

Pass-Through in Levels and the Incidence of Commodity Shocks

Kunal Sangani

November 2024

Disclaimer

This presentation 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.

Pass-Through in Logs and Levels

- Incomplete long-run pass-through of commodity cost changes.

E.g., Peltzman (2000), Kim and Cotterill (2008), Nakamura and Zerom (2010), Hong and Li (2017).

- When costs increase 10%, firms raise prices $< 10\%$.
- Incomplete even after accounting for commodity cost share and at long horizons.
- Prevailing explanation: curvature of demand (more concave than CES).

Pass-Through in Logs and Levels

- Incomplete long-run pass-through of commodity cost changes.
E.g., Peltzman (2000), Kim and Cotterill (2008), Nakamura and Zerom (2010), Hong and Li (2017).
 - When costs increase 10%, firms raise prices $< 10\%$.
 - Incomplete even after accounting for commodity cost share and at long horizons.
 - Prevailing explanation: curvature of demand (more concave than CES).
- Today: Measure commodity pass-through on a dollars-and-cents basis.
- Result: Firms in selected industries exhibit **complete pass-through in levels**.
 - Faced with \$1/unit increase in cost, firms tend to increase prices \$1/unit.
 - Do not increase prices by $\$1 \times \text{markup}$, so “incomplete” in logs.

Outline of Empirical Evidence

- In workhorse macro models, pass-through in levels should equal the markup, $\mu > 1$.
(E.g., Dixit and Stiglitz 1977, Melitz 2003.)

Outline of Empirical Evidence

- In workhorse macro models, pass-through in levels should equal the markup, $\mu > 1$.
(E.g., Dixit and Stiglitz 1977, Melitz 2003.)
- 1. Evidence from microdata on retail gasoline and several food products.
 - Complete pass-through in levels in nearly all markets.
 - Pass-through in logs is incomplete, even accounting for cost share.
 - Pass-through in levels rationalizes cross-sectional variation in “log pass-through.”

Outline of Empirical Evidence

- In workhorse macro models, pass-through in levels should equal the markup, $\mu > 1$.
(E.g., Dixit and Stiglitz 1977, Melitz 2003.)
- 1. Evidence from microdata on retail gasoline and several food products.
 - Complete pass-through in levels in nearly all markets.
 - Pass-through in logs is incomplete, even accounting for cost share.
 - Pass-through in levels rationalizes cross-sectional variation in “log pass-through.”
- 2. Evidence from firm profits, margins, and entry.
 - Multiplicative markups imply when costs 2x, per-unit profits 2x.
 - Increase in commodity costs leads to higher operating profits or new entry.

Outline of Empirical Evidence

- In workhorse macro models, pass-through in levels should equal the markup, $\mu > 1$.
(E.g., Dixit and Stiglitz 1977, Melitz 2003.)
- 1. Evidence from microdata on retail gasoline and several food products.
 - Complete pass-through in levels in nearly all markets.
 - Pass-through in logs is incomplete, even accounting for cost share.
 - Pass-through in levels rationalizes cross-sectional variation in “log pass-through.”
- 2. Evidence from firm profits, margins, and entry.
 - Multiplicative markups imply when costs 2x, per-unit profits 2x.
 - Increase in commodity costs leads to higher operating profits or new entry.
 - Data: No increase in either operating profits or entry.
 - Instead, ↓ gross margins, consistent with pass-through in levels.

Explaining Pass-Through in Levels

- Prevailing explanation for incomplete pass-through: Curvature of demand.
 - Variable markups \Rightarrow “cushion” cost increases by reducing markup.

Explaining Pass-Through in Levels

- Prevailing explanation for incomplete pass-through: Curvature of demand.
 - Variable markups \Rightarrow “cushion” cost increases by reducing markup.
 - But, any homothetic demand (e.g., Kimball) has long-run pass-through in levels of $\mu > 1$.

Explaining Pass-Through in Levels

- Prevailing explanation for incomplete pass-through: Curvature of demand.
 - Variable markups \Rightarrow “cushion” cost increases by reducing markup.
 - But, any homothetic demand (e.g., Kimball) has long-run pass-through in levels of $\mu > 1$.
 - Non-homothetic demand with global super-elasticity $= 1$ yields pass-through in levels.
Bulow and Pfleiderer (1983), Weyl and Fabinger (2013), Mrázová and Neary (2017).

Explaining Pass-Through in Levels

- Prevailing explanation for incomplete pass-through: Curvature of demand.
 - Variable markups \Rightarrow “cushion” cost increases by reducing markup.
 - But, any homothetic demand (e.g., Kimball) has long-run pass-through in levels of $\mu > 1$.
 - Non-homothetic demand with global super-elasticity = 1 yields pass-through in levels.
Bulow and Pfleiderer (1983), Weyl and Fabinger (2013), Mrázová and Neary (2017).
 - But, curvature of demand estimated directly in the data falls short.
 - Standard calibrations of logit demand do not predict uniform pass-through in levels.

Explaining Pass-Through in Levels

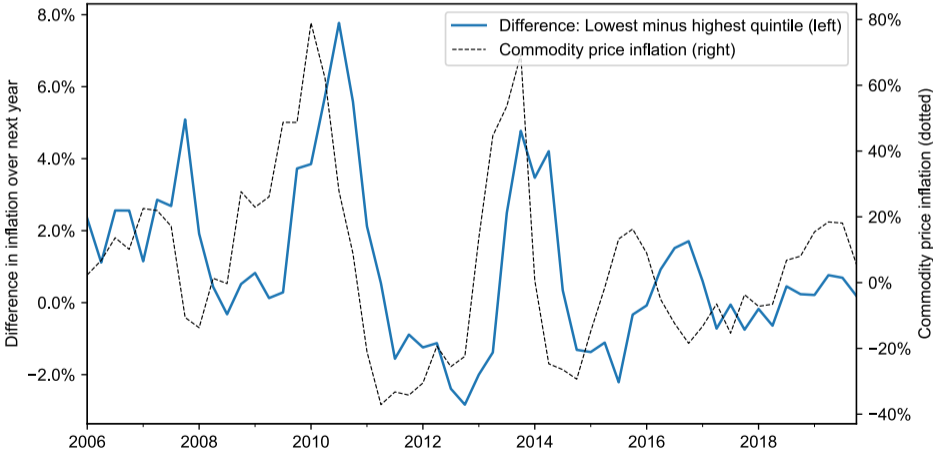
- Prevailing explanation for incomplete pass-through: Curvature of demand.
 - Variable markups \Rightarrow “cushion” cost increases by reducing markup.
 - But, any homothetic demand (e.g., Kimball) has long-run pass-through in levels of $\mu > 1$.
 - Non-homothetic demand with global super-elasticity = 1 yields pass-through in levels. Bulow and Pfleiderer (1983), Weyl and Fabinger (2013), Mrázová and Neary (2017).
 - But, curvature of demand estimated directly in the data falls short.
 - Standard calibrations of logit demand do not predict uniform pass-through in levels.
- Class of alternative models that can deliver complete pass-through in levels.
 - E.g., search/transport costs, limit pricing, kinked demand curves, price-setting heuristics.

Application: Cyclical, Within-Category Component of Inflation Inequality

- New, within-category, *cyclical* component of inflation inequality.
 - When commodity costs rise, absolute price changes similar across products.
 - But appears as larger inflation (in %) for low-margin products.

