frac{1}{\alpha}\frac{1-\alpha}{\alpha} y^{\frac{1-2\alpha}{\alpha}} \frac{dy}{dc} = 1 - (\sigma - 1)\frac{1-\alpha}{\alpha}\frac{w\ell}{\alpha c y + w\ell}\frac{dp}{dc},$$

where in the second equality we use $d \log y / d \log p = -\sigma$. For complete pass-through in levels, we require

$$\frac{w\ell}{\alpha c y + w\ell} = \frac{1}{\sigma(\sigma-1)}\frac{\alpha}{1-\alpha},$$

which cannot hold always since the share of spending on the non-commodity input varies with the commodity price.

Correlated non-commodity input costs. Suppose movements in the non-commodity input cost w are correlated with movements in the commodity cost. Then, to deliver complete pass-through in levels, we must have:

$$1 = \mu \frac{dmc}{dc} = \mu \left(1 + \frac{\partial w}{\partial c}\right), \qquad \Rightarrow \qquad \frac{\partial w}{\partial c} = \frac{-1}{\sigma}.$$

This negative correlation is unlikely to hold in practice; in most cases, we would expect the prices of other inputs to be positively correlated with commodity costs (e.g., shipping and transport costs in the retail gasoline market may mildly increase with gas prices).

B.3 Proof of Proposition 1

Proof. The equilibrium is described by the following system of equations:

$$\begin{aligned}
Q &= p^{-\theta}, && \text{(Aggregate demand)} \\
q &= \frac{Q}{N}, && \text{(Symmetry)} \\
p &= \frac{\sigma}{\sigma - 1} c, && \text{(Profit maximization)} \\
\pi^{\text{gross}} &= pq - cq, && \text{(Definition of variable profits)} \\
\pi^{\text{op}} &= \pi^{\text{gross}} - f_o, && \text{(Definition of operating profits)} \\
m^{\text{gross}} &= \frac{\pi^{\text{gross}}}{pq}, && \text{(Definition of gross margin)} \\
m^{\text{op}} &= \frac{\pi^{\text{op}}}{pq}, && \text{(Definition of operating margin)} \\
N &= N_0 \left(\pi^{\text{op}} - f_e\right)^{\zeta}. && \text{(Entry condition)}
\end{aligned}$$

First, by substituting the pricing condition and the definition of variable profits into the definition of gross margins, we find that gross margins are constant at $m^{\text{gross}} = 1/\sigma$.

To characterize the response of operating margins and the number of firms to changes in cost c, we log-linearize the system, taking the shock $d \log c$ as exogenous. Solving the fixed point,

$$d \log N = (1 - \theta) \frac{\zeta \left(\pi^{\text{op}} + f_o\right)}{\left(\pi^{\text{op}} - f_e\right) + \zeta \left(\pi^{\text{op}} + f_o\right)} d \log c.$$

Recall our assumptions that $\theta < 1$ and $\zeta \geq 0$. First, we can conclude that

$$\frac{d \log N}{d \log c} = 0 \quad \text{if } \zeta = 0, \qquad \text{and} \qquad \frac{d \log N}{d \log c} > 0 \quad \text{if } \zeta > 0, \quad \text{with} \quad \lim_{\zeta \to \infty} \frac{d \log N}{d \log c} = 1 - \theta.$$

The change in operating margins is given by

$$dm^{\mathrm{op}} = \frac{\sigma f_o \pi^{\mathrm{op}}}{\left[\sigma\left(\pi^{\mathrm{op}} + f_o\right)\right]^2} d\log \pi^{\mathrm{op}}.$$

For $\zeta > 0$, the change in operating profits is given by

$$d\log \pi^{\mathrm{op}} = \frac{\pi^{\mathrm{op}} + f_o}{\pi^{\mathrm{op}}} \frac{\left(\pi^{\mathrm{op}} - f_e\right)}{\zeta\left(\pi^{\mathrm{op}} + f_o\right)} d\log N, \tag{17}$$

and hence,

$$\frac{dm^{\mathrm{op}}}{d\log c} > 0, \qquad \text{with} \quad \lim_{\zeta\to\infty} \frac{dm^{\mathrm{op}}}{d\log c} = 0.$$

