Complete Pass-Through in Levels

Kunal Sangani
Stanford University*
March 19, 2025

Abstract

Empirical studies find that the pass-through of input cost changes to prices is incomplete: a 10 percent increase in upstream costs causes downstream prices to rise less than 10 percent, even at long horizons. Using microdata from 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 homothetic demand systems used in most macroeconomic models. We identify an alternative class of demand systems that yields pass-through in levels and highlight four implications. First, measuring pass-through in percentages can lead to spurious evidence of asymmetry and size-dependence. Second, pass-through in levels can explain dynamics of industry gross margins, operating profits, and entry in the data that are at odds with workhorse models. Third, demand systems that generate pass-through in levels can explain different pass-through rates for labor costs relative to other inputs. Finally, incorporating pass-through in levels into an input-output model of the U.S. economy can reconcile the low volatility of consumer price inflation with micro evidence of substantial markups.

JEL codes: E31, E32, L11.

Email: ksangani@stanford.edu. I am grateful to Adrien Bilal, Jeremy Bulow, Gabriel Chodorow-Reich, Robin Lee, Jesse Shapiro, Andrei Shleifer, Ludwig Straub, and Adi Sunderam for many helpful comments, as well as to seminar participants at the Society of Economic Dynamics, Northwestern, the Minneapolis Fed, Stanford, Princeton, and the Federal Reserve Board. This paper contains my own analyses calculated (or derived) based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the author and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

1 Introduction

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

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

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

Across the markets we study, we find that complete pass-through in levels explains not only the extent of incomplete pass-through but also the cross-sectional variation in log pass-through across firms and products in a market. In response to an aggregate 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 feature 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 expenditures, making them particularly tractable. However, this property of homothetic demand comes with a key implication—it predicts complete log pass-through of aggregate cost shocks. In response to aggregate

shocks, firms raise prices while maintaining constant percentage markups. As a result, pass-through in levels is equal to firms' gross markups, which are greater than one. This is true for the standard constant elasticity of substitution (CES) preferences as well as for 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 these richer demand systems can accommodate incomplete log pass-through of idiosyncratic shocks that affect only a subset of firms in an industry, they uniformly predict complete log pass-through of aggregate cost shocks, at odds with our evidence of complete pass-through in levels.

One way of reconciling complete pass-through in levels with complete log pass-through is if prices are perfectly competitive. If price equals marginal cost, then changes in cost will be 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.

Explaining complete pass-through in levels in markets with imperfect competition therefore requires that we depart from the class of homothetic preferences. We consider a broader class of demand systems by modeling demand as an aggregation of discrete choices made by consumers (Anderson, de Palma, and Thisse 1992). Following Anderson and de Palma (2020) and Birchall, Mohapatra, and Verboven (2024), we extend the standard discrete choice framework by allowing for any intensive margin elasticity of demand, denoted by η. The parameter η determines the rate at which the quantity a consumer purchases declines with the price she faces, conditional on buying from a given firm. Consumers buy a fixed quantity of product when $\eta = 0$, while they instead spend a fixed share of their budget when $\eta = 1$. We show that η parameterizes the departure from homothetic demand: in particular, demand is homothetic if and only if $\eta = 1$.

Our main theoretical result is that any demand system with $\eta = 0$ generates complete pass-through in levels of aggregate cost shocks. When $\eta = 0$, consumers buy a fixed quantity from any firm, and their choices depend on a comparison of absolute price differences across firms. An aggregate cost shock leads firms to increase their prices one-for-one with the shock, without altering price differences across firms or consumers' choices. In other words, firms maintain constant "additive markups"—defined as the absolute gap between price and marginal cost—in response to aggregate cost shocks.

It is worth emphasizing that our formulation preserves the model's neutrality with respect to changes in the aggregate price level. In our model, firms' additive markups

are set relative to the price of an outside, numeraire good. A shock to firms' input costs holding the numeraire price fixed leads to complete pass-through in levels. However, shocks to the aggregate price level that increase both firms' input costs and the numeraire price lead to proportionate increases in firms' prices.

While the class of demand systems that exhibit pass-through in levels excludes homothetic preferences, it encompasses a wide variety of alternative models. For example, the class of demand systems where $\eta = 0$ includes nested logit and mixed logit models, where heterogeneity in firm and consumer attributes generates rich patterns of substitution across firms (Berry, Levinsohn, and Pakes 1995; Nevo 2001). It also includes several models of spatial competition, such as the Hotelling (1929) and Salop (1979) models, in which firms' market power is derived from the transport costs that consumers incur to visit nearby versus faraway stores. Demand systems in which $\eta = 0$ can also vary in their predictions for how firms pass through idiosyncratic cost shocks, even though all models in this class predict complete pass-through in levels of aggregate cost shocks.

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

First, when pass-through is complete in levels, measuring pass-through in percentages can lead to evidence of asymmetry and size-dependence (i.e., different pass-through rates for large and small shocks), as well as systematic heterogeneity in pass-through by firm size and product quality. Since pass-through is complete in levels, the log pass-through is not a stable statistic. Asymmetry, size-dependence, and heterogeneity can all arise due to misspecification rather than the underlying economic process.

Second, pass-through in levels can explain dynamics of industry gross margins, operating margins, and entry in the data that are at odds with workhorse models. In standard models of industry dynamics à la Dixit and Stiglitz (1977), homothetic preferences imply that an increase in input costs leads to higher profits per unit sold. Rising input costs thus lead to more firm entry or, if frictions prevent entry, higher operating profits for incumbent firms. Neither of these patterns—swings in firm entry or operating profits—accompany fluctuations in input costs in the data. We show that replacing homothetic preferences with demand systems that generate pass-through in levels can explain this puzzle. Pass-through in levels instead leads gross margins to fall as input costs rise, 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 conforms with this prediction.

Third, integrating pass-through in levels into a multi-sector model can explain apparent differences in the pass-through of labor and materials costs. Okun (1981) observed

that firms seem to pass through materials costs on a "dollars-and-cents basis" but pass through changes in unit labor costs "with a percentage markup." These observations are difficult to explain in a rational model of firm behavior: why should a cost-minimizing firm treat one component of costs differently from others? We show that this puzzle can be resolved in a multi-sector model where the marginal goods consumed by households are primarily produced with labor. In this setting, changes in the price of labor affect the marginal value of consumption and thus the numeraire price. Even when firms pass through cost increases in levels, they can appear to have higher pass-through of labor costs because movements in the price of labor also change firms' desired markups. In the data, once we account for labor's role in determining the numeraire, we restore complete pass-through in levels for both labor and materials costs.

Finally, we show that pass-through in levels can explain the low volatility of consumer price inflation relative to commodity prices. We calibrate a standard 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 fixed additive markups, consistent with complete pass-through in levels. Given data on 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 average markups compared to empirical estimates. In contrast, the model with fixed additive markups naturally matches the volatility of consumer price inflation in the data while allowing for markups consistent with the microeconomic evidence.

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

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

[1]See e.g., Bulow and Pfleiderer (1983), Weyl and Fabinger (2013), Mrázová and Neary (2017), and Miravete, Seim, and Thurk (2022), as well as the list of empirical studies in Online Appendix Table A1.

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 industrial organization. We collect a list of previous studies that measure pass-through in logs and levels for various markets and types of cost shocks in Online Appendix Table A1 and discuss their findings in Section 6.[2] To preview our discussion, we find that the majority of these studies conform with complete pass-through in levels. Some studies of individual excise tax changes suggest that pass-through is greater than one; however, studies that employ a larger samples of tax change events generally find complete pass-through in levels.

Two closely related studies in this literature are Nakamura and Zerom (2010) and Butters, Sacks, and Seo (2022). Nakamura and Zerom (2010) document that retail and wholesale coffee prices move one-for-one with coffee commodity prices in levels. However, the main exercise in Nakamura and Zerom (2010) seeks to account for incomplete log pass-through, attributing incomplete pass-through to non-commodity input costs and adjustment in markups. Butters et al. (2022) study how local cost shocks affect retail stores' prices and find evidence of complete pass-through in levels for various cost shocks, including excise taxes, shipping costs, and regulated commodity prices. We add to this evidence by showing that complete pass-through in levels is not unique to retail stores but holds for a broader range of producers and markets. Studies of gasoline markets also typically measure pass-through in levels rather than in logs (e.g., Karrenbrock 1991; Borenstein, Cameron, and Gilbert 1997; Deltas 2008), but do not explore why complete pass-through in levels is an appropriate benchmark.[3]

Finally, our analysis of the demand systems that generate complete pass-through in levels builds on models of discrete choice with differentiated products, surveyed by Anderson et al. (1992) and recently by Berry and Haile (2021) and Gandhi and Nevo (2021). Like Anderson and de Palma (2020) and Birchall et al. (2024), we generalize the standard discrete choice framework to allow for a flexible intensive margin elasticity of demand. Our focus on characterizing pass-through in levels and logs across demand systems differs from these previous studies.

[2]Given the vast literature on pass-through, Online Appendix Table A1 focuses on papers that consider aggregate cost shocks and that measure pass-through using reduced form methods (rather than simulating pass-through using a structural model).

[3]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 $C(y)$:[4]

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

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

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

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

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 marginal cost (10 percent / 10 percent = 1) or equal to the cost share if measured with respect to the commodity cost (10 percent / 20 percent = 0.5).

We contrast the pricing rule in (1) with one where the firm's gap between output price and marginal cost, measured in dollars-and-cents, does not change in response to the

[4]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.2, we consider how pass-through changes if we relax Leontief production, constant returns to scale, or uncorrelated other variable costs. Each requires knife-edge conditions to deliver complete pass-through in levels.

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

					Pass-through	
	Initial		New	*% Change*	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

commodity cost:

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

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

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 prices to retail prices is statistically indistinguishable from one. Second, long-run log pass-through is incomplete even relative to the share of gasoline in stations' marginal costs. Third, there is little heterogeneity in pass-through in levels across stations in the sample, but substantial variation in log pass-through: stations with a larger gap between prices and costs have lower log pass-through. Using several instruments designed to isolate variation in stations' markups from stations' marginal costs, we find that stations

with higher markups have lower log pass-through. Fourth, complete pass-through in levels explain both cross-sectional heterogeneity in log pass-through and the overall level of incomplete log pass-through.

3.1 Station-Level Data from Perth, Australia

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

Long-run pass-through is complete in levels and incomplete in logs. To measure the long-run pass-through of cost changes to prices, we estimate the distributed lag regression

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

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 using an Augmented Dickey-Fuller test.[5] While commodity prices are approximately unit root, they appear stationary in first-differences, enabling correct inference in (3). We also check in Appendix Table A3 that the direction of causality runs from upstream input costs to downstream prices and not vice versa, using Granger causality tests. In all cases, we are unable to reject the null that downstream prices do not cause movements in 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 (Appendix Figure A2) are similar: the long-run pass-through in levels is statistically indistinguishable from one at 0.985 (0.036). Further increasing the horizon over which pass-through is estimated has little effect on the estimated long-run pass-through.

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

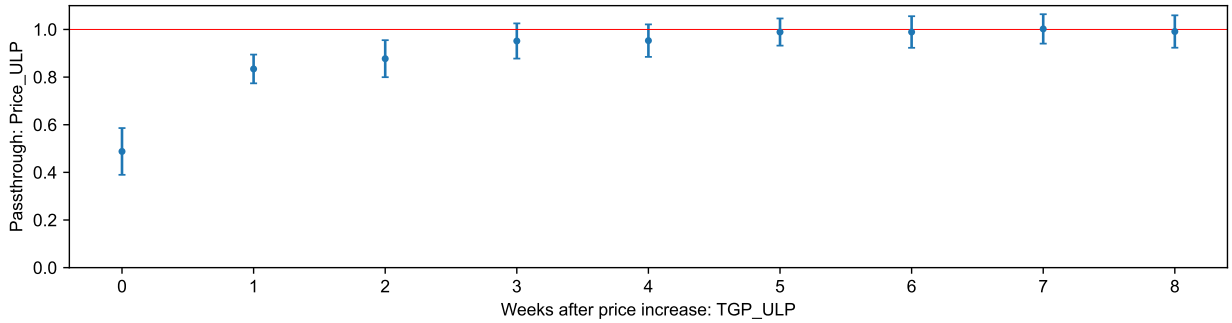
$$\Delta \log p_{it} = \sum_{k=0}^{K} \beta_k \Delta \log c_{t-k} + \alpha_i + \epsilon_{it}, \tag{4}$$

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

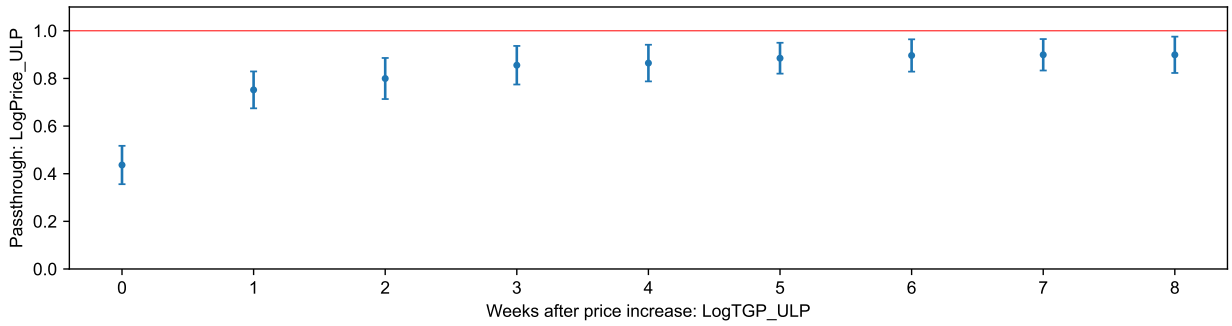
One reason that log pass-through may be incomplete is the presence of other variable

[5]When commodity prices are unit root, if firms have fixed percentage markups, the long-run pass-through in levels estimated using (3) should approach the markup μ. Appendix Proposition B1 shows formally that in a model with time-dependent pricing frictions, the long-run pass-through $\sum_{k=1}^{K} b_k = \mu$ as K becomes large and the persistence of the commodity cost $\rho \to 1$. Even if commodity prices are not exactly unit root, under reasonable parameters (e.g., firms reset prices every 12 months, and $\rho = 0.96$, which is the minimum autocorrelation in Appendix Table A2), the bias in the measure of μ is small.

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.

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. The presence of price cycles in this setting allows us to estimate a lower bound for the cost share of gasoline in stations' marginal costs. As previously documented by Byrne and de Roos (2019), retail prices in the Perth market follow weekly price cycles, jumping on Tuesdays or Thursdays and then falling over the course of the week. Under the assumption that gas stations never set prices below marginal cost,[6] we can use the days of the week at the lowest point of the price cycle to calculate an upper bound on the share of other variable costs in stations' marginal costs, and thus a lower bound for the cost share of gasoline. 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

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

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.

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

We use two measures for Avg. Markup_{it}, along with instruments for both that are intended to isolate variation in markups from variation in non-gasoline variable costs. The first measure exploits variation in markups across stations: 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 the course of the sample comove closely with the degree of coordination in price cycles, measured as the R^2 from

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

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

Note: The table reports the coefficients γ and β estimated using specification (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.

a regression of daily margins on day-of-week fixed effects. (The most dramatic change over time is the increase in both coordination and margins around 2010, but there is also subsequent variation in the strength of coordination and margins after 2010 owing to subsequent breakdowns in collusion.) We use this measure of price coordination over time—the quarterly R^2 of station margins on day-of-week dummies—as an instrument for Avg. Quarter Markup$_t$.

Table 2 reports the results. Column 1 omits the average markup and interaction term. A \$1 change in the wholesale cost of unleaded petrol (ULP) over 16 weeks is associated with a \$0.95 change in the retail station price over the same period. Columns 2–5 include the interaction of wholesale cost changes with markups, with columns 3 and 5 using the instruments discussed above. In all cases, the estimated coefficient on the interaction term $\beta \approx 0$, consistent with uniform pass-through in levels across stations and time periods. In other words, evidence exploiting cross-sectional and time series variation in the data do not support fixed percentage markups.

Pass-through in levels explains heterogenity in log pass-through. Table 3 reports estimates from an analogous specification that instead measures the pass-through of changes

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

in log costs to changes in log prices,[7]

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

Column 1 shows that a 1 percent change in wholesale costs over 16 weeks leads to a 0.870% change in retail prices, significantly below the cost share of gasoline. Columns 2–5 estimate specification (6), again exploiting cross-sectional variation in markups (columns 2–3) or time series variation in markups (columns 4–5) in turn. Two findings emerge. First, higher markups lead to more incomplete log pass-through.[8] Second, the gap between price and costs appears to fully account for incomplete pass-through: the coefficient on $\Delta \log c_t$ 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

[7]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.

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

cross-section and periods in the time series with higher markups. The size of the gap between output price and gasoline input cost 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 C describes the data sources for each). Incomplete log pass-through and complete pass-through in levels appear across all the studied markets. The evidence from other geographies suggests that complete pass-through in levels is not a quirk of the Australian data, but rather describes price dynamics across a number of retail gasoline markets.

One might be concerned that our estimates of pass-through are biased downward due to reverse causality from downstream demand to commodity prices. However, 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 shocks to OPEC production from Känzig (2021) as an instrument for upstream cost changes. While the instrumented regressions produce somewhat noisier estimates of long-run pass-through in levels and logs, they remain qualitatively consistent with our baseline results.

4 Evidence from Food Products

In this section, we explore the pass-through of commodity costs to retail prices for food products. These products are homogeneous enough that we can measure pass-through in levels by carefully matching amounts of commodity inputs required to produce the downstream products, yet exhibit substantially more differentiation than retail gasoline.

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 these product categories, we further document that uniform pass-through in levels explains systematic patterns of heterogeneity in log pass-through across products. Finally, extending our analysis to a broader array of food products, we find that prices of identical products sold across retail chains also conform with complete pass-through in levels.

4.1 Data on Food Retail and Commodity Prices

Retail prices. For retail prices of food products, we primarily rely on Average Price Data from the Bureau of Labor Statistics (BLS). While the BLS's consumer price index

data 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 over 200 retail chains operating across the U.S., reflecting over $2 billion in annual sales.

Commodity costs. We match retail food prices with data on commodity costs from the IMF Primary Commodities Prices database. These commodity price series draw from statistics of specialized trade organizations or from commodity futures markets—for example, the commodity price for frozen orange juice concentrate is from next-month futures contracts for the delivery of grade-A frozen concentrated orange juice solids traded on the Intercontinental Exchange (ICE). Appendix Table A5 provides a full list of the commodity price series and the underlying data sources used by the IMF.

Measuring pass-through in levels requires carefully matching units from commodity prices to retail prices. For example, to measure pass-through of wheat commodity prices to retail flour prices requires knowing the quantity of wheat needed per pound of flour produced. To construct these mappings from commodity units to retail units, we rely on previous literature and on documentation from the USDA. Appendix Table A6 provides the conversion factors from commodity prices to retail prices for each series and delineates the sources and assumptions used to build each conversion factor.[9]

Matched products. Of the food products tracked by the BLS Average Price Data, six can be clearly matched to IMF commodity input prices. These are roasted ground coffee, sugar, ground beef, white rice, all-purpose flour, and frozen orange juice concentrate. Appendix Table A6 lists the corresponding Average Price Data series IDs. For three of

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

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

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

Note: Long-run pass-through in levels and logs is $\sum_{k=0}^{K} b_k$ from specifications (3) and (4), using a horizon of $K = 12$ months. Newey-West standard errors in parentheses. † indicates estimates for which a pass-through of one is within the 90 percent confidence interval.

these products—rice, flour, and coffee—we also investigate cross-sectional pass-through patterns by matching the food product to a NielsenIQ product category.[10]

4.2 Empirical Results

Nearly all products exhibit complete pass-through in levels. We measure the pass-through of commodity costs to retail prices for each food product in levels and logs using the distributed lag regressions (3) and (4) described in Section 3. As in the case of gasoline, each of the food commodity price series has an autocorrelation coefficient close to one, but appears stationary in first-differences (Appendix Table A2), enabling correct inference with the standard distributed lag specification. We also verify using Granger causality tests that downstream retail price movements do not predict future changes in upstream commodity prices (Appendix Table A3). Note that the pass-through in levels of commodity costs to retail prices is a particularly strict test of fixed percentage markups, because it should detect if any firm along the chain of producers from commodity to retailer sets a gross markup greater than one.

