Complete Pass-Through in Levels

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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 leads to systematic fluctuations in relative price and markup dispersion that are not associated with changes in allocative efficiency. Third, 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. Finally, incorporating pass-through in levels into an input-output model of the U.S. economy better matches the volatility of consumer price inflation and the response of inflation to identified shocks.

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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 et al. 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 et al. 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 percentages 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. We stress that our evidence of complete pass-through in levels applies to common cost shocks—i.e., shocks that affect all producers in a market—and applies to shocks to the relative price of inputs, holding other prices in the economy (e.g., the aggregate price level) fixed.

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, under standard assumptions about firm profit-maximization and conduct, homothetic demand systems predict that industry-wide cost shocks are passed through completely in logs rather than in levels. 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 pass-through in levels.

Thus, explaining complete pass-through in levels requires departing either from scale-invariant demand or from standard assumptions about firm conduct. We argue that one natural way of generating complete pass-through in levels is to employ *shift-invariant* demand systems. 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 shift-invariant demand systems excludes homothetic preferences, it encompasses a variety of alternative models. For example, it includes the nested 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. Demand systems that satisfy shift invariance can also vary flexibly in their predictions for how firms pass through idiosyncratic cost shocks.

Shift-invariant demand systems generate complete pass-through in levels while maintaining standard assumptions about firm profit maximization and imperfect competition. 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.

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). These patterns arise from imposing a log specification to measure pass-through. Measuring pass-through in percentages can also lead to systematic heterogeneity in pass-through by firm size and product quality, because if markups tend to increase with firm size or quality, then the log pass-through of common cost shocks will mechanically decrease with size and quality.

Second, pass-through in levels of common shocks leads to mechanical changes in the dispersion of relative prices and markups. When firms maintain fixed additive markups, an increase in input costs compresses the distribution of log prices and percentage markups. Indeed, we document across several industries that measures of relative price and markup dispersion tend to fall when input costs rise. Changes in price and markup dispersion are often interpreted as signs of changes in allocative efficiency, because when demand is homothetic, a decline in markup dispersion implies a reallocation of resources toward firms with higher initial markups and a reduction in misallocation. However, when we look at the response of quantities to common cost shocks in the data, even though relative price dispersion falls, we do not find evidence of the reallocations implied by homothetic demand.

Third, 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 pass-through in levels can bridge this gap between model and data. When firms exhibit complete pass-through in levels, 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.

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, due to shift-invariant demand. 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 model with additive markups also better matches the response of consumer price inflation to identified cost shocks.

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 evidence of complete pass-through in levels: Section 3 measures pass-through in retail gasoline, Section 4 in food products, and Section 5 in manufacturing industries. Section 6 discusses implications for pass-through measurement, price and markup dispersion, and industry dynamics. Section 7 characterizes shift- and scale-invariant demand systems. Section 8 applies these demand systems in an input–output model, 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. (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

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

measure pass-through using reduced form methods, rather than simulating pass-through using a structural model.) The majority of studies 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. A few exceptions find evidence of under- or over-shifting of excise tax changes, perhaps due to retailers rounding posted prices up or down to discrete price points (see e.g., Conlon and Rao 2020). However, studies that employ larger-sized tax changes or a larger sample of tax change events tend to find complete pass-through in levels, consistent with our results.

Two closely related studies in this literature are Nakamura and Zerom (2010) and Butters et al. (2022). Nakamura and Zerom (2010) document that retail and wholesale coffee prices move one-for-one with coffee commodity prices in levels. Butters et al. (2022) show that retailers exhibit complete pass-through in levels of various local cost shocks, including excise taxes, shipping costs, and wholesale prices. We document that complete pass-through in levels extends beyond retail and fast-moving consumer goods to a broader array of markets. Moreover, while both studies document that the average degree of markup adjustment coincides with pass-through in levels, we show that pass-through in levels in fact rationalizes the extent of pass-through observed across individual products, firms, and markets. Studies of gasoline markets also typically measure pass-through in levels rather than in logs (e.g., Karrenbrock 1991; Borenstein et al. 1997; Deltas 2008), but do not explore why complete pass-through in levels is an appropriate benchmark.[2]

Finally, our characterization of shift- and scale-invariant demand systems relates to previous studies that explore the relationship between the shape of demand and pass-through. Bulow and Pfleiderer (1983) and Mrázová and Neary (2017) characterize how the elasticity and curvature of a firm's residual demand curve affect its pass-through of idiosyncratic cost shocks. Our focus is instead on the pass-through of common cost shocks, and we show in Section 7.5 how the statistics that determine the pass-through of common and idiosyncratic shocks differ. Section 7 also relates our results to popular parameterizations of demand, such as the (scale-invariant) homothetic demand systems defined by Matsuyama and Ushchev (2017) and the (shift-invariant) class of linear random utility models defined by McFadden (1981) and Anderson et al. (1992).

[2]For 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."

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 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,[4] firms' desired prices p^* are equal to marginal cost times a fixed *percentage markup*, μ:

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

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

How does an increase in the commodity price, Δc, affect the price set by the firm? Under the 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

[3]Constant 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.3, 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.

[4]For example, monopolistic competition with CES demand. 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

between output price and marginal cost, measured in dollars and cents, does not change in response to commodity cost changes:

$$p^* = c + w + m. \tag{2}$$

We refer to m as a fixed *additive markup*. Under (2), the firm's desired price instead rises one-for-one with the commodity cost: $\Delta p^* = \Delta c$. As shown in Table 1 row (2), 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.

Let us emphasize two features of how the empirical settings we study relate to the stylized example in Table 1. 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. In Section 7, we discuss how firms that exhibit complete pass-through in levels of common cost shocks may exhibit different pass-through rates for idiosyncratic cost shocks.

Second, as in the example in Table 1, we study how firms pass through an input cost shock holding fixed all other prices, such as overhead costs, entry costs, and the price level in the economy at large. In this sense, our estimates reflect the pass-through of a *relative* price shock to inputs. We do not suggest that pass-through in levels of these relative price shocks means that firms would adjust incompletely to a rise in the overall price level (e.g., if all nominal variables were to double).

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 wholesale 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, 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 explains both the cross-sectional heterogeneity in log pass-through and the overall level of incomplete log pass-through.

3.1 Data on Station-Level Prices and Wholesale Costs

We use station-level gasoline price data from FuelWatch, a Western Australia government program that has monitored retail gasoline prices since January 2001. 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

$$\Delta p_{it} = \sum_{k=0}^{K} b_k \Delta c_{t-k} + a_i + \varepsilon_{it}, \tag{3}$$

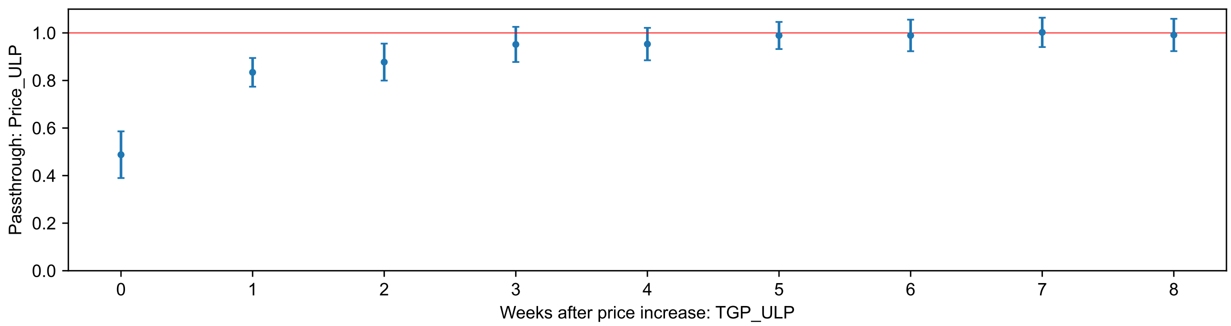
where Δp_{it} is the change in station i's retail price from week $t-1$ to t, Δc_{t-k} is the change in the input cost from $t-k-1$ to $t-k$, a_i are station fixed effects, and ε_{it} is a mean zero error term. The coefficients b_k measure the change in the output price associated with a change in input 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) 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. 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.

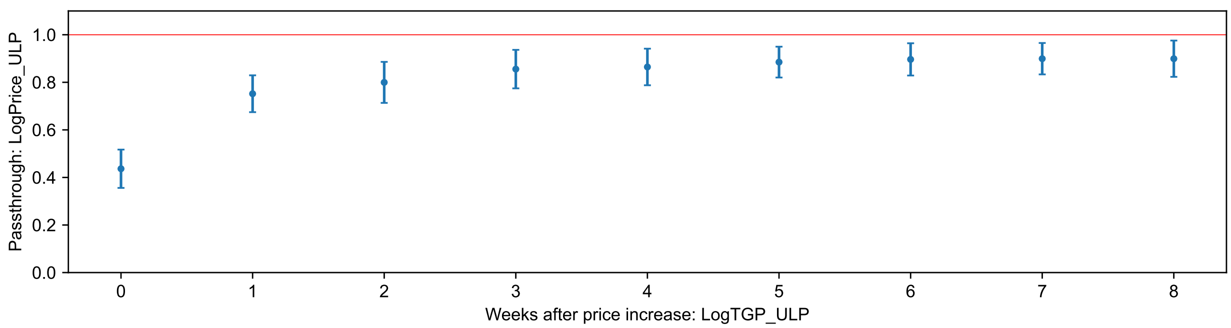
Figure 1 shows the estimated pass-through of changes in unleaded petrol (ULP) wholesale prices to station retail prices over a horizon of eight weeks. By three weeks, the pass-through in levels is statistically indistinguishable from one, and the point estimate for long-run pass-through at eight weeks is 0.991 (standard error 0.038). Estimates of the pass-through of premium unleaded (PULP) wholesale prices to retail prices are similar (see Appendix Figure A2): the long-run pass-through in levels is 0.985 (0.036). 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

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.

pass-through" using the specification,

$$\Delta \log p_{it} = \sum_{k=0}^{K} \beta_k \Delta \log c_{t-k} + \alpha_i + \varepsilon_{it}. \tag{4}$$

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,[5] 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.

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,

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

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. The coefficient δ reflects the average rate at which wholesale cost changes are passed through to prices across gas stations, and the coefficient β estimates heterogeneity in this pass-through rate across stations with high versus low markups. We further allow stations with low- and high-markups to have differences in price trends that are independent of fluctuations in wholesale costs, which are estimated by the coefficient γ.

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.

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

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

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

Note: The table reports the coefficients δ 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. For estimates of the coefficient δ on ΔCost_t, † indicates estimates for which a pass-through of one is within the 90 percent confidence interval. For estimates of the coefficient β on the interaction term, * indicates significance at the 10% level, ** at 5%.

The first measure exploits variation in markups across stations: 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 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 Avg. Quarter Markup_t. To instrument for Avg. Quarter Markup_t, we take advantage of the fact that the emergence of coordinated price cycles in the Perth market was, according to Byrne and de Roos (2019), "unrelated to market primitives." Appendix Figure A3 shows that average gas station margins over 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 time—the quarterly R^2 of station margins on day-of-week dummies—as an instrument for Avg. Quarter Markup_t.

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

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

Note: The table reports the coefficients δ 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. For estimates of the coefficient δ on $\Delta\log(\text{Cost})_t$, † indicates estimates for which a pass-through of one is within the 90 percent confidence interval. For estimates of the coefficient β on the interaction term, * indicates significance at the 10% level, ** at 5%.

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, rather than fixed percentage markups, across stations and time periods.

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,[6]

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

Column 1 shows that a 1 percent change in wholesale costs over 16 weeks leads to a 0.87% change in retail prices, significantly below the cost share of gasoline. Columns 2–5

[6]Since 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.

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.[7] 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 (Appendix E 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. The instrumented regressions produce noisier estimates but 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.

[7] In 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 $\mu^{\text{net},\%} = 100(\mu - 1)$.

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 the heterogeneity in log pass-through observed across products.

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.[8]

[8]This careful matching of units is why measuring pass-through in levels is difficult for highly differen-

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 some products, the Average Price Data include multiple price series that track different product sizes. We use all series available for each product when estimating pass-through. 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.[9]

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 specifications (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.[10] 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

tiated 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. We have two exercises that show how one can estimate pass-through in levels even without this careful matching of units. First, in Appendix C.1, we exploit the fact that retailers set different prices for identical products to test for pass-through in levels at the retail level across a wider sample of NielsenIQ products. Second, Section 5 exploits our assumption of Leontief production to test for pass-through in levels in manufacturing industries.

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

[10]Appendix Figure A10 plots sugar commodity and retail prices extending back to 1960 from the USDA. The pass-through in levels of sugar commodity prices to retail prices over the longer sample is 0.994 (se: 0.109). The lower estimate in our baseline sample is driven by incomplete pass-through of the rise and fall in sugar costs from 2009–2013. We speculate that incomplete pass-through over this period may have been due to offsetting movements in corn-based sweeteners, which are close substitutes.

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

		Pass-through (12 mos.)			
Commodity	Final Good (BLS)	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.

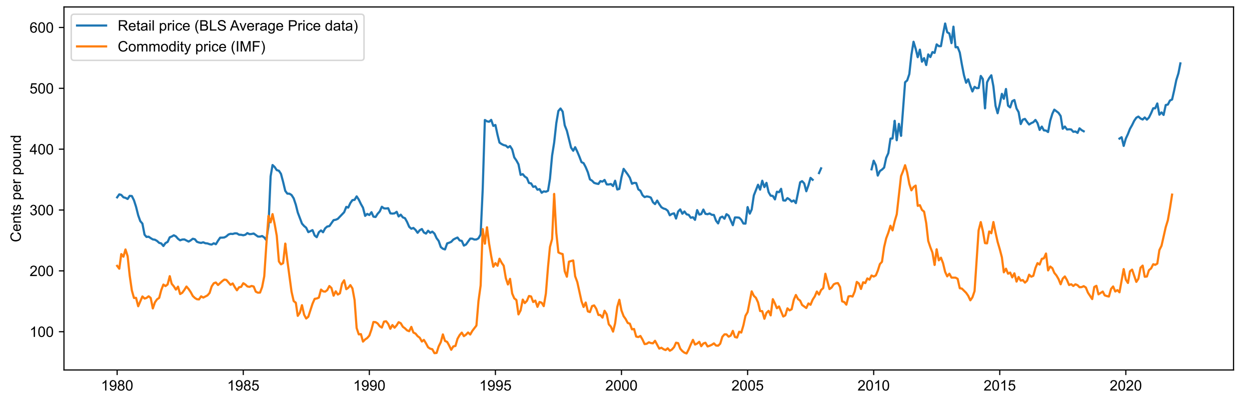
retailer sets a gross markup greater than one. Complete pass-through in levels implies log pass-through is incomplete and, as expected, we estimate that the long-run log pass-through is significantly below one for all six food products.

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.[11] These results are consistent with Nakamura and Zerom (2010), who estimate pass-through in the roasted ground coffee market from 2000–2005. Analogous figures for the other five food products are in Appendix A.

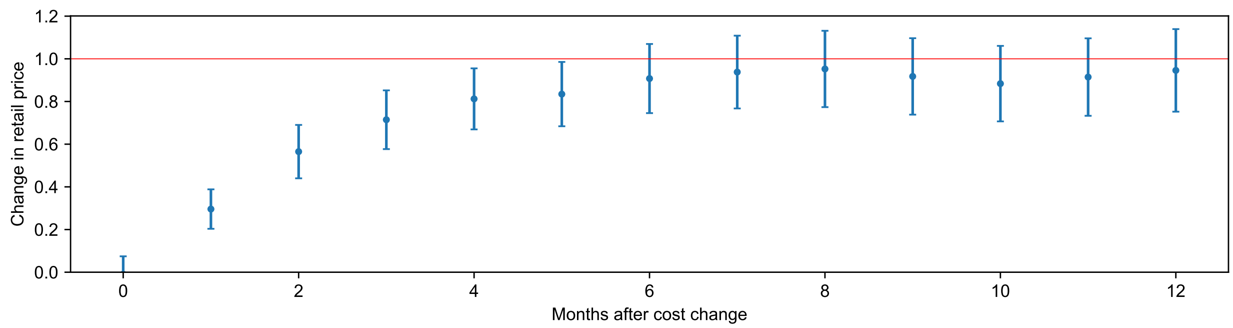
Pass-through in levels explains variation in log pass-through across products. The complete pass-through in levels documented in Table 4 has predictions for price changes in the cross-section of products. First, products that have higher markups and higher non-commodity input costs should exhibit lower 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.

[11] Appendix 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.

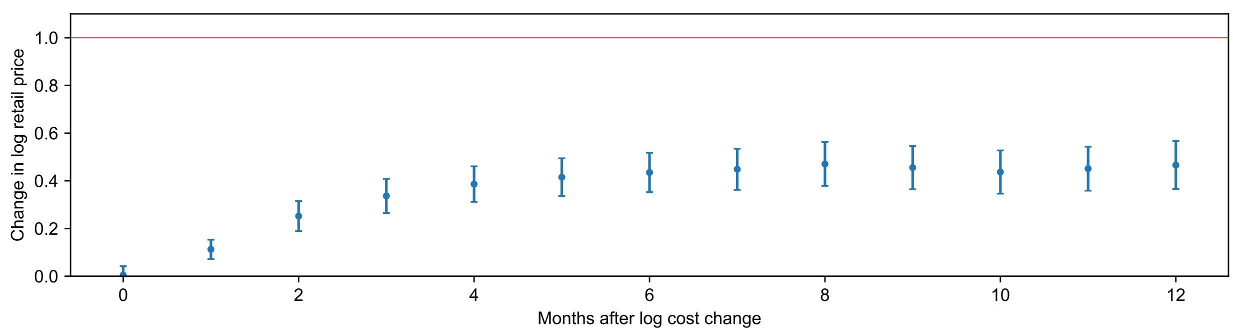
Figure 2: Pass-through of coffee commodity costs to retail prices.



(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.

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 ($\Delta \log p_{it} = \log p_{it+4} - \log p_{it}$). These price changes are measured year-over-year to 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 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 products, we estimate the following specifications,

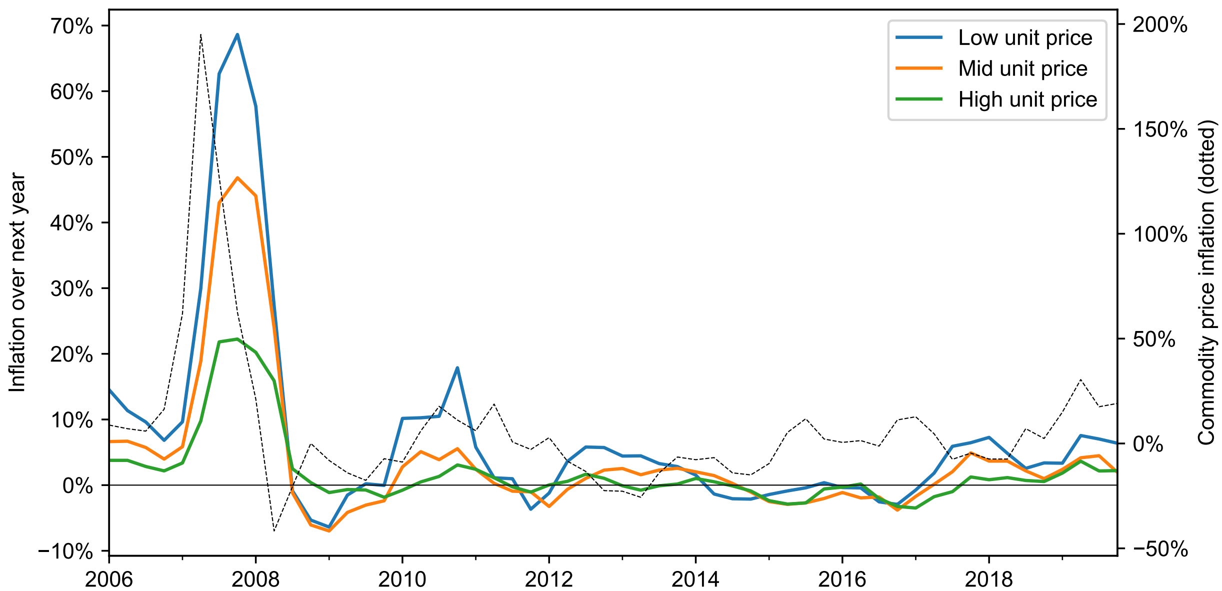
$$\Delta \log p_{it} = \alpha_i + \beta_1 \Delta \log c_t + \sum_{g=2}^{3} \beta_g \left(1\{G(i,t) = g\} \times \Delta \log c_t\right) + \varepsilon_{it}, \tag{7}$$

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

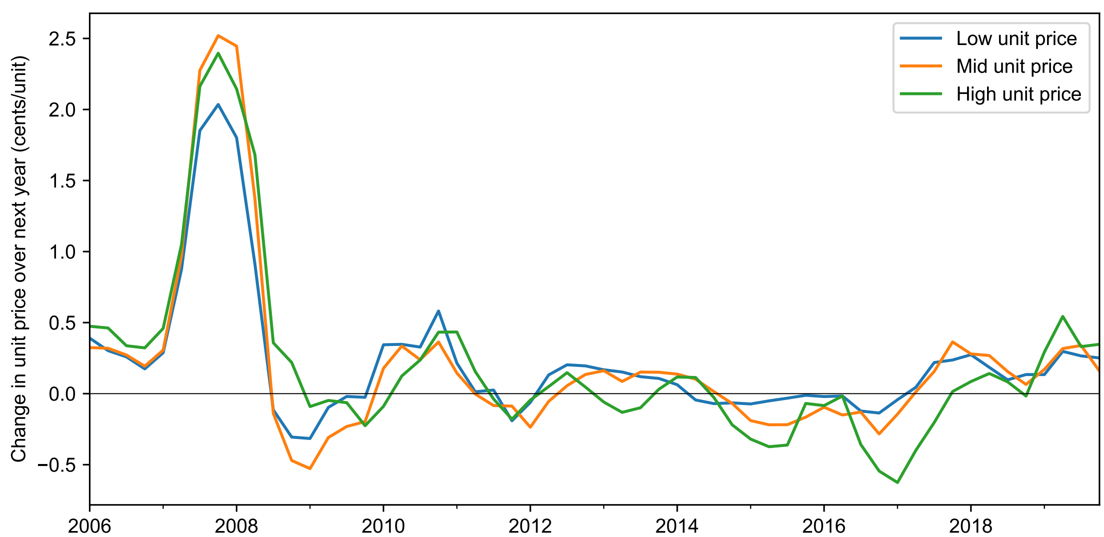
[12]Nakamura and Steinsson (2012) point out that using product-level data to measure pass-through may bias measurement when there is frequent product turnover. For these categories, over 75 percent of products in each quarter are observed in the following year, and turnover does not appear correlated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

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

Figure 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.

Panel A: In percentages			
	Δ Log Retail Price		
	Rice	Flour	Coffee
Δ Log Commodity Price × Mid Unit Price	−0.075**	−0.007	−0.064**
	(0.014)	(0.009)	(0.015)
Δ Log Commodity Price × High Unit Price	−0.150**	−0.045**	−0.091**
	(0.022)	(0.009)	(0.017)
UPC FEs	Yes	Yes	Yes
N (thousands)	399.4	101.4	1570.0
R^2	0.15	0.05	0.14

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

Note: Panel A reports results from specification (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%.

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.

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 few 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. The uniform pass-through in levels results in variable log pass-through rates across products, with lower log pass-through for higher-priced products.

Pass-through in levels by retailers. In Appendix C.1, we exploit the fact that different retail chains often sell the same UPC at different prices (Kaplan and Menzio 2015) to test for pass-through in levels at the retail level for a broader sample of products. Under the assumption that retailers face identical wholesale costs, we show that the covariance between retailers' initial prices and their subsequent price changes for a UPC can be used to differentiate between complete pass-through in levels and log pass-through, even when wholesale costs are not directly observed. This allows us to test for pass-through in levels for a broader sample of nearly one million product UPCs in the NielsenIQ data. We find that (i) retailers exhibit complete pass-through in levels and (ii) uniform pass-through in levels explains variation in log pass-through across retailers.

5 Evidence from Manufacturing Industries

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.