Application: Cyclical, Within-Category Component of Inflation Inequality

- New, within-category, *cyclical* component of inflation inequality. **E.g., coffee:**



Application: Cyclical, Within-Category Component of Inflation Inequality

- New, within-category, *cyclical* component of inflation inequality.
 - When commodity costs rise, absolute price changes similar across products.
 - But appears as larger inflation (in %) for low-margin products.
- Not captured by price indices that use only expenditure shares across categories (e.g. Jaravel 2024 Distributional CPIs).
- Low-income food-at-home inflation is 10% more volatile, responsive to costs.
- Implies large differences in food-at-home inflation from 2020–2023.
 - Predict prices for lowest-price decile of goods grew 21%, vs. 9% for highest-price.
 - Absent this channel, inflation inequality from 2020–2023 would have been 1/3 as large.

Selected Related Literature

- **Theoretical and empirical determinants of pass-through:**

- E.g., Bulow and Pfleiderer (1983); Nakamura and Zerom (2010); Weyl and Fabinger (2013); Hong and Li (2017); Minton and Wheaton (2022); (*Exchange rate*) Campa and Goldberg (2005); Burstein et al. (2006); Burstein and Gopinath (2014); Amiti et al. (2019); Mongey and Waugh (2023).
- Abstract from (1) asymmetry in speed of adjustment (Borenstein et al. 1997; Peltzman 2000; Benzarti et al. 2020) and (2) firm-specific shocks (e.g., Amiti et al. 2019).
 - Recently, Alvarez et al. (2024) find pass-through in levels of idiosyncratic shocks.

- **Studies that measure pass-through in levels (not exhaustive):**

- *Retail Gasoline: (Pass-through asymmetry)* Karrenbrock (1991), Borenstein et al. (1997), Lewis (2011) (*Cycles*) Wang (2009), Noel (2009, 2015), Lewis and Noel (2011), Atkinson et al. (2014), Byrne and de Roos (2017, 2019).
- *Food: (Coffee)* Bettendorf and Verboven (2000), Leibtag et al. (2007), Nakamura and Zerom (2010), Bonnet et al. (2013), (*Cheese*) Kim and Cotterill (2008), (*Spirits*) Conlon and Rao (2020), (*Cigarettes, Beer, Milk*) Butters et al. (2022).

Table of Contents

Empirical Evidence

Retail gasoline

Food commodities in U.S. CPI

Profits, Margins, and Entry

Explanations

The Incidence of Commodity Shocks

Pass-Through in Levels: Example

- Leontief production in commodity (\$1/unit) and other variable costs (\$1/unit).

Cost per unit	Baseline
Commodity	\$1
Other components of marginal cost	\$1
Total marginal cost	\$2
Price	\$4

Pass-Through in Levels: Example

- Leontief production in commodity (\$1/unit) and other variable costs (\$1/unit).

Cost per unit	Baseline	
Commodity	\$1	+\$0.20
Other components of marginal cost	\$1	
Total marginal cost	\$2	+\$0.20
Price	\$4	

Pass-Through in Levels: Example

- Leontief production in commodity (\$1/unit) and other variable costs (\$1/unit).

Cost per unit	Baseline		New
Commodity	\$1	+\$0.20	\$1.20
Other components of marginal cost	\$1		\$1.00
Total marginal cost	\$2	+\$0.20	\$2.20
Price	\$4	?	?

Pass-Through in Levels: Example

- Leontief production in commodity (\$1/unit) and other variable costs (\$1/unit).

Cost per unit	Baseline		New	% Change
Commodity	\$1	+\$0.20	\$1.20	+20%
Other components of marginal cost	\$1		\$1.00	
Total marginal cost	\$2	+\$0.20	\$2.20	+10%
Price	\$4	?	?	

Pass-Through in Levels: Example

- Leontief production in commodity (\$1/unit) and other variable costs (\$1/unit).

Cost per unit	Baseline		New	% Change
Commodity	\$1	+\$0.20	\$1.20	+20%
Other components of marginal cost	\$1		\$1.00	
Total marginal cost	\$2	+\$0.20	\$2.20	+10%
Price	\$4	+\$0.40	\$4.40	+10%

- Complete pass-through in logs: $p = \mu(c + w) \Rightarrow \Delta p = \mu \cdot \Delta c$.

Pass-Through in Levels: Example

- Leontief production in commodity (\$1/unit) and other variable costs (\$1/unit).

Cost per unit	Baseline		New	% Change
Commodity	\$1	+\$0.20	\$1.20	+20%
Other components of marginal cost	\$1		\$1.00	
Total marginal cost	\$2	+\$0.20	\$2.20	+10%
Price	\$4	+\$0.20	\$4.20	+5%

- Complete pass-through in logs: $p = \mu(c + w) \Rightarrow \Delta p = \mu \cdot \Delta c$.
- Complete pass-through in levels $\rightarrow \Delta p = \Delta c$. Appears incomplete in logs.

Canonical approach to measure pass-through of cost changes

- Specification à la Campa and Goldberg (2005), Nakamura and Zerom (2010), etc.
- Price change at time t in market m due to commodity cost changes in last K periods:

$$\Delta p_{m,t} = a_m + \sum_{k=0}^K b_k \Delta c_{m,t-k} + \varepsilon_{m,t}.$$

Long-run pass-through is $\sum_{k=0}^K b_k$.

- Details:
 - Ensure p is unit root, ensure Δp and Δc are non-unit root.
 - Check for one way Granger causality from Δc to Δp .
 - Use $K = 8$ weeks for gasoline, $K = 12$ months for all others.
 - Robustness: Estimate long-run pass-through using VAR.

Table of Contents

Empirical Evidence

Retail gasoline

Food commodities in U.S. CPI

Profits, Margins, and Entry

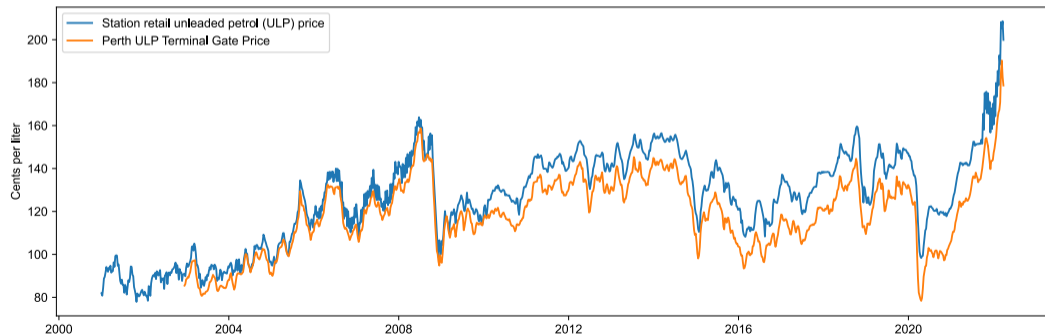
Explanations

The Incidence of Commodity Shocks

Station-level panel dataset of gas prices in Perth, Australia

- 2.3M price observations (2001-present) for 875 stations in Perth metropolitan area.
- Perth Terminal Gate Price (spot price sold to retailers) available daily.

Figure: Price for BP at 549 Abernethy Rd, Kewdale, Perth, Australia and Perth Terminal Gas Price.



