Price Setting in Online Markets:

Does IT Click?

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Price Rigidity: Background

Significant price rigidity in brick-and-mortar stores

- Bils and Klenow (2004), Klenow and Kryvtsov (2008), Nakamura and Steinsson (2008)

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Potential explanations:

- costs of nominal price adjustment (need to reprint price tags)
- search costs (consumers need to drive around multiple stores)
- costly to monitor competitors' prices
- informational frictions (uncertainty about demand, economy, etc.)
- customer markets (price fluctuations alienate consumers)

Importance of Sticky Prices

Price rigidity gives rise to monetary non-neutrality
and its source determines the degree of non-neutrality:

- the degree is lower in state- than in time-dependent models
  (e.g., menu cost vs. Calvo)
- models of "mechanical" rigidity may produce neutrality
  (e.g., Head et al. 2012)
- rigidity in posted and regular (excluding sales) prices affects MP
  (Kehoe and Midrigan 2012)
- even for a given source of rigidity, details matter
  (e.g., menu-cost models with multiproduct firms)

The source of price rigidity affects inflation persistence
(Fuhrer 2006, 2010)

Motivation

We look at markets where these frictions are smaller (online)

- lower costs of price changes
  expect shorter spells and smaller price changes
- lower search costs
  expect smaller price dispersion
- low cost of monitoring competitors' prices
  expect high synchronization
- unique opportunity for price experimentation
  expect dynamic pricing
- guarantees are partly outsourced to a shopping platform (e.g., Amazon Marketplace, Google Trusted Store)
  expect smaller role of reputation and customer relationship

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The market is shaped by many big players
(Amazon, Bestbuy, eBay, Google, Walmart)

- In 2015, Amazon's U.S. revenue was \$107 bln (\$74 bln Target)
- In 2013, Amazon sold 230 mln items ($\approx$30 times $>$ than Walmart)

This Paper

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using high-quality price data
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- Multiple sellers (necessary for price dispersion)
- Unique product code level (comparable to UPC for offline stores)
- Product description (up to a narrow category)

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- Product description (up to a narrow category)

- Data on clicks for each price quote (proxy for sales in offline data)

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- Models of menu and search costs are likely incomplete

1. Frequency of adjustment is higher online
2. The size of changes is similar to that offline
3. Synchronization is low (even over long time horizons)
4. Price dispersion is similar to that offline

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   (competition, size, returns to search, etc.)
6. Data on quantity margin (clicks) improves measurement
   but doesn't change qualitative conclusions
7. Striking similarities between the U.S. and the U.K.

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7. Striking similarities between the U.S. and the U.K.

8. No evidence of dynamic pricing at high frequencies
   but some evidence at low freq. for micro shocks

Relation to Literature

EMPIRICS

- *Price stickiness*
  - offline (Bils and Klenow 2004; Klenow and Kryvtsov 2008; Nakamura and Steinsson 2008, 2012; Klenow and Malin 2010; Eichenbaum, Jaimovich, and Rebelo 2011; Kryvtsov and Vincent 2014)
  - online (Cavallo 2012; Cavallo, Neiman, and Rigobon 2014; Gorodnichenko and Talavera 2014)
- *Price dispersion*
  - offline (Lach 2002; Kaplan and Menzio 2014; Sheremirov 2014)
  - online (Brynjolffson and Smith 2000; Chevalier and Goolsbee 2003; Baye, Morgan, and Scholten 2004, 2010; Lünnemann and Wintr 2011)
- *Responses to demand shocks* (Warner and Barsky 1995)

THEORY

- *Price stickiness* (Benabou 1988, 1992; Diamond 1993; Golosov and Lucas 2007; Guimaraes and Sheedy 2011; Midrigan 2011; Alvarez and Lippi 2014)
- *Dispersion and IO* (Reinganum 1979; MacMinn 1980; Varian 1980)

NOMINAL RIGIDITIES, MP, AND INFLATION PERSISTENCE

(Woodford 2003; Fuhrer 2006, 2010; Olivei and Tenreyro 2007; Head et al. 2012; Kehoe and Midrigan 2012)

A Typical Shopping Platform

Nabi 2 Kids 7 Android Tablet - NABI2NVA

$180 online

★★★★☆ 47 reviews Write a review Add to Shortlist

Handheld - Android OS - Wi-Fi Only - 7 inch - With Camera

The nabi 2 is a full-featured tablet made especially for kids. It comes preloaded with more than $200 worth of apps, including 25 free games, 50 free songs, 30 free books, and more. In addition, the nabi 2 features state-standardized, core curriculum in math, science, social ... more »