Data and specification. We use the NBER-CES Manufacturing Industry Database, which contains data on industry sales, costs, and input and output price indices for 459 four-digit SIC industries from 1958–2018. These data are constructed using the Census's Annual Survey of Manufacturers, the Census of Manufacturers, and the BLS Producer Price Index (PPI) program; we refer interested readers to documentation by Becker et al. (2021).

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, under certain assumptions that we delineate below, 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

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

where, on the right-hand side, we multiply both the numerator and denominator by units of output y. 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, $\Delta p/p \approx \Delta \log p$. Thus, to a first order approximation,

$$\Delta \log p \approx \rho^{\text{level}} \left(\frac{cy}{py}\right) \Delta \log c. \tag{9}$$

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.

Empirical results. We estimate the specifications,

$$\Delta \log p_{it} = \rho^{\log} \Delta \log c_{it} + \alpha_i + \varphi_t + \varepsilon_{it}, \tag{10}$$

$$\begin{aligned} \Delta \log p_{it} = {} & \rho^{\text{level}} \left(\Delta \log c_{it} \times (\text{InputCosts/Sales})_{it-1}\right) \\ & + \delta \Delta \log c_{it} + \gamma (\text{InputCosts/Sales})_{it-1} + \tilde{\alpha}_i + \tilde{\varphi}_t + \varepsilon_{it}, \end{aligned} \tag{11}$$

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, InputCosts/Sales$_{it-1}$ is industry i's revenue-share of input expenditures in year $t-1$, and α_i ($\tilde{\alpha}_i$) and φ_t ($\tilde{\varphi}_t$) are industry and year fixed effects, respectively.

The first specification (10) measures the reduced-form log pass-through of input price changes to output prices. The second specification (11) implements Equation (9). Assuming constant returns, Leontief production, (9) shows that the coefficient on the interaction term ρ^{level} in (11) identifies the pass-through in levels of the input cost change to output prices. Equation (9) also predicts that $\delta = \gamma = 0$, but we do not impose these restrictions for estimation. As discussed in Section 2, we are interested in the pass-through of shocks to the relative price of a firms' inputs, so we measure changes in each industry's input and output price indices deflated by the consumer price index.[14]

Table 6 presents the results from estimating (11) in the panel of manufacturing industries. In columns 1–2, we define input costs as each industry's materials costs. Column 1 shows industries exhibit incomplete log pass-through of materials input costs: a 1 percent increase in the materials input price index for an industry is associated with a 0.69 percent

[14] Estimating (11) using nominal price changes does not meaningfully change the results in Table 6, but we show in Appendix C.2 that it can affect estimates of pass-through across different categories of inputs.

Table 6: Pass-through for manufacturing industries.

	Δ *Log Output Price*$_t$					
Inputs:	Materials		+ Energy		+ Production Labor	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Log Input Price$_t$	0.690	0.079	0.704	0.005	0.796	0.052
	(0.072)	(0.132)	(0.073)	(0.134)	(0.083)	(0.232)
(InputCost/Sales)$_{t-1}$		0.004		0.008		0.023**
		(0.011)		(0.011)		(0.011)
Δ Log Input Price$_t$ $\times$ (InputCost/Sales)$_{t-1}$		0.947†		1.041†		0.984†
		(0.203)		(0.201)		(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. For estimates of ρ^{log} and ρ^{level}, † indicates estimates for which a pass-through of one is within the 90 percent confidence interval. For estimates of the coefficients δ and γ, * indicates significance at the 10% level, ** at 5%.

increase in output prices. Column 2 uses specification (11) to estimate the pass-through in levels. The estimated coefficient on the interaction term $\rho^{\text{level}} \approx 1$, consistent with complete pass-through in levels. Consistent with (9), we also estimate $\delta \approx 0$ and $\gamma \approx 0$.

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 ρ^{level} is very close to one, consistent with complete pass-through in levels of input cost changes to prices.

Our derivation in (9) rests on several assumptions: homogeneous firms within each industry, constant returns to scale, and Leontief production technologies. Appendix B.3 characterizes the potential biases introduced by these assumptions. For example, decreasing returns to scale in production would bias up our estimates ρ^{level}—i.e., would bias toward finding $\rho^{\text{level}} > \mu$ rather than $\rho^{\text{level}} = 1$. Allowing for substitutability between inputs (non-Leontief production) does not affect the first-order approximation in (9), but could bias downward the estimate of ρ^{level} for large cost shocks. The fact that we find $\rho^{\text{level}} \approx 1$ for various definitions of input costs in Table 6 allays concerns that substitutability between inputs or correlated input prices biases our estimates of the pass-through in levels.

Robustness. To address concerns about reverse causality due to demand shocks from downstream industries, we also estimate (11) using an instrumental variable approach. We use a decomposition of commodity price movements into demand shocks, 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 A9 reports that the estimated coefficient ρ^{level} 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 A10, we estimate (11) using changes in input and output prices at horizons ranging from one to five years. If anything, our estimate of ρ^{level} slightly declines with the horizon, and we cannot reject the hypothesis that $\rho^{\text{level}} = 1$ for any horizon.

6 Implications

We propose that pass-through in levels can be useful in understanding several features of the data. In this section, we discuss the implications of pass-through in levels for pass-through measurement, changes in the dispersion of relative prices and markups following cost shocks, and dynamics of industry margins and entry. Proofs for all propositions in this section are in Appendix B.1.

6.1 Pass-Through Measurement

When firms exhibit complete pass-through in levels, Proposition 1 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 1 (Asymmetry, size-dependence, and heterogeneity)**.** *Suppose firm j exhibits complete pass-through in levels, so that for a perturbation in firm j's costs dc_j, the firm's price changes by $dp_j = dc_j$. Let $\mu_j = p_j/c_j$ denote firm j's initial percentage markup. The measured "log* *pass-through" of firm j to a second-order approximation around $dc_j = 0$ 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 $\Delta \log c_j$.*

A large literature documents asymmetries in log pass-through (see e.g., Peltzman 2000), and recent work finds that firms pass through large shocks at higher rates than small shocks (e.g., Gagliardone et al. 2025). Although these patterns could arise from genuine differences in how firms respond to cost changes, Proposition 1 shows that using a log specification naturally generates asymmetry and size-dependence. With complete pass-through in levels, these effects arise because the log pass-through is not a stable statistic and depends on the size and direction of cost shocks.[15]

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 et al. 2012; Amiti et al. 2019; Gupta 2020) and with product quality (Chen and Juvenal 2016; Auer et al. 2018). Complete pass-through in levels naturally generates both patterns if markups increase with firm size and product quality, as is suggested by a large body of empirical work.[16]

6.2 Changes in the Dispersion of Relative Prices and Markups

Pass-through in levels also implies that common cost shocks affect the distribution of firms' relative prices and markups. Intuitively, if firms retain fixed additive markups in response to common cost shocks, an increase in costs mechanically leads to a fall in the dispersion of relative prices and percentage markups, as we formalize in Proposition 2.

[15] In particular, complete pass-through in levels can explain asymmetry and size-dependence in the *intensive* margin of price adjustment—i.e., the extent of pass-through conditional on a price change (e.g., Gagliardone et al. 2025 Figure 8), desired pass-through elicited in surveys (e.g., Bunn et al. 2024), or pass-through at long horizons (e.g., Peltzman 2000). It does not explain why the *extensive* margin of price adjustment, i.e., the likelihood or frequency of price change, varies with the sign or size of cost shocks. Benzarti et al. (2020), Cavallo et al. (2024), and Gagliardone et al. (2025) emphasize differences in the extensive margin of price adjustment in response to large *vs.* small and positive *vs.* negative shocks.

[16] See Melitz (2018) for a survey of studies relating firm size and markups, and e.g., Atkin et al. (2015) and Sangani (2022) on product quality and markups.

Proposition 2 (Dispersion in relative prices and revenue productivity)**.** *Suppose firms $j = 1, ..., J$ have identical Leontief production technologies so that the cost of producing y units of output is $C(y) = (c + \beta w)\, y$, where c is the unit cost of the commodity, w is the wage rate, and β determines labor's weight in production, and each firm's price p_j is equal to marginal cost plus a fixed additive markup m_j. Then, an increase in the cost of the commodity input leads to a fall in*

1. *the variance of **relative prices** $Var(\log p_j)$;*
2. *the variance of **log revenue productivity** $Var(\log TFPR_j)$, where $TFPR_j = p_j y_j / C(y_j)$; and*
3. *the variance of **log labor revenue productivity** $Var(\log LP_j)$, where $LP_j = p_j y_j / w\beta y_j$.*

Consider first the effect of common cost shocks on the distribution of relative prices. Pass-through in levels predicts that increases in input costs should not affect the dispersion of prices in levels—the price distribution should simply shift to the right—but should reduce the dispersion of log prices. We test this prediction in Appendix Table A11 using the data on rice, flour, and coffee products that we explored in Section 4. As predicted by Proposition 2, we find that an increase in commodity prices has no significant effect on the dispersion of price levels, but is associated with a decline in the dispersion of log prices across all three categories.

Likewise, complete pass-through in levels leads to a compression in the distribution of firms' percentage markups. Intuitively, when input costs rise, the firm-specific additive markups m_j become small relative to the common cost component, and so proportional differences across firms shrink. To test this prediction, we use measures of cross-sectional dispersion in total factor revenue productivity (TFPR) and labor revenue productivity (LP) within manufacturing industries from the BLS Dispersion in Productivity Statistics program. Foster et al. (2008) and Hsieh and Klenow (2009) show that when firms have common technologies and face common input prices, differences in TFPR and LP reflect differences in firms' markups.[17] Consistent with Proposition 2, Appendix Table A12 finds that input price increases for manufacturing industries are associated with a decline in the dispersion of both total factor revenue productivity and labor revenue productivity.

Declines in relative price and markup dispersion are often interpreted as indicating improvements in allocative efficiency. When demand is homothetic, firms' relative quantities are fully determined by their relative prices, so compressing the markup distribution

[17] When firms have heterogeneous labor intensities, differences in TFPR and LP across firms reflect both differences in markups and technologies. Appendix B.1 extends Proposition 2 to the case where production labor intensity β_j varies across firms. When β_j is heterogeneous, the effect of commodity cost increases on $Var(\log \mathrm{TFPR}_j)$ and $Var(\log \mathrm{LP}_j)$ is theoretically ambiguous. However, we show in simulations that both variances tend to decrease with c even with substantial heterogeneity in β_j.

reallocates resources toward firms with initially higher markups. This reallocation of resources to high-markup firms alleviates cross-sectional misallocation and raises efficiency.

If demand is not homothetic, however, a decline in markup dispersion need not reallocate resources to high-markup firms. Departing from homotheticity can therefore break the link between changes in markup dispersion and changes in allocative efficiency.[18]

We test whether the decline in markup dispersion induced by a common cost shock leads to the reallocations predicted by homothetic demand using quantity data for food products. A uniform absolute increase in products' prices represents a larger proportional increase for low-price products. If demand is homothetic, this should trigger a reallocation of quantities away from low-price products and toward higher-price products. Appendix Table A13 tests how quantity shares of low- and high-priced rice, flour, and coffee products respond to changes in commodity prices. We find no effect on quantity shares of low- *vs.* high-priced rice and flour products in response to commodity cost changes. For coffee, we observe if anything a reallocation *toward* low-price products when commodity costs rise, opposite the predictions of homothetic demand. Section 7 discusses nonhomothetic demand systems that can both rationalize complete pass-through in levels and account for the absence of the reallocations predicted by homothetic demand.

Thus, complete pass-through of common cost shocks leads to systematic fluctuations in the dispersion of relative prices and percentage markups. Since real input costs for manufacturing industries tend to be procyclical, this mechanism can help account for the countercyclical TFPR dispersion documented by Kehrig (2011). Moreover, while input cost changes lead to declines in relative price and markup dispersion, they do not induce the quantity reallocations that would be predicted by homothetic demand and thus do not necessarily imply improvements in allocative efficiency.

6.3 Dynamics of Industry Profits, Margins, and Entry

Whether firms maintain fixed percentage or additive markups in response to common cost shocks also has implications for the dynamics of industry profits, gross and operating margins, and entry. We show that the fixed additive markups consistent with pass-through in levels better match the response of these industry aggregates to input cost fluctuations.

The intuition for these results starts from the observation that if firms charge a fixed

[18] An important distinction is between the effect of marginal changes in markup dispersion and the effect of completely eliminating markup dispersion. Output is maximized when marginal revenue products are equalized across uses, regardless of whether or not demand is homothetic. But starting from an economy with dispersed markups, a marginal decline in markup dispersion need not improve allocative efficiency when demand is nonhomothetic. We provide an example with logit demand in Appendix B.1.

percentage markup over marginal cost, then as marginal costs increase, firms will make higher per-unit profits. For example, gas stations charging a fixed 5 percent markup would make five cents per gallon sold when the wholesale cost of gasoline is $1/gallon and ten cents per gallon sold when the cost of gasoline increases to $2/gallon. If aggregate industry demand is relatively inelastic, these higher per-unit profits must show up as higher profits of existing firms or be dissipated through the entry of new firms. In other words, fixed percentage markups predict that an increase in input costs should lead to higher operating margins, new firm entry, or both—predictions that we show are counterfactual below. In contrast, if firms maintain fixed additive markups, a rise in input costs instead lead to an erosion of industry gross margins, a pattern that we observe across several industries.

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. We consider two cases: either (i) firms set price equal to marginal cost times a fixed percentage markup ($p = \mu c$), or (ii) firms set price equal to marginal cost plus a fixed additive markup ($p = c + m$).

In addition to variable costs of production, firms incur overhead costs f_o. We use π^{gross} to denote variable profits and $\pi^{\text{op}} = \pi^{\text{gross}} - f_o$ to denote operating profits net of overhead costs. 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.[19] 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) as[20]

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

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

[19] Appendix Table A14 estimates $\theta \approx 0.33$ for retail coffee, using commodity prices, exchange rates, and weather shocks as instruments for retail prices. Studies that estimate demand for comparable industries find similar results: for example, Miller and Weinberg (2017) estimate $\theta \approx 0.60$–0.72 for beer; Backus et al. (2021) estimate $\theta \approx 0.34$–0.40 for ready-to-eat cereal; Conlon and Rao (2024) estimate $\theta \approx 0.50$–0.55 for spirits; and Grieco et al. (2024) estimate $\theta \approx 1.07$–1.44 for automobiles.

[20] We 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."

general condition that nests both as special cases:

$$N = N_0(\pi^{\text{op}} - f_e)^{\zeta}, \tag{12}$$

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 3 characterizes how industry aggregates—gross margins, operating margins, and the mass of firms—respond to changes in upstream costs.

Proposition 3 (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:*

		Gross margins dm^{gross}	*Operating margins* dm^{op}	*Mass of firms* $d \log N$
Complete pass-through in levels:				
$\zeta = 0$	*(Fixed mass)*	0	> 0	0
$\zeta \in (0, \infty)$		0	> 0	> 0
$\zeta \to \infty$	*(Free entry)*	0	0	> 0
Complete log pass-through:				
$\zeta = 0$	*(Fixed mass)*	< 0	≤ 0	0
$\zeta \in (0, \infty)$		< 0	≤ 0	≤ 0
$\zeta \to \infty$	*(Free entry)*	< 0	0	≤ 0

When firms have fixed percentage markups, an increase in costs leads to firms earnings higher profits on each unit sold. Since aggregate industry demand is inelastic, higher per-unit profits lead to higher aggregate profits for incumbent firms or else are dissipated by the entry of new firms. In other words, fixed percentage markups imply that an increase in input costs must lead to higher operating margins, new firm entry, or both.

In contrast, when firms have fixed additive markups, per-unit profits are invariant to changes in input costs. Thus, an increase in input costs no longer necessitates 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 3 using data on retail gasoline stations and manufacturing industries. For retail gas stations, we use data

Table 7: Response of gross margins, operating margins, and entry to input price changes.

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

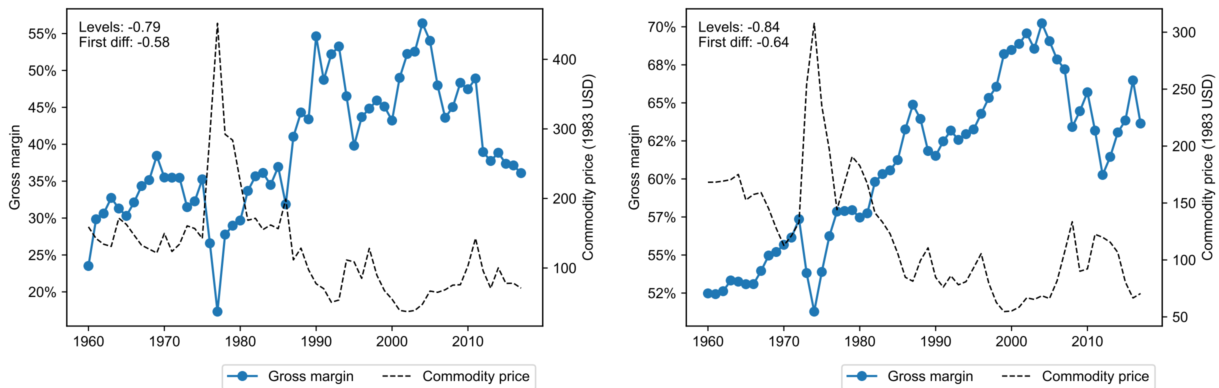
Note: Panel A presents results for retail gasoline. The wholesale gasoline price is from the EIA, deflated to constant dollars. ARTS is the Census Annual Retail Trade Survey, IRS are statistics for sole proprietorships, BDS is the Census Business Dynamics Statistics, and SUSB is the Census Statistics 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%.

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).[21] Data on the number of 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).

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, respectively). On the

[21] Sole 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 operating income as a percent of gross profits. To construct operating income, we start with reported net income, add back taxes and interest payments (payments of mortgage interest and other interest on debt), and subtract income from sources other than sales and operations.

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.

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:

$$\Delta \log y_t = \alpha + \beta \Delta \log c_t + \varepsilon_t. \tag{13}$$

Panel A of Table 7 reports results from specification (13) using the price of wholesale gasoline as the measure of input costs and using gross margins, operating margins, and entry as outcome variables.[22] Neither operating margins nor entry significantly increase with input costs, as would be predicted by the model with fixed percentage markups. Instead, rising input prices lead to a significant decline in gross margins, as predicted by the model with fixed additive markups.

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 7 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 additive markups in Proposition 3: 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

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

of gross margins to input price changes scales with the revenue share of input costs, consistent with the predictions of additive markups.

Thus, complete pass-through in levels offers a way of reconciling the response of industry aggregates to cost fluctuations with simple models of industry dynamics. In particular, it offers an explanation for why industry gross margins fall when input costs rise—a pattern also observed in the exchange rate literature, where Hellerstein (2008) and Campa and Goldberg (2010) document that distribution margins as a percent of sales contract with increases in import prices. More broadly, these results clarify how industry equilibrium clears in response to cost shocks. Whereas standard models rely on entry and exit to maintain zero-profit conditions, the modified model with pass-through in levels achieves equilibrium with less volatility in the number of firms or operating profits.

7 Scale- and Shift-Invariant Demand Systems

Many workhorse models in macroeconomics and trade employ homothetic demand systems. We show that these demand systems are *scale invariant* and, under standard conduct assumptions, imply complete log pass-through of common cost shocks, at odds with our evidence. Explaining complete pass-through in levels therefore requires departing from scale-invariant demand or standard assumptions about firm conduct. We identify a class of *shift invariant* demand systems that, under the same conduct assumptions, instead generate complete pass-through in levels of common cost shocks.

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 $\boldsymbol{p} = (p_1, ..., p_J)$ and the vector of prices for outside goods by $\boldsymbol{p_0}$. The demand system $D(\boldsymbol{p}, \boldsymbol{p_0}, Y)$ describes the quantity consumed of each good as a function of the prices of inside goods $\boldsymbol{p}$, the prices of outside goods $\boldsymbol{p_0}$, and income Y.[23]

Each inside good is produced and sold by a single firm. For $j \in \{1, ..., J\}$, firm j possesses a constant returns to scale production function with exogenous marginal cost c_j. 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.

[23] We assume throughout that D is a standard Marshallian demand system, and thus is homogeneous of degree zero in prices and income, i.e., $D(\lambda \boldsymbol{p}, \lambda \boldsymbol{p_0}, \lambda Y) = D(\boldsymbol{p}, \boldsymbol{p_0}, Y)$. A consequence is that all real variables—e.g., quantities and percentage markups—are neutral with respect to changes in the aggregate price level.

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

While Nash-in-prices is a standard assumption in macroeconomic models with imperfect competition, this assumption may be violated due to collusion (as in the case of Perth gas stations after 2010), strategic interactions between oligopolistic firms, or Cournot competition, among other reasons. Our goal in adopting Nash-in-prices is not to deny the possibility of other types of conduct, but to identify conditions under which standard models do (or do not) reproduce our results on complete pass-through in levels.

Given an exogenous vector of outside prices $\boldsymbol{p_0}$, income Y, and vector of marginal costs $\boldsymbol{c} = (c_1, ..., c_J)$, an equilibrium is a vector of prices $\boldsymbol{p}$ and quantities $\boldsymbol{q}$ such that, for $j = 1, ..., J$, $q_j = D_j(\boldsymbol{p}, \boldsymbol{p_0}, Y)$ 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 $\boldsymbol{p_0}$, income Y, and marginal costs $\boldsymbol{c}$, (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)**.** $D(\boldsymbol{p}, \boldsymbol{p_0}, Y)$ is *scale invariant in* $\boldsymbol{p}$ if there exist functions $\varphi_1, ..., \varphi_J$ such that $\partial \varphi_j / \partial p_j = 0$ for all j and, for any positive constant λ,

$$D_j(\lambda \boldsymbol{p}, \boldsymbol{p_0}, Y) = \lambda^{\varphi_j(\boldsymbol{p}, \boldsymbol{p_0}, Y, \lambda)} D_j(\boldsymbol{p}, \boldsymbol{p_0}, Y) \qquad \text{for all } j \in \{1, ..., J\}.$$

Definition 2 (Shift invariance). $D(\boldsymbol{p}, \boldsymbol{p_0}, Y)$ is *shift invariant in* $\boldsymbol{p}$ if there exist functions $\psi_1, ..., \psi_J$ such that $\partial\psi_j/\partial p_j = 0$ for all j and, for any constant λ,

$$D_j\left(\boldsymbol{p} + \lambda\mathbf{1}, \boldsymbol{p_0}, Y\right) = \left(1 + \lambda\psi_j(\boldsymbol{p}, \boldsymbol{p_0}, Y, \lambda)\right) D_j\left(\boldsymbol{p}, \boldsymbol{p_0}, Y\right) \qquad \text{for all } j \in \{1, ..., J\},$$

where $\mathbf{1} = (1, ..., 1)$ 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 uniform 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 4 and Proposition 5 show how these properties of demand determine the pass-through of common cost shocks to prices.

Proposition 4 (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 $j \in \{1, ..., J\}$, holding fixed outside prices $\boldsymbol{p_0}$ and income Y. If demand is **scale-invariant** in $\boldsymbol{p}$, then each inside good's price increases by $d\log p_j = d\log c$.*

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 5 (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 $j \in \{1, ..., J\}$, holding fixed outside prices $\boldsymbol{p_0}$ and income Y. If demand is **shift-invariant** in $\boldsymbol{p}$, then each inside good's price increases by $dp_j = dc$.*

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 4 increased all firms' costs by a fixed proportion, while the second type of cost shock in Proposition 5 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 6 shows that a demand system cannot be simultaneously scale invariant and shift invariant with respect to the same set of prices.

Proposition 6 (Scale and shift invariance are disjoint)**.** *If $D(\boldsymbol{p}, \boldsymbol{p_0}, Y)$ is scale invariant in $\boldsymbol{p}$, then $D(\boldsymbol{p}, \boldsymbol{p_0}, Y)$ is not shift invariant in $\boldsymbol{p}$. Equivalently, if $D(\boldsymbol{p}, \boldsymbol{p_0}, Y)$ is shift invariant in $\boldsymbol{p}$, then $D(\boldsymbol{p}, \boldsymbol{p_0}, Y)$ is not scale invariant in $\boldsymbol{p}$.*

Proposition 6 shows 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-Invariant Demand

Together, Propositions 4 and 6 imply that models with scale-invariant demand are inconsistent with pass-through in levels of common cost shocks (given Assumptions 1–2). Below, we show that homothetic demand systems commonly used in macroeconomics and trade fall into this category. Proofs for the examples that follow are in Appendix B.2.