Pass-through of terminal gas price to station gas prices: Unleaded

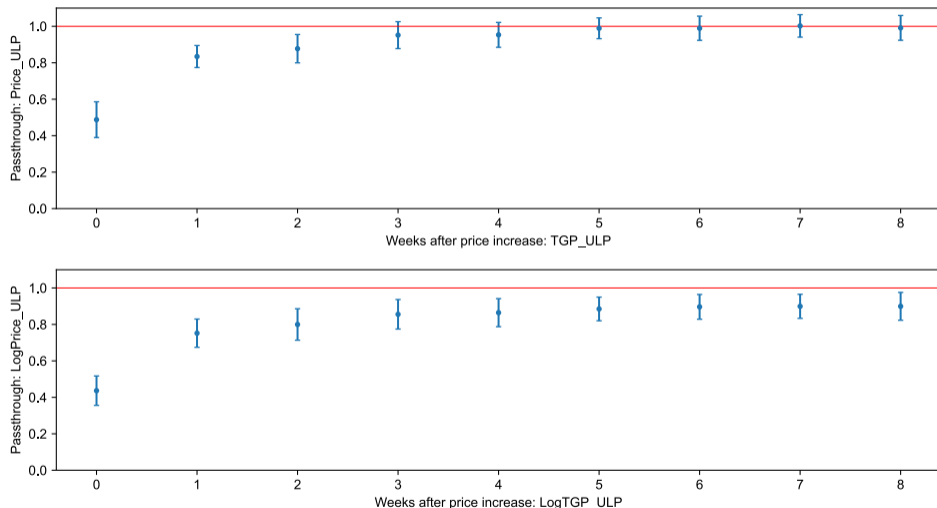


Figure: Passthrough in levels (top) and in logs (bottom). SEs two-way clustered by postcode \times year.

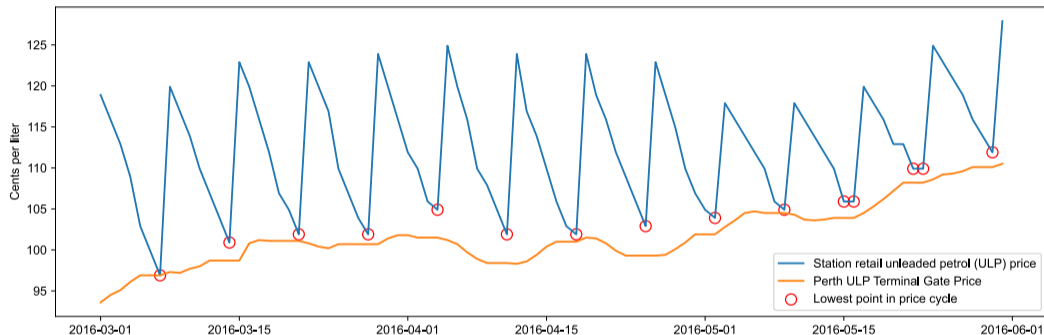
Summary of retail gasoline pass-through estimates

Description	Pass-through (8 weeks)			
	Logs		Levels	
Australia, station-level, 2001–2022				
Terminal to retail, Unleaded	0.899	(0.043)	0.991	(0.038)
Terminal to retail, Premium Unleaded	0.887	(0.041)	0.985	(0.036)
Canada, city-level, 2007–2022				
Crude to wholesale	0.553	(0.098)	0.927	(0.100)
Wholesale to retail (excl. taxes)	0.859	(0.016)	1.008	(0.022)
South Korea, station-level, 2008–2022				
Refinery to retail, Unleaded	0.926	(0.044)	0.997	(0.052)
United States, national, 1990–2022				
NY Harbor spot price to retail	0.570	(0.051)	0.954	(0.053)

- **Cannot reject complete pass-through in levels.** (Reject in logs for all.)

Log pass-through incomplete, even adjusting for cost share

Figure: Price for BP at 549 Abernethy Rd, Kewdale, Perth, with lowest points in price cycle.



- “Log pass-through” estimates: 0.899 (unleaded), 0.887 (premium unleaded).
- Cost shares using days at lowest end of price cycle: 0.98 (ULP), 0.96 (PULP).
- \Rightarrow Even accounting for cost share, log pass-through appears incomplete.

Exploiting variation in markups

- Low markups, hard to differentiate pass-through in levels of 1 from 1.02–1.05.
- Test: Pass-through in levels should be higher for stations with 5% vs. 2% markup.

$$\Delta p_{it} = \alpha + \beta_1 \Delta c_{it} + \delta \text{AvgMarkup}_{it} + \beta_2 (\Delta c_{it} \times \text{AvgMarkup}_{it}) + \varepsilon_{it},$$

- where $\Delta p_{i,t}$, $\Delta c_{i,t}$ are change in station retail price and wholesale cost over 16 weeks.

- Prediction: If constant multiplicative markup, $\beta_2 > 0$.

Exploiting variation in markups

- Low markups, hard to differentiate pass-through in levels of 1 from 1.02–1.05.
- Test: Pass-through in levels should be higher for stations with 5% vs. 2% markup.

$$\Delta p_{it} = \alpha + \beta_1 \Delta c_{it} + \delta \text{AvgMarkup}_{it} + \beta_2 (\Delta c_{it} \times \text{AvgMarkup}_{it}) + \varepsilon_{it},$$

- where $\Delta p_{i,t}$, $\Delta c_{i,t}$ are change in station retail price and wholesale cost over 16 weeks.
- Exploit cross-sectional / time series variation in AvgMarkup_{it} , with IVs to isolate markups.
 1. AvgMarkup_i = average markup (price / terminal cost) of station i over all periods.
 2. AvgMarkup_t = average markup of all stations in quarter t .
 3. IV1: Instrument for AvgMarkup_i with amplitude of price cycle by station.
 4. IV2: Instrument for AvgMarkup_t with level of pricing coordination.
- Prediction: If constant multiplicative markup, $\beta_2 > 0$.

Exploiting variation in margins

ΔPrice_{it}	(1)	(2)	(3)	(4)	(5)
	(OLS)	(OLS)	(IV1)	(OLS)	(IV2)
ΔCost_t	0.950**				
	(0.021)				
$\Delta\text{Cost}_t \times \text{Avg. Station Markup}_i$ (Net %)					
$\Delta\text{Cost}_t \times \text{Avg. Quarter Markup}_t$ (Net %)					
N	312215				
R^2	0.89				

Exploiting variation in margins

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

- Stations with higher markups do not have higher pass-through in levels ($\beta_2 \approx 0$).

Exploiting variation in margins

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

- Stations with higher markups do not have higher pass-through in levels ($\beta_2 \approx 0$).

Exploiting variation in margins

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

- Stations with higher markups do not have higher pass-through in levels ($\beta_2 \approx 0$).

IV2: Instrument for Avg. Markup using strength of price cycles

- Byrne and de Roos (2019) show emergence of coordinated price cycles in Perth market starting in 2010 “unrelated to market primitives.”

