Pass-Through and the Unequal Incidence of Commodity Shocks

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March 21, 2024

Abstract

Empirical studies of commodity cost pass-through find that pass-through is incomplete: a 10 percent increase in costs causes downstream prices to rise less than 10 percent, even at long horizons. Using microdata from gasoline and food products, I 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 an additive margin between marginal costs and prices. A model in which firms bound the risk of profits falling short of overhead costs can account for this pricing behavior. Due to complete pass-through in levels, 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. I document that food-at-home inflation is 10 percent more sensitive to upstream costs for households in the lowest income quintile than the highest. From 2020–2023, unequal commodity cost pass-through is responsible for two-thirds of the gap in food-at-home inflation rates experienced by low- and high-income households.

**Email:* ksangani@g.harvard.edu. I am grateful to Adrien Bilal, Jeremy Bulow, Gabriel Chodorow-Reich, Xavier Gabaix, Robin Lee, Kiffen Loomis, Jesse Shapiro, Andrei Shleifer, Ludwig Straub, Adi Sunderam, and seminar participants at Harvard for many helpful conversations. All errors are my own. This paper contains my own analyses calculated (or derived) based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the author and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

1 Introduction

Studies of how changes in commodity costs propagate downstream typically find evidence of *long-run incomplete pass-through*: when commodity prices increase 10 percent, downstream prices rise less than 10 percent (e.g., 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.

The leading explanation attributes incomplete pass-through to the shape of demand curves. When demand curves have a positive super-elasticity—i.e., the elasticity of demand increases with price—firms partly absorb increases in cost by reducing their markups. Theoretical work suggests myriad factors that can affect the super-elasticity of demand, such as market power (e.g., Atkeson and Burstein 2008), the extent of consumer heterogeneity (e.g., Mongey and Waugh 2023), or the underlying shape of consumer preferences (e.g., Klenow and Willis 2016). As a result, predicting the extent of commodity cost pass-through in practice requires estimating rich models of demand.

This paper studies the pass-through of commodity costs to downstream prices in a sample of markets where the amount of the commodity input required to produce downstream goods can be measured precisely. These markets, which include retail gasoline and several food products, allow me to measure pass-through both on a percentage basis—as pass-through is typically measured in the macro and international literatures—and on an absolute (dollars-and-cents) basis.

Nearly all of the studied markets 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 pass-through measured in percentages appears incomplete: when price is greater than marginal cost, a \$1/unit increase in price represents a smaller percentage increase in price than a \$1/unit increase in marginal cost.

Microdata from retail gasoline and food products suggests that complete pass-through in levels explains not only the presence of incomplete "log pass-through," but also cross-sectional heterogeneity in log pass-through across firms or products in a market. For example, I find that gas stations with higher markups and food products within a category with higher retail markups have lower log pass-through, but no systematic difference in pass-through in levels. Intuitively, higher markups increase the gap between price and marginal cost, creating a larger gap between the percentage changes in price and costs when absolute changes are identical.

Why do firms' prices exhibit complete pass-through in levels? In principle, the shape of demand curves could explain complete pass-through in levels if changes in the elasticity of demand along the demand curve lead firms to adjust their percentage markups in a way that coincides with complete pass-through in levels.[1] This is the case if the super-elasticity of demand curves is exactly equal to one.[2] At first blush, this explanation appears unlikely to justify complete pass-through in levels across markets, since estimated demand systems find variable super-elasticities of demand across products within a market, let alone across markets. Moreover, I find that super-elasticities of demand in my data, estimated using the technique developed by Burya and Mishra (2023), fall short of the magnitude required to explain pass-through in levels.

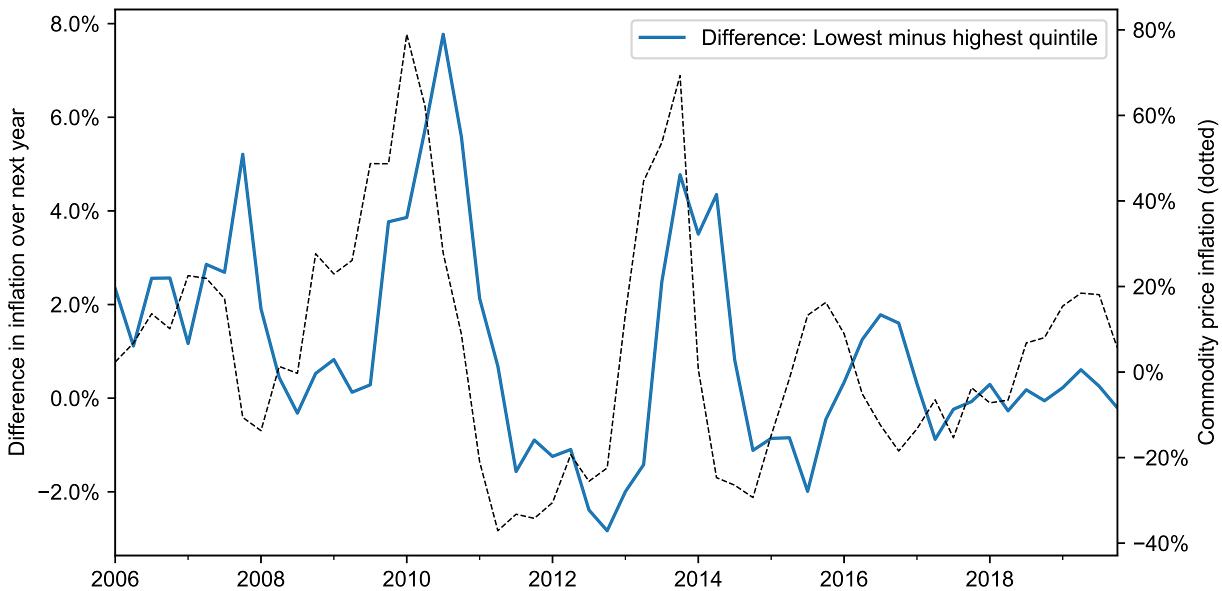
I thus propose a model where firms exhibit complete pass-through in levels despite facing isoelastic demand curves. In the model, firms have fixed overhead costs as well as variable costs for non-commodity inputs, which are bundled with the commodity into an output good sold to consumers. When firms set multiplicative markups over marginal cost, their variable profits scale with commodity costs, resulting in higher per-unit margins and entry when commodity costs are high and lower per-unit margins and exit when commodity costs are low. This variation in unit margins can be costly to firms. For example, in the presence of uncertainty over the level of demand, firms face a heightened risk of being unable to cover overhead expenses when commodity costs are low. When managers are averse to variable profits falling below overhead costs, firms can instead opt for an additive margin over marginal costs that is proportional to overhead costs. I show that a form of "safety margin constraint" pricing first discussed by Fellner (1948) (and subsequently explored by Day et al. 1971 and Altomonte et al. 2015) yields this pricing behavior. Since firms set an additive margin over marginal costs, changes in marginal costs are reflected one-for-one in changes in the output price.

This model generates additional predictions about the dynamics of entry and gross margins that I test in the data. While the standard multiplicative markup model predicts that entry rises with commodity costs while gross margins (variable profits as a share of sales) stay fixed, a model with safety margins predicts that entry is unrelated to commodity costs and gross margins fall when commodity costs rise. Using microdata from the markets

[1] An alternative explanation is perfect competition: firms price at marginal cost and hence changes in marginal costs are reflected one-for-one in changes in prices. Perfect competition is equivalent to the case where local costs (i.e., non-commodity input costs) account for the entirety of the gap between prices and commodity costs. Local costs have been an important explanation for incomplete pass-through of exchange rate shocks (e.g., Burstein et al. 2003, Corsetti and Dedola 2005, Burstein et al. 2006). However, the limiting case of perfect competition is at odds with several features of the data: sluggish price adjustment, price dispersion for identical products, finite firm-level demand elasticities, and evidence of substantial markups over marginal cost.

[2] The super-elasticity of demand is one when demand curves are semilog, i.e., $\log D(p) = -ap + b$. The fact that semilog demand curves generate complete pass-through in levels is discussed by Bulow and Pfleiderer (1983), Weyl and Fabinger (2013), and Mrázová and Neary (2017).

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



described above, as well as broader data that covers several manufacturing sectors, I find that the behavior of entry and gross margins in the data are consistent with the safety margins model rather than the standard model.

Complete pass-through in levels offers predictions for the extent of commodity cost pass-through that do not require estimating rich models of demand. In the final section of the paper, I demonstrate the relevance of these predictions by considering the implications of complete pass-through in levels for inflation inequality.

Specifically, I document a new, cyclical component of inflation inequality that arises due to complete pass-through in levels. Under complete pass-through in levels, low-margin products within a product category will exhibit higher inflation rates when commodity costs rise, even though absolute price changes are similar across products. Since low-income households tend to purchase lower-price and lower-margin products (Sangani 2022), rising commodity costs cause low-income households to face higher inflation rates 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 (e.g., in 2011 and 2014) and falls when commodity prices are falling (e.g., in 2012).

Aggregating over the food-at-home bundle, this pass-through behavior results in higher food-at-home inflation volatility for low-income households. I find that log pass-through of upstream food price indices to food-at-home inflation for households in the lowest income quintile is 10 percent higher than for the highest income quintile. As a result, the variance of annual inflation rates experienced by the lowest income quintile is 20 percent greater than that experienced by the highest income group.

I apply these estimates to changes in the food-at-home price level experienced by households since the onset of the COVID-19 pandemic in 2020. I estimate that food-at-home prices for the lowest income quintile grew 15.6pp from 2020–2023, compared to 13.7pp for the highest income quintile. Two-thirds of the estimated difference in price growth experienced by households in the lowest and highest income quintiles is due to differences in log pass-through resulting from complete pass-through in levels, while one-third is due to secular differences in inflation rates.

Related literature. This paper relates to a large literature on pass-through that studies theoretical and empirical determinants of pass-through (e.g., Bulow and Pfleiderer 1983, Leibtag 2009; Nakamura and Zerom 2010; Weyl and Fabinger 2013; Hong and Li 2017; Minton and Wheaton 2022). I focus on the long-run pass-through of commodity shocks that shift costs for all firms in a market. Thus, I abstract from two topics that have generated large empirical literatures: (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., Campa and Goldberg 2005; Berman et al. 2012; Burstein and Gopinath 2014; Amiti et al. 2019).

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 certain contexts. For example, Nakamura and Zerom (2010) find that retail coffee prices move one-for-one with coffee commodity prices. However, the central exercise in Nakamura and Zerom (2010) seeks to account for the incomplete pass-through in logs, attributing long-run incomplete log pass-through to both non-commodity input costs and a positive super-elasticity of demand. 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 provide a theoretical foundation for why complete pass-through in levels is an appropriate benchmark.[3] Other papers that measure pass-through in levels include Dutta et al. (2002), who document roughly

[3] 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 is derived from consumers' time cost of visiting other stations.

complete pass-through in levels for frozen orange juice concentrate, and Conlon and Rao (2020), who document pass-throughs in levels over one due to discrete price points in distilled spirits.

Most closely related to my 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 my evidence, Butters et al. (2022) find evidence of complete pass-through in levels of these cost changes.[4] This paper adds to this evidence by showing that that complete pass-through in levels is not a feature unique to retail stores, but holds along the chain of producers from commodity to retailer in the studied markets.[5]

The application of complete pass-through in levels to inflation inequality builds on a rich literature that documents heterogeneity in the inflation rates experienced by households (Hobijn and Lagakos 2005; Kaplan and Schulhofer-Wohl 2017; Jaravel 2019, 2021). My empirical findings confirm the secular differences in inflation across income groups documented in this literature, but also point to a new source of inflation inequality that varies with upstream costs. This channel is relevant for understanding why inflation inequality may surge in times when commodity costs are rising.

Finally, the model of additive unit margins in this paper also relates to a large literature on so-called full cost or cost-plus pricing. This literature was spawned by survey evidence that pricing managers predominantly use simple heuristics to set prices, and often set pricing based on average costs rather than marginal costs (see e.g., Hall and Hitch 1939; Kaplan et al. 1958; Lanzillotti 1958). Historical debates between marginal cost and full cost pricing theories are surveyed in Heflebower (1955) and Okun (1981). The model of safety margin constraint pricing developed in this paper draws on the verbal discussion of full cost pricing in Fellner (1948).

Layout. Section 2 motivates the empirical specifications used to measure pass-through in logs and in levels. Section 3 documents empirical patterns of pass-through in the retail gasoline market. Section 4 examines pass-through in food product markets. Section 5 explores explanations for pass-through in levels, develops a model of firm pricing, and tests its empirical predictions. Section 6 applies pass-through in levels to the unequal incidence of commodity shocks. Section 7 concludes.

[4]Butters et al. (2022) note that their results "are consistent with perfect competition, [though] perfect competition is inconsistent with the substantial evidence that retailers exhibit some degree of market power." This puzzle—pass-through dynamics resemble perfect competition while price levels do not—is the central puzzle addressed in this paper.

[5]In Appendix E, I explicitly test for complete pass-through in levels at different stages of the agricultural supply chain (farm to wholesale to retail). I find evidence of complete pass-through in levels at both steps of the supply chain.

2 Framework and Empirical Specification

Pass-through in logs and levels. I start by laying out a benchmark model of firm pricing that clarifies the differences between pass-through in logs and levels. Consider a firm that produces y units of an output good with a constant returns, Leontief production technology in a commodity input with unit price c and another input with unit price w:[6]

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

To fix ideas, Table 1 provides an example in which $c = \$1$ and $w = \$1$.

In standard models where buyers have CES preferences over varieties (e.g., Dixit and Stiglitz 1977), firms' desired prices p^* are equal to a fixed, multiplicative markup, μ, over marginal cost:

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

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

How does an increase in the commodity price, Δc, affect the price charged 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 commodity price changes is equal to the markup μ. In markets with imperfect competition, $\mu > 1$, and hence the standard model with fixed multiplicative markups implies pass-through in levels greater than one.

To fix ideas, Table 1 illustrates this benchmark of complete "log pass-through" for a \$0.20 increase in the commodity price. Since a \$0.20 increase in the commodity price results in a 10 percent increase in marginal costs, complete log pass-through implies that the output price should also rise by 10 percent, or by \$0.40. Note that the pass-through in levels—the ratio of the change in the output price to the change in the commodity cost—is equal to the markup, $\mu = 2$.

On the other hand, with complete pass-through in levels, the output price increases by the same amount as the commodity cost. In the example in Table 1, the \$0.20 increase in the commodity price results in a \$0.20 increase in the output price. In the case of complete

[6]The assumption of constant returns, Leontief production seems appropriate for the settings that I study empirically. In order to sell an ounce of ground coffee, a firm must buy the equivalent amount of coffee beans. Section 5 considers how relaxing the assumptions of constant returns to scale, Leontief production, and isoelastic demand each affect pass-through.

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

	Baseline		New	*% Change*
Components of marginal cost				
Commodity	\$1	+\$0.20	\$1.20	*+20%*
Other variable costs	\$1	–	\$1.00	
Total marginal cost	\$2	+\$0.20	\$2.20	*+10%*
Desired output price				
Complete pass-through in logs	\$4	+\$0.40	\$4.40	*+10%*
Complete pass-through in levels	\$4	+\$0.20	\$4.20	*+5%*

pass-through in levels, the firms' desired price is better described by the additive pricing rule

$$p^* = c + w + \alpha,$$

where the gap between the output price and marginal cost is the additive unit margin α. In Table 1, $\alpha = \$2$.

Note that when complete pass-through in levels is measured on a percentage basis, the change in the output price (5 percent) appears incomplete relative to the change in marginal cost (10 percent). It also appears incomplete relative to the change in the commodity price adjusted for the cost share of the commodity (20 percent $\times$ 0.5 = 10 percent). In other words, complete pass-through in levels is disguised as incomplete log pass-through.

Empirical specification. The aim of the empirical strategy is to measure how firms' desired prices p^* respond to changes in commodity costs, both in logs and in levels. Of course, at short horizons, price rigidities may prevent a firm from being able to change its posted price p in accordance with changes in its desired price p^*. Hence, the relevant measure of how changes in costs affect firms' desired prices is instead the pass-through of persistent changes in costs to prices at a long horizon where price rigidities are overcome.

I estimate this long-run pass-through of commodity cost changes using the standard distributed lag regression (see 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.[7]

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, $\sum_{k=0}^{K} b_k$. When c is a unit root process, under the constant markup pricing rule (1), the long-run pass-through estimate $\sum_{k=0}^{K} b_k \to \mu$ as K becomes large.

As a point of comparison, I also estimate the log pass-through regression,

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

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

For valid inference, changes in the commodity cost Δc_t must be stationary. I confirm this is the case for all commodity series used in this paper in Appendix Table A1. In all cases, autocorrelation estimates and Augmented Dickey-Fuller tests suggest that while the commodity costs series are approximately unit root, first differences in commodity costs are not.

3 Evidence from Retail Gasoline

Retail gasoline provides an ideal laboratory to study pass-through since rich data on upstream costs is readily available and gasoline prices exhibit little rigidity. My main analysis in this section uses data on the universe of retail gas stations in Perth, Australia (other studies using these data include Wang 2009a; Byrne and de Roos 2017, 2019, 2022). At the end of the section, I show that retail gasoline markets in the United States, Canada, and South Korea exhibit similar patterns.

I document four patterns in the retail gasoline data. 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.[8] Third, while there is little heterogeneity in pass-through in levels across stations and across years in the sample, there is substantial variation in log pass-through: stations with a larger gap between prices and costs have lower log pass-

[7] An alternative is to use a vector error correction (VEC) model, which allows for co-integrated cost and price series. Using these specifications produces broadly similar results to my baseline results; however, the estimates are substantially noisier.

[8] Weekly price cycles in the data (documented previously by Wang 2009a and Byrne and de Roos 2019) allow me to estimate a lower bound on the marginal cost share of gasoline.

through. Using several instruments designed to isolate variation in stations' markups from stations' marginal costs, I 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. These four patterns are consistent with retail gasoline stations setting prices as a fixed additive margin over marginal cost, rather than as a multiplicative markup over cost.

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 prices for each gas product (i.e., unleaded petrol, premium unleaded petrol, and diesel) 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 Byrne and de Roos (2019) and Byrne and de Roos (2022), who investigate price cycles and consumer search behavior.

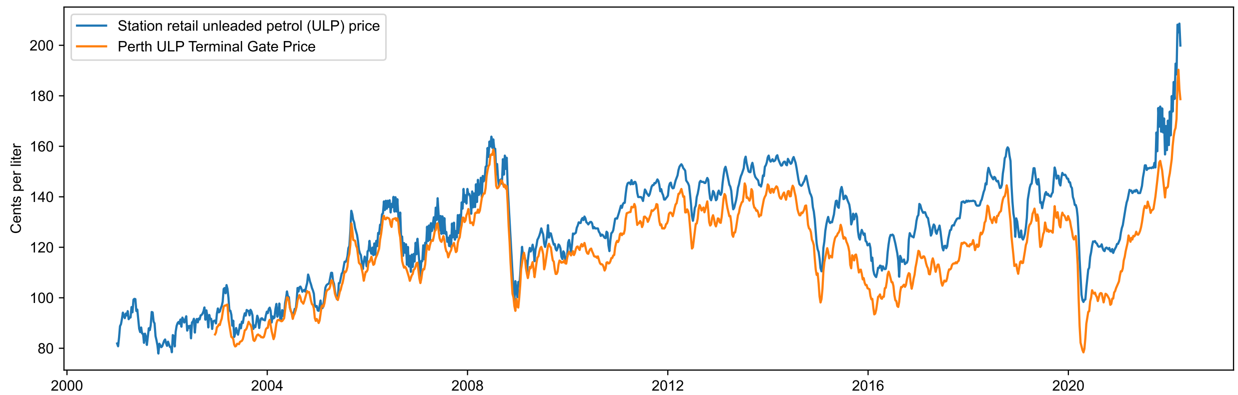
Following Byrne and de Roos (2019), I take the minimum terminal gas price offered by the six terminals each day as the commodity price that faces retail gas stations. Figure 2 shows the weekly average terminal gas price and the retail unleaded petrol (ULP) price for a single gas station from 2001 to 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 I exploit later in the analysis.[9]

3.2 Empirical Results

Figure 3 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 from five weeks the

[9]While the BP station in Kewdale shown in Figure 2 tracks wholesale prices quite closely, as is typical of most gas stations in the sample, some gas stations maintain prices significantly higher than the wholesale price and update prices less frequently. See, for example, ULP prices for the Rottnest Island Authority station shown in Appendix Figure A1.

Figure 2: Weekly average retail unleaded petrol (ULP) price and terminal gas price for BP station at 549 Abernethy Rd, Kewdale, Perth, Australia.



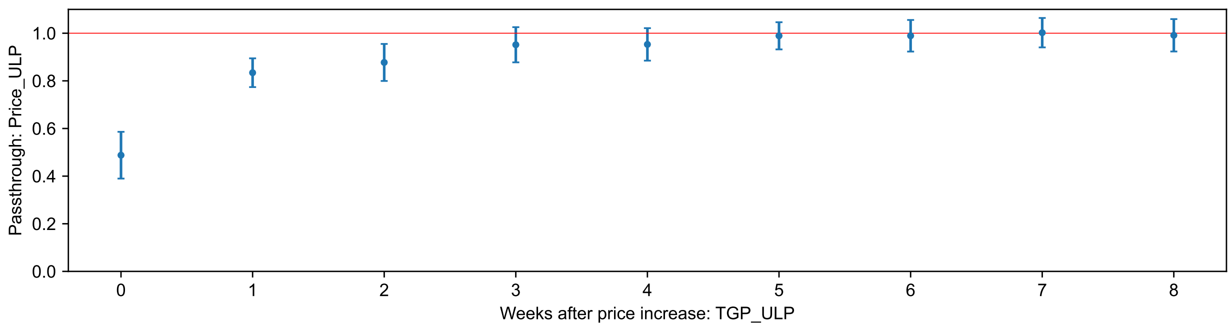
estimate is very close to one. The point estimate for long-run pass-through at eight weeks is 0.991 (standard error 0.035). Changing the horizon over which pass-through is estimated has little effect on the estimated long-run pass-through. In contrast to the complete pass-through in levels, the long-run log pass-through at eight weeks is 0.899 (0.039). This log pass-through is statistically different from one at a 1 percent level.

Estimates of the pass-through of premium unleaded (PULP) wholesale prices to retail prices, shown in Appendix Figure A2, are similar: the long-run pass-through in levels is statistically indistinguishable from one at 0.985 (0.032), while the long-run pass-through in logs is significantly below one at 0.887 (0.037).

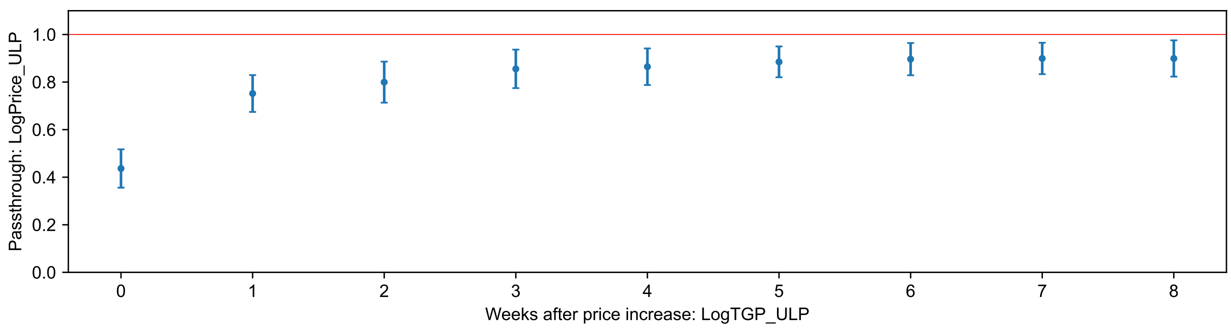
Incomplete log pass-through even accounting for cost share. If retail gas stations face other variable costs besides the cost of gasoline, the log pass-through should not be equal to one, but should instead equal the cost share of gasoline (as a share of stations' marginal costs). Luckily, the presence of price cycles in this setting allows us to estimate a lower bound for the cost share of gasoline in stations' costs in this setting and compare whether log pass-through is incomplete even relative to the gasoline cost share.

Figure 4 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 clear price cycles over the course of the week, typically jumping up on Tuesdays and then falling over the course of the week. Since gas stations are unlikely to set prices below marginal cost, we can use the days of the week at the lowest point of the price cycle to calculate a lower bound for the cost share of gasoline. The average cost share of gasoline calculated in this way is 0.98 for unleaded petrol and 0.96 for premium unleaded

Figure 3: Unleaded petrol (ULP) price pass-through in levels (top) and in logs (bottom).



(a) Pass-through in levels.



(b) Pass-through in logs.

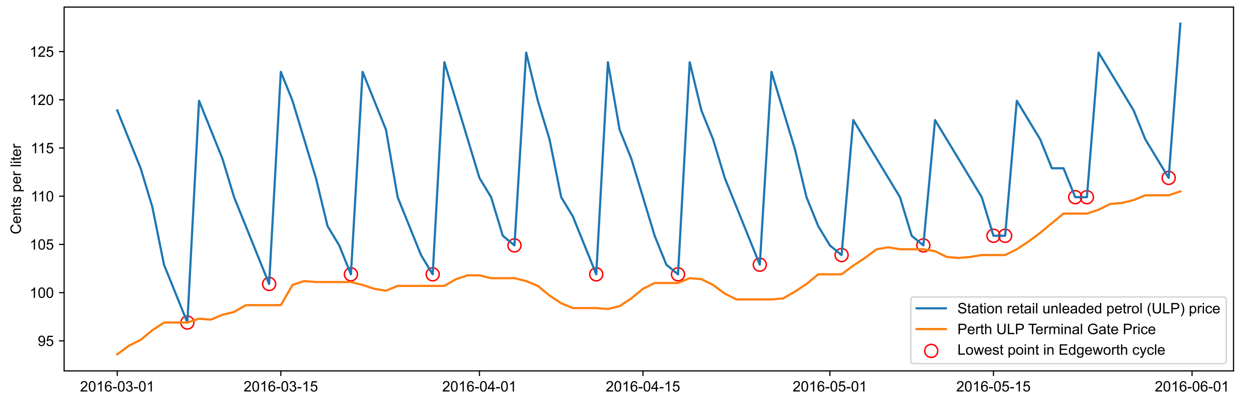
Note: Panels (a) and (b) show cumulative pass-through estimated from the specifications,

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

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

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 4: Daily retail unleaded petrol price for BP at 549 Abernethy Rd, Kewdale, Perth for three months in 2016, with lowest points in price cycle.



petrol.[10] The estimated log pass-throughs for unleaded and premium unleaded petrol, 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 accounting for the share of gasoline in variable costs.[11] The presence of an additive unit margin means that complete pass-through in levels is disguised as incomplete log pass-through.

Exploiting variation in markups. One might be concerned that that, while the point estimate for long-term pass-through in levels (0.991) is very close to one, it is hard to differentiate this pass-through from low single-digit markups that would be plausible in this setting. Indeed, the 95 percent confidence interval for pass-through in levels is $(0.921, 1.061)$, so we cannot reject markups on the order of 1–6 percent.

To investigate this, I exploit cross-sectional and time series variation in markups. If some stations charge higher markups than other stations, then the estimated pass-through in levels for these high-markup stations should be higher than their low-markup counterparts. (Similarly, time periods where the average markup charged by stations is

[10] This estimate is a lower bound if firms price at or above marginal cost on days at the lowest point of the price cycle, which is the case, for example, in Maskin and Tirole's (1988) model of price cycles.

[11] It is also unlikely that the difference between the average cost share and the log pass-through is due to higher order terms. Suppose stations are perfectly competitive ($p = c + w$), so that log pass-through to a first-order is indeed equal to the cost share. The change in log prices to a second order is

$$\Delta \log p \approx \chi(d \log c) + \chi(1 - \chi)(d \log c)^2,$$

where $\chi = c/(c + w)$ is the cost share of gasoline. The estimate of log pass-through averaged across time periods will be

$$\hat{\rho} = \mathbb{E}[\Delta \log p / d \log c] \approx \mathbb{E}[\chi] + \mathbb{E}[\chi(1 - \chi)(d \log c)].$$

That is, higher order terms would make measured log pass-through *higher*, rather than lower, than the cost share in the empirically relevant case of upward drift in nominal commodity prices over time ($\mathbb{E}[d \log c] > 0$).

high should see higher pass-through in levels on average than time periods where the average markup is low.)

I estimate the specification,

$$\Delta p_{i,t} = \alpha + \delta \Delta c_t + \gamma \text{Avg. Markup}_{i,t} + \beta(\Delta c_t \times \text{Avg. Markup}_{i,t}) + \varepsilon_{i,t}.$$

where $\Delta p_{i,t}$ and Δc_t are changes in the station retail price and wholesale cost over the prior sixteen weeks, Avg. $\text{Markup}_{i,t}$ is a measure that exploits cross-sectional or time series variation in markups, and $\varepsilon_{i,t}$ is a mean-zero error term.[12]

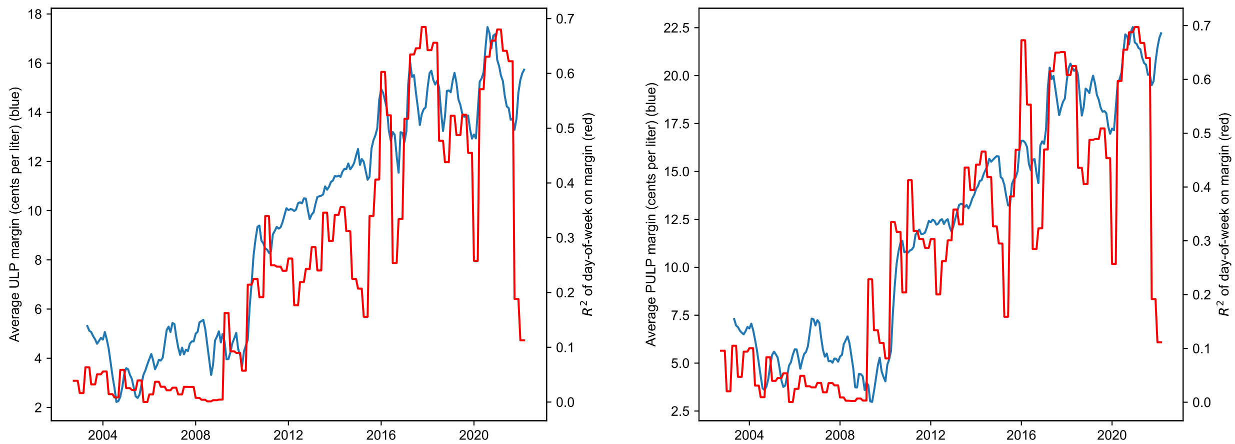
The constant markup model predicts that the coefficient on the interaction term $\beta > 0$. That is, since the pass-through in levels should be equal to the markup, stations or time periods with higher markups should result in higher pass-through. For example, if some stations set a constant markup of 2 percent and other stations set a constant markup of 5 percent, margins will be higher on average for the latter set of stations, and pass-through in levels should be 1.05 for the high-markup stations compared to 1.02 for the low-markup stations (thus, $\beta > 0$). On the other hand, if all stations set a constant unit margin and obey complete pass-through in levels, the interaction coefficient $\beta \approx 0$.

I use two proxies for Avg. $\text{Markup}_{i,t}$ along with instruments for both. The first measure exploits variation in markups across stations: Avg. Station Markup_i is the average markup (gasoline retail price / wholesale price) charged by station i for all weeks in the sample. I also instrument for Avg. Station Markup_i with the average amplitude of price cycles of station i. That is, for each station i, I calculate the difference between the maximum of minimum retail margin charged by i in each week, and then average across all periods. While the raw measure of station's markup may also capture variation in non-gasoline variable costs across stations, this instrument only relies on the amplitude of price cycles used by station i, thus cleansing the measure of different variable costs across stations.

The second measure instead exploits variation in markups over time: Avg. Markup_t is the average markup across all gas stations in year t. To instrument for Avg. Markup_t, I 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." As shown in Figure 5, average gas station margins on unleaded petrol and premium unleaded petrol co-move closely with a measure of coordinated price cycles (namely, the R^2 from a regression of daily margins on day-of-week fixed effects). While the most dramatic

[12] Since I find that pass-through is complete over an eight-week horizon, I take changes in station retail prices and costs over twice this period, or sixteen weeks (i.e., $\Delta p_{i,t} = p_{i,t} - p_{i,t-16}$). This ensures that cost changes in the first half of the period are fully passed through. Similar results obtain using different lengths choices of the price change horizon.

