

Complete Pass-Through in Levels

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May 20, 2025

Abstract

Empirical studies find that the pass-through of input cost changes to prices is incomplete: a 10 percent increase in costs causes downstream prices to rise less than 10 percent, even at long horizons. Using microdata from gas stations, food products, and manufacturing industries, we find that incomplete pass-through in percentages often disguises *complete pass-through in levels*: a \$1/unit increase in input costs leads to \$1/unit higher downstream prices. Pass-through appears incomplete in percentages due to a gap between prices and costs. Complete pass-through in levels contrasts with workhorse macroeconomic models that feature homothetic demand systems. We identify an alternative class of demand systems that yields pass-through in levels and highlight four implications. First, measuring pass-through in percentages can lead to spurious evidence of asymmetry and size-dependence. Second, pass-through in levels can explain dynamics of industry gross margins, operating profits, and entry in the data that are at odds with workhorse models. Third, demand systems that generate pass-through in levels can explain different pass-through rates for labor costs relative to other inputs. Finally, incorporating pass-through in levels into an input-output model of the U.S. economy can reconcile the low volatility of consumer price inflation with microeconomic estimates of markups.

JEL codes: E31, E32, L11.

*Email: ksangani@stanford.edu. I am grateful to David Baqaee, Ariel Burstein, Gideon Bornstein, Jeremy Bulow, Gabriel Chodorow-Reich, Robin Lee, Robbie Minton, Emi Nakamura, Matt Rognlie, Jesse Shapiro, Andrei Shleifer, Ludwig Straub, Adi Sunderam, and to seminar participants at the Society of Economic Dynamics, Federal Reserve Board, Minneapolis Fed, Northwestern, Princeton, San Francisco Fed, and Stanford. 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

Empirical work in macroeconomics and trade typically measures the pass-through of cost changes to prices in percentages. A large body of work studying pass-through in this way finds evidence of *incomplete pass-through*: when input costs rise by 10 percent, downstream prices increase by less than 10 percent (see, e.g., Hellerstein 2008; Nakamura and Zerom 2010; De Loecker, Goldberg, Khandelwal, and Pavcnik 2016). Pass-through remains incomplete even at long horizons and after accounting for the input’s share in variable costs. To account for this evidence, previous work has developed flexible demand systems in which the extent of pass-through is determined by forces such as market power, consumer heterogeneity, and the curvature of consumer preferences (e.g., Atkeson and Burstein 2008; Klenow and Willis 2016; Amiti, Itskhoki, and Konings 2019).

In this paper, we instead measure the pass-through of input costs to downstream prices on an absolute, “dollars-and-cents” basis. We study a set of markets where we can precisely measure this pass-through in levels. Specifically, we study the pass-through of wholesale gasoline costs to retail stations’ prices, the pass-through of food commodity costs to retail food prices, and the pass-through of input costs to output prices for industries spanning the U.S. manufacturing sector.

In nearly all cases, we find that firms exhibit *complete pass-through in levels*: a one dollar per unit increase in input costs leads downstream prices to increase by one dollar. Complete pass-through in levels explains why pass-through measured in percentage terms appears incomplete: when price is greater than marginal cost, a one dollar increase is a smaller percentage change in price than in marginal cost. Thus, complete pass-through in levels implies that the “log pass-through” is incomplete.

Across the markets we study, we find that complete pass-through in levels explains not only the extent of incomplete log pass-through but also the cross-sectional variation in log pass-through across firms and products in a market. In response to a common cost shock, products with a larger gap between prices and input costs have lower log pass-through. These systematic differences in pass-through disappear when pass-through is instead measured in levels.

Complete pass-through in levels poses a challenge for workhorse models in macroeconomics that represent industry demand using homothetic demand systems. Homothetic demand systems are widely used because they impose that the quantity demanded from each firm depends only on its price relative to other firms and total industry sales, making them particularly tractable. However, we show that homothetic demand systems predict that industry-wide cost shocks are passed through completely in logs, rather than in lev-

els. Complete log pass-through in turn implies that the pass-through in levels is equal to firms' gross markups and thus exceeds one.

This result arises because homothetic demand systems satisfy a property that we call *scale invariance*: a proportional change in all firms' prices leaves firms' demand elasticities unchanged. Thus, firms maintain constant percentage markups in response to an industry-wide cost shock. This applies to the standard constant elasticity of substitution (CES) preferences as well as to richer demand systems designed to account for incomplete pass-through, such as Kimball (1995) preferences, nested CES preferences (Atkeson and Burstein 2008), and HSA preferences (Matsuyama and Ushchev 2017). While those richer demand systems can accommodate incomplete pass-through of idiosyncratic shocks that affect only a subset of firms in an industry, they uniformly predict complete log pass-through of common cost shocks, at odds with our evidence of complete pass-through in levels.

We show that firms exhibit complete pass-through in levels of common cost shocks if demand instead satisfies a property that we term *shift invariance*. When demand is shift invariant with respect to the prices of a set of firms, a uniform shift in those firms' prices scales each firm's residual demand curve by a constant factor. As a result, when firms experience a common cost shock, they retain fixed "additive markups"—defined as the absolute gap between price and marginal cost—and pass the cost shock through to prices one-for-one in levels.

While the class of demand systems that satisfies shift invariance excludes homothetic preferences, it encompasses a variety of alternative models. For example, it includes models like the nested logit and mixed logit models, where heterogeneity in firm and consumer attributes generates rich patterns of substitution across firms (e.g., Nevo 2001). It also includes several models of spatial competition, such as the Hotelling (1929) and Salop (1979) models, in which firm market power is derived from the transport costs that consumers incur to visit nearby versus faraway stores. We show that demand systems that satisfy shift invariance can also vary flexibly in their predictions for how firms pass through idiosyncratic cost shocks and can preserve the neutrality of relative prices and quantities to changes in the aggregate price level.

It is worth emphasizing that shift-invariant demand systems generate complete pass-through in levels while maintaining standard assumptions about imperfect competition and the link between firm markups and demand elasticities. Of course, an alternative explanation for complete pass-through in levels is perfect competition. Under perfect competition, price equals marginal cost, and cost changes are reflected one-for-one in prices. Yet, perfect competition is at odds with several other features of the data: sluggish

price adjustment, price dispersion for identical products, finite firm-level demand elasticities, and evidence that firms' prices are elevated over available measures of costs. In other words, while the *dynamics* of prices relative to costs resemble perfect competition, price *levels* indicate some degree of imperfect competition. Shift-invariant demand systems offer a way of reconciling these seemingly conflicting empirical facts.

In the final part of the paper, we propose that complete pass-through in levels can explain several phenomena that are considerably more difficult to explain in standard models with homothetic preferences. We highlight four implications.

First, when pass-through is complete in levels, measuring pass-through in percentages can lead to asymmetry (different pass-through rates for cost increases *vs.* decreases) and size-dependence (different pass-through rates for large *vs.* small shocks), as well as systematic heterogeneity in pass-through by firm size and product quality. These patterns arise from imposing a log specification to measure pass-through when firms exhibit complete pass-through in levels.

Second, pass-through in levels can explain dynamics of industry gross margins, operating margins, and entry in the data that are at odds with workhorse models. In standard models of industry dynamics à la Dixit and Stiglitz (1977), homothetic preferences imply that an increase in input costs leads to higher profits per unit sold, which results in new firm entry or higher operating profits for incumbent firms. Neither of these patterns—swings in firm entry or operating profits—accompanies input cost fluctuations in the data. We show that replacing homothetic preferences with shift-invariant demand systems can bridge this gap between model and data. When demand is shift invariant, a rise in input costs leads gross margins to fall, reducing the degree to which operating profits or entry need to adjust to maintain equilibrium. The response of gross margins to input cost changes across industries confirms these predictions.

Third, a simple model with shift-invariant demand can explain apparent differences in the pass-through of labor and materials costs. Okun (1981) observed that firms seem to pass through materials costs on a “dollars-and-cents basis” but pass through changes in unit labor costs “with a percentage markup.” These observations are difficult to explain in a rational model of firm behavior: why should a cost-minimizing firm treat one component of costs differently from others? We show that a model in which consumers purchase varieties from firms alongside an outside, numeraire good produced with labor can resolve this puzzle. In this setting, the price of labor affects both firms' costs of production and households' marginal value of consumption. Thus, firms exhibit complete pass-through in levels of material costs but complete log pass-through of labor costs, because movements in the price of labor also change firms' desired additive markups. In the data, we show that

accounting for labor’s effect on the numeraire restores complete pass-through in levels for both labor and materials costs.

Finally, we show that pass-through in levels can explain the low volatility of consumer price inflation relative to commodity prices. We calibrate an input-output model of the U.S. economy and compare two cases: one where firms maintain fixed percentage markups, as in standard models, and another where firms have additive markups, consistent with complete pass-through in levels. Given the historical path of commodity prices, consumer price inflation in the model with fixed percentage markups is nearly twice as volatile as in the data. While one could reduce this volatility by expanding the definition of firms’ variable costs, doing so leads to implausibly low markups compared to empirical estimates. In contrast, the model with additive markups naturally matches the volatility of consumer price inflation in the data while allowing for markups consistent with the microeconomic evidence.

The outline of the paper is as follows. Section 2 presents a simple example of pass-through in levels and logs. The following three sections present empirical evidence of complete pass-through in levels: Section 3 measures pass-through in retail gasoline, Section 4 in food product markets, and Section 5 in manufacturing industries. We discuss this evidence and its relationship to prior work in Section 6. Section 7 identifies restrictions on demand that generate pass-through in levels. Section 8 explores implications of pass-through in levels, and Section 9 concludes.

Related literature. This paper relates to a large literature that studies theoretical and empirical determinants of pass-through.¹ We focus on the long-run pass-through of cost shocks that affect all firms in a market. Thus, we abstract from two topics that have generated large empirical literatures: (1) the pass-through of idiosyncratic shocks that only affect some firms in a market, and (2) how rigidities influence the speed of transmission.

While most studies in macroeconomics and trade measure pass-through on a percentage basis, there are several previous papers that measure pass-through in levels in specific contexts, especially in the industrial organization literature. We collect a list of previous studies that measure pass-through in logs and levels in Online Appendix Table A1 and discuss their findings in Section 6. To preview our discussion, we find that the majority of these studies find evidence of complete pass-through in levels. There is some variability in the estimates of pass-through of excise tax changes, with some studies finding evidence

¹See e.g., Weyl and Fabinger (2013), Burstein and Gopinath (2014), Mrázová and Neary (2017), Amiti et al. (2019), and Miravete, Seim, and Thurk (2023, 2025), as well as the list of empirical studies in Online Appendix Table A1.

of over-shifting or under-shifting of tax changes; however, studies that employ a larger sample of tax change events generally find complete pass-through in levels.

Two closely related studies in this literature are Nakamura and Zerom (2010) and Butters, Sacks, and Seo (2022). Nakamura and Zerom (2010) document that retail and wholesale coffee prices move one-for-one with coffee commodity prices in levels. However, the main exercise in Nakamura and Zerom (2010) seeks to account for incomplete log pass-through, which they attribute to non-commodity input costs and adjustment in markups. Butters et al. (2022) study how local cost shocks affect retail stores' prices and find evidence of complete pass-through in levels for various cost shocks, including excise taxes, shipping costs, and regulated commodity prices. We add to this evidence by showing that complete pass-through in levels is not unique to retail stores but holds for a broader range of producers and markets. Studies of gasoline markets also typically measure pass-through in levels rather than in logs (e.g., Karrenbrock 1991; Borenstein, Cameron, and Gilbert 1997; Deltas 2008), but do not explore why complete pass-through in levels is an appropriate benchmark.²

Finally, our characterization of demand systems that generate complete pass-through in levels relates to previous studies that explore the relationship between pass-through and demand. Our definition of shift invariance nests the well-known log-linearity condition on residual demand curves that lead a firm to pass through individual cost shocks in levels (see e.g., Bulow and Pfleiderer 1983, Weyl and Fabinger 2013, Mrázová and Neary 2017). It also nests the linear random utility models defined by McFadden (1981) and Anderson, de Palma, and Thisse (1992). We discuss the relationship between our restrictions and other common models of demand in Section 7.

2 Pass-Through in Logs and Levels: A Simple Example

To begin, we illustrate the differences between complete pass-through in logs and levels in a simple example. Consider a firm that produces an output good using two inputs. We assume that the firm has a constant returns, Leontief production technology, so that the

²For example, 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."

cost of producing y units of the output good is $C(y)$:³

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

where c is the price of the first input (the “commodity”), w is the price of the second input, and units of each input required to produce one unit of the output good are normalized to one. Table 1 shows an example in which $c = \$1$ and $w = \$1$.

In many models, firms’ desired prices p^* are equal to marginal cost times a fixed *percentage markup*, μ :⁴

$$p^* = \mu(c + w). \quad (1)$$

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

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

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

The pass-through in levels of a commodity price change to the firm’s desired price is equal to the markup μ . Typically, in markets with imperfect competition, $\mu > 1$, and so the pricing rule in (1) predicts that pass-through in levels is greater than one.

Table 1 row (1) shows the pass-through of a \$0.20 increase in the commodity price when the firm has a fixed percentage markup. Since a \$0.20 increase in the commodity price increases marginal costs by 10 percent, the output price also rises by 10 percent, or \$0.40. The pass-through in levels is equal to the markup, $\mu = 2$. The “log pass-through” is complete if measured with respect to the percent change in marginal cost (10 percent / 10 percent = 1) or equal to the cost share of the commodity input if measured with respect to the percent change in the commodity cost (10 percent / 20 percent = 0.5).

We contrast the pricing rule in (1) with an alternate pricing rule in which the firm’s gap between output price and marginal cost, measured in dollars and cents, does not change in response to commodity cost changes:

$$p^* = c + w + m. \quad (2)$$

³Constant returns, Leontief production seems appropriate for the markets we study: e.g., producing an ounce of ground coffee requires a fixed amount of coffee beans. In Appendix B.5, we consider how pass-through changes if we relax Leontief production, constant returns to scale, or uncorrelated other variable costs. Each requires knife-edge conditions to deliver complete pass-through in levels.

⁴For example, CES with monopolistic competition predicts fixed percentage markups. Even in many models of variable markups, firms retain fixed percentage markups in response to common cost shocks, as we will see in Section 7.

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

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

We refer to m as a fixed *additive markup*. Under (2), the firm’s desired price instead increases one-for-one with the change in the commodity cost: $\Delta p^* = \Delta c$. As shown in row (2) of Table 1, when the firm has a fixed additive markup, the percent change in the output price appears incomplete relative to the percent change in marginal cost (5 percent *vs.* 10 percent). The percent change in the output price relative to the commodity price is also incomplete relative to the initial cost share of the commodity input (5 percent / 20 percent = 0.25 *vs.* 0.5). In other words, complete pass-through in levels appears as incomplete log pass-through.

3 Evidence from Retail Gasoline

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

This section documents four facts. First, the long-run pass-through in levels of whole-sale costs to retail prices is statistically indistinguishable from one. Second, long-run log pass-through is incomplete even relative to the share of gasoline in stations’ marginal costs. Third, there is little heterogeneity in pass-through in levels across stations in the sample, but substantial variation in log pass-through: stations with a larger gap between prices and costs have lower log pass-through. Fourth, complete pass-through in levels explain both cross-sectional heterogeneity in log pass-through and the overall level of incomplete log pass-through.

3.1 Station-Level Data from Perth, Australia

We use station-level retail gasoline price data 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 report planned petrol prices by 2pm of the prior day. Since 2003, FuelWatch has also provided data on daily spot prices for wholesale gasoline, called the terminal gas price, across six terminals used by retail stations. Previous studies using these data include Wang (2009) and Byrne and de Roos (2017, 2019, 2022).

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

3.2 Empirical Results

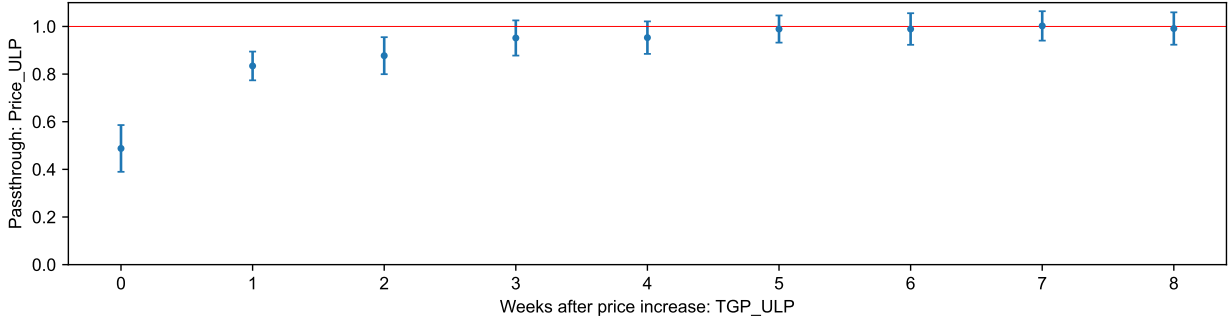
Complete pass-through in levels. We begin by measuring the pass-through in levels of wholesale gasoline costs to retail stations' prices. To measure the long-run pass-through of cost changes to prices, we estimate the distributed lag regression

$$\Delta p_{it} = \sum_{k=0}^K b_k \Delta c_{t-k} + a_i + \epsilon_{it}, \quad (3)$$

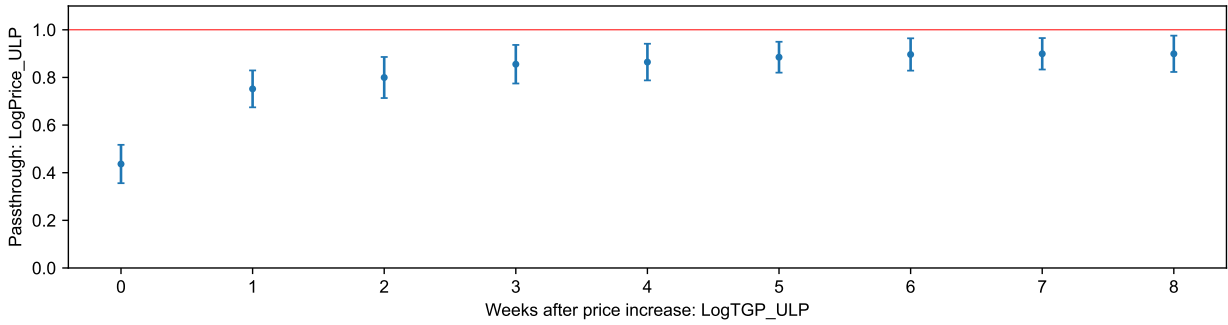
where Δp_{it} is the change in station i 's retail price from week $t-1$ to t , Δc_{t-k} is the change in the input cost from $t-k-1$ to $t-k$, a_i are station fixed effects, and ϵ_{it} is a mean zero error term. The coefficients b_k measure the change in the output price associated with a change in input costs k periods ago. Accordingly, the long-run pass-through of a change in the input cost Δc to prices is given by the sum of the coefficients, $\sum_{k=0}^K b_k$. This specification is standard for measuring the long-run pass-through of cost changes to prices (e.g., Campa and Goldberg 2005, Nakamura and Zerom 2010), though we measure both price and cost changes in levels rather than in logs.

Our use of specification (3) is due to the fact that, as in Campa and Goldberg (2005)

Figure 1: Pass-through of unleaded petrol wholesale costs to prices in levels and logs.



(a) Pass-through in levels.



(b) Pass-through in logs.

Note: Panels (a) and (b) show cumulative pass-through estimated from specifications (3) and (4). Standard errors are two-way clustered by postcode and year, and standard errors for cumulative pass-through coefficients $\sum_{k=0}^t b_k$ and $\sum_{k=0}^t \beta_k$ are computed using the delta method.

and Nakamura and Zerom (2010), our regressors are highly persistent. As we show in Appendix Table A2, autocorrelation coefficients for wholesale gasoline prices (and each of the other commodity price series we study) are very close to one, and we are unable to reject the hypothesis of a unit root in input prices using an Augmented Dickey-Fuller test.⁵ While commodity prices are approximately unit root, they appear stationary in first-differences, enabling correct inference in (3). We also check in Appendix Table A3 that the direction of causality runs from upstream input costs to downstream prices and not vice versa, using Granger causality tests. In all cases, we do not find evidence that downstream prices Granger-cause upstream commodity prices.

Figure 1 shows the estimated pass-through of changes in unleaded petrol (ULP) whole-

⁵We show formally in Appendix Proposition B1 that in a model with time-dependent pricing frictions, if firms have fixed percentage markups μ , the long-run pass-through $\sum_{k=1}^K b_k = \mu$ as K becomes large and the persistence of the commodity cost $\rho \rightarrow 1$. Even if commodity prices are not exactly unit root, under reasonable parameters (e.g., firms reset prices every 12 periods, and $\rho = 0.96$, which is the minimum autocorrelation in Appendix Table A2), the bias in the measure of μ is small.

sale prices to station retail prices over a horizon of eight weeks. By three weeks, the pass-through in levels is statistically indistinguishable from one, and the point estimate for long-run pass-through at eight weeks is 0.991 (standard error 0.038). Estimates of the pass-through of premium unleaded (PULP) wholesale prices to retail prices (Appendix Figure A2) are similar: the long-run pass-through in levels is 0.985 (0.036) and is statistically indistinguishable from one. Further increasing the horizon over which pass-through is estimated has little effect on the estimated long-run pass-through.

Incomplete log pass-through. For comparison with previous studies that measure pass-through using percentage changes in input costs and prices, we estimate the long-run “log pass-through” using the specification,

$$\Delta \log p_{it} = \sum_{k=0}^K \beta_k \Delta \log c_{t-k} + \alpha_i + \epsilon_{it}. \quad (4)$$

The long-run log pass-through is given by the sum of the coefficients, $\sum_{k=0}^K \beta_k$. The lower panel of Figure 1 shows that log pass-through of unleaded petrol (ULP) costs to retail prices at eight weeks is 0.899 (0.043) and is statistically different from one at a 1 percent level. The log pass-through of premium unleaded (PULP) wholesale costs to retail prices is likewise significantly below one at 0.887 (0.041) (see Appendix Figure A2).

One reason that log pass-through may be incomplete is the presence of other variable costs besides gasoline. When stations have fixed percentage markups, the log pass-through of changes in the wholesale gasoline cost should equal the share of stations’ marginal costs spent on gasoline. As previously documented by Byrne and de Roos (2019), retail prices in the Perth market follow weekly price cycles, jumping on Tuesdays or Thursdays and then falling over the course of the week. Under the assumption that gas stations never set prices below marginal cost,⁶ we can use the days of the week at the lowest point of the price cycle to calculate an upper bound on the share of other variable costs in stations’ marginal costs, and thus a lower bound for the cost share of gasoline. Averaging across all weeks and all stations, we find a lower bound for the cost share of gasoline of 0.98 for unleaded petrol and 0.96 for premium unleaded petrol. The estimated log pass-throughs, at 0.899 and 0.887, are significantly different from these cost shares at the 1 percent level. Thus, the log pass-through of gasoline costs is incomplete even after accounting for the cost share of gasoline.

⁶This is the case in the Maskin and Tirole (1988) model of price cycles.

Exploiting variation in markups. While our point estimates for pass-through in levels (0.991 and 0.985) are very close to one, they do not rule out low markups that would be plausible in this setting. We further test for whether firms set fixed percentage markups by exploiting cross-sectional and time series variation in markups. If stations set fixed percentage markups, and if some stations have higher markups than others, then the pass-through in levels for high-markup stations should be higher than their low-markup counterparts. We estimate the specification,

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

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

With fixed percentage markups, the coefficient on the interaction term $\beta > 0$. For example, if some stations set a fixed 2 percentage markup and other stations set a fixed 5 percentage markup, pass-through in levels should be 1.05 for the high-markup stations compared to 1.02 for the low-markup stations. On the other hand, if all stations exhibit complete pass-through in levels, the interaction coefficient $\beta \approx 0$. (An analogous intuition applies to time periods where stations charge higher or lower fixed percentage markups.)

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

The second measure instead exploits variation in markups over time: in each quarter t , we construct the average retail price over wholesale cost for all gas stations in Perth, denoted $\text{Avg. Quarter Markup}_t$. To instrument for $\text{Avg. Quarter Markup}_t$, we take advantage of the fact that the emergence of coordinated price cycles in the Perth market was, according to Byrne and de Roos (2019), "unrelated to market primitives." Appendix Figure A3 shows that average gas station margins over time co-move closely with the degree of coordination in price cycles, measured as the R^2 from a regression of daily margins on day-of-week fixed effects. We use this measure of price coordination over

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

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

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

time—the quarterly R^2 of station margins on day-of-week dummies—as an instrument for Avg. Quarter Markup_t.

Table 2 reports the results. Column 1 omits the average markup and interaction term. A \$1 change in the wholesale cost of unleaded petrol (ULP) over 16 weeks is associated with a \$0.95 change in the retail station price over the same period. Columns 2–5 include the interaction of wholesale cost changes with markups, with columns 3 and 5 using the instruments discussed above. In all cases, the estimated coefficient on the interaction term $\beta \approx 0$, consistent with uniform pass-through in levels across stations and time periods. In other words, we find evidence of complete pass-through in levels across stations and across time periods, rejecting the hypothesis of fixed percentage markups.