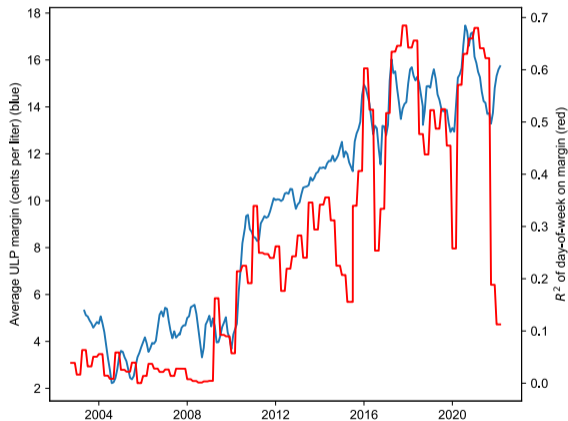


Figure: Margins (6mo. centered avg.) and R^2 of daily margins on day-of-week dummies.

Pass-through in levels explains extent & variation of “log pass-through”

$\Delta \log(\text{Price})_{it}$	(1) (OLS)	(2) (OLS)	(3) (IV1)	(4) (OLS)	(5) (IV2)
$\Delta \log(\text{Cost})_t$	0.870**				
	(0.031)				
$\Delta \log(\text{Cost})_t \times \text{Avg. Station Markup}_i$ (Net %)					
$\Delta \log(\text{Cost})_t \times \text{Avg. Quarter Markup}_t$ (Net %)					
N	312215				
R^2	0.88				

- As a result, stations with high margins appear to have “incomplete” pass-through.
- Intercept: Pass-through is complete as $\text{Net Markup}_{i,t} \rightarrow 0$.

Pass-through in levels explains extent & variation of “log pass-through”

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

- As a result, stations with high margins appear to have “incomplete” pass-through.
- Intercept: Pass-through is complete as $\text{Net Markup}_{i,t} \rightarrow 0$.

Pass-through in levels explains extent & variation of “log pass-through”

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

- As a result, stations with high margins appear to have “incomplete” pass-through.
- Intercept: Pass-through is complete as $\text{Net Markup}_{i,t} \rightarrow 0$.

Retail Gasoline: Taking Stock

- 1 Pass-through complete in levels.
 - 2 Pass-through incomplete in logs, even accounting for cost share of gasoline.
 - 3 No apparent heterogeneity in pass-through in levels.
 - 4 Differences in margins rationalize cross-sectional heterogeneity in log pass-through.
- In paper: Similar results from other geographies (Canada, South Korea, U.S.).
 - Similar results using Känzig (2021) OPEC announcement IV for upstream costs.

Table of Contents

Empirical Evidence

Retail gasoline

Food commodities in U.S. CPI

Profits, Margins, and Entry

Explanations

The Incidence of Commodity Shocks

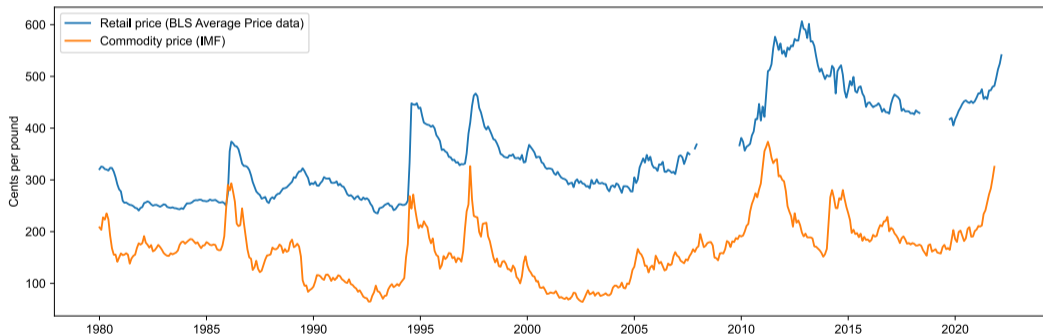
Test for six food commodities

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

- Monthly commodity prices from IMF, retail prices from U.S. CPI, 1990-Present.
- Match units (e.g., lbs flour per bushel of wheat, oz. roasted coffee per lbs bean).
- **Cannot reject complete pass-through in levels for 5 of 6.** (Reject in logs for all.)

Example: Pass-through of coffee commodity costs to CPI

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



Example: Pass-through of coffee commodity costs to CPI

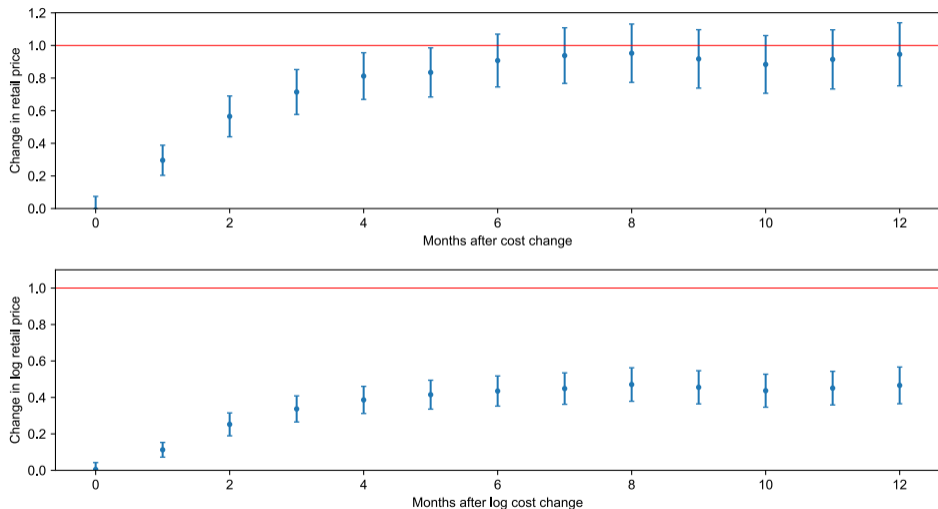
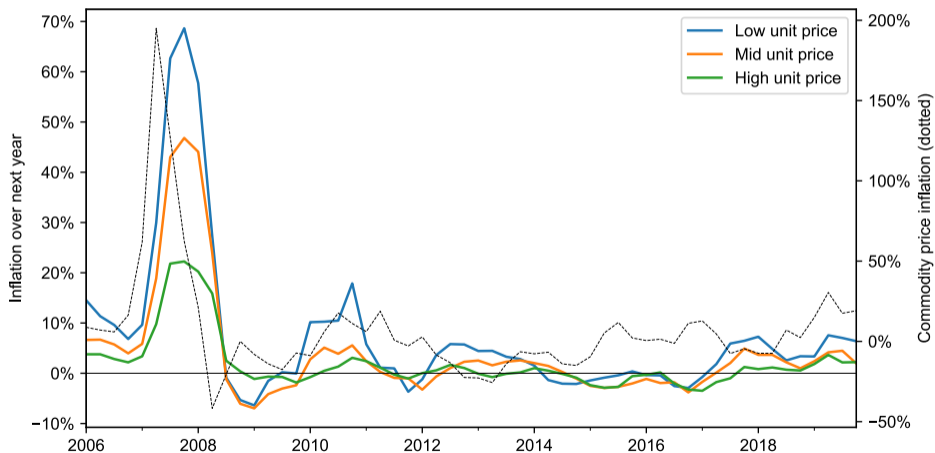


Figure: Passthrough in levels (top) and in logs (bottom)

Pass-through in levels implies variation in “log pass-through”

Figure: Inflation of Rice products in Nielsen data, split by tercile of unit price.