Example 1 (Homothetic preferences)**.** Suppose there are J goods, and a representative consumer chooses consumption of each good q_j to maximize utility $U(q_1, ..., q_J)$ subject to the budget constraint $\sum_j p_j q_j = Y$. If U is homothetic, then the quantities $\boldsymbol{q}$ chosen by the consumer can be represented by a scale-invariant demand system $D(\boldsymbol{p}, \boldsymbol{p_0}, Y)$, where $\boldsymbol{p_0} = \emptyset$ 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 6 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

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

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 $Q_n = u(q_{n1}, ..., q_{nJ})$ is a homothetic aggregate of consumption from firms in industry n.

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

7.4 Examples of Shift-Invariant Demand

Clearly, complete pass-through in levels requires deviating from either Assumptions 1–2 or from scale-invariant demand. Given the evidence that quantities do not respond to common cost shocks as homothetic demand would predict, a natural choice is to adopt demand systems that generate complete pass-through in levels while retaining standard conduct assumptions.

We present examples of such shift-invariant demand systems. We first show that an individual firm exhibits pass-through in levels of cost shocks when its residual demand curve is log-linear, as under logit demand with atomistic firms. We then describe a broader class of models that predict 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

$$D_j\left(p_j, \boldsymbol{p_0}, Y\right) = \exp\left(a_j(\boldsymbol{p_0}, Y) - b_j(\boldsymbol{p_0}, Y)p_j\right).$$

Then $D_j\left(p_j, \boldsymbol{p_0}, Y\right)$ is shift-invariant in p_j with $\psi_j(\boldsymbol{p_0}, Y, \lambda) = \left(\exp\left(-b_j(\boldsymbol{p_0}, Y)\lambda\right) - 1\right)/\lambda$.

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. 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, $-\partial \log D_j/\partial \log p_j = p_j b_j(\boldsymbol{p_0}, Y)$, so that the super-elasticity is equal to one.

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

Example 4 (Generalized 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

$$D_j(\boldsymbol{p}, p_0, Y) = \frac{\exp(a_j(p_0, Y) - b_j p_j/p_0)}{\int_1^J \exp(a_k(p_0, Y) - b_k p_k/p_0)dk}, \tag{14}$$

where $\boldsymbol{p}$ is a vector of prices of goods $j \in [1, J]$ and $b_j > 0$ for all j. Then, demand is shift invariant with respect to any vector of prices $\boldsymbol{p}^{\text{subset}} \subseteq \boldsymbol{p}$.

When firms are atomistic, the influence of firm j's own price on the denominator in (14) is vanishingly small, and hence logit demand becomes a special case of Example 3. The price set by firm j is equal to its marginal cost plus an additive markup priced relative to the outside good,

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

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:

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

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.[24]

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

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

is shift-invariant in $\boldsymbol{p}$ 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.[25] Thus, each of those demand systems is shift invariant

[24] 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.

[25] Barro (2024) characterizes firms' markups in a variant of the Salop (1979) model with an intensive

with respect to inside prices and generates complete pass-through in levels of common cost shocks.[26] Note that this class of demand systems also predicts that quantity shares do not change in response to a common cost shock, consistent with our evidence on rice and flour products in Appendix Table A13.

7.5 Relationship to Pass-Through of Idiosyncratic Shocks

Scale- and shift-invariance determine how firms pass through common cost shocks. These conditions differ from previous work that describes how firms pass through idiosyncratic cost shocks. For example, Bulow and Pfleiderer (1983), Mrázová and Neary (2017), and Matsuyama and Ushchev (2021) characterize the pass-through of idiosyncratic cost shocks in terms of the elasticity and curvature of firms' residual demand curves. The pass-through in levels of an idiosyncratic cost shock to firm j, holding all other firms' prices fixed, is

$$\left.\frac{\partial p_j}{\partial c_j}\right|_{dp_n=0 \text{ for } n\neq j} = \frac{\sigma_j}{\sigma_j + \varepsilon_{jj} - 1},$$

where $\sigma_j = -\partial \log D_j / \partial \log p_j$ is the demand elasticity and $\varepsilon_{jj} = \partial \log \sigma_j / \partial \log p_j$ is the super-elasticity of the firm's residual demand curve. Holding other prices fixed, firm j exhibits complete pass-through in levels of the idiosyncratic cost shock if the super-elasticity of demand is equal to one, $\varepsilon_{jj} = 1$. (In equilibrium, even if $\varepsilon_{jj} = 1$, firm j's pass-through of an idiosyncratic cost shock may still differ from one if it internalizes how changing its price will affect its competitors' prices.)

The relevant statistic for the pass-through of common cost shocks is different. In the case where firms are identical and demand is symmetric, we can express the pass-through in levels of common cost shocks as

$$\frac{dp}{dc} = \frac{\sigma_j}{\sigma_j + \bar{\varepsilon}_j - 1}, \qquad \text{where} \qquad \bar{\varepsilon}_j = \varepsilon_{jj} + \sum_{n\neq j}^{J} \varepsilon_{jn},$$

and $\varepsilon_{jn} = \partial \log \sigma_j / \partial \log p_n$ reflects how firm j's demand elasticity changes with firm n's

margin elasticity of demand. When the intensive margin elasticity of demand is zero, the Barro (2024) 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 5.

[26] The quasilinear preferences in Example 5 rule out income effects. To capture the effect of large purchases on the marginal utility of leftover income, studies sometimes posit other ways for income and prices to enter the indirect utility function. For example, Berry et al. (1995) and Petrin (2002) assume that indirect utility depends on $\log(Y_i - p_j)$. Griffith et al. (2018), Miravete et al. (2023), and Birchall et al. (2024) explore other departures from quasilinearity in discrete choice models. In general, the discrete choice demand systems they consider no longer satisfy shift invariance when prices enter the indirect utility function nonlinearly.

price. The statistic governing the pass-through of the common cost shock is the *aggregate* super-elasticity $\bar{\varepsilon}_j$, which generally differs from the super-elasticity of the firm's residual demand curve.[27] (Examples 3 and 4 are special cases in which $\sum_{n\neq j}^{J} \varepsilon_{jn} = 0$, so $\varepsilon_{jj} = \bar{\varepsilon}_j$.)

The gap between the aggregate super-elasticity and the super-elasticity of a firm's residual demand curve has two implications. First, the rate at which a firm passes through idiosyncratic cost shocks can generally differ from the rate at which it passes through common cost shocks. Imposing shift invariance disciplines the pass-through of common cost shocks while retaining flexibility to match different (and potentially firm-specific) pass-through rates for idiosyncratic cost shocks.

Second, two models can share identical residual demand super-elasticities yet have different predictions for the pass-through of common cost shocks. In their study of the coffee market, Nakamura and Zerom (2010) estimate a median super-elasticity of residual demand of 4.64 and argue that this curvature helps their model generate aggregate, incomplete log pass-through. However, a Kimball demand system calibrated to match the same super-elasticity of residual demand would instead predict complete log pass-through of common shocks. Thus, the super-elasticity of residual demand curves is generally not sufficient to predict the pass-through of common cost shocks.

8 Quantitative Application

In this section, we illustrate how integrating shift-invariant demand systems into an otherwise standard input-output model of the U.S. economy affects its predictions for the dynamics of consumer price inflation. We argue that the standard model with fixed percentage markups predicts inflation that is too volatile and too responsive to upstream shocks. Incorporating shift-invariant demand—and therefore complete pass-through in levels—into the model improves its predictions for both the unconditional volatility of consumer price inflation and the response of inflation to identified shocks, 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 $\mathcal{N}^{\text{exog}} \subset \{1, ..., N\}$ as exogenous. Each remaining good is produced by a single industry (we use subscripts i to refer to goods and industries interchangeably) that consists of a unit mass of firms indexed by f. Firms in each industry

[27] Appendix B.1 shows that $\bar{\varepsilon}_j = 1$ iff $\partial\psi_j(\boldsymbol{p}, \boldsymbol{p_0}, Y, 0)/\partial p_j = 0$, given the definition of ψ_j in Definition 2.

possess identical production functions, and the cost of producing y units for a firm in industry i is

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

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 (allowed to vary across industries). This case implies that demand curves facing firms are scale invariant. 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

$$y_{if} = \frac{\exp(-b_i\,p_{if}/w)}{\int_0^1 \exp(-b_i\,p_{ig}/w)\,dg} y_i, \tag{15}$$

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,[28]

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

The logit demand in (15) 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

[28]This pricing equation implies that changes in marginal cost arising from changes in production wages will be passed-through to prices more than one-for-one in levels, because wage changes also affect firms' desired additive markups. This relates to an observation by Okun (1981) that firms appear to pass through changes in material costs to prices "essentially on a dollars-and-cents basis, while [changes in labor costs] are passed through with a percentage markup." In Appendix C.2, we provide empirical evidence of Okun's conjecture and show that the differential pass-through of labor costs relative to other inputs disappears once we account for the fact that additive markups are priced relative to the wage, as implied by (15).

rigidities, the optimal reset price for firm f in industry i at time t solves

$$p_{ift} = \arg\max_p \sum_{k=0}^{\infty} \beta^k (1-\delta_i)^k (p - mc_{it+k}) y_{ift+k}(p), \tag{16}$$

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

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. Below, we briefly describe the data used for calibration. Online Appendix D provides a detailed account of the data sources, cleaning procedures, and solution method.

We take the 402 industries in the Bureau of Economic Analysis's (BEA) detailed input-output tables as the set of industries. We define $\mathcal{N}^{\text{exog}}$ as the set of "Stage 1" industries designated by the BLS, which correspond to industries that are most upstream from consumer demand. We use monthly price indices for these industries from 1982–2018 from the BLS Producer Price Index (PPI) program, and we take the average hourly earnings of production and nonsupervisory employees as our measure of production wages.

Prices for the remaining industries are determined by firms' endogenous pricing decisions in our model. Equation (16) shows that these pricing decisions in each industry depend on future marginal costs, Calvo rigidities, and firms' desired markups. Marginal costs depend on the prices of goods that the industry uses as inputs; to a first order, the log-deviation in industry i's marginal costs relative to steady-state at time t is given by

$$d \log mc_{it} = \sum_j \Omega_{ij} d \log p_{jt}, \tag{17}$$

where Ω_{ij} is the steady-state share of sector i's variable costs spent on good j. We take these expenditure shares from the 2012 BEA tables.[29] For Calvo frictions in each industry, we use data on monthly frequencies of price adjustment by industry from Pasten et al. (2020), who compute these probabilities of price adjustment using the firm-level data that underlies the BLS PPI.[30] We set the monthly discount factor to $\beta = (0.96)^{1/12}$.

[29] Around the steady state, (17) describes changes in marginal costs up to a first order regardless of elasticities of substitution in production. In Appendix Table D1, we report results allowing for the expenditure shares Ω_{ij} to respond endogenously to prices due to input complementarity.

[30] We are grateful to Raphael Schoenle for sharing these data.

Table 8: Volatility of consumer price inflation in calibrated input-output models.

	Std. deviation of annual inflation, 1982–2018	Cost-weighted average markup Mfg.	All
Data:			
Personal Consumption Expenditures (PCE) Price Index	1.1%		
Consumer Price Index for All Urban Consumers	1.3%		
Model:			
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").

Finally, we calibrate firms' desired markups in each industry to match the industry's ratio of sales to variable costs. 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. For each definition, we set σ_i to match each industry's ratio of sales to variable costs. For the model with additive markups, we likewise choose b_i in each industry to match value added as a share of sales.

Results for inflation volatility. Table 8 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.[31]

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

[31] If 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.

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 comparison, De Loecker et al. (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.[32]

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.

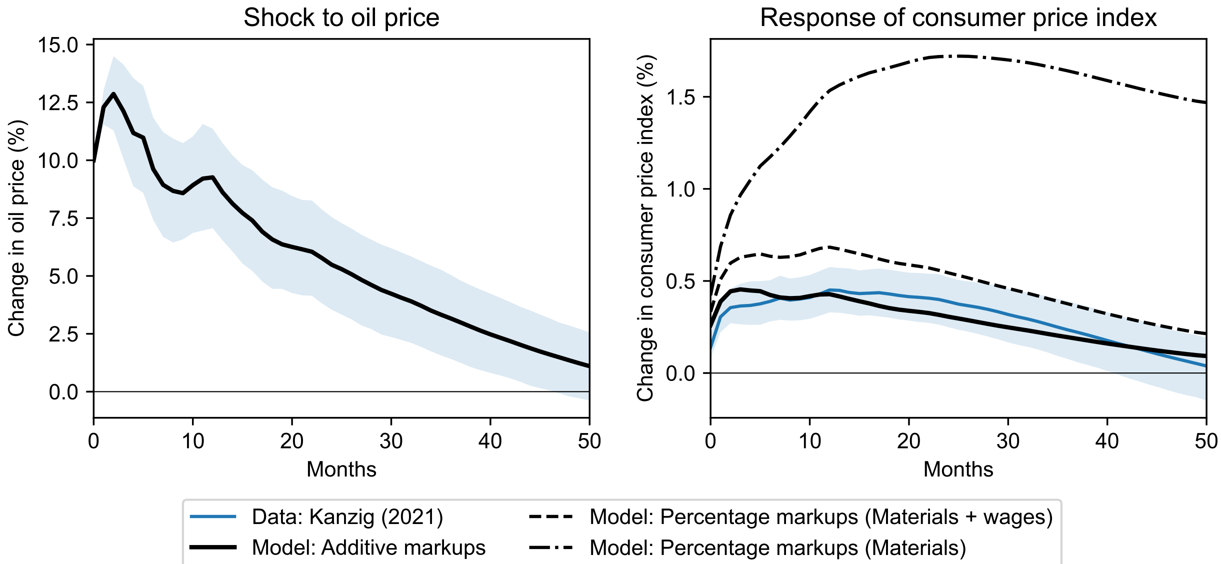
Results for oil price shock. The input-output model with additive markups not only accounts for the low volatility of consumer price inflation but also better matches the response of inflation to identified shocks. We demonstrate this using shocks to oil production constructed by Känzig (2021). The left panel of Figure 5 shows the path of oil prices following an oil supply news shock, which we feed into our calibrated model.[33]

The right panel of Figure 5 compares the response of consumer price inflation in the percentage-markup and additive-markup models to the data. Känzig (2021) estimates that the consumer price index reaches a maximum response of 45 log points at twelve months after an oil supply news shock. Compared to the data, the percentage-markup model predicts too much responsiveness in consumer price inflation: at twelve months

[32]The 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.

[33]We assume that the shock to the oil price, measured using the West Texas Intermediate crude oil price by Känzig (2021), corresponds to a shock to the Oil and Gas Extraction (211000) price in the model. Despite the Oil and Gas Extraction industry covering a broader scope of products, the two price series in the data are strongly correlated and exhibit similar volatilities. Over the period 1982–2018, the Oil and Gas Extraction industry price index and the WTI crude price have a correlation of 0.95, and the volatility of inflation rates for the Oil and Gas Extraction industry price index is 30%, compared to 32% for the WTI crude price.

Figure 5: Response of consumer price index to oil supply shocks in data and model.



Note: The solid blue lines are impulse responses to an oil supply news shock from Känzig (2021) (shaded areas indicate 68 percent confidence bands). Changes in the oil price in the left panel are treated as exogenous changes in the oil price in the model. In the right panel, the black lines plot the response of the personal consumption expenditures (PCE) price index to the oil price shock in the calibrated models.

the predicted response of the consumer price index is 56 log points (153 log points) when assuming variable costs include material and labor costs (material costs alone). In comparison, the response of consumer price inflation in the additive markup model lines up remarkably well with the data. The peak response at twelve months is 43 log points, and the predicted response of the consumer price index to the oil shock falls within the 68 percent confidence interval from Känzig (2021) at all horizons. Thus, the additive-markup model is better able to match the data than the model with percentage markups. As stressed above, the additive markups model also achieves this responsiveness while allowing for substantial firm markups consistent with micro evidence.

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 explain several other features of the data, such as asymmetry and size-dependence in log pass-through, heterogeneity in log pass-through by firm size and product quality, changes in relative price and markup dispersion, and dynamics of industry profits and entry.

Under standard assumptions about firm conduct, the homothetic demand systems commonly used in macroeconomics and trade are incompatible with our evidence. We propose that an alternative class of *shift invariant* demand systems can generate complete pass-through in levels of common cost shocks while maintaining standard conduct assumptions. We illustrate how to integrate these demand systems into an input-output model of the U.S. economy. We anticipate that integrating demand systems consistent with pass-through in levels into other workhorse models may be useful for understanding other features of the data.

References

Amiti, M., O. Itskhoki, and J. Konings (2019). International shocks, variable markups, and domestic prices. *The Review of Economic Studies 86*(6), 2356–2402.

Anderson, S. P., A. de Palma, and J.-F. Thisse (1992). *Discrete Choice Theory of Product Differentiation*. MIT Press.

Atkeson, A. and A. Burstein (2008). Pricing-to-market, trade costs, and international relative prices. *American Economic Review 98*(5), 1998–2031.

Atkin, D., A. Chaudhry, S. Chaudry, A. K. Khandelwal, and E. Verhoogen (2015). Markup and cost dispersion across firms: Direct evidence from producer surveys in Pakistan. *American Economic Review 105*(5), 537–544.

Auer, R. A., T. Chaney, and P. Sauré (2018). Quality pricing-to-market. *Journal of International Economics 110*, 87–102.

Backus, M., C. T. Conlon, and M. Sinkinson (2021). Common ownership and competition in the ready-to-eat cereal industry. Technical Report 28350, National Bureau of Economic Research.

Barro, R. J. (2024). Markups and entry in a circular Hotelling model. Technical Report 32660, National Bureau of Economic Research.

Becker, R. A., W. B. Gray, and J. Marvakov (2021). NBER-CES Manufacturing Industry Database (1958-2018, version 2021a). Technical report, National Bureau of Economic Research.

Benzarti, Y., D. Carloni, J. Harju, and T. Kosonen (2020). What goes up may not come down: Asymmetric incidence of value-added taxes. *Journal of Political Economy 128*(12), 4438–4474.

Berman, N., P. Martin, and T. Mayer (2012). How do different exporters react to exchange rate changes? *The Quarterly Journal of Economics 127*(1), 437–492.

Berry, S. T., J. A. Levinsohn, and A. Pakes (1995). Automobile prices in market equilibrium. *Econometrica 36*(4), 841–890.

Birchall, C., D. Mohapatra, and F. Verboven (2024). Estimating substitution patterns and demand curvature in discrete-choice models of product differentiation. *Review of Economics and Statistics*, 1–40.

Borenstein, S. (1991). Selling costs and switching costs: Explaining retail gasoline margins. *The RAND Journal of Economics*, 354–369.

Borenstein, S., A. C. Cameron, and R. Gilbert (1997). Do gasoline prices respond asymmetrically to crude oil price changes? *The Quarterly Journal of Economics 112*(1), 305–339.

Bulow, J. I. and P. Pfleiderer (1983). A note on the effect of cost changes on prices. *Journal of Political Economy 91*(1), 182–185.

Bunn, P., L. Anayi, E. Barnes, N. Bloom, P. Mizen, G. Thwaites, and I. Yotzov (2024). How curvy is the Phillips curve? Technical Report 33234, National Bureau of Economic Research.

Burstein, A. and G. Gopinath (2014). International prices and exchange rates. *Handbook of International Economics 4*, 391–451.

Butters, R. A., D. W. Sacks, and B. Seo (2022). How do national firms respond to local cost shocks? *American Economic Review 112*(5), 1737–1772.

Byrne, D. P. and N. de Roos (2017). Consumer search in retail gasoline markets. *The Journal of Industrial Economics 65*(1), 183–193.

Byrne, D. P. and N. de Roos (2019). Learning to coordinate: A study in retail gasoline. *American Economic Review 109*(2), 591–619.

Byrne, D. P. and N. de Roos (2022). Start-up search costs. *American Economic Journal: Microeconomics 14*(2), 81–112.

Calvo, G. A. (1983). Staggered prices in a utility-maximizing framework. *Journey of Monetary Economics 12*(3), 383–398.

Campa, J. M. and L. S. Goldberg (2005). Exchange rate pass-through into import prices. *Review of Economics and Statistics 87*(4), 679–690.

Campa, J. M. and L. S. Goldberg (2010). The sensitivity of the CPI to exchange rates: Distribution margins, imported inputs, and trade exposure. *The Review of Economics and Statistics 92*(2), 392–407.

Cavallo, A., F. Lippi, and K. Miyahara (2024). Large shocks travel fast. *American Economic Review: Insights 6*(4), 558–574.

Chen, N. and L. Juvenal (2016). Quality, trade, and exchange rate pass-through. *Journal of International Economics 100*, 61–80.

Childs, N. W. and J. Kiawu (2009). Factors behind the rise in global rice prices in 2008. Technical report, US Department of Agriculture, Economic Research Service.

Conlon, C. T. and N. L. Rao (2020). Discrete prices and the incidence and efficiency of excise taxes. *American Economic Journal: Economic Policy 12*(4), 111–143.

Conlon, C. T. and N. L. Rao (2024). The cost of curbing externalities with market power: Alcohol regulation and tax alternatives. Technical Report 30896, National Bureau of Economic Research.

De Loecker, J., J. Eeckhout, and G. Unger (2020). The rise of market power and the macroeconomic implications. *The Quarterly Journal of Economics 135*(2), 561–644.

De Loecker, J., P. Goldberg, A. K. Khandelwal, and N. Pavcnik (2016). Prices, markups, and trade reform. *Econometrica 84*(2), 445–510.

DellaVigna, S. and M. Gentzkow (2019). Uniform pricing in US retail chains. *The Quarterly Journal of Economics 134*(4), 2011–2084.

Deltas, G. (2008). Retail gasoline price dynamics and local market power. *The Journal of Industrial Economics 56*(3), 613–628.

Dixit, A. K. and J. E. Stiglitz (1977). Monopolistic competition and optimum product diversity. *American Economic Review 67*(3), 297–308.

Foster, L., J. Haltiwanger, and C. Syverson (2008). Reallocation, firm turnover, and efficiency: Selection on productivity or profitability? *American Economic Review 98*(1), 394–425.

Gagliardone, L., M. Gertler, S. Lenzu, and J. Tielens (2025). Micro and macro cost-price dynamics in normal times and during inflation surges. Technical Report 33478, National Bureau of Economic Research.

Grieco, P. L., C. Murry, and A. Yurukoglu (2024). The evolution of market power in the US automobile industry. *The Quarterly Journal of Economics 139*(2), 1201–1253.

Griffith, R., L. Nesheim, and M. O'Connell (2018). Income effects and the welfare consequences of tax in differentiated product oligopoly. *Quantitative Economics 9*(1), 305–341.

Gupta, A. (2020). Demand for quality, variable markups and misallocation: Evidence from india. Working paper.

Gutiérrez, G. and T. Philippon (2017). Declining competition and investment in the U.S. Technical Report 23583, National Bureau of Economic Research.

Hellerstein, R. (2008). Who bears the cost of a change in the exchange rate? Pass-through accounting for the case of beer. *Journal of International Economics 76*(1), 14–32.

Hotelling, H. (1929). Stability in competition. *The Economic Journal 39*(153), 41–57.

Hsieh, C.-T. and P. J. Klenow (2009). Misallocation and manufacturing TFP in China and India. *The Quarterly Journal of Economics 124*(4), 1403–1448.

Kabundi, A. and H. Zahid (2023). Commodity price cycles: Commonalities, heterogeneity, and drivers. Technical report, World Bank.

Känzig, D. R. (2021). The macroeconomic effects of oil supply news: Evidence from OPEC announcements. *American Economic Review 111*(4), 1092–1125.

Kaplan, G. and G. Menzio (2015). The morphology of price dispersion. *International Economic Review 56*(4), 1165–1206.

Karrenbrock, J. D. (1991). The behavior of retail gasoline prices: Symmetric or not? *Federal Reserve Bank of St. Louis Review 73*(4), 19–29.

Kehrig, M. (2011). The cyclicality of productivity dispersion. Technical Report CES-WP-11-15, US Census Bureau Center for Economic Studies.

Kimball, M. S. (1995). The quantitative analytics of the basic neomonetarist model. *Journal of Money, Credit and Banking 27*(4), 1241–77.