Table 4 reports estimates of long-run pass-through in levels and logs (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. For all six products, the log pass-through is significantly below one.

[10]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.

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.[11] 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 lags, but approaches complete pass-through by eight months and stays around one thereafter. The log pass-through, in panel (c), instead plateaus below one-half. These results are consistent with Nakamura and Zerom (2010), who estimate pass-through in the roasted ground coffee market from 2000–2005. Analogous figures for the other five food products are in Appendix A.

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

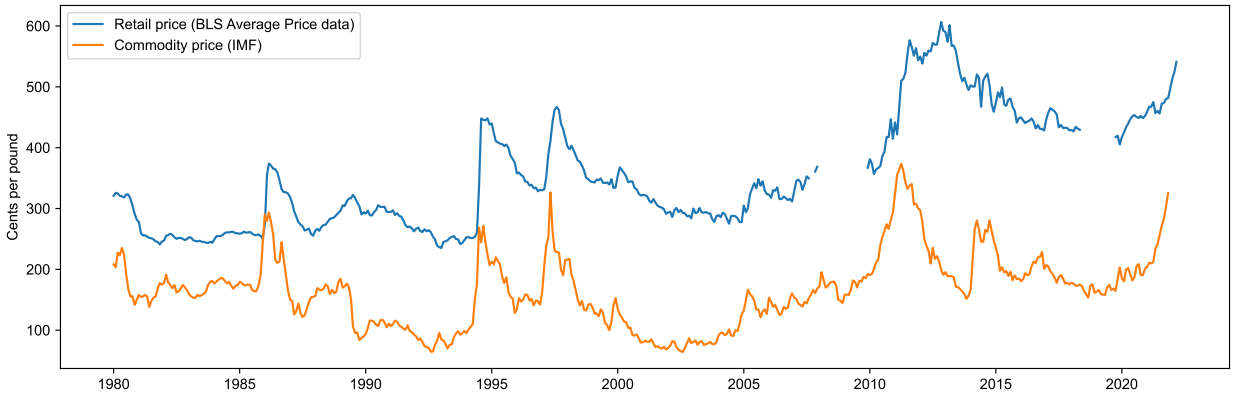
To test these predictions, we use NielsenIQ data on rice, flour, and coffee products from 2006 to 2020. We define a product as a specific UPC (universal product code, or product barcode) sold at a specific retail chain, since prices for a UPC tend to be fairly uniform within retail chains (DellaVigna and Gentzkow 2019). In each quarter t, we calculate the price p_{it} of product (i.e., UPC–retailer pair) 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 percentages ($\Delta \log p_{it} = \log p_{it+4} - \log p_{it}$). Since these price changes are measured year over year, they avoid seasonality effects that may bias measures of price changes calculated over smaller time increments.[12]

Under the assumption that firms face identical commodity costs, we can use the unit price (e.g., the price per ounce of coffee) as a measure of each product's non-commodity variable costs and markups. Thus, to test the above predictions for how pass-through in logs and levels varies with the level of non-commodity variable costs and markups,

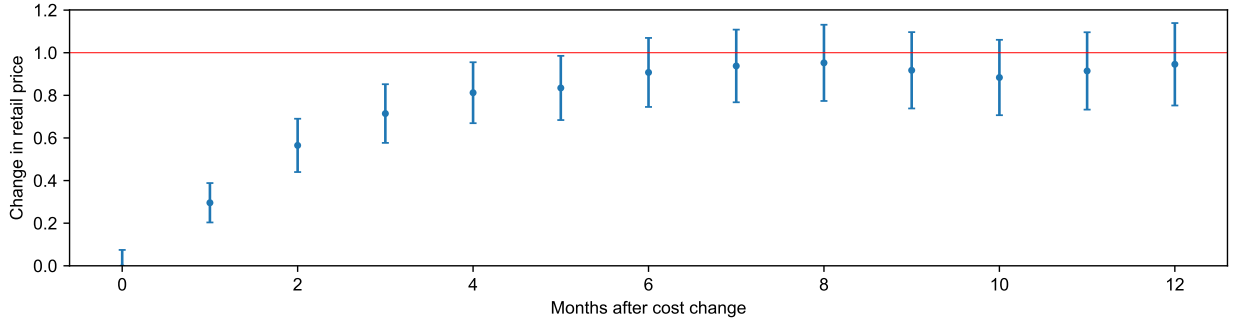
[11] See, e.g., New York Times: "*Coffee Hits a 20-Year High on Rumblings of a Shortage*" (1997) and New York Times: "*Heat Damages Colombia Coffee, Raising Prices*" (2011).

[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.

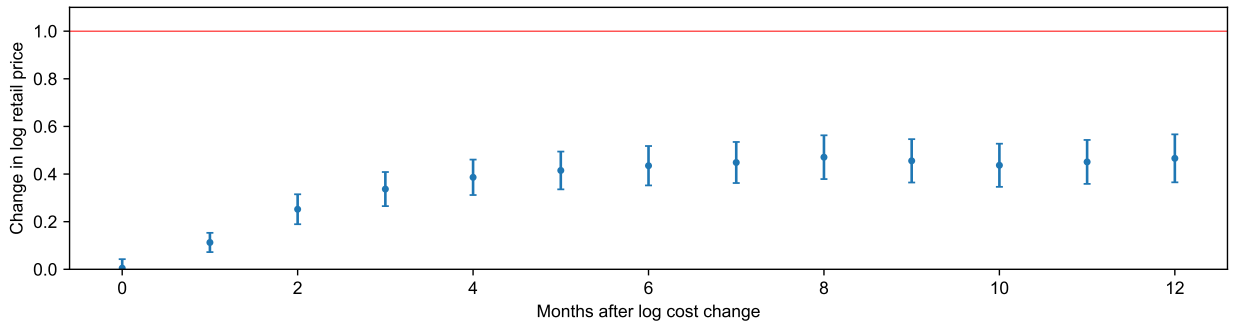
Figure 2: Pass-through of coffee commodity costs to retail prices.



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



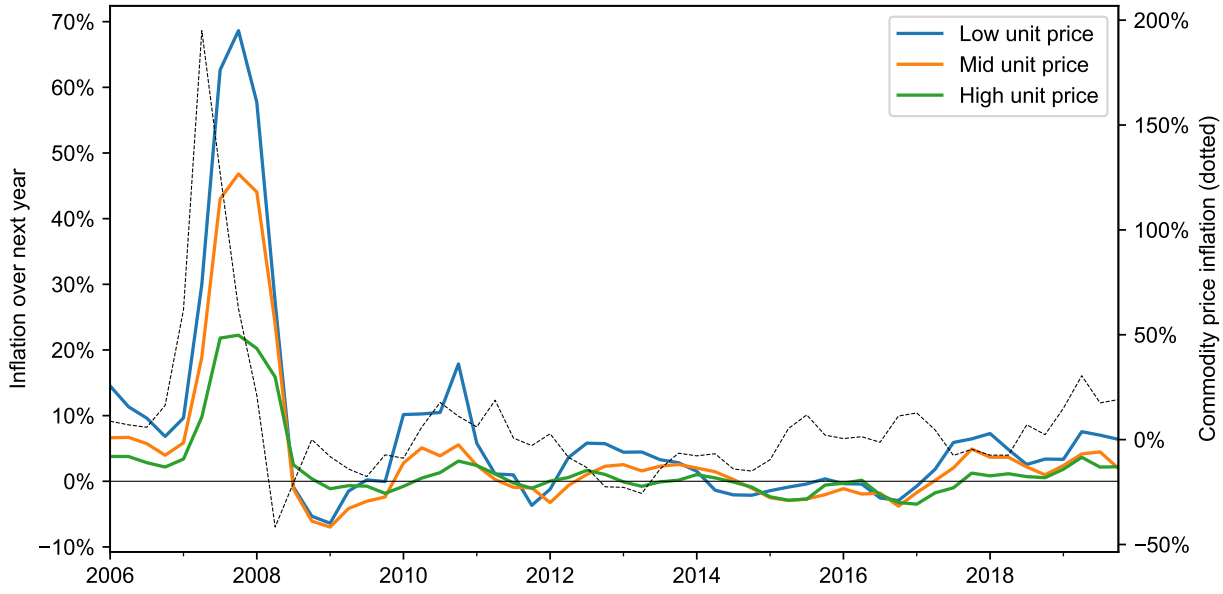
(b) Pass-through in levels.



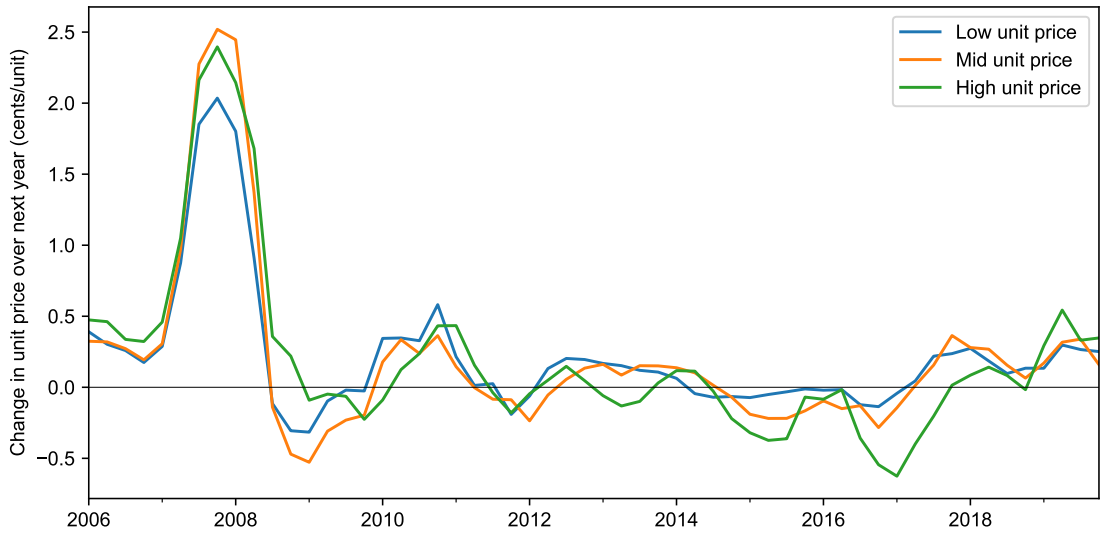
(c) Pass-through in logs.

Note: Panel (a) plots the time series of the commodity price from the IMF and the Average Price Data series from the BLS. The series are adjusted by the conversion factors in Appendix Table A6 so that the two series are in comparable units. Panels (b) and (c) plot the cumulative pass-through to month T, $\sum_{k=0}^{T} b_k$, from the specifications (3) and (4), using a total horizon of $K = 12$ months.

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



(a) Inflation (in percentages)



(b) Price change (in levels)

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

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

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

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

[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.

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,

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

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

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

Across product groups, panel A shows that the sensitivity of log retail prices to commodity inflation systematically declines with unit price across all three product categories (rice, flour, and coffee). In contrast, panel B finds little evidence of systematic differences in the sensitivity of retail price changes to commodity price changes *in levels* across unit price groups. Thus, evidence from all three categories is consistent with uniform pass-through in levels explaining heterogeneity in log pass-through across products. Appendix Table A7 shows similar results if we instead split products into five unit price groups.

Effects of cost changes on price distributions. Our approach so far has been to explore cross-sectional variation in the long-run pass-through of commodity costs to prices. A complementary approach is to identify how changes in commodity costs affect the entire distribution of prices. Pass-through in levels predicts that increases in commodity costs should have no long-run effect on the dispersion of prices in levels, but should condense the dispersion of relative prices (i.e., log prices). Conversely, complete log pass-through predicts that rising commodity costs should not affect relative prices and should increase dispersion in price levels.[14]

We test these predictions in Appendix Table A8 for rice, flour, and coffee products. Consistent with pass-through in levels, we find that an increase in commodity prices has little effect on the dispersion of price levels, but leads to a significant decline in the dispersion of log prices. Thus, the response of retail price distributions to commodity

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

cost changes for these goods is also consistent with complete pass-through in levels across products in each category.

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

So far, we have measured pass-through in levels for specific products by matching input costs to downstream prices. Our next exercise tests for pass-through in levels across a much broader range of product categories, albeit only at the retailer level. We exploit the fact that different retailers often sell the same product at different prices (Kaplan and Menzio 2015; Kaplan, Menzio, Rudanko, and Trachter 2019). Even without directly observing input costs, we can use price movements of the same product across different retailers to test for pass-through in levels and in logs.

Exploiting variation in prices across retailers. To fix ideas, consider two retail stores selling the same UPC, one at a low price (store A) and one with a high price (store B). As an example, Appendix Figure A9 shows the price of the same coffee UPC at two different stores in Philadelphia. Excluding some temporary sales, store A consistently charges a lower price than store B. If both stores A and B have fixed percentage markups, when the cost of the UPC rises, the price at store B (the retailer with the higher markup) should rise more in levels. On the other hand, if both stores exhibit complete pass-through in levels, when the cost of the UPC rises, the absolute price change in both store A and store B should be similar, and the price change in percentage terms for store B should be lower.

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

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

	Percentage markups $p_i = \mu_i c$	Additive markups $p_i = c + m_i$
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 (9), β^{level}	1	0
Logs specification (10), $\beta^{\log}$	0	-1

Note: We denote the cost of the UPC, common to all retailers, by c. The price of the UPC at retailer i is p_i, and the average price across all retailers is $\bar{p}$. Price changes relative to cost and relative to the average price are first-order approximations in the cost change dc, assuming that prices differences across retailers are small, $\log p_i/\bar{p} \sim O(dc)$.

We test these predictions using two specifications,

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

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

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.

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

Results. We estimate specifications (9) and (10) for rice, flour, and coffee products, as well as for the entire set of food-at-home product categories in the NielsenIQ data over

Table 7: 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$_{kt}$ $\times$ 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
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$_{kt}$ $\times$ RelativePrice$_{ikt}$	−1.004**	−1.014**	−1.261**	−1.043**
	(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

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

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

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

hypothesis that retailers set fixed percentage markups.[15]

5 Evidence from Manufacturing Industries

So far, we have documented pass-through in levels using microdata for specific goods. In this section, we extend our analysis to a panel of four hundred industries that span the U.S. manufacturing sector. We find that the pass-through of input cost changes to output prices across these industries conforms with the predictions of pass-through in levels. Thus, pass-through in levels appears to describe pricing behavior across a quite broad set of industries and markets.

5.1 Data and Empirical Approach

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

Testing for pass-through in levels. Unlike our earlier analysis of gasoline and food products, where we directly observed the level of input and output prices for specific

[15]This finding may be surprising in the light of Eichenbaum, Jaimovich, and Rebelo (2011), who find that when a retailer resets its reference price, the deviation in the realized markup from the average markup is largely uncorrelated with the deviation in the hypothetical markup absent a price reset from the average markup (Eichenbaum et al. 2011, Figure 8). While they conclude that "when the retailer changes reference prices it reestablishes the value of the unconditional [percentage] markup," this evidence is not necessarily inconsistent with our results. Fixed additive markups imply that the deviation in the realized percentage markup from the average is negatively correlated with the deviation in cost from average cost, but when costs are close to unit root, the deviation in cost from average cost may have a low correlation with the change in cost since the last reference price reset.

products, the NBER-CES includes output and input price indices that reflect average percentage changes in prices. Nevertheless, some simple algebra allows us to estimate the pass-through in levels using changes in log price indices and the revenue-share of input expenditures.

Let us denote the pass-through in levels of a change in input costs to prices by $\rho^{\text{level}} \equiv \Delta p / \Delta c$. Rearranging, we find

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

While we don't directly observe price levels or changes in price levels, to a first order, the ratio of the price change to the price level is equal to the change in the log price index, $\Delta p / p \approx \Delta \log p$. Thus, to a first order approximation,

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

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

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

5.2 Empirical Results

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

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

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

Table 8: 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. Both input and output price indices are deflated using CPI excluding food and energy. Standard errors two-way clustered by industry and year. ** indicates significance at 5%.

not impose these restrictions for estimation.

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

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

through in levels of the input cost changes to prices.[16]

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

A second concern is that nominal price rigidities may lead us to underestimate the long-run pass-through of input price changes to output prices. In Appendix Table A10, we estimate (12) using changes in input and output prices at horizons ranging from one to five years. If anything, our estimate of β slightly declines with the horizon, and we cannot reject the hypothesis that $\beta = 1$ for any horizon.

6 Discussion

Taking stock. Our empirical analysis suggests that complete pass-through in levels emerges across a broad set of industries and markets. To recap, we observe pass-through in levels in retail gasoline markets, from commodity to retail price in considerably more differentiated food products, at the retail level across the universe of food-at-home product categories in NielsenIQ data, and across industries spanning the U.S. manufacturing sector. Moreover, across these settings, we find that pass-through in levels accounts for the extent of incomplete log pass-through and the heterogeneity in log pass-through measured across products, across firms, and across industries.

It is useful to delineate a few common features of the settings in which we measure pass-through. First, the input price changes that we study are cost shocks that are common to all firms operating in a market. That is, our results capture responses to *aggregate* cost

[16]When estimating (12) in Table 8, we deflate both input and output price indices by the aggregate price index. This choice anticipates the model in Section 7, which shows that the additive markup set by firms depends on the price level in the economy. Estimating (12) using changes in the nominal input and output prices does not meaningfully change the results in Table 8, but we show in Section 8.3 that it can affect the measurement of pass-through across specific categories of inputs.

shocks and may not reflect how firms pass-through idiosyncratic cost shocks that only affect one or a subset of producers in a market. Second, the input prices in each of our empirical settings appear close to unit root (see Appendix Table A2). Thus, our findings are best understood as reflecting the long-run pass-through of persistent, industry-wide changes in costs. We leave the question of whether firms also exhibit pass-through in levels in response to temporary and/or idiosyncratic cost shocks to future work.

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

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

A few exceptions to complete pass-through in levels in Appendix Table A1 find evidence of "over-shifting" for excise tax changes. Conlon and Rao (2020) propose that over-shifting may not be due to fixed percentage markups, but instead to retailers rounding up to prices that end in 99 cents even when tax changes are small. Of the three tax changes in their sample, only one increases taxes per product by more than $1, and for that tax change Conlon and Rao (2020) find that pass-through in levels is slightly below and not significantly different from one. Many of the other studies that find evidence of over-shifting study only a single tax change (e.g., Kenkel 2005, Hanson and Sullivan 2009, and Cawley, Frisvold, Hill, and Jones 2020).[17] Butters et al. (2022) recently revisit the pass-through of excise tax changes using a larger sample of sixty-eight national and state excise tax changes. In this larger sample, Butters et al. (2022) estimate a pass-through in levels of 1.01 (standard error: 0.02).[18] The weight of evidence from studies that measure pass-through over a larger sample of excise tax changes or that use commodity and input price shocks—which offer more continuous variation for identification—points toward

[17]Since these studies focus on a single tax change event, the estimates hinge on whether the comparison group is a good control for price changes absent the tax. For example, Kenkel (2005) notes, "if there were cost shocks other than the tax hikes over this period, the estimates [of pass-through] may overstate the rate of tax pass-through."