For the case where $\zeta = 0$, (17) is not well defined, but we can instead use

$$d\log \pi^{\mathrm{op}} = (1-\theta)\, \frac{\pi^{\mathrm{op}} + f_o}{\pi^{\mathrm{op}}} \frac{\pi^{\mathrm{op}} - f_e}{\left(\pi^{\mathrm{op}} - f_e\right) + \zeta\left(\pi^{\mathrm{op}} + f_o\right)} d\log c,$$

to conclude that $\frac{d\log \pi^{\mathrm{op}}}{d\log c} > 0$ and hence $\frac{dm^{\mathrm{op}}}{d\log c} > 0$. ■

Appendix C Pass-Through in Logit Models

C.1 Analytical expressions for pass-through in logit models

Denote the elasticity and super-elasticity of the demand curve for product j by

$$\sigma_j = -\frac{\partial \log y_j}{\partial \log p_j}, \qquad \text{and} \qquad \varepsilon_j = \frac{\partial \log \sigma_j}{\partial \log p_j}.$$

These objects are sufficient to calculate pass-through in the case of a *single-product* firm, *holding all other firms' prices fixed*. Using the assumption of a single-product firm, the firm's profit-maximizing price and thus the firms' pass-through (in levels) is

$$p_j = \frac{\sigma_j}{\sigma_j - 1} mc_j. \qquad \Rightarrow \qquad dp_j = \frac{-1}{\left(\sigma_j - 1\right)^2} mc_j d\sigma_j + \frac{\sigma_j}{\sigma_j - 1} dmc_j. \tag{18}$$

Next, using the assumption that all other firms' prices are held fixed, we can rewrite $d\sigma_j$ in terms of the change in firm j's price only, yielding:

$$dp_j = \frac{-1}{\sigma_j - 1} \frac{\partial \log \sigma_j}{\partial \log p_j} dp_j + \frac{\sigma_j}{\sigma_j - 1} dmc_j \qquad \Rightarrow \qquad dp_j = \frac{\sigma_j}{\sigma_j + (\varepsilon_j - 1)} dmc_j.$$

Table C1 provides closed-form expressions for σ_j and ε_j in the logit and heterogeneous coefficient models. In the logit model, the super-elasticity ε_j is above one and approaches one as a firm's market share $y_j \to 0$. Thus, pass-through in levels is one for infinitesimal firms in the logit model, and is below one for large firms.

Table C1: Expressions for market share, elasticity, and super-elasticity of demand.

	Logit	Heterogeneous Coefficients
Market share (units) y_j	$\frac{\exp\left(\delta_j - \alpha p_j\right)}{\sum_k \exp(\delta_k - \alpha p_k)}$	$\int \frac{\exp\left(\delta_{ij} - \alpha_i p_j\right)}{\sum_k \exp(\delta_{ik} - \alpha_i p_k)} di$
Elasticity σ_j	$\alpha p_j \left(1 - y_j\right)$	$p_j \mathbb{E}_y \left[\alpha_i \left(1 - y_{ij}\right)\right]$
Super-elasticity ε_j	$1 + \alpha p_j y_j$	$1 + p_j \mathbb{E}_y \left[\alpha_i y_{ij}\right] - p_j \frac{Var_y\left[\alpha_i y_{ij}\right] + Var_y\left[\alpha_i\left(1 - y_{ij}\right)\right] - Cov_y\left[\alpha_i y_{ij}, \alpha_i\right]}{\mathbb{E}_y\left[\alpha_i\left(1 - y_{ij}\right)\right]}$

Note: The operator $\mathbb{E}_y$ is an average across agents i weighted by consumption of good j. That is, for any variable x_{ij}, $\mathbb{E}_y[x_{ij}] = \int \frac{y_{ij}}{\int y_{zj} dz} x_{ij} di$. The covariance is $Cov_y[x_{ij}, z_{ij}] = \mathbb{E}_y[x_{ij} z_{ij}] - \mathbb{E}_y[x_{ij}] \mathbb{E}_y[z_{ij}]$.

In a model with heterogeneous coefficients, the super-elasticity may be above or below one. As in the logit model, oligopolistic forces—or more precisely a higher market share amongst any customer group i—increases the super-elasticity and decreases pass-through. However, since as a firm raises price it retains its most price-insensitive customers, consumer heterogeneity tends to decrease the super-elasticity and increase pass-through (unless there is a sufficiently strong positive covariance between consumers' price sensitivity α_i and initial shares y_{ij}). These comparative statics are well-known in the industrial organization literature, see e.g. the discussion in Nakamura and Zerom (2010).