Klenow, P. J. and J. L. Willis (2016). Real rigidities and nominal price changes. *Economica 83*(331), 443–472.

Maskin, E. and J. Tirole (1988). A theory of dynamic oligopoly, II: Price competition, kinked demand curves, and Edgeworth cycles. *Econometrica*, 571–599.

Matsuyama, K. and P. Ushchev (2017). Beyond CES: Three alternative classes of flexible homothetic demand systems. Technical Report 17-109, Global Poverty Research Lab Working Paper.

Matsuyama, K. and P. Ushchev (2021). Constant pass-through. Working paper.

McFadden, D. (1981). *Structural Analysis of Discrete Data with Econometric Applications*, Chapter Econometric models of probabilistic choice, pp. 198–272. Cambridge, Mass: MIT Press.

Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica 71*(6), 1695–1725.

Melitz, M. J. (2018). Competitive effects of trade: Theory and measurement. *Review of World Economics 154*, 1–13.

Miller, N. H. and M. C. Weinberg (2017). Understanding the price effects of the MillerCoors joint venture. *Econometrica 85*(6), 1763–1791.

Miravete, E. J., K. Seim, and J. Thurk (2023). Pass-through and tax incidence in differentiated product markets. *International Journal of Industrial Organization 90*(102985).

Miravete, E. J., K. Seim, and J. Thurk (2025). Elasticity and curvature of discrete choice demand models. Working paper.

Mrázová, M. and J. P. Neary (2017). Not so demanding: Demand structure and firm behavior. *American Economic Review 107*(12), 3835–74.

Nakamura, E. and J. Steinsson (2012). Lost in transit: Product replacement bias and pricing to market. *American Economic Review 102*(7), 3277–3316.

Nakamura, E. and D. Zerom (2010). Accounting for incomplete pass-through. *The Review of Economic Studies 77*(3), 1192–1230.

Nevo, A. (2001). Measuring market power in the ready-to-eat cereal industry. *Econometrica 69*(2), 307–342.

Okun, A. M. (1981). *Prices and Quantities: A Macroeconomic Analysis*. The Brookings Institution.

Pasten, E., R. Schoenle, and M. Weber (2020). The propagation of monetary policy shocks in a heterogeneous production economy. *Journal of Monetary Economics 116*, 1–22.

Peltzman, S. (2000). Prices rise faster than they fall. *Journal of Political Economy 108*(3), 466–502.

Petrin, A. (2002). Quantifying the benefits of new products: The case of the minivan. *Journal of Political Economy 110*(4), 705–729.

Salop, S. C. (1979). Monopolistic competition with outside goods. *The Bell Journal of Economics*, 141–156.

Sangani, K. (2022). Markups across the income distribution: Measurement and implications. Working paper.

Verboven, F. (1996). The nested logit model and representative consumer theory. *Economics Letters 50*(1), 57–63.

Wang, Z. (2009). (Mixed) strategy in oligopoly pricing: Evidence from gasoline price cycles before and under a timing regulation. *Journal of Political Economy 117*(6), 987–1030.

Weyl, E. G. and M. Fabinger (2013). Pass-through as an economic tool: Principles of incidence under imperfect competition. *Journal of Political Economy 121*(3), 528–583.

Online Appendix to *Complete Pass-Through in Levels*

(Not for publication)

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
Studies measuring pass-through in levels:			
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 et al. (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 et al. (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 et al. (2012)	Cigarettes	Excise taxes	0.85–1.02 (Pass-through "stabilizes around one at 52 miles from tax border.")
DeCicca et al. (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 on 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"
Studies measuring pass-through in logs / percentages:			
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 et al. (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 et al. (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 et al. (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 retail gasoline, we run Granger causality tests using the fifty stations with the highest number of weekly observations.

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

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

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

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[34]	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[35])
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[36])
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.[37])

[34] For some products, multiple series are available which track different package sizes.
[35] Nakamura and Zerom (2010).
[36] USDA Conversion Table (p.41) for pounds white flour per bushel of wheat.
[37] 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.) Baseline		With Month FEs		Pass-through of future cost changes	
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 $\phi_{m(t)}$,

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

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.

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

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

Note: Panel A reports results from specification (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: Pass-through for manufacturing industries using commodity price instrument.

Inputs:	Materials (IV1)	+ Energy (IV2)	+ Production Labor (IV3)
	Δ *Log Output Price$_t$*		
Δ Log Input Price$_t$	0.115	0.097	0.303
	(0.205)	(0.205)	(0.326)
(InputCost/Sales)$_{t-1}$	0.012	0.016	0.023
	(0.013)	(0.015)	(0.014)
Δ Log Input Price$_t$ $\times$ (InputCost/Sales)$_{t-1}$	1.016†	1.019†	0.792†
	(0.244)	(0.246)	(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, ΔLog 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. For estimates of the coefficient ρ^{level} on the interaction term, † indicates estimates for which a pass-through of one is within the 90 percent confidence interval. For estimates of the coefficients δ and γ, * indicates significance at the 10% level, ** at 5%.

Table A10: Pass-through for manufacturing industries at alternate horizons.

Horizon (years):	$h = 1$ (1)	$h = 2$ (2)	$h = 3$ (3)	$h = 4$ (4)	$h = 5$ (5)
	Δ *Log Output Price$_{t-h\to t}$*				
Δ Log Input Price$_{t-h\to t}$	0.079	0.126	0.183	0.208	0.231*
	(0.132)	(0.132)	(0.125)	(0.130)	(0.137)
(InputCost/Sales)$_{t-h}$	0.004	0.021	0.035	0.045	0.050
	(0.011)	(0.019)	(0.024)	(0.031)	(0.036)
Δ Log Input Price$_{t-h\to t}$ $\times$ (InputCost/Sales)$_{t-h}$	0.947†	0.931†	0.895†	0.876†	0.829†
	(0.203)	(0.208)	(0.187)	(0.184)	(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 6. Columns 2–5 repeat the analysis, calculating changes in input costs and output prices over longer horizons from $h = 2, ..., 5$ years. Standard errors two-way clustered by industry and year. For estimates of the coefficient ρ^{level} on the interaction term, † indicates estimates for which a pass-through of one is within the 90 percent confidence interval. For estimates of the coefficients δ and γ, * indicates significance at the 10% level, ** at 5%.

Table A11: Effect of commodity cost changes on price dispersion.

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

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

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

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 A12: Effect of input price changes on the dispersion of labor revenue productivity (log LP) and total factor revenue productivity (log TFPR) for manufacturing industries.

	Dispersion in Log LP			*Dispersion in Log TFPR*		
Measure:	St. dev.	75-25 gap	90-10 gap	St. dev.	75-25 gap	90-10 gap
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Input Price)	−0.240**	−0.453**	−0.603**	−0.083*	−0.210*	−0.208*
	(0.045)	(0.092)	(0.131)	(0.049)	(0.116)	(0.106)
NAICS FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
N	11 618	11 618	11 618	11 618	11 618	11 618
R^2	0.89	0.86	0.87	0.84	0.76	0.85
Within-R^2	0.21	0.15	0.16	0.04	0.04	0.04

Input price indices are for six-digit NAICS industries from the NBER-CES data, and the dispersion statistics are activity-weighted measures for the corresponding four-digit NAICS industry from the BLS Dispersion Statistics on Productivity (DiSP) program. The table reports estimates of β from the specification,

$$\text{DispersionMeasure}_{it} = \beta \log(\text{InputPriceIndex}_{it}) + \alpha_i + \varphi_t + \varepsilon_{it},$$

where α_i and φ_t are industry and year FEs, respectively. The BLS Dispersion Statistics on Productivity program calculates TFPR (which they call "TFP") and LP by deflating firm-level sales and input expenditures by industry-level output and input price indices (see Cunningham et al. 2022), making dispersion in these statistics across firms in an industry consistent with the definitions of TFPR and LP in Proposition 2. Standard errors clustered by industry. * 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	0.002	0.029*
	(0.011)	(0.006)	(0.017)
Response of Quantity Share: Unit Price Group 2	0.003	−0.008	0.006
	(0.003)	(0.005)	(0.008)
Response of Quantity Share: Unit Price Group 3	−0.004**	0.000	−0.005
	(0.002)	(0.004)	(0.007)
Response of Quantity Share: Unit Price Group 4	−0.005	0.006	−0.013**
	(0.004)	(0.004)	(0.006)
Response of Quantity Share: Unit Price Group 5	0.001	0.001	−0.017**
	(0.002)	(0.002)	(0.008)
N	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: Estimates of aggregate elasticity of demand for retail coffee.

	Log Quantity			
	(OLS)	(IV1)	(IV2)	(IV3)
Log Unit Price	-0.268**	-0.324**	-0.332**	-0.338**
	(0.061)	(0.092)	(0.078)	(0.071)
Instruments	-	Commodity price	Lagged commodity price and exchange rates	Lagged commodity price and weather shocks
Time trend	Yes	Yes	Yes	Yes
Month-of-Year FEs	Yes	Yes	Yes	Yes
N	180	180	180	180
R^2	0.77	0.77	0.77	0.77
F-stat	-	101.2	25.0	13.6

Note: Quantity is total ounces of coffee sold in the NielsenIQ data in each month, and unit price is the average retail price per ounce of coffee sold. The OLS column reports results from the baseline specification

$$\text{LogQuantity}_t = \beta \text{LogUnitPrice}_t + \delta t + \alpha_{m(t)} + \varepsilon_t,$$

where δt is a linear time trend and $\alpha_{m(t)}$ are month-of-year fixed effects. Column IV1 uses the contemporaneous log commodity price for Arabica coffee beans as an instrument for log unit prices. Column IV2 uses the one year lag of coffee commodity prices and six lags of Brazil and Colombia exchange rates (FRED series `CCUSMA02BRM618N` and `COLCCUSMA02STM`) as instruments for log unit prices. Column IV3 uses the one year lag of coffee commodity prices and six 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) to instrument for log unit prices. Robust standard errors cumulated using the delta method. Newey-West standard errors with eight lags in parentheses. * indicates significance at 10%, ** at 5%.

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

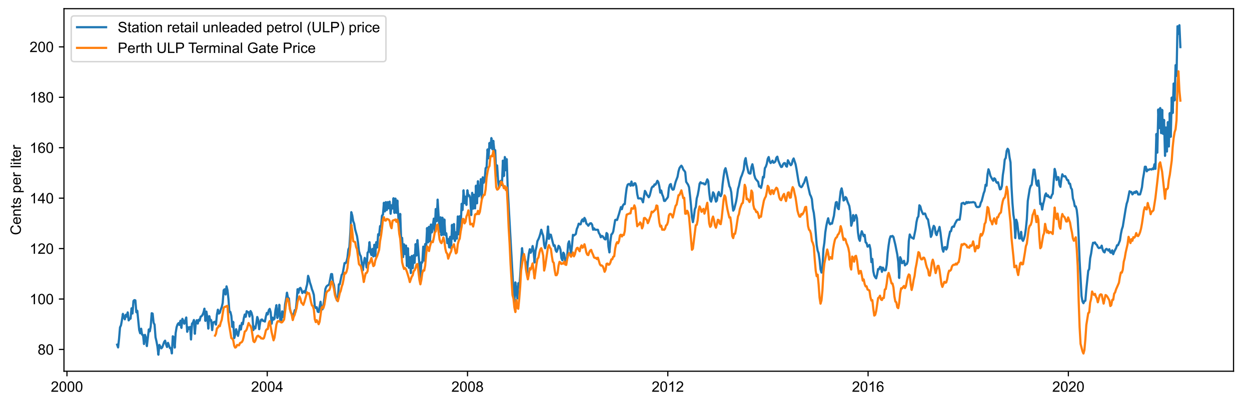
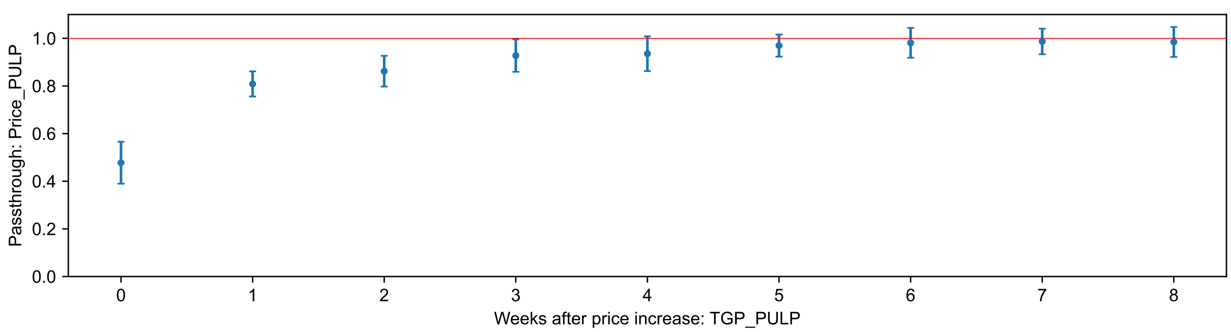
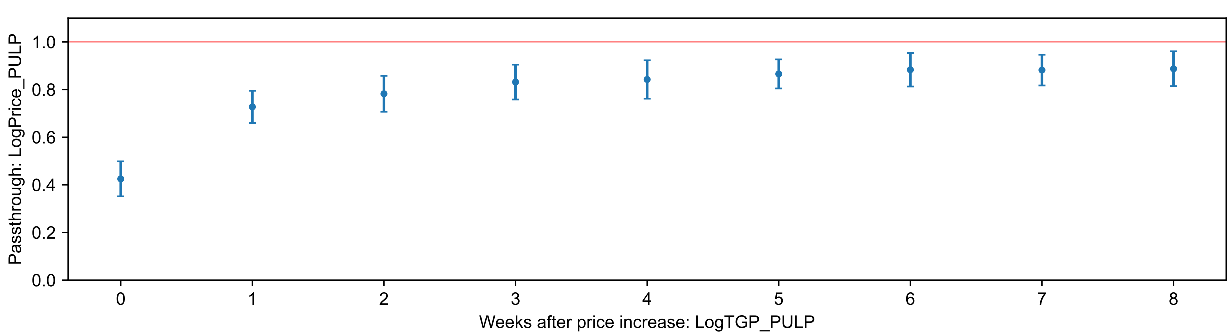


Figure A2: Pass-through of premium unleaded petrol wholesale costs to retail prices.



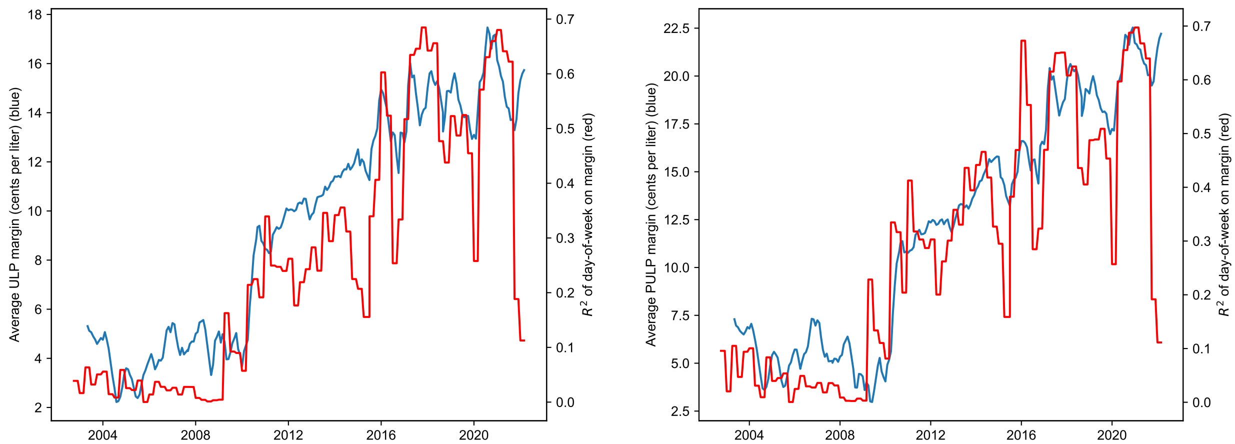
(a) Pass-through in levels.



(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.

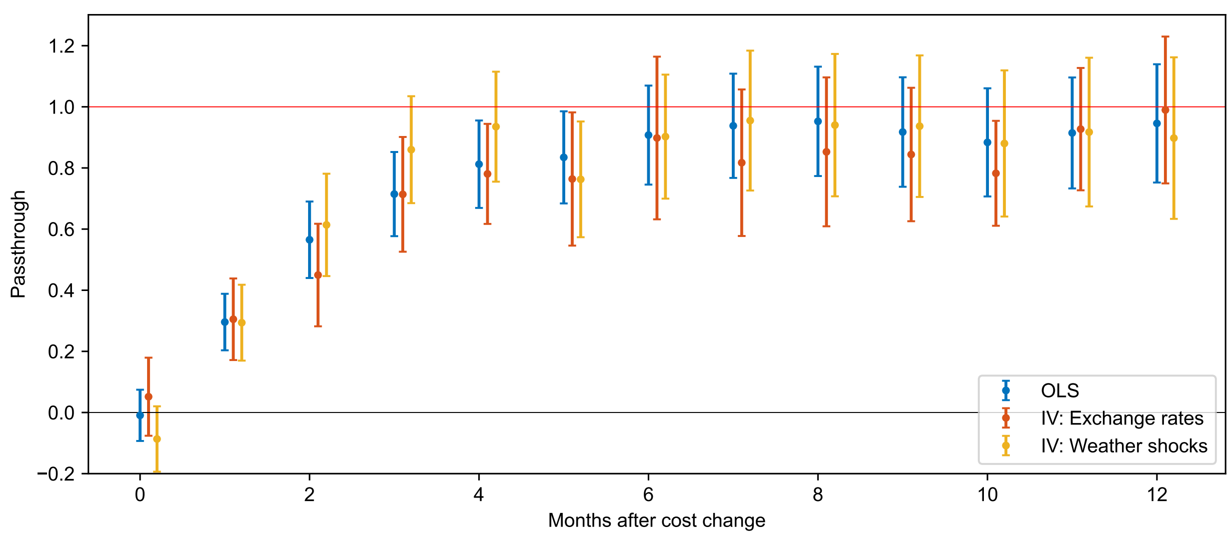
Figure A3: Comovement of retail gas margins with strength of weekly price cycles.



(a) Unleaded petrol (ULP). **(b)** Premium unleaded petrol (PULP).

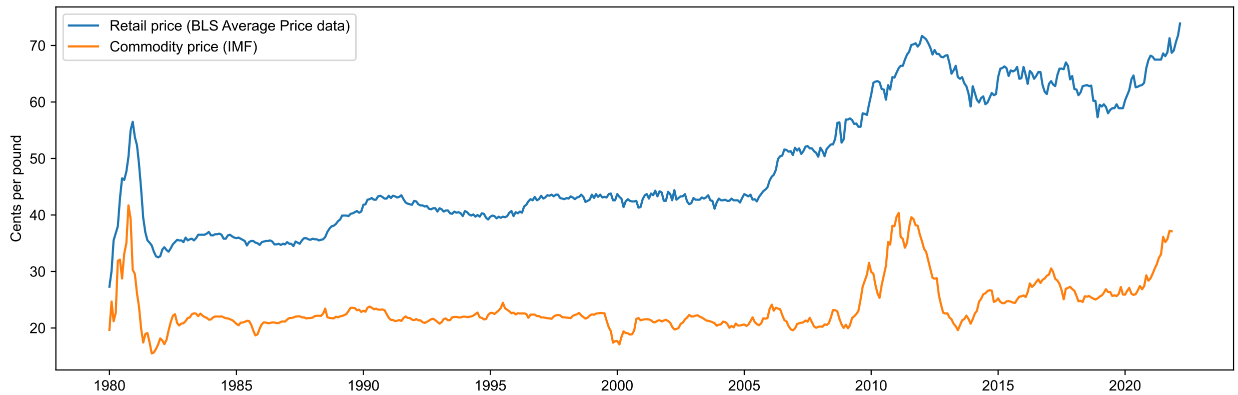
Note: In each panel, the blue line (left axis) plots the six-month moving average of margins across all stations. The red line (right axis) plots the R^2 from a regression of gas station margins of day-of-week dummies for each quarter.

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

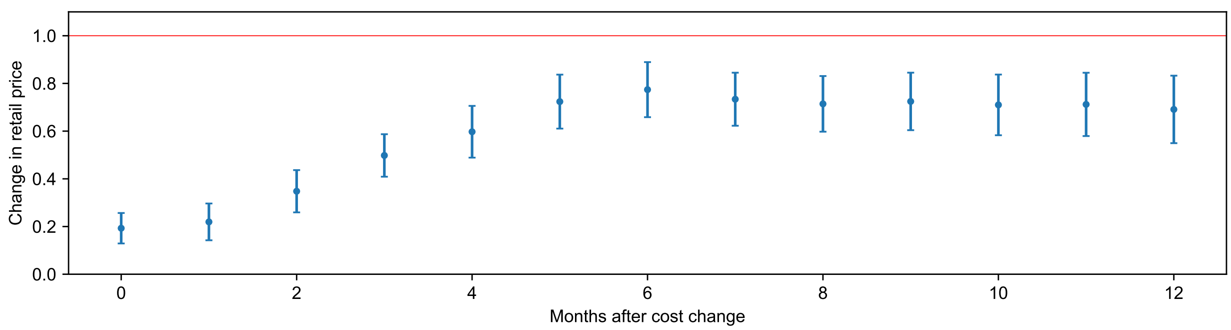


Note: The blue points are estimates of cumulative pass-through from specification (3). The red points use current and lagged Brazil and Colombia exchange rates (FRED series `CCUSMA02BRM618N` and `COLCCUSMA02STM`) and year fixed effects to instrument for commodity cost changes. The yellow points use twelve 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.

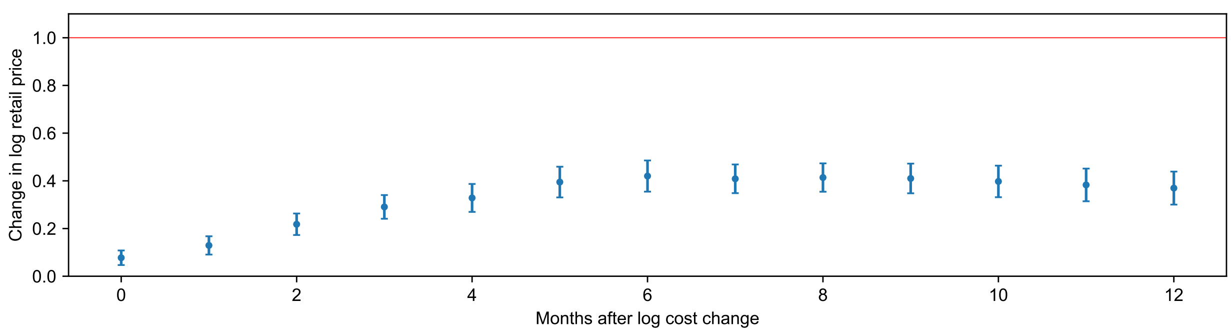
Figure A5: Pass-through of sugar commodity costs to retail prices.



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



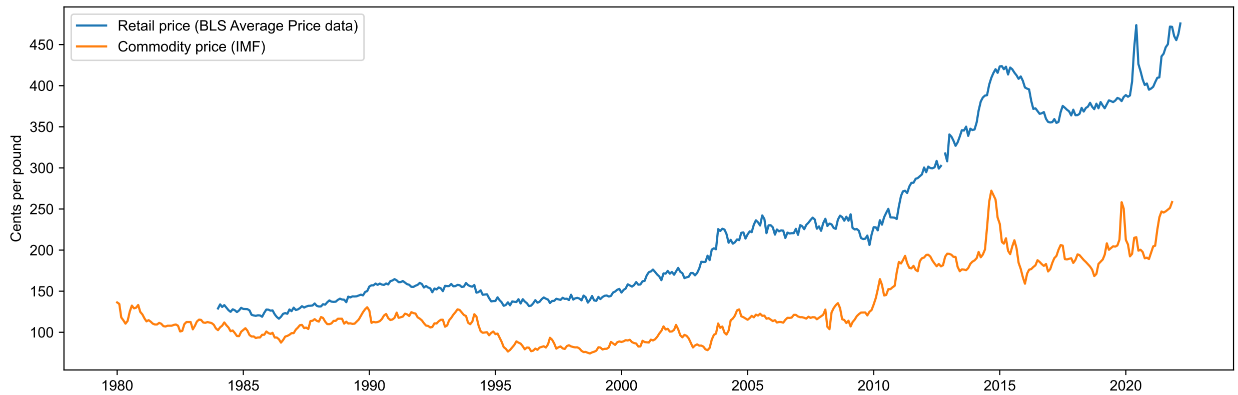
(b) Pass-through in levels.