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

complete pass-through in levels.

7 Explaining Pass-Through in Levels

In this section, we show that our evidence of complete pass-through in levels of aggregate shocks poses a challenge for homothetic demand systems, which instead predict complete log pass-through of aggregate cost shocks. We identify an alternate class of demand systems that exhibit pass-through in levels using a discrete choice model of demand.

7.1 Pass-Through Under Homothetic Demand

We begin by considering the pass-through of an aggregate cost shock under homothetic preferences. Homothetic preferences are ubiquitous in models in macroeconomics and trade. This class of preferences includes CES preferences, as well as demand systems that accommodate variable markups, such as Kimball (1995), nested CES (Atkeson and Burstein 2008), and HSA preferences (Matsuyama and Ushchev 2017).

Under standard assumptions for about firms' strategic conduct and price-setting objectives—firms take others' prices as given and choose prices to maximize profits—Proposition 1 shows that homothetic demand systems predict complete log pass-through of aggregate cost shocks, and thus are generally unable to deliver pass-through in levels in response to aggregate cost shocks.

Proposition 1 (Homothetic preferences: Pass-through of aggregate cost shock)**.** *Suppose there are J firms. Each firm $j = 1, ..., J$ possesses a constant returns to scale production function with (exogenous) marginal cost c_j and sets its price p_j to maximize profits, taking the prices set by other firms as given. A representative consumer chooses consumption of each good q_j to maximize utility $U(q_1, ..., q_J)$ subject to the budget constraint, $\sum_j p_j q_j = I$.*

If U is homothetic, then in response to a proportional increase in all firms' marginal costs ($d \log c_j = d \log c$ for all j), each firm's price increases by $d \log p_j = d \log c$.

Proof. See Appendix B.3. □

Under homothetic preferences, demand depends only on relative prices. When all firms raise their prices proportionally, relative prices remain fixed, and firms' demand curves and desired markups are unchanged. Thus, when all firms experience the same proportional increase in marginal costs, homothetic preferences imply that firms fully pass-through the cost increase *in logs*. This result applies to all homothetic demand systems regardless of whether those demand systems imply fixed percentage markups—as in CES

demand—or whether they accommodate variable markups, such as Kimball (1995) or HSA (Matsuyama and Ushchev 2017) preferences. The result also applies regardless of whether firms are atomistic, as in standard models of monopolistic competition, or granular, as in the Atkeson and Burstein (2008) nested CES oligopoly model.[19]

While the aggregate cost shock in Proposition 1 is defined as a proportional increase in all firms' marginal costs, the result implies that homothetic preferences are generally unable to generate complete pass-through in levels even for an aggregate cost shock that instead increases all firms' marginal costs in levels (i.e., if $dc_j = dc$ for all c). To take a simple example, if firms' marginal costs are initially identical, then Proposition 1 indicates that an aggregate cost shock dc will increase each firm's price by $dp_j = \mu_j dc$. As long as firms' prices are not perfectly competitive ($\mu_j > 1$), homothetic demand thus implies that pass-through in levels is greater than one.

This property makes homothetic demand systems incompatible with our evidence of long-run, complete pass-through in levels of aggregate cost shocks. Explaining pass-through in levels requires that we depart from the family of homothetic demand systems.[20]

7.2 A Discrete Choice Model of Demand

We structure our departure from homotheticity by modeling demand as an aggregation of discrete choices made by a continuum of consumers, following in the tradition of Anderson et al. (1992). We set up the model of discrete choice, compare the model to popular existing models of demand, and characterize the pass-through of aggregate cost shocks in the model.

7.2.1 Model Setup

Firms. There are J firms indexed by $j = 1, ..., J$. Each firm produces a single output good using a constant-returns-to-scale production function with marginal cost c_j. Each firm sets its price p_j to maximize profits, taking the prices set by other firms as given:

$$\max_{p_j} (p_j - c_j) D_j(p),$$

[19] For the Atkeson and Burstein (2008) model, Proposition 1 shows that log pass-through is complete if firms in all sectors experience a proportional increase in costs. It turns out that the Atkeson and Burstein (2008) model also exhibits complete log pass-through of a cost shock that only affects firms in one sector. This is because expenditures on each sector are isoelastic with respect to the sectoral price index.

[20] Appendix B.2 explores whether we can obtain pass-through in levels by maintaining homothetic preferences but relaxing Leontief production, constant returns, and uncorrelated other input costs. In each case, we find knife-edge conditions that appear unlikely to hold across a broad set of markets.

where $D_j(p)$ is the demand for firm j given the vector of prices p set by all firms.

Consumers. There is a mass M of consumers indexed by $i \in [0,1]$, each with income Y. Consumers gain utility from the consumption of goods $j = 1, ..., J$, which we refer to as *inside goods*, and from consumption of an outside, numeraire good. Consumer i's utility when purchasing from firm j is

$$u_{ij} = \delta_{ij} q_{ij} + q_{i0} \qquad \text{s.t.} \qquad p_j q_{ij} + p_0 q_{i0} \leq Y,$$

where q_{ij} is the quantity consumer i purchases from j, δ_{ij} is a consumer-specific taste-shifter for firm j, q_{i0} is the quantity of the numeraire good consumed by the household, and p_0 is the price of the numeraire good.

Assumption 1 (Intensive margin elasticity of demand)**.** Conditional on choosing to purchase from firm j, consumer i consumes the quantity,

$$q_{ij} = \bar{q}(Y/p_j)^{\eta}. \tag{13}$$

The parameter η dictates the elasticity of quantity consumed to a firm's price conditional on purchasing from that firm. Two important cases that we will focus on are when η is equal to either zero or one. When $\eta = 0$, consumers always purchase a fixed quantity $\bar{q}$, regardless of the firm they purchase from. When $\eta = 1$, consumers instead spend a fixed share of their income on the firm of their choice, and thus purchase a quantity that is inversely proportional to the firm's price.

While we impose (13) as an assumption, Anderson and de Palma (2020) and Birchall et al. (2024) show that one can micro-found (13) by assuming that consumers' indirect utility functions include a Box-Cox transformation of price and income.[21] Hence, one can interpret Assumption 1 as a consequence of assumptions about the form of consumers' indirect utility function. A specific choice of η can also reflect a combination of underlying technological constraints and preferences. For example, the assumption that consumers always demand one unit of a product in some settings can reflect a combination of the indivisibility of large purchases and diminishing marginal utility.

Consumers choose exactly one firm to purchase from to maximize utility,

$$U_i = \max_j \{u_{ij}\}.$$

[21] In particular, Birchall et al. (2024) show that quantities follow (13) if income and price enter u_{ij} with the Box-Cox transformation, $u_{ij} = \delta_{ij} + [(Y^{1-\eta} - 1)/\bar{q} - (p_j^{1-\eta} - 1)]/(1-\eta)$.

Our second assumption ensures that consumers almost surely do not face ties in utility when choosing between firms.

Assumption 2. For any two firms 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.

Aggregating across consumers, we get the demand for each firm j in terms of the vector of prices set by all firms p,

$$D_j(p) = \int_0^1 1\{u_{ij} > u_{ik} \text{ for all } k \neq j\} \, q_{ij} \, M \, di. \tag{14}$$

Assumption 2 ensures that there are no masses of consumers that have identical tastes, so that the aggregate demand curves are differentiable with respect to firms' prices. We denote the total expenditures on inside goods by $I \equiv \sum_{j=1}^{J} p_j D_j(p)$.

Equilibrium. Given an exogenous set of firms $1, ..., J$, costs of production c_j, numeraire price p_0, consumer income Y, and tastes δ_{ij}, an *equilibrium* is a set of quantities demanded and prices $(D_j(p), p_j)$ such that (1) each consumer chooses one firm to purchase from to maximize utility, taking income Y and prices p as given; and (2) firms choose prices to maximize profits, taking consumer demand and the prices set by all other firms as given.

7.2.2 Relationship to Popular Models of Demand

As shown by Anderson et al. (1992), the discrete choice approach can generate a wide range of demand systems that are common to the literature. Proposition 2 lists some of the demand systems used in previous work that can be accommodated with this setup.

Proposition 2 (Special cases)**.** *CES, nested CES (Atkeson and Burstein 2008), and mixed CES (Adao, Costinot, and Donaldson 2017) are special cases of the model when $\eta = 1$. 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) are special cases of the model when $\eta = 0$.*

Proof. See Appendix B.3 for assumptions on δ_{ij} that generate each demand system. □

A strength of the discrete choice framework is that it can reflect a variety of models built on different micro-foundations and forms of competition. For example, special cases of the framework include demand systems where choices made by consumers are due to idiosyncratic taste shocks, differences in consumers' ideal varieties, or transport costs that customers incur when traveling to nearby versus faraway firms. The framework

also nests cases where firms compete symmetrically against all other firms, face a greater degree of substitutability with some firms than other firms, or compete only against their closest neighbors.

One may notice that the demand systems most frequently used in the macroeconomics and trade literature require that $\eta = 1$. This is in fact not a coincidence: Proposition 3 shows that the demand system for inside goods is homothetic if and only if $\eta = 1$.

Proposition 3 (Homotheticity when $\eta = 1$)**.** *Let $D(p, I)$ denote the vector of demands for each inside good $1, ..., J$ given the vector of firms' prices p and total expenditures on inside goods I. If $J > 1$, the demand function $D(p, I)$ is homothetic if and only if $\eta = 1$.*

Proof. See Appendix B.3. □

Since the demand system for inside goods is homothetic only when $\eta = 1$, the intensive margin elasticity of demand η can be viewed as parameterizing the departure from homotheticity. As we will see, η also plays an important role in shaping the pass-through of aggregate cost shocks across demand systems.

7.2.3 Pass-Through of Aggregate Cost Shocks

We next characterize the pass-through of aggregate cost shocks in two cases where the intensive margin elasticity of demand is either one or zero. First, since demand is homothetic when $\eta = 1$, we can apply our result on the complete log pass-through of aggregate cost shocks from Proposition 1.

Proposition 4 (Complete log pass-through when $\eta = 1$)**.** *Suppose $\eta = 1$. If all firms' marginal costs increase by $d \log c_j = d \log c$, then firms' prices increase by $d \log p_j = d \log p = d \log c$.*

Proof. Follows from Proposition 1 and Proposition 3. □

While this result follows from Proposition 1, the discrete choice micro-foundations give us a different lens to understand why these demand systems exhibit complete log pass-through. When $\eta = 1$, each consumer spends a fixed share of their income on inside goods, and so the quantity of the numeraire good purchased by each consumer does not depend on the consumer's choice of firm. As a result, utility comparisons across firms reduce to a comparison of the ratio of the consumer's taste for the firm to its price, δ_{ij}/p_j. Since a proportional increase in all firms' prices does not alter the outcome of these comparisons, a proportional increase in all firms' marginal costs leads to a proportional increase in prices without altering firms' market shares and desired percentage markups.

An analogous intuition implies that demand systems with $\eta = 0$ generate complete pass-through in levels of aggregate cost shocks, as we show in Proposition 5.

Proposition 5 (Complete pass-through in levels when $\eta = 0$)**.** *Suppose $\eta = 0$. If all firms' marginal costs increase by $dc_j = dc$, then firms' prices increase by $dp_j = dp = dc$.*

Proof. See Appendix B.3. □

When $\eta = 0$, each consumer purchases a fixed quantity of inside goods, and so differences in firms' prices affect the leftover income that the consumer has to buy the numeraire good. Thus, utility comparisons across firms instead reduce to a comparison of the difference between the consumer's taste for the firm and its price relative to the numeraire, $\delta_{ij} - p_j/p_0$. A level shift in all firms' prices leaves the outcome of these comparisons unchanged. As a result, a common shock to firms' marginal costs leads to a level shift in firms' prices without altering firms' quantity shares and desired additive markups.

Proposition 5 shows that any demand system that can be represented as an aggregation of discrete choices by consumers with an inelastic intensive margin of demand will generate complete pass-through in levels. The class of demand systems that generates pass-through in levels excludes homothetic demand systems, but includes a variety of alternative demand systems such as those listed in Proposition 2 as special cases. While sharing the property that $\eta = 0$, this class of demand systems also encompasses different micro-foundations and allows for ample flexibility in matching firms' elasticities of demand and substitution patterns. For example, the differentiation across firm varieties can come from quality differences and consumers' idiosyncratic taste shocks, as in the mixed logit model, or alternatively from the transport costs that consumers incur to visit nearby versus faraway firms, as in the Hotelling (1929) and Salop (1979) models.[22] As shown by a vast literature in empirical industrial organization, demand systems like the mixed logit model also allow for rich patterns of substitution across firms and flexibility in how firms pass-through idiosyncratic cost shocks.

7.2.4 Prices, Markups, and Pass-Through with Symmetric Firms

While our results on the pass-through of aggregate cost shocks when $\eta = 1$ and $\eta = 0$ apply for any set of heterogeneous firms, we can derive tractable expressions for prices, markups, and the pass-through of aggregate cost shocks for any value of η in the case of homogeneous firms.

[22] Barro (2024) characterizes firms' markups in a variant of the Salop (1979) model with an intensive margin elasticity of demand. His model is not nested by our framework because he assumes transport costs are paid per unit of purchase. However, when the intensive margin elasticity of demand in his model is zero, the model coincides with a special case of our model with $\eta = 0$. For this case, Barro (2024) shows that firms have additive markups and exhibit complete pass-through in levels, consistent with Proposition 5.

Proposition 6 (Symmetric equilibrium with homogeneous firms)**.** *Suppose marginal costs $c_j = c$ for all j and tastes δ_{ij} are i.i.d. draws from a distribution F. Then, the symmetric equilibrium price $p_j = p$ satisfies*

$$(p - c)\left((1 - \eta)\frac{\phi_0}{p_0} + \eta\frac{\phi_1}{p}\right) = 1,$$

where ϕ_0 and ϕ_1 are constants defined in Appendix B.3 that depend only on the number of firms J and the taste distribution F. If $\eta = 1$, price equals cost c times a percentage markup,

$$p = \frac{\phi_1}{\phi_1 - 1}c. \tag{15}$$

If $\eta = 0$, price equals cost c plus an additive markup priced relative to the numeraire p_0,

$$p = c + \frac{p_0}{\phi_0}. \tag{16}$$

For general η, the pass-through of an (infinitesimal) aggregate cost shock in levels and logs is

$$\rho^{level} = 1 + \frac{\eta\phi_1(\mu - 1)^2}{\mu^2 - \eta\phi_1(\mu - 1)^2}, \qquad \text{and} \qquad \rho^{log} = 1 - \frac{(1 - \eta)\phi_0(\mu - 1)}{(1 - \eta)\phi_0\mu + \eta\phi_1\frac{p_0}{p}}.$$

Pass-through is complete in levels ($\rho^{level} = 1$) if and only if $\eta = 0$.

Proof. See Appendix B.3.[23] □

For general values of η, the gap between firms' prices and costs depends on the constants ϕ_0 and ϕ_1, which reflect the extent of variation in idiosyncratic tastes across firms, and scales with either the symmetric equilibrium price p or the numeraire price p_0. If $\eta = 0$, the gap between prices and costs is an additive markup priced relative to the numeraire, while if $\eta = 1$, the gap between prices and costs is priced relative to the output price p, leading to a percentage markup. For intermediate values of η, equilibrium prices move smoothly between these extremes of additive and percentage markups.

The transition from percentage markups when $\eta = 1$ to additive markups when $\eta = 0$ explains how pass-through varies with η. Log pass-through is complete when $\eta = 1$ and becomes incomplete as we decrease η, converging to $\rho^{\log} = 1/\mu$ when $\eta = 0$. Conversely, the pass-through in levels is equal to the markup when $\eta = 1$ and declines as we decrease η. We find that the pass-through in levels of an aggregate cost shocks is equal to one only

[23] The special cases of $\eta = 0$ and $\eta = 1$ in Proposition 6 are derived in earlier work. Sattinger (1984) derives the expression for the equilibrium price with symmetric firms when $\eta = 1$, and Perloff and Salop (1985) derive the price with symmetric firms when $\eta = 0$.

when $\eta = 0$ (or if prices are perfectly competitive, i.e. $\mu = 1$).

Proposition 6 also clarifies the role that the price of the numeraire p_0 plays in shaping markups and prices. Notice in (16) that when $\eta = 0$, the additive markup is priced relative to the price of the numeraire. Is it straightforward to verify that for any value of η, a shock to the aggregate price level that scales up both firms' production costs and the numeraire price by a constant factor also scales up firms' desired prices by the same amount. In other words, the model exhibits *long-run monetary neutrality* with respect to changes in the aggregate price level, while allowing for pass-through in levels of shocks that only affect costs of production (and not the numeraire price).

7.2.5 Discussion

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

Flexibility in the pass-through of idiosyncratic cost shocks. While demand systems with $\eta = 0$ generate complete pass-through in levels of aggregate cost shocks, this class of demand systems does not constrain the pass-through of idiosyncratic cost shocks.[24] Thus, one can choose a demand system that matches our evidence on complete pass-through in levels of aggregate cost shocks while retaining the flexibility to match different rates of pass-through for idiosyncratic shocks.

Our empirical evidence concerns the pass-through of aggregate cost shocks, and to date there is less evidence on the pass-through in levels of idiosyncratic cost shocks. A recent exception is Alvarez, Cavallo, MacKay, and Mengano (2024), who measure pass-through of cost shocks by a non-durables manufacturer and find complete pass-through in levels of both aggregate and idiosyncratic shocks. Logit demand with atomistic firms is a special case of our class of $\eta = 0$ demand systems that predicts complete pass-through in levels of both aggregate and idiosyncratic shocks, in line with this evidence.[25]

Outside options and pass-through in calibrated models. A large literature in industrial organization estimates mixed logit models of demand. Mixed logit demand systems are a special case of $\eta = 0$ (Proposition 2) and, in the absence of outside options, predict complete pass-through in levels of aggregate cost shocks. However, many of these calibrations often

[24] Equation (26) in Appendix B.3 expresses pass-through in terms of own-cost shocks and other firms' price changes, which can be used to solve for the pass-through of idiosyncratic shocks when $\eta = 0$.

[25] Logit demand with atomistic firms has the property that the "global" super-elasticity of demand is one: the price elasticity of demand facing all firms increases by 1 percent when all firms' prices increase by 1 percent. See e.g., Bulow and Pfleiderer (1983), Weyl and Fabinger (2013), and Mrázová and Neary (2017).

include an outside option that is not exposed to industry cost shocks. This means that firms no longer exhibit complete pass-through in levels of aggregate cost shocks, because cost shocks change the utility of purchasing from a firm relative to the outside option. A previous version of this paper estimated the pass-through of aggregate cost shocks in calibrated demand systems from Nevo (2001) and Nakamura and Zerom (2010). Due to the presence of an outside option, products in those models exhibit considerable variation in their pass-through of aggregate cost shocks, in contrast with our evidence of uniform pass-through in levels across products and firms in the data.

Evidence on the intensive margin elasticity of demand. The intensive margin elasticity of demand η plays an important role in determining the pass-through of aggregate cost shocks, and our results on pass-through in levels imply $\eta = 0$. While we are not aware of direct evidence on η, recent studies show that variation in sales across firms is largely driven by differences in the number of customers per firm, rather than differences in the quantity purchased per customer (Argente, Fitzgerald, Moreira, and Priolo 2021; Einav, Klenow, Levin, and Murciano-Goroff 2021; Afrouzi, Drenik, and Kim 2023). These findings are consistent with the quantities that customers purchase being relatively inelastic to a firm's price, even while choices across firms (i.e., on the extensive margin) may be influenced by firms' prices.