Prediction: Highest-price items exhibit lowest “log pass-through”

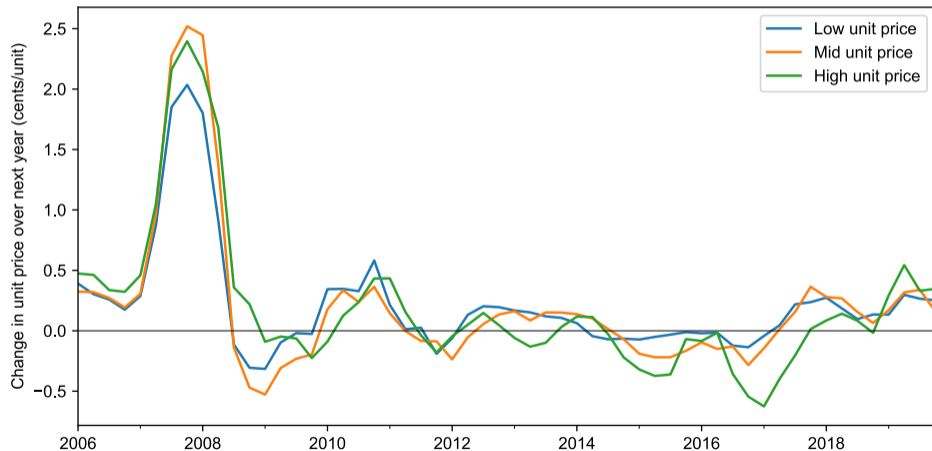
$$\Delta \log p_{it} = \alpha_i + \beta_1 \Delta \log c_t + \sum_{g=2}^3 \beta_g (1\{G(i, t) = g\} \times \Delta \log c_t) + \varepsilon_{it}.$$

Panel A: In percentages

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

Differences in pass-through disappear in absolute (level) terms

Figure: Change in unit price of Rice products in Nielsen data, split by tercile of unit price.



Differences in pass-through disappear in absolute (level) terms

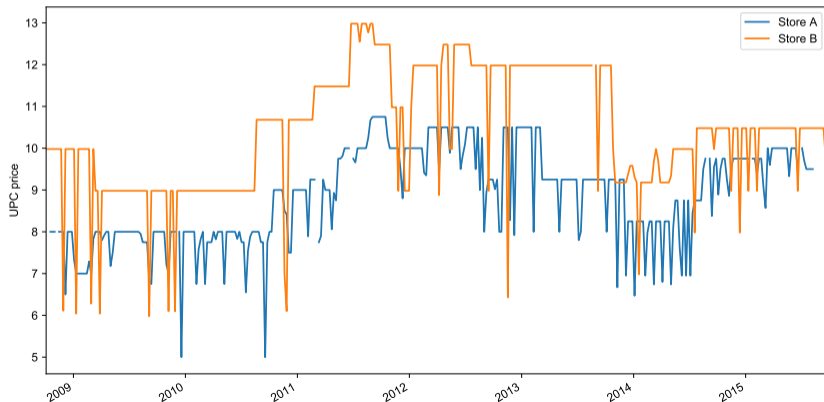
<i>Panel B: In levels</i>			
	Δ Retail price		
	Rice	Flour	Coffee
Δ Commodity Price \times Mid Unit Price	0.059 (0.052)	0.027 (0.040)	-0.069 (0.046)
Δ Commodity Price \times High Unit Price	0.042 (0.100)	-0.067 (0.044)	-0.099* (0.058)
UPC FEs	Yes	Yes	Yes
N (thousands)	399.4	101.4	1570.0
R^2	0.07	0.05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

- No systematic difference in [pass-through in levels](#) across unit price groups.

Exploiting variation in margins across retailers

- Consider two retailers selling the same UPC, with low and high markup.
- Test: When cost of UPC rises, retailer with high markup should increase more in levels.

Figure: Prices of identical coffee UPC in two stores in same 3-digit ZIP code in Philadelphia, PA.



Exploiting variation in margins across retailers

- Consider two retailers selling the same UPC, with low and high markup.
- When cost of UPC rises, retailer with high markup should increase price more in levels.

- Specification:

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

where

- Δp_{irt} is the change in price of UPC i at retailer r ,
 - $\overline{\Delta p_{it}}$ is the average change in the price of UPC i across all retailers,
 - μ_{irt} is the markup charged by retailer r on UPC i .
 - Proxy for μ : Deviation in retailer's price relative to average. $\hat{\mu}_{irt} = \log(p_{irt}/\bar{p}_{it})$.
- Prediction: If constant multiplicative markup, $\beta_2 > 0$.

Exploiting variation in margins across retailers

	Δ UPC Price (Δp_{irt})		
	Rice (1)	Flour (2)	Coffee (3)
Avg Δ UPC Price \times Markup $_{irt}$	-0.019 (0.111)	-0.200 (0.216)	-0.123 (0.352)
UPC-Quarter FEs	Yes	Yes	Yes
N (thousands)	399.4	101.4	1570.0
R^2	0.51	0.50	0.55

Note: Driscoll-Kraay standard errors. * indicates significance at 10%, ** indicates at 5%.

- Instead, $\beta_2 \approx 0 \Rightarrow$ retailers with higher margins change UPC price by same amount.

Exploiting variation in margins across retailers

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

Note: Driscoll-Kraay standard errors. * indicates significance at 10%, ** indicates at 5%.

- Instead, $\beta_2 \approx 0 \Rightarrow$ retailers with higher margins change UPC price by same amount.
- Makes “log pass-through” appear to decline with retailer markup.

Food Products: Taking Stock

- 1 Pass-through complete in levels for several food products.
- 2 Across products within a category, different non-commodity input costs + markups explain cross-sectional variation in “log pass-through.”
- 3 Across retailers selling same product, markups explain variation in “log pass-through.”

Empirical Results: Concerns and Extensions

- **Concern:** Are these product categories (coffee, rice, flour) special?
 - Complex goods with differentiated inputs may be different.
 - Variation in margins across stores exercise for all product categories in NielsenIQ.
 - Vast majority exhibit same patterns (e.g., log pass-through falls with markup for 90%).
- **Concern:** Is this pass-through behavior specific to retailers?
 - Pass-through from commodity to retail picks up if *any* firm sets fixed markup along chain.
 - In paper: Also test pass-through from farm → wholesale → retail in beef, pork.
 - Find complete pass-through in levels at each step in chain.

Empirical Results: Concerns and Extensions

- **Concern:** Relationship to results on pass-through heterogeneity by size / quality?
 - Previous work shows “log pass-through” declines with firm size and product quality. (Size: Berman et al. 2012; Amiti et al. 2019; Gupta 2020; Quality: Chen and Juvenal 2016; Auer et al. 2018).
 - If markups increase with firm size / quality, pass-through in levels yields both results.
 - Caution: Evidence from idiosyncratic shocks, while our evidence is on aggregate shocks.
- **Concern:** What about asymmetries in pass-through?
 - We find little systematic evidence of asymmetry in *long-run* pass-through in our setting.
 - Note that if firms charge additive margin, $p = c + a$, then to a second order

$$\hat{\rho}^{\log} = \frac{\Delta \log p}{\Delta \log c} \approx \frac{c}{p} \left(1 + \frac{a}{p} \Delta \log c \right).$$

- Misspecification can lead to (1) asymmetry ($\hat{\rho}_+^{\log} > \hat{\rho}_-^{\log}$), (2) convexity ($\hat{\rho}_{\text{big}}^{\log} > \hat{\rho}_{\text{small}}^{\log}$).