Of course, (18) does not describe pass-through of *aggregate cost shocks* to prices, because aggregate cost shocks will lead other firms' prices to change. In the absence of an outside option, logit and heterogeneous coefficient models have a pass-through of aggregate cost shocks exactly equal to one. To see this, consider a cost change Δc that affects all firms. We will conjecture and verify the solution $p_j^{\text{new}} = p_j + \Delta c$. Consumer i's shares are then

$$y_{ij}^{\text{new}} = \frac{\exp\left(\delta_{ij} - \alpha_i(p_j + \Delta c)\right)}{\sum_k \exp(\delta_{ik} - \alpha_i(p_k + \Delta c))} = \frac{\exp\left(\delta_{ij} - \alpha_i p_j\right)}{\sum_k \exp(\delta_{ik} - \alpha_i p_k)} = y_{ij},$$

where we use the fact that there is no outside option when we assume that prices of all options for the consumer increase by Δc.

Profit-maximization requires that

$$p_j - c_j = \frac{\int y_{ij} di}{\int (\partial y_{ij}/\partial p_j) di} = \frac{\int y_{ij} di}{\int \alpha_i y_{ij}(1 - y_{ij}) di}.$$

Since these margins depend only on y_{ij} and not p_j, and $y_j^{\text{new}} = y_{ij}$, we confirm that margins are unchanged and thus verify $p_j^{\text{new}} = p_j + \Delta c$.

C.2 Simulations

However, standard calibrations of these models feature an outside option. To evaluate the pass-through of aggregate cost shocks in these models, we rely on demand systems from two studies on breakfast cereal (Nevo 2001) and coffee (Nakamura and Zerom 2010).

Breakfast cereal. We use the fake cereal simulation data from Nevo (2000) and follow Conlon and Gortmaker (2020) in estimating a random coefficients logit model on this data. This approach allows for consumer heterogeneity in tastes for the outside option, price-sensitivity, and tastes for sugary and mushy products along the dimensions of income, age, the presence of a child, and an unobserved trait (i.e., a random coefficient); see Conlon and Gortmaker (2020) for details.

Figure C1 shows pass-through of idiosyncratic and aggregate cost shocks as a function of the super-elasticity of the residual demand curve for a product and as a function of the pass-through computed using Equation (18). The pass-through of idiosyncratic cost shocks declines with the super-elasticity of demand and rises about one-for-one with the pass-through predicted by (18), though there is considerable dispersion conditional on a predicted pass-through due to multi-product firms.

The same two patterns hold for the pass-through of aggregate cost shocks. Pass-through of aggregate cost shocks is attenuated toward one, but substantial variation in the pass-through of aggregate cost shocks nevertheless remains. Table C2 shows that increasing the super-elasticity of demand from one to two is associated with a reduction in pass-through of 0.22, and that a 0.10 increase in pass-through of idiosyncratic shocks is associated with a 0.069 increase in pass-through of aggregate cost shocks.

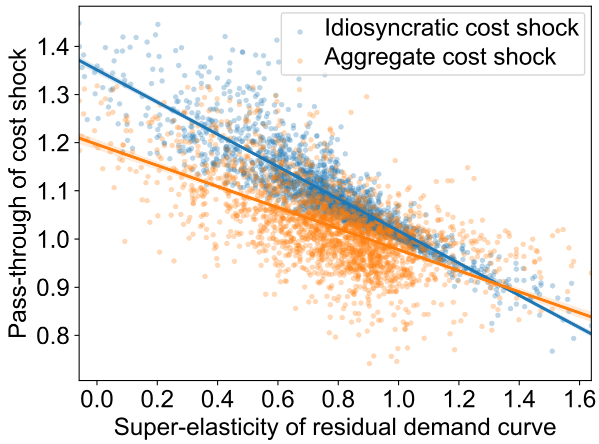
Coffee. We use the demand system for the coffee industry estimated by Nakamura and Zerom (2010). A challenge is that the underlying market data used by Nakamura and Zerom (2010) is from 2000–2004, which is not available through current agreements with NielsenIQ. We use data on the roasted coffee category from 2006–2020 and assume that the demand parameters estimated by Nakamura and Zerom (2010) are static over this period.

The difference in timeframe necessitates a few changes to the process used to assemble the data. We retain the set of products that Nakamura and Zerom (2010) include in their estimation, plus five additional brands that have substantial market shares in the later sample: Eight O' Clock, Millstone, Seattle's Best Coffee, Peets Coffee, New England, and Chase & Sanborn. All other products are grouped with the outside option. Ownership matrices are also updated to reflect subsequent acquisitions over 2006–2020. Rather than use demographic data from the CPS, we use demographic data from the Homescan consumer panel, aggregated using weights provided by NielsenIQ. Finally, we choose the relationship between the number of adults in a market and market size to match the median share of the outside option in Nakamura and Zerom (2010), which is 74%.