Figure 5: 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.

change over time is the increase in both coordination and margins around 2010, there is also subsequent variation in the strength of coordination and margins after 2010, which may owe to subsequent price wars documented by Byrne and de Roos (2019). Hence, I use this measure of price coordination over time—the quarterly R^2 of station margins on day-of-week dummies—as an instrument for the average year margin Avg. Margin_t.

Table 2 reports the results.[13] In column 1, I omit 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 16 weeks.[14] Columns 2–5 include the interaction of the cost change with the average station or annual markup, both reduced form and instrumenting for the markup using the strategies discussed above. In all cases, the $\beta > 0$ prediction of the constant-markup model is rejected. Instead, all point estimates for β are slightly negative and are statistically indistinguishable from zero.

The results in Table 2 suggest that there is little deviation from complete pass-through in levels in the cross-section of stations or in the time series. As an additional check, I compare the long-run pass-through of cost changes to price changes for stations grouped by their price relative to other stations in the same neighborhood.[15] Assuming unobserved

[13]The standard errors reported in Table 2 are two-way clustered by postcode and year. These reported standard errors are more conservative than Driscoll-Kraay standard errors.

[14]Since pass-through is only complete at horizons of 5–8 weeks, changes in cost in the final weeks of this 16 week difference, $\Delta c_t = c_t - c_{t-16}$, will not be completely passed through to prices, and hence this coefficient is slightly less than one.

[15]In particular, I calculate the relative price of each station as the average differential between its price and

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**	0.985**	0.973**
	(0.021)	(0.037)	(0.044)	(0.043)	(0.048)
ΔCost$_t$ $\times$ Avg. Station Markup$_i$ (Net %)		-0.005	-0.000		
		(0.003)	(0.005)		
ΔCost$_t$ $\times$ Avg. Year Markup$_t$ (Net %)				-0.004	-0.003
				(0.004)	(0.005)
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 from the specification,

$$\Delta \text{Price}_{i,t} = \alpha + \delta \Delta \text{Cost}_t + \gamma \text{Avg. Markup}_{i,t} + \beta(\Delta \text{Cost}_t \times \text{Avg. Markup}_{i,t}) + \varepsilon_{i,t}.$$

Changes in prices and costs ΔPrice$_{it}$ and ΔCost$_t$ are taken over 16 weeks, and Avg. Markup$_{i,t}$ is included on a net % basis (i.e., a markup of $p/c = 1.1$ is input as 10%). Column 3 (IV1) uses station i's average price cycle amplitude as an instrument for Avg. Margin$_i$. Column 5 (IV2) uses the quarterly R^2 of station margins on day-of-week dummies as an instrument for Avg. Margin$_t$. Standard errors are two-way clustered by postcode and year.

costs (e.g., transport, rent) are the same within a neighborhood, stations with higher relative price have higher markups and thus should exhibit higher pass-through in levels if prices are set with constant multiplicative markups. As shown in Appendix Figure A3, however, the estimate of long-run pass-through across is close to one and unchanging across all groups of relative prices within neighborhoods and within postcodes.

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,[16]

$$\Delta \log p_{i,t} = \alpha + \beta \Delta \log c_{i,t} + \delta \text{Avg. Markup}_{i,t} + \gamma(\Delta \log c_{i,t} \times \text{Avg. Markup}_{i,t}) + \varepsilon_{i,t}. \quad (4)$$

Column 1 omits the average markup and interaction term and estimates an average

the price of other stations in the same neighborhood on the same date, RelativePrice$_i$ = $(1/T_i)\sum_t(\text{Price}_{it} - \overline{\text{Price}}_{N_t(i),t})$, where T_i is the total number of days for which a retail price is observed for station i and $\overline{\text{Price}}_{N_t(i),t}$ is the average retail price on date t for all stations in i's neighborhood $N_t(i)$.

[16]Since Table 2 suggests that stations set a constant additive margin, rather than a multiplicative markup, one might find it preferable to estimate specification (4) using an interaction with Avg. Margin$_{i,t}$ rather than Avg. Markup$_{i,t}$. Results from that specification are quantitatively similar to the results in Table 3.

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

$\Delta\log(\text{Price})_{it}$	(1) (OLS)	(2) (OLS)	(3) (IV1)	(4) (OLS)	(5) (IV2)
$\Delta\log(\text{Cost})_t$	0.870**	0.998**	0.968**	0.985**	0.977**
	(0.031)	(0.035)	(0.041)	(0.035)	(0.040)
$\Delta\log(\text{Cost})_t \times$ Avg. Station Markup$_i$ (Net %)		-0.015**	-0.011**		
		(0.003)	(0.004)		
$\Delta\log(\text{Cost})_t \times$ Avg. Year Markup$_t$ (Net %)				-0.012**	-0.011**
				(0.003)	(0.004)
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 from the specification,

$$\Delta\log(\text{Price})_{i,t} = \alpha + \delta\Delta\log(\text{Cost})_t + \gamma\text{Avg. Markup}_{i,t} + \beta(\Delta\log(\text{Cost})_t \times \text{Avg. Markup}_{i,t}) + \varepsilon_{i,t}.$$

Changes in log prices and costs $\Delta\log(\text{Price})_{it}$ and $\Delta\log(\text{Cost})_t$ are taken over 16 weeks, and Avg. Markup$_{i,t}$ is included on a net % basis (i.e., a markup of $p/c = 1.1$ is input as 10%). Column 3 (IV1) uses station i's average price cycle amplitude as an instrument for Avg. Margin$_i$. Column 5 (IV2) uses the quarterly R^2 of station margins on day-of-week dummies as an instrument for Avg. Margin$_t$. Standard errors are two-way clustered by postcode and year.

log pass-through from cost changes to price changes of 0.870. Thus, like the long-run pass-through estimates, this log pass-through is significantly lower than one. 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 margins (and thus higher markups) lead to a measured log pass-through that is more incomplete.[17] Second, the gap between price and costs appears to fully account for incomplete pass-through: the coefficient on $\Delta\log(\text{Cost})_t$ shows that as the net station markup and annual markup approach zero, the log pass-through is tightly estimated around the cost share of 0.98. Both results hold across all four specifications in columns 2–5, including for the instrumented specifications in columns 3 and 5.

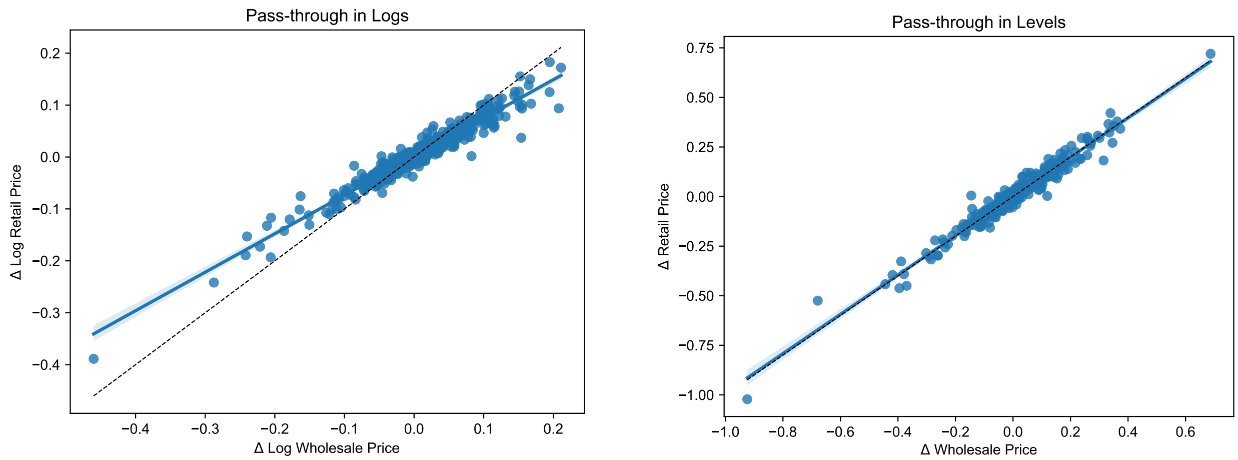
Thus, Table 3 shows that incomplete log pass-through is rationalized by the combination of complete pass-through in levels (documented in Table 2) with non-zero margins.

[17] The estimated interaction coefficient in the log specification $\beta \approx -0.01$ is not a coincidence. If stations set an additive unit margin α over marginal cost $c + w$, to a first order,

$$\Delta\log p \approx \frac{c}{c+w+\alpha}\Delta\log c = \chi\mu^{-1}\Delta\log c \approx \chi(1 - 0.01\mu^{\text{net},\%})\Delta\log c,$$

where $\chi = c/(c+w)$ is the cost share (0.96–0.98 in the data), $\mu = p/(c+w)$ is the markup, and $\mu^{\text{net},\%} = 100(\mu-1)$.

Figure 6: Pass-through of U.S. refiner wholesale prices to retail prices, 1983–2021.



(a) Logs (β = 0.74).

(b) Levels (β = 0.99).

Note: Refiner wholesale prices are monthly U.S. refiner gasoline prices for sale through retail outlets from the Energy Information Administration (EIA). Retail gasoline prices are from BLS Average Price Data. Price changes measured over one month.

In particular, because pricing follows complete pass-through in levels, log pass-through is lower both for stations in the cross-section with higher margins and for years in the time-series with higher margins. The presence of additive unit margins between costs and prices explains both the level of incomplete log pass-through (around 0.87) and variation in log pass-through across stations.

Evidence from other markets. One may wonder whether the pass-through patterns documented in the Perth retail gasoline market extend to other settings. Table 4 compares pass-through estimates from Perth to estimates from a panel of Canadian cities and to estimates from gas station-level data from South Korea (Appendix C describes the data sources used to construct these estimates). Incomplete log pass-through and complete pass-through in levels appear across all the studied markets.[18] Figure 6 shows that complete pass-through in levels also appears in U.S. data, using refiner wholesale prices from the Energy Information Administration (EIA) and retail prices from the BLS. The evidence from other geographies suggests that complete pass-through in levels is not a quirk of the Australian data, but rather appears to describe pricing behavior across a number of markets.

[18]For Canada, city-level wholesale prices are also available, which allows me to study the pass-through of crude prices to city-level wholesale prices in the panel of cities. Interestingly, these data also suggest complete pass-through in levels from crude to wholesale prices.

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

	Long-run pass-through (8 weeks)			
	Logs		Levels	
Description	Est.	IV	Est.	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)

Note: The table reports long-run pass-through at a horizon of eight weeks for station-level data from Perth, Australia, city-level data from Canada, and station-level data from South Korea. Driscoll-Kraay standard errors with eight lags in parentheses. The IV columns use eight lags of OPEC announcement shocks from Känzig (2021) as an instrument for commodity price changes. The F-stat for the instrument in all regressions is greater than 10. † indicates that an estimate is statistically indistinguishable from one.

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

4 Evidence from Food Products

Retail gasoline is by no means a representative market. To investigate whether these empirical patterns hold in other markets, in this section I 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).

For five out of the six product, the long-run pass-through of commodity costs in levels is statistically indistinguishable from one.[19] Using product-level scanner data for three food products (coffee, rice, and flour), I 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 marginal costs and margins.

Finally, I 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 conform to the predictions of an additive unit margin pricing model, rather than a fixed multiplicative markup model.

4.1 Data on Food Retail and Commodity Prices

Retail prices. For retail prices of food products, I 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 to minimize quality differences between included items. For example, the average price series for "Flour, white, all purpose, per lb." excludes any whole wheat, semolina, rye, or barley flours. In many cases, Average Price Data also defines items by package size (e.g.,

[19]The exception is sugar, where the estimate of long-run pass-through in levels is 0.691.

"Orange juice, frozen concentrate, 12 oz. can, per 16 oz."), thereby minimizing differences in size and quality.

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. However, studying cross-sectional heterogeneity across products in the same category requires richer data. For these investigations, I use Nielsen Retail Scanner data, which provides weekly barcode-level prices and quantities for 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.

Commodity costs. I 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, which is for delivery of cane sugar from the U.S. or another duty-free origin to New York, Baltimore, Galveston, New Orleans, or Savannah. 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, I rely on previous literature and on sources provided by 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. (This careful matching of units is one of the reasons why estimating pass-through in levels is difficult for non-staple, differentiated products, where the portion of costs attributed to upstream commodity prices is more difficult to assess than for these homogeneous, staple goods. In Section 6, I show that several other food-at-home products exhibit similar pass-through patterns to the homogeneous goods studied in this section, but I do so without the ability to match retail products directly to their commodity inputs.)

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 A4 lists the corresponding Average Price Data Series IDs and reported units. For three of these products—rice, flour, and coffee—I also investigate

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)	$0.946^{\dagger}$	(0.099)
Sugar, No. 16	Sugar, white	0.370	(0.035)	0.691	(0.072)
Beef	Ground beef, 100% beef	0.410	(0.068)	$0.899^{\dagger}$	(0.126)
Rice, Thailand	Rice, white, long grain, uncooked	0.307	(0.049)	$0.882^{\dagger}$	(0.169)
Wheat	Flour, white, all purpose	0.240	(0.048)	$0.819^{\dagger}$	(0.152)
Frozen orange juice	Orange juice, frozen concentrate	0.327	(0.040)	$1.006^{\dagger}$	(0.114)

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 that an estimate is statistically indistinguishable from one.

cross-sectional pass-through patterns by matching the food product to a Nielsen product category.[20]

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 and therefore incomplete. Of course, the incomplete log pass-through is partly due to the presence of other variable costs besides the commodity cost—the correct benchmark would compare the log pass-through to the commodity cost share—but the complete pass-through in levels rejects the possibility that changes in marginal cost are passed through fully on a percentage basis (unless firms price exactly at marginal cost, a possibility I provide evidence against in Section 5).

Figure 7 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 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

[20]The corresponding Nielsen product modules are Nielsen product module 1319 "Rice - Packaged and bulk" for rice, Nielsen product module 1393 "Flour - All purpose - White wheat" for flour, and Nielsen product module 1463 "Ground and whole bean coffee" for coffee. I exclude beef, sugar, and frozen orange juice concentrate, because beef products are spread across a number of product modules, while the "Sugar - granulated" and "Fruit juice - orange - frozen" product modules have fewer unique products.

Colombia.[21] These run-ups in commodity prices are followed by increases in the retail prices tracked by the BLS. The commodity and retail series appear roughly parallel, though the difference between the two expands slowly from 1980 to 2022. Accordingly, 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), plateaus around 0.5. 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 for food products in Table 5 has predictions for price changes in the cross-section of products. First, products that have higher margins and higher non-commodity variable 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 variable costs.

To test these predictions, I use Nielsen data on rice, flour, and coffee products from 2006 to 2020. I label each unique combination of retail chain and UPC (universal product code, or product barcode) as a product.[22] In each quarter t, I calculate the price $p_{i,t}$ of retailer-UPC product i as the quantity-weighted average unit price over all transactions k,

$$p_{i,t} = \frac{\sum_k p_{i,t,k} q_{i,t,k}}{\sum_k q_{i,t,k}}.$$

For each product in each quarter, I then measure the change in the product's price over the next year in levels ($\Delta p_{i,t}$) and in percentages ($\pi_{i,t}$) as

$$\Delta p_{i,t} = p_{i,t+4} - p_{i,t}, \qquad \pi_{i,t} = (p_{i,t+4}/p_{i,t}) - 1.$$

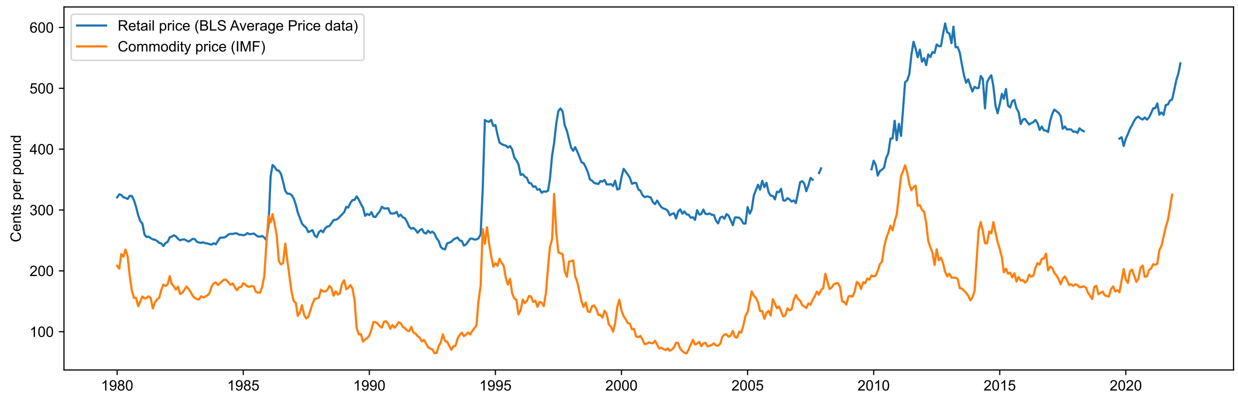
Since these price changes are measured year over year, they avoid seasonality effects that may bias measures of price changes calculated over smaller time increments.[23]

[21] For coverage of the weather conditions leading to these coffee price run-ups, see Washington Post: "*Big Rise Predicted in Coffee Prices*" (1986), New York Times: "*Coffee Futures Soar 25%, Biggest Daily Rise in 7 Years*" (1994), New York Times: "*Coffee Hits a 20-Year High on Rumblings of a Shortage*" (1997), New York Times: "*Heat Damages Colombia Coffee, Raising Prices*" (2011), and Business Insider: "*Why Coffee Prices are Exploding*" (2014).

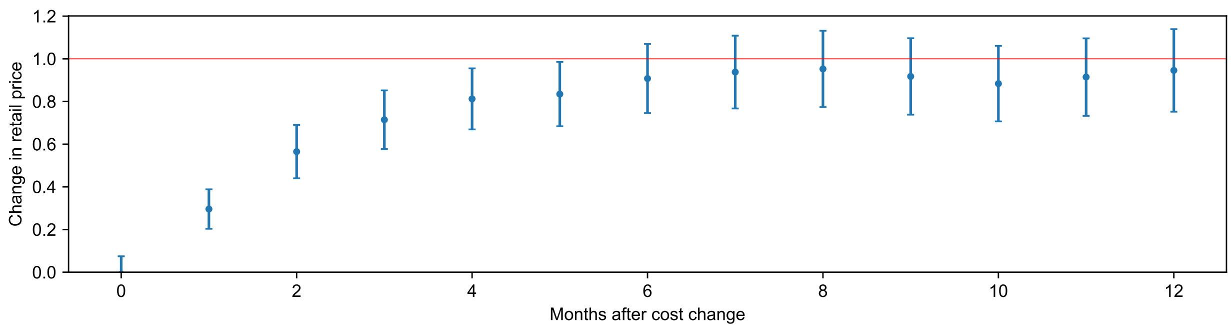
[22] As documented by DellaVigna and Gentzkow (2019), stores within a retail chain (especially in the same geographic area) tend to set uniform prices for each UPC at each point in time.

[23] 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 rice products in the data, 80.7% of quarterly retailer-UPC observations are also observed in the same quarter of the following year, which suggests

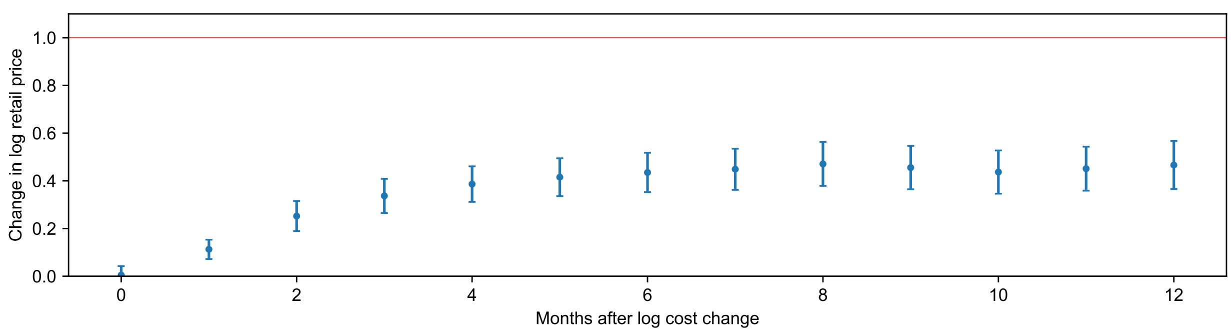
Figure 7: Passthrough of coffee commodity costs to retail prices.



(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.

Given that the commodity input constitutes the bulk of product volume in each of these categories, we can 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, I sort products into groups by unit price. In particular, in each quarter and in each product category, I create three product groups with equal sales. To ensure that these product groups capture persistent differences in unit price, I sort products by average unit price over the prior year.[24]

Figure 8 plots the sales-weighted average inflation rates (i.e., price changes in percentage terms) 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.[25] That is, consistent with the prediction that low margin products exhibit higher log pass-through, products with the lowest unit prices had the highest inflation rates following the increase in commodity prices. These differences disappear when comparing the price changes in levels across unit price groups in the bottom panel. (If anything, the lowest unit price group actually saw a slightly lower increase in price levels in 2008.)

To test this formally, Table 6 reports estimates from the following specifications,

$$\Delta\pi_{i,t} = \alpha_i + \sum_{g=1}^{3} \beta_g \left(1\{G(i,t) = g\} \times \pi_t^c\right) + \varepsilon_{i,t}, \tag{5}$$

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

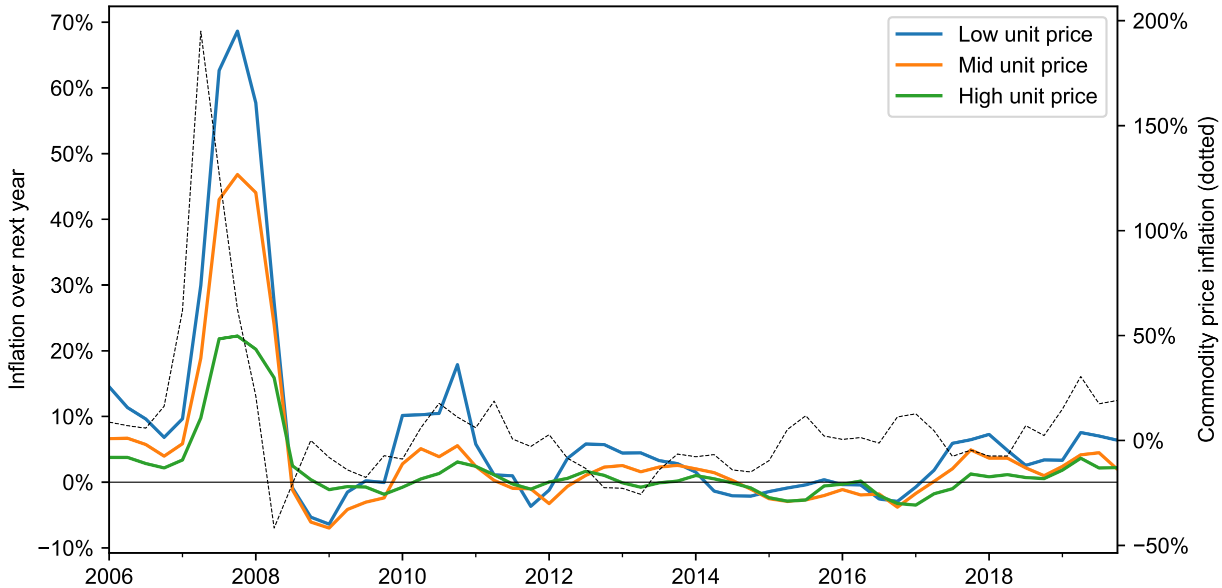
where $G(i,t) \in \{1,2,3\}$ is the unit price group of product i in quarter t, $\pi_t^c = (c_{t+4}/c_t) - 1$ is

that turnover is relatively low. (The corresponding figure is 83.7% for flour products and 74.7% for coffee products.) Moreover, product turnover does not appear to be correlated with commodity inflation rates in a way that would downward bias measured pass-through. The correlation of commodity inflation over the next year with the share of products in a quarter that are also observed in the following year is 0.03 for rice products (0.09 and 0.09 for flour and coffee products, correspondingly).

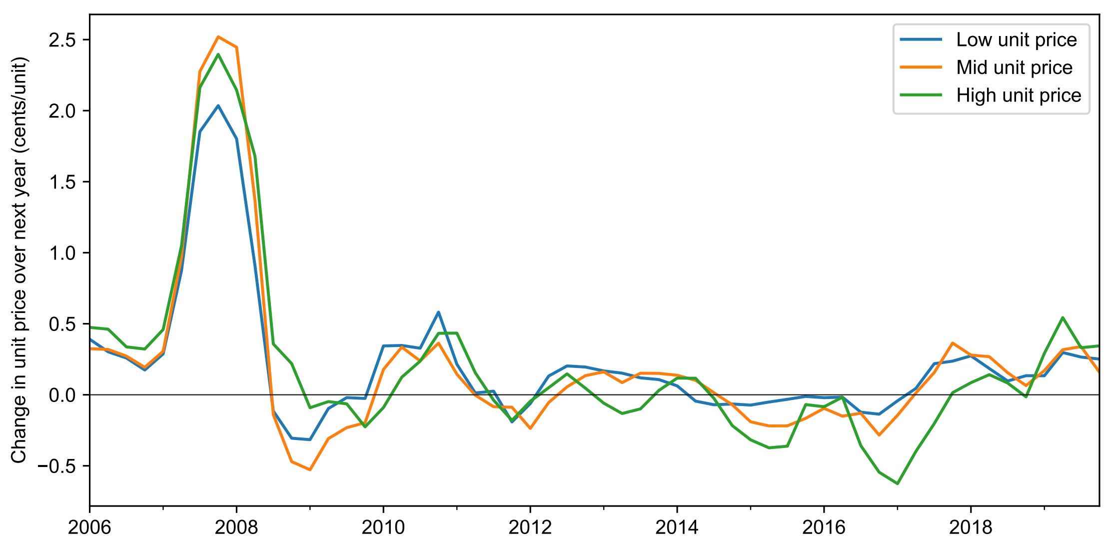
[24]Using the average unit price of the product over the prior year helps alleviate concerns that these groupings pick up temporary deviations in prices—mean reversion may then mechanically bias future price changes—though in practice all empirical results reported are very similar if we instead sort on products' unit price in only quarter t.

[25]Childs and Kiawu (2009) provide a detailed account of the factors leading to the rise in rice prices in 2008. The run-up 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.

Figure 8: 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 Nielsen scanner data. In each quarter, all UPCs are separated into three groups with equal quarterly sales by (quantity-weighted) 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.

the inflation in the commodity price over the next year and $\Delta c_t = c_{t+4} - c_t$ is the change in the commodity price in levels over the next year.[26] Panel A shows that retail price inflation is most sensitive to commodity price inflation for products in the lowest unit price group, and 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 shows that there are no systematic differences in the sensitivity of retail price changes to commodity price changes *in levels* across unit price groups. These results thus provide empirical support for the above predictions: products with higher margins and higher non-commodity variable costs (as proxied by higher unit prices) exhibit lower sensitivity of inflation (in percentage terms) to upstream prices, but similar sensitivity of price changes in levels.[27]

Exploiting variation in margins across retailers. Estimates from the cross-section of products show that products with higher margins and/or higher non-commodity variable costs have lower log pass-through and similar pass-through in levels to other products. To narrow in on how heterogeneity in product margins affects pass-through in levels and logs, I exploit the fact that different retailers often sell the same product at differing prices. To the degree that differences in prices charged for the same product across retailers primarily reflect different retail margins, rather than differences in marginal costs across retailers, differences in pass-through for the same product by different retailers isolates the effect of margins on pass-through.

To make the test concrete, consider two retailers selling the same UPC, one with a low markup (store A) and one with a high markup (store B). For example, Figure 9 shows the price of a single coffee UPC at two different stores in the same three-digit ZIP code in Philadelphia, PA. While both stores shown in the figure exploit temporary sales, the non-sale price charged by store A is consistently lower than the non-sale price charged by store B. If both stores choose a fixed percentage rule, 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 choose a fixed, additive unit margin, when the cost of 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.

[26]Specifications (5) and (6) do not measure long-run pass-through. Estimating long-run pass-through in logs and levels across the unit price groups of products yields similar qualitative patterns—log pass-through decreases with unit price, while pass-through in levels is about constant with unit price—but the results are noisier since long-run pass-through cumulates over several lags.

[27]Appendix Table A6 shows that results are very similar if we repeat the analysis with five unit price groups.

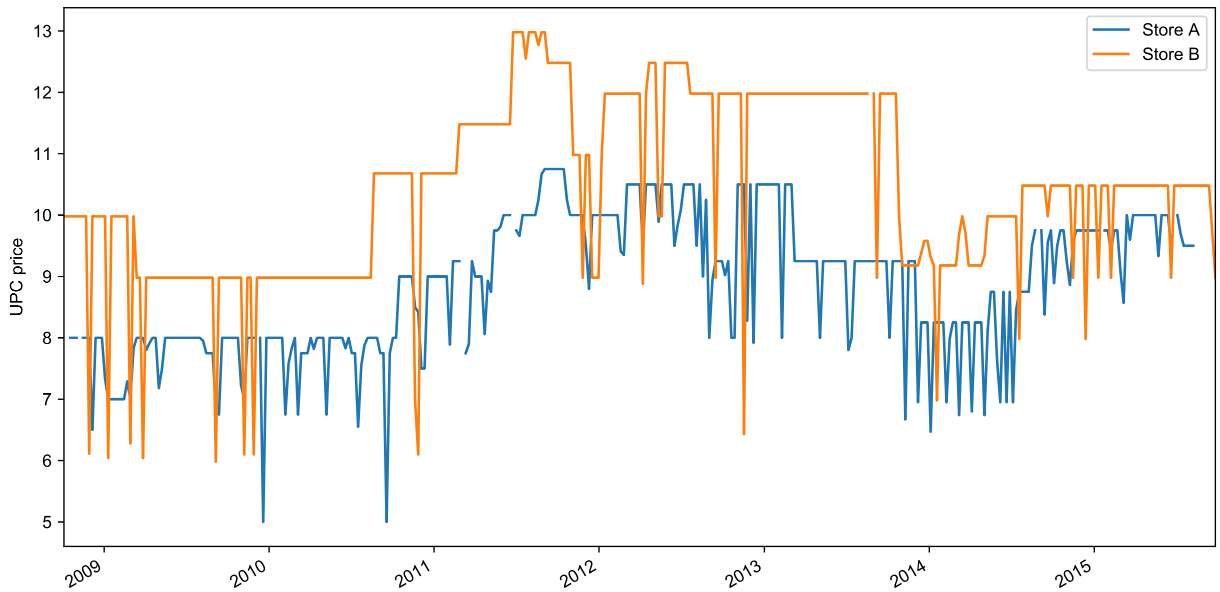
Table 6: Higher-priced products exhibit lower log pass-through, with no systematic difference in level pass-through.

Panel A: In percentages			
	Retail price inflation		
	Rice	Flour	Coffee
Commodity Inflation	0.226**	0.074**	0.110**
	(0.019)	(0.005)	(0.014)
Commodity Inflation × Unit Price Group 2	−0.075**	−0.007	−0.064**
	(0.014)	(0.009)	(0.015)
Commodity Inflation × Unit Price Group 3	−0.150**	−0.046**	−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	0.057**	0.035**	0.059**
	(0.007)	(0.007)	(0.008)
Δ Commodity Price × Unit Price Group 2	0.007	0.009	−0.020
	(0.006)	(0.013)	(0.013)
Δ Commodity Price × Unit Price Group 3	0.005	−0.023	−0.029*
	(0.012)	(0.015)	(0.017)
UPC FEs	Yes	Yes	Yes
N (thousands)	399.4	101.4	1570.0
R^2	0.07	0.05	0.16

Note: Panel A reports results from specification (5), and panel B reports results from specification (6). The three columns use products from rice, all purpose white flour, and roasted coffee, respectively. In each quarter, each retailer-UPC pair is assigned to three groups with equal sales by (quantity-weighted) average unit price over the past year. Unit Price Groups 2–3 are indicators for whether a retailer-UPC pair is assigned to the mid- or high-unit price group. Standard errors clustered by brand. * indicates significance at 10%, ** at 5%.

Figure 9: Price of same coffee UPC in two stores in same 3-digit ZIP in Philadelphia, PA.