Table of Contents

Empirical Evidence

Retail gasoline

Food commodities in U.S. CPI

Profits, Margins, and Entry

Explanations

The Incidence of Commodity Shocks

Profits, Margins, and Entry in Workhorse Macro Models

- First, formalize intuition that, with fixed markups, profits / entry rise with costs.
- Standard setup à la Dixit and Stiglitz (1977) and Melitz (2003).
 - Mass N of symmetric firms, constant returns production with marginal cost c .
 - Firms pay fixed cost f_e to enter, pay overhead cost for period f_o .
 - Output is CES aggregate with elasticity of substitution across varieties $\sigma > 1$.
 - Aggregate industry demand is relatively inelastic, $Q = p^{-\theta}$, with $\theta < 1$.

Profits, Margins, and Entry in Workhorse Macro Models

- First, formalize intuition that, with fixed markups, profits / entry rise with costs.
- Standard setup à la Dixit and Stiglitz (1977) and Melitz (2003).
 - Mass N of symmetric firms, constant returns production with marginal cost c .
 - Firms pay fixed cost f_e to enter, pay overhead cost for period f_o .
 - Output is CES aggregate with elasticity of substitution across varieties $\sigma > 1$.
 - Aggregate industry demand is relatively inelastic, $Q = p^{-\theta}$, with $\theta < 1$.
- Optimal prices and per-unit variable profits increase with cost c :

$$p = \frac{\sigma}{\sigma - 1}c, \quad \text{and} \quad p - c = \frac{1}{\sigma - 1}c.$$

Profits, Margins, and Entry in Workhorse Macro Models

- Gross and operating profits:

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

Let m denote corresponding margins as percent of sales ($m^{\text{gross}} = \pi^{\text{gross}} N / pQ$).

- Finally, close model with a condition that nests both free entry and fixed mass of firms:

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

- $\zeta = 0$: Fixed mass of firms.
- $\zeta \rightarrow \infty$: Free entry and zero profits.

Profits, Margins, and Entry in Workhorse Macro Models

Proposition (Response to increase in commodity costs)

In response to an increase in costs $d \log c > 0$:

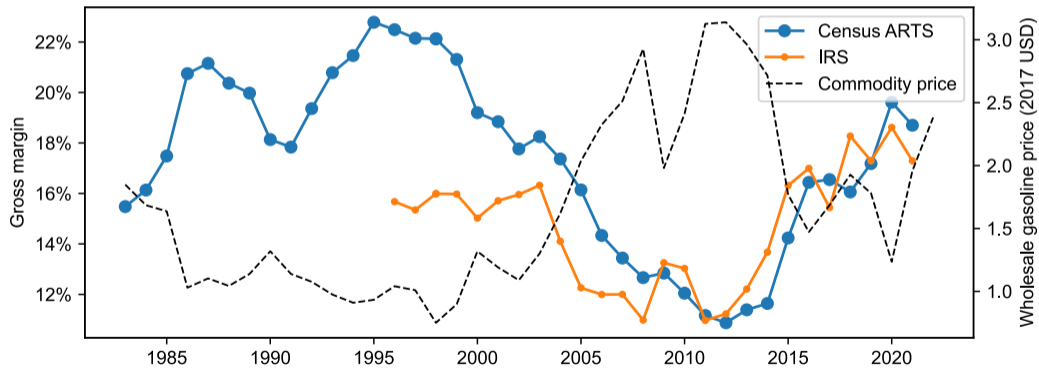
		Gross margins dm^{gross}	Operating margins dm^{op}	Mass of firms $d \log N$
$\zeta = 0$	(Fixed mass)	0	> 0	0
$\zeta \in (0, \infty)$		0	> 0	> 0
$\zeta \rightarrow \infty$	(Free entry)	0	0	> 0

Gross margins do not move.

Operating profits rise, firms enter, or both!

Profits, Margins, and Entry in the Data: Retail Gasoline

- In contrast, gross margins *do move* with commodity costs in the data.
- Retail gas stations: corr. with wholesale gas price is -0.94 (Census) and -0.74 (IRS).



Profits, Margins, and Entry in the Data: Retail Gasoline

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

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

- No increase in operating margins or entry.
- I.e., changes in prices must be maintaining constant per-unit profits!

Profits, Margins, and Entry in the Data: Retail Gasoline

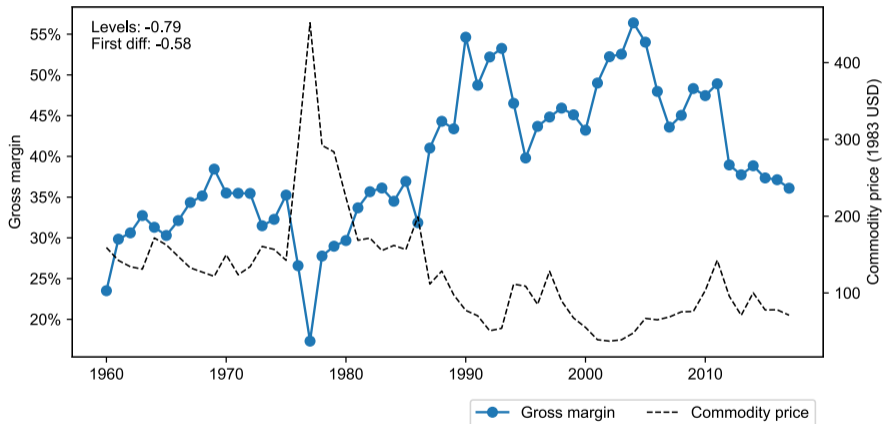
Table: Changes in gross margins, operating margins, and entry.

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

- No increase in operating margins or entry.
- I.e., changes in prices must be maintaining constant per-unit profits!
- Holmes: “The dog did nothing in the night-time. That was the curious incident.”

Profits, Margins, and Entry in the Data: Food Products

Figure: Roasted coffee manufacturing gross margins, with coffee commodity prices.



- In paper: Same for 14 manufacturing sectors matched to commodity inputs.
- No evidence of $\uparrow c$ leading to \uparrow entry or operating margins.

Table of Contents

Empirical Evidence

Retail gasoline

Food commodities in U.S. CPI

Profits, Margins, and Entry

Explanations

The Incidence of Commodity Shocks

Explaining pass-through in levels: Curvature of demand

- Prevailing explanation for incomplete “log pass-through”: log-concave demand curves.
- Suppose $D(p)$ has elasticity $\sigma = -\frac{\partial \log D}{\partial \log p}$ and super-elasticity $\varepsilon = \frac{\partial \log \sigma}{\partial \log p}$ at p_0 . Then:

$$\frac{dp}{dc} = \frac{\sigma}{\sigma - 1 + \varepsilon}.$$

Super-elasticity $\varepsilon = 1$ yields complete pass-through in levels!