Other explanations for pass-through in levels. We identify demand systems that generate complete pass-through in levels without modifying core assumptions about firm conduct, firm and consumer rationality, or firm objectives. We view this as an appealing feature of a demand-based explanation. Of course, it may be possible to explain pass-through in levels by instead relaxing these assumptions. For example, strategic interactions between oligopolistic firms can generate kinked demand curves or price cycles that break the standard relationship between markups and demand elasticities (e.g., Maskin and Tirole 1988). Fairness or implicit contracts between firms and customers may lead firms to only increase prices when costs visibly increase (e.g., Okun 1981; Rotemberg 2005; Westphal 2024). Finally, prices may reflect heuristics such as "full cost pricing" or "target returns pricing" (Hall and Hitch 1939; Lanzillotti 1958; Blinder 1994) or firm objectives beyond profit-maximization (e.g., Baumol's 1959 conjecture that firms maximize revenue subject to a profit constraint). Our empirical evidence on pass-through in levels across several markets is also useful for disciplining these alternative mechanisms.

8 Implications

Beyond describing the behavior of prices, we propose that demand systems that generate pass-through in levels can be useful in describing several features of the data. In this section, we demonstrate the usefulness of pass-through in levels in four applications.

8.1 Misspecification and Pass-Through Measurement

When firms exhibit complete pass-through in levels, using a log specification to measure pass-through imposes an incorrect, percentage-markup functional form on prices. First, Proposition 7 shows that this misspecification can lead to spurious evidence of asymmetry and size-dependence in log pass-through.

Proposition 7 (Asymmetry and size-dependence)**.** *Suppose firms are symmetric and $\eta = 0$, so that prices are given by* (16)*. Given a change in costs $\Delta \log c$, log pass-through to a first order in $\Delta \log c$ is*

$$\rho^{log} = \frac{\Delta \log p}{\Delta \log c} \approx \frac{c}{p}\left[1 + \frac{p_0}{\phi_0 p}\Delta \log c\right].$$

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

1. *Log pass-through is **asymmetric**: $\rho^{log}(x) > \rho^{log}(-x)$ for any $x > 0$.*
2. *Log pass-through is **size-dependent**: $\rho^{log}(x) > \rho^{log}(x')$ for any $x > x'$.*

Proof. Results follow from a second-order expansion of (16) with respect to $\Delta \log c$. □

A large literature documents asymmetries in log pass-through (see e.g., Peltzman 2000), and recent work suggests that firms pass through large shocks at higher rates than small shocks (Cavallo, Lippi, and Miyahara 2024; Gagliardone, Gertler, Lenzu, and Tielens 2025).[26] Although these patterns could arise from genuine differences in how firms respond to cost changes, Proposition 7 shows that simply using a log specification can generate apparent asymmetries and size-dependence. With complete pass-through in levels, these effects arise because log pass-through is not a stable statistic and depends on the size and direction of cost shocks.

Second, measuring pass-through in logs can also lead to systematic patterns of heterogeneity. Previous work documents that log pass-through declines with firm size (e.g., Berman, Martin, and Mayer 2012; Amiti et al. 2019; Gupta 2020) and with product quality

[26]The evidence on size-dependence in pass-through focuses on differences in the extensive margin of price adjustment to small and large shocks, but Gagliardone et al. (2025) also find evidence of greater responsiveness conditional on a price change.

(Chen and Juvenal 2016; Auer, Chaney, and Sauré 2018). Complete pass-through in levels naturally generates both patterns if markups increase with firm size and product quality, as is suggested by a large body of empirical work.[27]

8.2 Dynamics of Industry Profits, Margins, and Entry

Standard models of industry dynamics in macroeconomics and trade assume monopolistic competition with homothetic demand (i.e., $\eta = 1$). In this section, we consider how the predictions of such a model change when move from homothetic demand to demand systems with pass-through in levels (i.e., $\eta = 0$). The two classes of demand systems have different predictions for how fluctuations in input costs affect gross margins, operating margins, and firm entry. In the data, the dynamics of these industry aggregates across a range of industries line up with the predictions under pass-through in levels.

Profits, margins, and entry in a simple industry model. We embed the demand systems from Section 7 into a workhorse model of monopolistic competition, following Dixit and Stiglitz (1977) and Melitz (2003). A mass N of symmetric firms produce varieties of an output good at a constant marginal cost c and choose prices to maximize variable profits π^{gross},

$$\max_p \pi^{\text{gross}} = (p - c)D(p).$$

In addition to variable costs of production, firms incur overhead costs given by f_o. We denote each firm's operating profits by $\pi^{\text{op}} = \pi^{\text{gross}} - f_o$.

Aggregate industry demand is given by $Q = p^{-\theta}$. We assume that aggregate industry demand is inelastic ($\theta < 1$), which is the empirically relevant case for most of the industries studied in this paper.[28] The demand curves facing individual firms are determined by aggregating over choices made by a mass of consumers. We assume consumers' tastes for each firm are drawn i.i.d. from the distribution F, so that the symmetric equilibrium price

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

[28] Elasticities of aggregate demand for retail gasoline in the U.S. are close to zero (Eitches and Crain 2016), and the USDA estimates elasticities of aggregate demand for flour, rice, and coffee to be 0.07, −0.07, and −0.12, respectively (Okrent and Alston 2012). We can microfound the aggregate industry demand θ by assuming that consumption decisions are made in two stages: first, a unit mass of consumers chooses whether to purchase from any firm given the aggregate price p, and then the mass of consumers $M < 1$ that purchases realizes taste shocks and chooses which firm to purchase from. The elasticity of industry demand is θ when the first stage yields $M \propto p^{-(\theta-\eta)}$.

for firms is given by Proposition 6. Firm symmetry also allows us to express industry gross and operating margins (as a percent of sales) as

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

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

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

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

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

Proposition 8 (Gross margins, operating margins, and entry in monopolistic competition)**.** *Consider an increase in costs $dc > 0$. The response of industry gross margins, operating margins, and the mass of firms for $\eta = 0$ and $\eta = 1$ is summarized in the following table:*

		Gross margins dm^{gross}	*Operating margins* dm^{op}	*Mass of firms* $d \log N$
Homothetic: $\eta = 1$				
$\zeta = 0$	*(Fixed mass)*	0	> 0	0
$\zeta \in (0, \infty)$		0	> 0	> 0
$\zeta \to \infty$	*(Free entry)*	0	0	> 0
Unit demand: $\eta = 0$				
$\zeta = 0$	*(Fixed mass)*	< 0	< 0	0
$\zeta \in (0, \infty)$		< 0	< 0	≤ 0
$\zeta \to \infty$	*(Free entry)*	< 0	0	≤ 0

Proof. See Appendix B.4. □

When demand is homothetic ($\eta = 1$), firms have fixed percentage markups. Thus, when costs rise, firms make higher profits on each unit sold—for example, a firm charging

a fixed 10 percent markup makes \$0.10 per unit when unit costs are \$1, and \$0.20 per unit when unit costs are \$2. Since aggregate industry demand is inelastic, higher per-unit profits lead to higher aggregate profits for firms or else are dissipated by the entry of new firms. In other words, an increase in input costs leads to higher operating margins, new firm entry, or both.

In contrast, when $\eta = 0$, firms have fixed per-unit profits. Changes in input costs no longer necessitate changes to operating profits or the mass of firms in order to maintain equilibrium. Instead, the industry equilibrium primarily adjusts to rising costs via a decline in gross margins (measured as a share of sales).

Margins and entry in the data. The response of gross margins, operating margins, and entry to input cost fluctuations for retail gasoline stations and manufacturing industries is consistent with the predictions of Proposition 8 when $\eta = 0$, rather than $\eta = 1$.

For retail gas stations, we use data on gross and operating margins from the Census Annual Retail Trade Survey (ARTS) and, for complementary measures, calculate gross and operating margins from income statements of retail gas station sole proprietorships from the IRS Statistics of Income (SOI).[29] Data on the number of retail gas station firms and establishments in each year comes from two sources: the Census Business Dynamics Statistics (BDS) and the Census Statistics of U.S. Businesses (SUSB).

Appendix Figure A10 shows the time series for retail gasoline gross margins, operating margins, and establishment growth rates. Gross margins exhibit a strong negative relationship with input prices (gross margins from the Census ARTS and IRS SOI have correlations with the wholesale gasoline price of -0.94 and -0.74). On the other hand, operating margins and firm entry appear largely unresponsive to input prices.

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

$$\Delta \log y_t = \alpha + \beta \Delta \log c_t + \varepsilon_t. \tag{17}$$

Panel A of Table 9 reports results from specification (17) using the price of wholesale gasoline as the measure of input costs and using gross margins, operating margins, and entry as outcome variables.[30] Neither operating margins nor entry increase with input costs, as predicted by the model with $\eta = 1$. Instead, rising input prices lead to a decline in gross margins, exactly as predicted by the model with pass-through in levels ($\eta = 0$).

[29]Sole proprietorships account for one-fifth of all U.S. retail gas stations in 2016. We define sales in the IRS SOI as income from sales and operations. Gross margins are sales minus cost of sales, as a percent of sales, and operating margins are net income minus income from sources other than sales and operations plus taxes paid, payments of mortgage interest, and other interest on debt, as a percent of sales.

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

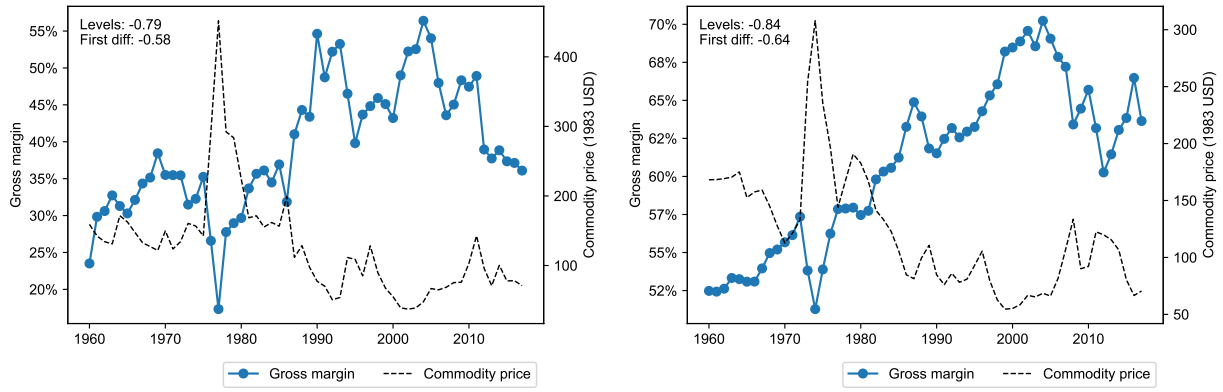
Table 9: Response of gross margins, operating margins, and entry to input price changes.

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**	0.218	−0.167	−0.002	0.001
	(0.045)	(0.061)	(0.377)	(0.331)	(0.006)	(0.007)
N	39	26	15	26	39	24
R^2	0.54	0.49	0.04	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	−0.122	0.095	0.007	−0.028
	(0.039)	(0.103)	(0.079)	(0.211)	(0.013)	(0.044)
Δ Log Input Price$_t$ × Inputs/Sales$_{t-1}$		−0.504**		−0.285		0.049
		(0.188)		(0.376)		(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	0.06	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 sales; 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%.

Similar patterns emerge for manufacturing industries in the NBER-CES database. Figure 4 plots industry gross margins against commodity costs for two manufacturing industries that use coffee and wheat as inputs. As predicted by the model with pass-through in levels, gross margins exhibit a strong negative correlation with input prices. Panel B of Table 9 reports how margins and firm entry respond to changes in input prices for the full set of manufacturing industries in the NBER-CES database. The response of all three industry aggregates to input costs is consistent with the predictions in Proposition 8 when $\eta = 0$: gross margins exhibit a strong negative response to input price increases, while operating margins and entry show no significant response. Moreover, we find that the response of gross margins to input price changes scales with the revenue-share of inputs, consistent with the change in gross margins being driven by changes in industry sales due to costs rising rather than changes in variable profits.

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.

Thus, altering the demand system in models of industry dynamics to comport with pass-through in levels makes sense of how industry aggregates respond to input cost fluctuations in the data. Beyond providing corroborating evidence for demand systems with $\eta = 0$, these results show that pass-through in levels is useful for understanding fluctuations in industry gross margins.[31] The results also clarify how industry equilibrium clears after input cost shocks: while standard models rely on waves of entry and exit to maintain a zero-profit equilibrium, our model with pass-through in levels achieves equilibrium with less volatility in the number of firms or operating profits.

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

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

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

[31] Pass-through in levels may help to explain an analogous result in the exchange rate pass-through literature, where Hellerstein (2008) and Campa and Goldberg (2010) document that distribution margins as a percent of sales fall when import prices rise.

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?

In this section, we suggest that pass-through in levels can resolve these puzzles. We first integrate the demand systems from Section 7 into a stylized model in which consumers purchase from a continuum of sectors. When $\eta = 0$ and the marginal sector that consumers purchase from primarily uses labor as a production input, the price of labor determines the size of firms' additive markups. As a result, firms appear to pass through changes in unit labor costs at a higher rate than other inputs.

We then show that these predictions 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 pass-through measures as suggested by the model, we restore complete pass-through in levels across all inputs.

Pass-through in levels in a stylized multi-sector model. A mass of consumers indexed by $i \in [0, 1]$ purchases from a continuum of sectors indexed by ω. Each sector ω consists of a mass of firms indexed by j. When a consumer purchases from sector ω, she chooses exactly one firm to purchase from. We use $q_{ij}(\omega)$ to denote the quantity consumer i buys from the firm $j(\omega)$ that she selects in sector ω, and $\delta_{ij}(\omega)$ and $p_{ij}(\omega)$ to denote the consumer's taste and price for her selected firm. As in Section 7, we impose that conditional on choosing to purchase from firm $j(\omega)$, the quantity consumer i buys is

$$q_{ij}(\omega) = \bar{q}(Y/p_{ij}(\omega))^{\eta},$$

where η is the intensive margin elasticity of consumption with respect to price.

The consumer maximization problem is

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

where Y is the consumer's (exogenous) income and Ω measures the mass of sectors from which the consumer purchases. We assume that consumers' tastes $\delta_{ij}(\omega)$ are i.i.d. draws from F_ω, where the distribution F_ω is allowed to vary by sector.

This setup embeds the demand systems from Section 7 into a multi-sector model. The key difference relative to Section 7 is that there is no longer a separate numeraire

good consumed by the household. Instead, the marginal utility of income to a consumer depends on the price of the marginal good she consumes. Changes in the price of this marginal good affects the markups and prices set by firms in all other sectors.

On the firm side, each sector consists of 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 ω is

$$mc(\omega) = \beta(\omega) w + (1 - \beta(\omega)) c,$$

where w is the wage, c is the cost of materials, and $\beta(\omega) \in [0, 1]$ determines the weights on labor and materials in production. We have in mind that $\beta(\omega)$ increases with ω, since the marginal goods purchased by households tend to be more labor-intensive and are often services (Aguiar and Bils 2015; Jaimovich, Rebelo, and Wong 2019; Orchard 2022).

In equilibrium, consumers choose the mass of sectors to purchase from (Ω) and which firm to purchase from in each sector ω 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 the 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 ω by $p(\omega)$ and $\mu(\omega) = p(\omega)/mc(\omega)$ respectively.

Proposition 9 characterizes the pass-through of unit material and labor costs in levels and logs in this model.

Proposition 9 (Differential pass-through of material and labor costs)**.** *Let $\rho_c^{level}(\omega)$ and $\rho_w^{level}(\omega)$ denote the pass-through in levels of unit materials costs and unit labor costs, and let $\rho_c^{log}(\omega)$ and $\rho_w^{log}(\omega)$ denote the log pass-through of materials and labor costs.*

1. *If $\eta = 1$, then $\rho_c^{log} = \rho_w^{log} = 1$ and $\rho_c^{level}(\omega) = \rho_w^{level}(\omega) = \mu(\omega)$.*

2. *If $\eta = 0$, then the pass-through in levels of unit material and labor costs are*

$$\rho_c^{level}(\omega) = 1 + [\mu(\omega) - 1] \frac{mc(\omega)}{mc(\Omega)} \frac{1 - \beta(\Omega)}{1 - \beta(\omega)},$$
$$\rho_w^{level}(\omega) = 1 + [\mu(\omega) - 1] \frac{mc(\omega)}{mc(\Omega)} \frac{\beta(\Omega)}{\beta(\omega)}.$$

   If sector ω uses labor less intensively than the marginal sector, $\beta(\omega) < \beta(\Omega)$, then firms in ω exhibit higher pass-through of unit labor costs than material costs, $\rho_w^{level}(\omega) > \rho_c^{level}(\omega)$.

3. *If $\eta = 0$ and the marginal sector only uses labor in production, i.e., $\beta(\Omega) = 1$, then firms exhibit complete pass-through in levels of materials costs, $\rho_c^{level}(\omega) = 1$ and $\rho_c^{log} < 1$, but*

complete log pass-through of labor costs, $\rho_w^{level}(\omega) \geq \mu(\omega)$ and $\rho_w^{log}(\omega) \geq 1$.
These pass-throughs in logs and levels for each input $x \in \{c, w\}$ can be measured as

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

where $Costs(\omega, x)$ is sector ω's expenditures on input x. The "adjusted pass-through in levels" of labor costs $\rho_w^{adj} = 1$, where

$$\frac{d \log p(\omega)}{d \log w} = \rho_w^{adj} \frac{LaborCosts(\omega) + VariableProfits(\omega)}{Sales(\omega)}.$$

Proof. See Appendix B.5. □

Proposition 9 shows that a demand system with $\eta = 0$ can generate different pass-through rates of material and labor costs. Furthermore, if the marginal sector only uses labor in production, the 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. Intuitively, the marginal dollar earned by consumers is spent on purchasing from the marginal sector Ω. If the marginal sector primarily uses labor in production, an increase in the price of labor therefore raises the price of the marginal unit of consumption. When $\eta = 0$, firms' additive markups are determined relative to the price of the marginal unit of consumption. As a result, an increase in labor costs is passed-through at a higher rate than materials costs because it increases both firms' marginal costs and additive markups.

Proposition 9 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 9 indicates that we should use the revenue-share of labor costs plus variable profits. Doing so takes into account that labor costs determine the level of firms' markups and restores complete pass-through in levels, $\rho_w^{\text{adj}} = 1$.

Empirical evidence. We now turn to the data to explore whether this stylized model can help 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 input categories and input price indices.

Let us start by exploring whether differences in the pass-through of materials and labor costs described by Okun (1981) appear in the data. We measure the pass-through

of input cost changes for each input $k \in \{\text{Materials, Energy, Production Labor}\}$ to output price changes using the specifications,

$$\Delta \log p_{it} = \sum_k \rho_k^{\log} \left(\frac{\text{Costs}_{ikt-1}}{\text{VariableCosts}_{it-1}} \times \Delta \log c_{ikt} \right) + \alpha_i + \phi_t + \varepsilon_{it}, \tag{18}$$

$$\Delta \log p_{it} = \sum_k \rho_k^{\text{level}} \left(\frac{\text{Costs}_{ikt-1}}{\text{Sales}_{it-1}} \times \Delta \log c_{ikt} \right) + \alpha_i + \phi_t + \varepsilon_{it}, \tag{19}$$

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 (across 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 (18) and (19) correspond to the pass-through rates defined in Proposition 9.