Browse Tablet Computers »

Online stores Nearby stores Related items Reviews Details

Online stores shipping to Berkeley, CA

[redacted] ☐ Free shipping ☐ Refurbished / used

Sponsored ⓘ

Sellers ▾	Seller Rating	Details	Base Price	Total Price	
RadioShack	★★★★★ (5,379)	Free shipping	$199.99 $17.50 tax	$217.49	Shop »
eBay - electronic_express	★★★★★ (605)	Free shipping, No tax	$206.97	$206.97	Shop »
Abt Electronics & Appliances [redacted]	★★★★★ (725)	No tax	$199.99 $7.13 shipping	$207.12	Shop »
TechieWarehouse.com	10 ratings	No tax	$269.99 $3.99 shipping	$273.98	Shop »
Walmart	★★★★☆ (140)	Free shipping	$179.99 $15.75 tax	$195.74	Shop »
eBay - save-on-retail + Show all 2	★★★★★ (369)	Free shipping, No tax	$229.98	$229.98	Shop »
eBay + Show all 25	No rating	No tax	$189.99 $6.85 shipping	$196.84	Shop »
eBay - essentialtreasure	★★★★★ (203)	Free shipping, No tax	$207.00	$207.00	Shop »

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- $>$50,000 goods in each country

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- Daily frequency
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- Price and Clicks for good, seller, date
- ≈27,000 sellers in the U.S. and ≈9,000 sellers in the U.K.
- >50,000 goods in each country
- Price distribution across goods, U.S. ($N = 52,776$)

	5th Percentile (1)	25th Percentile (2)	Median (3)	75th Percentile (4)	95th Percentile (5)
	\$4	\$11	\$25	\$71	\$474

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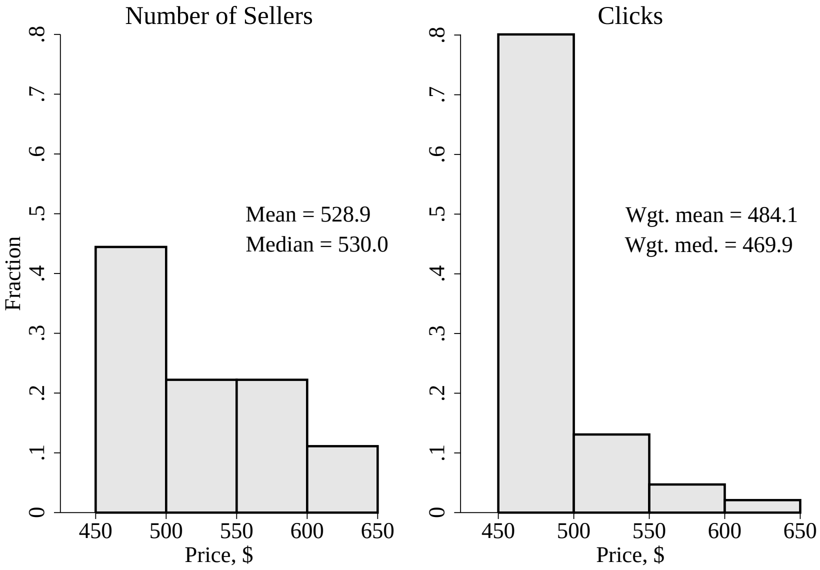
No weights	\$4	\$11	\$25	\$71	\$474
Click weighted	\$7	\$22	\$61	\$192	\$852

Coverage

Category	Goods (1)	Sellers (2)
Media	14,370	3,365
Electronics	7,606	8,888
Home and Garden	5,150	6,182
Health and Beauty	4,425	3,676
Arts and Entertainment	2,873	2,779
Hardware	2,831	3,200
Toys and Games	2,777	3,350
Apparel and Accessories	2,645	2,061
Sporting Goods	2,335	2,781
Pet Supplies	1,106	1,241
Luggage and Bags	1,077	1,549
Cameras and Optics	978	2,492
Office Supplies	849	1,408
Vehicles and Parts	575	1,539
Software	506	1,041
Furniture	334	1,253
Baby and Toddler	160	654
Business and Industrial	67	324
Food, Beverages and Tobacco	67	174
Mature	43	385
Services	26	119
Not Classified	1,976	3,465
Total	***52,776***	***27,308***