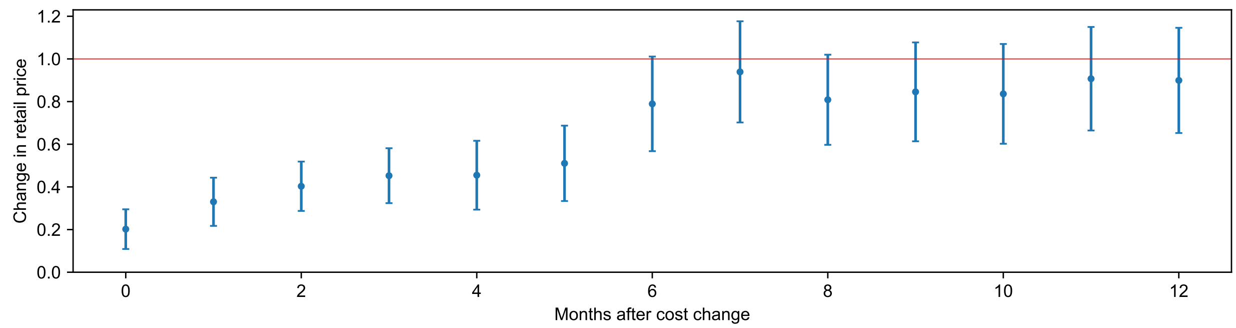
(c) Pass-through in logs.

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.

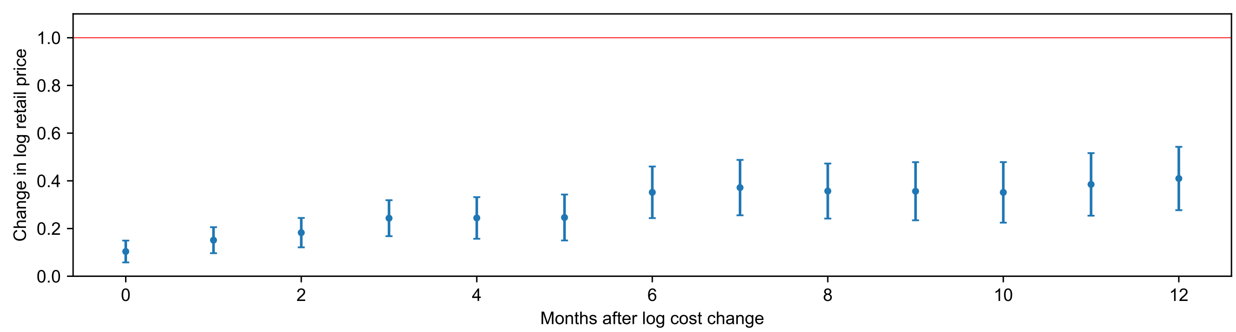
Figure A6: Pass-through of beef commodity costs to retail prices.



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



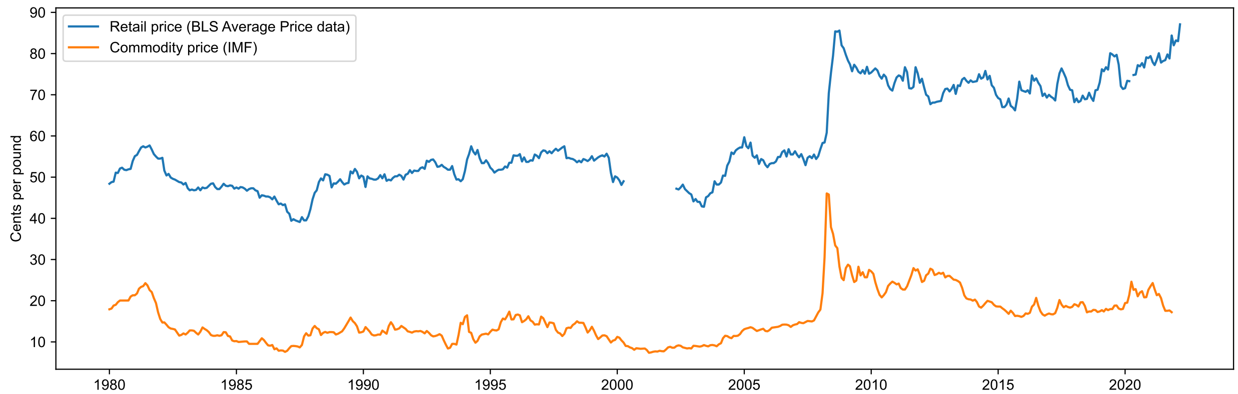
(b) Pass-through in levels.



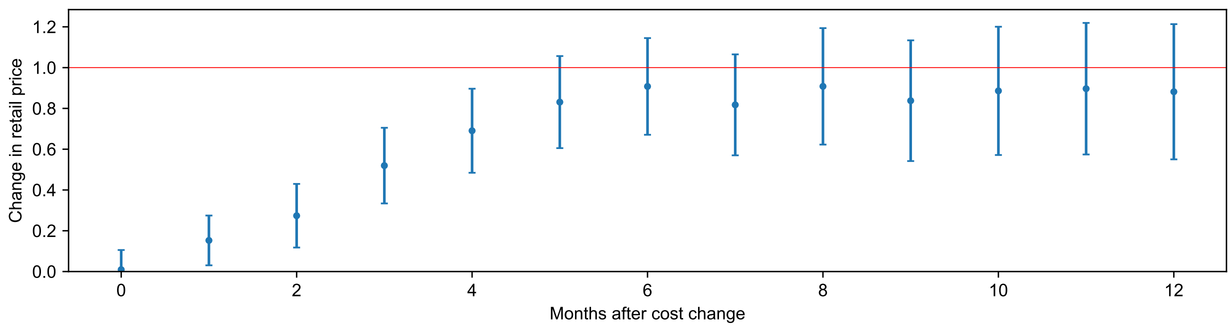
(c) Pass-through in logs.

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.

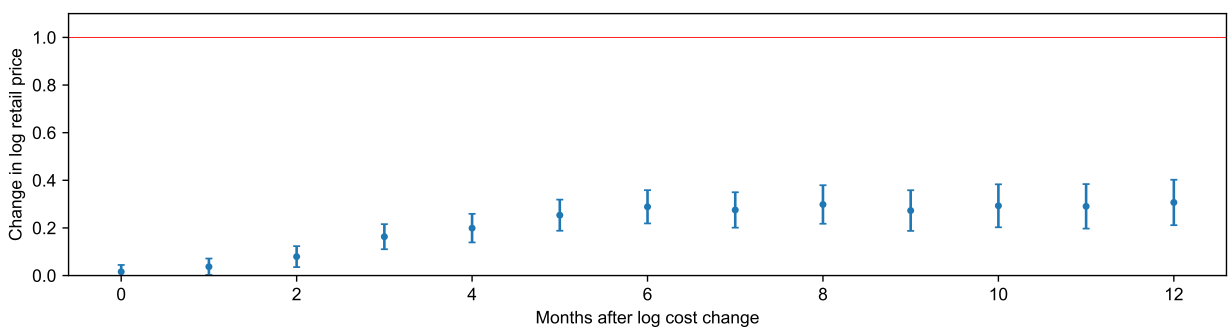
Figure A7: Pass-through of rice commodity costs to retail prices.



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



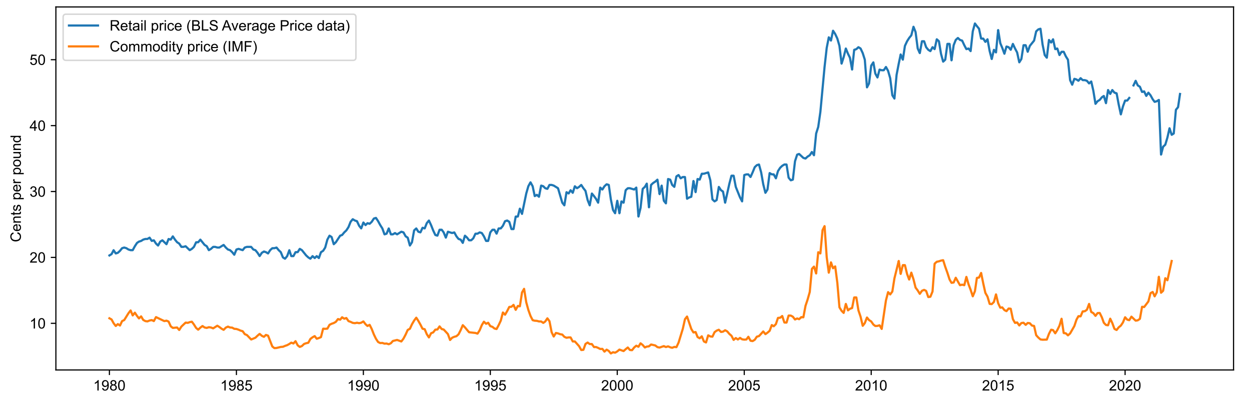
(b) Pass-through in levels.



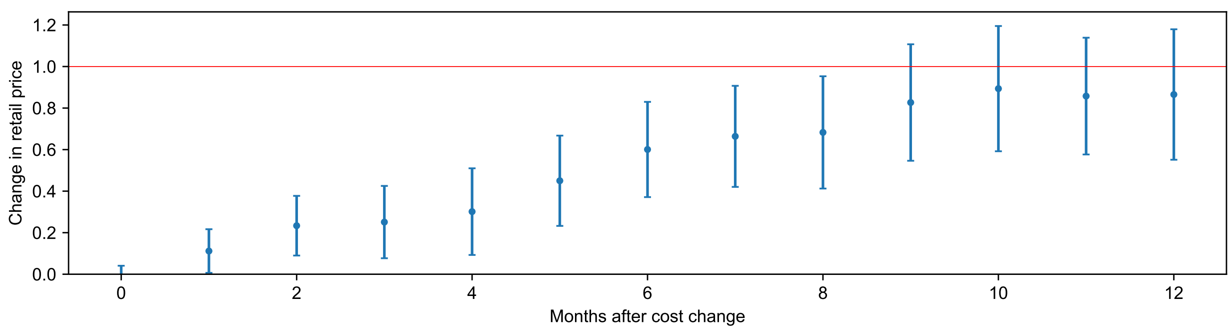
(c) Pass-through in logs.

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.

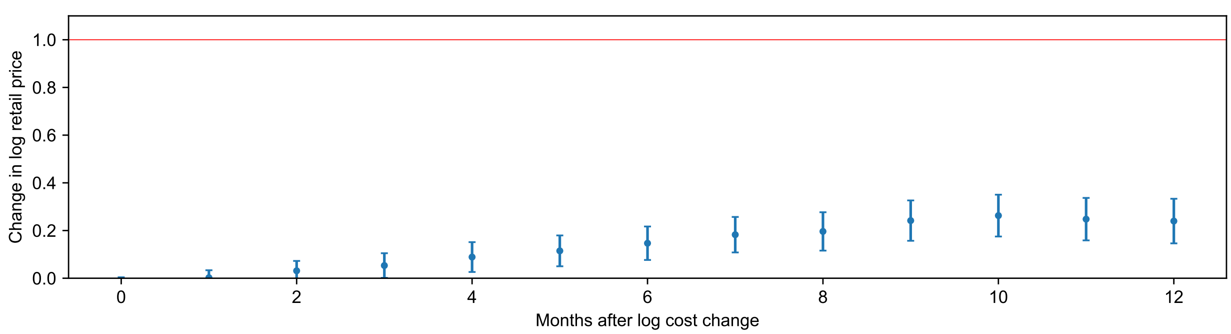
Figure A8: Pass-through of flour commodity costs to retail prices.



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



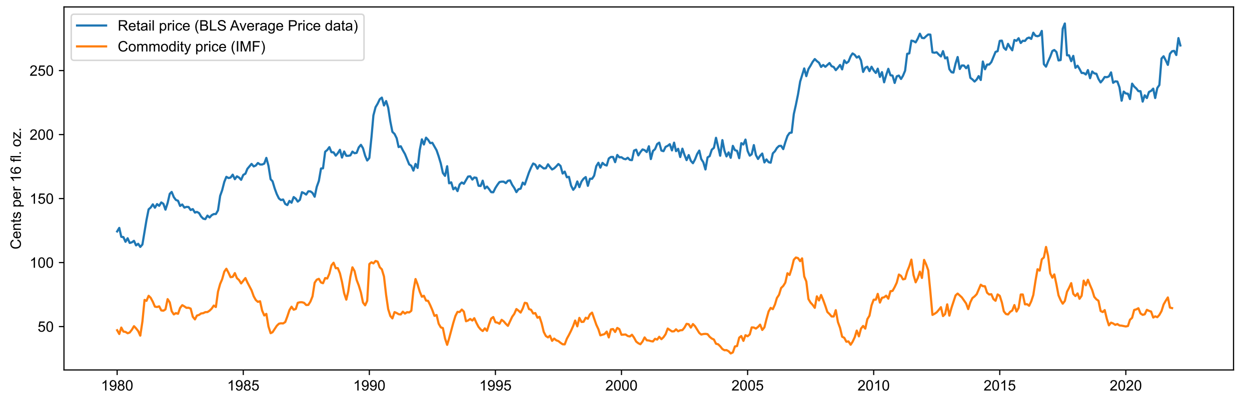
(b) Pass-through in levels.



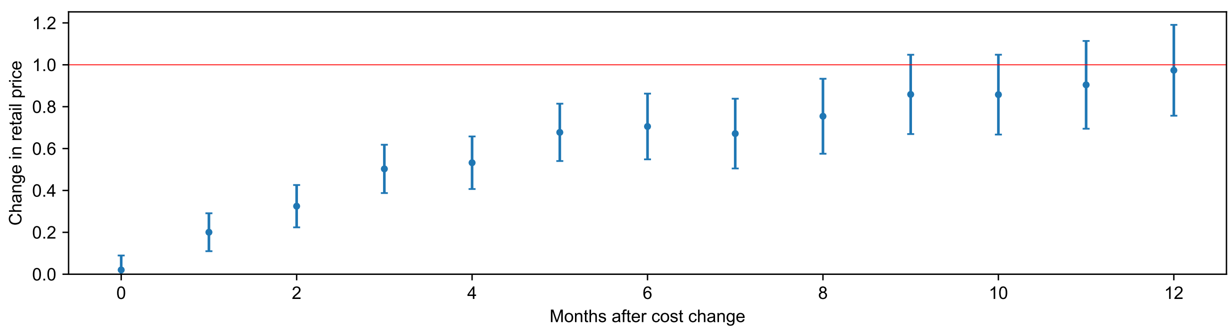
(c) Pass-through in logs.

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.

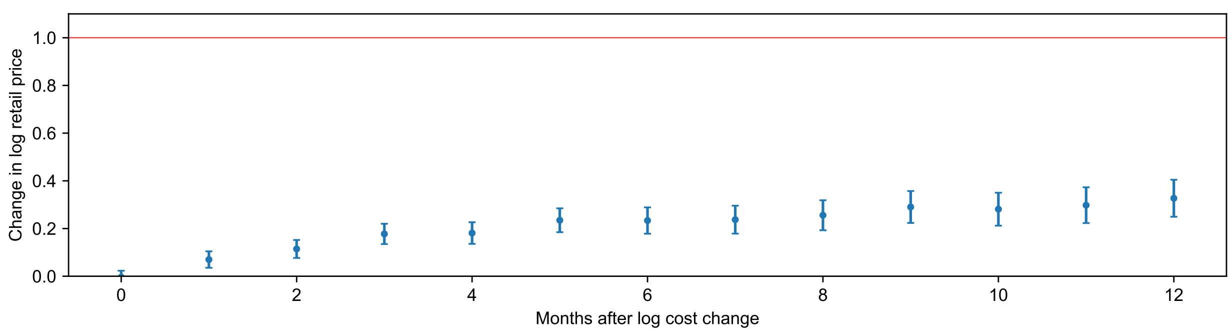
Figure A9: Pass-through of frozen orange juice commodity costs to retail prices.



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



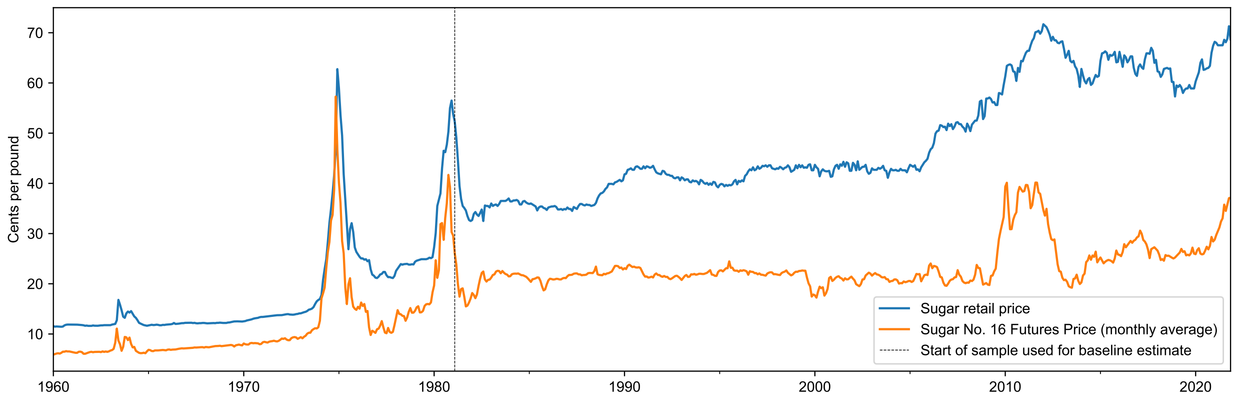
(b) Pass-through in levels.



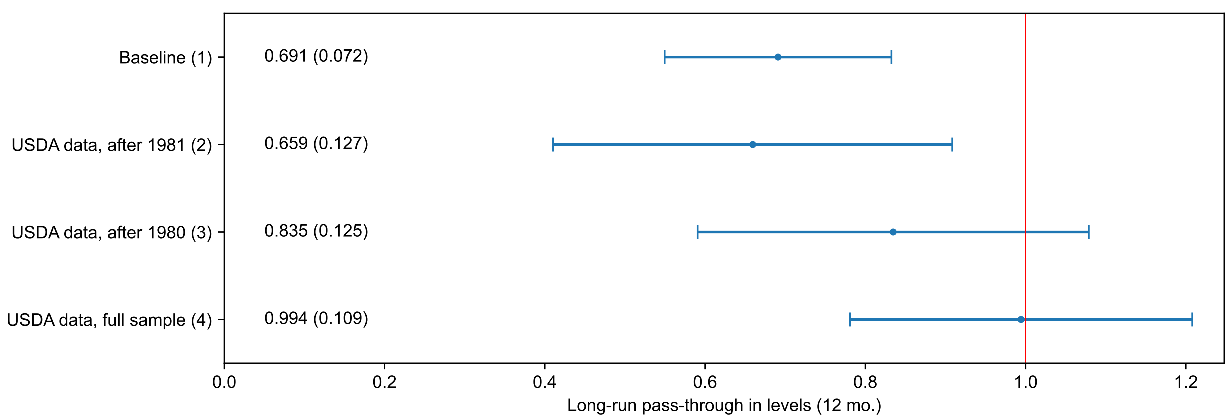
(c) Pass-through in logs.

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: Pass-through of sugar commodity costs to retail prices in extended sample.



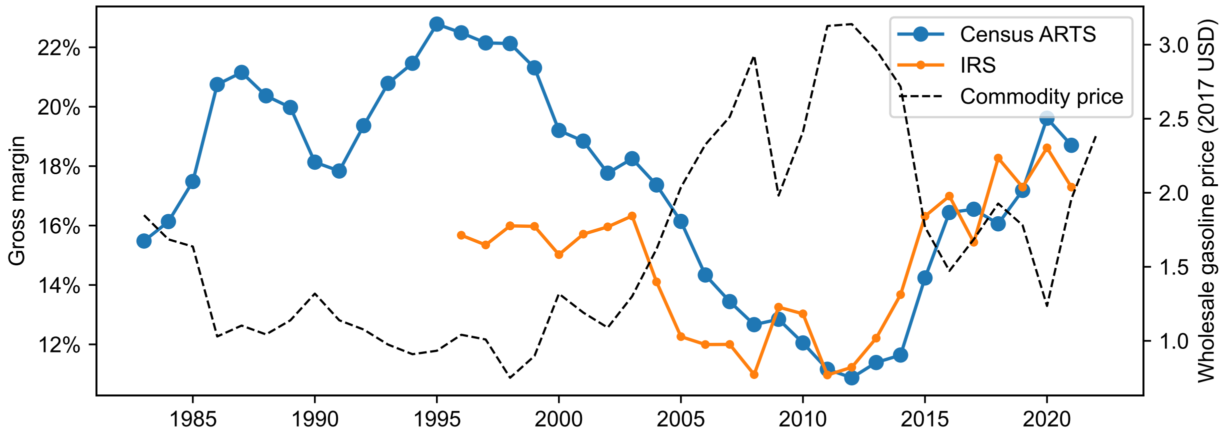
(a) Sugar No. 16 commodity costs (IMF) and retail white granulated sugar prices (U.S. CPI).



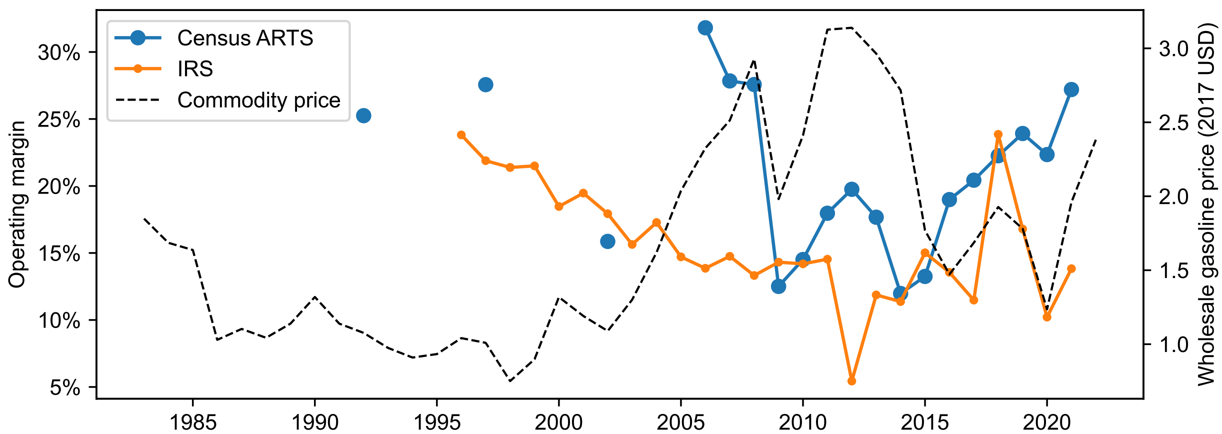
(b) Pass-through in levels.

Note: Panel (a) plots the Sugar No. 16 contract price and the retail price for sugar (BLS Average Price data, series 715211), both from the USDA Economic Research Service (ERS). Note that the commodity prices differ slightly from Figure A5, since the USDA reports the average price of the nearest futures contract available for the entire duration of the month, while our baseline estimates use monthly averages over the nearest futures contract available on each date of the month (for sugar, the two have a correlation of $\rho = 0.98$). Panels (b) plots the pass-through at 12 months using specification (3). (1) are the estimates reported in Table 4. (2) are estimates using the USDA ERS data over the same sample window (results differ due to the commodity price series differences and because the baseline estimates use both retail price series 715211 and 715212). (3) are estimates using the USDA ERS data starting in Jan 1980. (4) are estimates using the USDA ERS data starting in Jan 1960.