Pass-through in levels explains heterogeneity 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,⁷

$$\Delta \log p_{it} = \alpha + \delta \Delta \log c_t + \gamma \text{Avg. Markup}_{it} + \beta (\Delta \log c_t \times \text{Avg. Markup}_{it}) + \varepsilon_{it}. \quad (6)$$

Column 1 shows that a 1 percent change in wholesale costs over 16 weeks leads to a

⁷Since Table 2 suggests that stations' markups are “additive,” it may be preferable to estimate specification (6) using a measure of stations' additive markups. We find that doing so yields similar results.

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

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

Note: The table reports the coefficients γ and β estimated using specification (6). Changes in log retail prices and log wholesale costs are taken over 16 weeks. For readability, we include Avg. Markup_{it} on a net % basis (i.e., a markup of 1.1 is a 10% net markup). Column 3 (IV1) uses the average amplitude of stations' price cycles as an instrument for Avg. Station Markup_i. Column 5 (IV2) uses the quarterly R^2 of station margins on day-of-week dummies as an instrument for Avg. Quarter Markup_t. Standard errors two-way clustered by postcode and year.

0.87% change in retail prices, significantly below the cost share of gasoline. Columns 2–5 estimate specification (6), exploiting cross-sectional variation in markups (columns 2–3) or time series variation in markups (columns 4–5) in turn. Two findings emerge. First, higher markups lead to more incomplete log pass-through.⁸ Second, the gap between price and costs appears to fully account for incomplete pass-through: the coefficient on $\Delta \log c_t$ in columns 3 and 5 shows that as net markups approach zero, the log pass-through is tightly estimated around the cost share of 0.98.

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

Robustness. Appendix Table A4 compares pass-through estimates from Perth to estimates from retail gasoline markets in Canada, South Korea, and the United States (Ap-

⁸In fact, complete pass-through in levels predicts that the interaction coefficient in the log specification $\beta \approx -0.01$. If stations set prices $p = c + w + m$, where m is an additive markup, to a first order, $\Delta \log p \approx \chi \mu^{-1} \Delta \log c \approx \chi(1 - 0.01\mu^{\text{net},\%}) \Delta \log c$, where $\chi = c/(c + w)$ is the cost share (0.96–0.98 in the data), $\mu = p/(c + w)$ is the percentage markup, and $\mu^{\text{net},\%} = 100(\mu - 1)$.

pendix C describes the data sources for each). Incomplete log pass-through and complete pass-through in levels appear across all the studied markets. The evidence from other geographies suggests that complete pass-through in levels is not a quirk of the Australian data, but rather describes price dynamics across a number of retail gasoline markets.

One might be concerned that our estimates of pass-through are biased downward due to reverse causality from downstream demand to commodity prices. While the Granger causality tests in Appendix Table A3 suggest that causality primarily runs from upstream commodity prices to downstream retail prices, as an additional check, Appendix Table A4 estimates pass-through using oil supply news shocks from Känzig (2021) to instrument for upstream cost changes. While the instrumented regressions produce somewhat noisier estimates of long-run pass-through in levels and logs, they remain qualitatively consistent with our baseline results.

4 Evidence from Food Products

In this section, we explore the pass-through of commodity costs to retail prices for food products. We are able to measure pass-through in levels for these goods by carefully matching the amount of commodity inputs required to produce each downstream product.

For five out of six staple food products, we find that pass-through in levels is statistically indistinguishable from one. Using scanner data to compare individual products within product categories, we further document that uniform pass-through in levels explains systematic patterns of heterogeneity in log pass-through across products. Finally, extending our analysis to a broader array of food products, we find that prices of identical products sold across retail chains also conform with complete pass-through in levels.

4.1 Data on Food Retail and Commodity Prices

Retail prices. For retail prices of food products, we use Average Price Data from the Bureau of Labor Statistics (BLS). In contrast to the consumer price index data, which reflect relative price changes, the Average Price Data track price levels for a select number of staple products. For each price series, the BLS chooses narrowly defined, homogeneous item categories (e.g., “Orange juice, frozen concentrate, 12 oz. can, per 16 oz.”) to minimize input, quality, and package size differences between included items.

While the BLS Average Price Data allow us to study pass-through of commodity costs to retail prices over a long time series—many of the series record prices back to 1980—studying cross-sectional heterogeneity across products in a category requires richer data.

For these investigations, we use NielsenIQ Retail Scanner data, which includes weekly barcode-level prices and quantities for products sold at participating stores from 2006 to 2020. These data are collected from point-of-sale systems in retail chains operating across the U.S., reflecting over \$2 billion in annual sales.

Commodity costs. We match these 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 commodity price for frozen orange juice concentrate is from next-month futures contracts for the delivery of grade-A frozen concentrated orange juice solids traded on the Intercontinental Exchange (ICE). Appendix Table A5 provides a full list of the commodity price series and the underlying data sources used by the IMF.

Measuring pass-through in levels requires carefully matching units from commodity prices to retail prices. For example, to measure pass-through of wheat commodity prices to retail flour prices requires knowing the quantity of wheat needed per pound of flour produced. To construct these mappings from commodity units to retail units, we rely on previous literature and on documentation from the USDA. Appendix Table A6 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.⁹

Matched products. Of the food products tracked by the BLS Average Price Data, six can be clearly matched to IMF commodity inputs. These are roasted ground coffee, sugar, ground beef, white rice, all-purpose flour, and frozen orange juice concentrate. Appendix Table A6 lists the corresponding Average Price Data series IDs. For three of these products—rice, flour, and coffee—we also investigate cross-sectional pass-through patterns by matching the food product to a NielsenIQ product category.¹⁰

⁹This careful matching of units is why measuring pass-through in levels is difficult for highly differentiated products. The challenges in measuring pass-through in levels, along with the fact that homothetic preferences imply a benchmark of complete log pass-through, are perhaps why pass-through in levels has not been measured across a wide set of markets previously. At the end of the section, we exploit the fact that retailers set different prices for identical products to test for pass-through in levels at the retail level across several other products in the NielsenIQ data.

¹⁰The corresponding NielsenIQ product modules are “Rice - Packaged and bulk,” “Flour - All purpose - White wheat,” and “Ground and whole bean coffee.” Beef products are spread across several modules, and the “Sugar - granulated” and “Fruit juice - orange - frozen” modules have few unique products.

Table 4: Long-run pass-through of commodity costs to retail food prices.

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

Note: Long-run pass-through in levels and logs is $\sum_{k=0}^K b_k$ and $\sum_{k=0}^K \beta_k$ from specifications (3) and (4), using a horizon of $K = 12$ months. For goods with several BLS Average Price series, we report Driscoll-Kraay standard errors; otherwise, we use Newey-West standard errors. [†] indicates estimates for which a pass-through of one is within the 90 percent confidence interval.

4.2 Empirical Results

Nearly all products exhibit complete pass-through in levels. We measure the pass-through of commodity costs to retail prices for each food product in levels and logs using the distributed lag regressions (3) and (4) described in Section 3. As in the case of gasoline, each of the food commodity price series has an autocorrelation coefficient close to one, but appears stationary in first-differences (Appendix Table A2), enabling correct inference with the standard distributed lag specification. We also verify that retail price movements do not predict future changes in upstream commodity prices using Granger causality tests (Appendix Table A3) and by estimating the pass-through of leads of commodity cost changes to retail prices (Appendix Table A7).

Table 4 reports estimates of long-run pass-through in levels and logs from specifications (3) and (4) 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. Note that the pass-through in levels of commodity costs to retail prices is a particularly strict test of fixed percentage markups, because it should detect if any firm along the chain of producers from commodity to retailer sets a gross markup greater than one. Complete pass-through in levels implies log pass-through is incomplete and, as expected, we estimate that the long-run log pass-through is significantly below one for all six food products.

Figure 2 shows an example of the price series and pass-through estimates for roasted ground coffee. As shown in panel (a), Arabica coffee commodity prices exhibit substantial volatility, with large spikes in 1986, 1994, 1997, 2011, and 2014 due largely to weather

conditions in Brazil and Colombia. These run-ups in commodity prices are followed by increases in the retail prices recorded by the BLS. Panel (b) shows the pass-through in levels from coffee commodity prices to retail prices occurs with a lag, but approaches complete pass-through by eight months and stays around one thereafter. The log pass-through, in panel (c), instead plateaus below one-half. These results are consistent with Nakamura and Zerom (2010), who estimate pass-through in the roasted ground coffee market from 2000–2005. Analogous figures for the other five food products are in Appendix A.¹¹

Pass-through in levels explains variation in log pass-through across products. The complete pass-through in levels documented in Table 4 has predictions for price changes in the cross-section of products. First, products that have higher markups and higher non-commodity input costs should exhibit lower log pass-through (as we saw in the cross-section of retail gas stations in Section 3). Second, pass-through in levels should be similar across products regardless of their markups and non-commodity input costs.

To test these predictions, we use NielsenIQ data on rice, flour, and coffee products from 2006 to 2020. We define a product as a specific UPC (universal product code, or product barcode) sold at a specific retail chain, since prices for a UPC tend to be fairly uniform within retail chains (DellaVigna and Gentzkow 2019). In each quarter t , we calculate the price p_{it} of product i as the quantity-weighted average unit price over all transactions. For each product in each quarter, we then measure the change in the product’s price over the next year in levels ($\Delta p_{it} = p_{it+4} - p_{i,t}$) and in logs ($\Delta \log p_{it} = \log p_{it+4} - \log p_{it}$). Since these price changes are measured year over year, they avoid seasonality effects that may bias measures of price changes calculated over smaller time increments.¹²

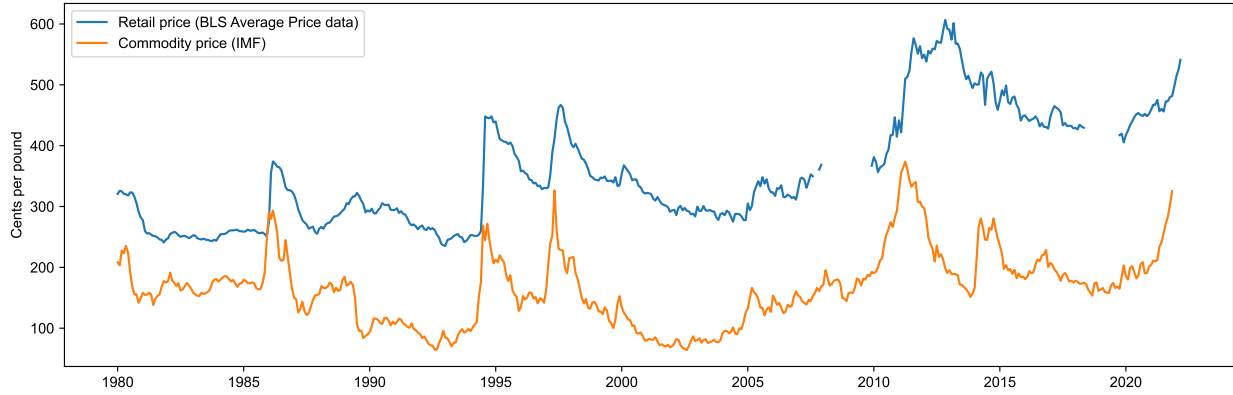
Under the assumption that firms face identical commodity costs, we can use the unit price (e.g., the price per ounce of coffee) as a measure of each product’s non-commodity variable costs and markups. Thus, to test the above predictions for how pass-through in logs and levels varies with the level of non-commodity variable costs and markups, we group products in each product category by unit price in each quarter t . To ensure that these product groups capture persistent differences in unit price, we use products’ average unit prices over the prior year.

As an example, Figure 3 plots average inflation rates and price changes in levels for

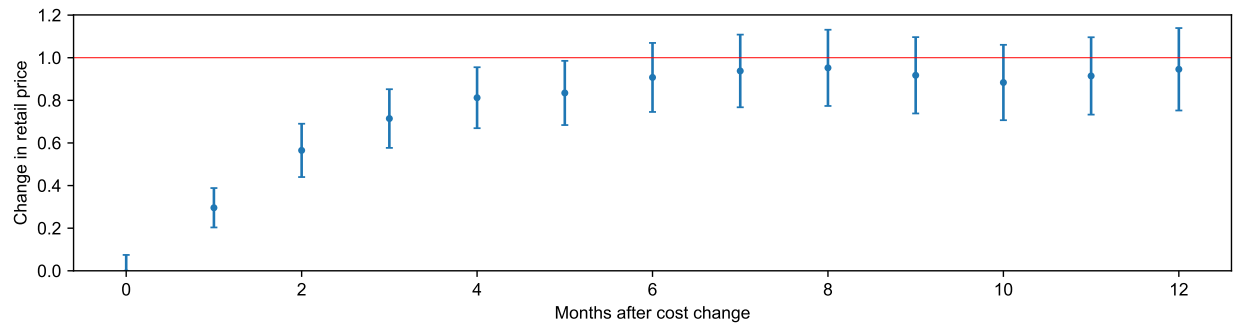
¹¹Appendix Figure A4 shows that the pass-through in levels of coffee commodity cost changes to retail prices is similar using exchange rate shocks and weather shocks to instrument for commodity prices.

¹²Nakamura and Steinsson (2012) point out that using product-level data to measure pass-through may bias measurement when there is frequent product turnover. For these categories, over 75 percent of products in each quarter are observed in the following year, and turnover does not appear correlated with commodity inflation in a way that would downward bias measured pass-through: the correlation of commodity inflation with turnover is -0.03 for rice, -0.09 for flour, and -0.09 for coffee products.

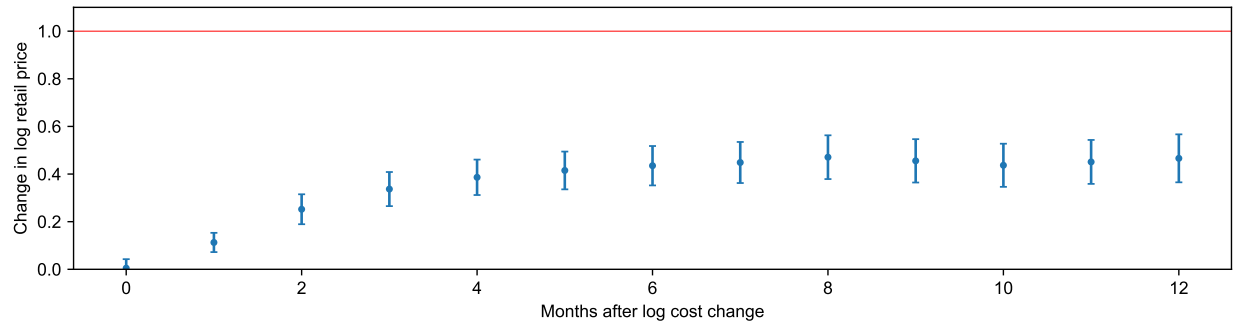
Figure 2: Pass-through of coffee commodity costs to retail prices.



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



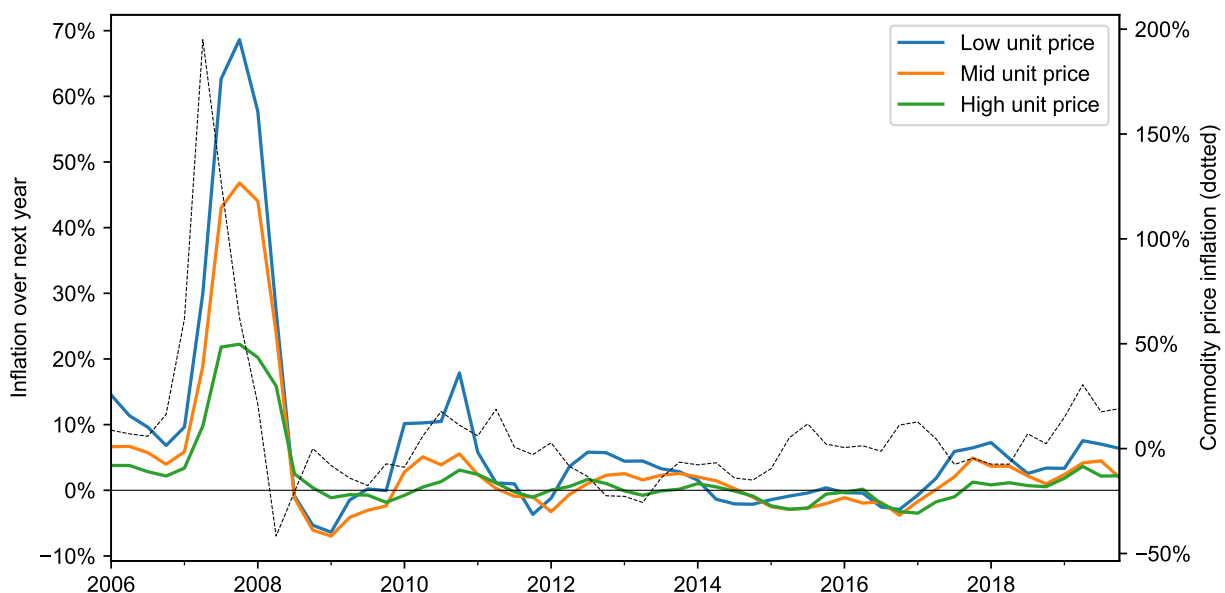
(b) Pass-through in levels.



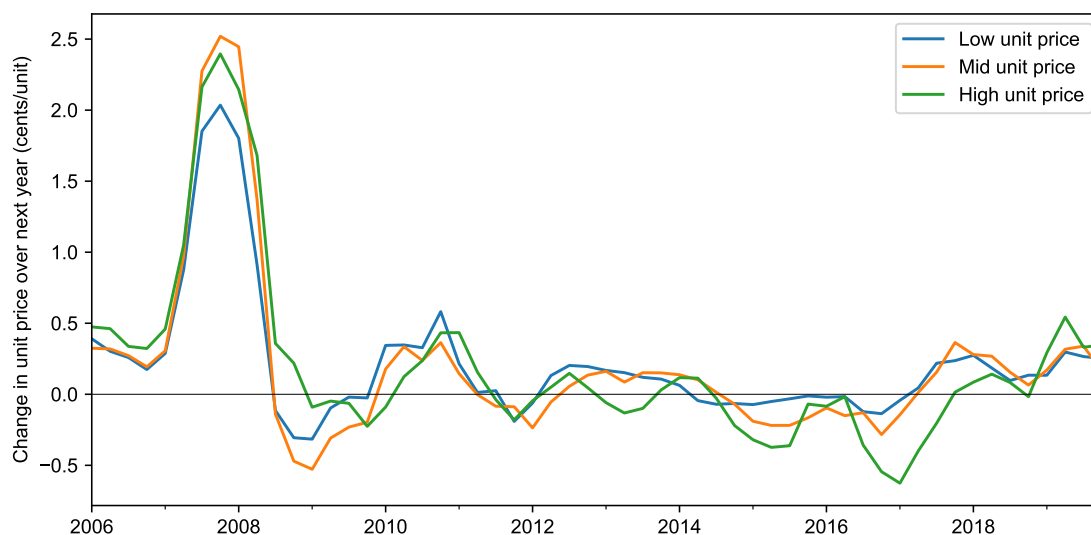
(c) Pass-through in logs.

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 A6 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 (3) and (4), using a total horizon of $K = 12$ months.

Figure 3: Inflation and price changes of rice products by tercile of unit price.



(a) Inflation (in percentages)



(b) Price change (in levels)

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

Table 5: Higher-priced products have lower log pass-through, but no systematic difference in pass-through in levels.

<i>Panel A: In percentages</i>			
	Δ Log Retail Price		
	Rice	Flour	Coffee
Δ Log Commodity Price \times Mid Unit Price	−0.075** (0.014)	−0.007 (0.009)	−0.064** (0.015)
Δ Log Commodity Price \times High Unit Price	−0.150** (0.022)	−0.045** (0.009)	−0.091** (0.017)
UPC FEs	Yes	Yes	Yes
N (thousands)	399.4	101.4	1570.0
R ²	0.15	0.05	0.14
<i>Panel B: In levels</i>			
	Δ Retail Price		
	Rice	Flour	Coffee
Δ Commodity Price \times Mid Unit Price	0.059 (0.052)	0.027 (0.040)	−0.069 (0.046)
Δ Commodity Price \times High Unit Price	0.042 (0.100)	−0.067 (0.044)	−0.099* (0.058)
UPC FEs	Yes	Yes	Yes
N (thousands)	399.4	101.4	1570.0
R ²	0.07	0.05	0.14

Note: Panel A reports results from specification (7), and panel B reports results from specification (8). In each quarter, products are split into three groups with equal sales by average unit price over the past year; the Mid- and High Unit Price variables are indicators for the middle and highest-priced groups. Regressions weighted by sales. Standard errors clustered by brand. * indicates significance at 10%, ** at 5%.

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.¹³ These differences disappear when comparing the price changes in levels in the bottom panel: products in all unit price groups had roughly the same increase in absolute prices.

To formally test how pass-through in logs and levels varies in the cross-section of

¹³The run-up in rice prices was prompted by adverse weather shocks to wheat-growing areas from 2006–2008, and subsequent trade restrictions by Vietnam, India, and other major rice-exporting countries to ensure adequate rice supply for their domestic markets. See Childs and Kiawu (2009) for a detailed account.

products, we estimate the following specifications,

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

$$\Delta p_{it} = \alpha_i + \beta_1 \Delta c_t + \sum_{g=2}^3 \beta_g (1\{G(i, t) = g\} \times \Delta c_t) + \varepsilon_{it}, \quad (8)$$

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

Across product groups, panel A shows that the sensitivity of log retail prices to commodity inflation systematically declines with unit price across all three product categories (rice, flour, and coffee). In contrast, panel B finds little evidence of systematic differences in the sensitivity of retail price changes to commodity price changes *in levels* across unit price groups. Appendix Table A8 shows similar results if we instead split products into five unit price groups.

Thus, evidence from all three categories suggests that products exhibit uniform pass-through in levels of commodity cost changes. This uniform pass-through results in heterogeneous log pass-through rates across products, with lower log pass-through for higher-priced products.

Effects of cost changes on price distributions. A complementary approach is to identify how changes in commodity costs affect the distribution of retail prices across products in a category. Pass-through in levels predicts that increases in commodity costs should have no long-run effect on the dispersion of prices in levels—the price distribution should simply shift to the right—but should reduce the dispersion of log prices.¹⁴ We test these predictions in Appendix Table A9 for rice, flour, and coffee products. We find that an increase in commodity prices has no significant effect on the dispersion of price levels, but leads to a decline in the dispersion of log prices. Thus, the response of retail price distributions to commodity cost changes for these goods is also consistent with complete pass-through in levels across products in each category.

¹⁴In the short run, cost changes may increase price dispersion due to nominal rigidities, which are separate from the effects of cost changes on the long-run price distribution. It is challenging to cleanly isolate the effects of commodity costs on the long-run price distribution from short-run effects on price dispersion. Measuring the long-run pass-through to prices of individual products is comparatively straightforward.

4.3 Pass-Through at the Retail Level: Evidence from Identical Products

So far, we have measured pass-through in levels for specific products by matching input costs to downstream prices. Our next exercise tests for pass-through in levels across a much broader range of product categories, albeit only at the retailer level. We exploit the fact that different retailers often sell the same product at different prices (Kaplan and Menzio 2015). Even without directly observing input costs, we can use price movements of the same product across different retailers to test for pass-through in levels and in logs.

Exploiting variation in prices across retailers. To fix ideas, consider two retail stores selling the same UPC, one at a low price (store A) and one with a high price (store B). As an example, Appendix Figure A10 shows the price of the same coffee UPC at two different stores in Philadelphia. Excluding some temporary sales, store B consistently charges a higher price than store A. If both stores A and B have fixed percentage markups, when the cost of the UPC rises, the price at store B (the retailer with the higher markup) should rise more in levels. On the other hand, if both stores exhibit complete pass-through in levels, when the cost of the UPC rises, the absolute price change in both store A and store B should be similar, and the price change in percentage terms for store B should be lower.

We formalize this logic in Table 6, which predicts how the price of a UPC at retailer i changes in levels and logs, depending on whether retailers set fixed percentage markups or additive markups. The first part of the table shows the pass-through of UPC cost changes to prices in both levels and logs. If retailers have fixed percentage markups, the pass-through is equal to the retailer's markup μ_i in levels and is complete in logs. If retailers have fixed additive markups, the pass-through is instead complete in levels and equal to the ratio of the UPC cost to the retailer's price in logs. The second part of the table shows that, even without directly observing changes in the cost of a UPC, we can differentiate between percentage and additive markups by comparing how the retailer's price for a UPC changes compared to the average price change across retailers for the same UPC. Intuitively, if retailers have fixed percentage markups, then a retailer with high prices should exhibit higher pass-through in levels than the average, while if retailers have fixed additive markups, a retailer with high prices should exhibit lower log pass-through than the average.