Prices for a Smartphone in May 2011



Weighting Schemes

Let f_{is} be a stickiness measure for good i sold by seller s

We compute 3 aggregate measures:

1. Unweighted mean

$$\bar{f} = \sum_i \frac{1}{N} \sum_s f_{is} \frac{1}{S}$$

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2. Within-good weighted mean

$$\bar{f}^{\text{within}} = \sum_i \frac{1}{N} \sum_s f_{is} \cdot \frac{Q_{is}}{\underbrace{\sum_s Q_{is}}_{\text{within-good weights}}}$$

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$$\bar{f}^{\text{within}} = \sum_i \frac{1}{N} \sum_s f_{is} \cdot \underbrace{\frac{Q_{is}}{\sum_s Q_{is}}}_{\substack{\text{within-good} \\ \text{weights}}}$$

3. **Between-good weighted mean**

$$\bar{f}^{\text{between}} = \sum_i \underbrace{\frac{\sum_s Q_{is}}{\sum_i \sum_s Q_{is}}}_{\substack{\textbf{between-good} \\ \textbf{weights}}} \cdot \sum_s f_{is} \cdot \underbrace{\frac{Q_{is}}{\sum_s Q_{is}}}_{\substack{\textbf{within-good} \\ \textbf{weights}}}$$

Regular and Posted Prices

Lots of price changes last for a limited period of time
(Nakamura and Steinsson 2008,
Eichenbaum, Jaimovich, and Rebelo 2011)

Excluding temporary changes (sales) increases duration of spells
from 4 to 8–11 months
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Sales do not affect monetary non-neutrality
(Kehoe and Midrigan 2012, Guimaraes and Sheedy 2011)
are acyclical (Coibion, Gorodnichenko, and Hong 2012)
may interact with regular prices (Sheremirov 2014)
are part of “sticky price plans” (Anderson et al. 2014)

Frequency of Sales

	Mean Freq. (1)	Standard Deviation (2)	Med. Freq. (3)
No	1.3	3.1	0.0
W	1.5	3.2	0.0
B	1.7	1.9	1.4

One-week two-sided sales filter (Anderson et al. 2014)

Frequency of Sales

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B	1.7	1.9	1.4
Offline	1.9		

One-week two-sided sales filter (Anderson et al. 2014)

Sales are almost as frequent online as offline

Frequency and Size of Sales

	Mean Freq. (1)	Standard Deviation (2)	Med. Freq. (3)	Med. Size (4)
Online				
No	1.3	3.1	0.0	10.5
W	1.5	3.2	0.0	4.8
B	1.7	1.9	1.4	4.4
Offline	1.9			29.5

One-week two-sided sales filter (Anderson et al. 2014)

Sales are almost as frequent online as offline

However, consumers get a better discount offline

Synchronization of Sales

$$\text{Synchronization Rate} = \frac{A-1}{B-1}, A \geq 1, B \geq 2$$

where A is # of sellers with sales and B is total # of sellers

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	Across Sellers		
	Mean (1)	Std. (2)	Med. (3)
No	0.8	5.2	0.0
W	1.0	6.3	0.0
B	1.8	4.7	0.2

Sales are not particularly synchronized

consistent with models of segmented markets

(e.g., Guimaraes and Sheedy 2011)

Synchronization of Sales

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	Across Sellers			Across Goods		
	Mean (1)	Std. (2)	Med. (3)	Mean (4)	Std. (5)	Med. (6)
No	0.8	5.2	0.0	2.1	9.6	0.0
W	1.0	6.3	0.0	2.4	11.4	0.0
B	1.8	4.7	0.2	2.1	1.0	2.4

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consistent with models of segmented markets

(e.g., Guimaraes and Sheedy 2011)

Online retailers conduct sales for specific products

Are prices more flexible online?