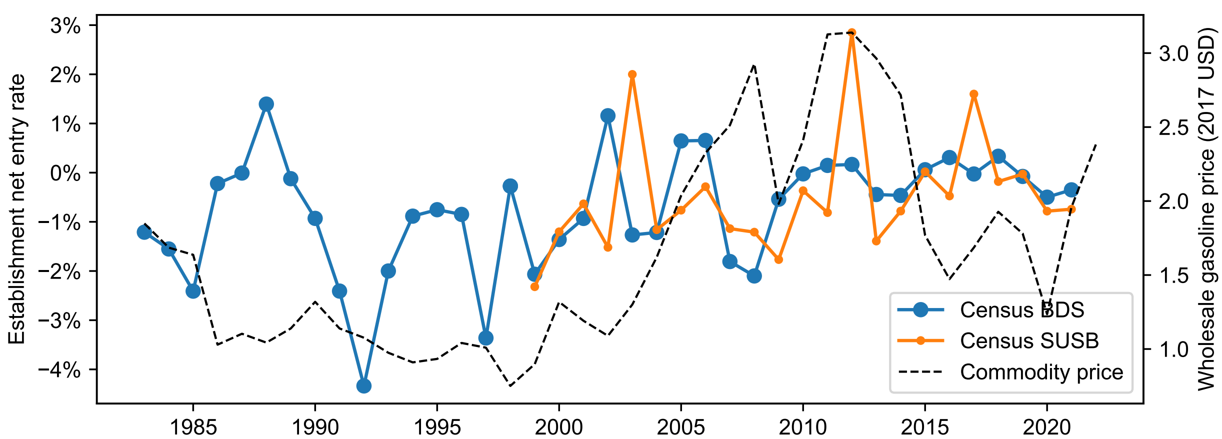
Figure A11: Gross margins, operating margins, and entry for retail gas stations.



(a) Gross margin.

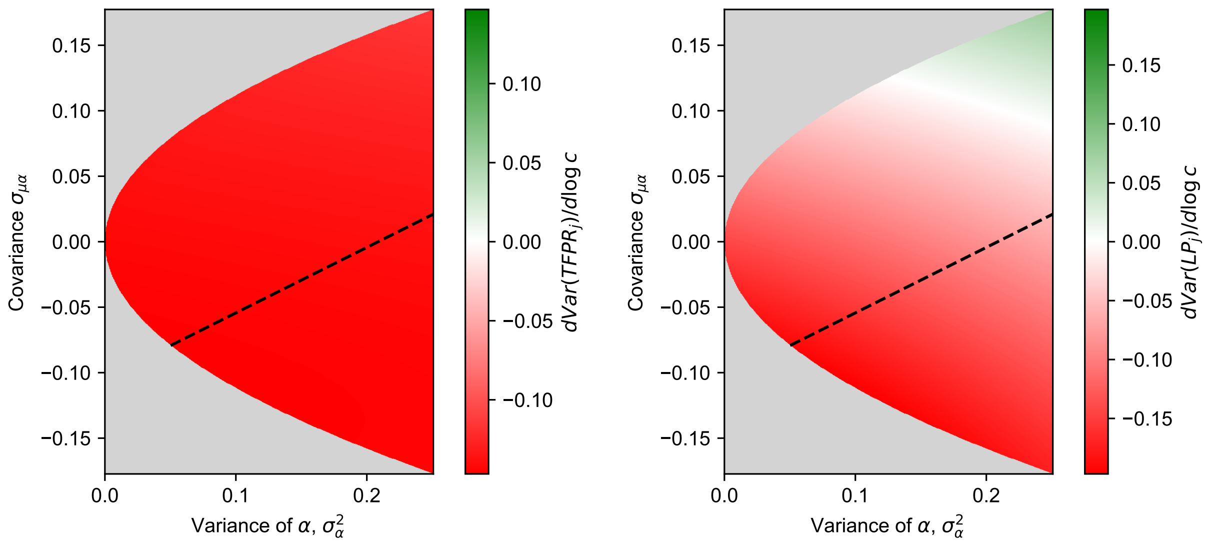


(b) Operating margin (defined as operating income / gross profits).



(c) Entry.

Figure A12: Response of $Var(\log \text{LP})$ and $Var(\log \text{TFPR})$ to an increase in input cost c.



(a) Response of $Var(\log \text{TFPR}_j)$ to increase in c. **(b)** Response of $Var(\log \text{LP}_j)$ to increase in c.

Note: The two subfigures plot the change in the variance of $\log \text{TFPR}_j$ and $\log \text{LP}_j$ for various values of σ_α^2 and $\sigma_{\mu\alpha}$. The dotted line indicates values of $\sigma_{\mu\alpha}$ where $\text{Var}(\log \text{LP}_j) = 0.334$, which is the median variance of log LP across industries from the BLS Dispersion Statistics.

B Proofs

B.1 Proofs of Propositions

Proof of Proposition 1. Consider a perturbation in production costs dc_j and assume complete pass-through in levels, so that $dp_j = dc_j$. Then,

$$d\log p_j = \frac{dp_j}{p_j} = \frac{c_j}{p_j}\frac{dc_j}{c_j} = \frac{c_j}{p_j}d\log c_j,$$

where the second equality imposes $dp_j = dc_j$. Differentiating further,

$$\begin{aligned} d^2\log p_j &= \frac{dc_j}{p_j}d\log c_j - \frac{c_j}{p_j^2}dp_j d\log c_j + \frac{c_j}{p_j}d^2\log c_j \\ &= \frac{c_j}{p_j}\left(d\log c_j\right)^2 - \frac{c_j^2}{p_j^2}\left(d\log c_j\right)^2 + \frac{c_j}{p_j}d^2\log c_j. \end{aligned}$$

Thus, a second order Taylor expansion of $\log p_j$ in dc_j yields

$$\begin{aligned} \Delta\log p_j &\approx d\log p_j + \frac{1}{2}d^2\log p_j \\ &= \frac{c_j}{p_j}d\log c_j + \frac{1}{2}\left[\frac{c_j}{p_j}\left(1-\frac{c_j}{p_j}\right)\left(d\log c_j\right)^2 + \frac{c_j}{p_j}d^2\log c_j\right] \\ &= \frac{c_j}{p_j}\left(d\log c_j + \frac{1}{2}d^2\log c_j\right) + \frac{1}{2}\left[\frac{c_j}{p_j}\left(1-\frac{c_j}{p_j}\right)\left(d\log c_j\right)^2\right] \\ &\approx \frac{1}{\mu_j}\left(\Delta\log c_j\right) + \frac{1}{2}\frac{1}{\mu_j}\left(1-\frac{1}{\mu_j}\right)\left(\Delta\log c_j\right)^2, \end{aligned}$$

where the last line holds to a second order in dc_j. Dividing by $\Delta\log c_j$ yields the expression for $\rho_j^{\log}$ in Proposition 1. $\square$

Proof of Proposition 2. We consider a generalization of Proposition 2 where the production weights on labor β_j are allowed to vary across firms. Log prices, log TFPR, and log LP are

$$\begin{aligned} \log p_j &= \log\left(c + \beta_j w + m_j\right). \\ \log \text{TFPR}_j &= \log\left[\left(c + \beta_j w + m_j\right)y_j / \left(cy_j + \beta_j w y_j\right)\right]. \\ \log \text{LP}_j &= \log\left[\left(c + \beta_j w + m_j\right)y_j / \left(\beta_j w y_j\right)\right]. \end{aligned}$$

To characterize how the variance of each responds to an increase in c, first note that for any variable x_j,

$$\frac{d}{d\log c}Var(x_j) = 2Cov\left(x_j, \frac{dx_j}{d\log x_j}\right).$$

For the variance of log prices, we have:

$$\frac{d}{d\log c}Var(\log p_j) = 2Cov\left(\log p_j, \frac{d\log p_j}{d\log c}\right) = 2Cov\left(\log p_j, \frac{c}{p_j}\right) < 0.$$

The change in the variance of log TFPR and log LP with heterogeneous labor intensity β_j are more complicated. It will be convenient to define the percentage markup μ_j and ratio of labor costs to total variable costs α_j:

$$\mu_j = \frac{c + \beta_j w + m_j}{c + \beta_j w}, \qquad \alpha_j = \frac{\beta_j w}{c + \beta_j w}.$$

Solving,

$$Cov\left(\log \text{TFPR}_j, \frac{d\log \text{TFPR}_j}{d\log c}\right) = Cov\left(\log \mu_j, \left(1-\alpha_j\right)\left(\frac{1}{\mu_j} - 1\right)\right).$$

$$Cov\left(\log \text{LP}_j, \frac{d\log \text{LP}_j}{d\log c}\right) = Cov\left(\log \frac{\mu_j}{\alpha_j}, \frac{1-\alpha_j}{\mu_j}\right).$$

When β_j (and thus α_j) is uniform across firms, both TFPR_j and LP_j are proportional to the percentage markup μ_j, and these covariances are both proportional to $Cov(\log \mu_j, 1/\mu_j) < 0$, leading to the result in Proposition 2.

We conduct an illustrative simulation for how the responses change if we allow for heterogeneous β_j and thus α_j. We assume that μ_j and α_j are drawn from a joint lognormal distribution. We use the median ratio of sales to variable costs across NBER-CES industries to set $\mathbb{E}[\log \mu_j] = \log(1.530)$ and the median ratio of labor costs to variable costs to set $\mathbb{E}[\log \alpha_j] = \log(0.182)$. We set $\sigma_\mu^2 = 0.125$ to match the median of the variance of log TFPR across industries from the BLS Dispersion Statistics.

Appendix Figure A12 shows the sign of $dVar(\log \text{TFPR}_j)/d\log c$ and $dVar(\log \text{LP}_j)/d\log c$ as we vary σ_α^2 between $[0, 2\sigma_\mu^2]$ and allow $\sigma_{\mu\alpha}$ to vary over all feasible values. When $\sigma_\alpha^2 = 0$, both variances always decline with an increase in c, as in Proposition 2. The response of both variances to an increase in c continues to be negative for modest heterogeneity in labor intensity α_j, though when σ_α^2 is large and labor intensity is positively correlated with markups, the response of $Var(\text{LP}_j)$ flips in sign.

□

Markup dispersion and allocative efficiency. We use logit demand to illustrate that marginal changes in markup dispersion need not improve allocative efficiency when demand is nonhomothetic. Anderson et al. (1992) show that a representative consumer has logit demand if utility takes the form,

$$u\left(c_0, c_1, ..., c_J\right) = \begin{cases} c_0 + \frac{1}{\alpha}\sum_{j=1}^{J}\delta_j c_j - \frac{1}{\alpha}\sum_{j=1}^{J} c_j \log c_j & \text{if } \sum_{j=1}^{J} c_j = 1 \\ -\infty & \text{otherwise} \end{cases},$$

where c_0 is the consumption of the outside good and $c_1, ..., c_J$ are consumptions of inside goods $1, ..., J$.

To characterize allocative efficiency, we need to specify firm's production technologies, pricing, and the equilibrium. Suppose that all goods $0, ..., J$ are produced from labor, which is in fixed supply L. Each good is produced with constant returns to scale with productivity A_j, and each good's price is equal to marginal cost times an exogenous markup μ_j. Profits are distributed as dividends back to the representative consumer.

Given productivities A_j and markups μ_j, the quantities consumed of each good are

$$c_0 = \frac{A_0}{\mu_0}\left(L - \sum_{j=1}^{J}\frac{1}{A_j}c_j\right), \qquad \text{and} \qquad c_j = \frac{\exp\left(\delta_j - \alpha\frac{\mu_j}{\mu_0}\frac{A_0}{A_j}\right)}{\sum_{k=1}^{J}\exp\left(\delta_k - \alpha\frac{\mu_k}{\mu_0}\frac{A_0}{A_k}\right)} \text{ for } j \in \{1, ..., J\}.$$

Plugging these in yields an expression for utility in terms of the exogenous markups μ_j:

$$u = A_0 L + \frac{\sum_{j=1}^{J}\frac{A_0}{A_j}\left(\frac{\mu_j}{\mu_0} - 1\right)\exp\left(\delta_j - \alpha\frac{\mu_j}{\mu_0}\frac{A_0}{A_j}\right)}{\sum_{j=1}^{J}\exp\left(\delta_j - \alpha\frac{\mu_j}{\mu_0}\frac{A_0}{A_j}\right)} + \frac{1}{\alpha}\log\sum_{j=1}^{J}\exp\left(\delta_j - \alpha\frac{\mu_j}{\mu_0}\frac{A_0}{A_j}\right).$$

Optimality requires

$$\frac{\mu_j - \mu_0}{A_j} = \sum_{k=1}^{J}\frac{\mu_k - \mu_0}{A_k}c_k, \text{ for each } j \in \{1, ..., J\}.$$

Clearly, one way of achieving efficiency is to set $\mu_j = \mu_0$ for all j—i.e., to eliminate markup dispersion entirely. However, efficiency is also obtained when $\mu_j = \mu_0 + bA_j$ for all j, for any constant b. When A_j are heterogeneous, this means that the efficient equilibrium can obtain with dispersed markups. Moreover, starting from an equilibrium with dispersed markups in which $\mu_j = \mu_0 + bA_j$ for all j, perturbing the markup distribution must weakly reduce welfare, even if it decreases markup dispersion. □

Proof of Proposition 3. The equilibrium is described by the following system of equations:

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

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, $d\log c$. The log-linearized pricing equation is

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

with $\rho^{\log} = 1$ if log pass-through is complete and $\rho^{\log} = (c/p)$ if pass-through is complete in levels. For gross margins,

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

Thus, gross margins are constant if $\rho^{\log} = 1$ and $d\log m^{\text{gross}}/d\log c < 0$ if $\rho^{\log} < 1$. When pass-through is complete in levels, 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 $\Pi^{\text{gross}} = (p-c)\,Q$.

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

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

$$d\log m^{\text{op}} = \frac{f_o}{\pi^{\text{op}}} \frac{\left(\pi^{\text{op}} - f_e\right)}{\left(\pi^{\text{op}} - f_e\right) + \zeta\pi^{\text{gross}}} d\log\Pi^{\text{gross}}$$

$$d \log N = \frac{\zeta \pi^{\text{gross}}}{(\pi^{\text{op}} - f_e) + \zeta \pi^{\text{gross}}} d \log \Pi^{\text{gross}}.$$

□

Proof of Proposition 4. Profit maximization yields the following first-order conditions for prices

$$1 = \left(\frac{p_j - c_j}{p_j} \right) \frac{-\partial \log D_j (\boldsymbol{p}, \boldsymbol{p_0}, Y)}{\partial \log p_j}.$$

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 $d \log p_n$,

$$d \log p_j = d \log c_j - \frac{p_j - c_j}{c_j} \left(\frac{-\partial \log D_j}{\partial \log p_j} \right)^{-1} \sum_{n=1}^{J} \frac{-\partial^2 \log D_j}{\partial \log p_j \partial \log p_n} d \log p_n. \tag{18}$$

Given a proportional increase in all firms' marginal costs $d \log c_j = d \log c$ for all $j \in \{1, ..., J\}$, under Assumption 2, complete log pass-through (i.e., $d \log p_j = d \log c$ for all j) is a solution to (18) if and only if for all j,

$$\sum_{n=1}^{J} \frac{\partial^2 \log D_j (p)}{\partial \log p_j \partial \log p_n} = 0. \tag{19}$$

If D is scale invariant in inside prices,

$$\log D_j (\lambda \boldsymbol{p}, \boldsymbol{p_0}, Y) = \varphi_j (\boldsymbol{p}, \boldsymbol{p_0}, Y, \lambda) \log \lambda + \log D_j (\boldsymbol{p}, \boldsymbol{p_0}, Y).$$

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

$$\log D_j (\lambda \boldsymbol{p}, \boldsymbol{p_0}, Y) \approx \log D_j (\boldsymbol{p}, \boldsymbol{p_0}, Y) + \sum_{n=1}^{J} \frac{\partial \log D_j}{\partial \log p_n} \log \lambda.$$

Setting the two equal,

$$\sum_{n=1}^{J} \frac{\partial \log D_j}{\partial \log p_n} = \varphi_j (\boldsymbol{p}, \boldsymbol{p_0}, Y, 1).$$

Since scale invariance in inside prices imposes $\partial \varphi_j / \partial p_j = 0$, (19) is satisfied. □

Proof of Proposition 5. Profit maximization yields the standard first-order condition,

$$p_j - c_j = \frac{D_j (\boldsymbol{p}, \boldsymbol{p_0}, Y)}{-\partial D_j (\boldsymbol{p}, \boldsymbol{p_0}, Y) / \partial p_j}.$$

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,

$$dp_j = dc_j - \left(\frac{\partial D_j}{\partial p_j}\right)^{-1} \sum_{n=1}^{J} \left(\frac{\partial D_j}{\partial p_n} + \frac{D_j}{-\partial D_j/\partial p_j} \frac{\partial^2 D_j}{\partial p_j \partial p_n}\right) dp_n. \tag{20}$$

Given an identical increase in all firms' costs, $dc_j = dc$ for all $j \in \{1, ..., J\}$, under Assumption 2, complete pass-through in levels (i.e., $dp_j = dc$ for all j) is a solution to (20) if and only if for all j,

$$\frac{D_j(p)}{\frac{\partial D_j(p)}{\partial p_j}} \left[\frac{\partial}{\partial p_j} \sum_{n=1}^{J} \frac{\partial D_j}{\partial p_n}\right] = \sum_{n=1}^{J} \frac{\partial D_j}{\partial p_n}. \tag{21}$$

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

$$D_j(\boldsymbol{p} + \lambda \mathbf{1}, \boldsymbol{p_0}, Y) \approx D_j(\boldsymbol{p}, \boldsymbol{p_0}, Y) + \sum_{n=1}^{J} \frac{\partial D_j}{\partial p_n} \lambda.$$

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

$$\sum_{n=1}^{J} \frac{\partial D_j}{\partial p_n} = \psi_j(\boldsymbol{p}, \boldsymbol{p_0}, Y, 0) D_j(\boldsymbol{p}, \boldsymbol{p_0}, Y).$$

Noting that shift invariance in inside prices also imposes $\partial \psi_j / \partial p_j = 0$, substitute this expression into (21) to confirm that (21) is satisfied. □

Proof of Proposition 6. We prove by contradiction. Suppose $D(\boldsymbol{p}, \boldsymbol{p_0}, Y)$ is both scale invariant and shift invariant. Scale invariance and shift invariance imply, respectively, that for any price vector $\boldsymbol{p}$ and any j,

$$\sum_{n=1}^{J} \frac{\partial \log D_j}{\partial \log p_n} = \varphi_j(\boldsymbol{p}, \boldsymbol{p_0}, Y, 1) \tag{22}$$

$$\text{and} \qquad \sum_{n=1}^{J} \frac{\partial D_j}{\partial p_n} \frac{1}{D_j} = \psi_j(\boldsymbol{p}, \boldsymbol{p_0}, Y, 0). \tag{23}$$

Consider first a vector of identical prices $\boldsymbol{p_1} = p\mathbf{1}$, where $p > 0$ and $\mathbf{1} = (1, ..., 1)$ is a vector of ones of length J. Multiplying both sides of (23) by p and setting equal to (22) yields,

$$\sum_{n=1}^{J} \frac{\partial \log D_j}{\partial \log p_n}\bigg|_{\boldsymbol{p}=\boldsymbol{p_1}} = \varphi_j(\boldsymbol{p_1}, \boldsymbol{p_0}, Y, 1) = p\, \psi_j(\boldsymbol{p_1}, \boldsymbol{p_0}, Y, 0).$$

Now consider a vector of prices $\boldsymbol{p_2} = p\mathbf{1} + (p_j - p)\mathbf{1}^j$, 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, $\boldsymbol{p_2}$ is identical to $\boldsymbol{p_1}$ 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:

$$\sum_{n=1}^{J} \frac{\partial \log D_j}{\partial \log p_n}\bigg|_{p=\boldsymbol{p_2}} = \varphi_j\left(\boldsymbol{p_2}, \boldsymbol{p_0}, Y, 1\right) = \varphi_j\left(\boldsymbol{p_1}, \boldsymbol{p_0}, Y, 1\right) = p\,\psi_j\left(\boldsymbol{p_1}, \boldsymbol{p_0}, Y, 0\right). \tag{24}$$

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

$$\sum_{n} \frac{\partial D_j}{\partial p_n}\frac{1}{D_j}\bigg|_{p=\boldsymbol{p_2}} = \psi_j\left(\boldsymbol{p_2}, \boldsymbol{p_0}, Y, 0\right) = \psi_j\left(\boldsymbol{p_1}, \boldsymbol{p_0}, Y, 0\right).$$

We use this to rewrite:

$$\sum_{n=1}^{J} \frac{\partial \log D_j}{\partial \log p_n}\bigg|_{p=\boldsymbol{p_2}} = \sum_{n=1}^{J} \frac{\partial D_j}{\partial p_n}\frac{p}{D_j} + \frac{\partial D_j}{\partial p_j}\frac{p_j - p}{D_j} = p\,\psi_j\left(\boldsymbol{p_1}, \boldsymbol{p_0}, Y, 0\right) + \frac{\partial D_j}{\partial p_j}\frac{p_j}{D_j}\frac{p_j - p}{p_j}.$$

Setting this expression equal to (24), 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. $\square$

Relationship to pass-through of idiosyncratic shocks. Starting from Equation (20), we can write (i) the pass-through of an idiosyncratic shock dc_j setting $dp_n = 0$ for all $n \neq j$ and (ii) the pass-through of a common cost shock imposing $dc_j = dc$ and $dp_j = dp$ for all j as

$$\frac{dp_j}{dc_j} = \left[2 - \frac{D_j\left(p\right)}{\left(\frac{\partial D_j(p)}{\partial p_j}\right)^2}\frac{\partial^2 D_j\left(p\right)}{\partial p_j^2}\right]^{-1},$$

$$\frac{dp}{dc} = \left[1 + \left(\frac{\partial D_j\left(p\right)}{\partial p_j}\right)^{-1}\sum_{n}\left(\frac{\partial D_j(p)}{\partial p_n} + \frac{D_j\left(p\right)}{-\frac{\partial D_j(p)}{\partial p_j}}\frac{\partial^2 D_j\left(p\right)}{\partial p_j \partial p_n}\right)\right]^{-1}.$$

Substituting in expressions for the demand elasticity σ_j and super-elasticities ε_{jj} and ε_{jn},

$$\sigma_j = -\frac{\partial D_j}{\partial p_j}\frac{p_j}{D_j}, \qquad \varepsilon_{jj} = \frac{\frac{\partial^2 D_j}{\partial p_j^2}p_j}{\frac{\partial D_j}{\partial p_j}} + 1 + \sigma_j, \qquad \text{and} \qquad \varepsilon_{jn} = \frac{\frac{\partial^2 D_j}{\partial p_j \partial p_n}p_n}{\frac{\partial D_j}{\partial p_j}} - \frac{\partial D_j}{\partial p_n}\frac{p_n}{D_j},$$

yields,

$$\frac{dp_j}{dc_j} = \frac{\sigma_j}{\sigma_j + \varepsilon_{jj} - 1}, \qquad \text{and} \qquad \frac{dp}{dc} = \frac{\sigma_j}{\sigma_j + \varepsilon_{jj} + \sum_{n \neq j}\frac{p_j}{p_n}\varepsilon_{jn} - 1}.$$

The assumption of identical firms and thus $p_j = p_n$ yields the expressions in the main text. Using $\psi_j(\boldsymbol{p}, \boldsymbol{p_0}, Y, 0) = \sum_n \frac{\partial D_j}{\partial p_n}\frac{1}{D_j}$ from (23), when demand is shift-invariant we can write

$$\varepsilon_{jj} + \sum_{n \neq j}\frac{p_j}{p_n}\varepsilon_{jn} - 1 = p_j\left[\sum_n\left(\frac{\frac{\partial^2 D_j}{\partial p_j \partial p_n}}{\frac{\partial D_j}{\partial p_j}} - \frac{\partial D_j}{\partial p_n}\frac{1}{D_j}\right)\right] = -\frac{p_j^2}{\sigma_{jj}}\frac{\partial \psi_j(\boldsymbol{p}, \boldsymbol{p_0}, Y, 0)}{\partial p_j} = 0.$$

□

B.2 Proofs for Example Demand Systems

Proof of Example 1. The Marshallian demand function $D(\boldsymbol{p}, \boldsymbol{p_0}, Y)$ must be homogeneous of degree zero in prices and income, so that for any $\lambda > 0$,

$$D_j(\lambda \boldsymbol{p}, \lambda Y) = D_j(\boldsymbol{p}, Y) \qquad \forall j.$$

Homotheticity further implies that Engel curves are linear,

$$D_j(\boldsymbol{p}, \lambda Y) = \lambda D_j(\boldsymbol{p}, Y), \qquad \forall j.$$

Combining the two yields, $D_j(\lambda \boldsymbol{p}, Y) = \lambda^{-1} D_j(\boldsymbol{p}, Y)$ for all j, which conforms with scale invariance in Definition 1 with $\varphi_j = -1$ for all j and $\boldsymbol{p_0} = \emptyset$. □

Proof of Example 2. Let $\boldsymbol{p_n} = (p_{n1}, ..., p_{nJ})$ denote the vector of prices in industry n, and let $\boldsymbol{p_{-n}} = \{(p_{n1}, ..., p_{nJ})\}_{m \in [0,1], m \neq n}$ denote the vector of prices of all firms in industries outside n.