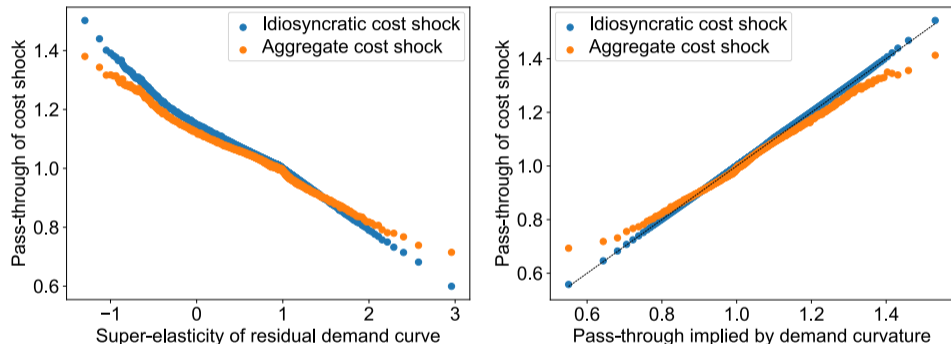
- Note: Homothetic demand systems depend on *relative price*, so super-elasticity of residual demand curve not sufficient.
 - E.g., in nested CES, Kimball: in long-run, relative prices are fixed and thus $dp/dc = \mu$.
- But **logit demand** (used extensively in IO) has global super-elasticity of one!

Some concerns with the demand curvature explanation

- In logit demand systems:
 - Without outside option, pass-through of agg. cost shocks is (exactly) complete in levels!
 - But with outside option, shape of residual demand curve matters.
- 1. Standard calibrations (e.g., Nevo 2001, Nakamura and Zerom 2010) include an outside option, and thus have wide range in super-elasticities and pass-throughs.
- 2. Direct estimates of demand curvature too low to explain pass-through.

Logit: Heterogeneity in super-elasticities and pass-through

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



Note: 1,000 bins. Implied pass-through is $\hat{\rho}_i = \sigma_i / (\sigma_i + \varepsilon_i - 1)$, where σ_i , ε_i are elasticity, super-elasticity of demand curve.

- Nakamura and Zerom (2010) report median super-elasticity of 4.64, implies pass-through of 0.49–0.71.

Estimates of super-elasticities in the data too low to explain pass-through

- Estimate super-elasticity κ/η using technique from Burya and Mishra (2023):

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

- Hausman IV for $\log p_{it}$, estimated individually for top UPCs at each store.

Estimates of super-elasticities in the data too low to explain pass-through

- Estimate super-elasticity κ/η using technique from Burya and Mishra (2023):

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

- Hausman IV for $\log p_{it}$, estimated individually for top UPCs at each store.
- Result: Estimated super-elasticities fall short of level explaining pass-through in levels.

Table: Share of store-product estimates with curvature ≤ 1 .

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

Three classes of alternative explanations

- 1 Firm market power derives from cost of switching to alternative providers.
 - Explicit price difference (limit pricing) or search/transport costs. (e.g., Hotelling 1929).
 - These costs do not vary as commodity costs fluctuate.
 - 2 Conduct of competition leads to kinked demand curves facing firms.
 - Edgeworth cycles due to repeated game (Maskin and Tirole 1988).
 - Threat of entry deters raising price over a limit (e.g., Bain 1949; Modigliani 1958).
 - 3 Pricing heuristics.
 - Okun (1981) speculates “special role for material costs”: only mark-up value added.
 - “Full cost pricing” or “target returns pricing” (e.g., Hall and Hitch 1939).
- ⇒ Empirical evidence can be used for future refinements of these models.

Table of Contents

Empirical Evidence

Retail gasoline

Food commodities in U.S. CPI

Profits, Margins, and Entry

Explanations

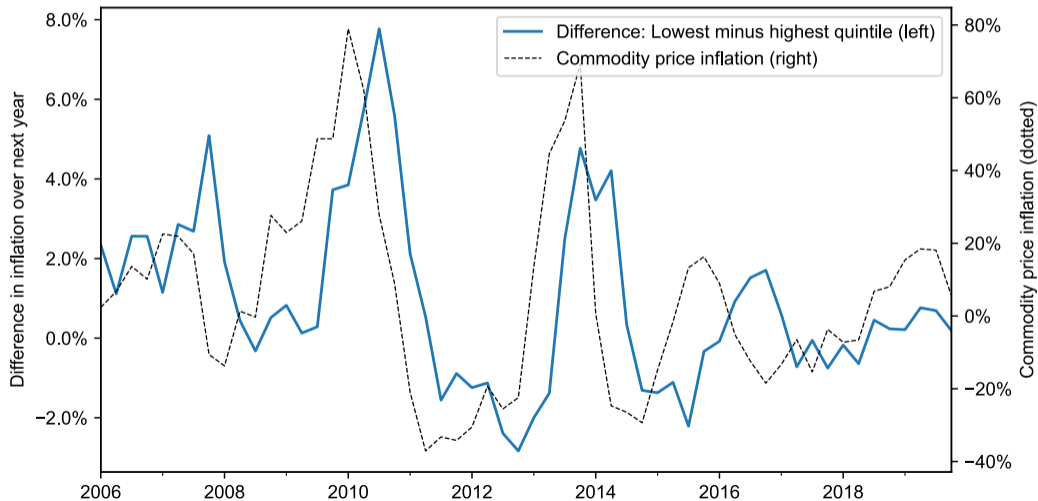
The Incidence of Commodity Shocks

Cyclical inflation inequality within narrow categories (e.g. coffee)

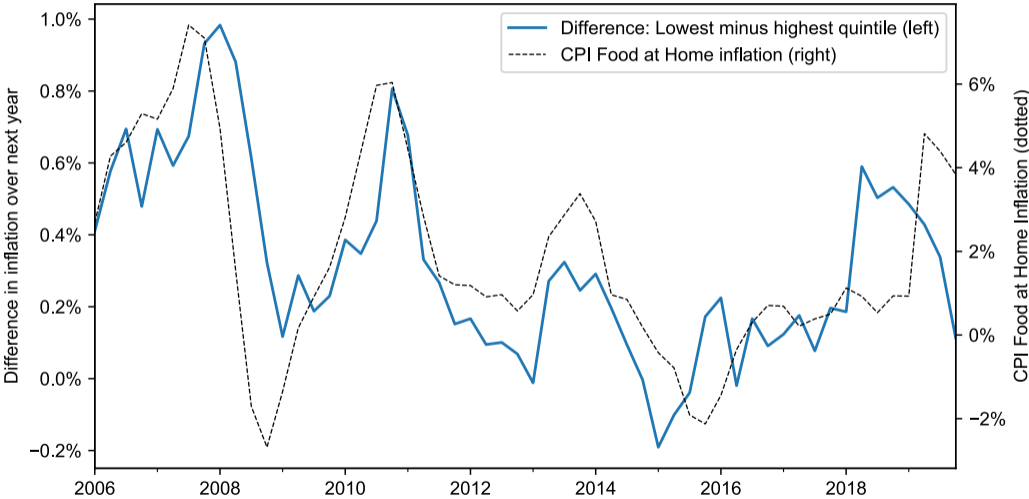
- Same Δp across products \rightarrow higher % inflation for low-price products.

Cyclical inflation inequality within narrow categories (e.g. coffee)

- Same Δp across products \rightarrow higher % inflation for low-price products.