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

Table 10 column 1, which reports results from (18), 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 appears to be the "special" case. Column 2, which estimates (19), 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 9 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 costs by accounting for the fact that additive markups, and thus variable profits, scale with the price of labor.

Table 10: 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 (18) and (19). Column 3 estimates a variant of (19) replacing the revenue-share of labor input with the revenue-share of labor inputs plus variable profits. Variable costs in column 1 are defined as the sum of material, energy, and production labor costs, and variable profits in column 3 are defined as sales less variable costs. Standard errors two-way clustered by industry and year. ** indicates significance at 5%.

8.4 Dynamics of Consumer Price Inflation

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

Model 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 an industry that consists of a unit mass of firms indexed by f. Firms in each industry possess identical production functions, and the cost of producing y units for a firm in industry i is

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

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. 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[32]

$$\frac{y_{if}}{\int_0^1 y_{ig} dg} = \frac{\exp(-\frac{\phi_i}{w} p_{if})}{\int_0^1 \exp(-\frac{\phi_i}{w} p_{ig}) dg}. \tag{20}$$

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

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

The logit demand system in (20) is a member of the class of demand systems where $\eta = 0$ and, as can be seen from this expression, predicts complete pass-through in levels of marginal cost changes. Logit demand is also especially tractable for our purposes because, like CES demand, it implies that firms' desired prices depend only on their own marginal costs and not the marginal costs or prices of other firms.

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

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

[32]While this logit demand system is typically microfounded with discrete choice, Anderson, de Palma, and Thisse (1988) show that these demand curves result when industry output y_i is an aggregate of varieties y_{if} given by

$$y_i = \int_0^1 y_{if} df + \frac{\kappa_i}{\phi_i} \left[\left(\int_0^1 y_{if} df \right) \log \left(\int_0^1 y_{if} df \right) - \left(\int_0^1 y_{if} \log y_{if} df \right) \right] + \kappa_i l_i.$$

Note that l_i is labor that can be used to produce the industry output y_i in lieu of firms' varieties. One must choose κ_i so that the wage w pins down firms' additive markups and $l_i = 0$ in equilibrium.

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

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

Calibration. We calibrate a log-linearized version of the model. The set of goods includes the 402 industries in the Bureau of Economic Analysis's (BEA) detailed input-output tables. We define the set of goods with exogenous prices $\mathcal{N}^{\text{exog}}$ as "Stage 1" industries designated by the BLS.[33] Data on price indices for these goods, p_{it}^{exog}, are from the BLS Producer Price Index (PPI) program from 1982–2018. We use replication 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 take the average hourly earnings of production and nonsupervisory employees as our measure of production wages.

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

$$d \log mc_{it} = \sum_j \Omega_{ij} d \log p_{jt}, \tag{21}$$

where Ω_{ij} is the steady-state share of sector i's variable costs spent on good j. For our baseline results, we take these expenditure shares from the 2012 BEA tables.[34] Likewise, the retail sector's expenditures across industries are given by personal consumption expenditures across industries from the BEA. For Calvo frictions in each industry, we use data on monthly frequencies of price adjustment by industry from Pasten, Schoenle, and Weber (2020), who compute these probabilities of price adjustment using the firm-level data that underlies the BLS PPI.

For the model with percentage markups, we consider three definitions of variable costs: (1) materials costs, (2) materials costs and employee compensation, and (3) materials costs, employee compensation, and consumption of fixed capital. Material costs and employee compensation are reported in the BEA input-output tables. We compute consumption

[33] The BLS organizes industries into four stages of production flow: Stage 4 identifies downstream industries that largely sell to consumers and Stage 1 identifies industries that are most upstream from consumer demand. The most recent mapping from BEA industries to BLS stage assignments is from 2012 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`.

[34] Around the steady state, (21) describes changes in marginal costs up to a first-order regardless of elasticities of substitution in production. In Appendix Table A11, we report results allowing for the expenditure shares Ω_{ij} to respond endogenously to prices due to input complementarity.

of fixed capital by multiplying gross operating surplus for each industry by the ratio of consumption of fixed capital to gross operating surplus for each industry reported in the BEA's components of value added. For each definition of variable costs, we set σ_i to match each industry's ratio of sales to variable costs. For the model with additive markups, we likewise choose ϕ_i in each industry to match gross operating surplus as a share of sales.

Results for inflation volatility. Table 11 reports the volatility of consumer price inflation in the calibrated model from 1982–2018. The standard deviation of annual inflation rates in the model with 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.[35]

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

However, reducing the volatility of consumer price inflation in this way implies average markups that appear too low relative to markups estimated in microdata. The cost-weighted average markup across industries falls from 2.19 to 1.31 when we include labor costs, and falls further to 1.17 when we include consumption of fixed capital as part of variable costs. The implied markups for manufacturing industries are even lower. In comparison, De Loecker, Eeckhout, and Unger (2020) estimate a cost-weighted average markup of 1.25 among public firms and average markups in excess of 1.7 for firms in the Census of Manufacturing. Estimates of this magnitude are also typical in industry-specific studies in the industrial organization literature.[36]

The additive-markup model 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. In the

[35] If 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.

[36] 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) find an aggregate markup around 1.10, estimating markups as firms' operating margins less depreciation.

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

	Std. deviation of annual inflation, 1982–2018	Cost-weighted average markup	
		Mfg.	All
Data:			
Personal Consumption Expenditures (PCE) Price Index	1.1%		
Consumer Price Index for All Urban Consumers	1.3%		
Model:			
Percentage markups ($\eta = 1$)			
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
Additive markups ($\eta = 0$)	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").

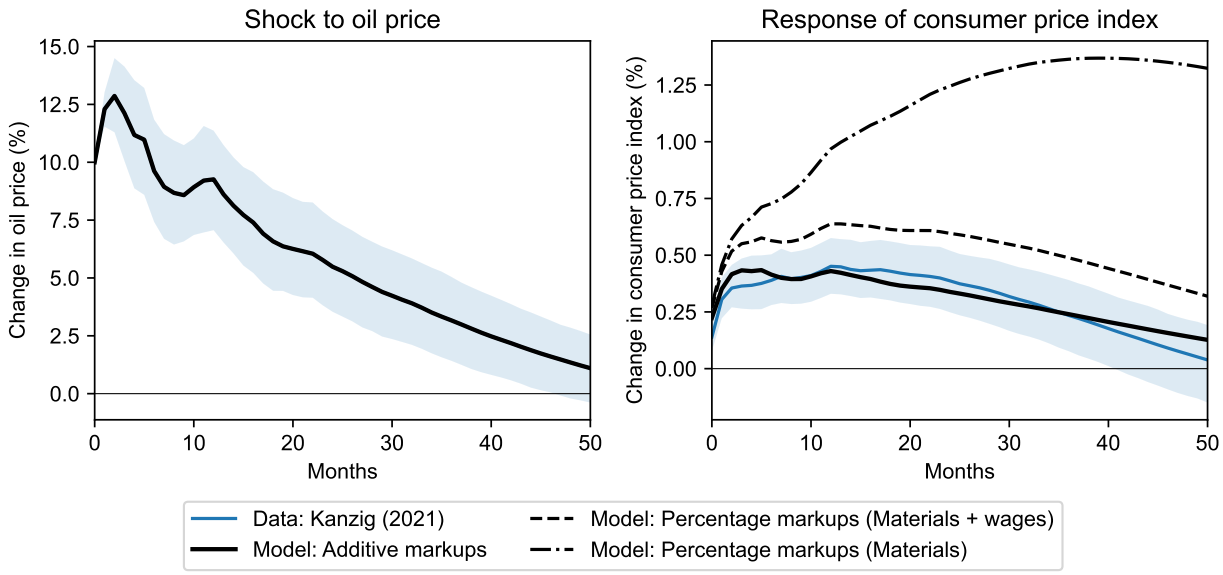
percentage-markup model, larger markups amplify the effect of upstream price movements on downstream prices and inflation, while in the additive-markup model, upstream price movements are passed through in levels regardless of the size of markups.

Response to a shock to the oil price. The input-output model with additive markups not only accounts for the aggregate volatility of inflation but also better matches the response of consumer price inflation to specific, identified shocks. We demonstrate this using shocks to oil production constructed by Känzig (2021).

We feed the path of oil prices following an oil supply news shock, shown in the left panel of Figure 5, into the calibrated model.[37] The right panel of Figure 5 shows that the consumer price index in the data reaches a maximum response of 45 log points at twelve months after the shock. Compared to the data, the percentage-markup model predicts too much responsiveness of consumer price inflation to the shock: at twelve months the predicted response of consumer price inflation 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 response of consumer inflation at twelve months

[37]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.

is 43 log points, and the predicted response of consumer price inflation to the oil supply shock falls within the 68 percent confidence interval from the data at all horizons.

This exercise provides further evidence that the responsiveness of consumer price inflation to upstream price movements in the additive-markup model more closely matches 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. This evidence of long-run, complete pass-through in levels is a useful for discriminating between models of demand. While homothetic demand systems commonly used in macroeconomics and trade are incompatible with our evidence, we identify an

alternative class of demand systems that accords with complete pass-through in levels.

Integrating demand systems that generate pass-through in levels into workhorse models not only brings the behavior of prices in those models in line with the data, but also generates new insights. In this paper, we explore how integrating pass-through in levels into models of industry dynamics, multi-sector models, and models with input-output linkages affects the predictions of each model. These are only a sample of the potential applications. For example, in a companion paper we explore how pass-through in levels interacts with differences in consumption patterns across the income distribution (Sangani 2025). Since low-income households tend to purchase products with lower markups (Sangani 2022), pass-through in levels generates cyclical fluctuations in inflation inequality over the commodity cost cycle. We anticipate that pass-through in levels may be useful for understanding a variety of other price and firm dynamics in the data.

References

Adao, R., A. Costinot, and D. Donaldson (2017). Nonparametric counterfactual predictions in neoclassical models of international trade. *American Economic Review 107*(3), 633–689.

Afrouzi, H., A. Drenik, and R. Kim (2023). Concentration, market power, and misalloation: The role of endogenous customer acquisition. Technical Report 31415, National Bureau of Economic Research.

Aguiar, M. and M. Bils (2015). Has consumption inequaltiy mirrored income inequality. *American Economic Review 105*(9), 2725–2756.

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. and A. de Palma (2020). Decoupling the ces distribution circle with quality and beyond: Equilibrium distributons and the CES-logit nexus. *The Economic Journal 130*(628), 911–936.

Anderson, S. P., A. de Palma, and J.-F. Thisse (1988). A representative consumer theory of the logit model. *International Economic Review 29*(3), 461–466.

Anderson, S. P., A. de Palma, and J.-F. Thisse (1992). *Discrete choice theory of product differentiation*. MIT Press.

Argente, D., D. Fitzgerald, S. Moreira, and A. Priolo (2021). How do entrants build market share? The role of demand frictions. *American Economic Review: Insights*.

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.

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.

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

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

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

Baumol, W. J. (1959). *Business Behavior, Value, and Growth*. New York: MacMillan.

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.

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. and P. A. Haile (2021). Foundations of demand estimation. *Handbook of Industrial Organization 4*(1), 1–62.

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

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.

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.

Blinder, A. S. (1994). On sticky prices: Academic theories meet the real world. *Monetary Policy*, 117–150.

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.

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.

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.

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.

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.

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.

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.

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.

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.

Eichenbaum, M., N. Jaimovich, and S. Rebelo (2011). References prices, costs, and nominal rigidities. *American Economic Review 101*(1), 234–262.

Einav, L., P. J. Klenow, J. D. Levin, and R. Murciano-Goroff (2021). Customers and retail growth. Technical Report 29561, National Bureau of Economic Research.

Eitches, E. and V. Crain (2016). Using gasoline data to explain inelasticity. *Bureau of Labor Statistics "Beyond the Numbers" 5*(5).

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

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.

Gandhi, A. and A. Nevo (2021). Empirical models of demand and supply in differentiated products industries. *Handbook of Industrial Organization 4*(1), 63–139.

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.

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.

Hall, R. L. and C. J. Hitch (1939). Price theory and business behavior. *Oxford Economic Papers* (2), 12–45.

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.

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

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

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.

Kaplan, G., G. Menzio, L. Rudanko, and N. Trachter (2019). Relative price dispersion. *American Economic Journal: Microeconomics 11*(3), 68–124.

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

Kenkel, D. S. (2005). Are alcohol taxes fully passsed 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.

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

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.

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

Lanzillotti, R. F. (1958). Pricing objectives in large companies. *American Economic Review 48*(5), 921–940.

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.

Maskin, E. and J. Tirole (1988). A theory of dynamic oligoply, 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.

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.

Miravete, E. J., K. Seim, and J. Thurk (2022). Robust pass-through estimation in discrete choice 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.

Okrent, A. and J. Alston (2012). The demand for disaggregated food-away-from-home and food-at-home products in the United States. Technical Report 139, USDA-ERS Economic Research Report.

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

Orchard, J. (2022). Cyclical demand shifts and cost of living inequality. Working paper.

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.

Rotemberg, J. J. (2005). Customer anger at price increases, changes in the frequency of price adjustment and monetary policy. *Journal of Monetary Economics 52*(4), 829–852.

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

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.

Sangani, K. (2025). Pass-through in levels and the unequal incidence of commodity inflation. Working paper.

Sattinger, M. (1984). Value of an additional firm in monopolistic competition. *Review of Economic Studies 51*(2), 321–332.

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.

Werning, I. (2022). Expectations and the rate of inflation. Technical Report 30260, National Bureau of Economic Research.

Westphal, R. M. (2024). What you don't know can't pass through: Consumer beliefs and pass-through rates. Working paper.

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.

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

Online Appendix

(Not for publication)

A Additional Tables and Figures **2**

B Proofs **23**

C Retail Gasoline Data from Other Markets **35**

Appendix A Additional Tables and Figures

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

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

Harding, Leibtag, and Lovenheim (2012)	Cigarettes	Excise taxes	0.85–1.02 (Pass-through "stabilizes around one at 52 miles from tax border.")
DeCicca, Kenkel, and Liu (2013)	Cigarettes	Excise taxes	1.02 ("We cannot reject the hypothesis that the rate of shifting is 1.")
Fabra and Reguant (2014)	Electricity	Emissions costs	0.83–0.86 ("Except for off-peak hours, we are unable to reject full pass-through in all specifications.")
Chiou and Muehlegger (2014)	Cigarettes	Excise taxes	0.80 (premium cigarettes), 0.92 (discount cigarettes).
Conlon and Rao (2020)	Distilled spirits	Excise taxes	0.80–3.78
Cawley et al. (2020)	Sugar-sweetened beverages	Excise taxes	0.61 ("Stores in Oakland raised prices of taxed beverages by 1.00 cent per ounce on average after on year, which is exactly the amount of the tax." The lower pass-through estimate is due to difference-in-differences 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, Ashmore, Baker, and McKernan (1998)	Office supplies	Merchandise costs	0.15 (idiosyncratic shocks), 0.85 (aggregate shocks, estimated indirectly using sum of reaction to own and competitors' cost shocks)
Gron and Swenson (2000)	Cars	Wage costs	0.38–0.47

Peltzman (2000)	Variety of PPI and CPI 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) (Uses same data sources as Leibtag et al. 2007.)
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)
Auer et al. (2018)	Cars	Exchange rate	0.17 (average, ranging from 0.03 for low-quality cars to 0.25 for high-quality cars)
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)
Alexander, Han, Kryvtsov, and Tomlin (2024)	Wholesalers	Merchandise costs	0.79 (aggregate cost shocks), 0.69 (idiosyncratic shocks)

Table A2: Unit root tests for commodity cost series.

	Levels			First differences		
	Autocorrelation (β) (std. error)		ADF test p-value	Autocorrelation (γ) (std. error)		ADF test p-value
Retail gasoline						
Unleaded terminal	0.996	(0.007)	0.731	0.449	(0.058)	0.000
Premium unleaded terminal	0.995	(0.006)	0.665	0.442	(0.058)	0.000
Food products						
Coffee	0.983	(0.010)	0.322	0.229	(0.052)	0.000
Sugar	0.975	(0.018)	0.242	0.199	(0.083)	0.000
Beef	0.997	(0.008)	0.939	0.238	(0.042)	0.000
Rice	0.987	(0.010)	0.165	0.347	(0.078)	0.000
Flour	0.984	(0.011)	0.343	0.213	(0.047)	0.000
Orange	0.967	(0.013)	0.028	0.238	(0.045)	0.000
Manufacturing input costs						
Materials	0.987	(0.013)	0.549	0.334	(0.083)	0.072
Materials + energy	0.992	(0.010)	0.537	0.347	(0.086)	0.079
Materials + energy + prod. labor	0.989	(0.010)	0.562	0.362	(0.092)	0.094

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

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

Columns 2 and 5 report Newey-West standard errors with four lags. Columns 3 and 6 report the p-value from Augmented Dickey-Fuller tests for unit roots, where the null hypothesis is that the series is a unit root process. For manufacturing input costs, we report median p-values across all industries.

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

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

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

Table 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[38]	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[39])
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[40])
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.[41])

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

Table A7: 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). Standard errors clustered by brand. * indicates significance at 10%, ** at 5%.

Table A8: Commodity costs and price dispersion, in levels and logs.

Panel A: Price Dispersion	*Std. Unit Price*			*Std. Log Unit Price*		
	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. Unit Price*			*Δ Std. Log Unit Price*		
	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

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

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

where $\text{UnitPriceDispersion}_t$ is the standard deviation of average 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 a 5% level.

Table A9: Pass-through for manufacturing industries using commodity price instrument.

Inputs:	Δ *Log Output Price*$_t$		
	Materials (IV1)	+ Energy (IV2)	+ Production Labor (IV3)
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. ** indicates significance at 5%.

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

Horizon (years):	Δ *Log Output Price*$_{t-h\to t}$				
	$h=1$ (1)	$h=2$ (2)	$h=3$ (3)	$h=4$ (4)	$h=5$ (5)
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 8. 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. * indicates significance at 10%, ** at 5%.

Table A11: Volatility of consumer price inflation, allowing for endogenous changes in expenditure shares due to Leontief production.

	Std. deviation of annual inflation, 1982–2018	
	Baseline (Cobb-Douglas)	Leontief inputs
Percentage markups ($\eta = 1$):		
Variable costs = Materials	2.5%	2.5%
Variable costs = Materials + wages	1.7%	2.0%
Variable costs = Materials + wages + fixed capital cons.	1.6%	1.7%
Additive margins ($\eta = 0$)	1.3%	1.4%

Note: In the baseline, we assume each industry's expenditure shares on inputs Ω_{ij} are constant. This table reports the volatility of inflation rates if we instead assume that each industry's production functions are Leontief in all inputs, using the deviation in each industry's prices from 2012 to discipline the changes in expenditure shares.