Frequency and Size of Price Changes

	Raw			Offline
Weights:	No	W	B	Offline
	(1)	(2)	(3)	(4)
Median Freq., %	14.0	16.7	19.3	4.7
Duration, weeks	6.6	5.5	4.7	20.8

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	Raw			
Weights:	No (1)	W (2)	B (3)	Offline (4)
Median Freq., %	14.0	16.7	19.3	4.7
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Absolute Size, %	11.0	10.7	11.2	10.7

Frequency and Size of Price Changes

	Raw			
Weights:	No	W	B	Offline
	(1)	(2)	(3)	(4)
Posted Price				
Median Freq., %	14.0	16.7	19.3	4.7
Duration, weeks	6.6	5.5	4.7	20.8
Absolute Size, %	11.0	10.7	11.2	10.7
Regular Price				
Median Freq., %	8.8	10.8	14.5	2.1
Duration, weeks	10.9	8.7	6.4	47.1
Absolute Size, %	10.9	10.6	10.9	8.5

Sales filter: 1-week two-sided filter

Frequency and Size of Price Changes

	Raw			Imputed			
Weights:	No (1)	W (2)	B (3)	No (4)	W (5)	B (6)	Offline (7)
Posted Price							
Median Freq., %	14.0	16.7	19.3	7.2	9.3	16.3	4.7
Duration, weeks	6.6	5.5	4.7	13.4	10.2	5.6	20.8
Absolute Size, %	11.0	10.7	11.2				10.7
Regular Price							
Median Freq., %	8.8	10.8	14.5	6.3	8.0	13.5	2.1
Duration, weeks	10.9	8.7	6.4	15.5	12.1	6.9	47.1
Absolute Size, %	10.9	10.6	10.9				8.5

Sales filter: 1-week two-sided filter

Imputation: {2,2,.,.,2}==>{2,2,2}, up to 4 weeks

Weighting by clicks improves measurement (imputation)

Composition Effect

	Posted Price			Regular Price		
	Online			Online		
	No	B	Offline	No	B	Offline
	(1)	(2)	(3)	(4)	(5)	(6)
Audio Players and Recorders	17.1	23.5	6.2	10.8	19.8	1.8
Bedding	20.0	17.1	10.1	12.5	13.3	1.3
Books	20.0	23.8	1.7	14.2	16.7	1.3
Camera Accessories	7.4	16.4	4.7	4.9	12.4	2.0
Cameras	17.6	34.9	5.2	15.6	30.3	2.7
Camping, Backpacking, and Hiking	13.3	18.0	3.4	7.8	14.5	1.1
Computer Software	12.1	23.8	2.8	7.7	19.1	2.0
Cookware	13.2	17.7	4.8	7.7	10.6	0.7
Costumes	10.8	13.2	7.2	6.1	7.3	0.9
Cycling	15.8	16.5	3.6	10.3	12.5	1.7
Doors and Windows	13.4	8.8	4.3	10.6	5.7	0.8
Gardening	12.5	12.8	2.3	6.8	9.1	1.3
Hair Care	14.3	22.4	5.2	9.7	14.7	1.7
Household Climate Control	11.3	15.7	3.7	7.0	11.1	0.8
Kitchen Appliances	13.4	13.2	5.7	9.3	10.6	0.9
Musical String Instruments	1.9	2.1	2.4	0.7	1.6	1.5
Oral Care	14.4	23.5	1.8	11.3	17.5	1.2
Tableware	11.1	17.6	5.2	6.3	16.1	0.7
Telephony	15.9	23.4	4.7	9.1	22.8	2.7
Vacuums	15.2	32.1	7.1	11.6	25.4	2.0
Vision Care	1.3	5.7	2.9	0.0	5.7	1.4
Watches	12.2	11.8	5.7	7.9	9.0	1.0

Product Substitution

Product substitution is a channel of price adjustment (Nakamura and Steinsson 2012)

Cavallo, Neiman, and Rigobon (2014) scrape online data from Apple, IKEA, H&M, and Zara

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from Apple, IKEA, H&M, and Zara

1. 77% of products in the U.S. sample have constant price
2. duration of life is short (15 weeks)
3. longer life duration ==> price changes are more likely

Product Substitution

	All Products	
	Const. Price (1)	Not Const. (2)
Share of goods, %	11.9	88.1
Share of clicks, %	1.3	98.7

Only 12% of products have constant price (unlike in CNR)

Product Substitution

	All Products		Apparel, One Seller	
	Const. Price (1)	Not Const. (2)	Const. Price (3)	Not Const. (4)
Share of goods, %	11.9	88.1	31.0	69.0
Share of clicks, %	1.3	98.7	25.7	74.3

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The difference is due to sample composition

Product Substitution

	All Products		Apparel, One Seller		—excl. Jewelry and Watches	
	Const. Price (1)	Not Const. (2)	Const. Price (3)	Not Const. (4)	Const. Price (5)	Not Const. (6)
Share of goods, %	11.9	88.1	31.0	69.0	42.4	57.6
Share of clicks, %	1.3	98.7	25.7	74.3	30.8	69.2