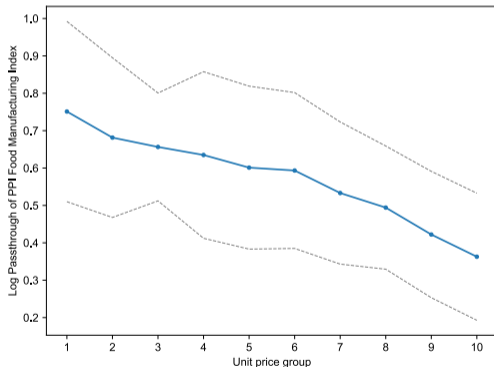


Cyclical inflation inequality over entire food-at-home bundle

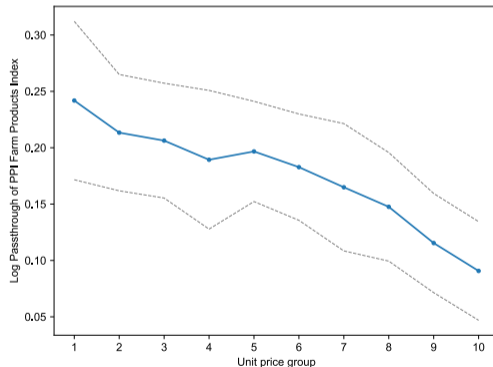


In logs, low-margin products more sensitive to upstream costs

(a) Log pass-through of Food Manufacturing PPI.

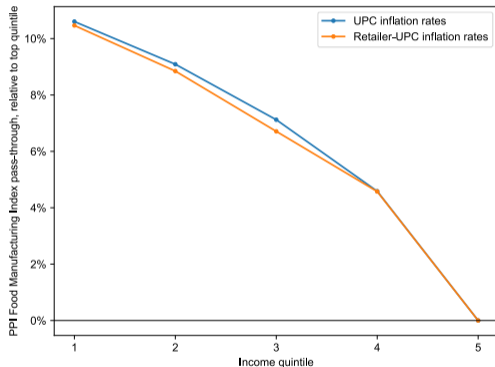


(b) Log pass-through of Farm Products PPI.

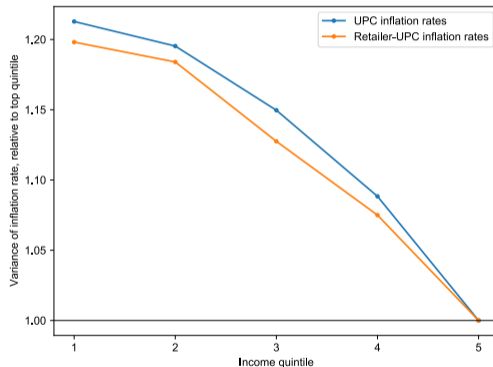


Food-at-home inflation across income groups

- Inflation for low-income groups more sensitive to upstream costs, more volatile.



(a) Log pass-through of Food Manufacturing PPI.



(b) Variance of annual inflation rates.

Attention to inflation of low-end products in 2021

Jack Monroe @BootstrapCook

Woke up this morning to the radio talking about the cost of living rising a further 5%. It infuriates me the index that they use for this calculation, which grossly underestimates the real cost of inflation as it happens to people with the least. Allow me to briefly explain.

7:30 AM · Jan 19, 2022

37.1K Retweets 9,873 Quote Tweets 82.7K Likes

Jack Monroe @BootstrapCook · Jan 19, 2022
Replying to @BootstrapCook
This time last year, the cheapest pasta in my local supermarket (one of the Big Four), was 29p for 500g. Today it's 70p. That's a 141% price increase as it hits the poorest and most vulnerable households.

171 3,532 16.5K

Jack Monroe @BootstrapCook · Jan 19, 2022
This time last year, the cheapest rice at the same supermarket was 45p for a kilogram bag. Today it's £1 for 500g. That's a 344% price increase as it hits the poorest and most vulnerable households.

119 2,785 13.5K

Jack Monroe @BootstrapCook · Jan 19, 2022
Baked beans: were 22p, now 32p. A 45% price increase year on year.

46 1,164 9,532

Office for National Statistics

Article

Tracking the price of the lowest-cost grocery items, UK, experimental analysis: April 2021 to September 2022

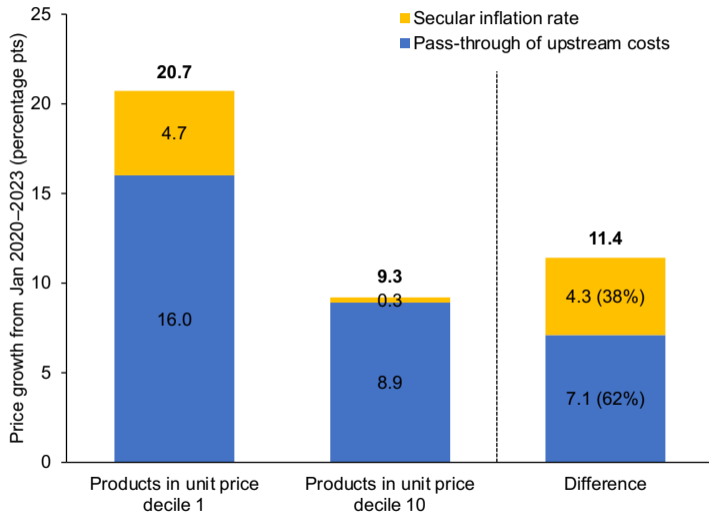
How the prices of the lowest-cost products for 30 everyday items have changed since April 2021.

Contact: Emily Hopson cpi@ons.gov.uk +44 1633 455 592	Release date: 25 October 2022	Next release: To be announced
--	----------------------------------	----------------------------------

- Discussion: “supermarkets are recouping their margins on value/budget products.”

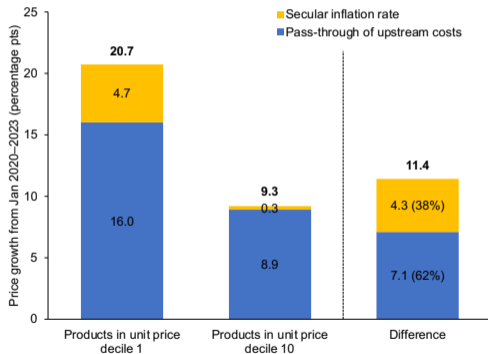
Predictions for food-at-home inflation, 2020–2023

- 20pp price growth for low-price products.
- 11pp higher than high-price products.
- 60% due to pass-through vs. secular inflation diffs.

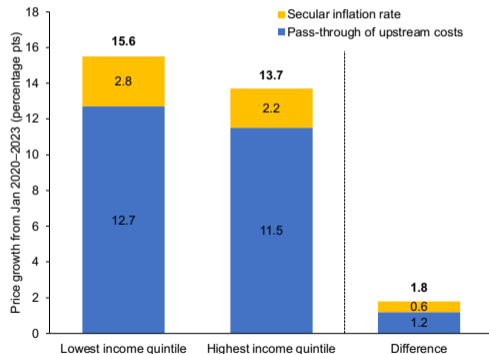


Estimated differences in 2020–2023 price growth

- Estimated 11pp higher price growth for low-price products within product categories.
- Translates to 2pp differential food-at-home price growth for low-income households.



(a) Least vs. most expensive products.



(b) Low vs. high income.

Conclusion

- Empirical evidence: Pass-through of commodity costs tends to be complete in *levels*.
- Taking pass-through in levels as benchmark helps us understand pricing dynamics:
 - Long-term incomplete pass-through.
 - Dynamics of profits, margins, and entry.
 - Unequal incidence of commodity inflation across income distribution.
- What micro-foundations explain complete pass-through in levels?
 - Shape of demand?
 - Competitive conduct, source of market power, pricing heuristics, others?