Define the ideal price index for industry n, P_n, as

$$P_n(\boldsymbol{p_n}) = \min_{q_{nj} \geq 0} \sum_j p_{nj} q_{nj} \qquad \text{such that} \qquad u(q_{n1}, ..., q_{nJ}) \geq 1.$$

From this definition, the ideal price index satisfies $P_n(\lambda \boldsymbol{p_n}) = \lambda P_n(\boldsymbol{p_n})$ for $\lambda > 0$.

First, consider the demand for variety j within industry n. Let $d_{nj}(\boldsymbol{p_n}, E_n)$ denote the conditional demand for variety j in industry n when the consumer devotes E_n expenditures to industry n. The proof of Example 1 shows that homotheticity implies for any $\lambda > 0$,

$$d_{nj}(\lambda \boldsymbol{p_n}, E_n) = \lambda^{-1} d_{nj}(\boldsymbol{p_n}, E_n) \qquad \text{and} \qquad d_{nj}(\boldsymbol{p_n}, \lambda E_n) = \lambda d_{nj}(\boldsymbol{p_n}, E_n).$$

Next, consider the allocation of expenditures across industries. Since preferences across industries are CES, the consumer's expenditure on each industry are

$$E_n = \frac{P_n^{1-\sigma}}{\int_0^1 P_m^{1-\sigma} dm} Y.$$

Combining this expression with the fact that P_n is homogeneous of degree one in $\boldsymbol{p_n}$,

$$E_n(\lambda \boldsymbol{p_n}, \boldsymbol{p_{-n}}, Y) = \lambda^{1-\sigma} E_n(\boldsymbol{p_n}, \boldsymbol{p_{-n}}, Y).$$

Putting the within-industry and across-industry pieces together,

$$\begin{aligned} D_j(\lambda \boldsymbol{p_n}, \boldsymbol{p_{-n}}, Y) &= d_{nj}\left(\lambda \boldsymbol{p_n}, E_n(\lambda \boldsymbol{p_n}, \boldsymbol{p_{-n}}, Y)\right) \\ &= \lambda^{-1} d_{nj}\left(\boldsymbol{p_n}, \lambda^{1-\sigma} E_n(\boldsymbol{p_n}, \boldsymbol{p_{-n}}, Y)\right) \\ &= \lambda^{-\sigma} d_{nj}\left(\boldsymbol{p_n}, E_n(\boldsymbol{p_n}, \boldsymbol{p_{-n}}, Y)\right) \\ &= \lambda^{-\sigma} D_j\left(\boldsymbol{p_n}, \boldsymbol{p_{-n}}, Y\right). \end{aligned}$$

Thus, demand for each good j in industry n conforms with scale invariance in Definition 1, with $\varphi_j = -\sigma$ for all j and $\boldsymbol{p_0} = \boldsymbol{p_{-n}}$. □

Proof of Example 3. Given $D_j(p_j, \boldsymbol{p_0}, Y) = \exp\left(a_j(\boldsymbol{p_0}, Y) - b_j(\boldsymbol{p_0}, Y) p_j\right)$,

$$\begin{aligned} D_j(p_j + \lambda, \boldsymbol{p_0}, Y) &= \exp\left(a_j(\boldsymbol{p_0}, Y) - b_j(\boldsymbol{p_0}, Y)(p_j + \lambda)\right) \\ &= \exp\left(-b_j(\boldsymbol{p_0}, Y)\lambda\right) \exp\left(a_j(\boldsymbol{p_0}, Y) - b_j(\boldsymbol{p_0}, Y) p_j\right) \\ &= \Bigg[1 + \lambda \underbrace{\frac{1}{\lambda}\left(\exp\left(-b_j(\boldsymbol{p_0}, Y)\lambda\right) - 1\right)}_{\psi_j(\boldsymbol{p_0}, Y, \lambda)}\Bigg] D_j(p_j, \boldsymbol{p_0}, Y), \end{aligned}$$

conforming with shift invariance in Definition 2. □

Proof of Example 4. Let $\boldsymbol{p}^{\text{incl}}$ be any subset of $\boldsymbol{p}$. Without loss, reorder the indices j so that goods $p_j \in \boldsymbol{p}^{\text{incl}}$ if $j \in [1, J^*]$ and $p_j \notin \boldsymbol{p}^{\text{incl}}$ if $j \in (J^*, J]$, where $1 \leq J^* \leq J$. Let $\boldsymbol{p}^{\text{excl}} = \boldsymbol{p} \setminus \boldsymbol{p}^{\text{incl}}$

denote the vector of prices not in $\boldsymbol{p}^{\text{incl}}$. Given (14), the demand for any good $j \in [1, J^*]$ is:

$$
\begin{aligned}
D_j(\boldsymbol{p}^{\text{incl}} + \lambda \mathbf{1}, \boldsymbol{p}^{\text{excl}}, p_0, Y) &= \frac{\exp\left(a_j(p_0, Y) - b_j(p_j + \lambda)/p_0\right)}{\int_1^{J^*} \exp\left(a_k(p_0, Y) - b_k(p_k + \lambda)/p_0\right) dk + \int_{J^*}^1 \exp\left(a_k(p_0, Y) - b_k p_k/p_0\right) dk} \\
&= \frac{\exp\left(-b_j \lambda/p_0\right)\left[\int_1^J \exp\left(a_k(p_0, Y) - b_k p_k/p_0\right) dk\right]}{\int_1^{J^*} \exp\left(a_k(p_0, Y) - b_k(p_k + \lambda)/p_0\right) dk + \int_{J^*}^1 \exp\left(a_k(p_0, Y) - b p_k/p_0\right) dk} \\
&\quad \times \frac{\exp\left(a_j(p_0, Y) - b_j p_j/p_0\right)}{\int_1^J \exp\left(a_k(p_0, Y) - b_k p_k/p_0\right) dk} \\
&= \left(1 + \psi_j(\boldsymbol{p}^{\text{incl}}, \boldsymbol{p}^{\text{excl}}, p_0, Y, \lambda)\right) D_j(\boldsymbol{p}^{\text{incl}}, \boldsymbol{p}^{\text{excl}}, p_0, Y),
\end{aligned}
$$

where

$$
\begin{aligned}
&\psi_j(\boldsymbol{p}^{\text{incl}}, \boldsymbol{p}^{\text{excl}}, p_0, Y, \lambda) = \\
&\qquad \frac{1}{\lambda}\left[\frac{\exp\left(-b_j \lambda/p_0\right)\left[\int_1^J \exp\left(a_k(p_0, Y) - b_k p_k/p_0\right) dk\right]}{\int_1^{J^*} \exp\left(a_k(p_0, Y) - b_k(p_k + \lambda)/p_0\right) dk + \int_{J^*}^1 \exp\left(a_k(p_0, Y) - b p_k/p_0\right) dk} - 1\right].
\end{aligned}
$$

Since each firm is atomistic, the effect of p_j on the integrals in $\psi_j(\boldsymbol{p}^{\text{incl}}, \boldsymbol{p}^{\text{excl}}, p_0, Y, \lambda)$ is measure zero, and thus $\partial \psi_j / \partial p_j = 0$. Thus, this demand system conforms with the definition of shift invariance (Definition 2) with respect to $\boldsymbol{p}^{\text{incl}}$. □

Proof of Example 5. Substituting in the budget constraint, we can write, for any constant λ,

$$
\begin{aligned}
D_j(\boldsymbol{p}, p_0, Y) &= \int_0^1 1\left\{\delta_{ij} + \frac{Y - p_j}{p_0} > \delta_{ik} + \frac{Y - p_k}{p_0}, \quad \text{for all } k \neq j\right\} di \\
&= \int_0^1 1\left\{p_0 \delta_{ij} - p_j > p_0 \delta_{ik} - p_k, \quad \text{for all } k \neq j\right\} di \\
&= \int_0^1 1\left\{p_0 \delta_{ij} - p_j - \lambda > p_0 \delta_{ik} - p_k - \lambda, \quad \text{for all } k \neq j\right\} di \\
&= D_j(\boldsymbol{p} + \lambda \mathbf{1}, p_0, Y).
\end{aligned}
$$

Thus, this demand system conform with shift invariance in Definition 2 with $\psi_j = 0$. □

B.3 Relaxing Assumptions on Production Technology

This section explores whether relaxing assumptions about the production technology affects the interpretation of our estimates. Our estimates of the pass-through of input cost changes to prices combine the pass-through of marginal cost changes to prices and the response of marginal costs to input cost changes:

$$\rho_{p,c}^{\text{level}} = \frac{dp}{dc} = \underbrace{\rho_{p,mc}^{\text{level}}}_{\substack{\text{Pass-through of marginal} \\ \text{cost change to prices}}} \times \underbrace{\frac{dmc}{dc}}_{\substack{\text{Effect of input cost change} \\ \text{on marginal costs}}} .$$

Under constant returns, Leontief production, $dmc/dc = 1$, so that $\rho_{p,c}^{\text{level}} = \rho_{p,mc}^{\text{level}}$.

Suppose the production technology takes the more general form,

$$y = \left(\omega x^{\frac{\theta-1}{\theta}} + (1-\omega) l^{\frac{\theta-1}{\theta}}\right)^{\alpha \frac{\theta}{\theta-1}}, \tag{25}$$

where y is the firm's output, x is quantity of the commodity input (i.e., the input whose pass-through we measure) with price c, l is a bundle of all other inputs with unit price w, θ is the elasticity of substitution between the commodity and other inputs, and α are returns to scale. How does 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, $dw/dc \neq 0$ affect the comparison between $\rho_{p,c}^{\text{level}}$ and $\rho_{p,mc}^{\text{level}}$?

It will be useful to work with elasticities rather than changes in levels. Rearranging yields:

$$\frac{dp}{p} = \rho_{p,mc}^{\text{level}} \frac{mc}{p} \frac{dmc/mc}{dc/c} \frac{dc}{c}.$$

Using $dx/x \approx d\log x$ to a first order approximation, we have:

$$d\log p = \rho_{p,mc}^{\text{level}} \frac{mc}{p} \frac{d\log mc}{d\log c} d\log c.$$

Multiplying the numerator and denominator by units of output y, and using $C(y) = cx(y;c,w) + wl(y;c,w)$ to denote the total costs of producing y units of output and $ac = C(y)/y$ to denote average costs, we obtain

$$d\log p = \rho_{p,mc}^{\text{level}} \frac{C(y)}{py} \frac{d\log C(y)}{d\log c} \frac{mc}{ac} \frac{\frac{d\log mc}{d\log c}}{\frac{d\log C(y)}{d\log c}} d\log c.$$

Now, we substitute into this equation using the production technology (25). First, note that $mc = (1/\alpha)ac$. Thus, $mc/ac = 1/\alpha$. Second, we can use Shephard's lemma to express:

$$\frac{d\log C(y)}{d\log c} = \frac{\partial \log C(y)}{\partial \log c} + \frac{\partial \log C(y)}{\partial \log w}\frac{d\log w}{d\log c} = \frac{cx(y,c,w)}{C(y)} + \frac{wl(y,c,w)}{C(y)}\frac{d\log w}{d\log c}.$$

Thus:

$$d\log p = \rho^{\text{level}}_{p,mc}\frac{1}{\alpha}\left(\frac{cx}{py} + \frac{wl}{py}\frac{d\log w}{d\log c} + \frac{1-\alpha}{\alpha}\frac{C(y)}{py}\frac{d\log y}{d\log c}\right)d\log c.$$

Multiplying by p, and using the normalization of units of x so that initially one unit of x is required to produce one unit of y (i.e., $x/y = 1$ at the initial point), we find

$$dp = \underbrace{\rho^{\text{level}}_{p,mc}\frac{1}{\alpha}\left(1 + \frac{wl}{cy}\frac{d\log w}{d\log c} + \frac{1-\alpha}{\alpha}\frac{C(y)}{cy}\frac{d\log y}{d\log c}\right)}_{\rho^{\text{level}}_{p,c}}dc. \tag{26}$$

From (26), we can evaluate how correlated input costs and decreasing returns to scale will bias our estimates of $\rho^{\text{level}}_{p,c}$ relative to $\rho^{\text{level}}_{p,mc}$:

1. A positive correlation between input price c and the price of other inputs, $d\log w/d\log c > 0$, will bias *up* our estimate of $\rho^{\text{level}}_{p,c}$ relative to $\rho^{\text{level}}_{p,mc}$.

2. Holding fixed output $d\log y/d\log c = 0$, decreasing returns to scale $\alpha < 1$ will bias *up* our estimate of $\rho^{\text{level}}_{p,c}$ relative to $\rho^{\text{level}}_{p,mc}$.

3. If each firms' output falls when costs of production rise, $d\log y/d\log c < 0$, this will bias *down* our estimate of $\rho^{\text{level}}_{p,c}$ relative to $\rho^{\text{level}}_{p,mc}$ if firms have decreasing returns $\alpha < 1$.

Absent from this list is the elasticity of substitution θ. This is because, to a first order, the effect of the change in the input cost c on costs of production $C(y)$ is summarized by the expenditure share on the input (Shephard's lemma). A higher elasticity of substitution θ dampens the effect of an increase in c on $C(y)$, but these terms only show up in a second-order (or higher order) approximation.

When firms have fixed percentage markups, we would expect $\rho^{\text{level}}_{p,mc} = \mu$. Instead, we find $\rho^{\text{level}}_{p,c} = 1$. These results suggest that positively correlated input prices or decreasing returns to scale would not explain the fact that we find $\rho^{\text{level}} < \mu$. On the other hand, a negative correlation between input prices, a combination of declining output when production costs rise with decreasing returns to scale, or a high elasticity of substitution between the measured input and other production inputs could bias downward our estimates of $\rho^{\text{level}}_{p,c}$ relative to $\rho^{\text{level}}_{p,mc}$.

It is worth noting from (26) that obtaining $\rho_{p,c}^{\text{level}} = 1$ when $\rho_{p,mc}^{\text{level}} = \mu$ would require knife-edge conditions about the correlation between input costs or the degree to which output declines when production costs rise, which are unlikely to hold across the multiple empirical settings that we explore.

C Additional Empirical Results

C.1 Pass-Through at the Retail Level: Evidence from Identical Products

In this appendix, we test for pass-through in levels by retailers across a broad range of product categories, exploiting the fact that different retailers often sell the same product at different prices (Kaplan and Menzio 2015). Under the assumption that retail chains face identical wholesale costs for any given product, we show that we can use price movements of the same product across different retailers to test for pass-through in levels, even without directly observing retailers' costs.

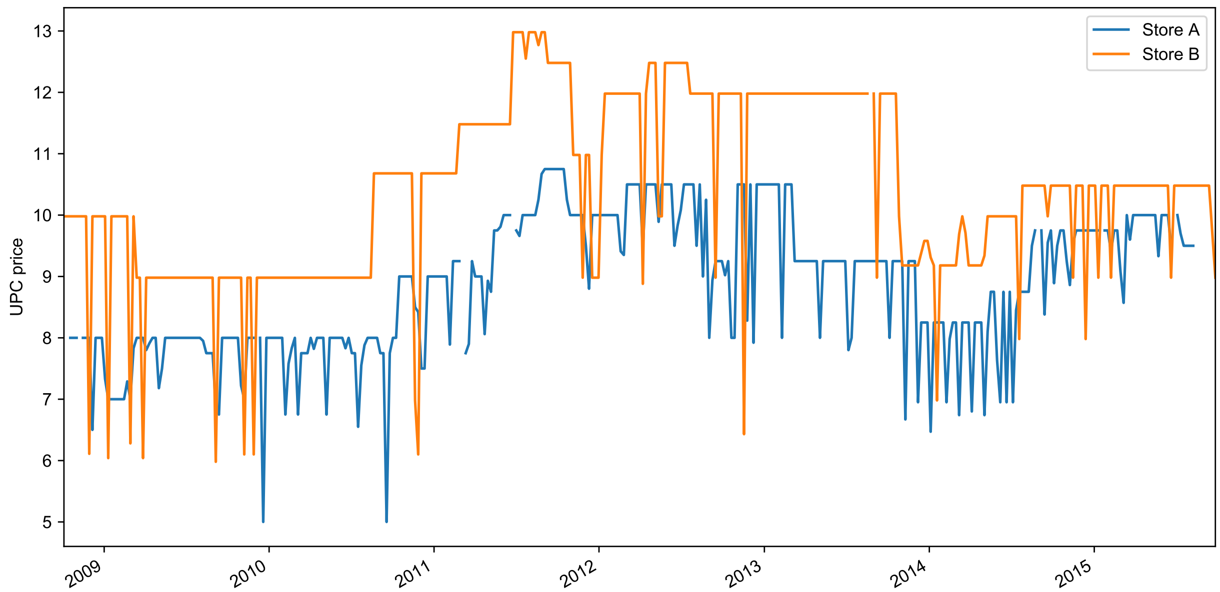
Exploiting variation in prices across retailers. To fix ideas, consider two retail stores selling the same UPC, one at a low price (store A) and one with a high price (store B). As an example, Figure C1 shows the price of the same coffee UPC at two different stores in Philadelphia. Excluding some temporary 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 C1, 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 the predictions using two specifications,

$$\Delta p_{ikt} = \beta^{\text{level}} \left(\Delta \bar{p}_{kt} \times \text{RelativePrice}_{ikt} \right) + \gamma \text{RelativePrice}_{ikt} + \alpha_{kt} + \varepsilon_{ikt}, \tag{27}$$

Figure C1: Price of a coffee UPC in two stores in same 3-digit ZIP in Philadelphia, PA.



$$\Delta \log p_{ikt} = \beta^{\log} \left(\Delta \log \bar{p}_{kt} \times \text{RelativePrice}_{ikt} \right) + \tilde{\gamma}\text{RelativePrice}_{ikt} + \tilde{\alpha}_{kt} + \varepsilon_{ikt}, \qquad (28)$$

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. We also include controls for retailers' initial prices in both specifications, so that systematic differences in price changes between retailers with initially high and low prices for a UPC (e.g., due to mean reversion) unrelated to the average change in a UPC's price are absorbed by the coefficients γ and $\tilde{\gamma}$.

The final panel of Table C1 summarizes the predicted coefficients β^{level} and $\beta^{\log}$ under the two pricing rules. If firms have fixed percentage markups, we predict $\beta^{\text{level}} \approx 1$ and $\beta^{\log} \approx 0$. 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 $\beta^{\log} \approx -1$.

The predictions in Table C1 obtain under the assumption that the cost of each UPC is uniform across retailers. In practice, replacement costs for a UPC may vary across retailers due to heterogeneity in bargaining power or other components of variable costs, such as different costs of shipping to central or remote stores. Suppose each retailer's

Table C1: Predictions for pass-through across retailers selling identical UPCs.

	Percentage markups $p_i = \mu_i c$	Additive markups $p_i = c + m_i$
Price change relative to cost:		
Levels (dp_i/dc)	μ_i	1
Logs ($d\log p_i/d\log c$)	1	c/p_i
Price change relative to average:		
Levels ($dp_i/d\bar{p}$)	$\approx 1 + \log(p_i/\bar{p})$	1
Logs ($d\log p_i/d\log\bar{p}$)	1	$\approx 1 - \log(p_i/\bar{p})$
Predicted interaction coefficient:		
Levels specification (27), β^{level}	1	0
Logs specification (28), $\beta^{\log}$	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 $\bar{p}$.

cost is $c + w_i$, where c is the common component of the UPC cost and w_i is a retailer-specific cost component. If retailers set fixed percentage markups, $p_i = \mu_i(c + w_i)$, then the estimates for β^{level} and $\beta^{\log}$ will move toward 0 and -1, but will not fully reach the "additive markup" predictions unless the correlation between firms' prices and markups is zero or idiosyncratic costs w_i change differentially across retailers in response to common cost changes in a way that systematically offsets the effects of fixed markups on prices.

Results. We estimate specifications (27) and (28) 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 the 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.

Panel A of Table C2 shows that estimating the levels specification (27) 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 C1 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 (28). We find that $\beta^{\log} \approx -1$ 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., $\beta^{\log} = 0$) at

Table C2: Exploiting variation in prices of identical products across retailers.

Panel A: In levels	Δ UPC Price (Δp_{ikt})			
	Rice	Flour	Coffee	All Products
	(1)	(2)	(3)	(4)
Avg Δ Price$_{kt}$ × RelativePrice$_{ikt}$	−0.022	0.058	0.192	−0.001
	(0.141)	(0.209)	(0.170)	(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
Panel B: In logs	Δ Log UPC Price ($\Delta \log p_{ikt}$)			
	Rice	Flour	Coffee	All Products
	(1)	(2)	(3)	(4)
Avg Δ Log Price$_{kt}$ × RelativePrice$_{ikt}$	$-1.004^{\dagger}$	$-1.014^{\dagger}$	−1.261	$-1.043^{\dagger}$
	(0.125)	(0.184)	(0.084)	(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 (27), and panel B reports results from (28). 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 in parentheses. For estimates of the coefficient $\beta^{\log}$, † indicates estimates for which a value of −1 is within the 90 percent confidence interval.

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.

C.2 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?[38]

In this appendix, we develop a simple multi-sector model with shift-invariant demand that can resolve these puzzles. In the model, the marginal goods consumed by households are largely produced with labor. Thus, firms set additive markups, but those additive markups are priced relative to the marginal utility of consumption, and thus relative to the cost of labor. As a result, firms in all sectors 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.

A simple model with differential pass-through. A mass of consumers indexed by $i \in [0, 1]$ purchases from a continuum of sectors indexed by s. Each sector s consists of J identical firms indexed by j. When a consumer purchases from sector s, she chooses exactly one firm to purchase one unit from. Let $p_{ij}(s)$ denote the price consumer i pays for a unit of the good from the firm $j(s)$ that she selects in sector s, and $\delta_{ij}(s)$ denote the consumer's taste for the good produced by firm $j(s)$. The consumer maximization problem is

$$U_i = \max_{S, j(s)} \int_0^S \delta_{ij}(s) q_{ij}(s) ds, \qquad \text{s.t.} \qquad \int_0^S p_{ij}(s) q_{ij}(s) ds = Y,$$

where Y is the consumer's (exogenous) income, $q_{ij}(s)$ is equal to one if the consumer consumes from sector s and zero otherwise, and S measures the mass of sectors from which the consumer purchases. Note that S is an endogenous object: if the consumer chooses products with lower prices in sectors $s < S$, she can expand the mass of sectors she consumes from until her income is exhausted.[39] We assume that consumers' tastes

[38]Okun (1981) makes this observation on the pass-through of material costs as a caveat to his theory that firms apply "a constant [percentage] 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.

[39]This setup is based on Murphy et al. (1989) and Matsuyama (2002), who also consider models in which households consume one unit each from an ordered continuum of sectors. However, the model presented here is partial equilibrium: we take consumer income Y and firms' marginal costs as exogenous parameters.

$\delta_{ij}(s)$ are i.i.d. draws from a distribution F.

On the firm side, each sector consists of J identical firms that possess a Leontief production technology in labor and materials. The proportions with which labor and materials are combined vary across sectors, so that the marginal cost of producing one unit of output in sector s is

$$mc(s) = \beta_s w + (1 - \beta_s)c,$$

where w is the wage, c is the cost of materials, and $\beta_s \in [0, 1]$ determines the weights on labor and materials in production. We assume that β_s is smooth in s, and we have in mind that β_s increases with s, since the marginal goods purchased by households tend to be more labor-intensive (Jaimovich et al. 2019).