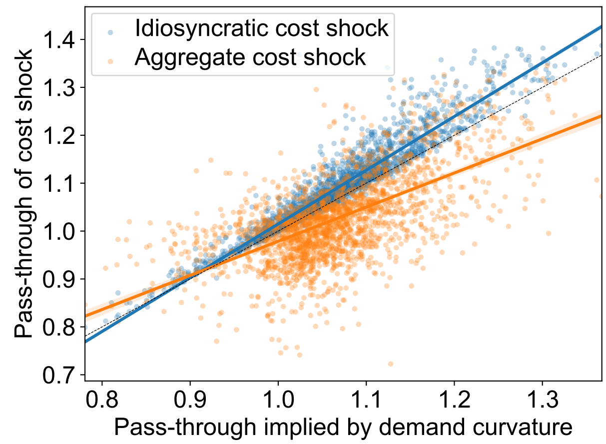
Combining demand system parameters from Nakamura and Zerom (2010) with this market share and demographic data, we can invert the demand system in each market and each month to recover the common utility component for each product (δ_{jmt} in the notation of Nakamura and Zerom 2010). The model is then fully specified to simulate pass-through of idiosyncratic and aggregate shocks.

As in the breakfast cereal simulation, Figure 9 (in the main text) shows that both the

Figure C1: Pass-through in breakfast cereal simulation.



(a) Super-elasticity of demand.



(b) Pass-through implied by Equation (18).

pass-through of idiosyncratic and aggregate cost shocks decrease with the super-elasticity of demand and increase with the pass-through predicted by (18). Table C2 reports that a 0.10 increase in pass-through predicted by (18) is associated with a 0.087 increase in pass-through of aggregate cost shocks. As in the breakfast cereal simulation, higher firm market shares and super-elasticities of demand are associated with substantial declines in the pass-through of aggregate cost shocks.

A disadvantage of using market data from 2006–2020 is that some features of the roasted coffee market appear to have changed since the 2000–2004 period. In particular, besides Maxwell House and Folgers, higher-end coffee brands like Starbucks and Peets have substantial market shares in nearly all markets from 2006–2020. Thus, markets appear less concentrated than as described by Nakamura and Zerom (2010) in 2000–2004.

This difference means that the super-elasticities of demand in the replication using 2006–2020 data are lower than in the original study by Nakamura and Zerom (2010). Super-elasticities in the 2006–2020 replication are largely below 3, while Nakamura and Zerom (2010) report that the median super-elasticity of demand for products in their data is 4.64. For product-market-time observations in the replication for which the super-elasticity of demand is above 3, the average pass-through of aggregate cost shocks is 0.71 (std. 0.12), substantially below complete pass-through in levels.

Table C2: Determinants of pass-through of aggregate cost shocks in model simulations.

	Pass-through of aggregate cost shocks					
	Breakfast cereal			Coffee		
	(1)	(2)	(3)	(4)	(5)	(6)
Firm market share	-0.452**			-0.890**		
	(0.029)			(0.019)		
Super-elasticity		-0.219**			-0.153**	
		(0.011)			(0.001)	
Predicted pass-through eq. (18)			0.690**			0.865**
			(0.042)			(0.009)
Intercept	1.091**	1.197**	0.289**	1.058**	1.125**	0.115**
	(0.005)	(0.010)	(0.044)	(0.001)	(0.002)	(0.009)
N	2170	2170	2170	374607	374607	374607
R^2	0.20	0.39	0.38	0.40	0.80	0.80

Appendix D Retail Gasoline Data from Other Markets

D.1 Canada

We use weekly price data for 71 cities in 10 Canadian provinces provided by Kalibrate solutions.[33] These prices are collected across cities through a daily survey of pump prices funded by the Government of Canada and used for analyses by National Resources Canada.

D.2 South Korea

We use daily station-level price data from Opinet, a service started in 2008 by the Korea National Oil Corporation to provide customer transparency about petroleum product prices and enable research.[34] These data cover all gas stations within each city in South Korea; data files are available by city/county within each province. However, some stations appear to have incomplete coverage. Hence, for all results using these data, we limit our analyses to stations that have at least 500 daily price observations (i.e., at least 10% of days during the full sample period). Opinet also provides weekly average refinery supply prices, which we use as the measure of costs facing retail stations.