Denote (with some abuse of notation) the quantity-weighted average price of UPC i sold by retailer r in quarter t by $p_{i,r,t}$. I test these predictions using the specification,

$$\Delta p_{i,r,t} = \gamma \overline{\Delta p_{i,t}} + \beta \left(\mu_{i,r,t} \times \overline{\Delta p_{i,t}} \right) + \delta \mu_{i,r,t} + \alpha_i + \varepsilon_{i,r,t}. \tag{7}$$

where $\Delta p_{i,r,t} = p_{i,r,t+4} - p_{i,r,t}$ is the year-over-year change in the price charged by retailer r for UPC i starting in quarter t, $\overline{\Delta p_{i,t}}$ is the average year-over-year change in the price charged by all retailers for UPC i starting in quarter t, $\mu_{i,r,t}$ is a measure of the markup charged by retailer r for UPC i, and α_i are UPC fixed effects. If retailers choose constant percentage markups, then high-markup retailers should increase their prices more than other retailers when the cost of UPC i increases, and therefore we should find $\beta > 0$. On the other hand, if retailers set constant additive unit margins, we should find $\beta \approx 0$.

Note that, since we cannot observe retail markups directly, I use the log deviation in the price retailer r charges for UPC i relative to the average UPC price as an empirical proxy for $\mu_{i,r,t}$:

$$\widehat{\mu}_{i,r,t} = \log \left(p_{i,r,t} / \overline{p_{i,t}} \right).$$

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

4–6 further test for the interaction between price changes and retailers' margins using UPC-time fixed effects and yield the same conclusion.

Panel B of Table 7 reports results from the analogous specification measuring price changes in percentage terms,

$$\pi_{i,r,t} = \tilde{\gamma}\overline{\pi_{i,t}} + \tilde{\beta}\left(\mu_{i,r,t} \times \overline{\pi_{i,t}}\right) + \tilde{\delta}\mu_{i,r,t} + \tilde{\alpha}_i + \varepsilon_{i,r,t}, \tag{8}$$

where $\pi_{i,r,t} = (p_{i,r,t+4}/p_{i,r,t}) - 1$ is the year-over-year percentage change in the price charged by retailer r for UPC i starting in quarter t, and $\overline{\pi_{i,t}}$ is the average year-over-year percent change in the price charged by all retailers for UPC i starting in quarter t. As shown in Panel B, variation in retailers' initial prices for the same UPC explain have different price changes when measured in percentage terms. These estimates support the interpretation that retailers charging higher margins for the same product exhibit lower log pass-through, since the margin is an additive unit margin rather than a constant percentage markup.[28]

Thus, by exploiting variation in margins charged by retailers for the same product, we come to the same conclusion that we found in the cross-section of products: products within a category have similar pass-through in levels, which appears as lower log pass-through for high margin products.

Since this approach does not require information on upstream commodity costs, we can extend this analysis to a broader set of product modules in the data. I estimate specifications (7) and (8) for each product module and report the share of modules with significant positive and negative interaction coefficients in Table 8.[29] The results suggest that similar patterns emerge for the majority of product categories in the data: fewer than 10 percent of product modules exhibit the positive interaction between retailer margins and inflation sensitivity that would be predicted by constant-markup pricing. As a result, for over 85 percent of product modules (accounting for over 96 percent of total sales in the data), products at high-margin retailers exhibit significantly lower log pass-through.[30]

[28]The fact that the estimated interaction coefficient, $\tilde{\beta}$, is close to one in all specifications in Table 7 is predicted by the fixed unit margin model. Suppose retailer r sets price $p_{i,r} = c_i + \alpha_{i,r}$. Following a change in the product cost c_i, the retailer's price change in percentage terms is approximately $d\log p_{i,r} \approx c_i/(c_i + \alpha_{i,r}) d\log c_i$. If all other retailers also charge fixed additive unit margins, 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 $d\log p_{i,r} \approx (1 - \log(p_{i,r}/\bar{p}_i)) d\log\bar{p}_i$.

[29]This analysis is limited to the 766 product modules in Nielsen departments that fall within the food-at-home basket (departments for dry grocery, frozen foods, dairy, deli, packaged meat, and produce). I also omit very sparse product modules that have fewer than 250 observations (the median product module has about 100,000 observations), leaving 616 product modules.

[30]As a robustness exercise, Appendix Table A9 reports results analogous to Table 8, but instead using a leave-one-out measure of the average UPC price change and UPC inflation across retailers. Under that specification, in over 50 percent of product modules (accounting for nearly 80 percent of total sales), products at high-margin retailers exhibit significantly lower log pass-through.

Table 7: Exploiting variation in margins across retailers.

Panel A: In levels						
	ΔUPC Price at Retailer					
	Rice	Flour	Coffee	Rice	Flour	Coffee
	(1)	(2)	(3)	(4)	(5)	(6)
Avg. ΔUPC Price	0.815**	0.853**	0.909**			
	(0.048)	(0.064)	(0.018)			
Avg. ΔUPC Price $\times \log(p_{i,r,t}/\overline{p_{i,t}})$	−0.243*	−0.321	−0.080	−0.019	−0.200	−0.123
	(0.140)	(0.286)	(0.192)	(0.111)	(0.216)	(0.352)
UPC FEs	Yes	Yes	Yes			
UPC-Time FEs				Yes	Yes	Yes
N (thousands)	399.4	101.4	1570.0	399.4	101.4	1570.0
R^2	0.38	0.41	0.49	0.51	0.50	0.55

Panel B: In percentages						
	UPC Inflation at Retailer					
	Rice	Flour	Coffee	Rice	Flour	Coffee
	(1)	(2)	(3)	(4)	(5)	(6)
UPC Avg. Inflation	0.895**	0.943**	0.915**			
	(0.042)	(0.035)	(0.013)			
UPC Avg. Infl. $\times \log(p_{i,r,t}/\overline{p_{i,t}})$	−0.841**	−0.853**	−0.958**	−0.988**	−0.879**	−1.386**
	(0.052)	(0.177)	(0.084)	(0.104)	(0.250)	(0.213)
UPC FEs	Yes	Yes	Yes			
UPC-Time FEs				Yes	Yes	Yes
N (thousands)	399.4	101.4	1570.0	399.4	101.4	1570.0
R^2	0.58	0.55	0.53	0.64	0.60	0.58

Note: Panel A reports results from specification (7), and panel B reports results from specification (8). The latter three columns add UPC-quarter fixed effects. The average change in the UPC price and the average UPC inflation are sales-weighted averages over all stores in the Nielsen Retail Scanner dataset, which includes some stores that cannot be assigned to a retail chain. $\log(p_{i,r,t}/\overline{p_{i,t}})$ denotes the log deviation of the (quantity-weighted) average price for UPC i at retail chain r in quarter t from UPC i's average price across all stores in quarter t. Standard errors clustered by brand. * indicates significance at 10%, ** at 5%.

Table 8: Exploiting variation in margins 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 (7) (for panel A) and (8) (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. Driscoll-Kraay standard errors used in all specifications.

Comparison to alternative models of pass-through. So far, our empirical results suggest that in selected staple food products, like in retail gasoline, firms exhibit complete pass-through in levels. Complete pass-through in levels and variation in firms' margins explains cross-sectional heterogeneity in log pass-through. The final empirical exercise in this section provides suggestive evidence that this model has greater explanatory power for cross-sectional heterogeneity in log pass-through than two common alternatives.

The first attributes variation in log pass-through to heterogeneity in market share or firm size. The prediction that firms with larger market share exhibit lower log pass-through arises from models of nested oligopoly (such as Atkeson and Burstein 2008) or models in which the firms' residual demand curves satisfy certain conditions (see Melitz 2018, Matsuyama and Ushchev 2022). When log pass-through declines with market share, $\beta < 0$ in the specification,

$$\pi_{i,t} = \gamma \pi_t^c + \beta \left(\pi_t^c \times \text{SalesShare}_{i,t}\right) + \delta \text{SalesShare}_{i,t} + \alpha_i + \varepsilon_{i,t}, \tag{9}$$

where $\pi_{i,t}$ is the year-over-year percent price change of product i starting in quarter t, π_t^c is the year-over-year percent change in the commodity price starting in quarter t, $\text{SalesShare}_{i,t}$ is a measure of product i's market share, and α_i are product fixed effects.

The second attributes variation in log pass-through to differential changes in the price elasticity of firms' customers over the business cycle (e.g., Li 2019). For example, if the price elasticity of demand for low-income households is more countercyclical than that

Table 9: Comparison to two alternative models of log pass-through: Rice products.

		Market share		Buyer elasticity	
Retail product inflation	(1)	(2)	(3)	(4)	(5)
Commodity Inflation	0.118**	0.174**	0.113**	0.133**	0.117**
	(0.006)	(0.015)	(0.010)	(0.016)	(0.008)
Commodity Infl. × Log(Unit Price)	−0.100**		−0.101**		−0.105**
	(0.012)		(0.012)		(0.016)
Commodity Infl. × Log(Brand Sales Share)		0.006*	−0.002		
		(0.003)	(0.003)		
Wage Inflation				1.179**	0.452**
				(0.105)	(0.113)
Wage Infl. × Log(Buyer Income)				−2.364**	−0.654
				(0.770)	(0.566)
UPC FEs	Yes	Yes	Yes	Yes	Yes
N (thousands)	399.4	399.4	399.4	329.8	329.8
R^2	0.18	0.12	0.18	0.13	0.19

Note: Log(Unit Price), Log(Brand Sales Share), and Log(Buyer Income) are all normalized relative to the average within each quarter, so that these three terms represent log deviations from the average unit price, sales share, and buyer income across all products in the quarter. Standard errors clustered by brand. * indicates significance at 10%, ** at 5%.

of high-income households, firms selling to low-income households may increase their markups by more during booms and cut their markups more during recessions. To test this second model of variation in log pass-through, I use the specification,

$$\pi_{i,t} = \gamma\pi_t^c + \phi\pi_t^w + \beta\left(\pi_t^w \times \text{BuyerIncome}_{i,t}\right) + \delta\text{BuyerIncome}_{i,t} + \alpha_i + \varepsilon_{i,t}, \qquad (10)$$

where π_t^w is year-over-year wage inflation starting in quarter t (as a proxy for position over the business cycle) and $\text{BuyerIncome}_{i,t}$ is a measure of the average income of product i's buyers.

Table 9 tests how these two models perform in explaining variation in log pass-through across rice products compared to our baseline, where products exhibit complete pass-through in levels and thus differences in log pass-through are explained by heterogeneity in unit price. Column 1 reports the specification from the baseline model, reporting that the sensitivity of retail inflation to commodity inflation declines with unit price. Column 2 tests specification (9), using the sales share of i's brand in the product category as a proxy for $\text{SalesShare}_{i,t}$.[31] While there is a mildly significant association between sales share and log pass-through, it has the opposite sign than predicted by models where pass-through declines with market share, and sales share is no longer a significant determinant of log pass-through in column 3 once the product's unit price is included. Column 4 tests specification (10) using the growth rate of average hourly earnings for private production and nonsupervisory employees as a proxy for wage inflation.[32] Products with a higher-income customer base have lower inflation rates when wage inflation is high (consistent with low-income households having more countercyclical price elasticities), but this effect disappears after accounting for the product's unit price (column 5).

While Table 9 is not a comprehensive test of all other mechanisms proposed by the literature, it suggests that complete pass-through in levels and variation in margins provides a better fit for the variation in log pass-through across products observed in the data. Moreover, as evidenced by the R-squared associated with each specification in Table 9, the inclusion of additional variables in columns 2–5 does little to improve the fit in describing log pass-through compared to complete pass-through in levels.[33]

5 Explaining Complete Pass-Through in Levels

Why do firms in the studied industries exhibit complete pass-through in levels? The simplest explanation is that these industries are well approximated by perfect competition. However, as I show in Section 5.1, evidence from these industries suggests firms face downward-sloping demand curves and set prices above marginal cost, at odds with the predictions of perfect competition.

Section 5.2 then explores whether relaxing various assumptions—e.g., isoelastic demand, Leontief production, and constant returns to scale—can explain complete pass-through in levels. Indeed, semilog demand curves or deviations from Leontief production can match pass-through patterns in the data. But I show that matching pass-through patterns in the data by relaxing these assumptions implies restrictions that do not appear

[31] Using the UPC's sales share or the firm's sales share (as measured by aggregating UPCs with the same six-digit prefixes) yields qualitatively similar results.

[32] Similar results obtain using the growth in the employment cost index (ECI) or using the unemployment rate as a proxy for the business cycle.

[33] Appendix Tables A7 and A8 repeat the exercise for flour and coffee products, respectively. The findings are qualitatively similar to Table 9: once our baseline model is included, estimated coefficients on the variables that explain heterogeneity in pass-through in the other models are no longer significant at the 5 percent level. The single exception is the coefficient on the interaction between market share and commodity inflation for coffee products. However, the estimated coefficient is positive, while the model suggests pass-through should be declining in sales share.

supported by the data, and moreover are unlikely to hold across the several markets explored above.

Section 5.3 provides an alternative micro-foundation for complete pass-through in levels. In particular, a combination of overhead costs with a *safety margin constraint*—an aversion by firm managers to variable profits falling below overhead costs—can generate pass-though in levels. This model also yields predictions for the behavior of entry and gross margins that differ from the workhorse Dixit and Stiglitz (1977) model. Lastly, Section 5.4 provides empirical evidence for these predictions.

5.1 Perfect Competition

One explanation for complete pass-through in levels is that firms in the studied industries set prices equal to marginal cost. This implies that the markup $\mu = 1$, and hence pass-through is complete in levels.

Perfect competition appears at odds with several other features of the data, however. In the case of retail gasoline, three patterns in those data challenge the possibility of perfect competition: the presence of price cycles, the presence of substantial price dispersion, and empirical findings of finite price elasticities. First, the price cycles shown in Figure 4 are difficult to rationalize under perfect competition. In particular, perfect competition would imply that weekly price cycles are due to variation in marginal costs over days of the week. As documented by Byrne and de Roos (2019), the timing of price cycles during the week change over the course of the sample period, which make it unlikely that systematic variations in costs over the week could explain these price cycles. Second, gas stations in the data exhibit substantial price dispersion, even within postcodes or narrowly defined neighborhoods (Appendix Table A5 reports the standard deviation of unleaded petrol prices within a neighborhood on any given day average 2.4 cents). Third, Wang (2009b) collects data from seven gas stations in the Perth, Australia market and estimates elasticities of demand between 6 and 19. While high, these price elasticities imply demand curves that are far from the perfectly horizontal.

Downward-sloping demand curves and prices above marginal cost challenge the likelihood of perfect competition in the context of food products as well. Table 10 tabulates estimates of markups from three sources for three food products (coffee, rice, and flour). First, I calculate retail markups as average retail prices over wholesale costs for matched UPCs.[34] Second, I use Hausman (1996) instruments to estimate elasticities of demand for

[34] These wholesale costs come from PromoData Price-Trak. Sangani (2022) provides a detailed overview of these wholesale cost data, and I report median retail markups constructed in a manner identical to the retail markups studied in Sangani (2022).

Table 10: Evidence on markups in studied food products.

Markup (Median [Q1 Q3])	Coffee	Rice	Flour
1. Retail markup	14% [3%, 35%]	49% [33%, 72%]	24% [14%, 34%]
2. Demand elasticity	40% [26%, 72%]	90% [30%, –]	206% [57%, –]
3. Literature	58%[a]	43–75%[b]	n/a

Note: Retail markups for each UPC are calculated as the quantity-weighted average price over PromoData wholesale cost. Demand elasticity markup estimates are constructed using the standard Lerner index, with demand elasticities estimated using a Hausman (1996) instrument described in Appendix D. Literature estimates are from ([a]) Nakamura and Zerom (2010) and ([b]) Park (2013).

each UPC at each store, and calculate implied markups using the usual Lerner formula. (The details on estimating these demand elasticities are relegated to Appendix D.) Estimated demand elasticities are moderate in magnitude, suggesting substantial markups over marginal cost. Finally, I draw from previous literature that has estimated markups in these markets: Nakamura and Zerom (2010) for coffee products, and Park (2013) for rice products.

All three measures suggest substantial markups over marginal cost, inconsistent with the perfectly horizontal demand curves and prices equal to marginal cost implied by perfect competition.

5.2 Explaining Pass-Through by Relaxing Assumptions

Curvature of demand. Pass-through may also be complete in levels if the demand curves facing firms are more concave than the isoelastic demand curves typically assumed. In particular, I show in Appendix B that pass-through is complete in levels if the super-elasticity of demand, or the rate at which the elasticity of demand changes with respect to the price, is exactly equal to one:

$$\frac{\partial \log \sigma}{\partial \log p} = 1.$$

As shown by Bulow and Pfleiderer (1983), semilog demand curves (i.e., demand curves of the form $D(p) = a - b \log p$) satisfy this requirement. Hence, one explanation for the observed pass-through in levels is that this functional form provides a better fit for the demand curves truly facing firms than demand curves with a constant elasticity of demand.

Table 11: Share of store-UPC pairs with estimated super-elasticity of demand below one.

Percent of store-UPC pairs	Coffee	Rice	Flour
Point estimate below one	90.0	98.7	79.2
Reject over one at $p = 0.05$	62.6	89.2	52.5
N (thousands)	18.6	9.7	7.1

Burya and Mishra (2023) develop a technique to measure the super-elasticity of demand. In particular, they show that by estimating the specification,

$$\log q_{i,t} = \eta \log p_{i,t} + \kappa(\log p_{i,t})^2 + \gamma X_{i,t} + \varepsilon_{i,t},$$

the ratio κ/η provides an estimate of the super-elasticity of demand. I adopt their approach, using a Hausman (1996) instrument for prices, to estimate the super-elasticity of demand individually for each UPC in each store in the coffee, rice, and flour product categories. This estimation procedure is described in detail in Appendix D.

Table 11 reports the share of store-UPC pairs in each product category where the estimated super-elasticity of demand is below one. In the vast majority of cases, estimated super-elasticities of demand fall short of one, implying that demand curves in the data are not sufficiently concave to generate pass-through in levels. Moreover, Table 11 shows that a super-elasticity of demand over one is rejected at a five percent significance level in over half of the store-UPC observations. These estimates suggest that complete pass-through in levels arises from a source other than the curvature of demand.

Relaxing Leontief, constant returns, and uncorrelated costs. What if we relax the other restrictions we have imposed so far, such as constant returns and Leontief production? In Appendix B, I allow production to take the more general form,

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

where θ is the elasticity of substitution across inputs, ω are weights in production on the two inputs, and $\alpha < 1$ generates decreasing returns to scale in the non-commodity input. I show that relaxing any one assumption—i.e., relaxing Leontief production, constant returns to scale, or uncorrelated other variable costs—requires knife-edge conditions to deliver complete pass-through in levels that are unlikely to hold in practice.

5.3 Price and Entry Dynamics in a Model with Safety Margins

The model consists of two sets of firms, commodity suppliers and downstream retailers. Suppliers are perfectly competitive and produce a commodity x at price c. Retailers purchase this commodity input from suppliers in order to produce an output good for consumers. The focus of the model will be on the dynamics of prices and entry for retailers.

Retailers' production of the output good is Leontief in the commodity input and in another variable input, denoted ℓ for labor, which captures distribution services that must be bundled with the commodity:

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

Denote the wage (the per-unit labor cost) by w.

In addition to variable commodity and labor costs, retailers also face an overhead cost, paid in units of labor, given by $wf_o N^{-\zeta}$. Here, N is the number of retailers in the market, and $-\zeta$ is the elasticity of the overhead cost to the number of retailers in the market. When $\zeta > 0$, overhead costs rise when the number of retailers in the market decreases, which may reflect external economies of scale or the fact that overhead costs scale with expected capacity (for instance, a small number of retailers serving a large market may have to pay higher rent costs for larger floor space). As we will see below, $\zeta > 0$ is not necessary in the standard multiplicative-markup model, but is necessary to close the equilibrium with free entry in the additive margin model.

Thus, the cost function for each retailer is given by

$$C(y) = (c + w)y + wf_o N^{-\zeta},$$

and retailer profits are given by

$$\pi(p) = pD(p) - C(D(p)).$$

Retailers face downward-sloping residual demand curves. The demand curve for each retailer depends on its price p, the aggregate market price P, the elasticity of substitution across retailers' outputs $\sigma > 1$, the number of competing firms N, and a demand shock ε,

$$D(p) = \varepsilon \frac{1}{N} \left(\frac{p}{P}\right)^{-\sigma}. \tag{11}$$

I assume that ε has an expected value of one and is drawn from a distribution with CDF H. Crucially, the demand shock ε introduces a source of uncertainty for the firm. As we will see below, each retailer sets its price before the shock ε is realized. Hence, while the retailer is correct about its profits in expectation, the level of demand may fluctuate around its expected value.[35]

In the face of this uncertainty, I introduce a *safety margin constraint* by which firms bound the risk that their profits fall below some pre-specified level. This safety margin constraint was first discussed by Fellner (1948) and was later formalized by Day et al. (1971). In particular, this form of the safety margin constraint assumes that retailers maximize expected profits subject to the constraint that the probability of profits fall below zero is at most ϕ,[36]

$$\Pr\left[\pi(p) \leq 0\right] \leq \phi. \tag{12}$$

Thus, the retailer problem is to choose an output price to maximize expected profits, subject to the residual demand curve (11) and to the safety margin constraint (12).

Finally, the model is closed with a standard free entry condition. Retailers pay a cost wf_e to enter in each period, and entry occurs until the sum of discounted expected future profits is equal to the entry cost:

$$\mathbb{E}_t \sum_{k=0}^{\infty} \beta^k \pi_{t+k} = w_t f_e, \qquad \text{for all } t. \tag{13}$$

I assume that wages are expected to grow at a constant rate g (i.e., $\mathbb{E}_t[w_{t+k}] = (1+g)^k w_t$), and that the ratio of the commodity cost to the wage, c_t/w_t, is a random walk with zero drift. For ease of notation, define $\Delta \equiv (1 - \beta(1+g))$.

Definition 1 (Equilibrium)**.** Given a path for commodity prices and wages (c_t, w_t), an equilibrium is a set (p_t, P_t, N_t) such that the price chosen by retailers in each period, p_t, maximizes expected profits subject to (11) and (12), the aggregate market price is equal to the price set by all firms, $P_t = p_t$, and the free entry condition (13) is satisfied in all periods.

We now move to characterizing prices and the number of retailers in equilibrium. First, we consider periods where the safety margin constraint (12) does not bind. Proposition 1 shows that the price is given by a multiplicative markup over marginal cost, as in the workhorse Dixit and Stiglitz (1977) model.

[35] Total industry demand in (11) is constant and normalized to one. Aggregate demand for retail gasoline and staple food products tends to be inelastic (though elasticities of substitution between firms within the industry may be large). For example, research by 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).

[36] This constraint is referred to as "strict safety-first" pricing by Day et al. (1971). This assumption has also been recently used by Altomonte et al. (2015), who consider this safety margin constraint as a rationale for full-cost pricing. As I show below, while this safety margin constraint implies that firms factor overhead costs into their pricing decisions, it does not necessarily imply that firms will price at average cost.

Proposition 1 (Dixit and Stiglitz 1977)**.** *In periods where the safety constraint does not bind, the output price is given by*

$$p_t^{DS} = \frac{\sigma}{\sigma - 1}(c_t + w_t).$$

Across these periods, the number of firms is positively correlated with the commodity cost, $dN_t^{DS}/(d(c_t/w_t)) > 0$, and gross margins are constant at $m_t^{DS} = 1/\sigma$.

Proposition 1 also describes the behavior of entry and gross margins. Regarding entry, since prices follow a multiplicative markup over marginal cost, firms' per-unit variable profits increase when commodity costs rise. Holding the number of retailers fixed, since aggregate industry demand is inelastic, each retailer makes higher profits. As a result, new firms enter until the variable profits fall to meet the free entry condition.[37] Regarding gross margins, since prices follow a multiplicative markup over marginal cost, gross margins (the ratio of variable profits to sales) is fixed.

Next, Proposition 2 describes the dynamics of prices, entry, and gross margins when the safety constraint binds.

Proposition 2 (Safety margin pricing)**.** *In periods where the safety constraint binds, the number of firms $N_t^{safe} = N^{safe}$ is constant, and the output price is given by*

$$p_t^{safe} = c_t + w_t + \alpha w_t f_o,$$

where the constant $\alpha > 1$. Across these periods, gross margins are negatively correlated with the commodity cost, $dm_t^{safe}/d(c_t/w_t) < 0$. Holding all parameters fixed, $p_t^{safe} \geq p_t^{DS}$ and $N_t^{safe} \geq N_t^{DS}$.

Rather than setting a multiplicative markup, retailers instead set price as an additive margin over marginal cost when the safety constraint binds. This additive margin is related to the overhead cost, since it is chosen to ensure that retailers bound the risk of being unable to meet their overhead costs in each period. As a result, changes in the commodity cost are passed through one-for-one in levels across periods where the safety constraint binds.

In contrast to the Dixit and Stiglitz (1977) model, in periods where the safety constraint binds, the number of retailers is unrelated to the commodity cost. Intuitively, since firms' variable profits are now unrelated to the commodity cost, changes in the commodity cost do not incentivize new retailers to enter or existing retailers to exit. Gross margins, on

[37] This prediction depends on the elasticity of aggregate industry demand. If aggregate industry demand has an elasticity greater than one, then the number of retailers will instead be negatively correlated with the commodity cost, and if the elasticity of demand is exactly equal to one, then the number of retailers will be constant.

the other hand, fall when the commodity cost rises, since complete pass-through in levels results in incomplete log pass-through.

When will price and entry dynamics resemble Proposition 1 versus Proposition 2? Proposition 3 shows that which pricing regime an industry falls into depends on the level of commodity costs relative to wages, as well as parameters such as the overhead cost and the cost share of commodity inputs.

Proposition 3 (When constraint binds)**.** *There exists a cutoff c^* such that the safety margin constraint binds whenever $c_t/w_t \leq c^*$ and does not bind otherwise. The cutoff c^* is increasing in f_o, decreasing in Δf_e when $\zeta \in [0, 1)$, decreasing in ϕ, and increasing in the variance of ε.*

The comparative statics in Proposition 3 are informative about the types of industries where price and entry dynamics are more likely to follow Proposition 2. In particular, industries are more likely to resemble Proposition 2 when overhead costs are high and demand is volatile. Intuitively, these are the industries where fluctuations in commodity costs increase the risk that overhead costs are not covered by variable profits. The safety margin constraint is also more likely to bind if the risk of negative profits that retailers are willing to tolerate is low or if entry costs are low.

5.4 Empirical Evidence on Entry and Margins

Propositions 1 and 2 show that the workhorse Dixit and Stiglitz (1977) model and safety margin pricing yield contrasting predictions for the behavior of prices, entry, and gross margins. If an industry is primarily in the Dixit and Stiglitz (1977) regime, prices follow a multiplicative markup over cost, entry is positively correlated with commodity costs, and gross margins are constant. On the other hand, if an industry is primarily in the safety margin pricing regime, pass-through of commodity costs is complete in levels, entry is uncorrelated with commodity costs, and gross margins fall when commodity costs rise. I test these predictions below.

I first test how the number of firms relates to commodity costs. Appendix Figure A10 plots the number of retail gas stations and the wholesale gas price from 2003–2023 in Perth. There appears to be little responsiveness of entry to commodity costs; indeed the correlation of month-over-month changes in the number of firms with changes in the wholesale gas price is 0.07 and statistically indistinguishable from zero. For food products, it is difficult to provide an exact count of the number of firms in the market using Nielsen data. As a proxy, I plot the market shares of the largest brands in the coffee, flour, and rice product categories in Appendix Figure A11. If the number of firms were positively correlated with commodity costs, the market share of top brands should erode when commodity costs increase. Instead, the data show no discernible relationship between commodity costs and market shares of top brands. Hence, the data on entry dynamics are more consistent with the predictions of the safety margin regime: the number of firms in an industry is unrelated to fluctuations in commodity costs.

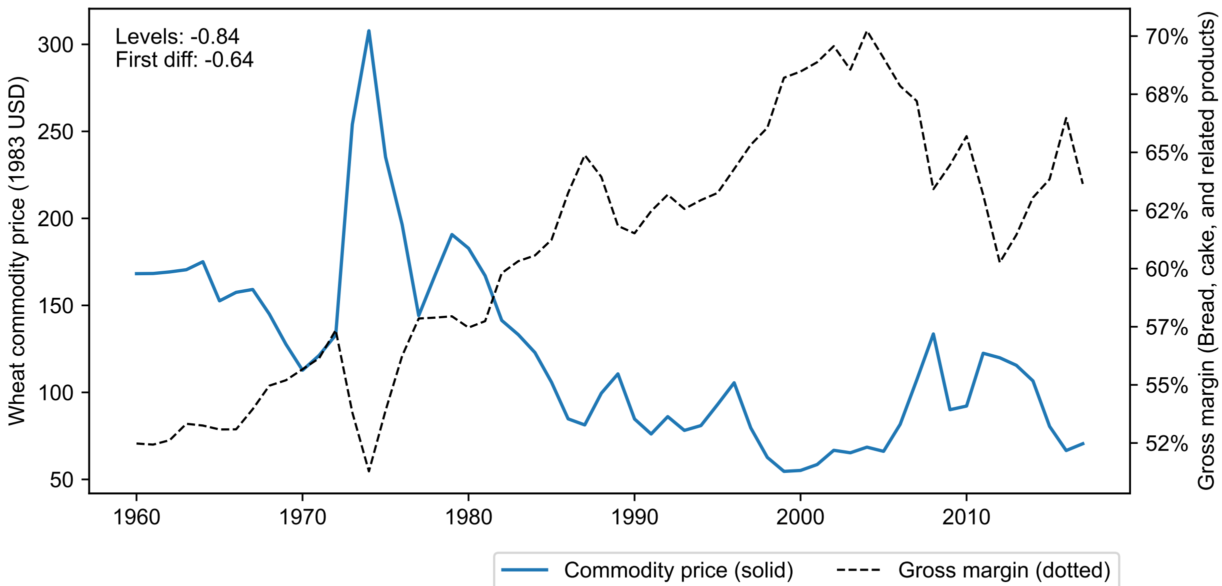
Of course, the absence of entry alone does not reject the standard Dixit and Stiglitz (1977) model. Several frictions could prevent the number of firms from adjusting to the changes in upstream commodity costs. The broader point, however, is that when prices are set with an additive unit margin, firm profits do not depend on the upstream commodity cost and there is no incentive for entry when commodity costs rise. Thus, the absence of entry during periods of rising commodity costs in the data is consistent with the lack of a commodity cost-dependent entry incentive.

Second, I test how industry gross margins correlate with upstream commodity costs. For this analysis, I use data on gross margins for manufacturing industries from the NBER-CES manufacturing industry database (Becker et al. 2021). These data include sales, cost of goods sold (materials costs), labor costs, and other aggregated industry-level data for four-digit SIC industries over 1958–2018. Thirteen of these industries can be clearly paired with an upstream commodity; for example, I pair candy and other confectionary products (SIC 2064) with sugar prices; bread, cake, and related products manufacturing with wheat prices; and so on. To take advantage of the long time span over which these data are available, I use annual commodity prices from UNCTADSTAT which extend back to 1960. (UNCTADSTAT does not contain commodity price data for milk, aluminum, and frozen orange juice prices, so for industries using those commodities I instead use the IMF commodity price data that were used in Section 4.)

As an example, Figure 10 plots gross margins (measured as sales minus costs of goods sold, as a percent of sales) for SIC industry 2051 (bread, cake, and related products) alongside the wheat commodity price from 1960–2017. Consistent with Proposition 2, there is a negative correlation both in levels ($\rho = -0.84$) and in first differences ($\rho = -0.64$) for the two series. Table 12 extends this analysis to all thirteen SIC industries that can be paired with an upstream commodity. In nearly all cases, we find a negative correlation between upstream commodity prices and downstream industry gross margins, whether the measure of variable costs includes or excludes labor and whether we calculate the correlation in levels or in first differences.

Both the behavior of entry and gross margins are consistent with the predictions of safety margin pricing (Proposition 2) rather than the workhorse Dixit and Stiglitz (1977) model (Proposition 1).

Figure 10: Wheat commodity costs and downstream (bread industry) gross margins.



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

Table 12: Correlation between commodity costs and downstream gross margins.