We test these predictions using two specifications,

$$\Delta p_{ikt} = \beta^{\text{level}} (\Delta \bar{p}_{kt} \times \text{RelativePrice}_{ikt}) + \delta \text{RelativePrice}_{ikt} + \alpha_{kt} + \varepsilon_{ikt}, \quad (9)$$

$$\Delta \log p_{ikt} = \beta^{\text{log}} (\Delta \log \bar{p}_{kt} \times \text{RelativePrice}_{ikt}) + \tilde{\delta} \text{RelativePrice}_{ikt} + \tilde{\alpha}_{kt} + \varepsilon_{ikt}, \quad (10)$$

Table 6: Predictions for pass-through across retailers selling identical UPCs.

	Percentage markups $p_i = \mu_i c$	Additive markups $p_i = c + m_i$
<i>Price change relative to cost:</i>		
Levels (dp_i/dc)	μ_i	1
Logs ($d \log p_i / d \log c$)	1	c/p_i
<i>Price change relative to average:</i>		
Levels ($dp_i/d\bar{p}$)	$\approx 1 + \log(p_i/\bar{p})$	1
Logs ($d \log p_i / d \log \bar{p}$)	1	$\approx 1 - \log(p_i/\bar{p})$
<i>Predicted interaction coefficient:</i>		
Levels specification (9), β^{level}	1	0
Logs specification (10), β^{log}	0	-1

Note: The UPC cost is c , the price of the UPC at retailer i is p_i , and the average price across all retailers is \bar{p} .

where Δp_{ikt} is the change in the price of UPC k at retailer i from quarter t to quarter $t + 4$, $\Delta \log p_{ikt}$ is same price change measured in logs, $\Delta \bar{p}_{kt}$ is the average change in the price of UPC k from quarter t to quarter $t + 4$ across all retailers, $\Delta \log \bar{p}_{kt}$ is the average log change in price, and $\text{RelativePrice}_{ikt} = \log(p_{ikt}/\bar{p}_{kt})$ is the log-deviation of UPC k 's price at retailer i in quarter t relative to the UPC's average price across retailers. Notice in both specifications that UPC-quarter fixed effects (α_{kt} and $\tilde{\alpha}_{kt}$) absorb the average price change in UPC k across retailers, as well as arbitrary UPC demand shocks over time.

The final panel of Table 6 summarizes the predicted coefficients β^{level} and β^{log} under the two pricing rules. If firms have fixed percentage markups, we predict $\beta^{\text{level}} \approx 1$ and $\beta^{\text{log}} \approx 0$. On the other hand, when firms exhibit complete pass-through in levels, the price change in levels is similar across retailers, so $\beta^{\text{level}} \approx 0$, and the log pass-through appears to decline with initial price, so $\beta^{\text{log}} \approx -1$.¹⁵

Results. We estimate specifications (9) and (10) for rice, flour, and coffee products, as well as for the entire set of food-at-home product categories in the NielsenIQ data over the period 2006–2020. Since these specifications do not require information on input costs, they allow us to test for pass-through in levels at the retail level for a much broader set of products: the latter dataset contains nearly one million unique UPCs sold across 235 retail chains.

¹⁵Table 6 assumes that the cost of a UPC is uniform across retailers. If retailers set fixed percentage markups but also have other, heterogeneous variable costs, i.e., $p_i = \mu_i(c + w_i)$, then the estimates for β^{level} and β^{log} would move toward 0 and -1 , but would not fully reach the “additive markup” predictions unless prices were perfectly competitive (i.e., the percentage markups $\mu_i = 1$).

Table 7: Exploiting variation in prices of identical products across retailers.

<i>Panel A: In levels</i>	Δ UPC Price (Δp_{ikt})			
	Rice (1)	Flour (2)	Coffee (3)	All Products (4)
Avg Δ Price $_{kt} \times$ RelativePrice $_{ikt}$	−0.022 (0.141)	0.058 (0.209)	0.192 (0.170)	−0.001 (0.839)
UPC-Quarter FEs	Yes	Yes	Yes	Yes
N (millions)	0.399	0.101	1.570	100.4
R^2	0.46	0.48	0.51	0.59
Within- R^2	0.04	0.07	0.10	0.00
<i>Panel B: In logs</i>	Δ Log UPC Price ($\Delta \log p_{ikt}$)			
	Rice (1)	Flour (2)	Coffee (3)	All Products (4)
Avg Δ Log Price $_{kt} \times$ RelativePrice $_{ikt}$	−1.004** (0.125)	−1.014** (0.184)	−1.261** (0.084)	−1.043** (0.073)
UPC-Quarter FEs	Yes	Yes	Yes	Yes
N (millions)	0.399	0.101	1.570	100.4
R^2	0.62	0.61	0.58	0.61
Within- R^2	0.13	0.14	0.16	0.12

Note: Panel A reports results from (9), and panel B reports results from (10). RelativePrice $_{ikt}$ is the log deviation in the price set by retailer i for UPC k in quarter t compared to the average price set by retailers, $\log(p_{ikt}/\bar{p}_{kt})$. Regressions weighted by sales. Driscoll-Kraay standard errors. ** indicates significance at 5%.

Panel A of Table 7 shows that estimating the levels specification (9) yields $\beta^{\text{level}} \approx 0$ across each of the three product categories and for the entire dataset. That is, retailers selling the same UPC have similar price changes in levels when the cost of a UPC changes. Note that if retailers had fixed percentage markups, Table 6 predicts an interaction coefficient of one. For each of the individual product categories (though not for the dataset as a whole), we can in fact reject the hypothesis that $\beta^{\text{level}} = 1$ at the 5 percent level.

Panel B likewise reports the results from the log specification (10). We find that $\beta^{\text{log}} \approx -1$ in each of the three product categories and for the broader NielsenIQ dataset. In all cases, we can reject the hypothesis of fixed percentage markups (i.e., $\beta^{\text{log}} = 0$) at the 5 percent level. Thus, results from both specifications suggest that retailers exhibit complete pass-through in levels across a broad array of product categories.¹⁶

¹⁶This finding may be surprising in the light of Eichenbaum, Jaimovich, and Rebelo (2011), who find that when a retailer resets its reference price, the deviation in the realized markup from the average markup is largely uncorrelated with the deviation in the hypothetical markup absent a price reset from the average markup (Eichenbaum et al. 2011, Figure 8). However, this evidence is not necessarily inconsistent with our results. Fixed additive markups imply that the deviation in the realized percentage markup from the

5 Evidence from Manufacturing Industries

So far, we have documented pass-through in levels using microdata for specific goods. In this section, we extend our analysis to a panel of industries that span the U.S. manufacturing sector. We find that the pass-through of input cost changes to output prices across this broader sample of industries conforms with the predictions of pass-through in levels.

5.1 Data and Empirical Approach

Data on manufacturing industries. We use the NBER-CES Manufacturing Industry Database (Becker, Gray, and Marvakov 2021), which contains data on industry sales, costs, output price indices, and input price indices for 459 four-digit SIC industries from 1958–2018. Industry shipments, materials costs, costs of fuels and electricity, and production worker wages in the database are drawn from the Census’s Annual Survey of Manufacturers and the Census of Manufacturers. Output price indices are constructed by linking each industry to producer price data from the BLS Producer Price Index (PPI) program. Material input price indices are constructed by matching each industry to PPI data for its inputs, using the BEA’s quinquennial detail input-output tables. Energy price indices for each industry are constructed using direct data on electricity usage costs and by combining Manufacturing Energy Consumption Survey data on the composition of fuel sources used by each industry with BLS PPI commodity data.

Testing for pass-through in levels. Unlike our earlier analysis of gasoline and food products, where we observed the level of input and output prices for specific products, the NBER-CES data include output and input price indices that reflect average percentage changes in prices. Nevertheless, we can estimate the pass-through in levels using changes in log price indices and the revenue-share of input expenditures.

Denote the pass-through in levels of a change in input costs to prices by $\rho^{\text{level}} \equiv \Delta p / \Delta c$. Rearranging yields

$$\frac{\Delta p}{p} = \rho^{\text{level}} \frac{cy}{py} \frac{\Delta c}{c}.$$

While we don’t directly observe price levels or changes in price levels, to a first order, the ratio of the price change to the price level is equal to the change in the log price index,

average is negatively correlated with the deviation in cost from average cost, but when costs are close to unit root, the deviation in cost from average cost may have a low correlation with the change in cost since the last reference price reset.

$\Delta p/p \approx \Delta \log p$. Thus, to a first order approximation,

$$\Delta \log p \approx \rho^{\text{level}} \left(\frac{cy}{py} \right) \Delta \log c. \quad (11)$$

Note that under the assumption of constant returns, Leontief production, the term in parentheses (cy/py) is simply the ratio of expenditures on the input to total sales.

Thus, we can test for pass-through in levels by estimating how changes in each industry's output price index relate to changes in its input price index multiplied by the revenue share of input costs. If firms exhibit complete pass-through in levels, changes in the output price index should move one-for-one with changes in the input price index multiplied by the revenue share of inputs. On the other hand, if firms have fixed percentage markups, the estimated pass-through in levels ρ^{level} will be greater than one.

5.2 Empirical Results

Pass-through in levels across manufacturing industries. We implement (11) by estimating the specification,

$$\begin{aligned} \Delta \log p_{it} = & \rho^{\text{level}} (\Delta \log c_{it} \times (\text{InputCosts/Sales})_{it-1}) \\ & + \delta \Delta \log c_{it} + \gamma (\text{InputCosts/Sales})_{it-1} + \alpha_i + \phi_t + \varepsilon_{it}, \end{aligned} \quad (12)$$

where $\Delta \log p_{it}$ ($\Delta \log c_{it}$) is the change in the log output (input) price index of industry i from year $t-1$ to t , $\text{InputCosts/Sales}_{it-1}$ is industry i 's revenue-share of input expenditures in year $t-1$, and α_i and ϕ_t are industry and year fixed effects. Assuming constant returns, Leontief production, (11) shows that the coefficient on the interaction term ρ^{level} identifies the pass-through in levels of the input cost change to output prices. Equation (11) also predicts that $\delta = \gamma = 0$, but we do not impose these restrictions for estimation.

Table 8 presents the results from estimating (12) in the panel of manufacturing industries. In columns 1–2, we define input costs as each industry's materials costs. Column 1 shows that a 1 percent increase in the materials input price index for an industry is associated with a 0.69 percent increase in output prices. That is, industries exhibit incomplete log pass-through of materials input costs. Column 2 uses specification (12) to estimate the pass-through in levels. We find that the estimated coefficient on the interaction term $\rho^{\text{level}} \approx 1$, consistent with complete pass-through in levels. In other words, the incomplete log pass-through in column 1 appears to be explained by complete pass-through in levels in our panel of manufacturing industries.

Table 8: Pass-through for manufacturing industries.

Inputs:	Materials		$\Delta \text{Log Output Price}_t$ + Energy		+ Production Labor	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \text{Log Input Price}_t$	0.690** (0.072)	0.079 (0.132)	0.704** (0.073)	0.005 (0.134)	0.796** (0.083)	0.052 (0.232)
$(\text{InputCost}/\text{Sales})_{t-1}$		0.004 (0.011)		0.008 (0.011)		0.023** (0.011)
$\Delta \text{Log Input Price}_t \times (\text{InputCost}/\text{Sales})_{t-1}$		0.947** (0.203)		1.041** (0.201)		0.984** (0.286)
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
N	27 381	27 381	27 381	27 381	27 381	27 381
R^2	0.40	0.42	0.40	0.42	0.41	0.42

Note: Columns 1–2 use input costs and prices for materials, columns 3–4 use input costs and prices for materials plus energy, and columns 5–6 use input costs and prices for materials, energy, and production labor. Input price inflation is an expenditure-weighted average across components of cost. Input and output price indices are deflated using CPI excluding food and energy. Standard errors two-way clustered by industry and year. ** indicates significance at 5%.

Columns 3–6 find similar results when we extend our definition of inputs to include energy and production labor. In each case, we construct the change in the input price index as the weighted average of changes in price indices for each input, using the industry's expenditures on each input in the prior year as weights. We use the average hourly earnings of production and nonsupervisory employees in manufacturing as the price index for production labor across all industries to ensure that the labor price index is not biased by rent-sharing of profits with employees. In all cases, we find that the estimated coefficient on the interaction term β is very close to one, consistent with complete pass-through in levels of input cost changes to prices.¹⁷

Robustness. One might be concerned that our estimates of the pass-through of input price movements to industry output prices are attenuated by reverse causality, since demand shocks downstream of an industry could propagate upward from output prices to input prices. To address this concern, we estimate (12) using an instrumental variable approach. We use a decomposition of commodity price movements into demand shocks,

¹⁷When estimating (12) in Table 8, we deflate both input and output price indices by changes in the consumer price index. This choice anticipates Section 7, where we show that additive markups may be priced relative to the price level in the economy. Estimating (12) using changes in nominal input and output prices does not meaningfully change the results in Table 8, but we show in Section 8.3 that it can affect the estimated pass-through across specific categories of inputs.

industry productivity shocks, and commodity market shocks from Kabundi and Zahid (2023). By construction, the commodity market shocks they measure are orthogonal to aggregate demand shocks and downstream industry productivity shocks, so we use these commodity price shocks interacted with industry fixed effects as instruments for changes in each industry’s input prices. Appendix Table A10 reports that the estimated coefficient β remains close to one using this instrumental variable approach.

A second concern is that nominal price rigidities may lead us to underestimate the long-run pass-through of input price changes to output prices. In Appendix Table A11, we estimate (12) using changes in input and output prices at horizons ranging from one to five years. If anything, our estimate of β slightly declines with the horizon, and we cannot reject the hypothesis that $\beta = 1$ for any horizon.

6 Discussion

Taking stock. Complete pass-through in levels emerges across a broad set of industries and markets. To recap, we find complete pass-through in levels in retail gasoline markets, from commodity costs to retail prices in food product markets, at the retail level across the universe of food-at-home products in NielsenIQ data, and across industries spanning the U.S. manufacturing sector. Moreover, across these settings, we find that pass-through in levels accounts for the extent of incomplete log pass-through and the heterogeneity in log pass-through observed across products, across firms, and across industries.

Our findings are best understood as reflecting the long-run pass-through of *industry-wide, persistent* cost changes. First, the cost shocks that we study are input price changes that affect all producers in a market. That is, our estimates capture the response of prices to industry-wide, or “common,” cost shocks, rather than idiosyncratic cost shocks that only affect one or a subset of producers in a market. Second, input prices in each of the markets we study are close to unit root (see Appendix Table A2), meaning that input cost changes are highly persistent. In the remainder of the paper, we will focus on explaining why firms pass through persistent, common cost shocks in levels, allowing for the possibility that the pass-through in levels of an idiosyncratic or temporary cost shock could differ.

Comparison to previous estimates. In Appendix Table A1, we survey previous studies that measure pass-through in levels and logs. Given the vast literature on pass-through, we focus on papers that study the pass-through of industry-wide cost shocks, rather than idiosyncratic shocks, and that measure pass-through using reduced form methods, rather than simulating pass-through using a structural model.

The majority of studies that measure pass-through in levels in Appendix Table A1 are unable to reject complete pass-through in levels, and point estimates in many of the studies are tightly estimated around one. These studies span an array of industries and, in addition to commodity and input cost changes, consider other types of cost shocks such as excise tax changes and shipping costs.

A few exceptions to complete pass-through in levels in Appendix Table A1 find evidence of under- or over-shifting of excise tax changes (e.g., Kenkel 2005; Hanson and Sullivan 2009; Cawley, Frisvold, Hill, and Jones 2020; and Conlon and Rao 2020). Our impression is that some of these exceptions may owe to shocks that are small in magnitude or small samples of excise tax changes. For example, Conlon and Rao (2020) propose that over-shifting may not be due to fixed percentage markups, but instead to retailers rounding up to prices that end in 99 cents even when tax changes are small. Indeed, of the three tax changes in their sample, only one increases taxes per product by more than \$1, and for that tax change Conlon and Rao (2020) find that pass-through in levels is slightly below and not significantly different from one. Likewise, pass-through estimates from Kenkel (2005), Hanson and Sullivan (2009), and Cawley et al. (2020) each come from studying a single tax change event. Butters et al. (2022) recently revisit the pass-through of excise tax changes using a larger sample of sixty-eight national and state excise tax changes. In this larger sample, Butters et al. (2022) estimate a pass-through in levels of 1.01 (standard error: 0.02).¹⁸ Thus, evidence from studies that measure pass-through over a larger sample of excise tax changes or that use commodity and input price shocks—which offer more continuous variation for identification—points toward complete pass-through in levels.

7 Explaining Pass-Through in Levels

In this section, we characterize restrictions on demand that lead firms to pass through cost shocks in levels. We show that complete pass-through in levels requires that demand be *shift invariant* with respect to the prices of goods exposed to the cost shock. This restriction is violated by homothetic demand systems used in workhorse macroeconomic models, which are instead *scale invariant* with respect to prices. We identify an alternate class of demand systems that exhibit shift invariance and thus generate complete pass-through in levels.

¹⁸For some sub-samples, the estimates from Butters et al. (2022) vary more widely. For example, their estimates of pass-through for beer, liquor, and sugar-sweetened beverage taxes range from 0.72–1.42, but these estimates are from only 2–4 tax change events, compared to 68 excise tax changes in their full sample. The variability of these sub-sample estimates underscores the high variance in pass-through estimates that can arise from a small sample of tax changes.

7.1 Environment

Suppose there is a set of goods that is partitioned into a set of $J \geq 1$ *inside* goods and $K \geq 0$ *outside* goods. Denote the vector of prices for inside goods by $\mathbf{p} = (p_1, \dots, p_J)$ and the vector of prices for outside goods by \mathbf{p}_0 . The demand system $D(\mathbf{p}, \mathbf{p}_0, Y)$ describes the quantity consumed of each good as a function of the prices of inside goods \mathbf{p} , the prices of outside goods \mathbf{p}_0 , and income Y .

Each inside good is produced and sold by a single firm. For $j \in \{1, \dots, J\}$, firm j possesses a constant returns to scale production function with exogenous marginal cost c_j . As in standard models, we assume that each firm sets its price p_j to maximize profits, taking the prices set by other firms and consumer demand curves as given.

Assumption 1 (Nash-in-prices). For each $j \in \{1, \dots, J\}$, the price p_j is set to maximize firm j 's profits, taking all other prices and the demand system D as given.

Given an exogenous vector of outside prices \mathbf{p}_0 , income Y , and vector of marginal costs $\mathbf{c} = (c_1, \dots, c_J)$, an equilibrium is a vector of prices \mathbf{p} and quantities \mathbf{q} such that, for $j = 1, \dots, J$, $q_j = D_j(\mathbf{p}, \mathbf{p}_0, Y)$ and p_j maximizes the profits of firm j taking all other prices as given.

We will be interested in the pass-through of a change in the costs of producing the inside goods, starting from an initial equilibrium. For all results that follow, we impose Assumption 2, which guarantees that such an equilibrium exists and that firm's residual demand curves are downward-sloping in this initial equilibrium.

Assumption 2 (Equilibrium existence and downward-sloping demand). Given outside prices \mathbf{p}_0 , income Y , and marginal costs \mathbf{c} , (1) an equilibrium exists, and (2) own-price elasticities of demand for each inside good $\partial \log D_j / \partial \log p_j$ are strictly negative and finite.

The assumption of finite elasticities of demand precludes perfect competition, in which firms face perfectly elastic residual demand curves. Of course, under perfect competition, firms' prices equal marginal costs and thus changes in marginal cost are passed through one-for-one in levels to prices. However, several other features of the markets that we study are at odds with perfect competition: these industries exhibit price dispersion for identical products, prices that are elevated over available measures of costs, and small and finite demand elasticities. Thus, we will seek to characterize restrictions on demand that yield pass-through in levels in such environments with imperfect competition.

7.2 Scale Invariance, Shift Invariance, and Pass-Through

We define the following properties of the demand system.

Definition 1 (Scale invariance). $D(\mathbf{p}, \mathbf{p}_0, Y)$ is *scale invariant in \mathbf{p}* if there exist functions $\varphi_1, \dots, \varphi_J$ such that $\partial \varphi_j / \partial p_j = 0$ for all j and, for any positive constant λ ,

$$D_j(\lambda \mathbf{p}, \mathbf{p}_0, Y) = \lambda^{\varphi_j(\mathbf{p}, \mathbf{p}_0, Y, \lambda)} D_j(\mathbf{p}, \mathbf{p}_0, Y) \quad \text{for all } j \in \{1, \dots, J\}.$$

Definition 2 (Shift invariance). $D(\mathbf{p}, \mathbf{p}_0, Y)$ is *shift invariant in \mathbf{p}* if there exist functions ψ_1, \dots, ψ_J such that $\partial \psi_j / \partial p_j = 0$ for all j and, for any constant λ ,

$$D_j(\mathbf{p} + \lambda \mathbf{1}, \mathbf{p}_0, Y) = (1 + \lambda \psi_j(\mathbf{p}, \mathbf{p}_0, Y, \lambda)) D_j(\mathbf{p}, \mathbf{p}_0, Y) \quad \text{for all } j \in \{1, \dots, J\},$$

where $\mathbf{1} = (1, \dots, 1)$ is a J -length vector of ones.

Scale and shift invariance are restrictions on how changes to the prices of all inside goods affect demand. *Scale invariance* imposes that, if the price of every inside good is multiplied by the same factor, the quantity demanded of each good changes by a factor that does not depend on the good's own price. Thus, a proportional price change to all inside goods leaves the elasticities of the residual demand curves facing each firm unchanged. *Shift invariance* instead restricts how the quantity demanded of each good changes when the price of each inside good changes by the same absolute amount. Under shift invariance, a shift in all prices scales the demand schedule facing each firm, so that the level and slope of the residual demand curve for each firm scale by the same (potentially firm-specific) factor.

Our main results in Proposition 1 and Proposition 2 show how these properties of demand determine the pass-through of common cost shocks to prices.

Proposition 1 (Complete log pass-through). *Consider a shock that increases the marginal cost of production for all inside goods proportionally by $d \log c_j = d \log c$ for all $j \in \{1, \dots, J\}$, holding fixed outside prices \mathbf{p}_0 and income Y . If demand is **scale-invariant** in \mathbf{p} , then each inside good's price increases by $d \log p_j = d \log c$.*

Proof. See Appendix B.2. □

When demand is scale invariant in inside prices, firms exhibit complete log pass-through of a common (proportional) cost shock. Intuitively, scale invariance implies that when all firms completely pass through the aggregate cost shock in logs, the elasticities of demand facing firms are unchanged, and firms have no further motive to change their percentage markups. Thus, firms exhibit fixed percentage markups when faced by common, proportional cost shocks.

Analogously, a common (absolute) cost shock to firms is passed through completely in *levels* when demand is shift invariant.

Proposition 2 (Complete pass-through in levels). *Consider a shock that increases the marginal cost of production for all inside goods by $dc_j = dc$ for all $j \in \{1, \dots, J\}$, holding fixed outside prices p_0 and income Y . If demand is **shift-invariant** in p , then each inside good's price increases by $dp_j = dc$.*

Proof. See Appendix B.2. □

When demand is shift-invariant in inside prices, a uniform absolute increase to inside goods' prices scales the demand schedule facing each firm. This scaling means that each firm's desired additive markup, which is equal to the ratio of a firm's demand to the slope of its residual demand curve, remains unchanged. Thus, firms retain fixed additive markups in response to a common cost shock.

For the purpose of characterizing pass-through, we have considered two different types of cost shocks: the first type of cost shock in Proposition 1 increased all firms' costs by a fixed proportion, while the second type of cost shock in Proposition 2 increased all firms' costs by a fixed amount. One may wonder whether the differences in pass-through behavior are due to differences in the type of aggregate cost shock. This is not the case: Proposition 3 shows that a demand system cannot be simultaneously scale invariant and shift invariant with respect to the same set of prices.

Proposition 3 (Scale and shift invariance are disjoint). *If $D(p, p_0, Y)$ is scale invariant in p , then $D(p, p_0, Y)$ is not shift invariant in p . (Equivalently, if $D(p, p_0, Y)$ is shift invariant in p , then $D(p, p_0, Y)$ is not scale invariant in p .)*

Proof. See Appendix B.2. □

Proposition 3 implies that if a set of firms exhibit complete log pass-through of a common, proportional shock to costs, those firms cannot exhibit complete pass-through in levels of a common, absolute cost increase. Likewise, if a demand system implies complete pass-through in levels of a common absolute cost shock to a set of firms, those firms will not exhibit complete log pass-through of a proportional cost shock.

7.3 Examples of Scale- and Shift-Invariant Demand

We can use these restrictions to explore which models of demand are consistent with our evidence of complete pass-through in levels. We begin by showing that homothetic demand systems commonly used in macroeconomics and trade are scale invariant and thus are inconsistent with our evidence of complete pass-through in levels. We then identify examples of demand systems that satisfy shift invariance.

7.3.1 Examples of Scale-Invariant Demand

Many workhorse models in macroeconomics and trade feature homothetic demand systems. The following example shows that homothetic demand systems are scale invariant with respect to goods' prices.

Example 1 (Homothetic preferences). Suppose there are J goods, and a representative consumer chooses consumption of each good q_j to maximize utility $U(q_1, \dots, q_J)$ subject to the budget constraint $\sum_j p_j q_j = Y$. If U is homothetic, then the quantities q chosen by the consumer can be represented by a scale-invariant demand system $D(p, p_0, Y)$, where $p_0 = \emptyset$ and $\varphi_j = -1$.