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

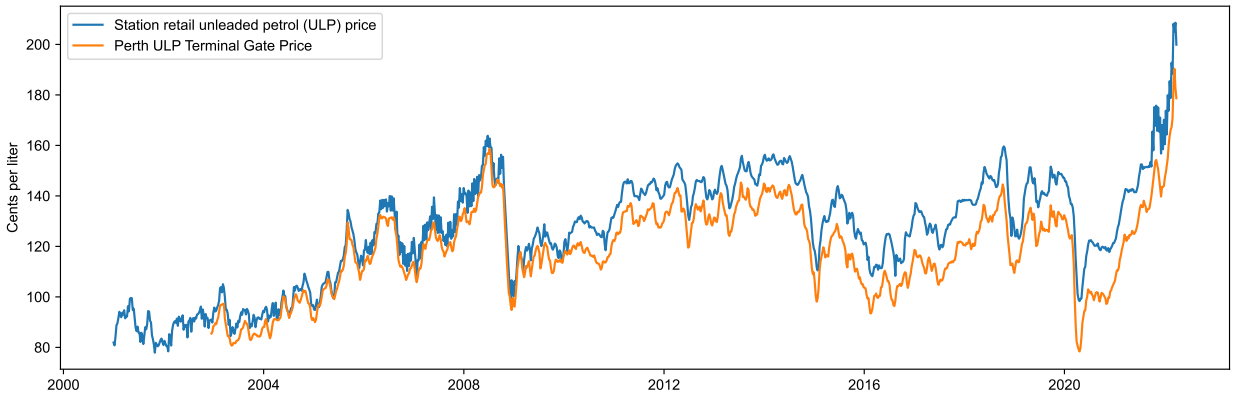
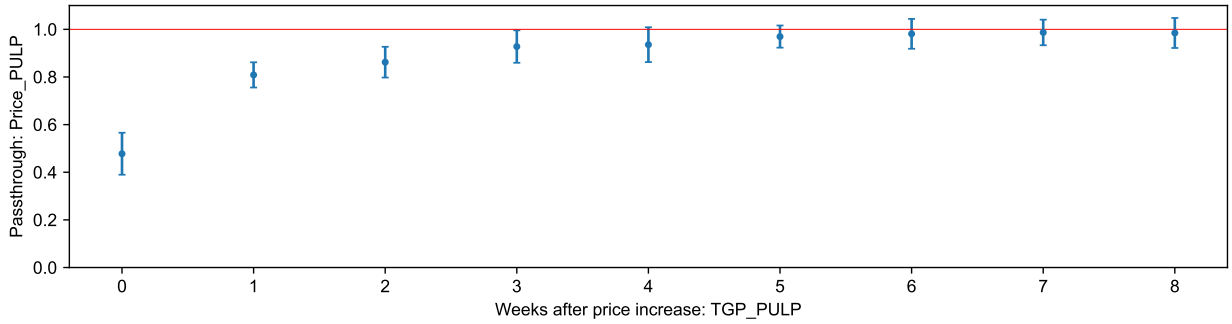
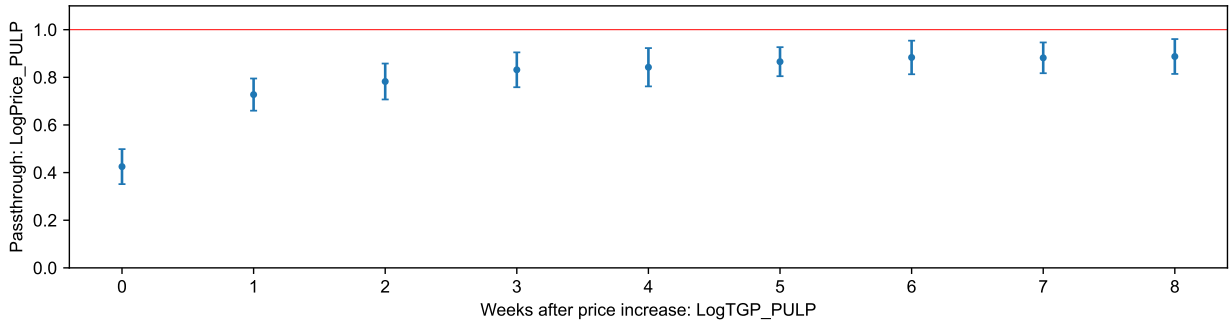


Figure A2: Pass-through of premium unleaded petrol wholesale costs to retail prices.



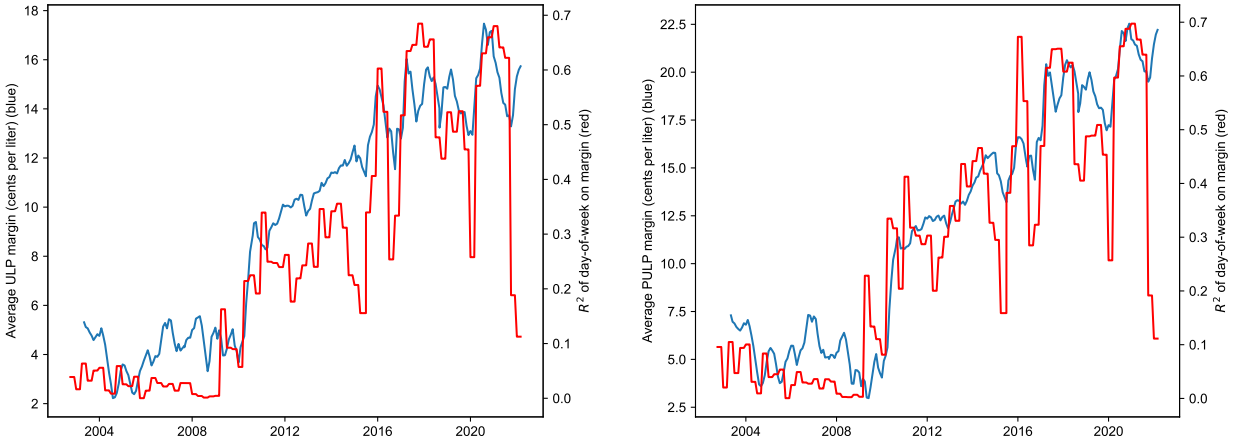
(a) Pass-through in levels.



(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.

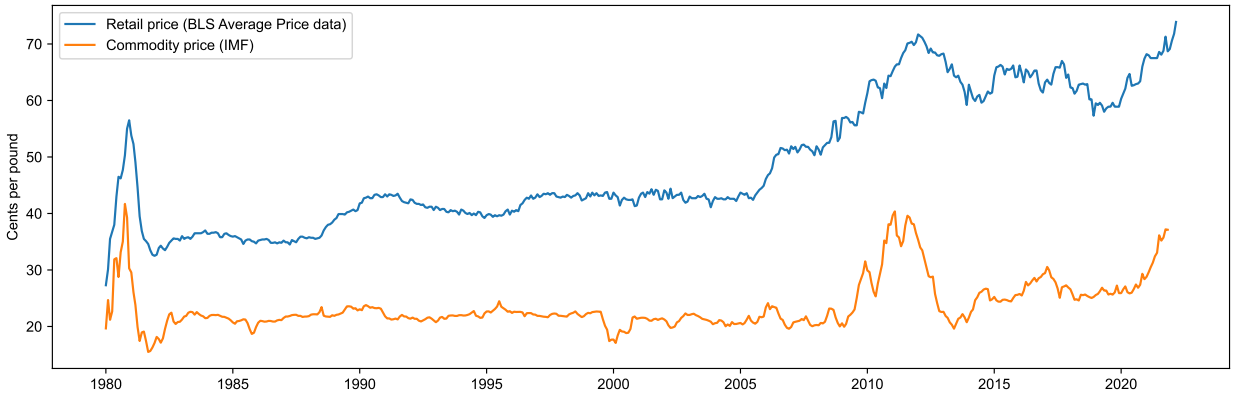
Figure A3: Comovement of retail gas margins with strength of weekly price cycles.



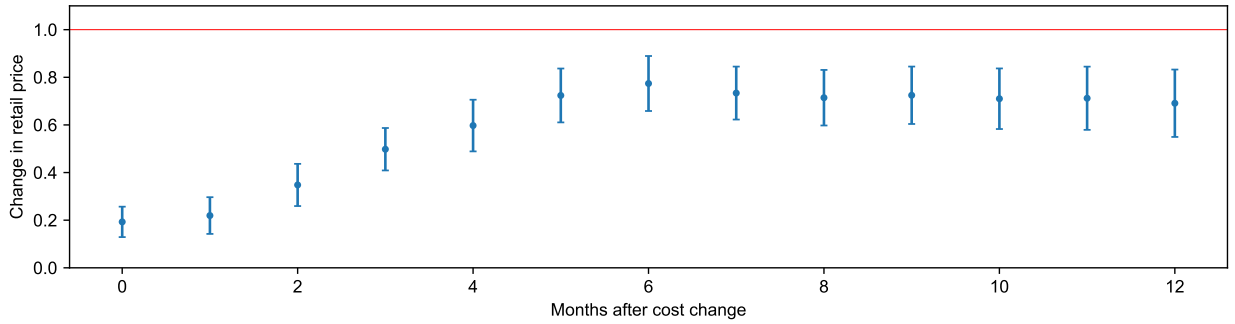
(a) Unleaded petrol (ULP). **(b)** Premium unleaded petrol (PULP).

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.

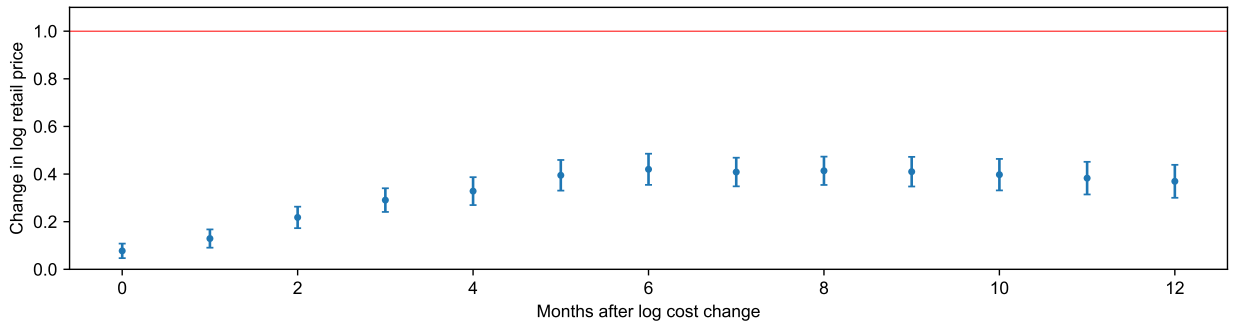
Figure A4: Passthrough of sugar commodity costs to retail prices.



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



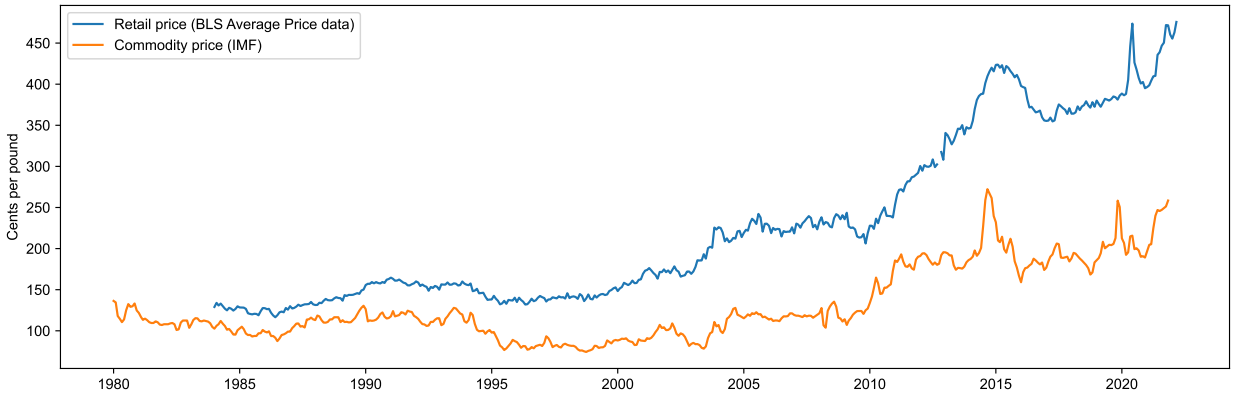
(b) Pass-through in levels.



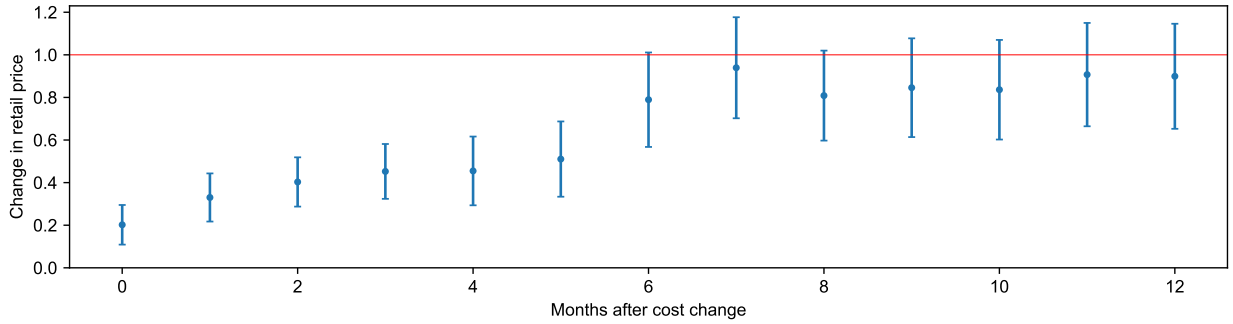
(c) Pass-through in logs.

Note: Panel (a) plots the time series of the commodity price from the IMF and the Average Price Data series from the BLS. The series are adjusted by the conversion factors in Appendix Table A6 so that the two series are in comparable units. Panels (b) and (c) plot the cumulative pass-through to month T, $\sum_{k=0}^{T} b_k$, from the specifications (3) and (4), using a total horizon of $K = 12$ months.

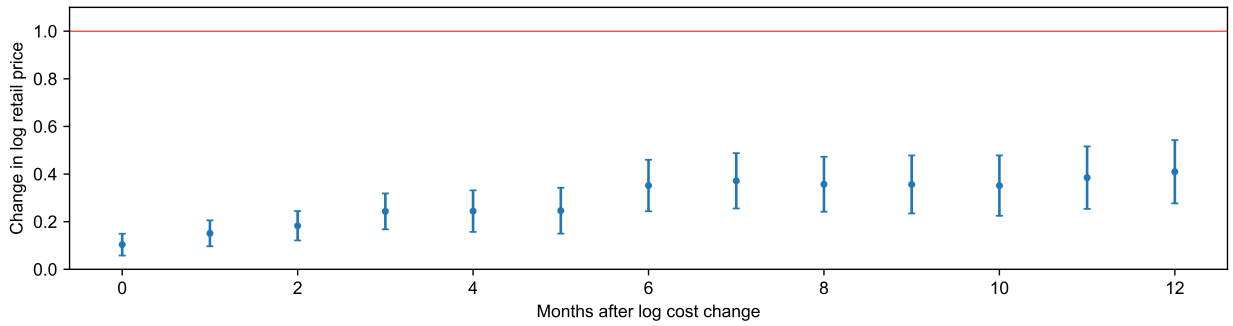
Figure A5: Passthrough of beef commodity costs to retail prices.



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



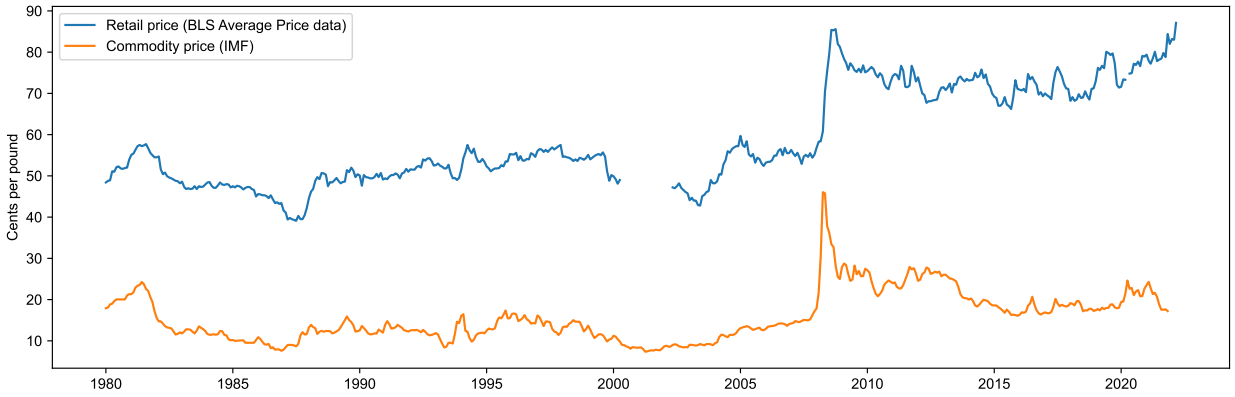
(b) Pass-through in levels.



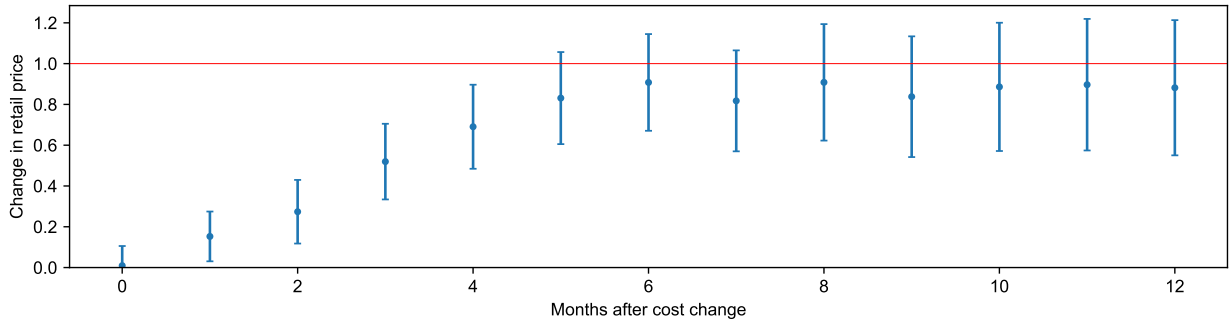
(c) Pass-through in logs.

Note: Panel (a) plots the time series of the commodity price from the IMF and the Average Price Data series from the BLS. The series are adjusted by the conversion factors in Appendix Table A6 so that the two series are in comparable units. Panels (b) and (c) plot the cumulative pass-through to month T, $\sum_{k=0}^{T} b_k$, from the specifications (3) and (4), using a total horizon of $K = 12$ months.

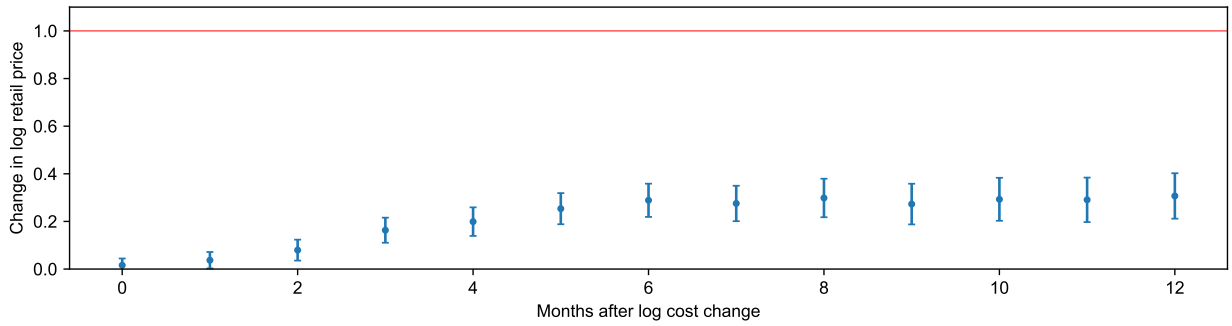
Figure A6: Passthrough of rice commodity costs to retail prices.