	Gross margins from SIC industry		Correlation Costs = Materials		Correlation Mat., Energy, Labor	
Commodity	Description	SIC	Levels	First diff.	Levels	First diff.
Sugar	Candy and confectionery products	2064	-0.58**	-0.37**	-0.51**	-0.22*
Beef	Sausages and other prepared meats	2013	-0.82**	-0.39**	-0.82**	-0.30**
Wheat	Flour and other grain mill products	2041	-0.80**	-0.55**	-0.73**	-0.46**
Wheat	Prepared flour mixes and doughs	2045	-0.80**	-0.57**	-0.79**	-0.50**
Wheat	Bread, cake, and related products	2051	-0.84**	-0.64**	-0.80**	-0.54**
Rice	Rice milling	2044	-0.70**	-0.17	-0.60**	-0.09
Coffee	Roasted coffee	2095	-0.79**	-0.58**	-0.78**	-0.56**
Cocoa beans	Chocolate and cocoa products	2066	-0.36**	-0.07	-0.35**	-0.03
Cotton	Broadwoven fabric mills, cotton	2211	0.02	-0.42**	-0.66**	-0.39**
Milk	Cheese; natural and processed	2022	-0.66**	-0.61**	-0.56**	-0.50**
Milk	Dry, condensed, evaporated products	2023	-0.52**	-0.58**	-0.51**	-0.53**
Aluminum	Aluminum sheet, plate, and foil	3353	-0.73**	-0.41**	-0.71**	-0.30*
Aluminum	Aluminum die-castings	3363	-0.63**	-0.57**	-0.63**	-0.25
Orange juice	Frozen fruits and vegetables	2037	-0.63**	-0.18	-0.70**	-0.17

Note: Industry data from NBER-CES manufacturing database (1958–2018). Variable costs defined as material costs or sum of material, energy, and production labor costs. 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%.

6 The Unequal Incidence of Commodity Shocks

This section explores the implications of complete pass-through in levels for inflation experienced by households with different incomes. As shown in Section 4, complete pass-through in levels results in larger percentage price changes for low-price and low-margin products. Since low-income households tend to purchase products with lower prices and markups within each product category (Sangani 2022), this means that inflation rates for low-income households will be more sensitive to upstream commodity prices.

First, in Section 6.1, I show that inflation rates for low-income households are more sensitive to commodity costs in granular product categories like coffee, rice, and flour. Then, in Section 6.2, I extend the analysis to the entire food-at-home bundle. I show that similar patterns emerge when looking across the food-at-home bundle and quantify differences in log pass-through of upstream prices and inflation volatility across income groups.

6.1 Within-Category Inflation Inequality

Section 4 showed that log pass-through is higher for products with low unit prices. Since products with high markups and higher income customer bases tend to have higher unit prices, this means that log pass-through is also negatively correlated with retail markups and the average income of a product's customers.

To measure retail markups, I match retail prices with data on wholesale costs facing retailers from PromoData Price-Trak. I follow the procedures to match PromoData wholesale costs to retail prices described in Sangani (2022); see Appendix A of that paper for a detailed overview. Since product coverage by PromoData varies substantially from year to year, I use data from a single year (2008) for which the match rate of UPCs from PromoData to the Nielsen scanner data is highest to calculate an average retail markup for each UPC. I construct a measure of average buyer income for each UPC using Nielsen Homescan data, which tracks purchases of fast-moving consumer goods by a nationally representative panel of households. For each UPC in each quarter, I measure buyer income as the sales-weighted average of buyers' incomes across all observed transactions of the UPC in the Homescan panel.

To test how the sensitivity of retail price inflation to commodity price inflation varies with retail markups and with buyer income, I use the specification,

$$\pi_{i,t} = \gamma \pi_t^c + \beta(\pi_t^c \times X_{i,t}) + \delta X_{i,t} + \alpha_i + \varepsilon_{i,t}.$$

Table 13: Products with high retail markups and high-income buyers have lower log pass-through.

	Rice		Flour		Coffee	
Retail product inflation	(1)	(2)	(3)	(4)	(5)	(6)
Commodity Inflation	0.155**	0.149**	0.053**	0.054**	0.104**	0.057**
	(0.018)	(0.016)	(0.011)	(0.008)	(0.011)	(0.012)
Comm. Infl. × Log(Retail Markup)	−0.207**		−0.119**		−0.198**	
	(0.078)		(0.049)		(0.048)	
Comm. Infl. × Log(Buyer Income)		−0.135**		−0.114**		−0.219**
		(0.043)		(0.036)		(0.049)
UPC FEs	Yes	Yes	Yes	Yes	Yes	Yes
N (thousands)	197.7	329.8	64.7	79.6	253.3	1269.3
R^2	0.11	0.13	0.02	0.03	0.11	0.13

Note: Standard errors clustered by brand. * indicates significance at 10%, ** at 5%.

where $\pi_{i,t} = (p_{i,t+4}/p_{i,t}) - 1$ is the year-over-year growth in the retail price of product i starting in quarter t, $\pi_t^c = (c_{t+4}/c_t) - 1$ is the year-over-year growth of the commodity price, $X_{i,t}$ stands in for either the log retail markup of the product or log buyer income, and α_i are UPC fixed effects. Table 13 reports results for the three product categories—rice, flour, and coffee—studied in Section 4.

Consistent with our predictions, columns 1, 3, and 5 show that the sensitivity of retail product inflation to commodity inflation is lower for products with high retail markups. Given the link between retail markups and buyer income, columns 2, 4, and 6 thus show that retail price inflation rates for products with a high-income customer base are less sensitive to commodity inflation. While the magnitude of the results vary by product category, across all categories, increasing the a product's retail markup or average buyer income by 10 percent decreases the sensitivity to commodity inflation by about 10 percent or more.

I now turn to quantifying differences in category-level inflation rates experienced by households over the income distribution. To construct a measure of category-level inflation rates experienced by households in each income group, I use households' expenditure shares on products within each category from the Nielsen Homescan panel. I calculate the inflation rate experienced by households in quintile j, π_t^j, as the expenditure-weighted average of inflation rates on each individual product i purchased by households in quintile

j,

$$\pi_t^j = \frac{\sum_i \lambda_{i,t}^j \pi_{i,t}}{\sum_i \lambda_{i,t}^j},$$

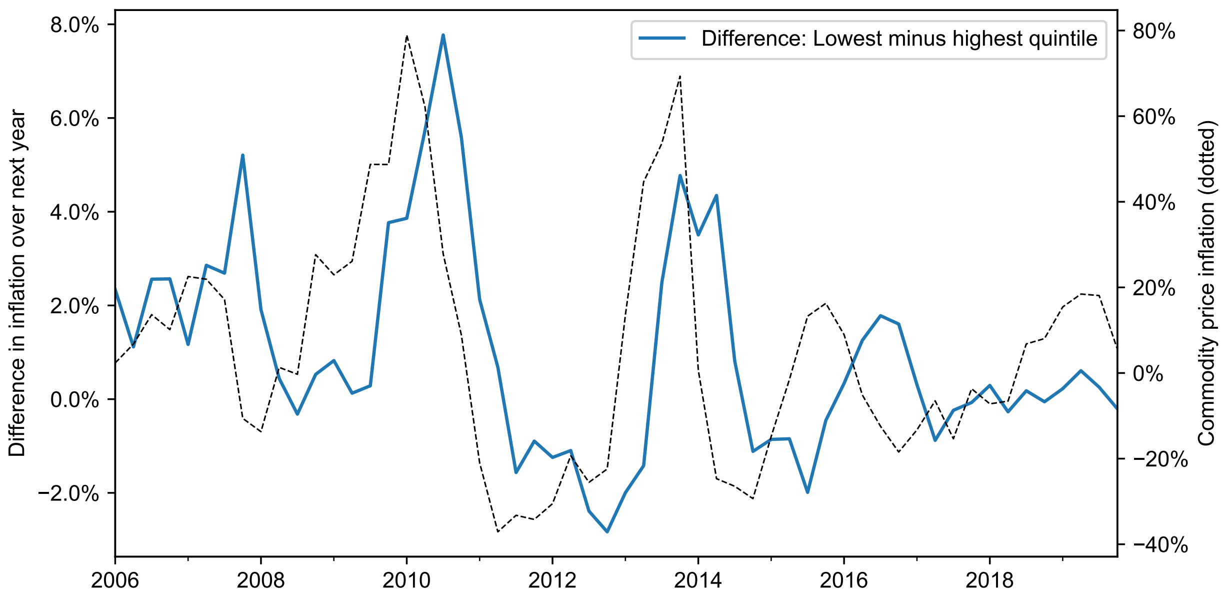
where $\lambda_{i,t}^j$ are the total expenditures on product i by households in quintile j at time t and $\pi_{i,t}$ is the inflation rate of product i over the next year starting in quarter t.

As an example, Figure 11a 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 that appear coincident with increases in coffee commodity costs during those years. While the fact that the inflation gap is positive on average likely owes to secular drivers of inflation inequality documented by Jaravel (2019, 2021), the cyclical swings in the inflation gap are aptly described by complete pass-through in levels. Note that this cyclical driver of inflation inequality means that during periods of commodity price deflation, such as in 2012–2013, the inflation gap between low-income and high-income households can actually be negative, since the price of retail products consumed by low-income households actually fall by more (in percentage terms) during those periods.

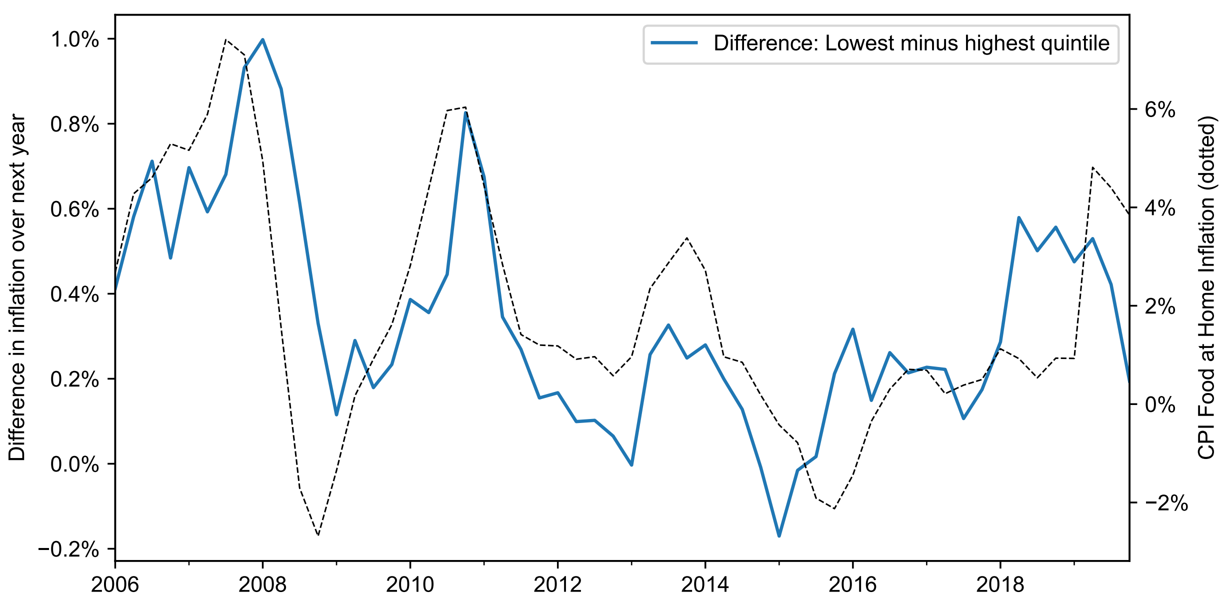
To formalize this, I calculate the long-run log pass-through of commodity costs into retail prices for each household income quintile. Figure 12 shows how log pass-through of commodity costs for each income quintile compares to log pass-through for the highest income quintile in each category (flour, rice, and coffee). Importantly, differences in log pass-through experienced by households with different incomes depends 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 (the average unit price paid by households in the lowest income quintile for flour products is only 4 percent lower than that paid by households in the highest income quintile), and thus the long-run log pass-through of commodity costs to flour prices paid by different income groups is relatively small (2 percent higher for the lowest-income quintile). 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 the long-run log pass-through of coffee commodity costs to prices paid for the lowest income quintile is more than 40 percent greater than that for the highest income quintile.

Taken together, these results suggest that, when low-income households buy lower-priced and lower-markup products within a category, they can experience substantially higher log pass-through of commodity costs to the prices they pay. Moreover, this source

Figure 11: Gap in inflation rates: Households in lowest vs. highest income quintile.

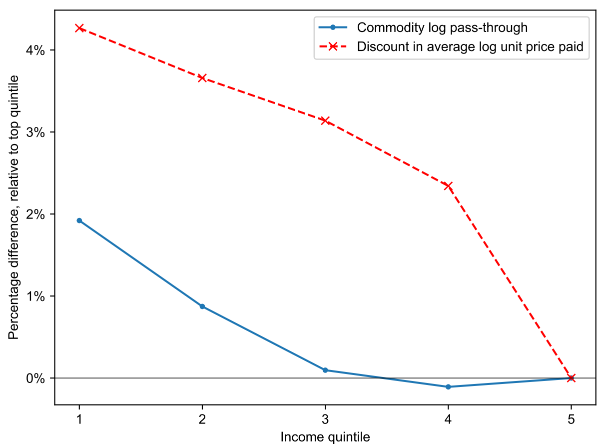


(a) Within-category inflation inequality: Coffee (with coffee commodity inflation).

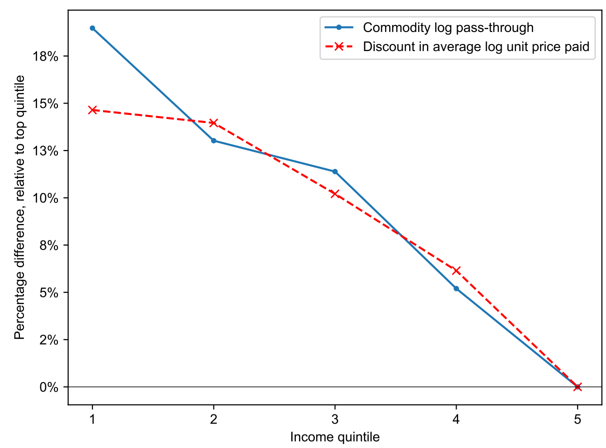


(b) Inflation inequality: Food-at-home inflation (with CPI food-at-home inflation).

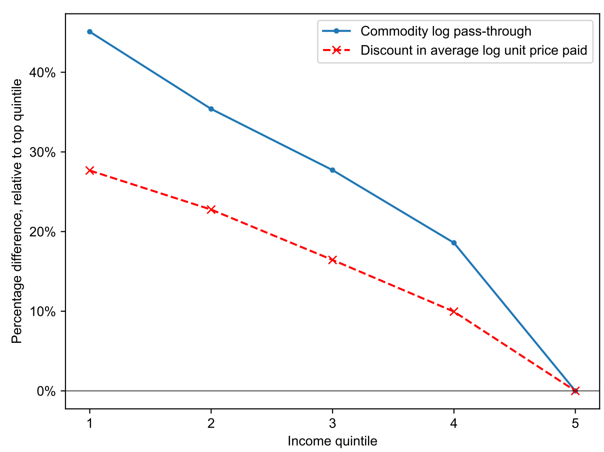
Figure 12: Log pass-through of commodity costs by income quintile.



(a) Flour: 2% higher sensitivity.



(b) Rice: 20% higher sensitivity.



(c) Coffee: 45% higher sensitivity.

of inflation inequality, which varies over the commodity cost cycle, can be quite large, comparable in magnitude to the average level of inflation inequality that is driven by secular forces.

6.2 Food-at-Home Inflation Inequality

While the previous analyses demonstrate how complete pass-through in levels can generate inflation inequality within narrow product categories, one may wonder whether complete pass-through in levels can generate quantitatively important differences in the overall inflation rates experienced by households over the income distribution. To this end, I now extend my analysis to overall food-at-home inflation.

Note that, when looking at overall food-at-home inflation, it is no longer possible to construct the detailed matches from commodity costs to retail prices and measure pass-through in levels. Hence, in this section, I will rely on log pass-through from upstream price indices to downstream price indices. In particular, I focus on the log pass-through of producer price indices for Farm Products and Food Manufacturing to consumer food-at-home price indices (see Appendix Figure A12 for the evolution of these producer and consumer price indices since 2006).

The analysis proceeds in three steps. First, I describe how I build a retail scanner price index that co-moves closely with food-at-home consumer price index from the Bureau of Labor Statistics. Second, I disaggregate this retail scanner price index by product "quality" (measured as unit price relative to other products in the same category) and show that price indices constructed from lower quality products have higher log pass-through of upstream producer price indices. Finally, I use the retail scanner price data to construct food-at-home indices by income quintile and show that food-at-home inflation for the lowest quintile is more sensitive to upstream producer price indices and more volatile.

Reconstructing the food-at-home price index using scanner data. Beraja et al. (2019) show that price indices constructed from Nielsen Retail Scanner data can closely match consumer price indices released by the Bureau of Labor Statistics. I undertake a similar exercise as Beraja et al. (2019) to create a Retail Scanner Price Index that mimics the BLS food-at-home consumer price index. In particular, for all food products in the Nielsen data,[38] I calculate the inflation rate over the next year as the sales-weighted inflation rate

[38] I.e., products in dry grocery (department code 1), frozen foods (department code 2), dairy (department code 3), deli (department code 4), packaged meat (department code 5), and fresh produce (department code 6).

for all products,

$$\pi_t^{\text{Retail Scanner Index}} = \frac{\sum_i \lambda_{i,t}(p_{i,t+4}/p_{i,t} - 1)}{\sum_i \lambda_{i,t}}, \tag{14}$$

where $p_{i,t+4}/p_{i,t} - 1$ is the year-over-year growth in the quantity-weighted average price of product i from quarter t to quarter $t+4$ and $\lambda_{i,t}$ is the total sales of retailer-UPC i in quarter t.[39] I construct this Retail Scanner Price Index at two levels of disaggregation: the first denotes takes each UPC as a single product, and the second takes a unique retailer-UPC pair as a single product. The advantage of using the latter, finer level of disaggregation is that the same UPC may be priced quite differently across retail chains, but tends to have uniform pricing with a retailer (DellaVigna and Gentzkow 2019). On the other hand, taking the UPC as the lowest level of disaggregation increases the likelihood that the price of the product will be observed the following year, thus reducing the potential bias associated with discontinued products (Appendix Table A10 reports the share of product observations for which a price in the following year is available at both levels of disaggregation). Nevertheless, we will see that price indices constructed at both levels of disaggregation produce similar results.

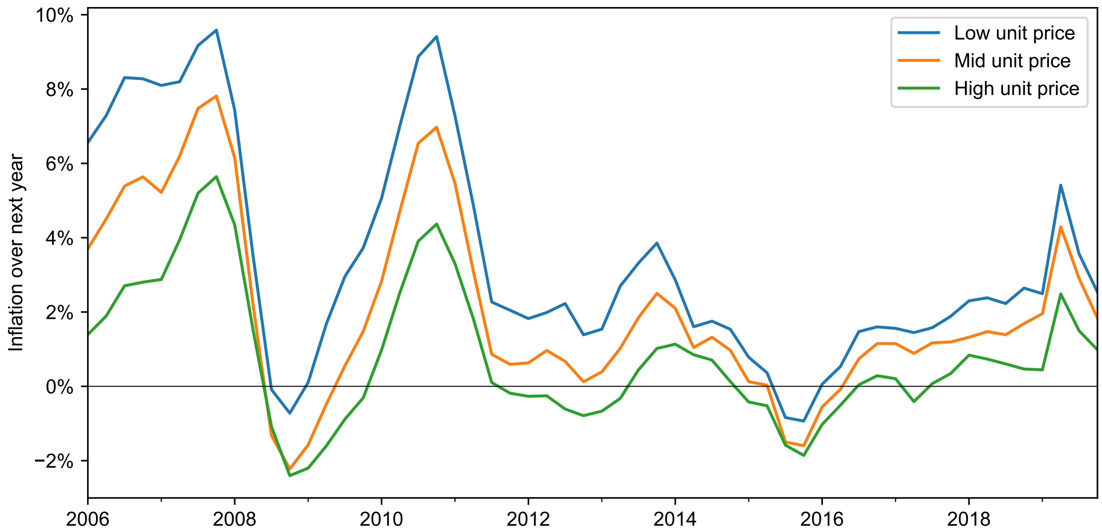
Appendix Figure A13 shows that year-over-year inflation for the resulting Retail Scanner Price Index—using either UPCs or retailer-UPC pairs as the lowest level of aggregation—co-moves closely with the BLS food-at-home consumer price index. The correlation between year-over-year inflation for the Retail Scanner Price Index (constructed at either level of aggregation) and the food-at-home CPI is 0.96.

Disaggregating by quality. We can use the Retail Scanner Price Index to investigate how log pass-through of upstream prices, such as producer prices for Farm Products and Food Manufacturing, varies across products with different unit prices. To do so, in each quarter, I rank all products within each product category by average unit price over the prior year. For simplicity, I will refer to average unit price as "quality": low-quality products are those that have low unit prices relative to others in the same category, while high-quality products have relatively high unit prices.

For each product category in each quarter, I split the sample of products into n groups with equal sales. By combining these subsets of products across categories, I construct n

[39]One difference between the retail scanner price index I construct and the BLS's consumer price index is that the BLS instead takes a quantity-weighted average of products within each category and then aggregates across categories using expenditure weights, while I take an expenditure-weighted average across all products. Using quantity weights to aggregate products within categories produces very similar results to those reported here. An advantage to using expenditure weights within product category is that it allows me to disaggregate the price index into "quality groups" using groups with equal sales within each category.

Figure 13: Retail scanner price inflation for $n = 3$ groups of products split by unit price.

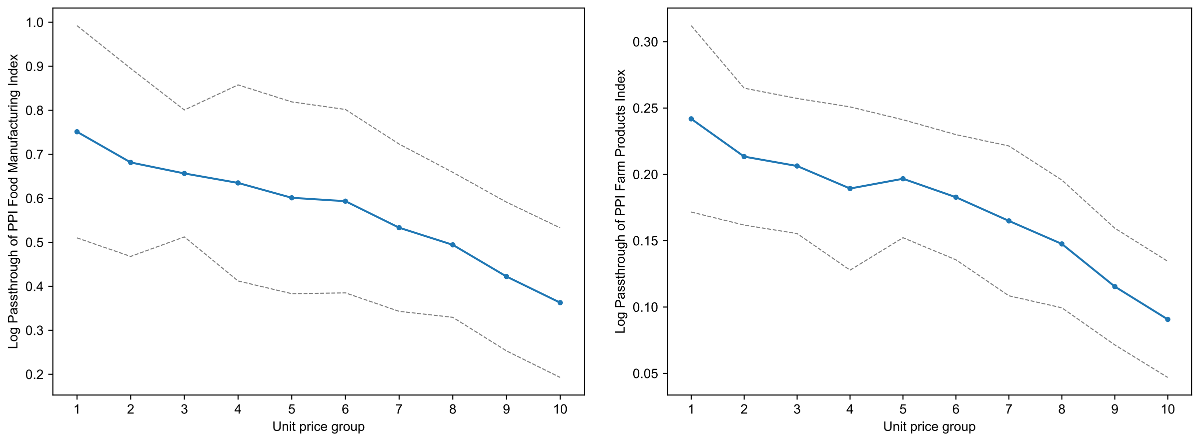


different price indices, such that the first price index reflects changes in prices of the lowest-quality products in each product category and the last price index reflects changes in prices of the highest-quality products in each product category. Note that the expenditure shares across product categories for each of these n price indices are identical to the expenditure shares across product categories for the entire Retail Scanner Price Index, since each product category is sliced into groups with equal sales.

Figure 13 plots year-over-year inflation rates for $n = 3$ quality groups. Two patterns emerge. First, inflation rates for the lowest-quality products are higher than inflation rates for the highest-quality products in each period. This secular difference in inflation rates for low- and high-quality products is documented by Jaravel (2019), who attributes lower inflation rates for high-quality products to rising demand and hence heightened entry and competitive pressure. Second, the volatility of inflation rates for the lowest-quality products is greater than that for the highest-quality products. When average inflation is low—such as in 2009 and late 2015—the gap in inflation rates between low-quality and high-quality products shrinks to about 1pp. On the other hand, when average inflation is high—in late 2007 and 2010—the gap in inflation rates between low- and high-quality products widens to over 4pp. This latter pattern is not discussed by previous work, and is consistent with complete pass-through in levels resulting in higher sensitivity of inflation rates to upstream prices for low-price and low-margin products.

I test the role of differential log pass-through in generating these differences in inflation

Figure 14: Low unit price products exhibit higher log pass-through of upstream PPI.



(a) Food Manufacturing PPI.

(b) Farm Products PPI.

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

volatilities by quality using the distributed lag specification,

$$\Delta \log p_t^{\text{Retail Scanner Index},q} = a^q + \sum_{k=0}^{K} b_k^q \Delta \log \text{PPI}_{t-k} + \varepsilon_t, \tag{15}$$

where $\Delta \log p^{\text{Retail Scanner Index},q}$ is the log change in the price index for products in quality group q, $\Delta \log \text{PPI}_t$ is the log change in the upstream PPI (either the Farm Products PPI or the Food Manufacturing PPI), and $\sum_{k=0}^{K} b_k^q$ measures the long-run log pass-through of upstream PPI changes to retail price changes for quality group q. For consistency with the other measures of pass-through for food products, I choose $K = 3$ to consider a long-run pass-through horizon of one year.

Figure 14 plots estimates of long-run pass-through from the Food Manufacturing and Farm Products PPIs to $n = 10$ quality groups constructed using the approach described above. The long-run log pass-through of both upstream price indices declines with product quality. The magnitudes of this decline are quite large: the log pass-through of Food Manufacturing price changes to products in the lowest quality decile is 0.75, nearly twice that of products in the highest-quality decile (0.39). Similarly, the log pass-through of Farm Products price changes to products in the lowest quality decile is more than double that of products in the highest quality decile. These differences in log pass-through are independent of secular trends (i.e., unrelated to upstream PPIs) that cause inflation differences across unit price groups, which are instead captured by the intercept coefficients a^q. Appendix Figure A14 shows that the estimated intercept coefficients also decrease with quality, consistent with the secular drivers of inflation differences documented by Jaravel (2019).

These results suggest that the same patterns in log pass-through attributed to complete pass-through in levels in narrow product categories also emerge across the entire food-at-home bundle. Accordingly, low-priced and low-margin food products exhibit greater greater inflation volatility and sensitivity to upstream prices when measured in percentage terms.

Differences across income groups. In the above section, we saw that the pass-through of commodity costs to prices paid by different income groups depended on the extent to which households in different income groups buy products with different unit prices and margins. How large are these effects for differences in aggregate food-at-home inflation experienced by income groups?

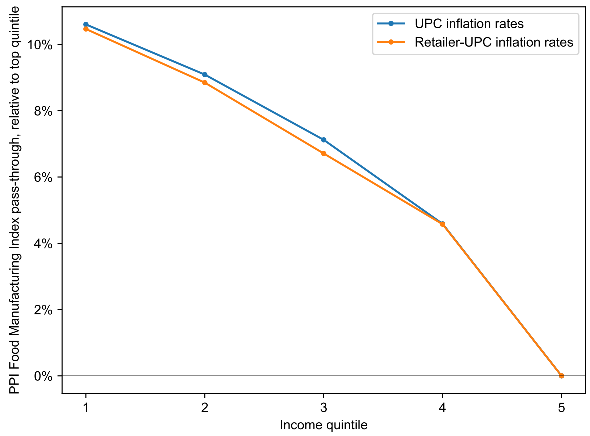
I construct income group retail scanner price indices using the same approach as in (14), but now using expenditures from Nielsen Homescan panelists in each income group to weight price changes rather than sales in the scanner data.[40] As above, I construct these price indices using either each UPC or each retailer-UPC pair as the finest level of disaggregation.

Figure 11b 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 also significant cyclical variation in the level of inflation inequality that coincides with the average level of food-at-home inflation. Since low-income households purchase lower-price and lower-margin products within each product category, these products experience greater inflation (on a percentage basis) when upstream prices rise, and hence inflation inequality grows when overall price levels are rising.

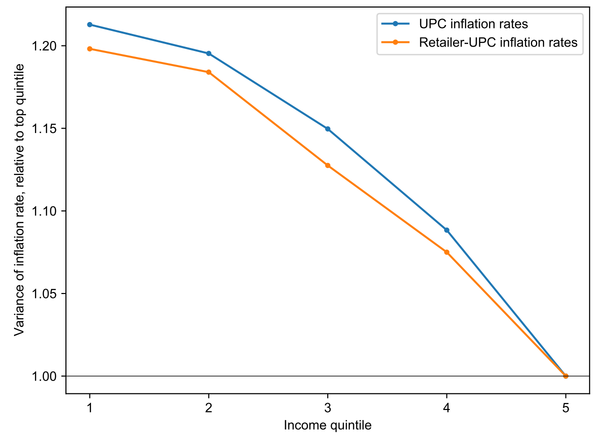
To quantify the difference in exposure to upstream prices, I calculate the long-run pass-through of upstream price indices to the food-at-home price index for each income group. As shown in Figure 15a, the log pass-through of upstream producer prices (the Food Manufacturing PPI) to the price index experienced by the lowest income quintile is 10 percent higher than that of the highest income quintile. That is, since low-income households purchase low quality products that are more sensitive to upstream price changes, the sensitivity of total food-at-home inflation to upstream prices is higher for

[40]The Nielsen Homescan panel reports household income in sixteen brackets. To sort households into income quintiles, I rank households first by income bracket, and within income bracket by total expenditures divided by the square-root of household size. This adjustment for household size follows from the OECD Income Distribution Database and Handbury (2021).

Figure 15: Food-at-home inflation for lower income quintiles is more sensitive to upstream PPI and has higher variance.



(a) Pass-through of Food Manufacturing PPI.



(b) Variance of inflation rates.

low-income households. This heightened sensitivity to upstream prices translates to more volatile food-at-home inflation rates, shown in Figure 15b. The variance of food-at-home inflation rates for the lowest income quintile is 20 percent higher than that of the highest income quintile, mapping nearly one-for-one with the differences in sensitivity to upstream prices. Appendix Figure A16 reports similar results by income decile.

Implications for food-at-home inflation, 2020–2023. At the time of writing, the most recent Nielsen data available through the Kilts Center ends in December 2020. In this section, I construct back-of-the-envelope estimates for inflation inequality over the recent period using data on upstream PPIs. These estimates suggest sizable differences in inflation rates over the product quality distribution and 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, I use fitted values for the intercept and long-run pass-through from a distributed lag specification, such as (15), to calculate

$$\Delta \log(\text{PriceIndex}_{i,t}) \approx \alpha_i t + \rho_i^{\text{PPI}}(\Delta \log \text{PPI}_t), \tag{16}$$

where t is the number of quarters since January 2020, α_i is the intercept from the pass-through specification, and $\rho_i^{\text{PPI}} = \sum_{k=0}^{K} b_k^i$ is the long-run pass-through of changes in the upstream PPI to price index i. Accordingly, the two terms on the right-hand side of (16) capture two distinct channels that contribute to growth in price index i: the first term, which depends on α_i, captures secular trends in the average inflation rate for price index

Table 14: Unequal price growth from January 2020 to January 2023: Predicted changes using growth in upstream PPI (Food Manufacturing).

	Predicted growth in price index		
	Total	Due to PPI pass-through	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**

i, while the second term, which depends on the pass-through ρ_i^{PPI}, captures how changes in upstream costs contribute to price growth for price index i.

Table 14 uses the log pass-through estimates by decile of product quality (Figure 14) and by income quintile (Figure 15a) to predict the difference in price growth for low- vs. high-quality products and for low- vs. high-income households. These baseline estimates aggregate inflation rates at the UPC level and use changes in the Food Manufacturing PPI for upstream costs. Using retailer-UPC pairs as the lowest level of aggregation produces similar results (see Appendix Table A11).[41] Differences in both pass-through and secular inflation rates across quality groups suggest that products in the lowest quality decile have seen prices grow by 11pp more than products in the highest quality decile. 60 percent of this differential price growth is due to differences in the pass-through of upstream prices across products. Accordingly, these estimates suggest 1.8pp higher price index growth for households in the lowest income quintile compared to households in the highest income quintile. Two-thirds of this recent inflation inequality is due to differences in the pass-through of upstream producer prices, rather than secular differences in inflation rates.[42]

[41] Appendix Table A11 also reports results using the Farm Products PPI, rather than the Food Manufacturing PPI. In general, long-run pass-through estimates from the Farm Products PPI to downstream price indices are noisier, attenuating the portion of the differences in predicted price growth due to differential pass-through, though the estimates are qualitatively similar.