Since homothetic demand systems are scale invariant, they predict that firms retain constant percentage markups in response to aggregate, proportional cost shocks. This result applies to any homothetic demand system, regardless of whether the demand system implies fixed percentage markups—as in CES demand—or whether it accommodates variable markups, as in Kimball (1995) or HSA (Matsuyama and Ushchev 2017) preferences. This result also applies regardless of whether firms are atomistic, as in models of monopolistic competition, or granular, as in the Atkeson and Burstein (2008) oligopoly model. While the latter models can account for incomplete log pass-through of idiosyncratic cost shocks, they uniformly predict complete log pass-through of aggregate (proportional) cost shocks due to their scale invariance. Moreover, Proposition 3 implies that since homothetic demand systems are scale invariant, they are not shift invariant and thus are inconsistent with our evidence of complete pass-through in levels of common cost shocks.

An analogous result applies to the pass-through of industry-wide cost shocks in models where preferences are a CES nest over homothetic industry aggregates.

Example 2 (Nested homothetic preferences). Suppose there is a continuum of industries indexed by $n \in [0, 1]$, each of which consists of J firms. A representative consumer maximizes

$$U = \left(\int_0^1 Q_n^{\frac{\sigma-1}{\sigma}} dn \right)^{\frac{\sigma}{\sigma-1}} \quad \text{s.t.} \quad \int_0^1 \sum_j p_{nj} q_{nj} dn = Y,$$

where p_{nj} is the price of firm j in industry n , q_{nj} is the quantity purchased from firm j in industry n , σ is the elasticity of substitution across industries, Y is the consumer's income, and $Q_n = u(q_{n1}, \dots, q_{nJ})$ is a homothetic aggregate of consumption from firms in industry n .

Then, for any industry n , the quantities $q_n = (q_{n1}, \dots, q_{nJ})$ can be represented by a demand system $D(p, p_0, Y)$, where $p = (p_{n1}, \dots, p_{nJ})$ is the vector of prices for the J firms in industry n , p_0 is the vector of prices of all firms outside industry n , and $D(p, p_0, Y)$ is scale invariant in p with $\varphi_j = -\sigma$.

Example 2 includes the nested CES demand system from Atkeson and Burstein (2008) and the nested Kimball demand system from Amiti et al. (2019) as special cases. In these models, demand is scale invariant with respect to the prices of firms in an industry, and so firms exhibit complete log pass-through of industry-wide (proportional) cost shocks. Thus, any model of industry demand that can be expressed as a special case of Example 2 will not exhibit complete pass-through in levels of common cost shocks.

7.3.2 Examples of Shift-Invariant Demand

Which demand systems can generate complete pass-through in levels? We first show that an individual firm exhibits complete pass-through in levels of cost shocks when its residual demand curve is log-linear, as is the case under logit demand with atomistic firms. Then, we characterize a broader class of models that satisfy shift invariance and thus generate complete pass-through in levels of common cost shocks.

Example 3 (Log-linear demand curves). Suppose the demand for good j can be written as

$$D_j(p_j, \mathbf{p}_0, Y) = \exp(a_j(\mathbf{p}_0, Y) - b_j(\mathbf{p}_0, Y)p_j).$$

Then $D_j(p_j, \mathbf{p}_0, Y)$ is shift-invariant in p_j with $\psi_j(\mathbf{p}_0, Y, \lambda) = (\exp(-b_j(\mathbf{p}_0, Y)\lambda) - 1)/\lambda$.

The log-linear functional form means that level changes in a firm's price scale its demand curve up or down by a multiplicative factor, thus satisfying shift invariance. Several previous studies characterizing the pass-through of idiosyncratic cost shocks based on the shape of residual demand curves note this special property of log-linear demand curves (e.g., Bulow and Pfleiderer 1983; Weyl and Fabinger 2013; Mrázová and Neary 2017). In some of this previous work, this special property of log-linear demand is expressed in terms of the “super-elasticity” of demand: under log-linear demand, the elasticity of demand is proportional to price, $-\partial \log D_j / \partial \log p_j = p_j b_j(\mathbf{p}_0, Y)$, so that the super-elasticity is equal to one.

A popular special case of Example 3 is logit demand with atomistic firms.

Example 4 (Logit demand with atomistic firms). Suppose there are a continuum of goods indexed by $j \in [1, J]$ and an outside good with price p_0 , and that the demand for good $j \in [1, J]$ is given by

$$D_j(\mathbf{p}, p_0, Y) = \frac{\exp(a_j(p_0, Y) - bp_j/p_0)}{\int_1^J \exp(a_k(p_0, Y) - bp_k/p_0) dk}, \quad (13)$$

where \mathbf{p} is a vector of prices of goods $j \in [1, J]$ and b is a positive constant. Then, demand is shift invariant with respect to any vector of prices $\mathbf{p}^{\text{subset}} \subseteq \mathbf{p}$.

When firms are atomistic, the influence of firm j 's own price on the denominator in (13) becomes vanishingly small, and hence logit demand becomes a special case of Example 3. Under this demand system, the price set by firm j is equal to its marginal cost plus an additive markup priced relative to the outside good,

$$p_j = c_j + \frac{p_0}{b}.$$

Thus, logit demand with atomistic firms yields complete pass-through in levels of any cost shock to inside firms, whether that shock is idiosyncratic to firm j , affects a subset of firms, or affects all inside firms [1, J].

Log-linear demand curves and logit demand are functional forms that yield complete pass-through in levels of idiosyncratic shocks. However, a much broader class of demand systems satisfies shift invariance with respect to a set of firms' prices and thus generates complete pass-through in levels of common cost shocks, as we show in Example 5.

Example 5 (Discrete choice with quasilinear preferences). Suppose there is a unit mass of consumers indexed by $i \in [0, 1]$, each with income Y . There are J inside goods and a single outside good ("the numeraire"). Each consumer purchases one unit of one of the J inside goods and spends the rest of her income on the numeraire. Consumer i 's utility maximization problem is:

$$U_i = \max_j \{u_{ij}\} \quad \text{s.t.} \quad \begin{cases} u_{ij} = \delta_{ij} + q_{i0} & \text{(Utility)} \\ p_j + p_0 q_{i0} = Y & \text{(Budget constraint)} \end{cases}$$

where p_0 is the price of the numeraire, q_{i0} are units purchased of the numeraire, and δ_{ij} are consumer-specific tastes for each inside good. Assume further that consumers almost-surely do not face ties in utility between goods (i.e., for any two goods j, n where $j \neq n$, the set of consumers where $a\delta_{ij} - b\delta_{in} = c$ for any positive constants $a, b > 0$ and for any constant c is measure zero).

Then, the demand system $D(\mathbf{p}, p_0, Y)$ given by aggregating over all consumers, so that

$$D_j(\mathbf{p}, p_0, Y) = \int_0^1 1\{u_{ij} > u_{ik} \text{ for all } k \neq j\} di,$$

is shift-invariant in \mathbf{p} with $\psi_j = 0$.

The class of discrete choice demand system in Example 5 is a special case of shift invariance where a common cost shock leaves firms' demand curves entirely unchanged (i.e., $\psi_j = 0$). This class of demand systems is sometimes referred to as translation-

invariant choice systems (McFadden 1981) or linear random utility models (Anderson et al. 1992). Anderson et al. (1992) show that this class nests several demand systems used in the industrial organization literature as special cases. For example, logit, nested logit (Verboven 1996), mixed logit (Nevo 2001), multinomial probit, competition on a line (Hotelling 1929), and competition on a unit circle (Salop 1979) can all be expressed in terms of the framework above.¹⁹ Thus, each of those demand systems is shift invariant with respect to inside prices and generates complete pass-through in levels of common cost shocks.

7.4 Discussion

We have shown that demand systems that satisfy *shift invariance* lead firms to exhibit complete pass-through in levels of common cost shocks. While the homothetic demand systems commonly used in macroeconomics and trade do not satisfy this property, a variety of alternative demand systems, including several from the industrial organization literature, satisfy this property. This class of demand systems also encompasses different micro-foundations and allows for ample flexibility in matching firms' elasticities of demand and substitution patterns.

We discuss a few features of the demand systems that generate complete pass-through in levels, as well as other mechanisms that may explain pass-through in levels.

Pass-through of idiosyncratic cost shocks. A demand system may be shift invariant with respect to the prices of a set of firms without being shift invariant with respect to firms' individual prices. Thus, one can choose a demand system that matches our evidence on complete pass-through in levels of common cost shocks while retaining the flexibility to match different rates of pass-through for idiosyncratic shocks.

To date, there is less evidence on the pass-through in levels of idiosyncratic cost shocks. A recent exception is Alvarez, Cavallo, MacKay, and Mengano (2024), who measure pass-through of cost shocks by a non-durables manufacturer and find complete pass-through in levels of both aggregate and idiosyncratic shocks. Logit demand with atomistic firms is a special case that predicts complete pass-through in levels of both aggregate and idiosyncratic shocks, as shown in Example 4.

¹⁹Barro (2024) characterizes firms' markups in a variant of the Salop (1979) model with an intensive margin elasticity of demand. When the intensive margin elasticity of demand in his model is zero, his model coincides with a special case of Example 5. For this case, Barro (2024) shows that firms have additive markups and exhibit complete pass-through in levels, consistent with Proposition 2.

Neutrality. Likewise, a demand system can be shift invariant with respect to the prices of a set of firms while being scale invariant with respect to a broader set of prices in the economy. Take the demand systems in Example 5. These demand systems are shift invariant in the vector of inside prices \mathbf{p} , so that common cost shocks are passed through one-for-one in levels. But, they also satisfy the property that, for any positive constant λ , $D_j(\lambda\mathbf{p}, \lambda p_0, Y) = D_j(\mathbf{p}, p_0, Y)$ for all $j \in 1, \dots, J$. This means that a shock to the aggregate price level that scales both costs of production and the numeraire price p_0 leads to a proportional change in firms' prices (i.e., no change in firms' percentage markups). Thus, models that exhibit pass-through in levels of industry-wide cost shocks can also preserve the neutrality of relative prices and quantities to changes in the aggregate price level.

Evidence on quantities. Scale-invariant and shift-invariant demand systems have different predictions for how a uniform level price increase across firms affects relative quantities demanded. When demand is homothetic, the uniform absolute price increase represents a larger proportional price increase for low-price products, which should result in a reallocation of quantities away from low-price products and toward higher-price products.²⁰ Meanwhile, several models that satisfy shift invariance do not make this prediction: for example, in the family of demand systems given in Example 5, a uniform shift in firms' prices has no effect on quantity shares across firms.

We test how quantity shares of low- and high-priced rice, flour, and coffee products respond to changes in commodity prices in Appendix Table A13. We find no effect on quantity shares of low- *vs.* high-priced rice and flour products in response to commodity cost changes; for coffee products, we observe if anything a reallocation toward low-price products when commodity costs rise, in contrast with the predictions of homothetic demand. Thus, the response of quantities demanded to commodity cost changes provides complementary evidence that matching the data requires deviating from workhorse homothetic models of demand.

Other explanations for pass-through in levels. Demand systems that satisfy shift invariance generate complete pass-through in levels without modifying core assumptions about firm conduct, firm and consumer rationality, or firm objectives. Of course, it may be possible to explain pass-through in levels by instead relaxing these assumptions. For example, strategic interactions between oligopolistic firms can generate kinked demand curves or price cycles that break the standard relationship between markups and demand

²⁰Baqae, Farhi, and Sangani (2024) explore an example with homothetic (Kimball 1995) preferences where higher log pass-through for low-markup firms leads to a reallocation of resources away from low-markup firms and toward high-markup firms.

elasticities (e.g., Maskin and Tirole 1988). Fairness or implicit contracts between firms and customers may lead firms to only increase prices when costs visibly increase (e.g., Okun 1981; Rotemberg 2005; Westphal 2024). Finally, prices may reflect heuristics such as “full cost pricing” or “target returns pricing” (Hall and Hitch 1939; Lanzillotti 1958; Blinder 1994) or firm objectives beyond profit maximization (e.g., Baumol’s 1959 conjecture that firms maximize revenue subject to a profit constraint). Our empirical evidence on pass-through in levels across several markets is also useful for disciplining these alternative explanations.

8 Implications

We propose that demand systems that generate pass-through in levels can be useful in understanding several features of the data. In this section, we first discuss the implications of pass-through in levels for pass-through measurement, and then discuss broader implications that arise from integrating demand systems that generate pass-through in levels into popular macroeconomic models.

8.1 Pass-Through Measurement

When firms exhibit complete pass-through in levels, Proposition 4 shows that using a log specification to measure pass-through can lead to asymmetry, size-dependence, and systematic heterogeneity in pass-through across firms.

Proposition 4 (Asymmetry, size-dependence, and heterogeneity). *Suppose $D(\mathbf{p}, \mathbf{p}_0, Y)$ is shift invariant in \mathbf{p} , and denote the initial markup of firm j by $\mu_j = p_j/c_j$. In response to a common cost shock, the log pass-through of firm j to a first order in $\Delta \log c_j$ is*

$$\rho_j^{\log} = \frac{\Delta \log p_j}{\Delta \log c_j} \approx \frac{1}{\mu_j} \left[1 + \frac{1}{2} \frac{\mu_j - 1}{\mu_j} \Delta \log c_j \right].$$

Let $\rho_j^{\log}(\cdot)$ denote log pass-through as a function of the log cost change $\Delta \log c_j$. Then,

1. Log pass-through is **asymmetric**: $\rho_j^{\log}(x) > \rho_j^{\log}(-x)$ for any $x > 0$.
2. Log pass-through is **size-dependent**: $\rho_j^{\log}(x) > \rho_j^{\log}(x')$ for any $x > x'$.
3. Log pass-through is **decreasing in markups**: $\partial \rho_j^{\log} / \partial \mu_j < 0$ for small $\Delta \log c_j$.

Proof. Results follow from a second-order expansion of $dp_j = dc$ with respect to $\Delta \log c_j$. \square

A large literature documents asymmetries in log pass-through (see e.g., Peltzman 2000), and recent work suggests that firms pass through large shocks at higher rates than small shocks (Cavallo, Lippi, and Miyahara 2024; Gagliardone, Gertler, Lenzu, and Tielens 2025).²¹ Although these patterns could arise from genuine differences in how firms respond to cost changes, Proposition 4 shows that using a log specification naturally generates such asymmetry and size-dependence. With complete pass-through in levels, these effects arise because log pass-through is not a stable statistic and depends on the size and direction of cost shocks.

Measuring pass-through in logs can also lead to systematic patterns of heterogeneity. Previous work documents that log pass-through tends to decline with firm size (e.g., Berman, Martin, and Mayer 2012; Amiti et al. 2019; Gupta 2020) and with product quality (Chen and Juvenal 2016; Auer, Chaney, and Sauré 2018). Complete pass-through in levels naturally generates both patterns if markups increase with firm size and product quality, as is suggested by a large body of empirical work.²²

8.2 Dynamics of Industry Profits, Margins, and Entry

Standard models of industry dynamics in macroeconomics and trade assume monopolistic competition with homothetic demand. We explore how the predictions of such a model change when we substitute homothetic demand for a demand system that exhibits shift invariance and thus generates complete pass-through in levels. This change alters the model's predictions for how fluctuations in input costs affect gross margins, operating margins, and firm entry. In the data, the dynamics of these industry aggregates across a range of industries line up with the predictions of the model with shift-invariant demand.

Profits, margins, and entry in a simple industry model. We consider a workhorse model of monopolistic competition, following Dixit and Stiglitz (1977) and Melitz (2003). An industry consists of a mass N of symmetric firms that produce varieties of an output good with a constant marginal cost c . The demand for any individual firm j , denoted $D_j(\mathbf{p}, \mathbf{p}_0, Y)$, depends on the vector of prices set by all firms in the industry \mathbf{p} , an exogenous vector of outside prices \mathbf{p}_0 , and consumer income Y . We consider the cases where $D(\mathbf{p}, \mathbf{p}_0, Y)$ is

²¹These studies focus on differences in the extensive margin of price adjustment to small *vs.* large shocks, but Gagliardone et al. (2025) also find evidence of greater responsiveness conditional on a price change.

²²See Melitz (2018) on firm size and markups and e.g., Atkin, Chaudhry, Chaudry, Khandelwal, and Verhoogen (2015) and Sangani (2022) on product quality and markups. We caution that some of the existing evidence on heterogeneity in log pass-through is identified using idiosyncratic shocks. As discussed in Section 7, our evidence on pass-through comes from industry-wide cost shocks, and demand systems that yield pass-through in levels of common shocks need not do so for idiosyncratic shocks.

either scale invariant in p , as in standard formulations with homothetic demand, or shift invariant in p , yielding complete pass-through in levels.

Each atomistic firm chooses its price to maximize variable profits π^{gross} , taking as given all other firms' prices. In addition to variable costs of production, firms incur overhead costs f_o , so that operating profits are $\pi^{\text{op}} = \pi^{\text{gross}} - f_o$. We denote the output price chosen by firms in the symmetric equilibrium by p .

Aggregate industry demand is $Q = p^{-\theta}$. We assume that aggregate industry demand is inelastic ($\theta < 1$), which is the empirically relevant case for most of the industries studied in this paper.²³ Firm symmetry allows us to express industry *gross margins* (i.e., gross profits as a percent of sales) and *operating margins* (i.e., operating profits as a percent of gross profits) as²⁴

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

We close the model by specifying how the mass of firms evolves. Two common approaches are to assume a fixed mass of firms or to assume free entry. We choose a general condition that nests both as special cases:

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

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

Proposition 5 characterizes how industry aggregates—gross margins, operating margins, and the mass of firms—respond to changes in upstream costs when industry demand is either scale invariant or shift invariant.

Proposition 5 (Gross margins, operating margins, and entry). *Consider an increase in costs $dc > 0$. The response of industry gross margins, operating margins, and the mass of firms is summarized in the following table:*

²³Elasticities of aggregate demand for retail gasoline in the U.S. are close to zero (Eitches and Crain 2016), and the USDA estimates elasticities of aggregate demand for flour, rice, and coffee to be 0.07, -0.07 , and -0.12 , respectively (Okrent and Alston 2012).

²⁴We define operating margins as the ratio of operating profits to gross profits, rather than sales. This ratio is sometimes instead referred to as the “operating-profit conversion rate” or “operating efficiency.”

		Gross margins dm^{gross}	Operating margins dm^{op}	Mass of firms $d \log N$
<i>Demand is scale invariant in p:</i>				
$\zeta = 0$	(Fixed mass)	0	> 0	0
$\zeta \in (0, \infty)$		0	> 0	> 0
$\zeta \rightarrow \infty$	(Free entry)	0	0	> 0
<i>Demand is shift invariant in p:</i>				
$\zeta = 0$	(Fixed mass)	< 0	≤ 0	0
$\zeta \in (0, \infty)$		< 0	≤ 0	≤ 0
$\zeta \rightarrow \infty$	(Free entry)	< 0	0	≤ 0

Proof. See Appendix B.3. □

When demand is scale invariant in p , firms have fixed percentage markups in response to changes in the input cost c . Thus, when costs rise, firms make higher profits on each unit sold—for example, a firm charging a fixed 10 percent markup makes \$0.10 per unit when unit costs are \$1, and \$0.20 per unit when unit costs are \$2. Since aggregate industry demand is inelastic, higher per-unit profits lead to higher aggregate profits for firms or else are dissipated by the entry of new firms. In other words, an increase in input costs leads to higher operating margins, new firm entry, or both.

In contrast, when demand is shift-invariant, firms have fixed additive markups and thus fixed per-unit profits. Changes in input costs no longer necessitate changes to operating profits or the mass of firms in order to maintain equilibrium. Instead, the industry equilibrium primarily adjusts to rising costs via a decline in gross margins.

Margins and entry in the data. We test the predictions of Proposition 5 using the response of gross margins, operating margins, and entry to input cost fluctuations for retail gasoline stations and manufacturing industries. For retail gas stations, we use data on gross and operating margins from the Census Annual Retail Trade Survey (ARTS) and from retail gas station sole proprietorships in the IRS Statistics of Income (SOI).²⁵ Data on the number of retail gas station firms and establishments in each year comes from two sources: the Census Business Dynamics Statistics (BDS) and the Census Statistics of U.S. Businesses (SUSB).

²⁵Sole proprietorships account for one-fifth of U.S. retail gas stations in 2016. We define sales as income from sales and operations in the SOI. Gross margins are gross profits (sales minus cost of sales) as a percent of sales. Operating margins are net income minus income from sources other than sales and operations plus taxes paid, payments of mortgage interest, and other interest on debt, as a percent of gross profits.

Table 9: Response of gross margins, operating margins, and entry to input price changes.

<i>Panel A: Retail Gasoline</i> Source:	Δ Log Gross Margin		Δ Log Oper. Margin		Δ Log Num. Estabs	
	ARTS (1)	IRS (2)	ARTS (3)	IRS (4)	BDS (5)	SUSB (6)
Δ Log Wholesale Price _t	−0.263** (0.045)	−0.291** (0.061)	0.490 (0.328)	0.125 (0.284)	−0.002 (0.006)	0.001 (0.007)
<i>N</i>	39	26	15	26	39	24
<i>R</i> ²	0.54	0.49	0.20	0.01	0.00	0.00
<i>Panel B: Manufacturing Industries</i>	Δ Log Gross Margin		Δ Log Oper. Margin		Δ Log Num. Estabs	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Log Input Price _t	−0.188** (0.039)	0.154 (0.103)	0.071 (0.048)	−0.086 (0.130)	0.007 (0.013)	−0.028 (0.044)
Δ Log Input Price _t × Inputs/Sales _{t−1}		−0.504** (0.188)		0.270 (0.221)		0.049 (0.063)
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	27 381	27 381	27 305	27 305	18 201	18 201
<i>R</i> ²	0.05	0.11	0.02	0.04	0.22	0.23

Note: Panel A presents results for retail gasoline. The wholesale gasoline price is from the EIA, deflated to constant dollars. ARTS is the Census Annual Retail Trade Survey, IRS are statistics for sole proprietorships, BDS is the Census Business Dynamics Statistics, and SUSB is the Census Statistics of U.S. Businesses. HAC-robust standard errors in parentheses. Panel B reports results for manufacturing industries. The input price is the price index for materials, deflated to constant dollars; Inputs/Sales is the ratio of material costs to sales; gross margins are sales less material costs as a share of sales; operating margins are sales less material costs, energy costs, and payroll, as a share of gross profits; and num estabs are counts of establishments from the Census Business Dynamics Statistics (BDS). Standard errors two-way clustered by industry and year. ** indicates significance at 5%.

Appendix Figure A11 shows the time series for retail gasoline gross margins, operating margins, and establishment growth rates. Gross margins exhibit a strong negative relationship with input prices (gross margins from the Census ARTS and IRS SOI have correlations with the wholesale gasoline price of −0.94 and −0.74). On the other hand, operating margins and firm entry appear largely unresponsive to input prices.

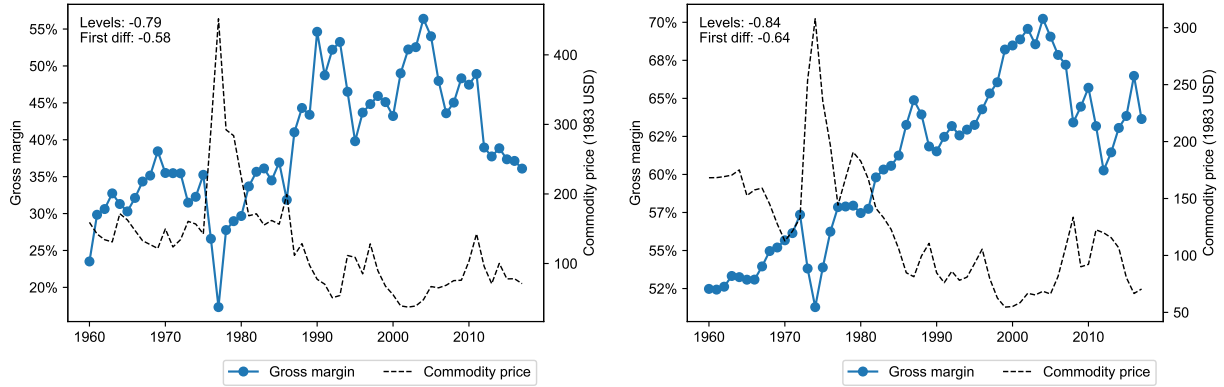
We test the relationship between outcome y_t and the input price c_t using the first-differences specification:

$$\Delta \log y_t = \alpha + \beta \Delta \log c_t + \varepsilon_t. \quad (14)$$

Panel A of Table 9 reports results from specification (14) using the price of wholesale gasoline as the measure of input costs and using gross margins, operating margins, and entry as outcome variables.²⁶ Neither operating margins nor entry significantly increase

²⁶We obtain similar results using crude oil spot prices or nominal rather than deflated wholesale prices.

Figure 4: Gross margin and input commodity price for two food manufacturing industries.



(a) Roasted coffee manufacturing *vs.* coffee commodity price. **(b)** Bread, cake & related products manufacturing *vs.* wheat commodity price.