D.3 United States

United States weekly gasoline price data come from the Energy Information Administration (EIA). For upstream prices, we use the New York Harbor Conventional Gasoline Regular Spot Price (EIA sourcekey EER_EPMRU_PF4_Y35NY_DPG), which is a wholesale spot price for RBOB gasoline. For retail prices, we use weekly U.S. regular conventional retail gas prices (EIA sourcekey EMM_EPMRU_PTE_NUS_DPG).

[33] Weekly prices can be downloaded from `https://charting.kalibrate.com`.

[34] These data are available for download at `https://www.opinet.co.kr`.

Appendix E Demand Curve Estimates

In each product category, we select the top fifty UPCs by sales, and estimate demand curves for each UPC in each of the top two thousand stores s by sales in which the UPC appears in the data. Our specification follows from DellaVigna and Gentzkow (2019) and Burya and Mishra (2023),

$$\log q_{ist} = \eta \log p_{ist} + \kappa(\log p_{ist})^2 + \alpha_{isy} + \gamma_{isw} + \varepsilon_{ist},$$

where q_{ist} is log quantity of product i sold in store s in week t, p_{ist} is the price of i in store s in week t, α_{isy} are product-store-year fixed effects, γ_{isw} are product-store-week-of-year fixed effects, and ε_{ist} is an error term.

Following DellaVigna and Gentzkow (2019), we address the endogeneity of prices by instrumenting for the log price of i at store s using the price of i at stores in the same retail chain as s, but outside s's designated market area. (Designated market areas are large, non-overlapping geographic regions defined by NielsenIQ.) These Hausman (1996) instruments are strongly correlated with true prices, due to retailers' tendencies to set uniform prices across locations, and hence have a strong first stage.

The specification developed by Burya and Mishra (2023) estimates the super-elasticity of a firm's residual demand curve, but it is possible for firms for firms to have complete pass-through in levels if the elasticity of demand they face changes as aggregate market prices change. Hence, we estimate three additional specifications where we instead interact a product's price with measures of the aggregate price:

$$\log q_{ist} = \eta \log p_{ist} + \kappa(\log p_{ist} \times \log \bar{p}_{st}) + \alpha_{isy} + \gamma_{isw} + \varepsilon_{ist}, \tag{19}$$

$$\log q_{ist} = \eta \log p_{ist} + \kappa(\log p_{ist} \times \log \bar{p}_{mt}) + \alpha_{isy} + \gamma_{isw} + \varepsilon_{ist}, \tag{20}$$

$$\log q_{ist} = \eta \log p_{ist} + \kappa(\log p_{ist} \times \log \bar{c}_{t}) + \alpha_{isy} + \gamma_{isw} + \varepsilon_{ist}, \tag{21}$$

where the first specification uses the average unit price of products in the same category in the same store, $\bar{p}_{st}$, the second specification uses the average unit price of products in the same category in the same designated market area, and c_t uses the commodity price.

Table E1 summarizes the demand elasticities and super-elasticities estimated using this approach. Demand elasticities are estimated to be negative for the majority of UPC-store pairs in each product category. Among cases where the estimated demand elasticity is negative, median demand elasticities are in line with previous work (e.g., Nakamura and Zerom 2010; Park 2013), and median super-elasticities of demand are slightly positive and small.

Table E1: Median demand elasticity and super-elasticity estimates.

	Rice	Flour	Coffee
Share with negative estimated demand elasticities ($\eta < 0$)	0.77	0.76	0.86
Median demand elasticity ($-\eta$)	2.12	2.02	4.41
Median super-elasticity (η/κ)	0.11	0.17	0.21

Table E2: Share of products in category with estimated κ/η below one.

	κ/η point estimate below one			κ/η above one rejected at $p = 0.05$		
Price interaction	Coffee	Rice	Flour	Coffee	Rice	Flour
Own price	98.3%	99.9%	88.5%	52.9%	90.6%	51.7%
Average unit price in store	97.4%	99.5%	89.6%	78.8%	91.3%	57.9%
Average unit price in DMA	96.7%	99.5%	89.4%	70.5%	88.1%	51.0%
Commodity price	93.6%	95.9%	95.6%	75.3%	82.2%	80.9%

Note: Each row reports the share of point estimates for κ/η that are below one and the share of estimates for κ/η where a value above one is rejected at the 5 percent level. Estimates of κ and η for row 1 are from specification (11), and for rows 2–4 are from specifications (19)–(21). Standard errors for κ/η are generated using the delta method.