[42] Across the robustness exercises in Table A11, the contribution of secular changes to differences in inflation rates experienced by the lowest and highest income quintiles is between 0.6–1.5pp, or 0.2–0.5pp per year. These estimates are smaller than inflation inequality of about 0.7pp estimated by Jaravel (2019). However, the inflation inequality documented by Jaravel (2019) does not differentiate between secular and cyclical sources of inflation inequality. Since upstream prices rose during the sample period over which those estimates of inflation inequality were made (from 2004 to 2015, the Food Manufacturing and Farm Products PPIs each rose about 40 percent), some part of the 0.7pp inflation inequality estimated by Jaravel

7 Conclusion

Pass-through plays a central role in determining how changes in upstream costs are transmitted to downstream prices. This paper documents that empirical patterns of incomplete log pass-through and markup adjustment may better be understood in terms of complete pass-through in levels and a lack of adjustment in unit margins. In the markets for retail gasoline and food products studied, complete pass-through in levels appears to be the predominant pattern of commodity cost pass-through, and empirical exercises suggest similar patterns may describe pass-through across a broader array of consumer goods captured in the food-at-home price index. While predominant explanations attribute variation in pass-through to variation in the super-elasticities of demand facing firms, complete pass-through in levels across products and markets suggest that considerations of price-setters beyond the elasticity of demand may be important to explain pass-through. This paper provides one such explanation, where managers choose a pricing rule with an additive margin over marginal cost due to an aversion to variable profits falling short of overhead costs. Finally, patterns of complete pass-through in levels can be important for understanding macroeconomic phenomena such as inflation inequality. For example, I show that pass-through in levels generates a cyclical, within-category source of inflation inequality that generates substantially higher inflation volatility for low-income households.

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(2019) may in fact be attributed to pass-through of cyclical upstream prices.

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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		
	Autocorrelation coefficient (β)	Standard error	ADF test p-value	Autocorrelation coefficient (γ)	Standard error	ADF test p-value
Canada Crude*	0.982	(0.009)	0.721	-0.090	(0.097)	0.000
Canada Wholesale*	0.987	(0.010)	0.961	0.139	(0.048)	0.000
Australia Terminal Unleaded	0.996	(0.007)	0.731	0.449	(0.058)	0.000
Australia Terminal Premium Unleaded	0.995	(0.006)	0.665	0.442	(0.058)	0.000
Australia Terminal Diesel	0.999	(0.007)	0.919	0.302	(0.142)	0.000
Beef Farm Price	0.993	(0.007)	0.555	0.280	(0.041)	0.000
Pork Farm Price	0.930	(0.018)	0.000	0.170	(0.039)	0.000
Skim Milk*	0.950	(0.006)	0.498	-0.029	(0.018)	0.000
Butterfat*	0.904	(0.008)	0.149	0.150	(0.018)	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. * Asterisk rows contain multiple series by markets. For these rows, standard errors are reported are Driscoll-Kraay standard errors, and the reported Augmented Dickey-Fuller test for unit root report the maximum p-value across all markets.

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

	Granger causality test p-value	
	1 to 2	2 to 1
Canada, city-level, 2007–2022		
Crude to wholesale	0.003	0.908
Crude to retail (excl. taxes)	0.053	0.999
Wholesale to retail (excl. taxes)	0.000	1.000
Australia, station-level, 2001–2022		
Terminal ULP to Station Price ULP	0.000	0.001
Terminal PULP to Station Price PULP	0.000	0.001
Terminal Diesel to Station Price Diesel	0.000	0.120
USDA ERS		
Beef Farm to Wholesale	0.000	0.205
Beef Farm to Retail	0.000	0.126
Beef Farm to Fresh Retail	0.044	0.567
Beef Wholesale to Retail*	0.000	0.003
Beef Wholesale to Fresh Retail	0.000	0.441
Pork Farm to Wholesale*	0.000	0.007
Pork Farm to Retail	0.000	0.069
Pork Wholesale to Retail	0.063	0.785
Dairy Commodity to Whole Retail**	0.000	0.877
Dairy Commodity to Reduced Fat Retail**	0.003	0.826
U.S. CPI commodities		
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: * Starred entries note relationships where reverse causality is a likely concern. ** Uses four lags instead of twelve

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[43]	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[44])
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	0.0650 (100 dollars per cent / 2204.62 lbs per metric ton wheat / 42 lbs flour per 60 lbs (1 bushel) wheat)
Global price of Orange	PORANGUSDM	Dollars per Pound	Orange juice, frozen concentrate, 12 oz. can, per 16 oz. (473.2 mL)	713111	66.9 (100 dollars per cent $\times$ 41.8 retail brix / 62.5 futures brix[45])

[43] For some products, multiple series are available which track different package sizes.
[44] Nakamura and Zerom (2010).
[45] Dutta et al. (2002) for retail brix content and ICE for futures contract brix content.

Table A5: Unleaded price dispersion across Perth gas stations.

Stdev. daily prices (cents per liter)	All	Within Brand	Within Neighborhood
Mean	4.74	3.43	2.35
Quartile 1	3.59	1.22	0.42
Median	4.31	2.40	1.26
Quartile 3	5.36	4.43	3.00

Table A6: 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	0.248**	0.077**	0.125**
	(0.017)	(0.008)	(0.013)
Commodity Inflation × Unit Price Group 2	−0.070**	−0.003	−0.034
	(0.017)	(0.018)	(0.022)
Commodity Inflation × Unit Price Group 3	−0.095**	−0.004	−0.089**
	(0.015)	(0.005)	(0.021)
Commodity Inflation × Unit Price Group 4	−0.127**	−0.045**	−0.102**
	(0.018)	(0.010)	(0.019)
Commodity Inflation × Unit Price Group 5	−0.197**	−0.055**	−0.106**
	(0.021)	(0.008)	(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	0.056**	0.033**	0.061**
	(0.006)	(0.006)	(0.007)
Δ Commodity Price × Unit Price Group 2	0.001	0.013	−0.001
	(0.008)	(0.009)	(0.012)
Δ Commodity Price × Unit Price Group 3	0.010	0.016**	−0.030
	(0.007)	(0.008)	(0.018)
Δ Commodity Price × Unit Price Group 4	0.006	−0.017	−0.035*
	(0.008)	(0.021)	(0.021)
Δ Commodity Price × Unit Price Group 5	0.006	−0.029**	−0.027**
	(0.016)	(0.013)	(0.014)
UPC FEs	Yes	Yes	Yes
N (thousands)	399.4	101.4	1570.0
R^2	0.07	0.05	0.17

Note: Panel A reports results from specification (5), and panel B reports results from specification (6). The three columns use products from rice, all purpose white flour, and roasted coffee, respectively. In each quarter, each retailer-UPC pair is assigned to five groups with equal sales by (quantity-weighted) average unit price over the past year. Unit Price Groups 2–5 are indicators for whether a retailer-UPC pair is assigned to the low-mid to the highest unit price group. Standard errors clustered by brand. * indicates significance at 10%, ** at 5%.

Table A7: Comparison to two alternative models of log pass-through: Flour products.

Retail product inflation	(1)	Market share (2)	(3)	Buyer elasticity (4)	(5)
Commodity Inflation	0.053**	0.049**	0.042**	0.042**	0.047**
	(0.006)	(0.014)	(0.007)	(0.009)	(0.008)
Commodity Infl. × Log(Unit Price)	−0.065**		−0.069**		−0.075**
	(0.010)		(0.010)		(0.019)
Commodity Infl. × Log(Brand Sales Share)		−0.003	−0.005		
		(0.005)	(0.003)		
Wage Inflation				2.145**	1.791**
				(0.280)	(0.268)
Wage Infl. × Log(Buyer Income)				0.222	0.553
				(2.487)	(2.530)
UPC FEs	Yes	Yes	Yes	Yes	Yes
N (thousands)	101.4	101.4	101.4	79.6	79.6
R^2	0.04	0.03	0.04	0.04	0.05

Note: Log(Unit Price), Log(Brand Sales Share), and Log(Buyer Income) are all normalized relative to the average within each quarter, so that these three terms represent log deviations from the average unit price, sales share, and buyer income across all products in the quarter. Standard errors clustered by brand. * indicates significance at 10%, ** at 5%.

Table A8: Comparison to two alternative models of log pass-through: Coffee products.

Retail product inflation	(1)	Market share (2)	(3)	Buyer elasticity (4)	(5)
Commodity Inflation	0.051**	0.141**	0.112**	0.058**	0.056**
	(0.010)	(0.029)	(0.018)	(0.021)	(0.011)
Commodity Infl. × Log(Unit Price)	−0.080**		−0.060**		−0.085**
	(0.014)		(0.015)		(0.016)
Commodity Infl. × Log(Brand Sales Share)		0.024**	0.017**		
		(0.005)	(0.004)		
Wage Inflation				−0.240	−0.794**
				(0.245)	(0.264)
Wage Infl. × Log(Buyer Income)				0.598	2.173*
				(1.127)	(1.167)
UPC FEs	Yes	Yes	Yes	Yes	Yes
N (thousands)	1570.0	1570.0	1570.0	1269.3	1269.3
R^2	0.16	0.14	0.16	0.13	0.16

Note: Log(Unit Price), Log(Brand Sales Share), and Log(Buyer Income) are all normalized relative to the average within each quarter, so that these three terms represent log deviations from the average unit price, sales share, and buyer income across all products in the quarter. Standard errors clustered by brand. * indicates significance at 10%, ** at 5%.

Table A9: Exploiting variation in margins across retailers: Summary of results across all product modules using leave-one-out change in prices.

Share of modules	Unweighted	Observations-weighted	Sales-weighted
Panel A: In levels			
Positive coefficient	9.1	7.7	9.1
Negative coefficient	19.5	32.8	33.5
Panel B: In logs			
Positive coefficient	1.8	0.8	0.4
Negative coefficient	56.8	79.3	79.5

Note: Summary of results from specifications (7) (for panel A) and (8) (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. Driscoll-Kraay standard errors used in all specifications.

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

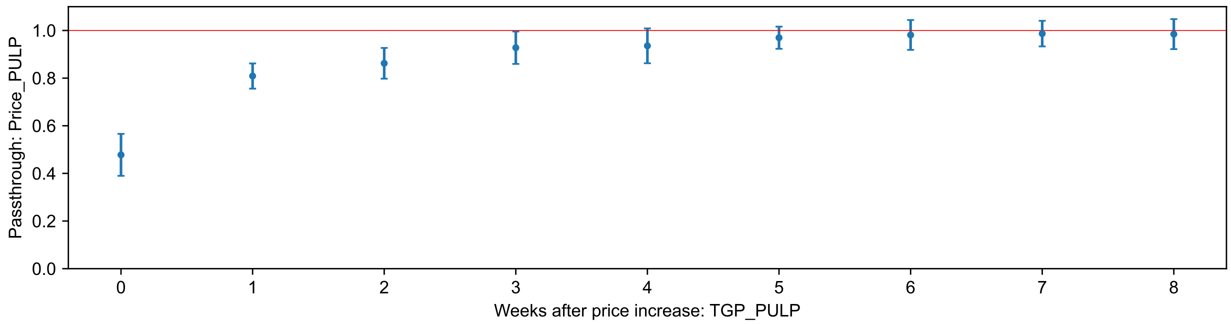
Income quintile	Matched to UPC		Matched to retailer-UPC	
	Total	With infl.	Total	With infl.
1	60.2	52.7	22.5	18.5
2	59.9	52.6	23.1	19.0
3	60.2	53.5	24.0	20.1
4	60.7	54.5	25.7	21.7
5	59.7	52.6	27.2	22.7

Table A11: Unequal price growth from January 2020 to January 2023: Predicted changes using alternative measures.

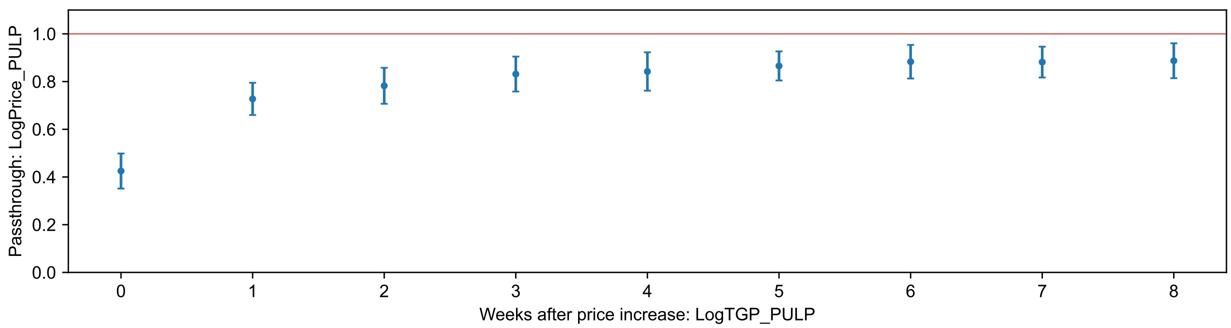
	Predicted growth in price index		
	Total	Due to PPI pass-through	Due to intercept
Food Manufacturing PPI, UPC aggregation (baseline)			
Products in quality decile 1	20.7pp	16.0pp	4.7pp
Products in quality decile 10	9.3pp	8.9pp	0.3pp
Difference	**11.4pp**	**7.1pp**	**4.3pp**
Lowest income quintile	15.6pp	12.7pp	2.8pp
Highest income quintile	13.7pp	11.5pp	2.2pp
Difference	**1.8pp**	**1.2pp**	**0.6pp**
Food Manufacturing PPI, Retailer-UPC aggregation			
Quality decile 1	26.3pp	19.5pp	6.9pp
Quality decile 10	7.5pp	9.4pp	-1.9pp
Difference	**18.9pp**	**10.1pp**	**8.8pp**
Lowest income quintile	18.7pp	13.5pp	5.2pp
Highest income quintile	16.3pp	12.3pp	4.0pp
Difference	**2.4pp**	**1.3pp**	**1.1pp**
Farm Products PPI, UPC aggregation			
Quality decile 1	18.1pp	10.2pp	7.9pp
Quality decile 10	7.0pp	4.9pp	2.2pp
Difference	**11.0pp**	**5.3pp**	**5.7pp**
Lowest income quintile	12.7pp	7.2pp	5.5pp
Highest income quintile	11.5pp	6.9pp	4.6pp
Difference	**1.3pp**	**0.3pp**	**0.9pp**
Farm Products PPI, Retailer-UPC aggregation			
Quality decile 1	23.8pp	13.0pp	10.8pp
Quality decile 10	4.9pp	4.9pp	-0.0pp
Difference	**18.9pp**	**8.1pp**	**10.8pp**
Lowest income quintile	15.7pp	7.5pp	8.1pp
Highest income quintile	13.8pp	7.2pp	6.6pp
Difference	**1.9pp**	**0.4pp**	**1.5pp**

Figure A1: Retail unleaded petrol (ULP) price and terminal gas price for Rottnest Island Authority station at Thompson Bay Fuel Jetty, Cockburn, Perth, Australia.

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.

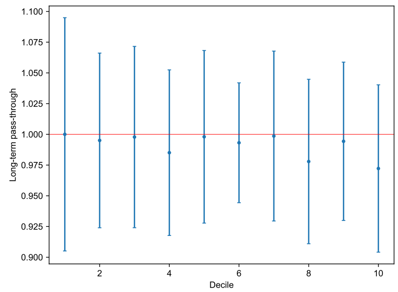
Note: Panels (a) and (b) show cumulative pass-through estimated from the specifications,

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

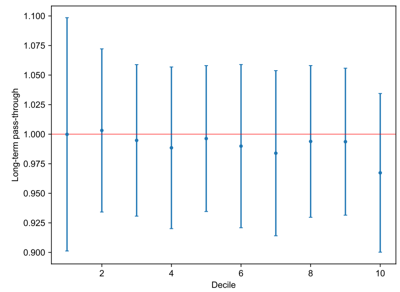
$$\Delta \log p_{i,t} = \sum_{k=0}^{k=8} \beta_k \Delta \log c_{i,t-k} + \alpha_i + \varepsilon_{i,t}.$$

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.

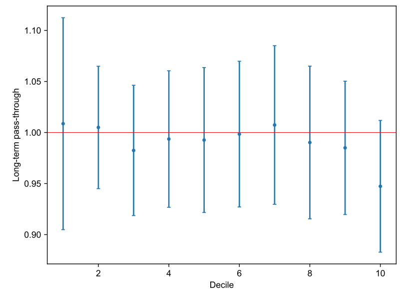
Figure A3: Pass-through in levels across groups of relative price.



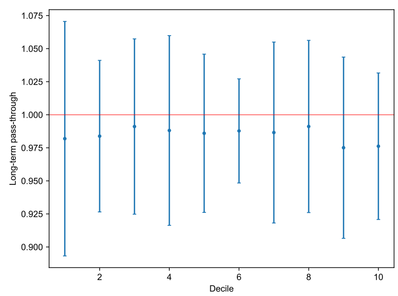
(a) Unleaded petrol: Groups within neighborhood.



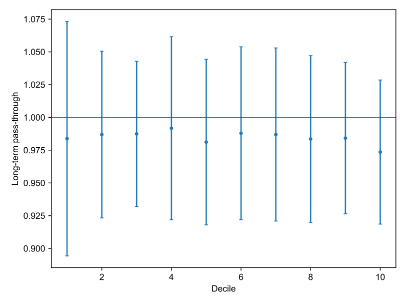
(b) Unleaded petrol: Groups within postcode.



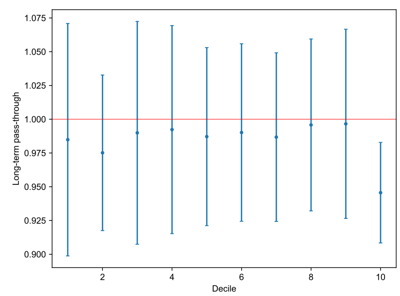
(c) Unleaded petrol: Groups across all stations.



(d) Premium unleaded petrol: Groups within neighborhood.



(e) Premium unleaded petrol: Groups within postcode.



(f) Premium unleaded petrol: Groups across all stations.

Note: These charts plot the long-run pass-through estimated from the specification,

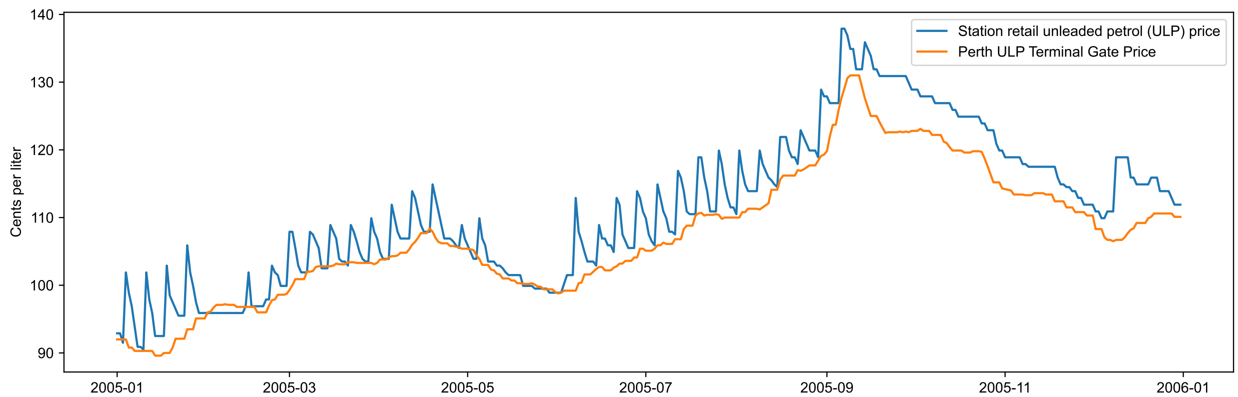
$$\Delta p_{i,t} = \sum_{k=0}^{k=8} b_k \Delta c_{i,t-k} + a_i + \varepsilon_{i,t}.$$

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. For each figure, the specification is estimated separately across ten deciles of RelativePrice_i, where

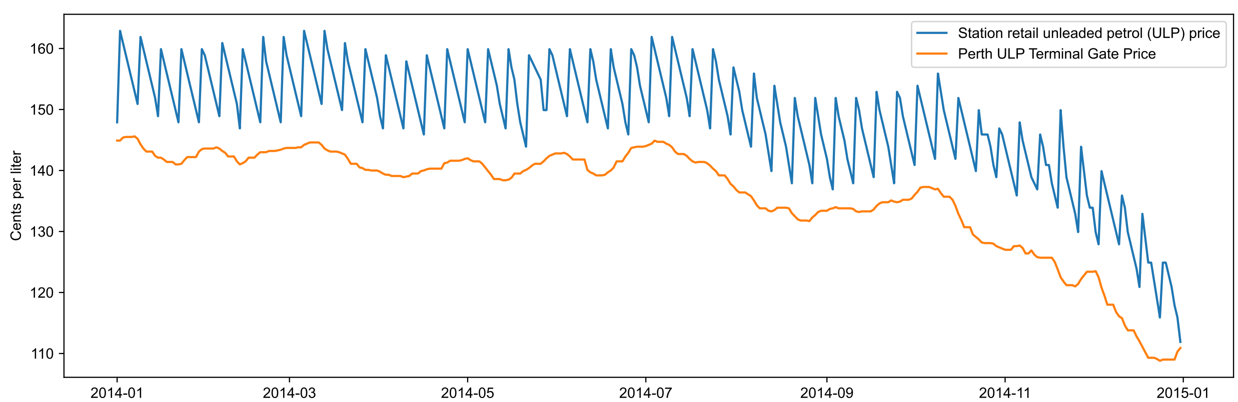
$$\text{RelativePrice}_i = \frac{1}{T_i} \sum_t \left(\text{Price}_{i,t} - \frac{1}{|N_t(i)|} \sum_{j \in N_t(i)} \text{Price}_{j,t} \right),$$

T_i is the number of daily observations in the sample for station i, $\text{Price}_{i,t}$ is i's retail price on day t, and $N_t(i)$ is the set of stations in i's neighborhood or postcode on date t.

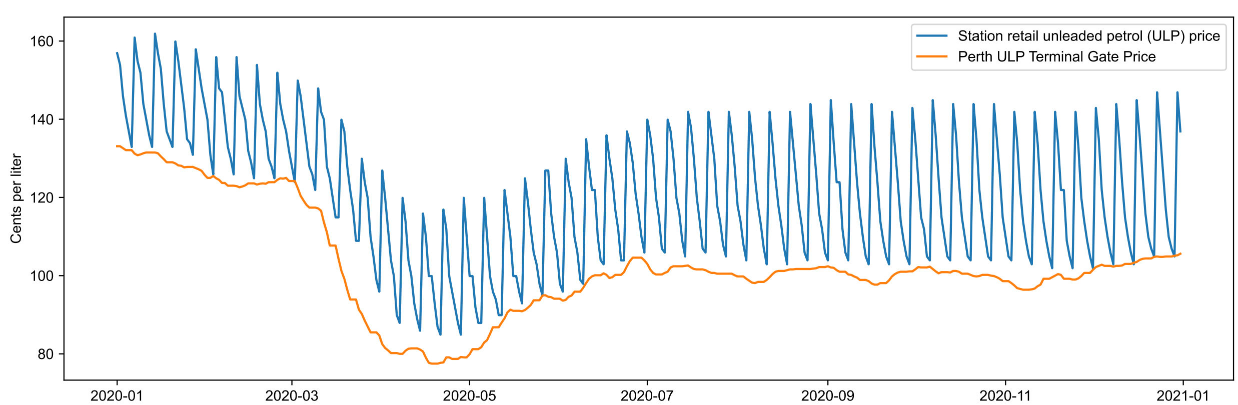
Figure A4: Price cycles in unleaded petrol (ULP) for BP station at 549 Abernethy Rd, Kewdale, Perth, Australia.



(a) 2005.

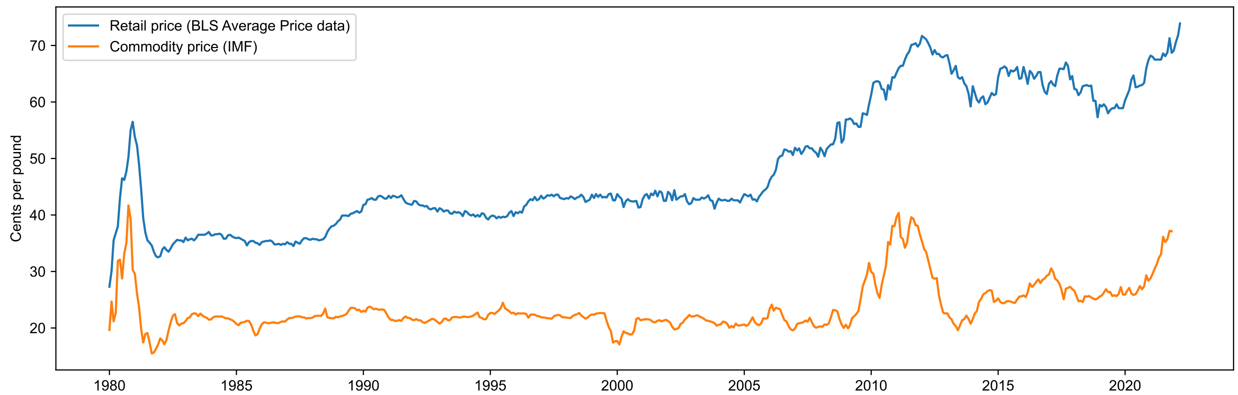


(b) 2014.

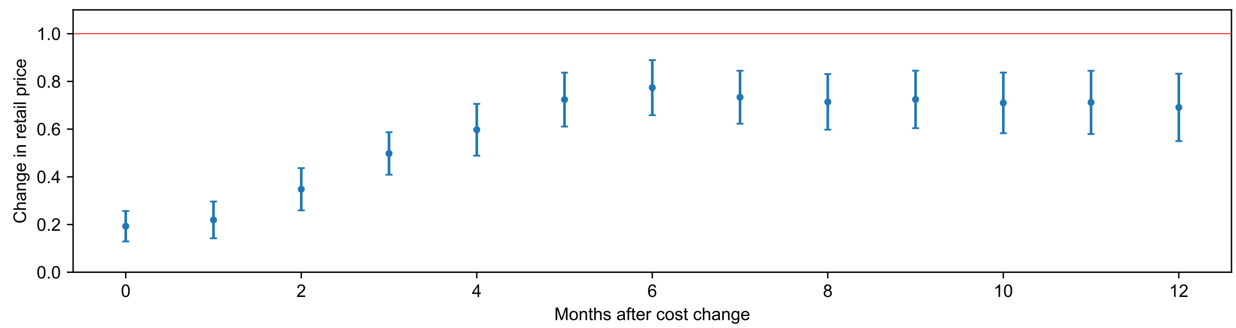


(c) 2020.

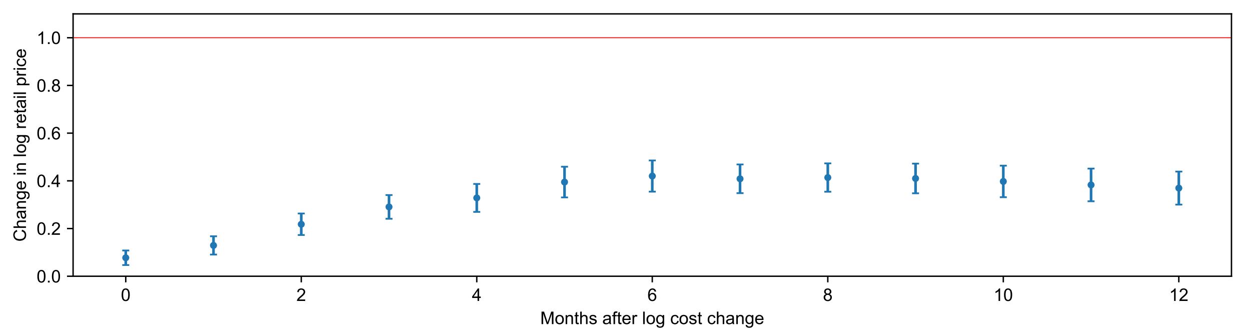
Figure A5: Passthrough of sugar commodity costs to retail prices.



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



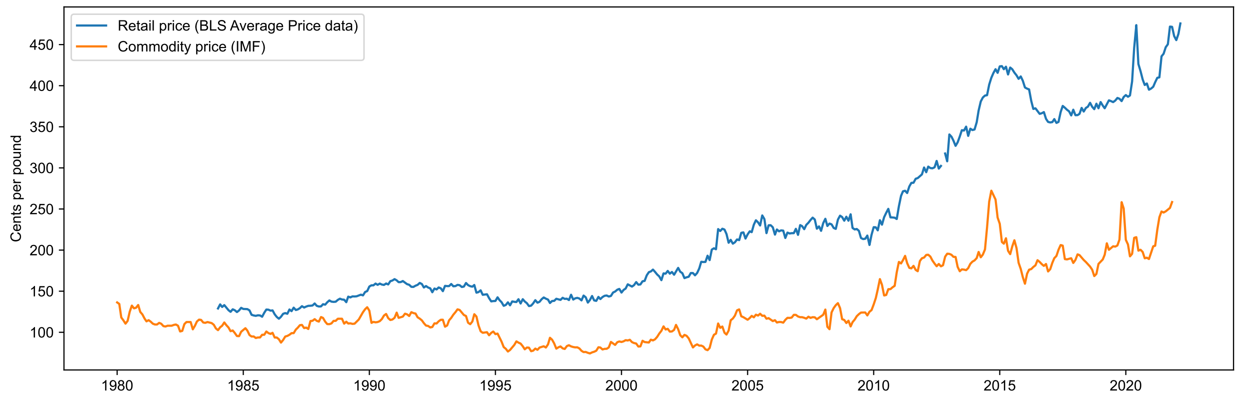
(b) Pass-through in levels.



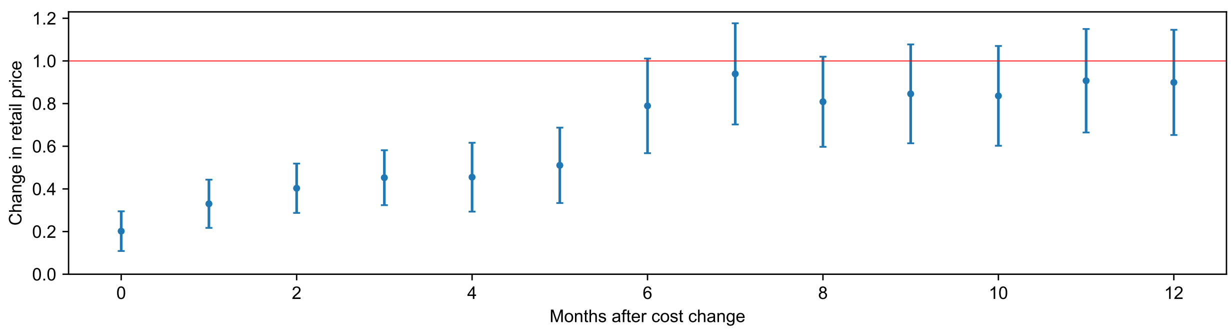
(c) Pass-through in logs.

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.

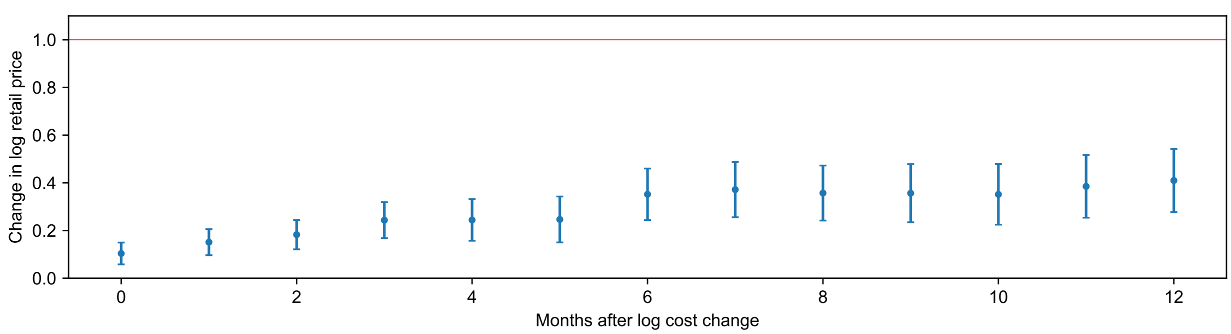
Figure A6: Passthrough of beef commodity costs to retail prices.