Note: Gross margins are sales minus costs of goods sold as a share of sales, from the NBER-CES manufacturing database. Annual coffee and wheat commodity prices from 1960–2018 are from the UN Trade and Development (UNCTAD) data hub, deflated using the CPI excluding food and energy.

with input costs, as predicted by the model with scale-invariant demand. Instead, rising input prices lead to a significant decline in gross margins, as predicted by the model with shift-invariant demand and complete pass-through in levels.

Similar patterns emerge for manufacturing industries. Figure 4 plots industry gross margins against commodity costs for two manufacturing industries that use coffee and wheat as inputs. As predicted by the model with pass-through in levels, gross margins exhibit a strong negative correlation with input prices. Panel B of Table 9 reports how margins and firm entry respond to changes in input prices for the full set of manufacturing industries in the NBER-CES database. The response of all three industry aggregates to input costs is consistent with the predictions of shift-invariant demand in Proposition 5: gross margins exhibit a strong negative response to input price increases, while operating margins and entry show no significant response. Moreover, we find that the response of gross margins to input price changes scales with the revenue share of input costs, consistent with the predictions of shift-invariant demand.

Thus, altering the demand system to match complete pass-through in levels reconciles the model's predictions with how industry aggregates respond to input cost fluctuations in the data. Beyond providing corroborating evidence for shift-invariant demand systems, these results show that pass-through in levels is useful for understanding fluctuations in industry gross margins. Pass-through in levels may help to explain an analogous result in the exchange rate pass-through literature, where Hellerstein (2008) and Campa and Goldberg (2010) document that distribution margins as a percent of sales fall when import

prices rise. These results also clarify how industry equilibrium clears after input cost shocks: while standard models rely on waves of entry and exit to maintain a zero-profit equilibrium, the modified model with pass-through in levels achieves equilibrium with less volatility in the number of firms or operating profits.

8.3 Okun's (1981) "Special Role of Materials Costs"

In *Prices and Quantities*, Okun (1981) suggests a "special role for materials costs," speculating that firms may pass-through materials costs differently than labor costs:

Some views of marking up direct costs distinguish increases in the costs of purchased materials from increases in standard unit labor costs, implying that the former are likely to be passed through to customers essentially on a dollars-and-cents basis, while the latter are passed through with a percentage markup.

Okun's observations are difficult to explain in a rational model of firm behavior. Why should a cost-minimizing firm treat one component of costs differently from others? And why should materials costs in particular exhibit this special quality?²⁷

In this section, we suggest that demand systems that generate pass-through in levels can resolve these puzzles. We develop a simple extension of Example 5 in which firms produce varieties using materials and labor, and households consume these varieties alongside an outside good that is produced with labor. In this model, firms set additive markups consistent with pass-through in levels, but those additive markups are priced relative to the price of the outside good. As a result, firms appear to pass through changes in unit labor costs at a higher rate than material costs, because changes in the price of labor affect both costs of production and firms' additive markups.

We then show that this model can explain the pass-through of labor and materials costs in the data. Manufacturing industries indeed appear to pass through labor costs at a higher rate than material costs. However, the pass-through of energy costs behaves more like materials than labor, suggesting a "special role for labor" rather than the special role for materials proposed by Okun (1981). Moreover, once we adjust the measurement of pass-through as suggested by the model, we restore complete pass-through in levels across all inputs.

²⁷Okun (1981) makes this observation on the pass-through of material costs as a caveat to his theory that firms apply "a constant markup over direct costs" (p. 164). While he does not attempt to resolve this puzzle, he suggests that his own reading of the evidence is that the pass-through of material costs lies "somewhere in the middle" between dollars-and-cents pass-through and log pass-through. He also notes that "the percentage markup of material costs would make the price level more volatile cyclically than would a dollars-and-cents pass-through," anticipating our exercise in Section 8.4.

A simple model with differential pass-through. Suppose there are J identical firms indexed by $j = 1, \dots, J$. Each firm produces a variety using a constant returns, Leontief production function in materials and labor, so that the variable costs to produce y units of output are

$$C(y) = (\beta c + (1 - \beta)w) y,$$

where β determines the relative weights of materials and labor in production, c is the (exogenous) price of materials, and w is the (exogenous) wage rate. Each firm sets its price to maximize profits, taking as given the prices set by all other firms.

In addition to these J varieties, there is an outside good with price p_0 . The outside good is produced from labor by a competitive sector, so that the price of the outside good is $p_0 = w/A$, where A is the productivity of the outside good-producing sector.

Demand follows the discrete choice framework from Example 5: a continuum of households indexed by $i \in [0, 1]$ consume exactly one unit of an inside good from one of the J firms and spend the rest of their income Y on the outside good. The utility maximization problem for household i is

$$U_i = \max_j \{u_{ij}\} \quad \text{s.t.} \quad \begin{cases} u_{ij} = \delta_{ij} + q_{i0} & \text{(Utility)} \\ p_j + p_0 q_{i0} = Y & \text{(Budget constraint)} \end{cases}$$

We further impose that tastes δ_{ij} are independent draws from a distribution F . Given that firms $j \in \{1, \dots, J\}$ have identical costs and face identical demand curves, in equilibrium the firms choose a symmetric output price, which we denote p . Denote the corresponding percentage markup over marginal cost by $\mu = p/(\beta c + (1 - \beta)w)$.

Given this environment, Proposition 6 characterizes the pass-through of exogenous changes to the cost of materials c and to wages w .

Proposition 6 (Differential pass-through of material and labor costs). *Let ρ_c^{level} and ρ_w^{level} denote the pass-through in levels of an exogenous change to unit materials prices and unit wages, and let ρ_c^{log} and ρ_w^{log} denote the analogous log pass-throughs.*

1. For each input $x \in \{c, w\}$, these pass-through rates can be measured as

$$\frac{d \log p}{d \log x} = \rho_x^{log} \frac{Costs(x)}{C(y)}, \quad \text{and} \quad \frac{d \log p}{d \log x} = \rho_x^{level} \frac{Costs(x)}{py},$$

where $Costs(c) = \beta c y$ and $Costs(w) = (1 - \beta)w y$ are material and labor variable costs.

2. Firms exhibit complete pass-through in levels of materials costs, $\rho_c^{level} = 1$ and $\rho_c^{log} < 1$.

3. Firms exhibit (more than) complete log pass-through of labor costs, $\rho_w^{level} \geq \mu$ and $\rho_w^{log} \geq 1$.

4. The “adjusted pass-through in levels” of labor costs $\rho_w^{adj} = 1$, where

$$\frac{d \log p}{d \log w} = \rho_w^{adj} \frac{Costs(w) + VariableProfits}{py},$$

and where $VariableProfits = py - C(y)$.

Proof. See Appendix B.4. □

Proposition 6 shows that this simple model can generate different pass-through rates for material and labor costs, matching the patterns described by Okun (1981): material costs are passed-through completely in levels, while labor costs are passed-through with a percentage markup. The central idea is that, while changes in wages affect marginal costs of production in the same way that changes in materials costs do, changes in wages also affect the price of the outside good, which in turn affects firms’ desired additive markups. In terms of the demand system, not only is $D(\mathbf{p}, p_0, Y)$ shift invariant in \mathbf{p} , but also for any firm j , $D_j(\lambda \mathbf{p}, \lambda p_0, Y) = D_j(\mathbf{p}, p_0, Y)$. This means that scaling both marginal costs and the outside good price by a fixed factor leads firms to retain fixed percentage markups.²⁸

Proposition 6 also shows how we can correct our measure of the pass-through of labor costs to account for the special role that the price of labor plays in determining firms’ additive markups. Rather than using the revenue share of labor input costs, Proposition 6 indicates that we should use the revenue share of labor costs plus variable profits. Doing so takes into account that the price of labor determines the level of firms’ markups and restores complete pass-through in levels, $\rho_w^{adj} = 1$.

Empirical evidence. We now explore whether this stylized model can explain the pass-through of labor and material costs in the data. We use the NBER-CES data on manufacturing industries from Section 5, since these data record expenditures on both materials and labor inputs. As in Section 5, we use the average hourly earnings of production and nonsupervisory employees in manufacturing as the price index for production labor across all industries, to ensure that the labor price index is not biased by rent-sharing of profits with employees.²⁹

²⁸The presence of materials costs means that a change in the wage actually results in a larger proportional change in p_0 than in marginal costs, leading to more-than-complete log pass-through of wage changes.

²⁹This is also most consistent with Okun (1981), who reports results from regressing “the price level of the nonfarm economy [...] to wages in logarithmic form” (p. 163). Okun’s puzzle disappears if we instead use the ratio of production worker costs to hours as the measure of wages in each industry. However, this latter measure may also capture changes in the composition of workers or rent-sharing with workers.

Let us start by exploring whether differences in the pass-through of materials and labor costs described by Okun (1981) appear in the data. We measure the pass-through of input cost changes for each input $k \in \{\text{Materials, Energy, Production Labor}\}$ to output price changes using the specifications,

$$\Delta \log p_{it} = \sum_k \rho_k^{\log} \left(\frac{\text{Costs}_{ikt-1}}{\text{VariableCosts}_{it-1}} \times \Delta \log c_{ikt} \right) + \alpha_i + \phi_t + \varepsilon_{it}, \quad (15)$$

$$\Delta \log p_{it} = \sum_k \rho_k^{\text{level}} \left(\frac{\text{Costs}_{ikt-1}}{\text{Sales}_{it-1}} \times \Delta \log c_{ikt} \right) + \alpha_i + \phi_t + \varepsilon_{it}, \quad (16)$$

where $\Delta \log p_{it}$ is the change in the log output price index of industry i from year $t-1$ to t , $\Delta \log c_{ikt}$ is the change in the log input price index of input k used by industry i , Costs_{ikt-1} are the industry's expenditures on input k in year $t-1$, $\text{VariableCosts}_{it-1}$ and Sales_{it-1} are the total expenditures on variable inputs (materials, energy, and production labor) and sales for industry i in year $t-1$, and α_i and ϕ_t are industry and time fixed effects. The coefficients ρ_k^{\log} and ρ_k^{level} in specifications (15) and (16) correspond to the pass-through rates defined in Proposition 6.

An advantage of these data is that we observe energy costs in addition to both material and labor costs. Energy is a third input category that we can compare with both materials and labor to check whether differences in pass-through are due to material costs being “special,” as Okun (1981) conjectured, or due to labor costs playing a special role in determining firms' additive markups.

Table 10 column 1, which reports results from (15), finds that while the log pass-through of materials and energy costs is incomplete, labor costs exhibit complete log pass-through. The complete log pass-through of labor costs is consistent with Okun's conjecture that labor costs are passed-through with a percentage markup. However, across the three inputs, labor clearly is the “special” case. Column 2, which estimates (16), finds complete pass-through in levels of both material and energy costs, but estimates that the pass-through in levels of labor costs is significantly greater than one.

Proposition 6 predicts that we can correct for the special role that labor costs play in determining firms' additive markups by replacing the revenue share of labor costs with the revenue share of labor costs plus variable profits. Indeed, column 3 shows that correcting the measured pass-through of labor costs in this way restores complete pass-through in levels of labor costs and the same pass-through in levels across all three categories of inputs. Thus, the stylized model with pass-through in levels can explain why material costs and labor costs appear to be passed-through to prices at different rates, as Okun (1981) conjectured and as we verify in the data. Moreover, the model demonstrates

Table 10: Revisiting Okun’s (1981) “special role of materials costs.”

	$\Delta \text{Log Output Price}_t$		
	(1)	(2)	(3)
	Cost Shares	Sales Shares	Sales Shares
$\Delta \text{Log Material Price}_t \times \text{Material Share}_{t-1}$	0.798** (0.085)	1.046** (0.108)	1.049** (0.109)
$\Delta \text{Log Energy Price}_t \times \text{Energy Share}_{t-1}$	0.715** (0.271)	0.859** (0.378)	0.997** (0.362)
$\Delta \text{Log Production Wage}_t \times \text{Labor Share}_{t-1}$	1.070** (0.217)	2.095** (0.281)	
$\Delta \text{Log Production Wage}_t \times (\text{Labor} + \text{Variable Profits}) \text{Share}_{t-1}$			0.951** (0.209)
$p\text{-value, } \rho_{\text{material}} = \rho_{\text{labor}}$	0.23	0.00	0.65
$p\text{-value, } \rho_{\text{energy}} = \rho_{\text{labor}}$	0.34	0.02	0.91
Industry FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
N	27 374	27 374	27 374
R^2	0.49	0.50	0.49

Note: Columns 1–2 report estimates from specifications (15) and (16). Column 3 estimates a variant of (16) replacing the revenue share of labor costs with the revenue share of labor costs plus variable profits. Variable costs in column 1 are defined as the sum of material, energy, and production labor costs, and variable profits in column 3 are defined as sales less variable costs. Standard errors two-way clustered by industry and year. ** indicates significance at 5%.

how one can correct for the special role of labor by accounting for the fact that additive markups, and thus variable profits, scale with the price of labor.

8.4 Dynamics of Consumer Price Inflation

Finally, we integrate pass-through in levels into an otherwise standard input-output model of the U.S. economy. The input-output model with pass-through in levels better fits the volatility of consumer price inflation relative to upstream commodity prices, while allowing for substantial markups in line with the microeconomic evidence.

Setup. The economy consists of production labor and N goods that are used for consumption or as intermediate inputs in production. We take the wage for production labor and prices for a subset of goods $\mathcal{N}^{\text{exog}} \subset \{1, \dots, N\}$ as exogenous. Each remaining good is produced by an industry that consists of a unit mass of firms indexed by f . Firms in each industry possess identical production functions, and the cost of producing y units for a firm in industry i is

$$C_i(y) = mc_i(p_1, \dots, p_N, w)y + wF_i,$$

where w is the wage rate for labor, p_j is the price of good j , $mc_i(\cdot)$ is the marginal cost of production, and F_i is an overhead cost paid in units of labor.

The output of industry i is an aggregate of firms' differentiated varieties in the industry. We compare two cases. The first case assumes that each industry's output is a CES aggregate of firm varieties with an elasticity of substitution σ_i . This case implies that demand curves facing firms in each industry are scale invariant with respect to firms' prices in the industry. In the absence of nominal rigidities, firms' desired prices equal a fixed percentage markup times marginal cost,

$$p_{if}^* = \frac{\sigma_i}{\sigma_i - 1} mc_i.$$

The second case instead assumes that the demand for the variety produced by firm f is given by the logit demand system

$$y_{if} = \frac{\exp(-b_i p_{if}/w)}{\int_0^1 \exp(-b_i p_{ig}/w) dg} y_i, \quad (17)$$

where y_i is total industry output. In the absence of nominal rigidities, these demand curves imply that firms' desired prices are equal to marginal cost plus an additive markup that is priced relative to the wage,

$$p_{if}^* = mc_i + \frac{w}{b_i}.$$

As shown in Example 4, these logit demand curves are shift invariant and predict complete pass-through in levels of marginal cost changes. Logit demand is a tractable special case for our purposes because, like CES demand, it implies that firms' desired prices depend only on their own marginal costs and not the marginal costs or prices of other firms.

We model nominal rigidities as Calvo (1983) frictions. In each period, only a fraction of firms δ_i in each sector are able to change their prices. In the presence of these nominal rigidities, the optimal reset price for firm f in industry i at time t is

$$p_{ift} = \arg \max_p \sum_{k=0}^{\infty} \beta^k (1 - \delta_i)^k (p - mc_{it+k}) y_{ift+k}(p),$$

where $y_{ift+k}(p)$ is the demand for the firm at time $t + k$ with output price p , taking as given the prices set by all other firms.

Finally, we include a retail sector that produces a consumption good using a constant-returns production function over the N goods. We define the consumer price index as the

price of a unit of output from the retail sector.

Calibration. We calibrate a log-linearized version of the model. The set of goods includes the 402 industries in the Bureau of Economic Analysis’s (BEA) detailed input-output tables. We define the set of goods with exogenous prices $\mathcal{N}^{\text{exog}}$ as “Stage 1” industries designated by the BLS.³⁰ Data on price indices for these goods, p_{it}^{exog} , are from the BLS Producer Price Index (PPI) program. We use code from Rubbo (2023) to fill in missing PPI data from 1982–2018 using a Lasso regression of PPI data on components of the personal consumption expenditures (PCE) price index. We take the average hourly earnings of production and nonsupervisory employees as our measure of production wages.

For industries with endogenous prices, the log-deviation in each industry’s marginal costs relative to steady-state at time t is given by

$$d \log mc_{it} = \sum_j \Omega_{ij} d \log p_{jt}, \quad (18)$$

where Ω_{ij} is the steady-state share of sector i ’s variable costs spent on good j . For our baseline results, we take these expenditure shares from the 2012 BEA tables.³¹ Likewise, for the retail sector’s expenditures across industries, we use personal consumption expenditures by industry from the BEA. For Calvo frictions in each industry, we use data on monthly frequencies of price adjustment by industry from Pasten, Schoenle, and Weber (2020), who compute these probabilities of price adjustment using the firm-level data that underlies the BLS PPI.³²

For the model with percentage markups, we consider three definitions of variable costs: (1) materials costs, (2) materials costs and employee compensation, and (3) materials costs, employee compensation, and consumption of fixed capital. Material costs and employee compensation are reported in the BEA input-output tables. We compute consumption of fixed capital by multiplying gross operating surplus for each industry by the ratio of consumption of fixed capital to gross operating surplus for each industry reported in the BEA’s components of value added. For each definition of variable costs, we set σ_i to match each industry’s ratio of sales to variable costs. For the model with additive markups, we

³⁰The BLS organizes industries into four stages of production flow. Stage 1 identifies industries that are most upstream from consumer demand. The most recent mapping from BEA industries to BLS stage assignments is from 2012. See <https://www.bls.gov/ppi/notices/2021/ppi-updates-to-2012-commodity-weight-allocations-for-the-final-demand-intermediate-demand-aggregation-structure.htm>.

³¹Around the steady state, (18) describes changes in marginal costs up to a first-order regardless of elasticities of substitution in production. In Appendix Table A14, we report results allowing for the expenditure shares Ω_{ij} to respond endogenously to prices due to input complementarity.

³²We are grateful to Raphael Schoenle for sharing these data.

Table 11: Volatility of consumer price inflation in calibrated input-output models.

	Std. deviation of annual inflation, 1982–2018	Cost-weighted average markup	
		Mfg.	All
<i>Data:</i>			
Personal Consumption Expenditures (PCE) Price Index	1.1%		
Consumer Price Index for All Urban Consumers	1.3%		
<i>Model:</i>			
CES demand (percentage markups)			
Variable costs (VC) = Materials	2.5%	1.48	2.19
VC = Materials + wages	1.7%	1.19	1.31
VC = Materials + wages + consumption of fixed capital	1.6%	1.11	1.17
Logit demand (additive markups)	1.3%	1.0–1.5	1.0–2.2

Note: The cost-weighted average markup is the ratio of total industry sales to total industry variable costs, for manufacturing industries (“Mfg.”) and for all industries (“All”).

likewise choose b_i in each industry to match gross operating surplus as a share of sales.

Results for inflation volatility. Table 11 reports the volatility of consumer price inflation in the calibrated model from 1982–2018. The standard deviation of annual inflation rates in the model with fixed percentage markups, using material costs as the measure of industry’s variable costs, is 2.5%, nearly double the volatility of consumer price inflation in the data over the same period. In other words, given the input-output structure of the economy and the volatility of commodity prices, the model with percentage markups generates too much volatility in consumer price inflation relative to the data.³³

We can reduce the volatility of inflation predicted by the percentage-markup model by expanding our definition of variable costs. Including wages and all other employee compensation costs in variable costs reduces the volatility of inflation rates in the model to 1.7% (still 30–50 percent higher than the data). Further including consumption of fixed capital reduces the volatility of inflation to 1.6% (20–40 percent higher than the data).

However, reducing the volatility of consumer price inflation in this way implies average markups that appear too low relative to markups estimated in microdata. The cost-weighted average markup across industries falls from 2.19 to 1.31 when we include labor costs, and falls further to 1.17 when we include consumption of fixed capital as part of variable costs. The implied markups for manufacturing industries are even lower. In

³³If we assumed the central bank targets a desired volatility of consumer price inflation, the percentage-markups model predicts *too little* volatility in upstream commodity prices relative to the data.

comparison, De Loecker, Eeckhout, and Unger (2020) estimate a cost-weighted average markup of 1.25 among public firms and average markups in excess of 1.7 for firms in the Census of Manufacturing. Estimates of this magnitude are also typical in industry-specific studies in the industrial organization literature.³⁴

The model with additive markups reconciles this tension between the low volatility of consumer price inflation and plausibly sized markups. The volatility of consumer price inflation in the additive-markup model is 1.3%, in line with the volatility of CPI inflation and modestly larger than the volatility of PCE inflation. Moreover, the model can accommodate a cost-weighted average markup anywhere between 1.0 and 2.2. While larger markups in the percentage-markup model amplify the effect of upstream price movements on downstream prices and inflation, in the additive-markup model, upstream price movements are passed through in levels regardless of the size of markups.

9 Conclusion

Incomplete log pass-through and adjustment in firms' percentage markups may be better understood in terms of complete pass-through in levels and fixed additive markups. Across a broad array of markets, we find that complete pass-through in levels explains both the extent of incomplete log pass-through and cross-sectional variation in log pass-through. Complete pass-through in levels may help to further rationalize other empirical patterns associated with log pass-through, such as asymmetry, size-dependence, and systematic patterns of heterogeneity by firm size and product quality.

We show that a restriction on demand that we call *shift invariance* can lead firms to exhibit complete pass-through in levels of common cost shocks. While homothetic demand systems commonly used in macroeconomics and trade are incompatible with our evidence—they are *scale invariant*, rather than shift invariant—we identify several alternative demand systems that accord with complete pass-through in levels.

Integrating these demand systems into workhorse models not only brings the behavior of prices in those models in line with the data, but also generates new insights. For example, this paper investigates how doing so in models of industry dynamics and models with input-output linkages alters the models' predictions about the dynamics of industry aggregates and consumer price inflation. These are only a sample of the potential applications. In a companion paper, we explore how pass-through in levels interacts with

³⁴The relevant statistic for pass-through in the percentage-markup model is the ratio of sales to variable costs. Studies that find evidence of lower aggregate markups are typically referring to markups as the ratio of sales to the sum of variable *and overhead* costs: for example, Gutiérrez and Philippon (2017), who find an aggregate markup around 1.10, estimate markups as firms' operating margins less depreciation.

differences in consumption patterns across the income distribution. Since low-income households tend to purchase lower-priced products, pass-through in levels generates cyclical fluctuations in inflation inequality over the commodity cost cycle (Sangani 2025). We anticipate that pass-through in levels may be useful for understanding a variety of other price and firm dynamics in the data.

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Online Appendix

(Not for publication)

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Appendix A Additional Tables and Figures

Table A1: Pass-through estimates from previous studies in levels and logs.

Study	Industry	Cost shock	Pass-through estimate and notes
<i>Studies measuring pass-through in levels:</i>			
Barzel (1976)	Cigarettes	Excise taxes	1.065
Genesove and Mullin (1998)	Refined sugar	Commodity costs	0.93–1.02
Bettendorf and Verboven (2000)	Coffee	Commodity costs	0.94
Young and Bielinska-Kwapisz (2002)	Alcohol	Excise taxes	0.41–1.86
Dutta, Bergen, and Levy (2002)	Orange juice	Commodity and wholesale costs	“We find that retail transaction prices[...] respond quickly and fully to changes in costs.”
Chouinard and Perloff (2004)	Gasoline	State excise taxes	1.01
Kenkel (2005)	Alcohol	Excise taxes	0.89–4.19 (“If there were cost shocks other than the tax hike over this period, the estimates in Table 1 may overstate the rate of tax pass-through.”)
Leibtag, Nakamura, Nakamura, and Zerom (2007)	Coffee	Commodity costs	0.86 (commodity to wholesale), 0.90 (commodity to retail), 1.02 (wholesale to retail) (“If a cost change persists for several periods it will be incorporated into manufacturer prices approximately cent-for-cent with the size of the change in the commodity cost.”)
Hanson and Sullivan (2009)	Cigarettes	Excise taxes	1.08–1.17
Nakamura and Zerom (2010)	Coffee	Commodity costs	0.85 (commodity to wholesale), 0.92 (commodity to retail), 0.96 (wholesale to retail) (Uses same data sources as Leibtag et al. 2007.)
Marion and Muehlegger (2011)	Gasoline and diesel	Excise taxes	1.03–1.06 (gasoline taxes), 1.07–1.09 (diesel taxes) (“We cannot reject a null hypothesis of merely full pass-through.”)