In equilibrium, consumers choose the mass of sectors to purchase from (S) and which firms to purchase from in each sector s to maximize utility, taking prices and income as given, and firms set prices to maximize profits, taking as given the prices set by other firms and input costs w and c. Since firms in each industry are symmetric, they choose identical prices in equilibrium. We denote the price and percentage markup of firms in sector s by $p(s)$ and $\mu(s) = p(s)/mc(s)$ respectively.

Lemma C1 (Sectoral prices)**.** *In equilibrium, the symmetric price set by firms in sector s is equal to marginal cost plus an additive markup priced relative to the price in sector S,*

$$p(s) = \beta_s w + (1 - \beta_s)c + \phi p(S),$$

where $p(S)$ is price set by firms in sector S, and ϕ is a constant that depends only on the number of firms in each sector J and the distribution of taste shocks F.

Proof. See proofs at the end of this appendix. □

Lemma C1 shows that prices in each sector equal marginal costs plus an additive markup that is priced relative to the price of goods in sector S, $p(S)$. Intuitively, consumer preferences over firms in each sector are analogous to the discrete choice preferences in Example 5. The key difference is that in Example 5, the marginal utility of income was determined by the price of the outside good p_0, while in this setting, the marginal utility of income to a consumer depends on the price of the marginal goods she consumes—i.e., the price in sector S. Changes in the price $p(S)$ thus affect markups and prices set by firms in all other sectors.

Given these expressions for prices, it is straightforward to characterize the pass-through of exogenous changes to the cost of materials c and to wages w.

Proposition C1 (Differential pass-through of material and labor costs). *Let $\rho_c^{level}(s)$ and $\rho_w^{level}(s)$ denote the pass-through in levels for sector s of an exogenous change to unit materials prices and unit wages, and let $\rho_c^{log}(s)$ and $\rho_w^{log}(s)$ denote the analogous log pass-throughs.*

1. *The pass-through in levels of unit material and labor costs are*

$$\rho_c^{level}(s) = 1 + [\mu(s) - 1] \frac{mc(s)}{mc(S)} \frac{1-\beta_S}{1-\beta_s},$$
$$\rho_w^{level}(s) = 1 + [\mu(s) - 1] \frac{mc(s)}{mc(S)} \frac{\beta_S}{\beta_s}.$$

   If sector s uses labor less intensively than the marginal sector, i.e., $\beta_s < \beta_S$, then firms in sector s exhibit higher pass-through of unit labor costs than material costs, $\rho_w^{level}(s) > \rho_c^{level}(s)$.

2. *If the marginal sector only uses labor in production, i.e., $\beta_S = 1$, then firms exhibit complete pass-through in levels of material costs ($\rho_c^{level}(s) = 1$ and $\rho_c^{log}(s) < 1$) and (more than) complete log pass-through of labor costs, ($\rho_w^{level}(s) \geq \mu(s)$ and $\rho_w^{log}(s) \geq 1$).*

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

$$\frac{d \log p(s)}{d \log x} = \rho_x^{log}(s) \frac{Costs(s,x)}{VariableCosts(s)}, \qquad \text{and} \qquad \frac{d \log p(s)}{d \log x} = \rho_x^{level}(s) \frac{Costs(s,x)}{Sales(s)},$$

   where $Costs(s,c)$ and $Costs(s,w)$ are variable material and labor costs for sector s, respectively.

4. *The "adjusted pass-through in levels" of labor costs $\rho_w^{adj}(s) = 1$, where*

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

   and where $VariableProfits(s) = Sales(s) - VariableCosts(s)$.

Proof. See proofs at the end of this appendix. □

Proposition C1 shows that when the marginal sector consumed by households produces exclusively with labor, this simple model generates 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 marginal value of income through the price $p(S)$, which in turn affects firms' desired additive markups.[40]

[40] In fact, for sectors with $\beta_s < 1$, a change in the wage actually results in a larger proportional change in $p(S)$ than in marginal costs, leading to more-than-complete log pass-through of wage changes.

Proposition C1 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 C1 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, $\rho_w^{\text{adj}} = 1$.

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.[41]

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 $k \in \{\text{Materials}, \text{Energy}, \text{Production Labor}\}$ to output price changes using the specifications,

$$\Delta \log p_{it} = \sum_k \rho_k^{\log} \left(\frac{\text{Costs}_{ikt-1}}{\text{VariableCosts}_{it-1}} \times \Delta \log c_{ikt} \right) + \alpha_i + \varphi_t + \varepsilon_{it}, \tag{29}$$

$$\Delta \log p_{it} = \sum_k \rho_k^{\text{level}} \left(\frac{\text{Costs}_{ikt-1}}{\text{Sales}_{it-1}} \times \Delta \log c_{ikt} \right) + \alpha_i + \varphi_t + \varepsilon_{it}, \tag{30}$$

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_{t-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 $\rho_k^{\log}$ and ρ_k^{level} in specifications (29) and (30) correspond to the pass-through rates defined in Proposition C1.

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

[41] This 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.

Table C3: Revisiting Okun's (1981) "special role of materials costs."

	Δ Log Output Price$_t$		
	(1)	(2)	(3)
	Cost Shares	Sales Shares	Sales Shares
Δ Log Material Price$_t$ $\times$ Material Share$_{t-1}$	0.798	1.046†	1.049†
	(0.085)	(0.108)	(0.109)
Δ Log Energy Price$_t$ $\times$ Energy Share$_{t-1}$	0.715†	0.859†	0.997†
	(0.271)	(0.378)	(0.362)
Δ Log Production Wage$_t$ $\times$ Labor Share$_{t-1}$	1.070†	2.095	
	(0.217)	(0.281)	
Δ Log Production Wage$_t$ $\times$ (Labor + Variable Profits) Share$_{t-1}$			0.951†
			(0.209)
p-value, $\rho_{\text{material}} = \rho_{\text{labor}}$	0.23	0.00	0.65
p-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 (29) and (30). Column 3 estimates a variant of (30) 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 estimates for which a pass-through of one is within the 90 percent confidence interval.

"special," as Okun (1981) conjectured, or due to labor costs playing a special role in determining firms' additive markups.

Table C3 column 1, which reports results from (29), 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 (30), 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 C1 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 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.

Proof of Lemma C1. We first differentiate the consumer budget constraint and utility function with respect to a change in the taste and price of the variety j chosen by a consumer in sector s, which we denote $d\delta_{ij}(s)$ and $dp_{ij}(s)$. From the budget constraint, the change in the mass of sectors from which the consumer purchases is

$$dS = -\frac{dp_{ij}(s)}{p(S)}ds,$$

where $p(S)$ is the price of firms in sector S.[42] The change in the consumer's utility is then

$$dU_i = \delta_{ij}(S)dS + d\delta_{ij}(s)ds = \left[d\delta_{ij}(s) - \frac{dp_{ij}(s)}{p(S)}\right]ds.$$

For firm j in sector s, demand is (dropping the s indices for convenience):

$$\begin{aligned} D_j &= \int_0^1 \prod_{n=1,\dots,J;n\neq j} 1\left\{U_{in} \leq U_{ij}\right\} di \\ &= \int_0^1 \prod_{n=1,\dots,J;n\neq j} 1\left\{\delta_{in} - \frac{p_n}{p(S)} \leq \delta_{ij} - \frac{p_j}{p(S)}\right\} di \\ &= \int_{-\infty}^{\infty} \left[F\left(\delta_{ij} + \frac{p_n}{p(S)} - \frac{p_j}{p(S)}\right)\right]^{J-1} f\left(\delta_{ij}\right) d\delta_{ij}, \end{aligned} \tag{31}$$

where the second equality uses our expression for dU_i and the last equality uses the fact that δ_{ij} are i.i.d. draws from F. Taking the derivative,

$$\frac{\partial D_j}{\partial p_j} = \left(-\frac{1}{p(S)}\right)(J-1)\int_{-\infty}^{\infty}\left[F\left(\delta_{ij} + \frac{p_n}{p(S)} - \frac{p_j}{p(S)}\right)\right]^{J-2} f\left(\delta_{ij} + \frac{p_n}{p(S)} - \frac{p_j}{p(S)}\right) f\left(\delta_{ij}\right) d\delta_{ij}. \tag{32}$$

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

$$p_j = mc - D_j/(\partial D_j/\partial p_j).$$

Evaluating (31) and (32) at the point where firms choose symmetric prices, we get the

[42] The assumptions that β_s is smooth in s and that taste shocks are drawn from an identical distribution across sectors guarantees that sectoral prices $p(s)$ do not change discontinuously around S.

following expression for the symmetric price p,

$$p(s) = \beta_s w + (1-\beta_s)c + \phi p(S), \qquad \text{where} \qquad \phi^{-1} = J(J-1)\int_{-\infty}^{\infty} \left[F\left(\delta_{ij}\right)\right]^{J-2}\left[f\left(\delta_{ij}\right)\right]^2 d\delta_{ij}.$$

(A similar result for firms' additive markups is derived by Perloff and Salop 1985.) $\square$

Proof of Proposition C1. The pass-through of a change to marginal costs $dmc(s)$ is

$$\frac{dp(s)}{dmc(s)} = 1 + \phi\frac{dp(S)}{dmc(s)} = 1 + (\mu(s)-1)\frac{mc(s)}{p(S)}\frac{dp(S)}{dmc(s)}.$$

Solving the fixed point for the case where $s = S$ and substituting in yields,

$$\frac{dp(s)}{dmc(s)} = 1 + (\mu(s)-1)\frac{mc(s)}{mc(S)}\frac{dmc(S)}{dmc(s)}. \tag{33}$$

Specializing (33) to changes in marginal costs coming from wage changes or materials cost changes yields the expressions for pass-through in part (1) of Proposition C1. When $\beta_S = 1$, for the pass-through of material costs, $dmc(S) = 0$, so

$$\frac{dp(s)}{(1-\beta_s)dc} = 1 \qquad \Rightarrow \qquad \frac{d\log p(s)}{d\log c} = \frac{(1-\beta_s)c}{p(s)} = \frac{\text{MaterialCosts}(s)}{\text{Sales}(s)}.$$

For the pass-through of labor costs when $\beta_S = 1$,

$$\begin{aligned}\frac{dp(s)}{\beta_s dw} &= \mu(s) + (\mu(s)-1)\frac{(1-\beta_s)c}{\beta_s w},\\ \frac{d\log p(s)}{d\log w} &= \frac{\beta_s w + (\mu(s)-1)mc(s)}{p(s)} = \frac{\text{LaborCosts}(s) + \text{VariableProfits}(s)}{\text{Sales}(s)}.\end{aligned}$$

$\square$

D Details of Quantitative Application

This appendix details our data sources and solution method for Section 8.

D.1 Data Sources and Cleaning

Input–output matrix, Ω. We construct the input–output matrix using the BEA's detailed supply and use tables from 2012, which report each industry's use of intermediate inputs, compensation of employees, and residual value added (gross operating surplus). For the representative household's expenditure shares across industries, we use personal consumption expenditures by industry in 2012 from the BEA. Our construction of direct input and labor requirements for each industry and for personal consumption expenditures follows Horowitz and Planting (2009) Ch. 12 and Rubbo (2023).

We assume that the price of imported goods follows the price charged by domestic producers in each industry. In effect, this means that for industries in $\mathcal{N}^{\text{exog}}$, the price index of imports is equal to the price index for domestic producers in the PPI data, and for industries with endogenous prices, the price index of imports follows the pricing decisions of domestic producers in (16). The BLS compares producer price indices (PPI)—which reflect prices of domestic producers—to import price indices (MPI) at the level of six-digit NAICS industries. PPIs and MPIs at the six-digit industry level are closely correlated: across industries, the median correlation between the PPI and MPI is 0.96.[43]

Industries with exogenous prices, $\mathcal{N}^{\text{exog}}$ and p_{it}^{exog}. We are interested in how volatility in upstream prices affects downstream prices and consumer price inflation. Thus, we take the price indices for a subset of industries $\mathcal{N}^{\text{exog}}$ directly from the data. To identify this set of upstream industries, we rely on the BLS's classification of industries into four stages of production flow. Stage 1 industries are those that are most upstream from consumer demand. We map BEA industries to BLS stage assignments and designate the BEA industries corresponding to Stage 1 as part of $\mathcal{N}^{\text{exog}}$ in our calibration.[44]

We use PPI data from 1982–2018 for p_{it}^{exog}, and we use code from Rubbo (2023) to fill in missing PPI data using a Lasso regression of PPI data on components of the personal consumption expenditures (PCE) price index. We use the average hourly earnings of production and nonsupervisory employees (`AHETPI`) as our measure of production wages.

[43] See `https://www.bls.gov/mxp/publications/additional-publications/import-export-price-indexes-producer-price-indexes-comparability-table-2023.htm`.

[44] The most recent mapping from BLS stage assignments to BEA industries is from 2012 and is available at `https://www.bls.gov/ppi/notices/2021/ppi-updates-to-2012-commodity-weight-allocations-for-the-final-demand-intermediate-demand-aggregation-structure.htm`.

Calvo frictions, δ_i. Pasten et al. (2020) compute industry-level frequencies of price adjustment using the microdata underlying the BLS producer price index. We use their estimates of monthly frequencies of price adjustment for Calvo frictions in each industry. There are no estimates for construction, educational services, repair and maintenance, and government, so for these industries we set the frequency of price adjustment equal to the median across all industries.

Variable costs. As discussed in the main text, we calibrate σ_i and b_i for three different 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.

D.2 Solution Method and Robustness

Our baseline results use the first-order approximation around the steady state in (17) and assume that firms have perfect foresight about the path of future prices and marginal costs (we consider robustness to each of these assumptions below). Given the path of wages and paths of prices for each industry, we calculate marginal costs for each industry in each month using (17). Given the path of marginal costs, optimal reset prices $d \log p_{it}^{\text{reset}}$ are given by log-linearizing (16), and the law of motion for the price index of industry i is given by

$$d \log p_{it} = \delta_i d \log p_{it}^{\text{reset}} + (1 - \delta_i) d \log p_{it-1}.$$

This yields paths of prices for each industry. We iterate this procedure to find a fixed point where all industries' prices are consistent with their paths of future marginal costs and paths of marginal costs are consistent with all industries' prices.

Robustness. We consider how relaxing the first-order approximation in (17) and relaxing perfect foresight affect our quantitative results. Assuming CES production technologies in each industry, input–output expenditure shares are

$$\Omega_{ijt} = \frac{\bar{\omega}_{ij} p_{jt} x_{jt}}{\sum_k \bar{\omega}_{ik} p_{kt} x_{kt}} = \frac{\bar{\omega}_{ij} p_{jt}^{1-\theta_i}}{\sum_k \bar{\omega}_{ik} p_{kt}^{1-\theta_i}},$$

Table D1: Volatility of consumer price inflation, allowing for endogenous changes in expenditure shares due to Leontief production.

	Std. deviation of annual inflation, 1982–2018		
	Baseline	Leontief inputs	Myopic expectations
CES demand (percentage markups):			
Variable costs = Materials	2.5%	2.5%	2.2%
Variable costs = Materials + wages	1.7%	2.0%	1.6%
Variable costs = Materials + wages + fixed capital cons.	1.6%	1.7%	1.5%
Logit demand (additive markups)	1.3%	1.4%	1.3%

Note: Baseline assumes expenditure shares Ω_{ij} are constant (as in the log-linearized model) and that firms have perfect foresight over the path of future marginal costs. This table reports the volatility of PCE inflation if we instead assume Leontief production or assume that firms have myopic expectations over future costs.

where $\bar{\omega}_{ij}$ are parameters that determine production weights, x_{ijt} is the quantity of inputs from industry j used by industry i in period t, and θ_i is the elasticity of substitution across inputs for industry i. Thus, input–output shares vary with industry prices according to

$$d\log\Omega_{ijt} = (1-\theta_i)\Big[d\log p_{jt} - \sum_k \Omega_{ik} d\log p_{kt}\Big].$$

The first-order approximation in (17) is exact if production functions are Cobb-Douglas. Table D1 shows how our results change if we instead assume production technologies are Leontief (i.e., $\theta_i = 0$) and use the deviation in each industry's prices from 2012 to discipline changes in input–output expenditure shares relative to 2012. Input complementarity increases the volatility of consumer price inflation, because the effect on marginal costs and prices of an increase in the relative price of an input is amplified by a reallocation of expenditure weights toward that input in production.

Second, we consider how our results change if we relax the assumption of perfect foresight and instead assume that firms expect marginal costs in all future periods to equal present marginal costs. Minton and Wheaton (2022) argue that delayed pass-through along supply chains suggests that firms have this form of "myopic expectations." In Table D1, we find that myopia slightly dampens the volatility of consumer price inflation predicted by the model, though not enough to bring the predictions of the fixed percentage markup models in line with the data.

E Retail Gasoline Data from Other Markets

E.1 Canada

We use weekly price data for 71 cities in 10 Canadian provinces provided by Kalibrate solutions.[45] 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.

E.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.[46] 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.

E.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`).

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

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

References for Online Appendix

Alexander, P., L. Han, O. Kryvtsov, and B. Tomlin (2024). Markups and inflation in oligopolistic markets: Evidence from wholesale price data. Technical Report 2024-20, Bank of Canada.

Alvarez, S. E., A. Cavallo, A. MacKay, and P. Mengano (2024). Markups and cost pass-through along the supply chain. Working paper.

Amiti, M., O. Itskhoki, and J. Konings (2019). International shocks, variable markups, and domestic prices. *The Review of Economic Studies 86*(6), 2356–2402.

Anderson, S. P., A. de Palma, and J.-F. Thisse (1992). *Discrete Choice Theory of Product Differentiation*. MIT Press.

Ashenfelter, O., D. Ashmore, J. B. Baker, and S.-M. McKernan (1998). Identifying the firm-specific cost pass-through rate. Federal Trade Commission, Bureau of Economics Report.

Auer, R. A., T. Chaney, and P. Sauré (2018). Quality pricing-to-market. *Journal of International Economics 110*, 87–102.

Auer, R. A. and R. Schoenle (2016). Market structure and exchange rate pass-through. *Journal of International Economics 98*, 60–77.

Barzel, Y. (1976). An alternative approach to the analysis of taxation. *Journal of Political Economy 84*(6), 1177–1197.

Bettendorf, L. and F. Verboven (2000). Incomplete transmission of coffee bean prices: Evidence from the Netherlands. *European Review of Agricultural Economics 27*(1), 1–16.

Butters, R. A., D. W. Sacks, and B. Seo (2022). How do national firms respond to local cost shocks? *American Economic Review 112*(5), 1737–1772.

Cavallo, A., G. Gopinath, B. Neiman, and J. Tang (2021). Tariff pass-through at the border and at the store: Evidence from US trade policy. *American Economic Review: Insights 3*(1), 19–34.

Cawley, J., D. Frisvold, A. Hill, and D. Jones (2020). Oakland's sugar-sweetened beverage tax: Impacts on prices, purchases and consumption by adults and children. *Economics and Human Biology 37*, 100865.

Chiou, L. and E. Muehlegger (2014). Consumer response to cigarette excise tax changes. *National Tax Journal 67*(3), 621–650.

Chouinard, H. and J. Perloff (2004). Incidence of federal and state gasoline taxes. *Economics Letters 83*(1), 55–60.

Conlon, C. T. and N. L. Rao (2020). Discrete prices and the incidence and efficiency of excise taxes. *American Economic Journal: Economic Policy 12*(4), 111–143.

Cunningham, C., L. Foster, C. Grim, J. Haltiwanger, S. W. Pabilonia, J. Stewart, and Z. Wolf (2022). Dispersion in dispersion: Measuring establishment-level differences in productivity. Technical Report 530, BLS Working Papers.

De Loecker, J., P. Goldberg, A. K. Khandelwal, and N. Pavcnik (2016). Prices, markups, and trade reform. *Econometrica 84*(2), 445–510.

DeCicca, P., D. Kenkel, and F. Liu (2013). Who pays cigarette taxes? The impact of consumer price search. *Review of Economics and Statistics 95*(2), 516–529.

Dutta, S., M. Bergen, and D. Levy (2002). Price flexibility in channels of distribution: Evidence from scanner data. *Journal of Economic Dynamics and Control 26*(11), 1845–1900.

Fabra, N. and M. Reguant (2014). Pass-through of emissions costs in electricity markets. *American Economic Review 104*(9), 2872–2899.

Genesove, D. and W. P. Mullin (1998). Testing static oligopoly models: Conduct and cost in the sugar industry, 1890–1914. *The RAND Journal of Economics 29*(2), 355–377.

Goldberg, P. and R. Hellerstein (2013). A structural approach to identifying the sources of local currency price stability. *Review of Economic Studies 80*(1), 175–210.

Gron, A. and D. L. Swenson (2000). Cost pass-through in the U.S. automobile market. *Review of Economics and Statistics 82*(2), 316–324.

Hanson, A. and R. Sullivan (2009). The incidence of tobacco taxation: Evidence from geographic micro-level data. *National Tax Journal 62*(4), 677–698.

Harding, M., E. Leibtag, and M. F. Lovenheim (2012). The heterogeneous geographic and socioeconomic incidence of cigarette taxes: Evidence from Nielsen Homescan data. *American Economic Journal: Economic Policy 4*(4), 169–198.

Hellerstein, R. (2008). Who bears the cost of a change in the exchange rate? Pass-through accounting for the case of beer. *Journal of International Economics 76*(1), 14–32.

Hellerstein, R. and S. B. Villas-Boas (2010). Outsourcing and pass-through. *Journal of International Economics 81*(2), 170–183.

Hong, G. H. and N. Li (2017). Market structure and cost pass-through in retail. *The Review of Economics and Statistics 99*(1), 151–166.

Horowitz, K. J. and M. A. Planting (2009). Concepts and methods of the US input–output accounts. Technical report, Bureau of Economic Analysis.

Jaimovich, N., S. Rebelo, and A. Wong (2019). Trading down and the business cycle. *Journal of Monetary Economics 102*, 96–121.

Känzig, D. R. (2021). The macroeconomic effects of oil supply news: Evidence from OPEC announcements. *American Economic Review 111*(4), 1092–1125.

Kaplan, G. and G. Menzio (2015). The morphology of price dispersion. *International Economic Review 56*(4), 1165–1206.

Kenkel, D. S. (2005). Are alcohol taxes fully passed through to prices? Evidence from Alaska. *American Economic Review 95*(2), 273–277.

Kim, D. and R. W. Cotterill (2008). Cost pass-through in differentiated product markets: The case of US processed cheese. *The Journal of Industrial Economics 56*(1), 32–48.

Kinnucan, H. W. and O. D. Forker (1987). Asymmetry in farm-retail price transmission for major dairy products. *American Journal of Agricultural Economics 69*(2), 285–292.

Leibtag, E. (2009). How much and how quick? Pass through of commodity and input cost changes to retail food prices. *American Journal of Agricultural Economics 91*(5), 1462–1467.

Leibtag, E., A. O. Nakamura, E. Nakamura, and D. Zerom (2007, March). Cost pass-through in the u.s. coffee industry. Economic Research Report 38, US Department of Agriculture.

Marion, J. and E. Muehlegger (2011). Fuel tax incidence and supply conditions. *Journal of Public Economics 95*(9-10), 1202–1212.

Matsuyama, K. (2002). The rise of mass consumption societies. *Journal of Political Economy 110*(5), 1035–1070.

Minton, R. and B. Wheaton (2022). Hidden inflation in supply chains: Theory and evidence. Working paper.

Murphy, K. M., A. Shleifer, and R. Vishny (1989). Income distribution, market size, and industrialization. *The Quarterly Journal of Economics 104*(3), 537–564.

Nakamura, E. and D. Zerom (2010). Accounting for incomplete pass-through. *The Review of Economic Studies 77*(3), 1192–1230.

Okun, A. M. (1981). *Prices and Quantities: A Macroeconomic Analysis*. The Brookings Institution.

Pasten, E., R. Schoenle, and M. Weber (2020). The propagation of monetary policy shocks in a heterogeneous production economy. *Journal of Monetary Economics 116*, 1–22.

Peltzman, S. (2000). Prices rise faster than they fall. *Journal of Political Economy 108*(3), 466–502.

Perloff, J. M. and S. C. Salop (1985). Equilibrium with product differentiation. *The Review of Economic Studies 52*(1), 107–120.

Rubbo, E. (2023). Networks, Phillips curves and monetary policy. *Econometrica 91*(4), 1417–1455.

Young, D. J. and A. Bielinska-Kwapisz (2002). Alcohol taxes and beverage prices. *National Tax Journal 55*(1), 57–73.