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



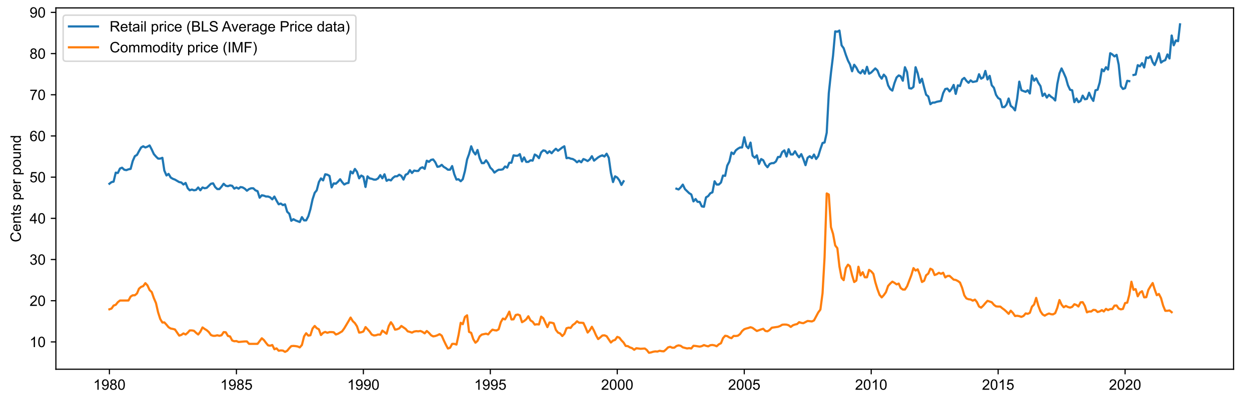
(b) Pass-through in levels.



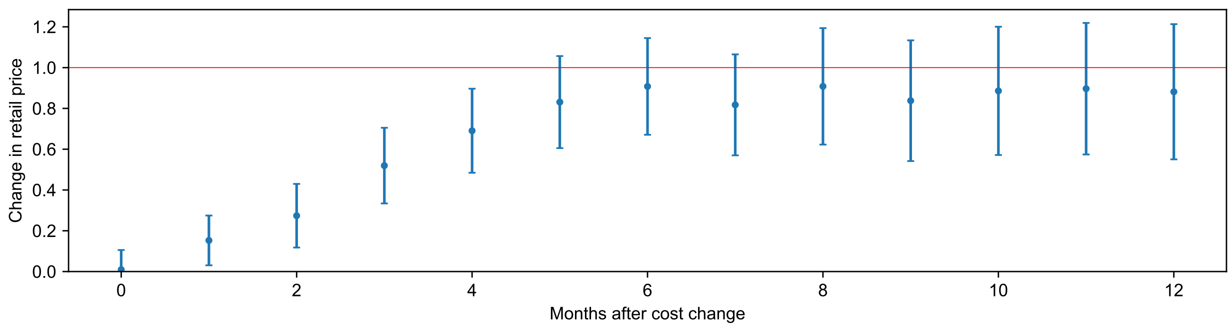
(c) Pass-through in logs.

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.

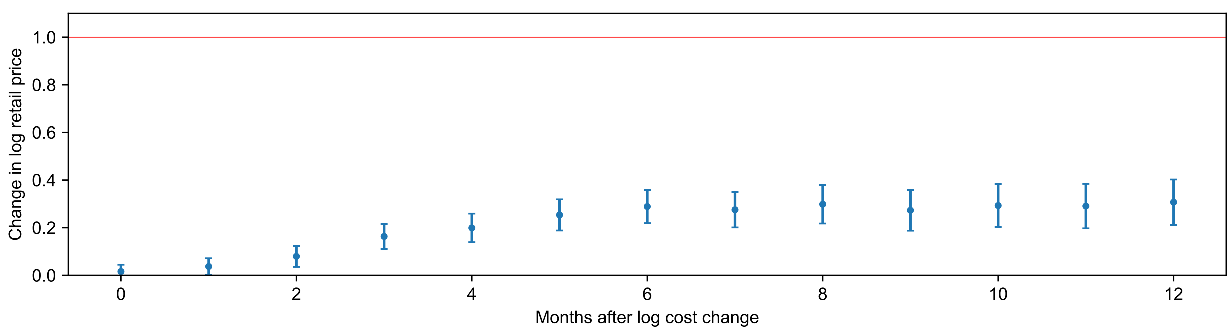
Figure A7: Passthrough of rice commodity costs to retail prices.



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



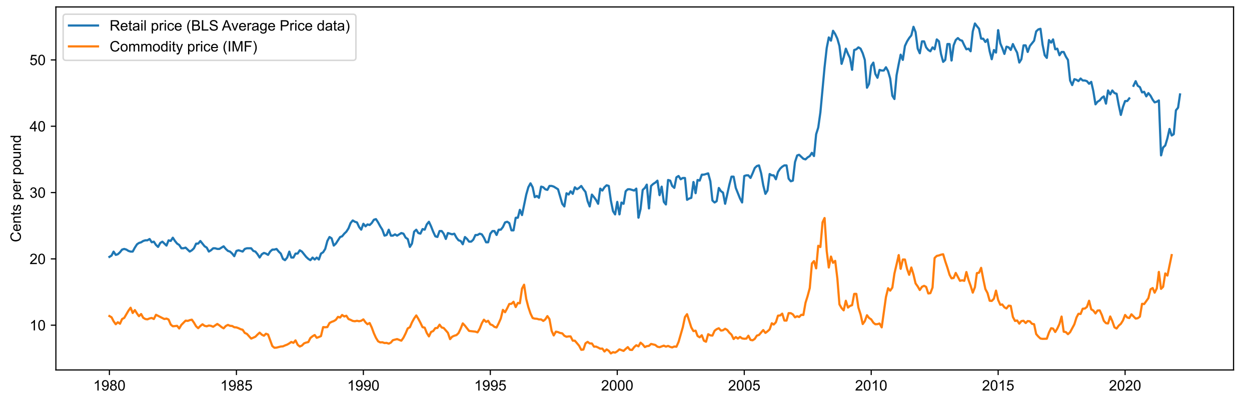
(b) Pass-through in levels.



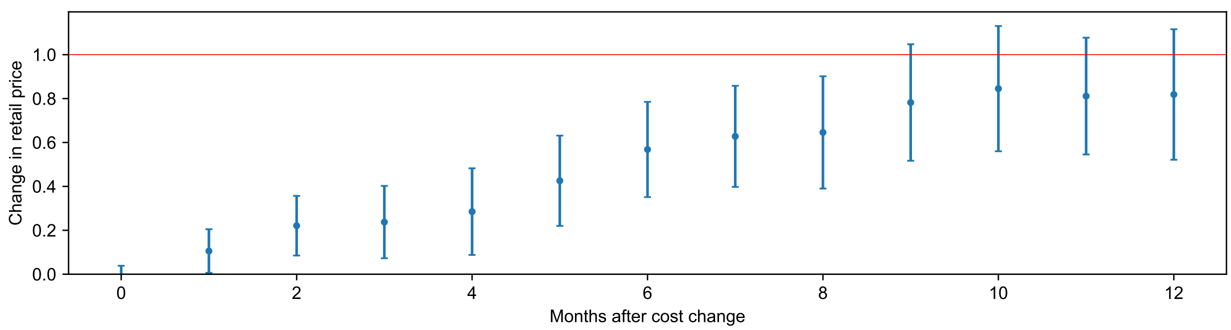
(c) Pass-through in logs.

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.

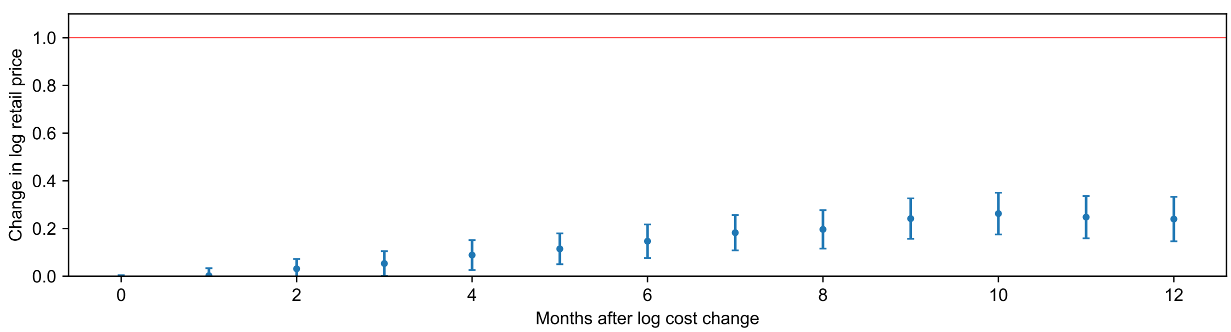
Figure A8: Passthrough of flour commodity costs to retail prices.



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



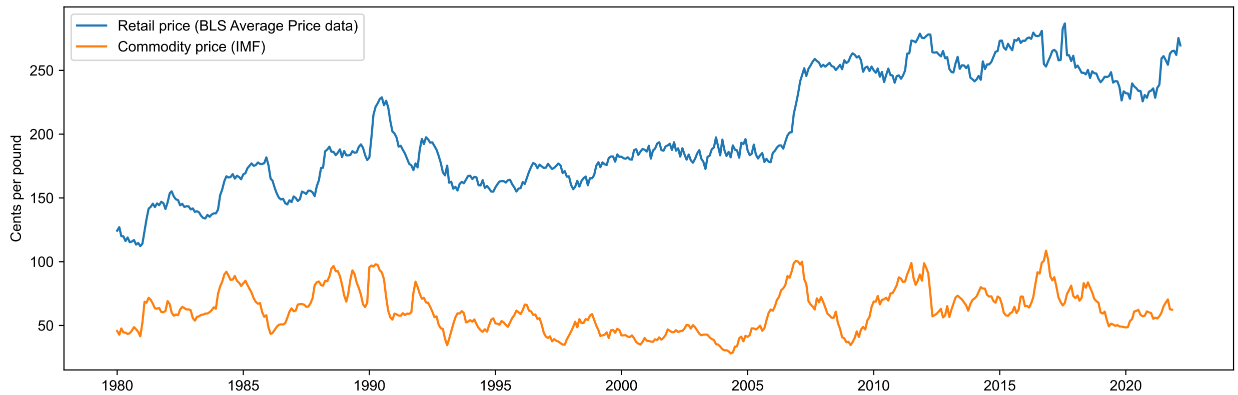
(b) Pass-through in levels.



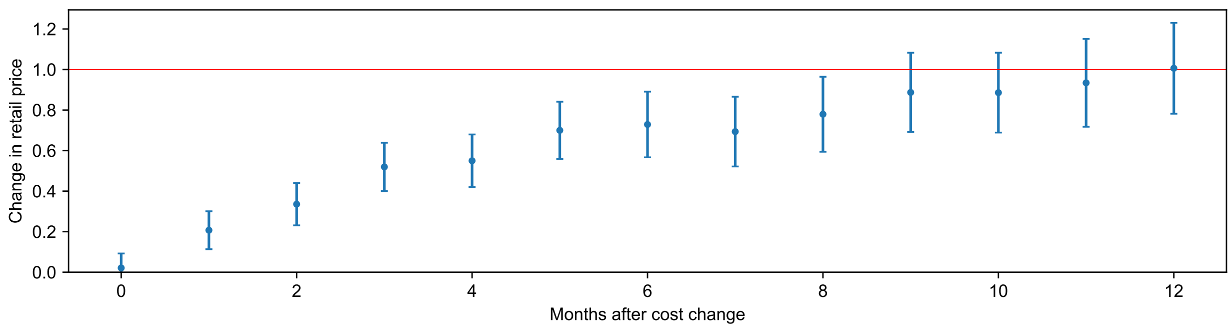
(c) Pass-through in logs.

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.

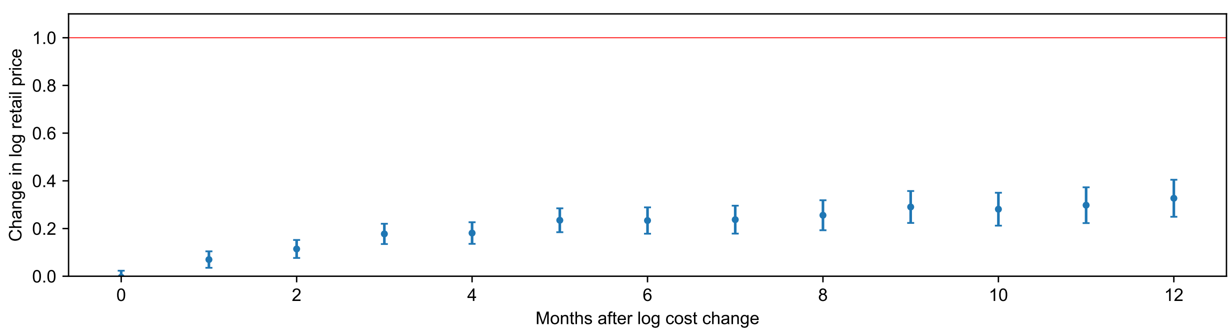
Figure A9: Passthrough of frozen orange juice commodity costs to retail prices.



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



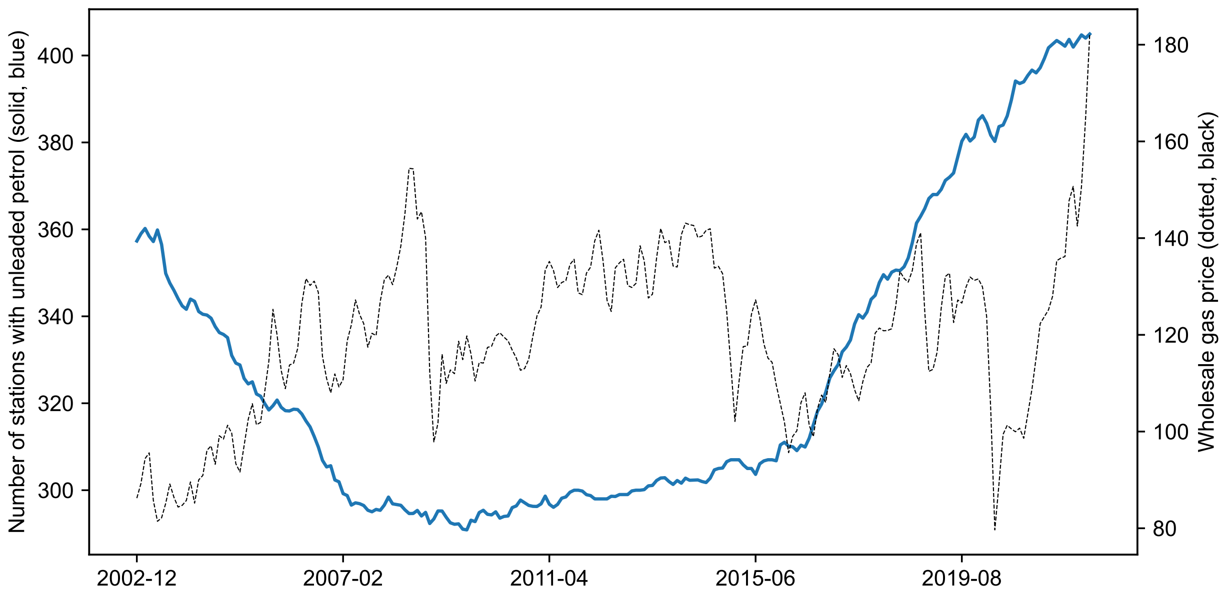
(b) Pass-through in levels.



(c) Pass-through in logs.

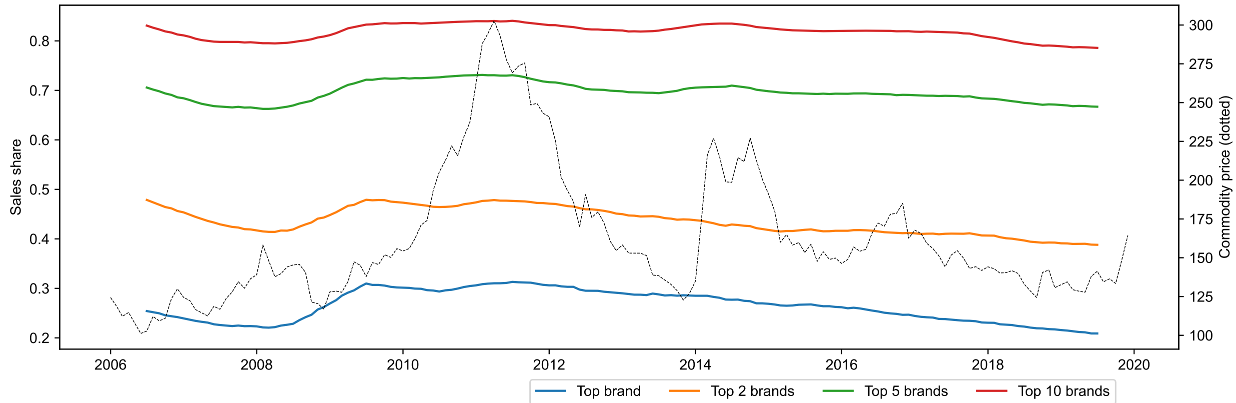
Note: Panel (a) plots the time series of the commodity price from the IMF and the Average Price Data series from the BLS. The series are adjusted by the conversion factors in Appendix Table A4 so that the two series are in comparable units. Panels (b) and (c) plot the cumulative pass-through to month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

Figure A10: Wholesale gas price and number of gasoline stations in Perth.

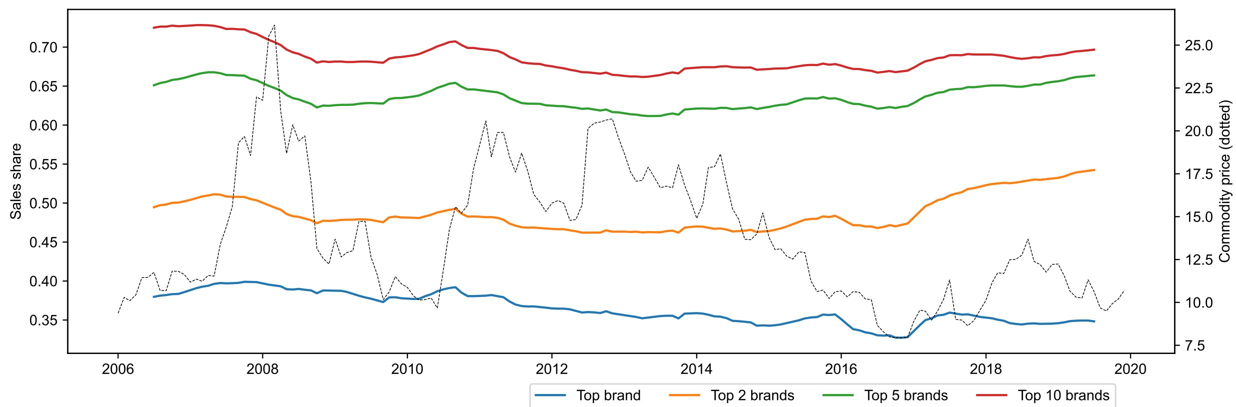


Note: Wholesale prices are TGP prices described in the text. The number of gas stations is the count of gas stations in the Perth metropolitan area with a non-missing unleaded petrol gas price.

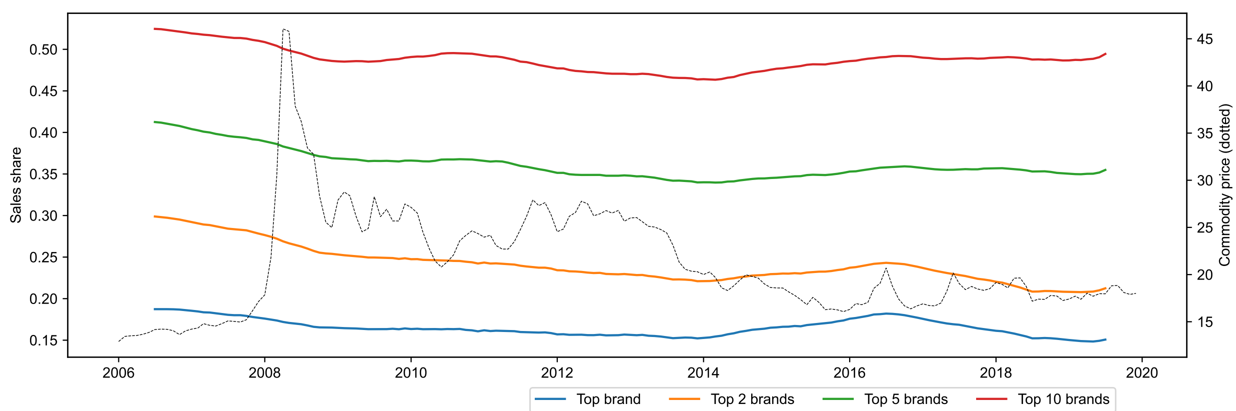
Figure A11: Commodity prices and market shares of top brands.



(a) Coffee



(b) Flour



(c) Rice

Note: Commodity prices are from the IMF. Brands are defined using unique brand identifiers provided by Nielsen. 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 A12: Food-at-home CPI, Food Manufacturing PPI, and Farm Products PPI.

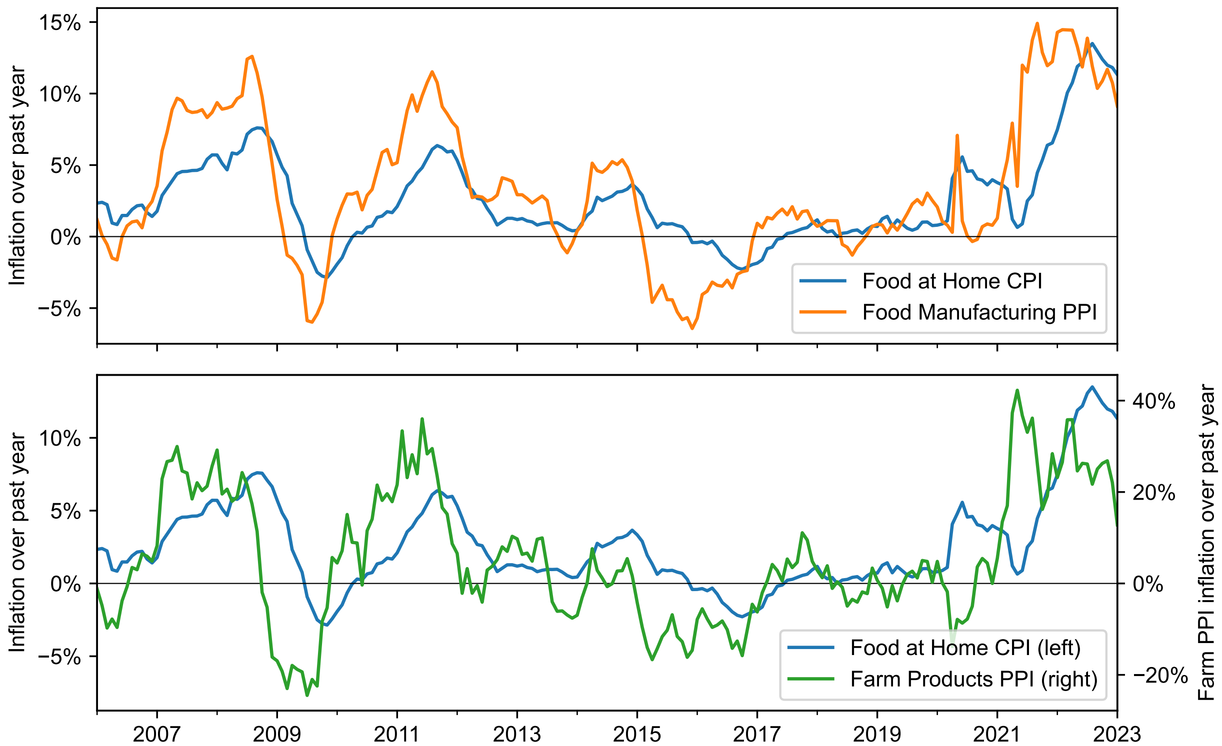
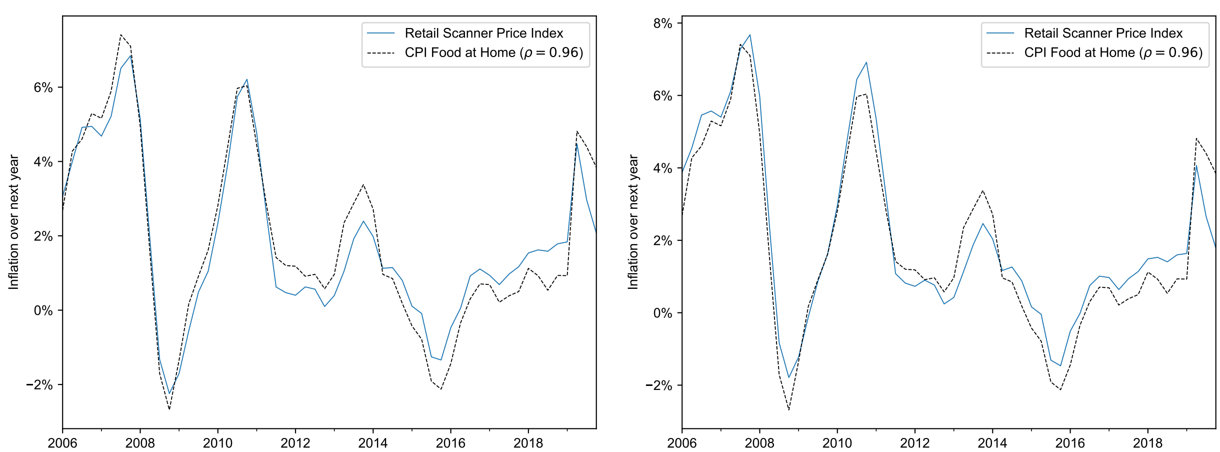


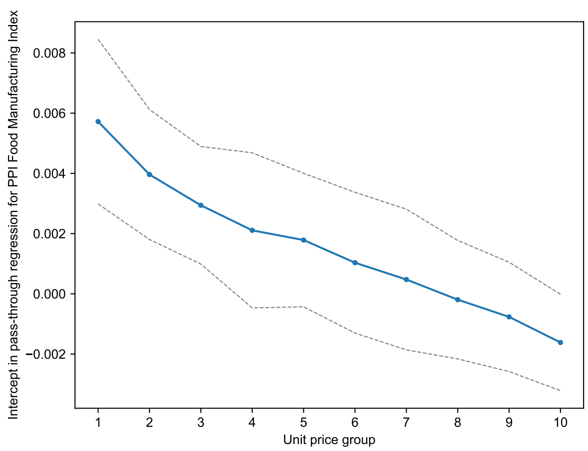
Figure A13: Inflation rates on food at home CPI and Retail Scanner price index.



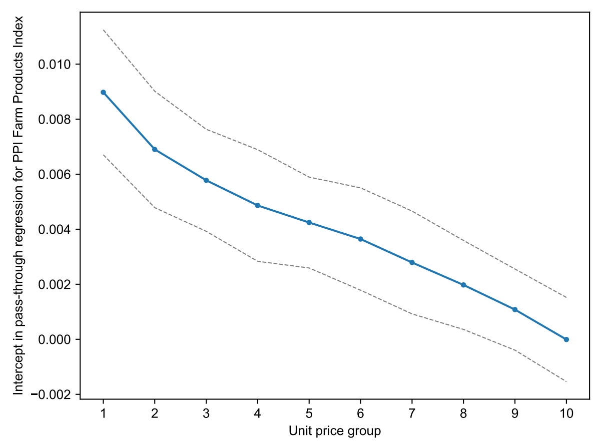
(a) Level of aggregation: UPC

(b) Level of aggregation: Retailer-UPC

Figure A14: Intercept in log pass-through regressions of upstream producer price indices.



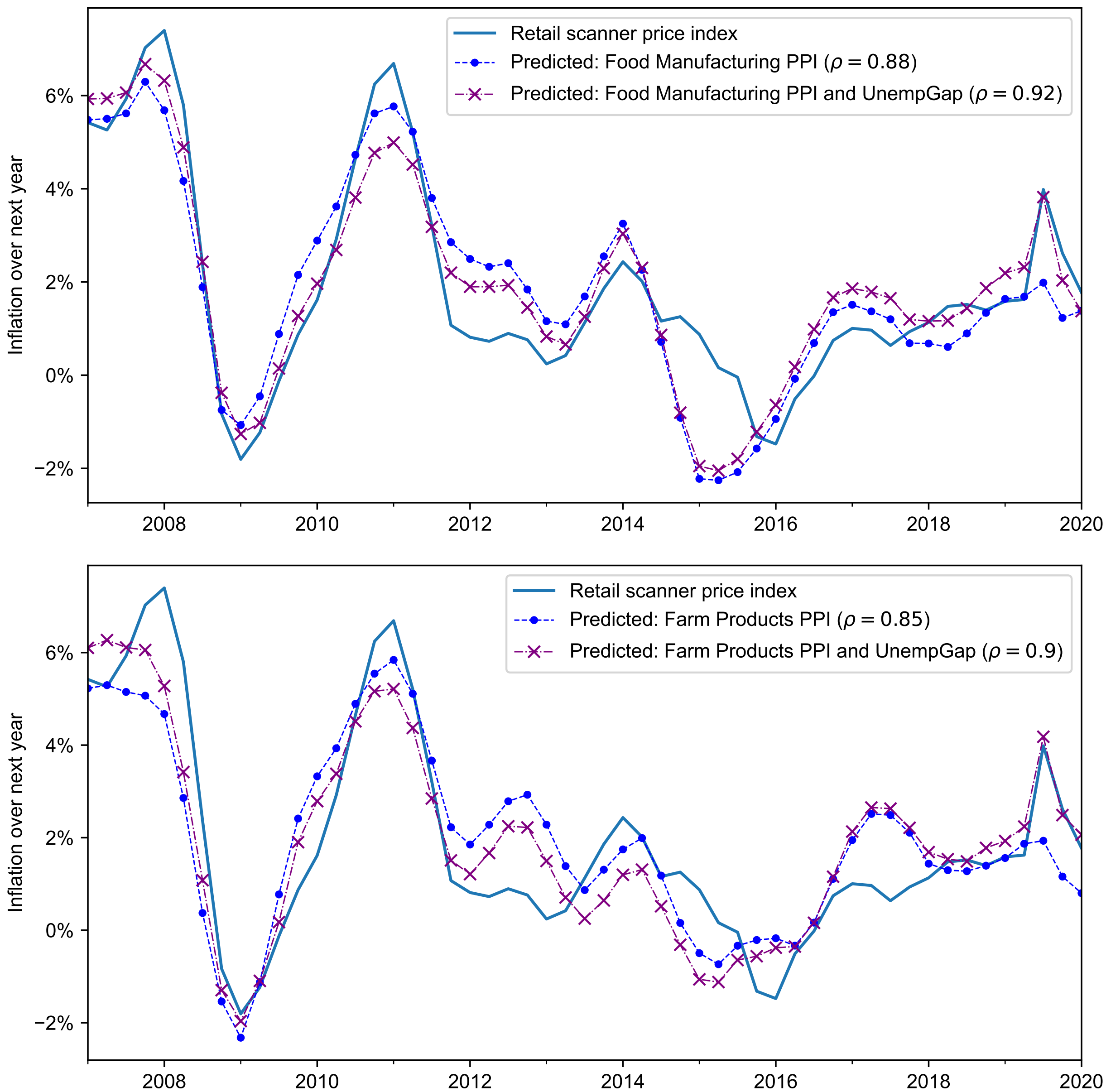
(a) Food Manufacturing PPI.



(b) Farm Products PPI.