Harding, Leibtag, and Lovenheim (2012)	Cigarettes	Excise taxes	0.85–1.02 (Pass-through “stabilizes around one at 52 miles from tax border.”)
DeCicca, Kenkel, and Liu (2013)	Cigarettes	Excise taxes	1.02 (“We cannot reject the hypothesis that the rate of shifting is 1.”)
Fabra and Reguant (2014)	Electricity	Emissions costs	0.83–0.86 (“Except for off-peak hours, we are unable to reject full pass-through in all specifications.”)
Chiou and Muehlegger (2014)	Cigarettes	Excise taxes	0.80 (premium cigarettes), 0.92 (discount cigarettes).
Conlon and Rao (2020)	Distilled spirits	Excise taxes	0.80–3.78
Cawley et al. (2020)	Sugar-sweetened beverages	Excise taxes	0.61 (“Stores in Oakland raised prices of taxed beverages by 1.00 cent per ounce on average after one year, which is exactly the amount of the tax.” The lower pass-through estimate is the difference relative to untaxed stores.)
Butters et al. (2022)	Several nondurable goods	Excise taxes, shipping costs, and commodity costs	1.01 (case study of Washington excise tax), 1.01 (all excise taxes, with category-specific estimates ranging from 0.72–1.42), 1.08 (national excise tax), 0.97 (sales taxes), 0.75 (wholesale prices), 1.01 (regulated milk farm prices), 1.20 (beer shipping costs)
Alvarez et al. (2024)	Nondurable household products	Materials costs	0.8–1.1 (aggregate shocks) “[Manufacturers] typically achiev[e] complete pass-through within two months for aggregate shocks and instantaneously for product-specific shocks. Retailers [... achieve] complete cost pass-through within five months for aggregate shocks”
<i>Studies measuring pass-through in logs / percentages:</i>			
Kinnucan and Forker (1987)	Dairy products	Commodity costs	0.33–0.46 (fluid milk), 0.50–0.58 (cheese), 0.42–0.71 (butter), 0.07–0.22 (ice cream)
Ashenfelter, Ashmore, Baker, and McKernan (1998)	Office supplies	Merchandise costs	0.15 (idiosyncratic shocks), 0.85 (aggregate shocks, estimated indirectly using sum of reaction to own and competitors’ cost shocks)
Gron and Swenson (2000)	Cars	Wage costs	0.38–0.47
Peltzman (2000)	CPI / PPI indices	Input costs	0.35–0.51

Leibtag et al. (2007)	Coffee	Commodity costs	0.26 (commodity to wholesale), 0.25 (commodity to retail)
Kim and Cotterill (2008)	Processed cheese	Input costs	0.034–0.375
Hellerstein (2008)	Beer	Exchange rates, inputs costs	0.11 (exchange rate), 0.34–0.39 (packaging, wages, and rent costs)
Leibtag (2009)	Agricultural products	Input costs	0.04–0.41 (commodity inputs to farm and wholesale prices), 0.02–0.18 (farm prices to retail prices), 0.00–0.05 (energy prices to retail prices), 0.00–0.15 (grocery store wages to retail prices)
Hellerstein and Villas-Boas (2010)	Manufacturing industries, cars	Exchange rates	0.35 (average across NAICS 3-digit industries), 0.38 (average across car models)
Nakamura and Zerom (2010)	Coffee	Commodity costs	0.26 (commodity to wholesale), 0.25 (commodity to retail)
Goldberg and Hellerstein (2013)	Beer	Exchange rate	0.07 (exchange rate to retail), 0.05 (exchange rate to wholesale), 1.05 (wholesale to retail)
Auer and Schoenle (2016)	Imports	Exchange rate	0.35 (average of aggregate pass-through rate across NAICS 3-digit industries)
De Loecker et al. (2016)	Manufacturing	Tariffs, other marginal cost changes	0.30–0.40 (pass-through of firms' estimated marginal costs to prices)
Hong and Li (2017)	Dairy, soft drinks, bread, and tomato paste/sauce	Commodity costs	Ranging from 0.01 (tomato products) to 0.30 (milk)
Cavallo, Gopinath, Neiman, and Tang (2021)	Imports from China	U.S. tariffs	0.94 (0.97 for differentiated goods, 0.73 for undifferentiated goods)
Auer et al. (2018)	Cars	Exchange rate	0.17 (average, pass-through is "half this rate for a car with one standard deviation above-average quality")
Amiti et al. (2019)	Manufacturing	Exchange rate	0.6 (own cost shocks), 1.0 (aggregate shocks, estimated indirectly using sum of reaction to own and competitors' cost shocks)
Minton and Wheaton (2022)	PPI indices	Oil / commodity costs	0.64–0.97 (adjusting for cost shares, at 1 year horizon)
Alexander, Han, Kryvtsov, and Tomlin (2024)	Wholesalers	Merchandise costs	0.79 (aggregate cost shocks), 0.69 (idiosyncratic shocks)

Table A2: Unit root tests for commodity cost series.

	Levels			First differences		
	Autocorrelation (β)	(std. error)	ADF test p -value	Autocorrelation (γ)	(std. error)	ADF test p -value
Retail gasoline						
Unleaded terminal	0.996	(0.007)	0.731	0.449	(0.058)	0.000
Premium unleaded terminal	0.995	(0.006)	0.665	0.442	(0.058)	0.000
Food products						
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
Manufacturing input costs						
Materials	0.987	(0.013)	0.549	0.334	(0.083)	0.072
Materials + energy	0.992	(0.010)	0.537	0.347	(0.086)	0.079
Materials + energy + prod. labor	0.989	(0.010)	0.562	0.362	(0.092)	0.094

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. For manufacturing input costs, we report median p -values across all industries.

Table A3: Granger causality tests for commodity and retail prices.

	Granger causality test p -value	
	Δc causes Δp	Δp causes Δc
Retail gasoline		
Terminal Unleaded to Station Price Unleaded	0.000	0.209
Terminal Premium ULD to Station Price Premium ULD	0.000	0.508
Food products		
Coffee Commodity (IMF) to Retail (BLS)	0.000	0.334
Sugar Commodity (IMF) to Retail (BLS)	0.003	0.652
Beef Commodity (IMF) to Retail (BLS)	0.688	0.956
Rice Commodity (IMF) to Retail (BLS)	0.353	0.877
Flour Commodity (IMF) to Retail (BLS)	0.700	0.931
Orange Commodity (IMF) to Retail (BLS)	0.053	0.979

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

Table A4: Pass-through in gasoline markets: Other geographies and Känzig (2021) IV.

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

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

Table A5: 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 A6: Food products commodity and retail price series with unit conversion factors.

Commodity series	IMF Series ID	Units	BLS Average Price Data series	Series ID ³⁵	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 ³⁶)
Global price of Sugar, No. 16, US	PSUGAUSAUSDM	Cents per Pound	Sugar, white, per lb.	715211, 715212	1
Global price of Beef	PBEEFUSDM	Cents per Pound	Ground beef, 100% beef, per lb. (453.6 gm)	703112	1
Global price of Rice, Thailand	PRICENPQUSDM	Dollars per Metric Ton	Rice, white, long grain, uncooked, per lb. (453.6 gm)	701312	0.0454 (100 dollars per cent / 2204.62 lbs per metric ton)
Global price of Wheat	PWHEAMTUSDM	Dollars per Metric Ton	Flour, white, all purpose, per lb. (453.6 gm)	701111	0.0613 (100 dollars per cent / 2204.62 lbs per metric ton wheat / 44.40 lbs flour per 60 lbs (1 bushel) wheat ³⁷)
Global price of Orange	PORANGUSDM	Dollars per Pound	Orange juice, frozen concentrate, 12 oz. can, per 16 oz. (473.2 mL)	713111	51.7 (100 dollars per cent × 4.133 lbs orange solids / gallon concentrate × (1/8) gallon per 16 fl oz. ³⁸)

³⁵ For some products, multiple series are available which track different package sizes.

³⁶ Nakamura and Zerom (2010).

³⁷ USDA Conversion Table (p.41) for pounds white flour per bushel of wheat.

³⁸ USDA Conversion Table (p.34) for orange solids per gallon of retail concentrate (41.8 retail brix from Dutta et al. 2002).

Table A7: Robustness: Pass-through of commodity costs to retail food prices.

Product category	Pass-through (12 mos.)				Pass-through of future cost changes	
	Baseline		With Month FEs			
Coffee	0.946 ⁺	(0.099)	0.952 ⁺	(0.094)	-0.038	(0.028)
Sugar	0.691	(0.072)	0.673	(0.070)	-0.052	(0.049)
Beef	0.899 ⁺	(0.126)	0.887 ⁺	(0.125)	0.018	(0.063)
Rice	0.882 ⁺	(0.169)	0.874 ⁺	(0.164)	-0.125	(0.068)
Flour	0.865 ⁺	(0.160)	0.872 ⁺	(0.148)	-0.099	(0.085)
Frozen orange juice	0.974 ⁺	(0.111)	0.983 ⁺	(0.110)	-0.051	(0.046)

Note: The first set of columns (“Baseline”) reports the long-run pass-through in levels $\sum_{k=0}^K b_k$ from specification (3), using a horizon of $K = 12$ months. The second set of columns (“With Month FEs”) reports the long-run pass-through in levels $\sum_{k=0}^K b_k$ from a specification augmented with month-of-year fixed effects,

$$\Delta p_{it} = \sum_{k=0}^K b_k \Delta c_{t-k} + a_i + \phi_{m(t)} + \varepsilon_{it},$$

where $\phi_{m(t)}$ denote month-of-year fixed effects. The third set of columns reports the pass-through of future commodity cost changes to prices, $\sum_{h=1}^H \beta_h$ from the specification,

$$\Delta p_{it} = \sum_{k=0}^K b_k \Delta c_{t-k} + \sum_{h=1}^H \beta_h \Delta c_{t+h} + a_i + \varepsilon_{it}.$$

We use three leads of costs ($H = 3$). For goods with several BLS Average Price series, we report Driscoll-Kraay standard errors; otherwise, we use Newey-West standard errors. ⁺ indicates estimates for which a pass-through of one is within the 90 percent confidence interval.

Table A8: Higher-priced products exhibit lower log pass-through, with no systematic difference in level pass-through: Five groups.

<i>Panel A: In percentages</i>			
	Retail price inflation		
	Rice	Flour	Coffee
Commodity Inflation \times Unit Price Group 2	−0.070** (0.017)	−0.001 (0.019)	−0.034 (0.022)
Commodity Inflation \times Unit Price Group 3	−0.095** (0.015)	−0.006 (0.006)	−0.088** (0.021)
Commodity Inflation \times Unit Price Group 4	−0.127** (0.018)	−0.044** (0.010)	−0.102** (0.019)
Commodity Inflation \times Unit Price Group 5	−0.197** (0.021)	−0.054** (0.009)	−0.105** (0.015)
UPC FEs	Yes	Yes	Yes
<i>N</i> (thousands)	399.4	101.4	1570.0
<i>R</i> ²	0.16	0.06	0.15
<i>Panel B: In levels</i>			
	Δ Retail price		
	Rice	Flour	Coffee
Δ Commodity Price \times Unit Price Group 2	0.007 (0.069)	0.048 (0.029)	−0.003 (0.040)
Δ Commodity Price \times Unit Price Group 3	0.084 (0.056)	0.048** (0.021)	−0.100 (0.063)
Δ Commodity Price \times Unit Price Group 4	0.052 (0.070)	−0.051 (0.063)	−0.120* (0.070)
Δ Commodity Price \times Unit Price Group 5	0.050 (0.133)	−0.084** (0.037)	−0.090* (0.046)
UPC FEs	Yes	Yes	Yes
<i>N</i> (thousands)	399.4	101.4	1570.0
<i>R</i> ²	0.07	0.05	0.15

Note: Panel A reports results from specification (7), and panel B reports results from specification (8). In each quarter, products are split into five groups with equal sales by average unit price over the past year, ordered from lowest (1) to highest unit price (5). Regressions weighted by sales. Standard errors clustered by brand. * indicates significance at 10%, ** at 5%.

Table A9: Effect of commodity cost changes on price dispersion.

<i>Panel A: Price Dispersion</i>	<i>Std. Dev of Unit Prices</i>			<i>Std. Dev. of Log Unit Prices</i>		
	Rice (1)	Flour (2)	Coffee (3)	Rice (4)	Flour (5)	Coffee (6)
Log Commodity Price	0.007 (0.007)	-0.052 (0.046)	-0.026 (0.016)	-0.098** (0.012)	-0.070** (0.028)	-0.108** (0.019)
Time Trend Control	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	60	60	60	60	60	60
<i>R</i> ²	0.38	0.90	0.11	0.62	0.86	0.83
<i>Panel B: Changes in Dispersion</i>	<i>Δ Std. Dev. of Unit Prices</i>			<i>Δ Std. Dev. of Log Unit Prices</i>		
	Rice (1)	Flour (2)	Coffee (3)	Rice (4)	Flour (5)	Coffee (6)
Commodity Inflation	-0.002 (0.002)	-0.014 (0.016)	0.004 (0.008)	-0.054** (0.013)	-0.020 (0.016)	-0.040** (0.014)
<i>N</i>	56	56	56	56	56	56
<i>R</i> ²	0.01	0.01	0.01	0.26	0.04	0.16

Note: Panels A and B present results from the following specifications

$$\text{StandardDeviation}(\text{UnitPrices})_t = \beta \log c_t + \delta t + \varepsilon_t, \quad (\text{Panel A})$$

$$\Delta \text{StandardDeviation}(\text{UnitPrices})_t = \beta \Delta \log c_t + \varepsilon_t, \quad (\text{Panel B})$$

where $\text{UnitPriceDispersion}_t$ is the standard deviation of unit prices (measured in either levels or logs) across products in the category in quarter t , and c_t is the commodity price in quarter t . Newey-West standard errors in parentheses. * indicates significance at 10%, ** at 5%.

Table A10: Pass-through for manufacturing industries using commodity price instrument.

Inputs:	$\Delta \text{Log Output Price}_t$		
	Materials (IV1)	+ Energy (IV2)	+ Production Labor (IV3)
$\Delta \text{Log Input Price}_t$	0.115 (0.205)	0.097 (0.205)	0.303 (0.326)
$(\text{InputCost}/\text{Sales})_{t-1}$	0.012 (0.013)	0.016 (0.015)	0.023 (0.014)
$\Delta \text{Log Input Price}_t \times (\text{InputCost}/\text{Sales})_{t-1}$	1.016** (0.244)	1.019** (0.246)	0.792** (0.393)
Industry FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
N	21 414	21 414	21 414
R^2	0.43	0.43	0.43

Note: In each column, $\Delta \text{Log Input Price}_t$ is instrumented with an interaction of the commodity price factor with SIC industry fixed effects. Column 1 uses input costs and prices for materials, column 2 uses input costs and prices for materials plus energy, and column 3 uses input costs and prices for materials, energy, and production labor. Input price inflation is an expenditure-weighted average across components of cost. Input and output price indices deflated using CPI excluding food and energy. Standard errors two-way clustered by industry and year. * indicates significance at 10%, ** at 5%.

Table A11: Pass-through for manufacturing industries at alternate horizons.

Horizon (years):	$\Delta \text{Log Output Price}_{t-h \rightarrow t}$				
	$h = 1$ (1)	$h = 2$ (2)	$h = 3$ (3)	$h = 4$ (4)	$h = 5$ (5)
$\Delta \text{Log Input Price}_{t-h \rightarrow t}$	0.079 (0.132)	0.126 (0.132)	0.183 (0.125)	0.208 (0.130)	0.231* (0.137)
$(\text{InputCost}/\text{Sales})_{t-h}$	0.004 (0.011)	0.021 (0.019)	0.035 (0.024)	0.045 (0.031)	0.050 (0.036)
$\Delta \text{Log Input Price}_{t-h \rightarrow t} \times (\text{InputCost}/\text{Sales})_{t-h}$	0.947** (0.203)	0.931** (0.208)	0.895** (0.187)	0.876** (0.184)	0.829** (0.192)
Industry FEs	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
N	27 381	26 922	26 463	26 004	25 545
R^2	0.42	0.49	0.54	0.58	0.60

Note: Column 1 replicates column (2) from Table 8. Columns 2–5 repeat the analysis, calculating changes in input costs and output prices over longer horizons from $h = 2, \dots, 5$ years. Standard errors two-way clustered by industry and year. * indicates significance at 10%, ** at 5%.

Table A12: Pass-through for manufacturing industries with below median frequency of price adjustment.

	$\Delta \text{Log Output Price}_t$			
	All Industries		Industries with Below Median FPA	
	(1)	(2)	(3)	(4)
$\Delta \text{Log Input Price}_t$	0.690** (0.072)	0.079 (0.132)	0.396** (0.069)	-0.035 (0.095)
$(\text{InputCost}/\text{Sales})_{t-1}$		0.004 (0.011)		-0.003 (0.008)
$\Delta \text{Log Input Price}_t \times (\text{InputCost}/\text{Sales})_{t-1}$		0.947** (0.203)		0.908** (0.203)
Industry FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
N	27 381	27 381	13 483	13 483
R^2	0.40	0.42	0.33	0.34

Note: Columns 1–2 replicate the first two columns from Table 8. Columns 3–4 repeat the analysis using industries with below median frequency of price adjustment. Industry-level frequencies of price adjustment are from Pasten et al. (2020). Standard errors two-way clustered by industry and year. * indicates significance at 10%, ** at 5%.

Table A13: Response of quantity shares to commodity price changes.

	Rice	Flour	Coffee
Response of Quantity Share: Unit Price Group 1	0.005 (0.011)	0.002 (0.006)	0.029* (0.017)
Response of Quantity Share: Unit Price Group 2	0.003 (0.003)	−0.008 (0.005)	0.006 (0.008)
Response of Quantity Share: Unit Price Group 3	−0.004** (0.002)	−0.000 (0.004)	−0.005 (0.007)
Response of Quantity Share: Unit Price Group 4	−0.005 (0.004)	0.006 (0.004)	−0.013** (0.006)
Response of Quantity Share: Unit Price Group 5	0.001 (0.002)	0.001 (0.002)	−0.017** (0.008)
<i>N</i>	68	68	68

Note: Each cell reports the coefficient β estimated from the specification,

$$\Delta \text{QuantityShare}_{gt} = \beta \Delta \log c_t + \phi_{q(t)} + \varepsilon_{gt}.$$

where $\Delta \log c_t$ is commodity price inflation from quarter t to quarter $t + 4$, and $\phi_{q(t)}$ are quarter-of-year fixed effects. The outcome variable $\Delta \text{QuantityShare}_{gt}$ is constructed as follows. In each quarter t , products in each category are split into groups of equal sales by average unit price over the past year. For the subset of products that are also observed in quarter $t + 4$, we calculate Quantity_{gt} and Quantity_{gt+4} as the total units (e.g., ounces of rice) sold of products in unit price group g in quarter t and quarter $t + 4$. Then,

$$\text{QuantityShare}_{gt} = \frac{\text{Quantity}_{gt}}{\sum_{g'=1}^5 \text{Quantity}_{g't}}.$$

Finally, $\Delta \text{QuantityShare}_{gt} = \text{QuantityShare}_{gt+4} - \text{QuantityShare}_{gt}$ is the change in the quantity share of products in unit price group g that are observed in quarter $t + 4$. Note that, by construction, $\sum_g \Delta \text{QuantityShare}_{gt} = 0$. Newey-West standard errors in parentheses. * indicates significance at 10%, ** at 5%.

Table A14: Volatility of consumer price inflation, allowing for endogenous changes in expenditure shares due to Leontief production.

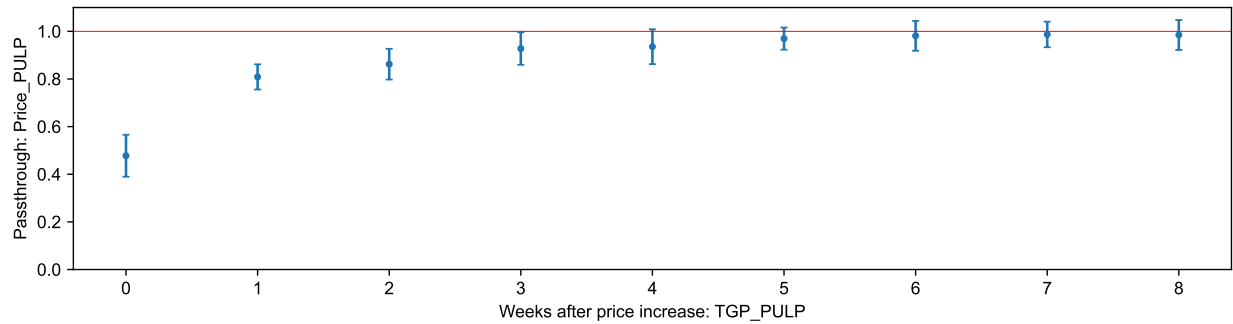
	Std. deviation of annual inflation, 1982–2018	
	Baseline (Cobb-Douglas)	Leontief inputs
CES demand (percentage markups):		
Variable costs = Materials	2.5%	2.5%
Variable costs = Materials + wages	1.7%	2.0%
Variable costs = Materials + wages + fixed capital cons.	1.6%	1.7%
Logit demand (additive markups)	1.3%	1.4%

Note: In the baseline, we assume each industry’s expenditure shares on inputs Ω_{ij} are constant (as in the log-linearized model). This table reports the volatility of inflation rates if we instead update industry expenditure shares in each period using the deviation in each industry’s prices from 2012 to discipline the changes in expenditure shares, under the assumption that industry production functions are Leontief in all inputs.

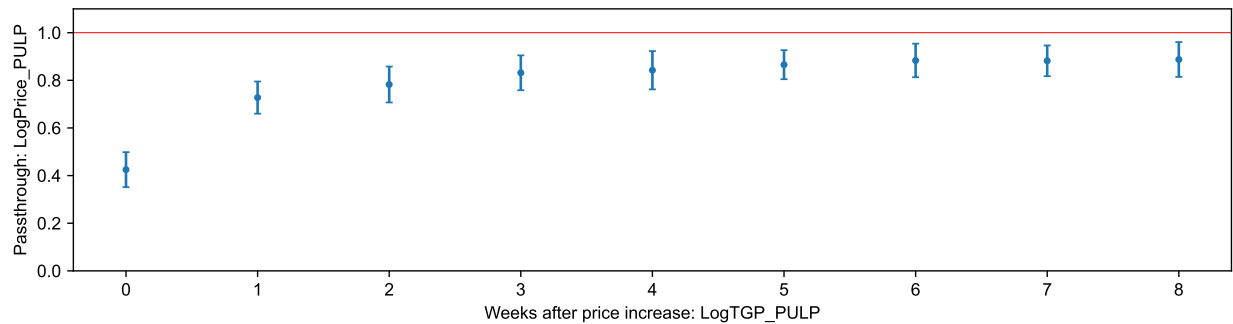
Figure A1: Weekly average retail unleaded petrol (ULP) price and terminal gas price for a station in Kewdale (Perth suburb).



Figure A2: Pass-through of premium unleaded petrol wholesale costs to retail prices.



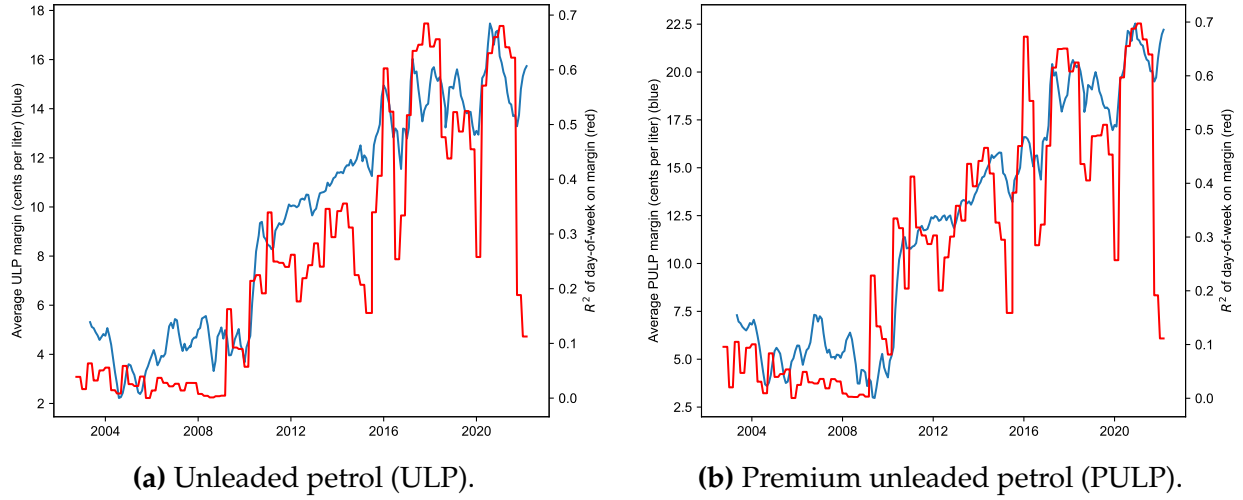
(a) Pass-through in levels.



(b) Pass-through in logs.