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



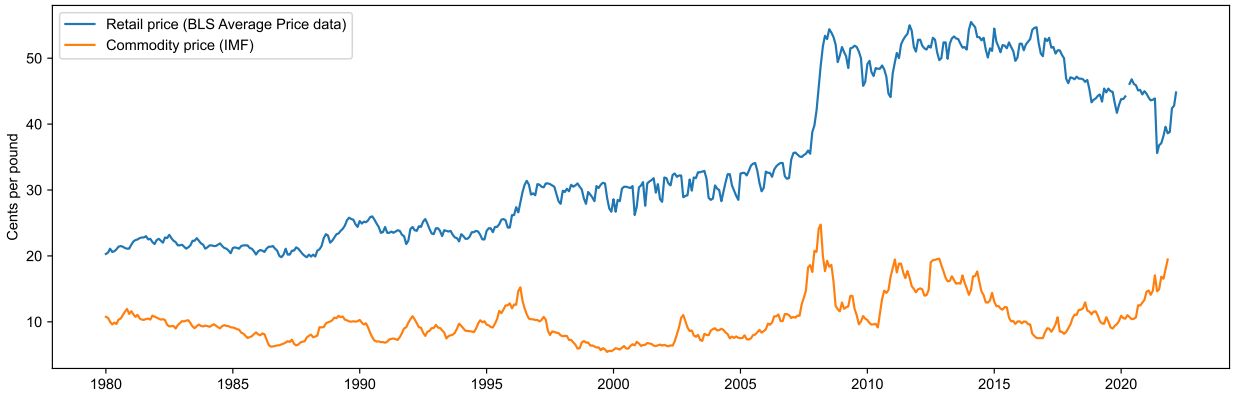
(b) Pass-through in levels.



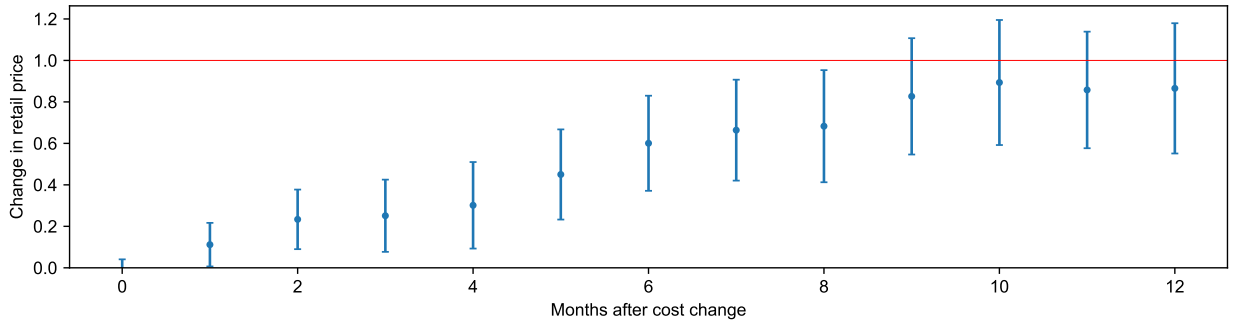
(c) Pass-through in logs.

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.

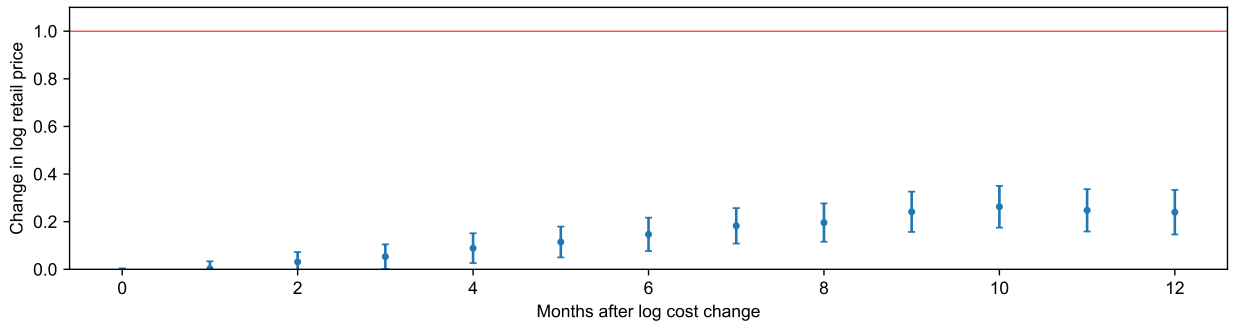
Figure A7: Passthrough of flour commodity costs to retail prices.



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



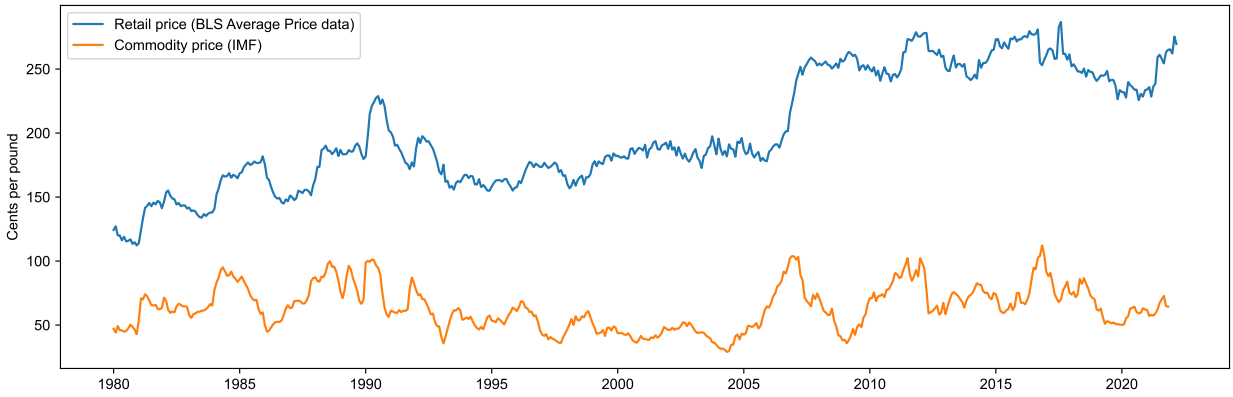
(b) Pass-through in levels.



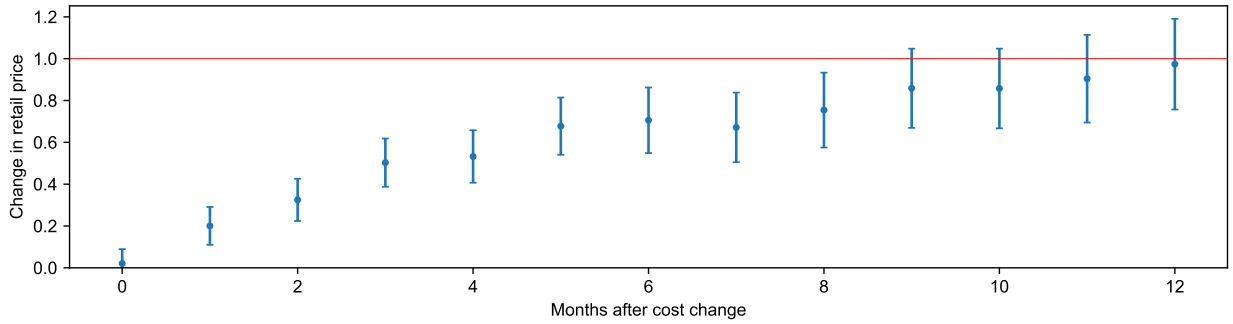
(c) Pass-through in logs.

Note: Panel (a) plots the time series of the commodity price from the IMF and the Average Price Data series from the BLS. The series are adjusted by the conversion factors in Appendix Table A6 so that the two series are in comparable units. Panels (b) and (c) plot the cumulative pass-through to month T, $\sum_{k=0}^{T} b_k$, from the specifications (3) and (4), using a total horizon of $K = 12$ months.

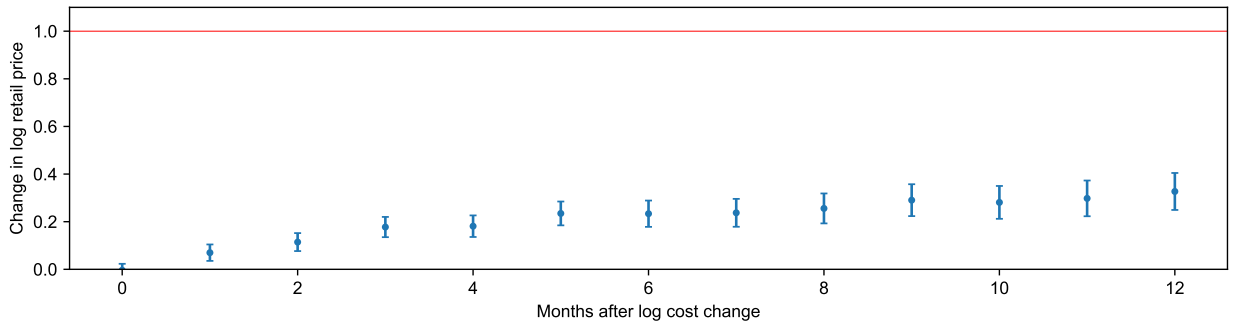
Figure A8: Passthrough of frozen orange juice commodity costs to retail prices.



(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 A9: Price of a coffee UPC in two stores in same 3-digit ZIP in Philadelphia, PA.

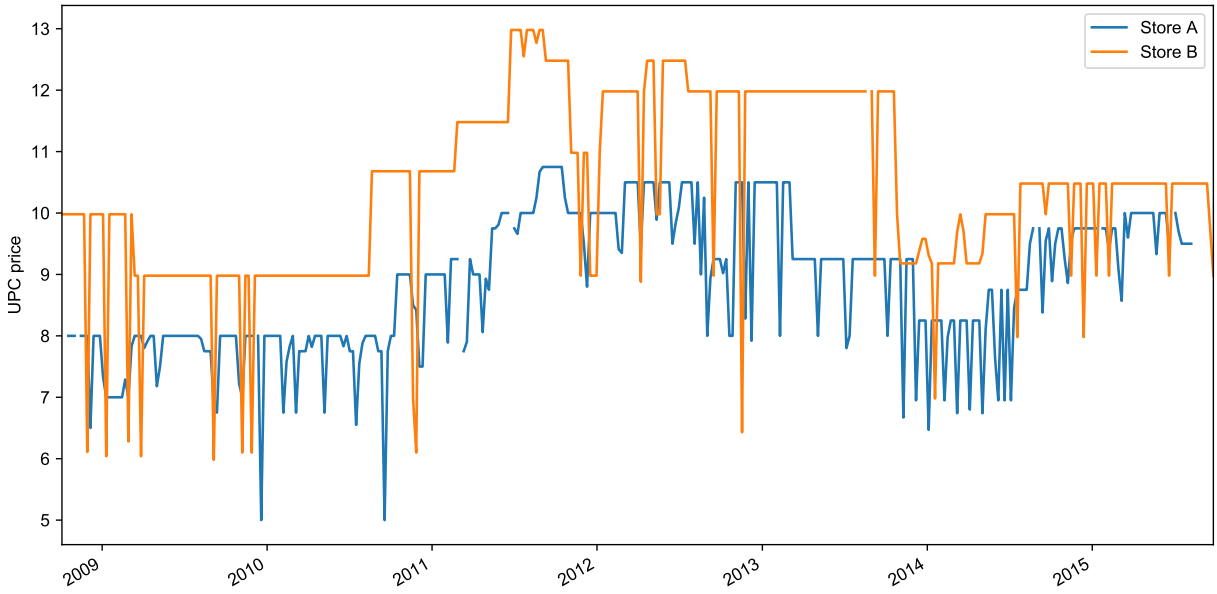
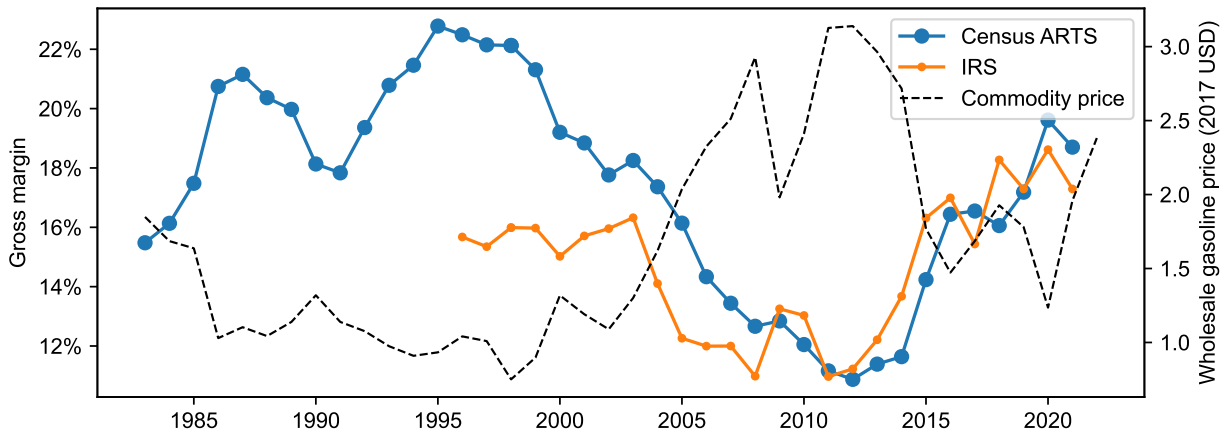
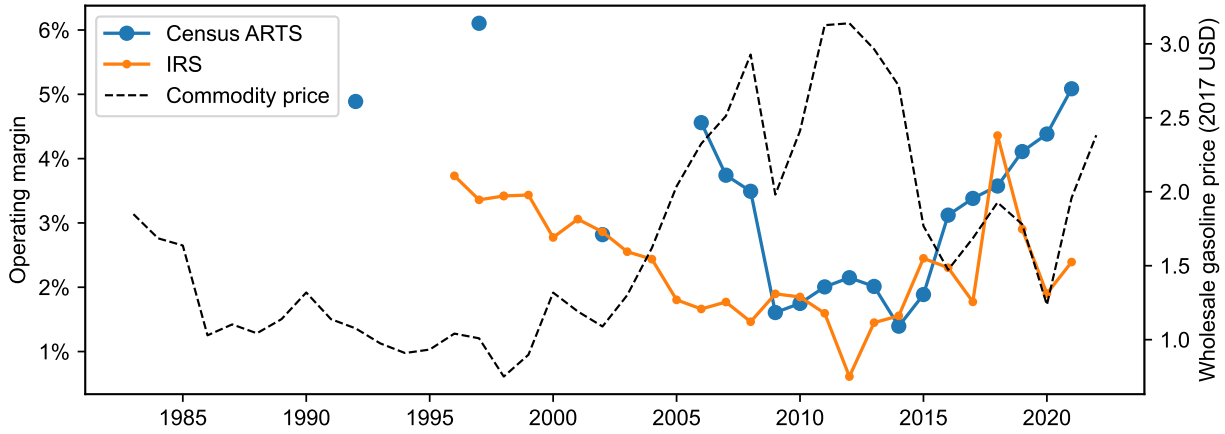


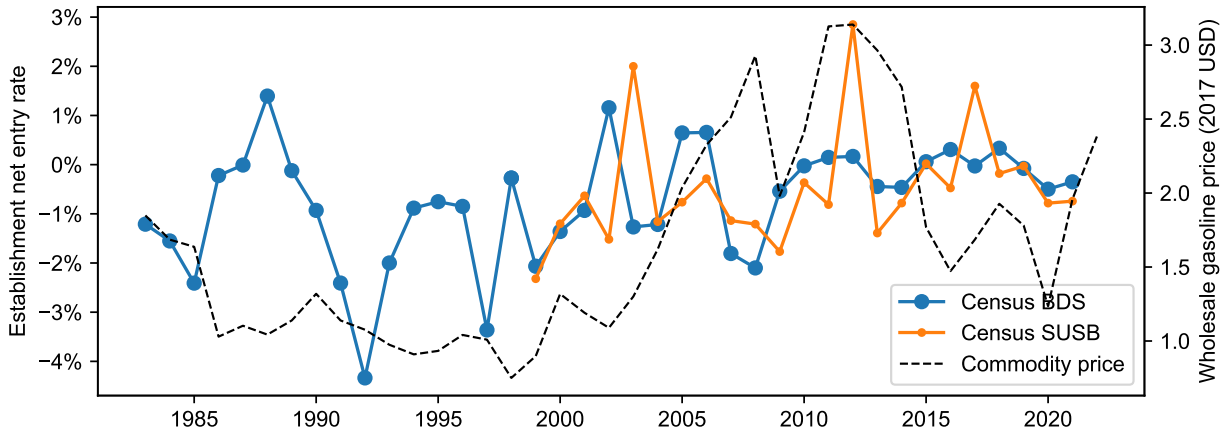
Figure A10: Gross margins, operating margins, and entry for retail gas stations.



(a) Gross margin.



(b) Operating margin.



(c) Entry.

Appendix B Proofs

B.1 Estimating Long-Run Pass-through

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

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

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

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

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

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

Assumption 3 (Profit-maximizing prices)**.** Absent nominal rigidities, a firm's desired price in period t is

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

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

Assumption 4 (Cost process)**.** The commodity cost process follows

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

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

Assumption 5. Firms' losses from setting price p_t are given by,

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

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

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

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

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

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

Firms' optimal reset prices solve the maximization problem,

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

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

$$p_t^{\text{reset}} = \mu \frac{\sum_{s=0}^{\infty} \beta^s S_s \mathbb{E}\left[c_{t+s}\right]}{\sum_{s=0}^{\infty} \beta^s S_s} + (\mu w + m) = \mu \frac{\sum_{s=0}^{\infty} \beta^s S_s \rho^s}{\sum_{s=0}^{\infty} \beta^s S_s} c_t + (\mu w + m). \tag{22}$$

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

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

In this expression, $\frac{S_k}{\sum_{s=0}^{\infty} S_s}$ is the fraction of ongoing price spells with a length of k periods, h_k is the probability that those firms will reset their price in the current period, and $p_t^{\text{reset}} - p_{t-k-1}^{\text{reset}}$ is the change in price they will choose if they reset their price today. By substituting in the reset price (22), we find that

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

As the number of lags $K \to \infty$, clearly $b_k = \mu\phi \frac{S_k}{\sum_{s=0}^{\infty} S_s}$. Thus, the estimated long-run pass-

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

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

B.2 Pass-Through Under Relaxed Assumptions

This section explores whether we can achieve pass-through in levels by retaining homothetic preferences, but relaxing assumptions about the production technology and correlations in input costs. Suppose each firm's price is equal to a markup μ times marginal cost mc:

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

Differentiating totally with respect to the commodity cost c, and imposing that the markup is related to the price elasticity of demand using the Lerner rule $\mu = \sigma/(\sigma - 1)$,

$$\frac{dp}{dc} = \frac{\sigma}{\sigma - 1 + \frac{d\log\sigma}{d\log p}} \frac{dmc}{dc}. \tag{23}$$

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

Curvature of demand. It follows immediately from (23) that if $dmc/dc = 1$ and the super-elasticity of demand $d\log\sigma/d\log p = 1$, then pass-through is complete in levels (see also Bulow and Pfleiderer 1983; Weyl and Fabinger 2013; Mrázová and Neary 2017). Note that the relevant notion of the super-elasticity of demand here is the percentage change in the elasticity of substitution across firms when all firms' prices rise by 1 percent. This is distinct from the super-elasticity of demand of the residual demand curve in models with homothetic demand. Logit demand with atomistic firms is the special case of $\eta = 0$ where this "global" super-elasticity of demand is equal to one (see Section 7).