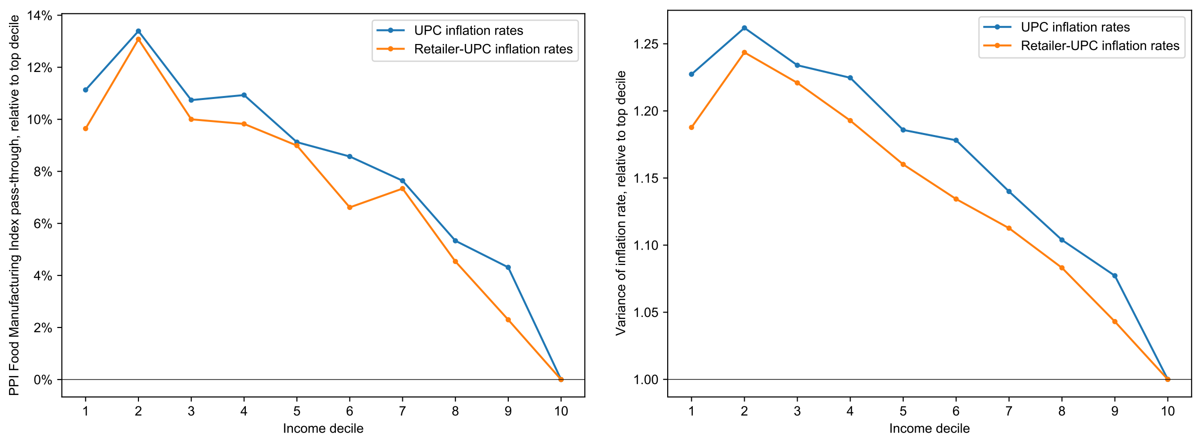
Note: Dotted lines indicate 95 percent confidence intervals using Driscoll-Kraay standard errors.

Figure A15: Predicted Retail Scanner index inflation using upstream PPIs and unemp. gap.



Note: The retail scanner index inflation plotted in each panel is constructed using retailer-UPC prices as the lowest level of aggregation. The top panel plots predicted values for year-over-year inflation from a long-run pass-through specification regressing changes in the retail scanner price index on four lags of Food Manufacturing PPI inflation and four lags of the unemployment gap. The coefficient ρ in the legend reports the correlation coefficient between the predicted values of year-over-year inflation and the actual retail scanner index inflation. The bottom panel repeats the exercise instead using Farm Products PPI inflation.

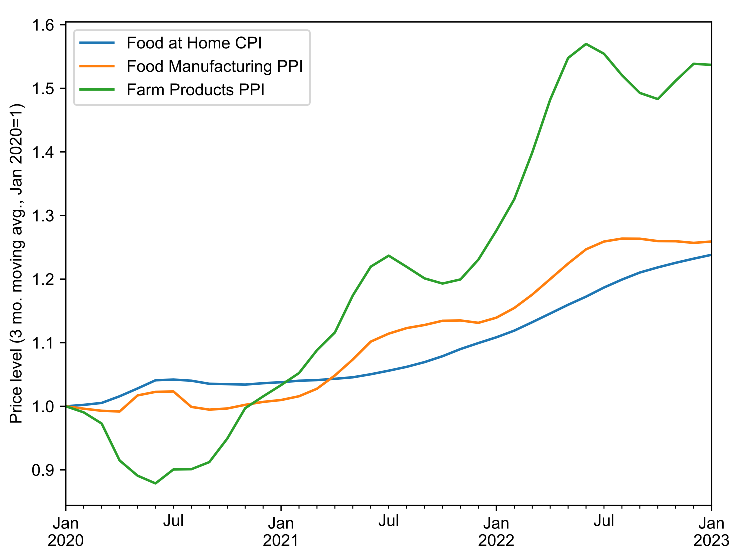
Figure A16: Differences by income decile: Sensitivity of food-at-home inflation to upstream PPI and variance of food-at-home inflation rates.



(a) Pass-through of Food Manufacturing PPI.

(b) Variance of inflation rates.

Figure A17: Price growth for food-at-home CPI, Farm Products PPI, and Farm Manufacturing PPI from January 2020 to January 2023.



Appendix B Proofs

B.1 Proofs for pass-through under relaxed assumptions

Let us consider how prices change (in levels) with a change in the commodity cost. Starting with a markup pricing rule,

$$p = \mu \times mc,$$

where mc is marginal cost, we totally differentiate with respect to the commodity cost c to get:

$$\begin{aligned}\frac{dp}{dc} &= \frac{d\mu}{dp}\frac{dp}{dmc}\frac{dmc}{dc} \times mc + \mu \times \frac{dmc}{dc} \\ &= \mu\left[\frac{d\log\mu}{d\log p}\frac{d\log p}{d\log mc} + 1\right]\frac{dmc}{dc}.\end{aligned}$$

Using the identity $d\log p = d\log\mu + d\log mc$, we simplify to get

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

In my most flexible generalization, changes in marginal cost in response to changes in the commodity cost can come about from three channels: (1) direct effects, (2) correlation between changes in the commodity cost and costs of the other variable input, and (3) non-constant returns to scale. Writing this out:

$$\frac{dp}{dc} = \mu\left[\frac{1}{1-\frac{d\log\mu}{d\log p}}\right]\left[\underbrace{\frac{\partial mc}{\partial c}}_{(1)} + \underbrace{\frac{\partial mc}{\partial w}\frac{dw}{dc}}_{(2)} + \underbrace{\frac{\partial mc}{\partial y}\frac{dy}{dp}\frac{dp}{dc}}_{(3)}\right].$$

Solving for the fixed point in dp/dc yields,

$$\frac{dp}{dc} = \frac{\mu}{1-\frac{d\log\mu}{d\log p}+\sigma\frac{\partial\log mc}{\partial\log y}}\left(\frac{\partial mc}{\partial c} + \frac{\partial mc}{\partial w}\frac{dw}{dc}\right).$$

Let us assume that the markup is set using the Lerner pricing rule, $\mu = \sigma/(\sigma - 1)$. Then, we finally get

$$dp = \underbrace{\frac{\mu}{1 + \frac{1}{\sigma-1}\frac{d\log\sigma}{d\log p} + \sigma\frac{\partial\log mc}{\partial\log y}}\left(\frac{\partial mc}{\partial c} + \frac{\partial mc}{\partial w}\frac{dw}{dc}\right)}_{\text{Pass-through in levels}} dc.$$

The bracketed expression is the pass-through in levels, which is equal to one under complete pass-through in levels. We can see that relative to baseline case considered in the main text (constant returns to scale, constant elasticity of demand, uncorrelated costs, and Leontief production), a positive super-elasticity of demand or decreasing returns to scale each lead to a decline in pass-through in levels, while a positive correlation between the commodity cost and other non-commodity inputs results in an increase in pass-through in levels.

How marginal costs change with the commodity price, the non-commodity input's price, and scale requires writing down a production function for output. I consider the generalized production function,

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

where y is total output, x and ℓ are commodity and other variable inputs, θ is the elasticity of substitution between the commodity and the other variable input, ω are weights on the usage of the two inputs, and α determines returns to scale in use of the non-commodity input.

To consider how relaxing the assumptions in the main text affect pass-through in levels, I consider the following in turns: (1) a non-zero super-elasticity of demand $\frac{d\log\sigma}{d\log p} \neq 0$, (2) non-Leontief production ($\theta \neq 0$), (3) correlated costs ($\frac{dw}{dc} \neq 0$), and (4) decreasing returns to scale $\alpha < 1$.

Super-elasticity of demand. When the super-elasticity of demand is non-zero (but all other baseline assumptions hold), we get:

$$\begin{aligned} dp &= \frac{\mu}{1 + \frac{1}{\sigma-1}\frac{d\log\sigma}{d\log p}} dc \\ &= \frac{\sigma}{\sigma - 1 + \frac{d\log\sigma}{d\log p}} dc. \end{aligned}$$

To get complete pass-through in levels, it is clear that we need $\frac{d \log \sigma}{d \log p} = 1$. This possibility is investigated empirically in the main text. A number of previous papers note that semilog demand curves ($\log y = -\alpha p + C$) yield complete pass-through in levels (Bulow and Pfleiderer 1983; Weyl and Fabinger 2013; Mrázová and Neary 2017). To see this, note that the elasticity of demand under semilog demand curves is

$$\sigma = -\frac{d \log y}{d \log p} = \alpha p,$$

and hence $\frac{d \log \sigma}{d \log p} = 1$.

Non-Leontief production. Suppose $\theta \neq 0$. Then, we find

$$dp = \mu \left(\frac{\partial mc}{\partial c} \right) dc = \mu \left(\frac{c}{\omega C} \right)^{-\theta} dc.$$

For complete pass-through in levels, we must have

$$\theta = \frac{\log \mu}{\log \frac{c}{\omega C}},$$

which cannot hold always, since the ratio c/C changes with fluctuations in the commodity cost c.

Correlated costs. Suppose $\frac{dw}{dc} \neq 0$. Then, we find

$$dp = \mu \left(1 + \frac{dw}{dc} \right) dc.$$

Complete pass-through in levels requires

$$\frac{dw}{dc} = \frac{1 - \mu}{\mu} = -\frac{1}{\sigma}.$$

This is unlikely to explain complete pass-through in levels across products or markets, since elasticities of demand for products within a market tend to exhibit considerable variation. Moreover, in most environments we expect input costs to be positively correlated. For example, in the market for retail gasoline, other variable inputs like shipping/transportation costs are likely to be increasing in the cost of gas.

Decreasing returns to scale. Suppose $\alpha < 1$. Pass-through in levels is then

$$dp = \frac{\mu}{1 + \sigma \frac{\partial \log mc}{\partial \log y}} dc,$$

which means that complete pass-through in levels requires

$$\frac{\partial \log mc}{\partial \log y} = \frac{\mu - 1}{\sigma} > 0.$$

In terms of production function primitives, the elasticity of marginal costs to output is

$$\frac{\partial \log mc}{\partial \log y} = \left(\frac{1-\alpha}{\alpha}\right) \frac{w \frac{1}{\alpha} y^{\frac{1-\alpha}{\alpha}}}{c + w \frac{1}{\alpha} y^{\frac{1-\alpha}{\alpha}}}.$$

It is clear that we need $\alpha < 1$, or decreasing returns to scale, to generate $\frac{\partial \log mc}{\partial \log y} > 0$. Note however that the elasticity of marginal costs to output depends on the commodity cost c and the level of output y. It is not possible to choose α so that $\frac{\partial \log mc}{\partial \log y}$ is positive and constant as the commodity cost c fluctuates.

B.2 Proofs for safety margin model

The firm maximization problem is

$$\max_p \mathbb{E}\left[\pi(p)\right],$$

where profits are

$$\pi(p) = (p - c - w)\, D(p) - f_o N^{-\zeta}., \qquad \text{and} \qquad D\left(p_t\right) = \varepsilon \frac{1}{N} \left(\frac{p}{P}\right)^{-\sigma},$$

subject to the safety margin constraint

$$\Pr\left[\pi(p) \leq 0\right] \leq \phi, \qquad \forall c, w, f_o.$$

Dixit Stiglitz equilibrium. Solving the first order condition yields the optimal price when the constraint does not bind,

$$p_t^{\text{DS}} = \frac{\sigma}{\sigma - 1} \left(c_t + w_t\right).$$

Plugging this into the expression for profits above, firms' expected profits are

$$\mathbb{E}\pi(p_t) = \frac{1}{\sigma - 1}(c_t + w_t)\frac{1}{N_t^{\text{DS}}} - w_t f_o \left(\frac{1}{N_t^{\text{DS}}}\right)^{\zeta}.$$

With free entry, discounted expected future profits equal the cost of entry $w_t f_e$. That is,

$$\mathbb{E}_t \sum_{k=0}^{\infty} \beta^k \pi_{t+k} = w_t f_e.$$

Plugging in the expression for profits, we get:

$$\mathbb{E}_t \sum_{k=0}^{\infty} \frac{w_{t+k}}{w_t}\beta^k \left[\frac{1}{\sigma - 1}\left(\frac{c_{t+k}}{w_{t+k}} + 1\right)\frac{1}{N_{t+k}^{\text{DS}}} - f_o\left(\frac{1}{N_{t+k}^{\text{DS}}}\right)^{\zeta}\right] = f_e.$$

Using the assumption that wages are expected to grow at a constant rate g and that the ratio of the commodity cost to the wage c_t/w_t is a random walk with zero drift, we can see that one solution to this equation is to set

$$\frac{1}{\sigma - 1}\left(\frac{c_t}{w_t} + 1\right)\frac{1}{N_t^{\text{DS}}} - f_o\left(\frac{1}{N_t^{\text{DS}}}\right)^{\zeta} = f_e\left[1 - \beta(1+g)\right].$$

Solving, we find that the number of firms satisfies

$$N_t^{\text{DS}} f_e\left[1 - \beta(1+g)\right] + f_o\left(N_t^{\text{DS}}\right)^{1-\zeta} = \frac{1}{\sigma - 1}\left(1 + \frac{c_t}{w_t}\right).$$

By taking the derivative with respect to c_t/w_t, we can see that the number of firms N_t^{DS} increases when the commodity price is high relative to the non-commodity input price:

$$\frac{dN_t^{\text{DS}}}{d\left(\frac{c_t}{w_t}\right)} = \frac{1}{\sigma - 1}\left[f_e\left[1 - \beta(1+g)\right] + f_o\left(N_t^{\text{DS}}\right)^{-\zeta}\right]^{-1} > 0.$$

The gross margin m_t is equal to total sales minus variable costs of goods sold as a fraction of sales, which is

$$m_t^{\text{DS}} = \frac{p_t^{\text{DS}} y_t - (c_t + w_t)y_t}{p_t^{\text{DS}} y_t} = \frac{1}{\sigma}.$$

Equilibrium when the safety constraint binds. When the safety constraint is binding, we have:

$$\Pr\left[\pi(p_t^{\text{safe}}) \leq 0\right] = \phi.$$

Substituting in for profits and rearranging, we get the condition:

$$\Pr\left[\varepsilon \leq \frac{w_t f_o \left(N_t^{\text{safe}}\right)^{1-\zeta}}{p_t^{\text{safe}} - c_t - w_t}\right] = \phi.$$

Let H be the CDF of the demand shock ε, and H^{-1} be its inverse. We get the pricing rule

$$p_t^{\text{safe}} = c_t + w_t + \frac{w_t f_o \left(N_t^{\text{safe}}\right)^{1-\zeta}}{H^{-1}\left(\phi\right)}.$$

As before, we use the free entry condition to solve for N_t^{safe}:

$$\mathbb{E}_t \sum_{k=0}^{\infty} \beta^k \left[(p_{t+k} - c_{t+k} - w_{t+k}) \frac{1}{N_{t+k}^{\text{safe}}} - w_{t+k} f_o \left(N_{t+k}^{\text{safe}}\right)^{-\zeta}\right] = w_t f_e.$$

Solving yields,

$$f_o \left[\frac{1}{H^{-1}\left(\phi\right)} - 1\right] \sum_{k=0}^{\infty} \beta^k \left(1+g\right)^k \left(N_{t+k}^{\text{safe}}\right)^{-\zeta} = f_e.$$

A solution to this equation is $N_{t+k}^{\text{safe}} = N^{\text{safe}}$, where

$$\left(N^{\text{safe}}\right)^{-\zeta} = \frac{\Delta f_e}{f_o} \frac{H^{-1}\left(\phi\right)}{1 - H^{-1}\left(\phi\right)}.$$

Note here that it becomes important to have $\zeta > 0$, since at $\zeta = 0$ it is impossible to satisfy this condition. Solving for the number of firms, we get the constant:

$$N^{\text{safe}} = \left[\frac{f_o}{\Delta f_e} \frac{1 - H^{-1}\left(\phi\right)}{H^{-1}\left(\phi\right)}\right]^{\frac{1}{\zeta}}.$$

Using our expression for the price p_t^{safe}, we find that gross margins decrease in c_t/w_t:

$$m_t^{\text{safe}} = \frac{1}{1 + \left(1 + \frac{c_t}{w_t}\right)\left[\frac{1 - H^{-1}\left(\phi\right)}{\Delta f_e N^{\text{safe}}}\right]}.$$

When does the safety constraint bind? The safety margin constraint binds when the Dixit-Stiglitz pricing rule violates the safety margin constraint.

$$\Pr\left[\pi(p_t^{\mathrm{DS}}) \leq 0\right] \geq \phi.$$

Plugging in our expression for profits in the Dixit-Stiglitz equilibrium and simplifying, we find that the constraint is binding if

$$\Pr\left[\varepsilon \leq \frac{f_o}{f_o + \Delta f_e \left(N_t^{\mathrm{DS}}\right)^{\zeta}}\right] \geq \phi.$$

In the case where $\zeta = 0$, this is simply,

$$\Pr\left[\varepsilon \leq \frac{f_o}{f_o + \Delta f_e}\right] \geq \phi.$$

When $\zeta > 0$, the likelihood that the constraint binds is decreasing in N_t^{DS}, and since N_t^{DS} is increasing in c_t/w_t, is decreasing in c_t/w_t. This monotonicity with respect to c_t/w_t means that there is a single cutoff c^* such that the constraint only binds if $c_t/w_t \leq c^*$.

At the cutoff c^*, the safety margin constraint is exactly binding. We will now explore the comparative static of c^* with respect to exogenous parameters of the model. Using H to denote the CDF of ε, the cutoff c^* satisfies

$$H\left(\frac{f_o}{f_o + \Delta f_e \left(N^{\mathrm{DS}}\left(c^*\right)\right)^{\zeta}}; Var(\varepsilon)\right) = \phi,$$

where $Var(\varepsilon)$ is the variance of ε and indexes the function H. An increase in $Var(\varepsilon)$ increases the mass to the left of any given point, so $\partial H / \partial Var(\varepsilon) > 0$. First, taking the comparative static of c^* with respect to $Var(\varepsilon)$, we find

$$\frac{dc^*}{dVar(\varepsilon)} = \frac{-\frac{\partial H}{\partial Var(\varepsilon)}}{H'\left(x\right)\frac{dx}{dc^*}} > 0.$$

where we use the shorthand $x \equiv \frac{f_o}{f_o + \Delta f_e \left(N^{\mathrm{DS}}(c^*)\right)^{\zeta}}$ and note that $dx/dc^* < 0$. Intuitively, increasing the variance of the demand shock increases the likelihood that the firms' variable profits will fall short of costs, and thus increases the likelihood of the safety constraint binding. Similarly, taking the derivative with respect to ϕ yields,

$$\frac{dc^*}{d\phi} = \frac{1}{H'(x)\frac{dx}{dc^*}} < 0.$$

Intuitively, a manager who is more tolerant of the risk of negative profits (as ϕ increases) is less likely to follow safety pricing.

Taking the comparative static with respect to f_o and Δf_e requires differentiating both the cutoff condition and the condition that pins down the number of firms N_t^{DS}. First, for f_o, differentiating the condition for the number of firms yields,

$$dN_t^{\mathrm{DS}}\left[\Delta f_e + f_o\left(1-\zeta\right)\left(N_t^{\mathrm{DS}}\right)^{-\zeta}\right] = \frac{1}{\sigma-1}dc^* - df_o\left(N_t^{\mathrm{DS}}\right)^{1-\zeta}.$$

Differentiating the cutoff condition yields

$$H'(x)\left(df_o - \frac{f_o}{f_o+\Delta f_e\left(N^{\mathrm{DS}}\left(c^*\right)\right)^{\zeta}}\left[df_o + \Delta f_e\zeta\left(N^{\mathrm{DS}}\right)^{\zeta-1}dN^{\mathrm{DS}}\right]\right) = 0.$$

Combining the two conditions and simplifying yields

$$\left[\frac{\Delta f_e\left(N^{\mathrm{DS}}\left(c^*\right)\right)^{\zeta}}{f_o} + \frac{\zeta\Delta f_e}{\Delta f_e + f_o\left(1-\zeta\right)\left(N_t^{\mathrm{DS}}\right)^{-\zeta}}\right]df_o = \frac{\Delta f_e\zeta\left(N^{\mathrm{DS}}\right)^{\zeta-1}}{\Delta f_e + f_o\left(1-\zeta\right)\left(N_t^{\mathrm{DS}}\right)^{-\zeta}}\left[\frac{1}{\sigma-1}dc^*\right].$$

The coefficients in front of both df_o and dc^* are positive, and hence c^* is increasing in f_o. Intuitively, when overhead costs are high, there is a greater chance that variable profits will not be able to cover the fixed costs of operation, and hence the safety constraint is more likely to bind.

Finally, for Δf_e. Differentiating the condition for the number of firms yields,

$$\left[\Delta f_e + \left(1-\zeta\right)f_o\left(N_t^{\mathrm{DS}}\right)^{-\zeta}\right]dN_t^{\mathrm{DS}} = -N_t^{\mathrm{DS}}d\left(\Delta f_e\right) + \frac{1}{\sigma-1}dc^*.$$

Differentiating the cutoff condition yields

$$d\left(\Delta f_e\right)\left(N^{\mathrm{DS}}\right)^{\zeta} + \zeta\Delta f_e\left(N^{\mathrm{DS}}\right)^{\zeta-1}dN^{\mathrm{DS}} = 0.$$

Combining the two and simplifying, we get

$$\frac{1-\zeta}{\zeta}\frac{\Delta f_e N^{\mathrm{DS}}+f_o\left(N_t^{\mathrm{DS}}\right)^{1-\zeta}}{\Delta f_e}d\left(\Delta f_e\right)=-\frac{1}{\sigma-1}dc^*.$$

Thus, for $\zeta\in(0,1)$, $dc^*/df_e<0$.

Comparing prices and number of firms in the two equilibria. When the constraint binds, how do the safety margin equilibrium prices and number of firms compare to the Dixit-Stiglitz benchmarks? Recall that when the safety margin constraint binds, we have

$$\Pr\left[\varepsilon\leq\frac{f_o}{f_o+\Delta f_e\left(N_t^{\mathrm{DS}}\right)^{\zeta}}\right]\geq\phi.$$

This means

$$H^{-1}\left(\phi\right)\leq\frac{f_o}{f_o+\Delta f_e\left(N_t^{\mathrm{DS}}\right)^{\zeta}}.$$

Rearranging, we get

$$\left(N_t^{\mathrm{DS}}\right)^{\zeta}\leq\frac{f_o}{\Delta f_e}\frac{1-H^{-1}\left(\phi\right)}{H^{-1}\left(\phi\right)}=\left(N^{\mathrm{safe}}\right)^{\zeta}.$$

Hence, $N_t^{\mathrm{DS}}\leq N^{\mathrm{safe}}$. To compare prices in both equilibria, we take the difference

$$\begin{aligned}p_t^{\mathrm{safe}}-p_t^{\mathrm{DS}}&=w_t\left(\frac{f_o\left(N^{\mathrm{safe}}\right)^{1-\zeta}}{H^{-1}\left(\phi\right)}-\frac{1}{\sigma-1}\left(\frac{c_t}{w_t}+1\right)\right)\\&\geq w_t\frac{f_o}{H^{-1}\left(\phi\right)}\left(\left(N^{\mathrm{safe}}\right)^{1-\zeta}-\left(N_t^{\mathrm{DS}}\right)^{1-\zeta}\right)>0.\end{aligned}$$

where in the last line, we used the fact that when the safety constraint binds,

$$\Pr\left[\varepsilon\leq1-\frac{(\sigma-1)\,\Delta f_e}{1+\frac{c_t}{w_t}}N_t^{\mathrm{DS}}\right]\geq\phi,$$

and hence,

$$\frac{1+\frac{c_t}{w_t}}{\sigma-1}\leq\frac{f_o\left(N_t^{\mathrm{DS}}\right)^{1-\zeta}}{H^{-1}\left(\phi\right)}.$$

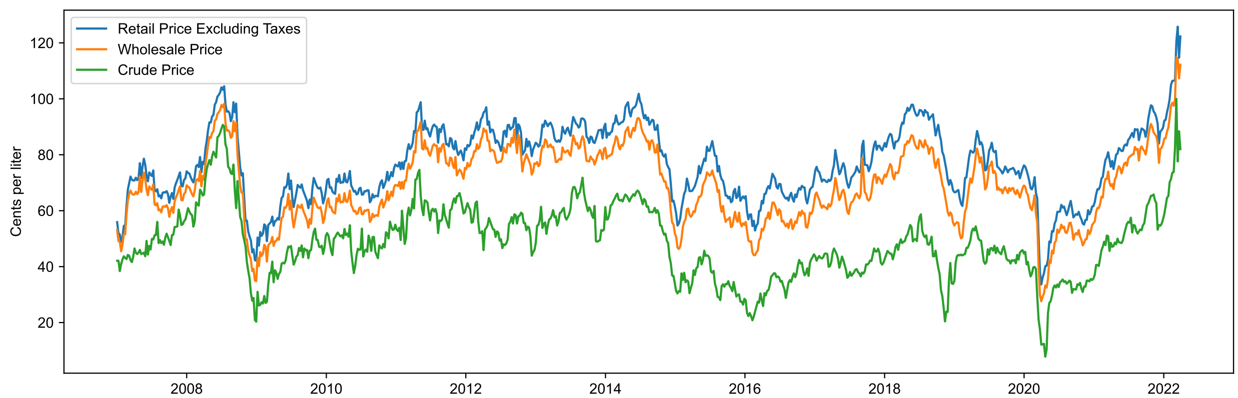
Thus, we conclude $p_t^{\mathrm{safe}}\geq p_t^{\mathrm{DS}}$.

Appendix C Retail Gasoline Evidence from Other Markets

C.1 Canada

I use weekly price data for 71 cities in 10 Canadian provinces provided by Kalibrate solutions.[46] 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. As an example, Figure C1 shows crude oil prices, wholesale prices, and retail prices excluding taxes for the City of Toronto.

Figure C1: Retail (excl. taxes), wholesale, and crude prices for the City of Toronto.



As in the analyses in the main text, I estimate long-run pass-through using a distributed lag regression over a horizon of eight weeks. Figure C2 and Figure C3 plot pass-through from zero to eight weeks estimated in both logs and levels; the long-run pass-through estimates are reported in the main text in Table 4. For both parts of the supply chain, pass-through from costs to prices is complete in levels, though it is incomplete in logs.

C.2 South Korea

I download 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.[47] As far as I am aware, 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 spotty coverage. Hence, for all results using these data, I limit my analyses to stations that have at least 500 daily price observations (i.e., at

[46]Weekly prices can be downloaded from `https://charting.kalibrate.com`.
[47]These data are available for download at `https://www.opinet.co.kr.`

Figure C2: Passthrough of Canadian crude prices to wholesale prices: Levels (top) and logs (bottom).

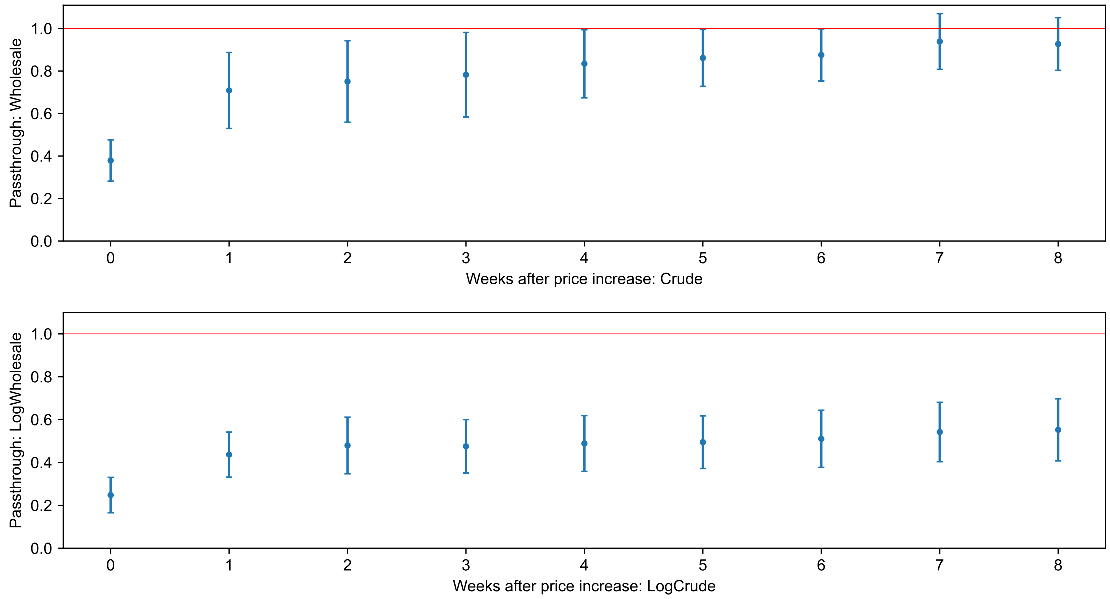


Figure C3: Passthrough of Canadian wholesale prices to retail prices excluding taxes: Levels (top) and logs (bottom).

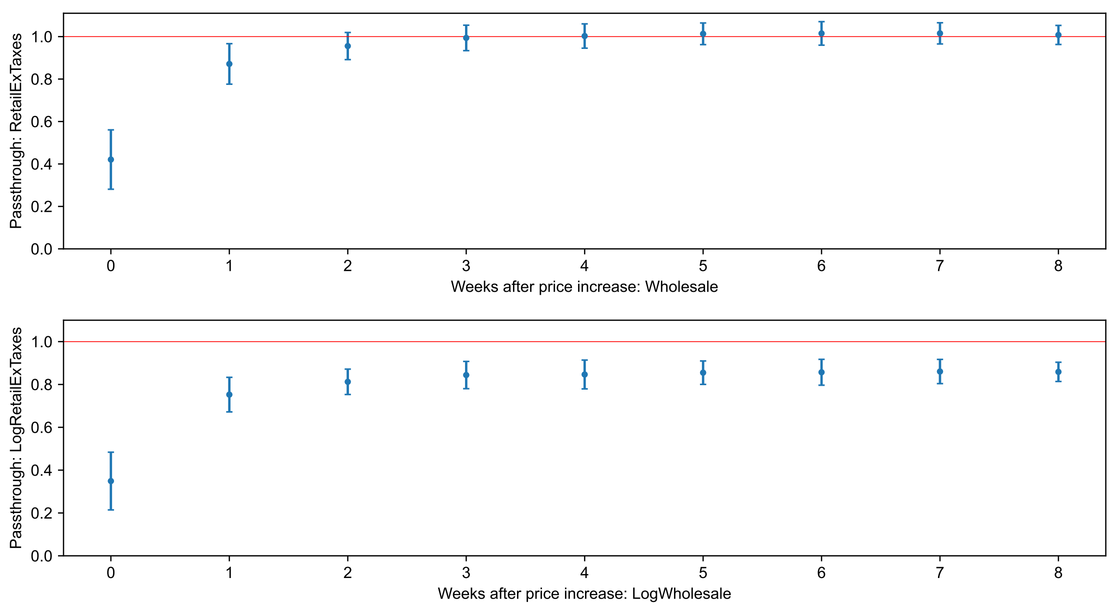
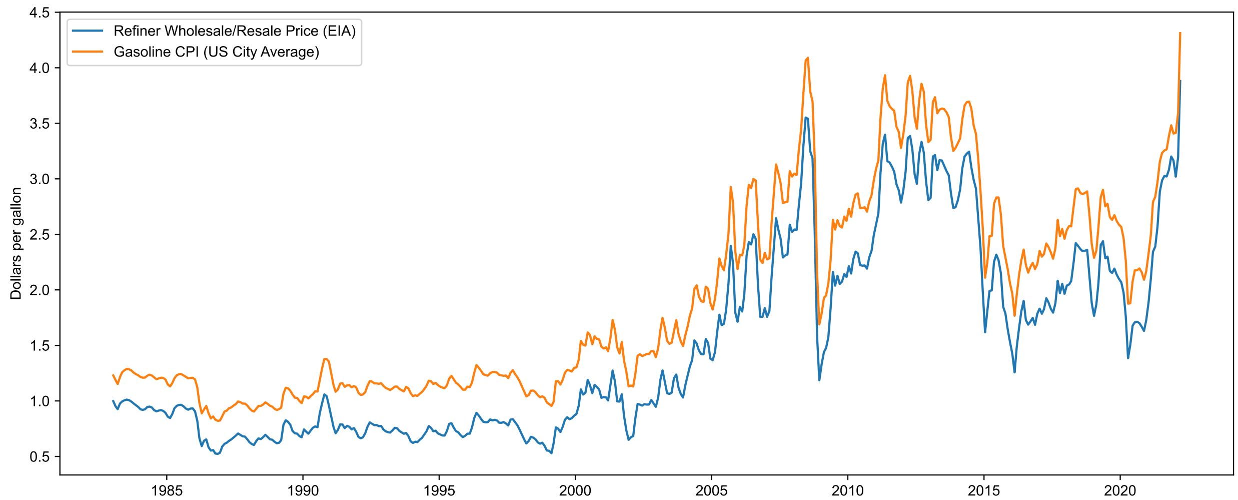


Figure C4: U.S. refiner wholesale/resale prices (EIA) and retail prices (BLS).