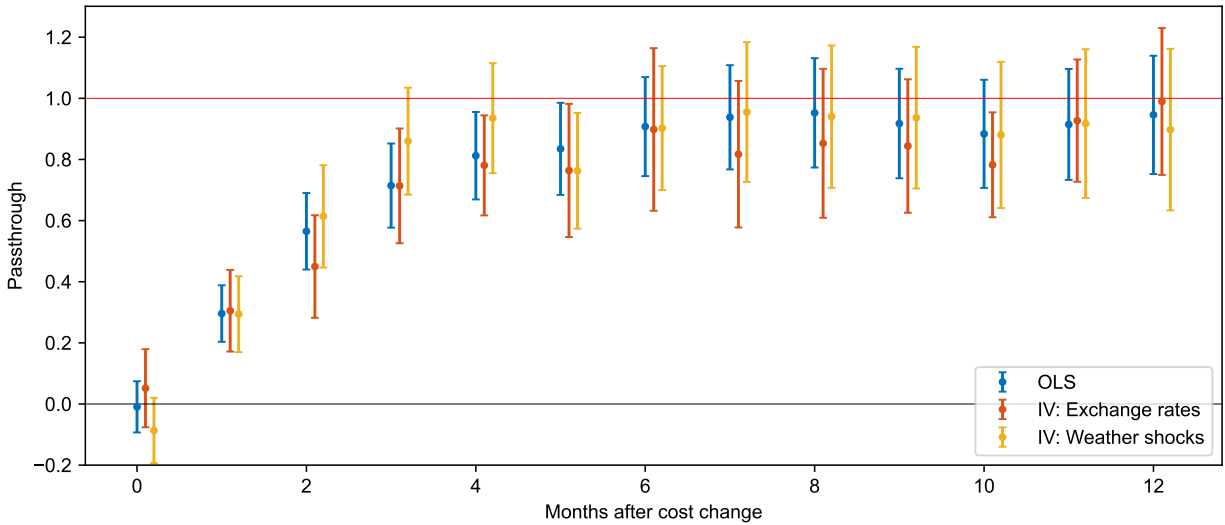
Note: Panels (a) and (b) show cumulative pass-through estimated from specifications (3) and (4). Standard errors are two-way clustered by postcode and year, and standard errors for cumulative pass-through coefficients $\sum_{k=0}^t b_k$ and $\sum_{k=0}^t \beta_k$ are computed using the delta method.

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



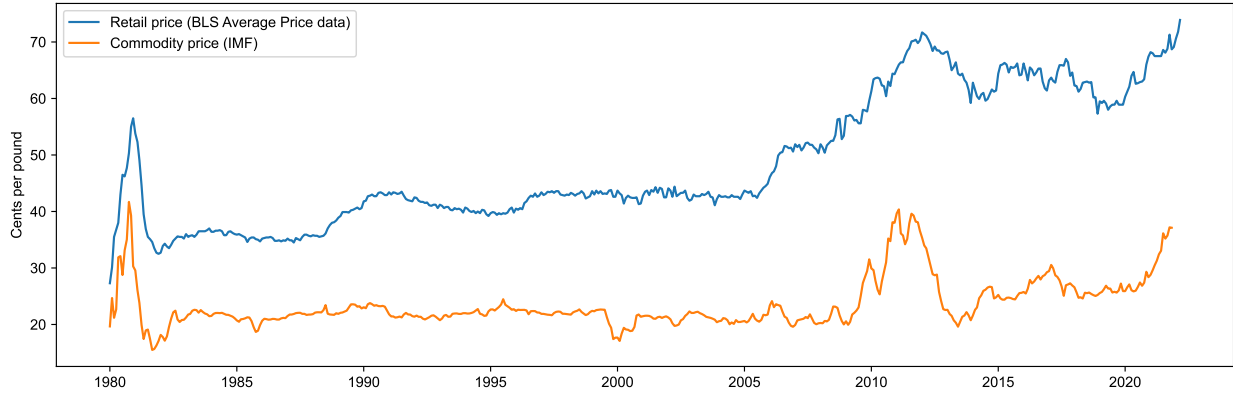
Note: In each panel, the blue line (left axis) plots the six-month moving average of margins across all stations. The red line (right axis) plots the R^2 from a regression of gas station margins of day-of-week dummies for each quarter.

Figure A4: Pass-through of coffee commodity costs to retail prices: IV estimates.

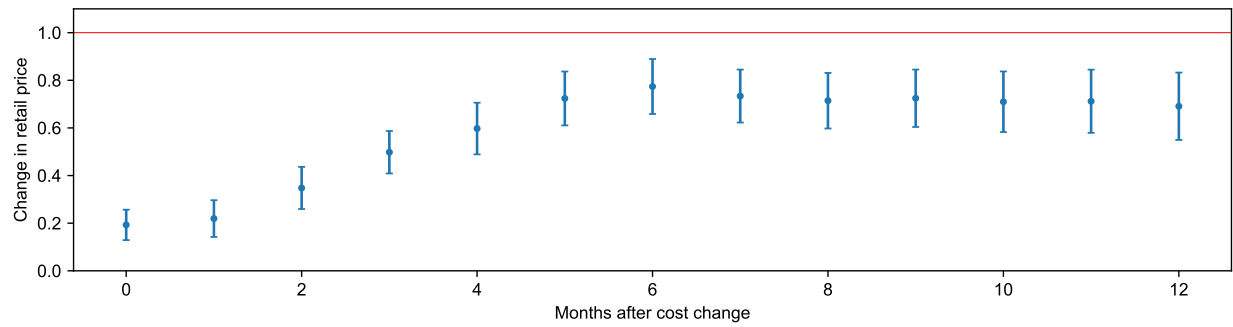


Note: The blue points are estimates of cumulative pass-through from specification (3). The red points use current and lagged Brazil and Colombia exchange rates (FRED series CCUSMA02BRM618N and COLCCUSMA02STM) and year fixed effects to instrument for commodity cost changes. The yellow points use twelve lags of minimum and maximum temperatures in coffee-growing regions in Brazil (21.55°S, 45.34°W) and Colombia (4.81°N, 75.70°W) and month-of-year fixed effects to instrument for commodity cost changes. Robust standard errors cumulated using the delta method.

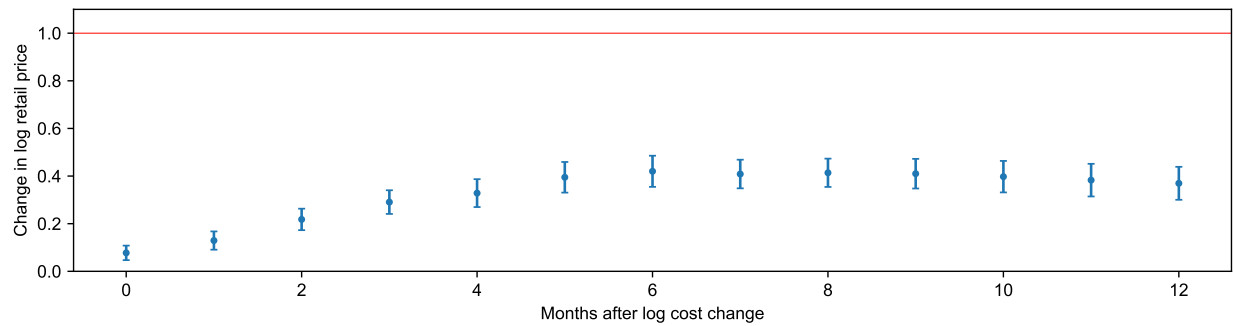
Figure A5: Passthrough of sugar commodity costs to retail prices.



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



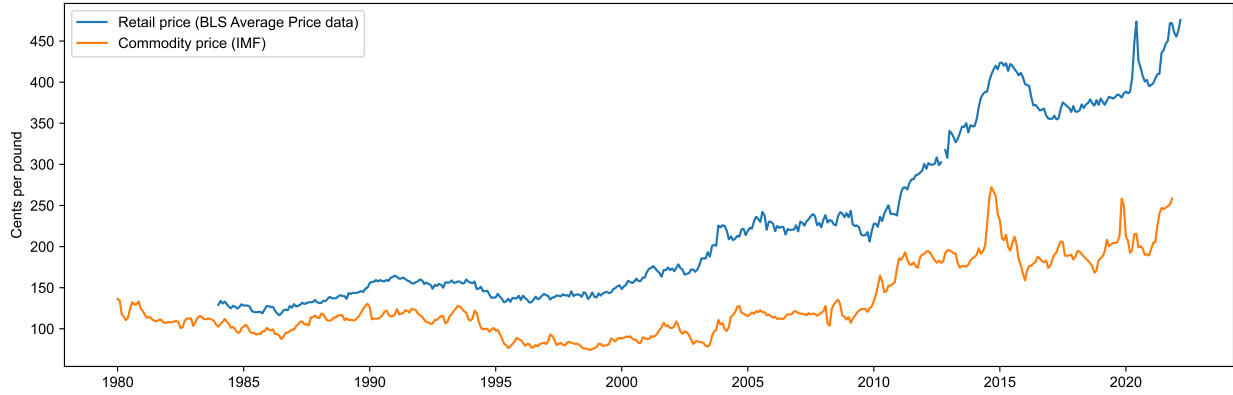
(b) Pass-through in levels.



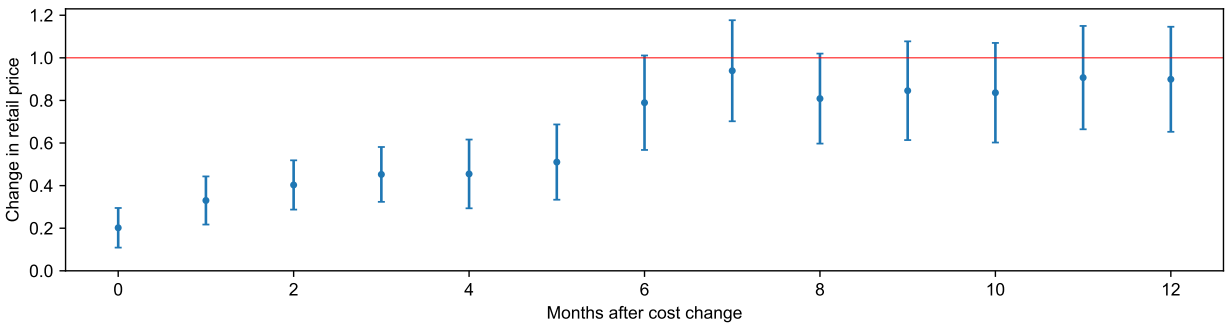
(c) Pass-through in logs.

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 A6 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 (3) and (4), using a total horizon of $K = 12$ months.

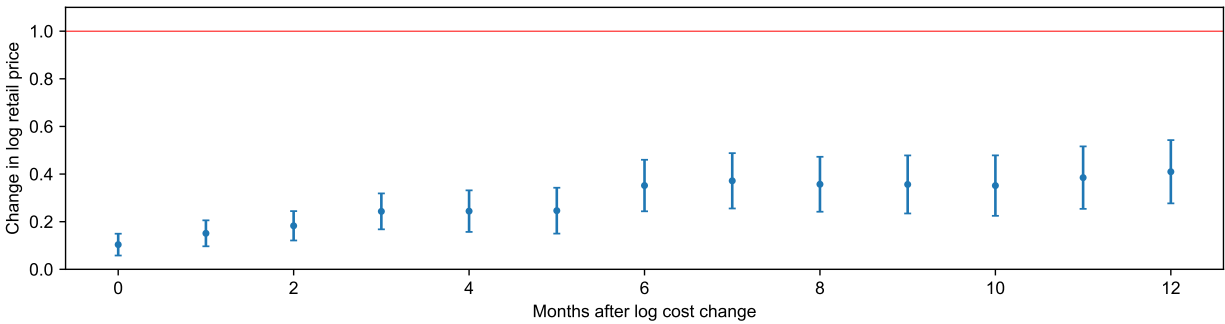
Figure A6: Passthrough of beef commodity costs to retail prices.



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



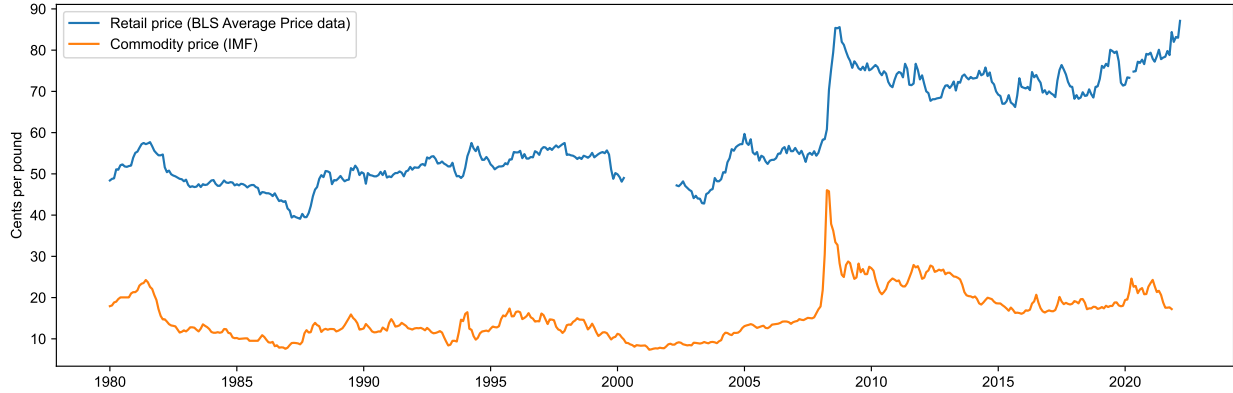
(b) Pass-through in levels.



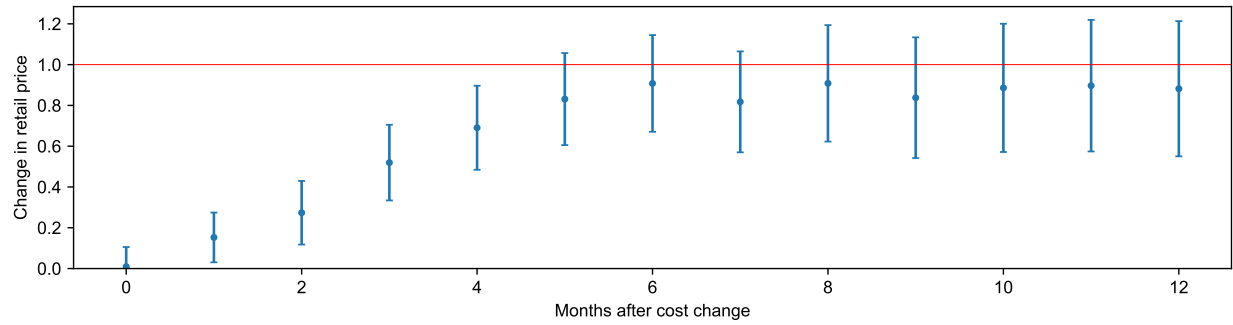
(c) Pass-through in logs.

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 A6 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 (3) and (4), using a total horizon of $K = 12$ months.

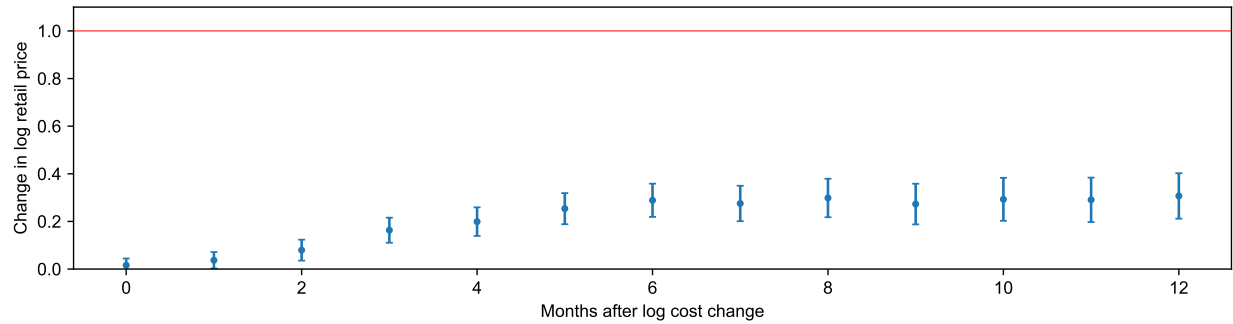
Figure A7: Passthrough of rice commodity costs to retail prices.



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



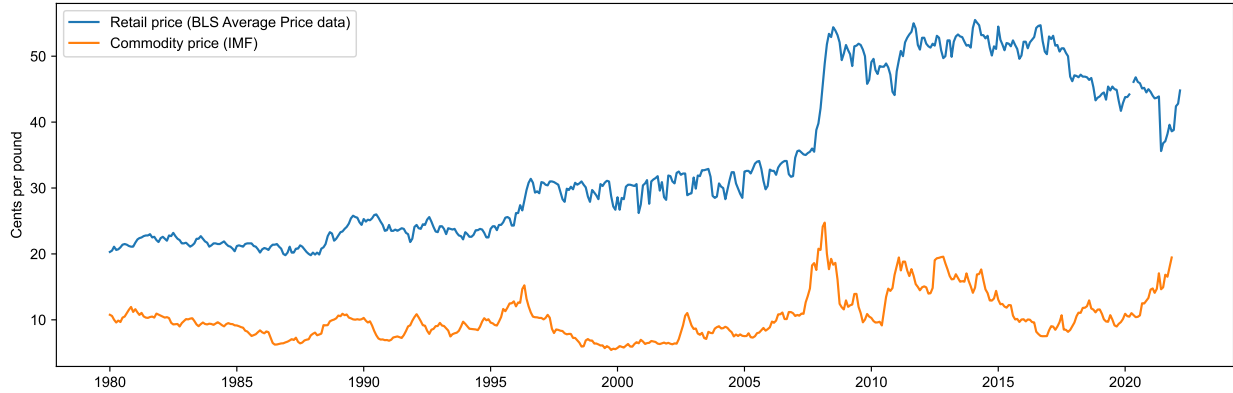
(b) Pass-through in levels.



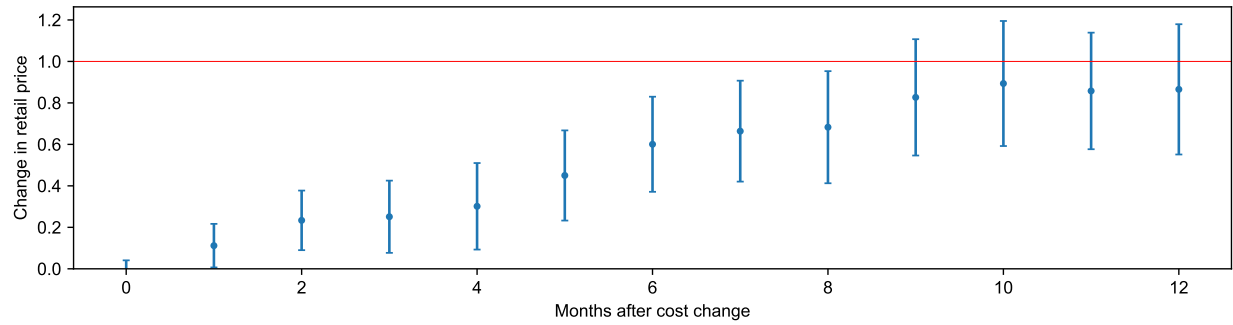
(c) Pass-through in logs.

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 A6 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 (3) and (4), using a total horizon of $K = 12$ months.

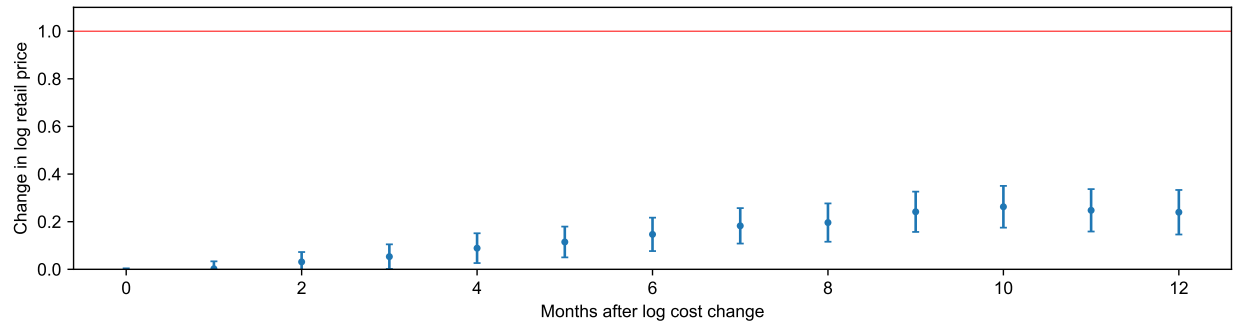
Figure A8: Passthrough of flour commodity costs to retail prices.



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



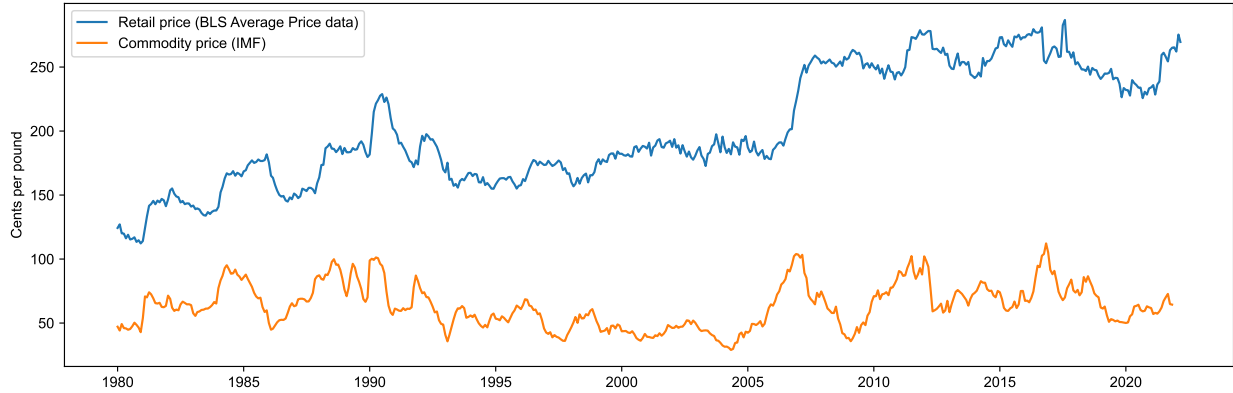
(b) Pass-through in levels.



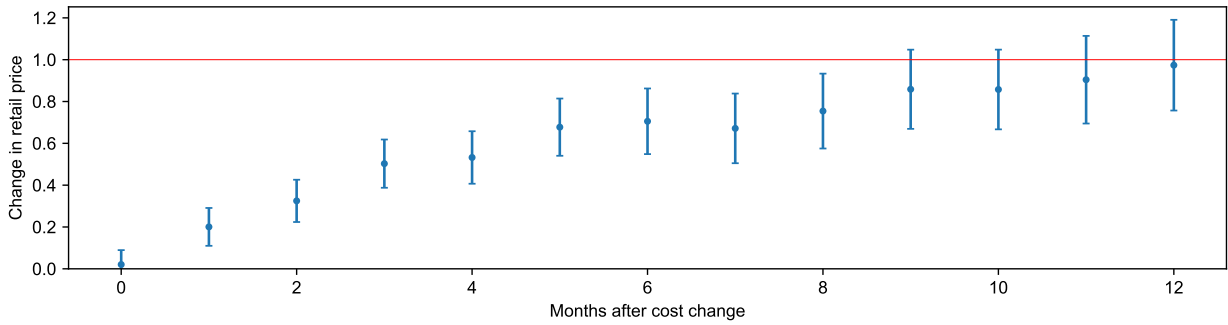
(c) Pass-through in logs.

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 A6 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 (3) and (4), using a total horizon of $K = 12$ months.

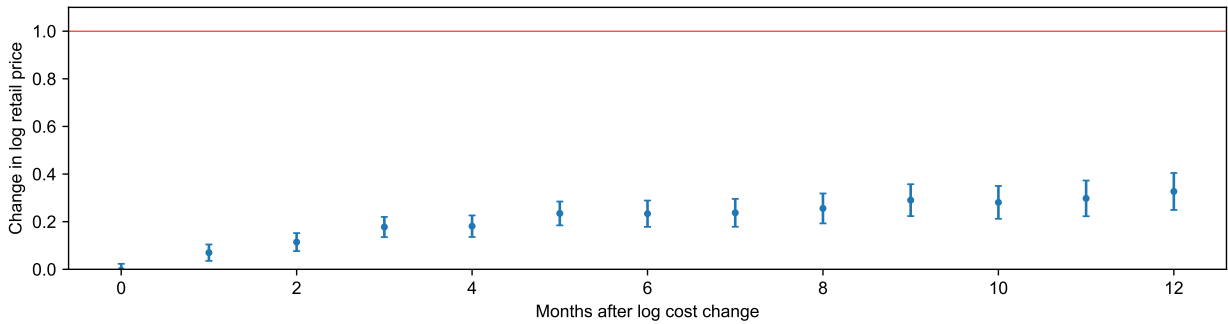
Figure A9: Passthrough of frozen orange juice commodity costs to retail prices.



(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 A6 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 (3) and (4), using a total horizon of $K = 12$ months.

Figure A10: Price of a coffee UPC in two stores in same 3-digit ZIP in Philadelphia, PA.