Relaxing Leontief production. Suppose production is given by

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

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

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

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

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

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

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

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

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

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

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

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

Correlated non-commodity input costs. Suppose movements in the non-commodity input cost w are correlated with movements in the commodity cost. Then, to deliver

complete pass-through in levels, we must have:

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

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

B.3 Proofs for Section 7

Proof of Proposition 1. For any demand system, demand is homogeneous of degree one, i.e., $q_j(p, I) = q_j(\alpha p, \alpha I)$. By Euler's homogeneous function theorem,

$$\sum_n \frac{\partial \log q_j}{\partial \log p_n} + \frac{\partial \log q_j}{\partial \log I} = 0.$$

Homothetic preferences additionally imply that income elasticities for all goods are equal to one. Thus,

$$\sum_n \frac{\partial \log q_j}{\partial \log p_n} = -1, \qquad \text{and} \qquad \sum_n \frac{-\partial^2 \log q_j}{\partial \log p_j \partial \log p_n} = 0. \tag{24}$$

For firms, profit maximization yields the following first-order conditions for prices

$$1 = \left(\frac{p_j - c_j}{p_j}\right) \frac{-\partial \log q_j(p)}{\partial \log p_j}.$$

Differentiating totally 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 $d \log p_n$,

$$d \log p_j = d \log c_j - \frac{p_j - c_j}{c_j} \left(\frac{-\partial \log q_j(p)}{\partial \log p_j}\right)^{-1} \sum_n \frac{-\partial^2 \log q_j(p)}{\partial \log p_j \partial \log p_n} d \log p_n.$$

Consider the case where all firms' costs change by the same proportion $d \log c_j = d \log c$. We can conjecture and verify the solution $d \log p_j = d \log p = d \log c$ for all j, with the result following from (24). □

Proof of Proposition 3. Total industry expenditures are

$$I = \int_0^1 \sum_j p_j q_{ij} M di = \bar{q} M Y^{\eta} \sum_j p_j^{1-\eta}.$$

Substituting this into the expression for demand (14), we get

$$D_j(p, I) = I \frac{p_j^{-\eta}}{\sum_j p_j^{1-\eta}} \int_0^1 1\left\{\left(\delta_{ij} - \frac{p_j}{p_0}\right) q_{ij} \geq \left(\delta_{ik} - \frac{p_k}{p_0}\right) q_{ik}, \forall k \neq j\right\} di.$$

Homothetic preferences require that $D_j(\alpha p, I) = (1/\alpha) D_j(p, I)$. This requires that for any vector of firms' prices,

$$\int_0^1 1\left\{\left(\delta_{ij} - \frac{\alpha p_j}{p_0}\right) q_{ij} \geq \left(\delta_{ik} - \frac{\alpha p_k}{p_0}\right) q_{ik}\right\} di = \int_0^1 1\left\{\left(\delta_{ij} - \frac{p_j}{p_0}\right) q_{ij} \geq \left(\delta_{ik} - \frac{p_k}{p_0}\right) q_{ik}\right\} di.$$

Equivalently,

$$\int_0^1 1\left\{\delta_{ij} p_j^{-\eta} - \delta_{ik} p_k^{-\eta} \geq \frac{\alpha}{p_0}\left(p_j^{1-\eta} - p_k^{1-\eta}\right)\right\} di = \int_0^1 1\left\{\delta_{ij} p_j^{-\eta} - \delta_{ik} p_k^{-\eta} \geq \frac{1}{p_0}\left(p_j^{1-\eta} - p_k^{1-\eta}\right)\right\} di.$$

For $J > 1$, this condition does not hold for any vector of prices unless $\eta = 1$, in which case the right-hand side of the expression inside both indicator functions is equal to zero. □

Proof of Proposition 2. We list the assumptions on η and δ_{ij} that yield each of the demand systems in Proposition 2.

1. **(CES).** Suppose $\eta = 1$ and $\delta_{ij} = \xi_j \varepsilon_{ij}$, where ε_{ij} are i.i.d. draws from a Frechet distribution, $F(x) = \exp\left(-x^{-(\sigma-1)}\right)$.[42] Then, firm demands $D_j(p, I)$ are

$$D_j(p, I) = \frac{\xi_j^{\sigma-1} p_j^{-\sigma}}{\sum_k \xi_k^{\sigma-1} p_k^{1-\sigma}} I,$$

   which are equivalent to the demands under CES preferences with an elasticity of substitution σ and taste-shifters ξ.

2. **(Nested CES).** (Verboven 1996). Suppose $\eta = 1$, and δ_{ij} are drawn from the multi-

[42] Equivalently, $\log \varepsilon_{ij}$ are i.i.d. draws from a Gumbel distribution, with $\Pr\left(\log \varepsilon_{ij} \leq x\right) = \exp\left(-e^{-(\sigma-1)x}\right)$.

variate CDF,

$$F(x_1, ..., x_J) = \exp\left[-\sum_m \left(\sum_{j \in \mathcal{J}(m)} x_j^{-(\sigma_1 - 1)}\right)^{\frac{\sigma_2 - 1}{\sigma_1 - 1}}\right],$$

where m indexes markets and each firm belongs to exactly one market ($j \in \mathcal{J}(m)$ for exactly one m). Then, the demands $D_j(p, I)$ are equivalent to the demands under the nested CES preferences,

$$U = \left(\sum_m \left(\sum_{j \in \mathcal{J}(m)} y_j^{\frac{\sigma_1 - 1}{\sigma_1}}\right)^{\frac{\sigma_1}{\sigma_1 - 1}\frac{\sigma_2 - 1}{\sigma_2}}\right)^{\frac{\sigma_2}{\sigma_2 - 1}}.$$

3. **(Mixed CES).** (Adao et al. 2017). The demand system is mixed CES if $\eta = 1$ and $\delta_{ij} = \xi_{ij}\varepsilon_{ij}$, where ξ_{ij} are tastes for each product j that may vary systematically with i, and ε_{ij} are i.i.d. draws from a Frechet distribution with a shape parameter that varies with i, $F_i(x) = \exp\left(-x^{-(\sigma_i - 1)}\right)$.

4. **(Logit).** Suppose $\eta = 0$ and $\delta_{ij} = \xi_{ij}/\sigma + \varepsilon_{ij}$, where ε_{ij} are i.i.d. draws from a Gumbel distribution, $F(x) = \exp\left(-e^{-\sigma x}\right)$. Then we have the logit demand system,

$$D_j(p, I) = \bar{q}M\frac{\exp(\xi_j - \sigma p_j)}{\sum_k \exp(\xi_k - \sigma p_k)}.$$

5. **(Nested logit).** (Verboven 1996). Suppose $\eta = 0$ and $\delta_{ij} = \xi_j + \varepsilon_{ij}$, where ε_{ij} are drawn from the multivariate CDF,

$$F\left(x_1, ..., x_J\right) = \exp\left[-\sum_m \left(\sum_{j \in \mathcal{J}(m)} e^{-\sigma_1 x_j}\right)^{\sigma_2/\sigma_1}\right].$$

   Then we have the nested logit demand system

$$D_j\left(p, I\right) = \bar{q}M\frac{\exp\left(\sigma_1\left(\xi_j - p_j\right)\right)}{\sum_{k \in \mathcal{J}(m_j)} \exp\left(\sigma_1\left(\xi_k - p_k\right)\right)}\frac{\exp\left(\sigma_2 \Xi_{m(j)}\right)}{\sum_m \exp\left(\sigma_2 \Xi_m\right)},$$

   where the group value for market m is $\Xi_m = \frac{1}{\sigma_1}\log\left(\sum_{k \in \mathcal{J}(m)} \exp\left(\sigma_1\left(\xi_k - p_k\right)\right)\right)$.

6. **(Mixed logit).** The demand system is mixed logit if $\eta = 0$ and $\delta_{ij} = \xi_{ij} + \varepsilon_{ij}$, where ξ_{ij} are tastes for each product j that may vary systematically with i, and ε_{ij} are

i.i.d. draws from a Gumbel distribution with a shape parameter that varies with i, $F_i(x) = \exp(-e^{-\sigma_i x})$.

7. **(Multinomial probit).** The demand system is multinomial probit if $\eta = 0$ and δ_{ij} are draws from a multivariate normal distribution $N(\mu, \Sigma)$.

8. **(Competition on line).** We generate the demand system from Hotelling (1929) if $\eta = 0$, consumers i are uniformly distributed along the unit line from $[0, 1]$, and for firm j at location $a(j)$, $\delta_{ij} = |i - a(j)|$.

9. **(Competition on unit circle).** We generate the demand system from Salop (1979) if $\eta = 0$, consumers i are uniformly distributed around the unit circle from $[0, 1]$, and for J firms uniformly distributed around the circle, $\delta_{ij} = \min\{|i - \frac{j}{J}|, |i - \frac{j}{J} - 1|\}$.

□

Proof of Proposition 5. For each good j, define $\delta_{in}^{(j)} = \delta_{in} - \delta_{ij}$, and define the multivariate cumulative distribution function $F^{(j)}\left(\{x_k\}_{k\neq j}\right) = \Pr\left(\delta_{i1}^{(j)} \leq x_1, ..., \delta_{iJ}^{(j)} \leq x_J\right)$. When $\eta = 0$, we can rewrite the expression for demand (14) as

$$D_j(p) = \int_0^1 \prod_{j\neq n} 1\left\{\delta_{ij} - p_j \geq \delta_{in} - p_n\right\} q_{ij} M di = \bar{q} M F^{(j)}\left(p_1 - p_j, ..., p_J - p_j\right).$$

Assumption 2 ensures the derivative of $F^{(j)}$ with respect to each argument is well-defined. We find:

$$\frac{\partial D_j(p)}{\partial p_n} = \begin{cases} F_n^{(j)}\left(p_1 - p_j, ..., p_J - p_j\right) & n \neq j \\ -\sum_k F_k^{(j)}\left(p_1 - p_j, ..., p_J - p_j\right) & n = j \end{cases}$$

This means that the demand function for each firm satisfies:

$$\sum_n \frac{\partial D_j(p)}{\partial p_n} = 0, \qquad \text{and} \qquad \sum_n \frac{\partial^2 D_j(p)}{\partial p_j \partial p_n} = 0. \tag{25}$$

For firms, profit maximizing yields the standard first-order condition,

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

Differentiating totally yields the change in firm j's price dp_j in terms of changes in own

costs dc_j and others' prices dp_n,

$$dp_j = dc_j - \left(\frac{\partial D_j(p)}{\partial p_j}\right)^{-1} \sum_n \left(\frac{\partial D_j(p)}{\partial p_n} + \left(p_j - c_j\right)\frac{\partial^2 D_j(p)}{\partial p_j \partial p_n}\right) dp_n. \tag{26}$$

Suppose all firms' costs change by the same amount, $dc_j = dc$. We can conjecture and verify the solution $dp_j = dp = dc$ for all j, with the result following from (25). □

Proof of Proposition 6. We can rewrite the expression for demand (14) as

$$\begin{aligned} D_j(p) &= \int_0^1 1\left\{\left(\delta_{in} - \frac{p_n}{p_0}\right) q_{in} \leq \left(\delta_{ij} - \frac{p_j}{p_0}\right) q_{ij}, \text{ for all } n \neq j\right\} q_{ij} M di \\ &= \bar{q} Y^\eta M \int_0^1 \prod_{n \neq j} 1\left\{\delta_{in} \leq \frac{\delta_{ij} p_j^{-\eta} + \frac{1}{p_0}\left(p_n^{1-\eta} - p_j^{1-\eta}\right)}{p_n^{-\eta}}\right\} p_j^{-\eta} di. \end{aligned}$$

Impose that δ_{ij}, δ_{in} are i.i.d. draws from distribution F, and that $p_n = p$ for all $n \neq j$. Then,

$$D_j(p) = \bar{q} Y^\eta M \int_{-\infty}^{\infty} \left[F\left(\frac{\delta_{ij} p_j^{-\eta} + \frac{1}{p_0}\left(p^{1-\eta} - p_j^{1-\eta}\right)}{p^{-\eta}}\right)\right]^{J-1} p_j^{-\eta} f\left(\delta_{ij}\right) d\delta_{ij}.$$

Taking the derivative with respect to p_j yields the (unwieldy) expression,

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

Evaluating both $D_j(p)$ and $\partial D_j(p)/\partial p_j$ at a symmetric equilibrium where $p_j = p$, we get

$$D_j(p) = \bar{q}\left(\frac{Y}{p}\right)^\eta \frac{M}{J}, \qquad \text{and} \qquad \frac{\partial D_j(p)}{\partial p_j} = -\left((1-\eta)\frac{\phi_0}{p_0} + \eta\frac{\phi_1}{p}\right) D_j(p),$$

where we define

$$\begin{aligned} \phi_0 &= \int_{-\infty}^{\infty} J(J-1)\left[F\left(\delta_{ij}\right)\right]^{J-2}\left[f\left(\delta_{ij}\right)\right]^2 d\delta_{ij}, \\ \phi_1 &= 1 + \int_{-\infty}^{\infty} J(J-1)\left[F\left(\delta_{ij}\right)\right]^{J-2}\left[f\left(\delta_{ij}\right)\right]^2 \delta_{ij} d\delta_{ij}. \end{aligned}$$

Finally, substituting into the first-order condition from profit maximization yields,

$$p - c = \frac{D_j(p)}{-\partial D_j(p)/\partial p_j} = \frac{1}{\left((1-\eta)\frac{\phi_0}{p_0} + \eta\frac{\phi_1}{p}\right)}.$$

□

B.4 Proofs for Section 8.2

Proof of Proposition 8. The equilibrium is described by the following system of equations:

$$\begin{aligned}
Q &= p^{-\theta}, && \text{(Aggregate demand)}\\
q &= \frac{Q}{N}, && \text{(Symmetry)}\\
1 &= (p-c)\left((1-\eta)\frac{\phi_0}{p_0} + \eta\frac{\phi_1}{p}\right), && \text{(Pricing)}\\
\pi^{\text{gross}} &= pq - cq, && \text{(Definition of variable profits)}\\
\pi^{\text{op}} &= \pi^{\text{gross}} - f_o, && \text{(Definition of operating profits)}\\
N &= N_0\left(\pi^{\text{op}} - f_e\right)^{\zeta}. && \text{(Entry condition)}
\end{aligned}$$

We log-linearize these equations and solve for endogenous variables in terms of an exogenous change in cost, $d\log c$. First, for gross margins, we find

$$d\log m^{\text{gross}} = -\frac{(1-\eta)\frac{\phi_0}{p_0}}{(1-\eta)\frac{\phi_0}{p_0}\frac{p}{c} + \eta\frac{\phi_1}{p}} d\log c.$$

Thus, gross margins are constant if $\eta = 1$ and $d\log m^{\text{gross}}/d\log c < 0$ if and only if $\eta < 1$. When $\eta = 0$, the change in gross margins becomes, $d\log m^{\text{gross}} = \frac{cq}{pq} d\log c$, and thus 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 $\Pi^{\text{gross}} = (p-c)Q$.

$$d\log \Pi^{\text{gross}} = d\log(p-c) - \theta d\log p = \frac{(1-\theta)\eta\frac{\phi_1}{p} - \theta(1-\eta)\frac{\phi_0}{p_0}}{(1-\eta)\frac{\phi_0}{p_0}\frac{p}{c} + \eta\frac{\phi_1}{p}} d\log c.$$

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

$$\eta^* = \frac{\theta\frac{\phi_0}{p_0}}{(1-\theta)\frac{\phi_1}{p} + \theta\frac{\phi_0}{p_0}} \in [0,1).$$

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

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

Note that when $\zeta \to \infty$, $\pi^{\text{op}} = 0$. Thus, $d\log\pi^{\text{op}}$ is undefined, but $d\pi^{\text{op}} = dm^{\text{op}} = 0$. □

B.5 Proofs for Section 8.3

Proof of Proposition 9. 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 ω, which we denote $d\delta_{ij}(\omega)$ and $dp_{ij}(\omega)$. From the budget constraint, the change in the mass of sectors from which the consumer purchases is

$$d\Omega = -(1-\eta)\frac{\left[p_{ij}(\omega)\right]^{-\eta}}{\left[p_{ij}(\Omega)\right]^{1-\eta}}dp_{ij}(\omega)\,d\omega.$$

The change in the consumer's utility is then

$$\begin{aligned} dU_i &= \delta_{ij}(\Omega)\,\bar{q}\left(Y/p_{ij}(\Omega)\right)^{\eta}d\Omega + \left[d\delta_{ij}(\omega) - \eta\frac{\delta_{ij}(\omega)}{p_{ij}(\omega)}dp_{ij}(\omega)\right]\bar{q}\left(Y/p_{ij}(\omega)\right)^{\eta}d\omega \\ &= \left[d\delta_{ij}(\omega) - \left[\eta\frac{\delta_{ij}(\omega)}{p_{ij}(\omega)} + (1-\eta)\frac{\delta_{ij}(\Omega)}{p_{ij}(\Omega)}\right]dp_{ij}(\omega)\right]\bar{q}\left(Y/p_{ij}(\omega)\right)^{\eta}d\omega. \end{aligned}$$

From here, it is straightforward to apply the same derivation from the proof of Proposition 6 to solve for prices $p(\omega)$. When $\eta = 0$, we find

$$p(\omega) - mc(\omega) = \frac{p(\Omega)}{\phi_0(\omega)},$$

where

$$\phi_0(\omega) = \int_0^1 J(J-1)\left[F_\omega\left(d\delta_{ij}\right)\right]^{J-2} f_\omega\left(d\delta_{ij}\right)\delta_{ij}(\Omega)\,di.$$

The pass-through of a change to marginal costs $dmc(\omega)$ is

$$\frac{dp(\omega)}{dmc(\omega)} = 1 + \frac{1}{\phi_0(\omega)} \frac{dp(\Omega)}{dmc(\omega)} = 1 + (\mu(\omega) - 1) \frac{mc(\omega)}{p(\Omega)} \frac{dp(\Omega)}{dmc(\omega)}.$$

Solving the fixed point for the case where $\omega = \Omega$ and substituting in yields,

$$\frac{dp(\omega)}{dmc(\omega)} = 1 + (\mu(\omega) - 1) \frac{mc(\omega)}{mc(\Omega)} \frac{dmc(\Omega)}{dmc(\omega)}. \tag{27}$$

Specializing (27) to changes in marginal costs coming from wage changes or materials cost changes yields the expressions for pass-through in levels in Proposition 9. In the case where $\beta(\Omega) = 1$, for the pass-through of material costs,

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

For the pass-through of labor costs,

$$\frac{dp(\omega)}{\beta(\omega) w} = \mu(\omega) + (\mu(\omega) - 1) \frac{(1 - \beta(\omega)) c}{\beta(\omega) w}.$$

Thus,

$$\frac{d \log p(\omega)}{d \log w} = \frac{\beta(\omega) w + (\mu(\omega) - 1) mc(\omega)}{p(\omega)} = \frac{\text{LaborCosts}(\omega) + \text{VariableProfits}(\omega)}{\text{Sales}(\omega)}.$$

This expression can be used to solve for the other pass-through rates in Proposition 9. □

Appendix C Retail Gasoline Data from Other Markets

C.1 Canada

We use weekly price data for 71 cities in 10 Canadian provinces provided by Kalibrate solutions.[43] These prices are collected across cities through a daily survey of pump prices funded by the Government of Canada and used for analyses by National Resources Canada.

C.2 South Korea

We use daily station-level price data from Opinet, a service started in 2008 by the Korea National Oil Corporation to provide customer transparency about petroleum product prices and enable research.[44] These data cover all gas stations within each city in South Korea; data files are available by city/county within each province. However, some stations appear to have incomplete coverage. Hence, for all results using these data, we limit our analyses to stations that have at least 500 daily price observations (i.e., at least 10% of days during the full sample period). Opinet also provides weekly average refinery supply prices, which we use as the measure of costs facing retail stations.

C.3 United States

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

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