Note: Refiner wholesale prices are U.S. refiner gasoline prices for sale through retail outlets from the Energy Information Administration (EIA). Retail gasoline prices are from the BLS Average Price Data for the U.S. city average (Series ID APU000074714).

least 10% of days during the full sample period). Opinet also provides weekly average refinery supply prices, which I use as the measure of costs facing retail stations.

Estimates of the long-run pass-through from this data are reported in the main text in Table 4.

C.3 United States

C.3.1 National Data

National U.S. refinery and retail gasoline prices used in Figure 6 come from two sources: refinery prices are U.S. refiner gasoline prices for sale through retail outlets from the Energy Information Administration (EIA sourcekey EMA_EPMR_PTR_NUS_DPG), and retail prices are from the BLS Average Price Data for the U.S. city average (Series ID APU000074714). Figure C4 plots both time series.

Figure 6 calculates pass-through as the relationship between one-month price changes in refinery and retail prices. Table C1 tabulates estimates of pass-through for alternative horizons (2-, 3-, 6-, and 12-month changes in refinery and retail prices). Pass-through in logs and levels measured at these alternative horizons are nearly identical.

Table C1: Pass-through of U.S. refinery prices to retail prices by horizon (months).

Horizon (months)	Logs	Levels
1	0.742	0.990
2	0.749	0.997
3	0.753	1.001
6	0.755	0.993
12	0.751	0.985

C.3.2 Evidence on Margin Adjustment

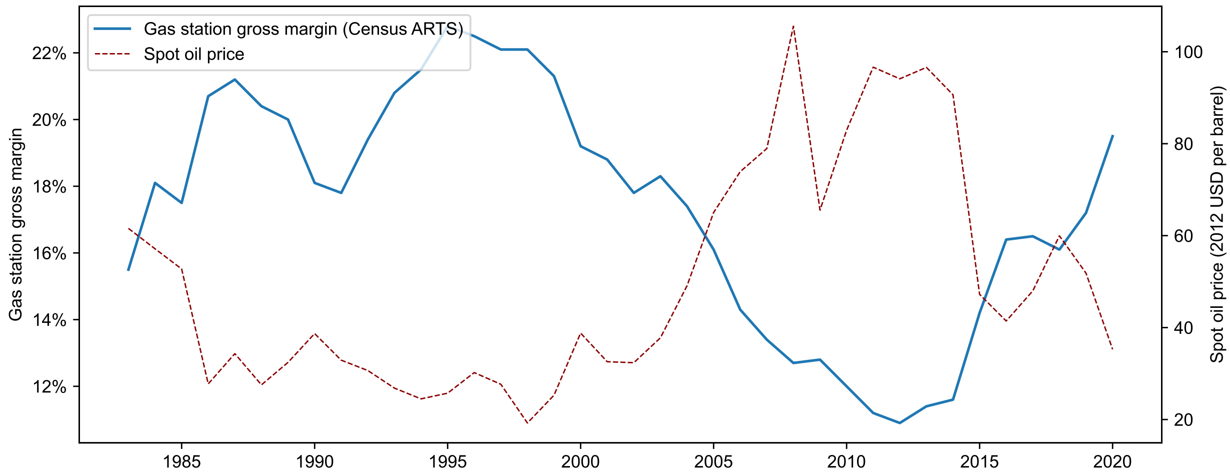
Complete pass-through in levels, and hence the presence of a fixed additive unit margin, implies that (1) margins measured on a percentage basis will be negatively correlated with upstream gasoline prices, and (2) margins measured on a dollars-and-cents basis in the long-run will not be responsive to changes in gasoline prices. This appendix provides evidence for both predictions.

The Census of Annual Retail Trade Statistics collects survey data on gross margins for gas stations on an annual basis from 1983–2020. Figure C5 plots these gross margins alongside the spot oil price. Gas station gross margins, defined as total sales minus total costs of goods sold as a percentage of sales, range between 11 and 23 percent. (Note that these gross margins also include other merchandise sold at convenience stores attached to gas stations, leading to higher margins overall than the margins presumably charged on gasoline alone.) These fluctuations in gross margins appear to closely follow spot gasoline prices; the correlation between the two series is $\rho = -0.93$. Hence, this annual data provides empirical support for the prediction that margins measured on a percentage basis will be negatively correlated with upstream gasoline prices.

To test the second prediction, I use gross margins for refiners and distributors estimated by the California Energy Commission from 1999–2022.[48] The California Energy Commission calculates the gross refiner margin as the wholesale price charged by refiners for a barrel of gasoline minus the cost of the equivalent amount of crude oil from the Alaska North Slope. The distribution margin is calculated as the weekly average retail sales price for branded and unbranded retail outlets minus the average statewide branded or unbranded refined "rack" price, obtained from the Oil Price Information Service (OPIS). Note that both these refiner and distribution margins are gross margins, meaning that they include profits as well as costs of refinery operations or distribution and marketing.

[48]These data are available for download from `https://www.energy.ca.gov/data-reports/energy-almanac/transportation-energy/estimated-gasoline-price-breakdown-and-margins`.

Figure C5: Retail gas station gross margins (Census ARTS) and average spot oil prices, 1983–2020.



Importantly, these margins are measured in dollars-and-cents terms, which allows us to measure pass-through in levels from gasoline cost changes to these margins.

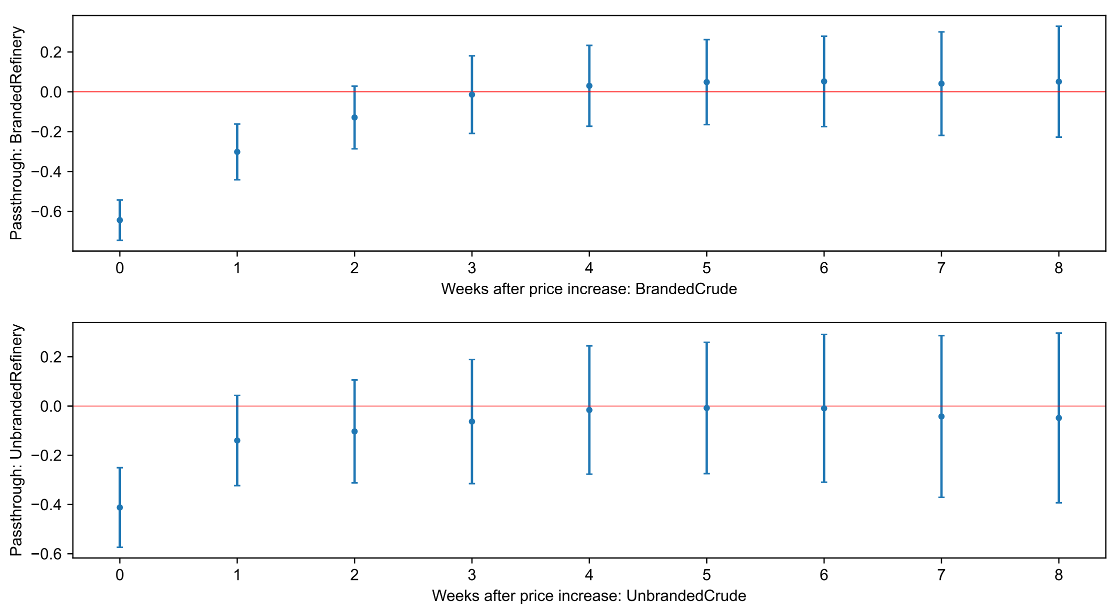
Table C2 reports estimates of the long-run pass-through (at a horizon of eight weeks) from crude costs to refiner margins and from wholesale costs to retail (distribution) margins. In all cases, the long-run impact of cost changes on margins, measured on a dollars-and-cents basis, is statistically indistinguishable from zero. The same is true using Känzig (2021) OPEC announcement shocks to instrument for upstream prices changes. Figure C6 and Figure C7 plot the estimated cumulative pass-through from upstream cost changes to margins.

Table C2: Long-run pass-through of upstream prices to downstream margins using data from California Energy Commission.

	Long-run pass-through (8 weeks)			
	Baseline		IV	
Branded margins				
Crude costs to refiner margin	0.051†	(0.142)	0.004†	(0.237)
Wholesale cost to retail margin	0.047†	(0.045)	-0.208†	(0.111)
Unbranded margins				
Crude costs to refiner margin	-0.048†	(0.176)	-0.005†	(0.328)
Wholesale cost to retail margin	0.013†	(0.048)	-0.281†	(0.158)

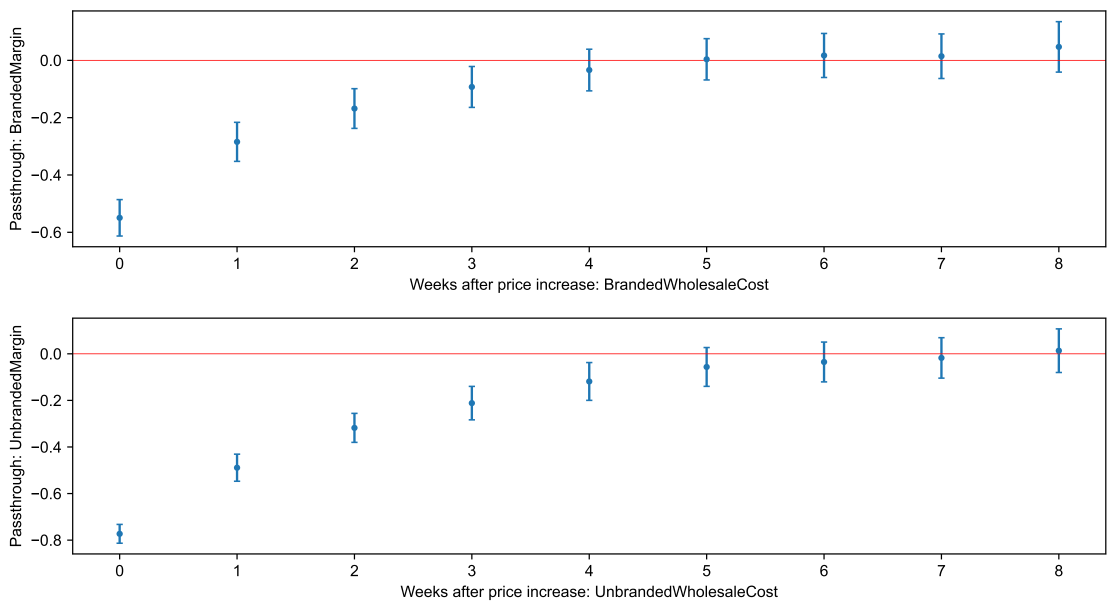
Note: IV columns use oil supply shocks from Känzig (2021). Newey-West standard errors in parentheses. † indicates that the estimate is statistically indistinguishable from zero.

Figure C6: Pass-through of crude costs to branded and unbranded refiner margin. Branded (top) and unbranded (bottom).



Note: Error bars are 95 percent confidence intervals using Newey-West standard errors.

Figure C7: Pass-through of branded and unbranded wholesale costs to branded and unbranded distribution margins. Branded (top) and unbranded (bottom).



Note: Error bars are 95 percent confidence intervals using Newey-West standard errors.

Appendix D Demand Elasticity Estimates

In each product category, I estimate demand elasticities separately for each UPC i at each store s. My baseline specification, which follows closely from DellaVigna and Gentzkow (2019), estimates the response of weekly log quantities to weekly log price, allowing for store-product-year and store-product-week-of-year fixed effects:

$$\log q_{i,s,t} = \eta \log p_{i,s,t} + \kappa(\log p_{i,s,t})^2 + \gamma \log p^{\text{store}}_{s,t} + \delta_{i,s,\text{year}(t)} + \alpha_{i,s,\text{week-of-year}(t)} + \varepsilon_{i,s,t}. \qquad (17)$$

Following DellaVigna and Gentzkow (2019), I address the endogeneity of prices by instrumenting for price of UPC i at store s using the price of i at stores in the same retail chain as s, but outside s's geographic market (DMA).[49] 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. Under the assumption that chain-level variation in prices are unrelated to local demand shocks at a specific store, it also avoids the endogeneity that would attenuate our estimates of the demand elasticity η.

There are two differences between (17) and the estimating equation in DellaVigna and Gentzkow (2019). First, (17) adds the squared log price, $(\log p_{i,s,t})^2$, as an additional independent variable. This follows Burya and Mishra (2023), who show that the super-elasticity of demand is identified by κ/η. Note that I use the Hausman (1996) instrument described above and its square to instrument for both log prices and squared log prices when estimating (17). Second, I also add the log average unit price in i's product category, $\log p^{\text{store}}_{s,t}$. This addition is made to reflect the fact that many models of log-concave demand curves consider how the elasticity of demand for a product changes as the product's price deviates from the average across other products. Nevertheless, I find in practice that results from estimating (17) are very similar whether or not we control for the average store price.

Appendix E Evidence from Other Food Products

In this appendix, I document complete pass-through in levels in two additional datasets on food product markets. First, I explore pass-through in the beef and pork markets using aggregate price data from the USDA. The advantage of these data is that they document prices at the farm, wholesale, and retail levels, allowing me to explore how pass-through

[49]DMAs (designated market areas) are large, non-overlapping geographic regions defined by Nielsen that typically include several counties.

behavior varies between farm to wholesale prices and wholesale to retail prices. In both parts of the market, I find evidence of complete pass-through in levels.

Second, I explore pass-through of corn farm prices to the prices of downstream products, such as corn starch, high-fructose corn syrup, and dextrose. I find that products that have a lower cost share of corn exhibit slower pass-through, but appear to converge to complete pass-through in levels at long horizons.

E.1 Beef and pork, from farm to retail

In this section, I use monthly data compiled by the US Department of Agriculture (USDA) on average farm, wholesale, and retail prices for beef and pork.[50] The USDA collects these retail prices from the Bureau of Labor Statistics and farm and wholesale prices from Agricultural Marketing Service reports. Figure E1 plots the time series of beef and pork farm, wholesale, and retail prices. For both beef and pork, there is a growing gap over time between wholesale and retail prices. The USDA also includes an additional price series for fresh retail beef products.

Table E1 documents the long-run pass-through (at a horizon of 12 months) of upstream beef and pork prices to downstream prices at various links in the chain from farm price to retail price. Across nearly all links, the estimated pass-through in levels is statistically indistinguishable from one, while the estimated log pass-through is always significantly less than one. The dynamics of pass-through for beef and pork products are shown in Figure E2 and Figure E3. In both cases, pass-through occurs slowly but converges to complete at around six months.

E.2 Corn downstream products

In this section, I use monthly data on the price of corn and downstream products from the USDA's Feed Grains Outlook. Table E2 lists the time series available from the USDA: in addition to the farm price of corn, the USDA reports the price of corn at nine corn markets across the US and monthly prices for six downstream products.

When considering the pass-through of corn farm prices to downstream products, it is important to take into account that manufacturing corn syrup and other downstream products from corn through the wet milling process produces byproducts—corn gluten feed and corn gluten meal—that are sold as feed for livestock. Hence, the commodity cost

[50]These data are available for download at `https://www.ers.usda.gov/data-products/meat-price-spreads`. The USDA also tracks a broiler prices, but these are a composite price index that includes several types of poultry.

Figure E1: Beef (top) and pork (bottom) prices over time.

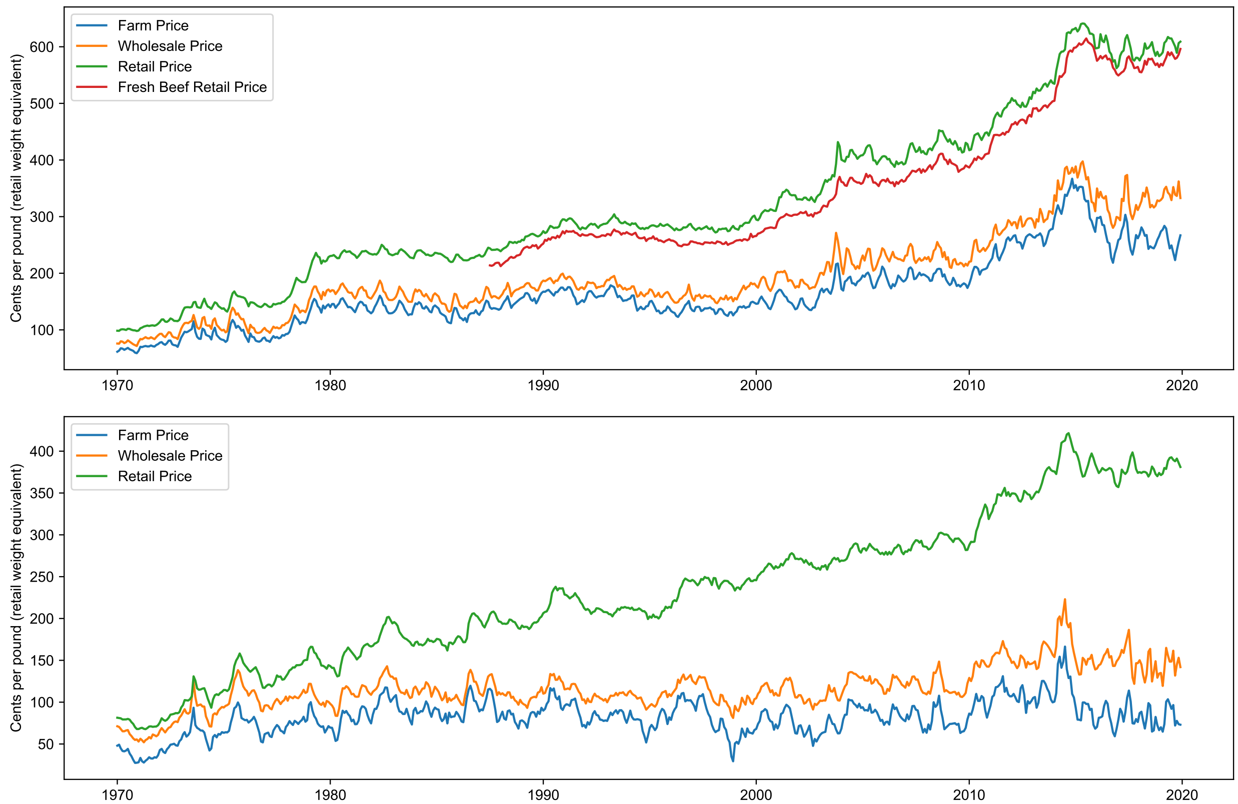
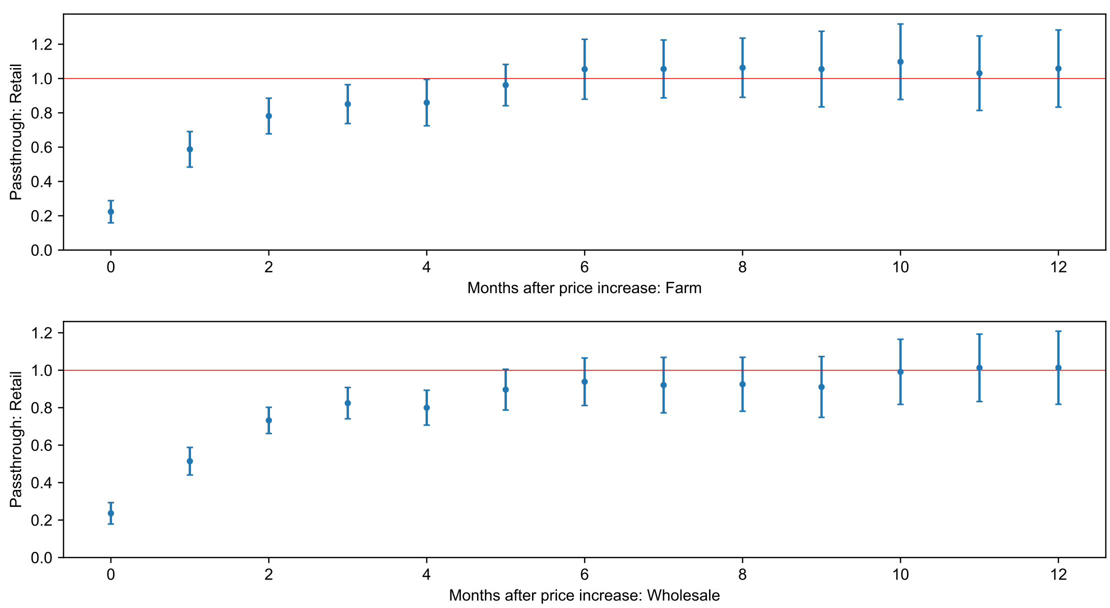
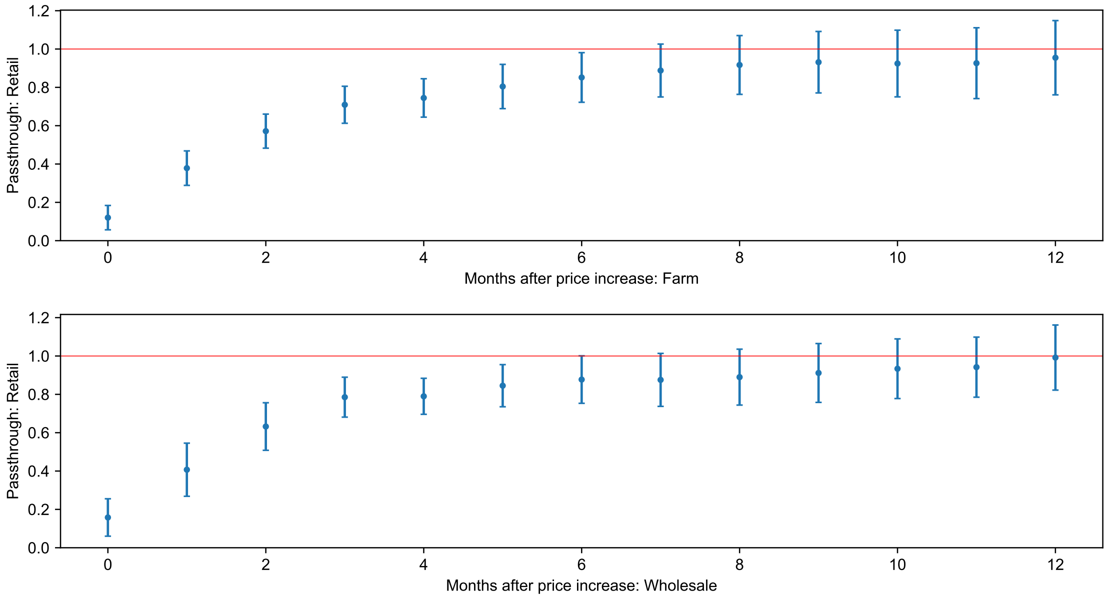


Figure E2: Pass-through of farm (top) and wholesale (bottom) beef prices to retail prices.



Note: Error bars are 95 percent confidence intervals using Newey-West standard errors.

Figure E3: Pass-through of farm (top) and wholesale (bottom) pork prices to retail prices.



Note: Error bars are 95 percent confidence intervals using Newey-West standard errors.

Table E1: Pass-through of beef and pork prices in logs and levels.

Description	Pass-through (12 mos.) Logs		Levels	
Beef				
Farm price to retail price	0.653	(0.048)	1.058†	(0.115)
Farm price to wholesale price	0.852	(0.031)	0.970†	(0.089)
Farm price to fresh beef retail price	0.547	(0.038)	0.911†	(0.106)
Wholesale price to retail price	0.760	(0.037)	1.013†	(0.100)
Pork				
Farm price to retail price	0.381	(0.058)	0.955†	(0.099)
Farm price to wholesale price	0.550	(0.057)	0.804	(0.063)
Wholesale price to retail price	0.628	(0.071)	0.992†	(0.087)

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 that an estimate is statistically indistinguishable from one.

of corn needs to be adjusted downward to take into account the sale of these byproducts. To do so, I subtract monthly corn gluten feed and corn gluten meal prices (also collected by the USDA) from the corn farm price.

Figure E4 shows time series of the corn farm price, the corn farm price after correcting for byproducts, and four downstream products. Notably, the downstream products exhibit considerable differences in how large the cost of corn is as a share of the product price as well as how sticky the output price appears to be. For example, corn prices constitute a large share of the total price of corn starch and corn meal, two products which exhibit high price flexibility, but a smaller share of the price of corn syrup and dextrose, which both exhibit more rigid prices.

Figure E5 plots the pass-through in levels at the six-month and twelve-month horizons from corn farm prices to corn market prices and downstream corn products. At the six month horizon, pass-through remains incomplete for a number of downstream products, especially those with lower corn cost shares. However, by twelve months, pass-through in levels is indistinguishable from one for the majority of the products.

Figure E6 illustrates how pass-through in levels and in logs varies for these downstream products at different horizons. Pass-through in levels at short horizons is positively correlated with the cost share of corn, but flattens and approaches one for all products at longer time horizons. Meanwhile, log pass-through is strongly correlated with the cost share of corn at all horizons.

Figure E4: Price series for corn and four downstream products.

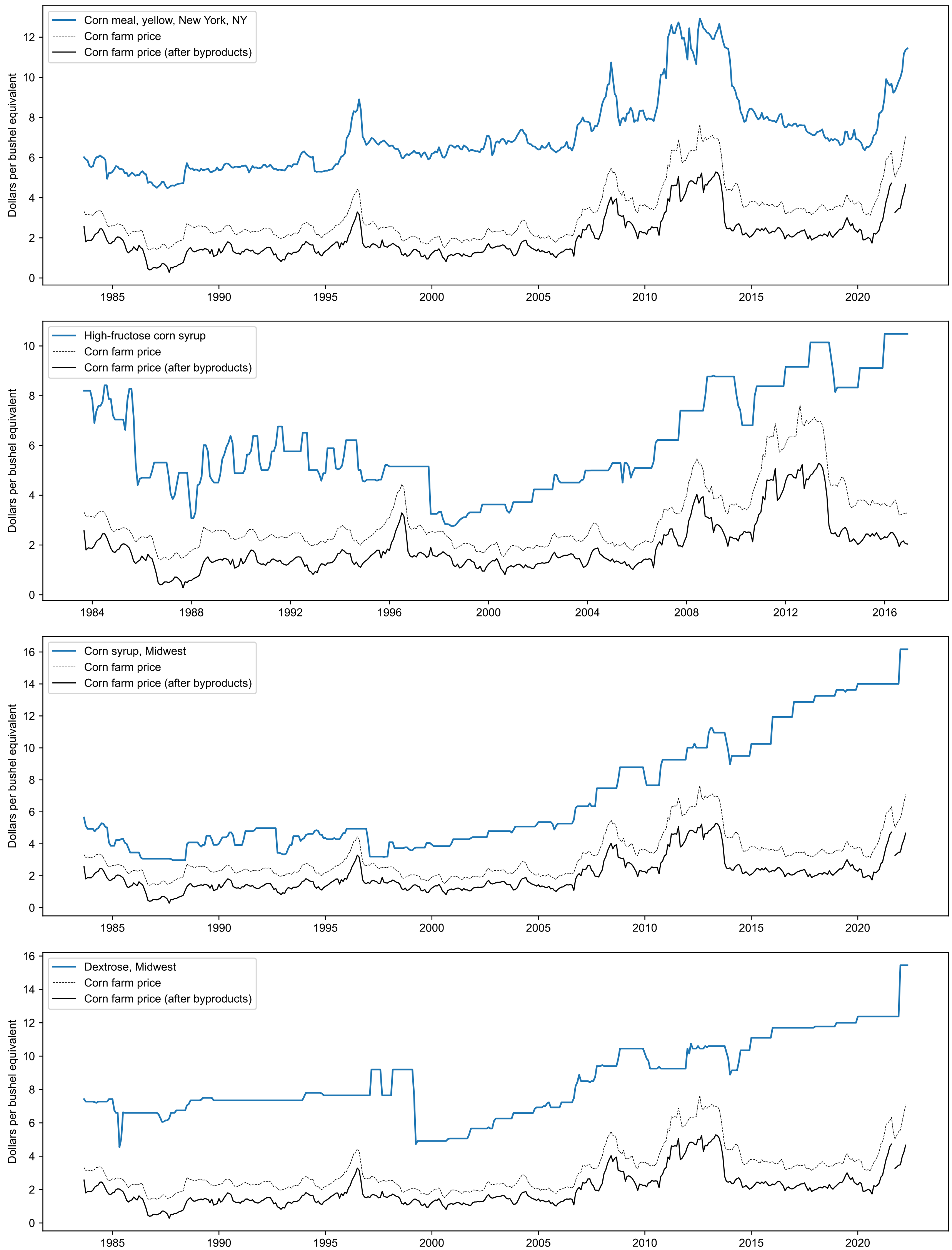


Table E2: Corn and downstream products.

Commodity	Average share of corn (farm price) as % of price
Corn markets:	
No. 2 yellow, Minneapolis, MN	101
No. 2 yellow, Omaha, NE	100
No. 2 yellow, Central IL	99
No. 2 yellow, Toledo, OH	96
No. 2 yellow, Kansas City, MO	95
No. 2 yellow, Chicago, IL	94
No. 2 yellow, St Louis, MO	93
No. 2 yellow, Memphis, TN	91
No. 2 yellow, Gulf ports, LA	85
Corn products:	
Corn starch, Midwest	50
Corn meal, Chicago	33
High-fructose corn syrup	31
Corn syrup, Midwest	31
Corn meal, New York	27
Dextrose, Midwest	23

Figure E5: Pass-through of corn farm price increases in levels.

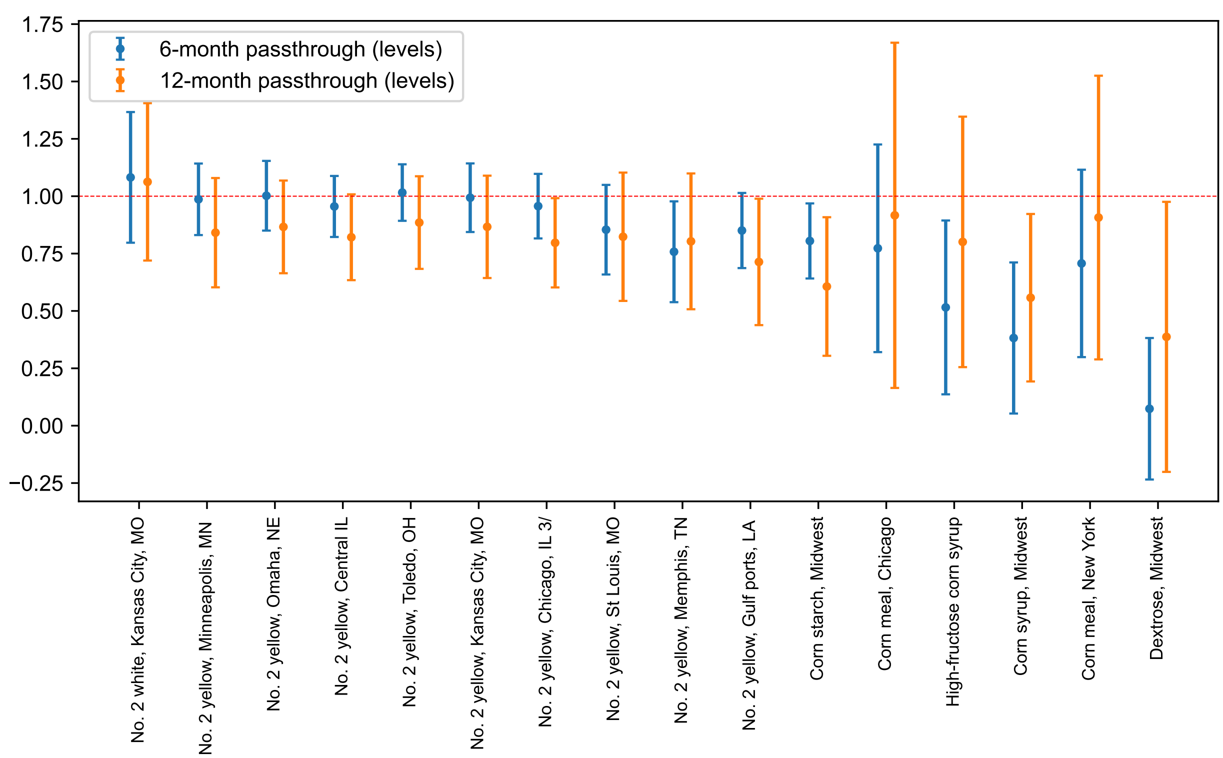


Figure E6: Pass-through of corn farm price to downstream products, in logs and levels.