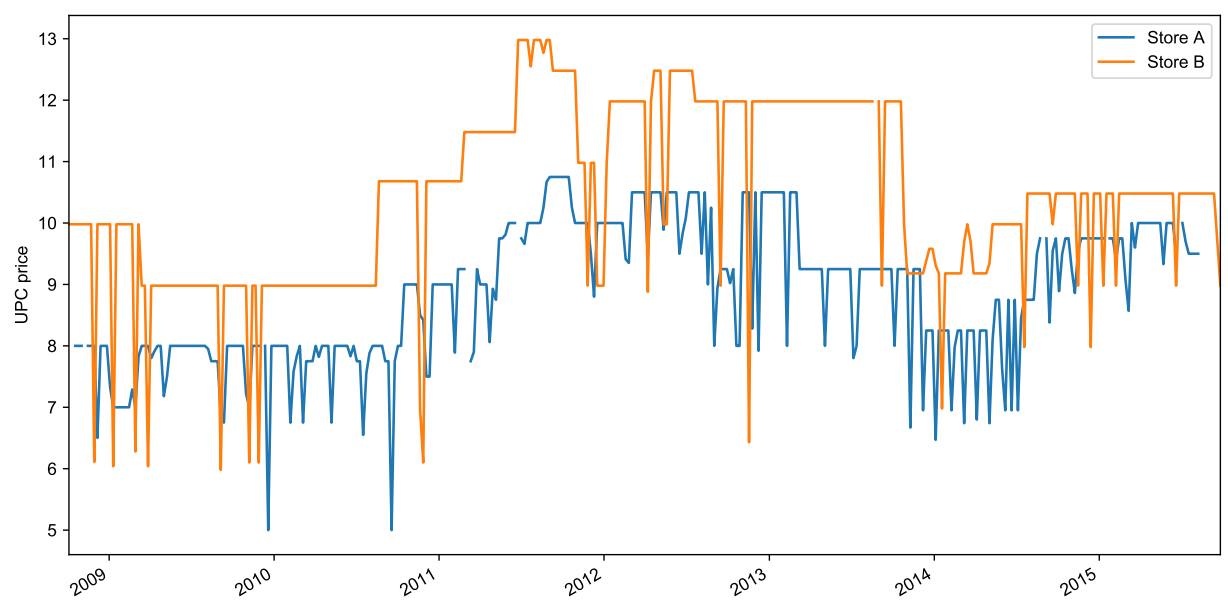
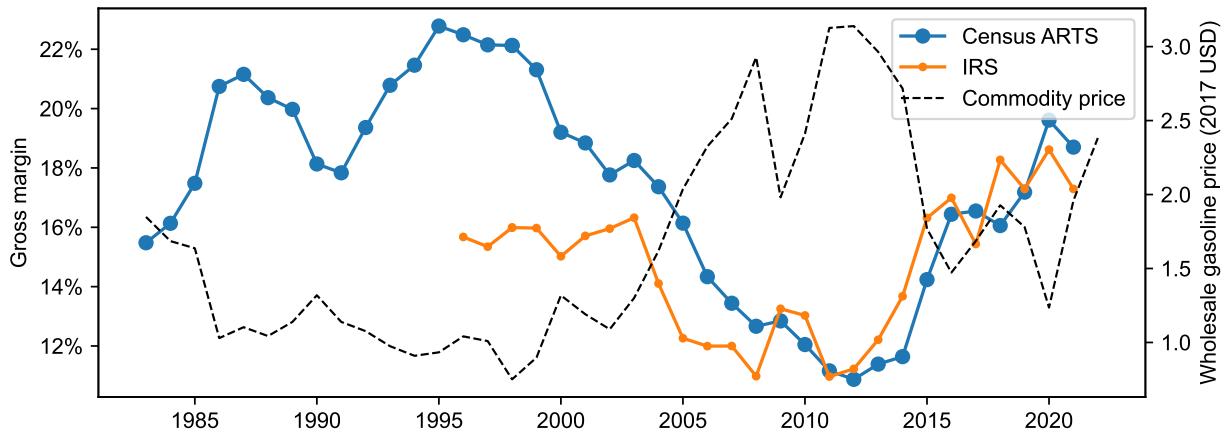
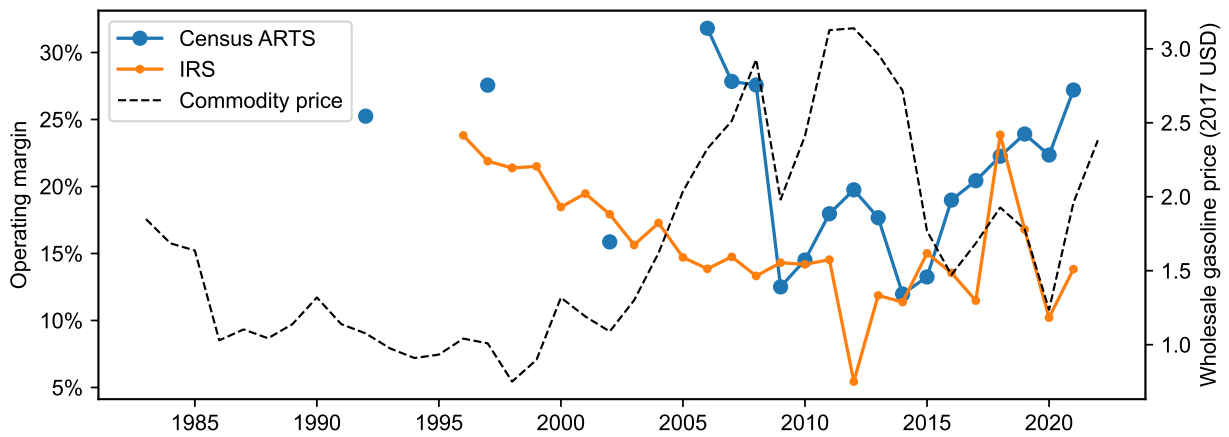


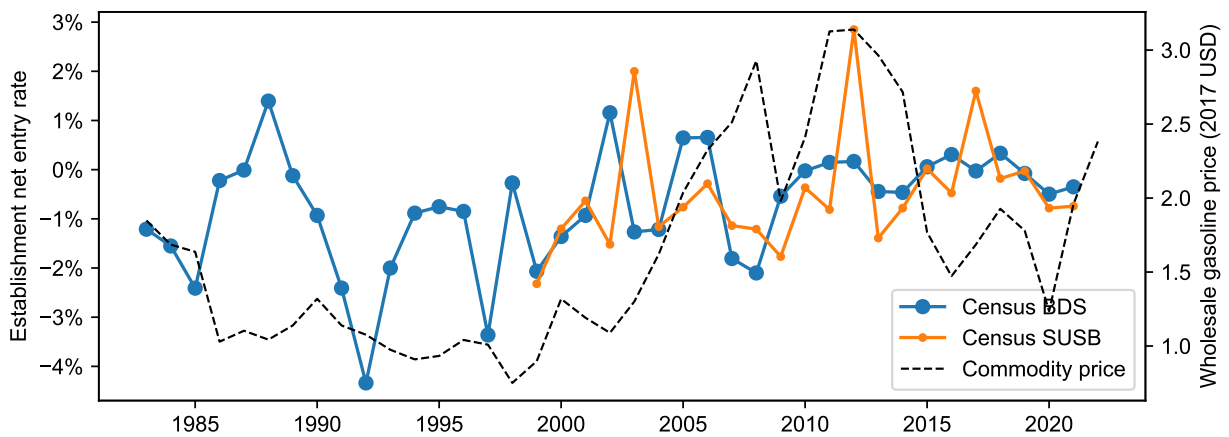
Figure A11: Gross margins, operating margins, and entry for retail gas stations.



(a) Gross margin.



(b) Operating margin (defined as operating income / gross profits).



(c) Entry.

Appendix B Proofs

B.1 Estimating Long-Run Pass-through

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

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

We define the survival probability S_s as the probability that a price spell lasts at least s periods,

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

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

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

Assumption B1 (Profit-maximizing prices). Absent nominal rigidities, a firm's desired price in period t is

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

where μ is a fixed percentage markup, w is the (constant) cost of non-commodity inputs, and m is a fixed additive markup.

Assumption B2 (Cost process). The commodity cost process follows

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

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

Assumption B3. Firms' losses from setting price p_t are given by,

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

Given these assumptions, Proposition B1 shows that the long-run pass-through estimated using a distributed lag regression is equal to the percentage markup μ when the

number of lags included in the regression is large and the commodity cost is unit root.

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

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

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

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

Firms' optimal reset prices solve the maximization problem,

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

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

$$p_t^{\text{reset}} = \mu \frac{\sum_{s=0}^{\infty} \beta^s S_s \mathbb{E}[c_{t+s}]}{\sum_{s=0}^{\infty} \beta^s S_s} + (\mu w + m) = \mu \frac{\sum_{s=0}^{\infty} \beta^s S_s \rho^s}{\sum_{s=0}^{\infty} \beta^s S_s} c_t + (\mu w + m). \quad (19)$$

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

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

In this expression, $\frac{S_k}{\sum_{s=0}^{\infty} S_s}$ is the fraction of ongoing price spells with a length of k periods, h_k is the probability that those firms will reset their price in the current period, and $p_t^{\text{reset}} - p_{t-k-1}^{\text{reset}}$ is the change in price they will choose if they reset their price today. By substituting in the reset price (19), we find that

$$\mathbb{E}[\Delta p_t] = \mu \phi \sum_{k=0}^{\infty} \sum_{j=k}^{\infty} \frac{h_j S_j}{\sum_{s=0}^{\infty} S_s} \Delta c_{t-k} = \mu \phi \sum_{k=0}^{\infty} \frac{\sum_{j=k}^{\infty} (S_j - S_{j+1})}{\sum_{s=0}^{\infty} S_s} \Delta c_{t-k} = \mu \phi \sum_{k=0}^{\infty} \frac{S_k}{\sum_{s=0}^{\infty} S_s} \Delta c_{t-k}.$$

As the number of lags $K \rightarrow \infty$, clearly $b_k = \mu \phi \frac{S_k}{\sum_{s=0}^{\infty} S_s}$. Thus, the estimated long-run pass-through $\sum_{k=0}^{\infty} b_k = \mu \phi$. When $\rho = 1$ (i.e., the commodity price is unit root), $\phi = 1$, and hence $\lim_{\rho \rightarrow 1} \sum_{k=0}^{\infty} b_k = \mu$. \square

Even when $\rho \neq 1$, ϕ is close to one for reasonable parameters. For example, suppose $\rho = 0.96$ (the minimum autocorrelation among commodity series in Table A2), $\beta = (0.96)^{1/12}$, and firms have Taylor pricing, resetting prices every 12 months. This yields a value of $\phi \approx 0.983$. If firms reset prices every 6 months, this rises to $\phi \approx 0.992$.

B.2 Proofs for Section 7

Proof of Proposition 1. Profit maximization yields the following first-order conditions for prices

$$1 = \left(\frac{p_j - c_j}{p_j} \right) \frac{-\partial \log D_j(\mathbf{p}, \mathbf{p}_0, Y)}{\partial \log p_j}.$$

Differentiating yields the change in firm j 's price $d \log p_j$ in terms of changes in own costs $d \log c_j$ and others' prices $d \log p_n$,

$$d \log p_j = d \log c_j - \frac{p_j - c_j}{c_j} \left(\frac{-\partial \log D_j}{\partial \log p_j} \right)^{-1} \sum_{n=1}^J \frac{-\partial^2 \log D_j}{\partial \log p_j \partial \log p_n} d \log p_n. \quad (20)$$

Given a proportional increase in all firms' marginal costs $d \log c_j = d \log c$ for all $j \in \{1, \dots, J\}$, under Assumption 2, complete log pass-through (i.e., $d \log p_j = d \log c$ for all j) is a solution to (20) if and only if for all j ,

$$\sum_{n=1}^J \frac{\partial^2 \log D_j(p)}{\partial \log p_j \partial \log p_n} = 0. \quad (21)$$

If D is scale invariant in inside prices,

$$\log D_j(\lambda \mathbf{p}, \mathbf{p}_0, Y) = \varphi_j(\mathbf{p}, \mathbf{p}_0, Y, \lambda) \log \lambda + \log D_j(\mathbf{p}, \mathbf{p}_0, Y).$$

A first-order expansion around $\lambda \approx 1$ also yields

$$\log D_j(\lambda \mathbf{p}, \mathbf{p}_0, Y) \approx \log D_j(\mathbf{p}, \mathbf{p}_0, Y) + \sum_{n=1}^J \frac{\partial \log D_j}{\partial \log p_n} \log \lambda.$$

Setting the two equal,

$$\sum_{n=1}^J \frac{\partial \log D_j}{\partial \log p_n} = \varphi_j(\mathbf{p}, \mathbf{p}_0, Y, 1).$$

Since scale invariance in inside prices imposes $\partial \varphi_j / \partial p_j = 0$, (21) is satisfied. \square

Proof of Proposition 2. Profit maximization yields the standard first-order condition,

$$p_j - c_j = \frac{D_j(\mathbf{p}, \mathbf{p}_0, Y)}{-\partial D_j(\mathbf{p}, \mathbf{p}_0, Y) / \partial p_j}.$$

Differentiating yields the change in firm j 's price dp_j in terms of changes in own costs dc_j and others' prices dp_n ,

$$dp_j = dc_j - \left(\frac{\partial D_j}{\partial p_j} \right)^{-1} \sum_{n=1}^J \left(\frac{\partial D_j}{\partial p_n} + \frac{D_j}{-\partial D_j / \partial p_j} \frac{\partial^2 D_j}{\partial p_j \partial p_n} \right) dp_n. \quad (22)$$

Given an identical increase in all firms' costs, $dc_j = dc$ for all $j \in \{1, \dots, J\}$, under Assumption 2, complete pass-through in levels (i.e., $dp_j = dc$ for all j) is a solution to (22) if and only if for all j ,

$$\frac{D_j(p)}{\frac{\partial D_j(p)}{\partial p_j}} \left[\frac{\partial}{\partial p_j} \sum_{n=1}^J \frac{\partial D_j}{\partial p_n} \right] = \sum_{n=1}^J \frac{\partial D_j}{\partial p_n}. \quad (23)$$

Note that a first-order expansion of demand around $\lambda \approx 0$ yields,

$$D_j(\mathbf{p} + \lambda \mathbf{1}, \mathbf{p}_0, Y) \approx D_j(\mathbf{p}, \mathbf{p}_0, Y) + \sum_{n=1}^J \frac{\partial D_j}{\partial p_n} \lambda.$$

Setting this equal to the expression for demand under shift invariance in inside prices (Definition 2),

$$\sum_{n=1}^J \frac{\partial D_j}{\partial p_n} = \psi_j(\mathbf{p}, \mathbf{p}_0, Y, 0) D_j(\mathbf{p}, \mathbf{p}_0, Y).$$

Noting that shift invariance in inside prices also imposes $\partial \psi_j / \partial p_j = 0$, substitute this expression into (23) to confirm that (23) is satisfied. \square

Proof of Proposition 3. We prove by contradiction. Suppose $D(\mathbf{p}, \mathbf{p}_0, Y)$ is both scale invariant and shift invariant. Scale invariance and shift invariance imply, respectively, that for any price vector \mathbf{p} and any j ,

$$\sum_{n=1}^J \frac{\partial \log D_j}{\partial \log p_n} = \varphi_j(\mathbf{p}, \mathbf{p}_0, Y, 1) \quad (24)$$

$$\text{and} \quad \sum_{n=1}^J \frac{\partial D_j}{\partial p_n} \frac{1}{D_j} = \psi_j(\mathbf{p}, \mathbf{p}_0, Y, 0). \quad (25)$$

Consider first a vector of identical prices $\mathbf{p}_1 = p \mathbf{1}$, where $p > 0$ and $\mathbf{1} = (1, \dots, 1)$ is a

vector of ones of length J . Multiplying both sides of (25) by p and setting equal to (24) yields,

$$\sum_{n=1}^J \frac{\partial \log D_j}{\partial \log p_n} \bigg|_{p=p_1} = \varphi_j(\mathbf{p}_1, \mathbf{p}_0, Y, 1) = p \psi_j(\mathbf{p}_1, \mathbf{p}_0, Y, 0).$$

Now consider a vector of prices $\mathbf{p}_2 = p\mathbf{1} + (p_j - p)\mathbf{1}^j$, where $p_j \neq p$ and $\mathbf{1}^j$ is a vector of length J with a one in row j and zeros otherwise. In words, \mathbf{p}_2 is identical to \mathbf{p}_1 except for the price of good j , which is now p_j rather than p . Under scale invariance, $\partial \varphi_j / \partial p_j = 0$, so:

$$\sum_{n=1}^J \frac{\partial \log D_j}{\partial \log p_n} \bigg|_{p=p_2} = \varphi_j(\mathbf{p}_2, \mathbf{p}_0, Y, 1) = \varphi_j(\mathbf{p}_1, \mathbf{p}_0, Y, 1) = p \psi_j(\mathbf{p}_1, \mathbf{p}_0, Y, 0). \quad (26)$$

Likewise, under shift invariance, $\partial \psi_j / \partial p_j = 0$, so:

$$\sum_n \frac{\partial D_j}{\partial p_n} \frac{1}{D_j} \bigg|_{p=p_2} = \psi_j(\mathbf{p}_2, \mathbf{p}_0, Y, 0) = \psi_j(\mathbf{p}_1, \mathbf{p}_0, Y, 0).$$

We use this to rewrite:

$$\sum_{n=1}^J \frac{\partial \log D_j}{\partial \log p_n} \bigg|_{p=p_2} = \sum_{n=1}^J \frac{\partial D_j}{\partial p_n} \frac{p}{D_j} + \frac{\partial D_j}{\partial p_j} \frac{p_j - p}{D_j} = p \psi_j(\mathbf{p}_1, \mathbf{p}_0, Y, 0) + \frac{\partial D_j}{\partial p_j} \frac{p_j}{D_j} \frac{p_j - p}{p_j}.$$

Setting this expression equal to (26), we find

$$\frac{\partial \log D_j}{\partial \log p_j} \frac{p_j - p}{p_j} = 0.$$

This contradicts Assumption 2 that $\partial \log D_j / \partial \log p_j < 0$, concluding the proof. \square

B.3 Proofs for Section 8.2

Proof of Proposition 5. The equilibrium is described by the following system of equations:

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

as well as a pricing equation that relates p to c . We log-linearize these equations and solve for endogenous variables in terms of an exogenous change in cost, $d \log c$. Note that the log-linearized form of the pricing equation is

$$d \log p = \rho^{\log} d \log c,$$

with $\rho^{\log} = 1$ if demand is scale invariant and $\rho^{\log} = (c/p)$ if demand is shift invariant. For gross margins,

$$d \log m^{\text{gross}} = -\frac{c}{p-c} (1 - \rho^{\log}) d \log c.$$

Thus, gross margins are constant if demand is scale invariant and $d \log m^{\text{gross}} / d \log c < 0$ if demand is shift invariant. When demand is shift invariant, the change in gross margins is, $d \log m^{\text{gross}} = -\frac{cq}{pq} d \log c$, which increases with the ratio of input costs to sales.

For operating margins and the number of firms, it will be useful to first define gross industry profits $\Pi^{\text{gross}} = (p - c) Q$.

$$d \log \Pi^{\text{gross}} = d \log (p - c) - \theta d \log p = \frac{\rho^{\log} (1 - \theta) p - (1 - \theta \rho^{\log}) c}{p - c} d \log c.$$

Thus, $d \log \Pi^{\text{gross}} / d \log c > 0$ if and only if $\rho^{\log} > \rho^*$, where

$$\rho^* = \frac{c}{p} \frac{1}{1 - \theta (p - c)/p} \in [c/p, 1).$$

We can then solve for the responses of operating margins and the number of firms using

$$\begin{aligned} d \log m^{\text{op}} &= \frac{f_o}{\pi^{\text{op}}} \frac{(\pi^{\text{op}} - f_e)}{(\pi^{\text{op}} - f_e) + \zeta \pi^{\text{gross}}} d \log \Pi^{\text{gross}} \\ d \log N &= \frac{\zeta \pi^{\text{gross}}}{(\pi^{\text{op}} - f_e) + \zeta \pi^{\text{gross}}} d \log \Pi^{\text{gross}}. \end{aligned}$$

□

B.4 Proofs for Section 8.3

Proof of Proposition 6. From the perspective of firm j , demand is

$$D_j = \int_0^1 \prod_{n \neq j} 1 \left\{ \delta_{in} - \frac{p_n}{p_0} \leq \delta_{ij} - \frac{p_j}{p_0} \right\} di = \int_{-\infty}^{\infty} \left[F \left(\delta_{ij} + \frac{p_n}{p_0} - \frac{p_j}{p_0} \right) \right]^{I-1} f(\delta_{ij}) d\delta_{ij}, \quad (27)$$

where the second equality uses the fact that δ_{ij} are i.i.d. draws from F . Taking the derivative yields,

$$\frac{\partial D_j}{\partial p_j} = \left(-\frac{1}{p_0}\right)(J-1) \int_{-\infty}^{\infty} \left[F\left(\delta_{ij} + \frac{p_n}{p_0} - \frac{p_j}{p_0}\right)\right]^{J-2} f\left(\delta_{ij} + \frac{p_n}{p_0} - \frac{p_j}{p_0}\right) f(\delta_{ij}) d\delta_{ij}. \quad (28)$$

From the firm's first order condition, we can write its optimal price as

$$p_j = \beta c + (1 - \beta)w + \frac{D_j(\mathbf{p}, p_0, Y)}{-\partial D_j / \partial p_j}.$$

Evaluating (27) and (28) at the point where firms choose symmetric prices, we get the following expression for the symmetric price p ,

$$p = \beta c + (1 - \beta)w + \frac{w}{Ab}, \quad \text{where} \quad b = J(J-1) \int_{-\infty}^{\infty} [F(\delta_{ij})]^{J-2} [f(\delta_{ij})]^2 d\delta_{ij}.$$

(A similar result for firms' additive markups is derived in Perloff and Salop 1985.) The term w/Ab is the additive markup and is priced relative to the wage. Note that b depends only on the number of firms J and the distribution F , and so is independent of material or labor prices. It is straightforward to verify the remaining claims on the pass-through of changes in c and w to prices p using this closed-form expression. \square

B.5 Relaxing Assumptions on Production Technology

This section explores whether relaxing assumptions about the production technology can generate pass-through in levels of input cost changes. Suppose the production technology takes 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 y is the firm's output, x is quantity of the commodity input with price c , ℓ is the non-commodity input with price w , θ is the elasticity of substitution between the commodity and non-commodity inputs, and α are returns to scale in the non-commodity input. Given this production technology, the firm's price is equal to a markup μ times marginal cost mc .

In the main text, we assumed that $\theta = 0$, $\alpha = 1$, and $dw/dc = 0$, and characterized how the markup μ must change in response to cost changes to yield complete pass-through in levels. In this appendix, we instead assume μ is fixed and explore whether we can generate complete pass-through in levels of changes to the commodity cost ($dp/dc = 1$),

allowing for (1) non-Leontief production $\theta > 0$, (2) decreasing returns to scale $\alpha < 1$, and (3) correlation between the cost of other inputs with the commodity cost, $dw/dc \neq 0$.

Relaxing Leontief production. Suppose we allow for any elasticity of substitution θ , holding fixed $\alpha = 1$ and $dw/dc = 0$. The change in marginal cost resulting from a change in the commodity cost is

$$dmc = \left(\frac{c}{\omega C} \right)^{-\theta} dc.$$

Changes in the commodity cost translate one-for-one into changes in marginal cost when $\theta = 0$. For complete pass-through in levels $dp/dc = 1$, we must have:

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

This cannot always hold, since c/C fluctuates with the level of the commodity cost.

Decreasing returns to scale. Now suppose $\alpha \leq 1$, holding fixed $\theta = 0$ and $dw/dc = 0$. Decreasing returns to scale dampens the effect of increases in the commodity cost on marginal cost, since as price increases, the firm shrinks and the effective cost of the non-commodity input falls.

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

where in the second equality we denote $-d \log y / d \log p = \sigma$ and assume markups are given by the Lerner formula $\mu = \sigma / (\sigma - 1)$. For complete pass-through in levels, we must have

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

which cannot hold always since the non-commodity input's share in marginal costs varies with the commodity price.

Correlated input costs. Now suppose $\theta = 0$ and $\alpha = 1$. We can generate complete pass-through in levels if $dw/dc = -(\mu - 1)/\mu$. While this can generate complete pass-through in levels in principle, we think this negative correlation is unlikely to hold in practice. For example, in retail gasoline, other input costs such as shipping and transport costs are instead probably positively correlated with gasoline costs.

Appendix C Retail Gasoline Data from Other Markets

C.1 Canada

We use weekly price data for 71 cities in 10 Canadian provinces provided by Kalibrate solutions.³⁹ 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.

C.2 South Korea

We use daily station-level price data from Opinet, a service started in 2008 by the Korea National Oil Corporation to provide customer transparency about petroleum product prices and enable research.⁴⁰ These data cover all gas stations within each city in South Korea; data files are available by city/county within each province. However, some stations appear to have incomplete coverage. Hence, for all results using these data, we limit our analyses to stations that have at least 500 daily price observations (i.e., at least 10% of days during the full sample period). Opinet also provides weekly average refinery supply prices, which we use as the measure of costs facing retail stations.

C.3 United States

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

³⁹Weekly prices can be downloaded from <https://charting.kalibrate.com>.

⁴⁰These data are available for download at <https://www.opinet.co.kr>.