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	All Products		Apparel, One Seller		—excl. Jewelry and Watches	
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Share of goods, %	11.9	88.1	31.0	69.0	42.4	57.6
Share of clicks, %	1.3	98.7	25.7	74.3	30.8	69.2
Av. # of sellers	1.3	5.1	1.0	1.0	1.0	1.0
Life duration, weeks	36.2	57.2	27.9	37.4	22.3	30.3

Only 12% of products have constant price (unlike in CNR)

The difference is due to sample composition

Duration of life is shorter for apparel

shorter duration ==> price changes are less likely (as in CNR)

but the frequency is almost the same

Do micro factors play a role in price adjustment?

Predictors of Price Stickiness

We run the following regressions:

$$f_i^{\mathrm{w}} = \beta_1 \log S_i + \beta_2 \mathrm{HHI}_i + \beta_3 \log Q_i + \beta_4 \overline{\log P}_i + \beta_5 \overline{\log P}_i^2 + \varepsilon_i$$

f_i^{w} is click-weighted frequency, size, or sync. for good i
S_i — number of sellers; HHI_i — Herfindahl index based on clicks, $(0,1]$
Q_i — total number of clicks
$\overline{\log P}_i$ — median log price
Category FE; SE clustered at narrow categories; obs. weighted by clicks

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Determinant	Freq. (1)	Abs. Size (2)	Sync. (3)
Log Number of Sellers	10.7***	−1.3*	2.8***
	(0.6)	(0.7)	(0.6)
R^2	0.09	0.12	0.05
N	14,483	17,053	9,937

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	(0.6)	(0.7)	(0.6)
Concentration, HHI, $(0,1]$	24.9***	−6.6***	13.3***
	(2.8)	(1.5)	(2.9)
R^2	0.09	0.12	0.05
N	14,483	17,053	9,937

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S_i — number of sellers; HHI_i — Herfindahl index based on clicks, $(0,1]$
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$\overline{\log P}_i$ — median log price
Category FE; SE clustered at narrow categories; obs. weighted by clicks

Determinant	Freq. (1)	Abs. Size (2)	Sync. (3)
Log Number of Sellers	10.7***	−1.3*	2.8***
	(0.6)	(0.7)	(0.6)
Concentration, HHI, (0, 1]	24.9***	−6.6***	13.3***
	(2.8)	(1.5)	(2.9)
Log Total Clicks	−4.2***	0.3	−0.6*
	(0.3)	(0.3)	(0.4)
R^2	0.09	0.12	0.05
N	14,483	17,053	9,937

Predictors of Price Stickiness

We run the following regressions:

$$f_i^w = \beta_1 \log S_i + \beta_2 \mathrm{HHI}_i + \beta_3 \log Q_i + \beta_4 \overline{\log P}_i + \beta_5 \overline{\log P}_i^2 + \varepsilon_i$$

f_i^w is click-weighted frequency, size, or sync. for good i
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	(2.8)	(1.5)	(2.9)
Log Total Clicks	−4.2***	0.3	−0.6*
	(0.3)	(0.3)	(0.4)
Log Median Price	0.1	−9.2***	2.0***
	(0.7)	(0.7)	(0.6)
Log Median Price, sq.	−0.1	0.7***	−0.1*
	(0.1)	(0.1)	(0.1)
R^2	0.09	0.12	0.05
N	14,483	17,053	9,937

Is there more price convergence online?

Price Dispersion: Importance

- In theory, should be small without menu & search costs

- Is tightly related to welfare
  - $MC = MR_1 = MR_2$ is violated
  - opportunity for store switching

- Allows distinguishing between various micro and macro theories
  - spatial vs. temporal
  - dynamics since product introduction
  - comovement with inflation

Price Dispersion, % or log-p.

	CV $std(P)/\bar{P}$ (1)	$std(\log P)$ (2)
No	21.5	23.6
W	21.4	22.9
B	19.9	20.3

The same order of magnitude as offline

Kaplan and Menzio (2014): CV=19% in the Nielsen data

Sheremirov (2014): $std(\log P) = 10$ log-p. in the IRI data

Price Dispersion, % or log-p.

	CV $std(P)/\bar{P}$ (1)	$std(\log P)$ (2)	VI $\bar{p}-p_1$ (3)	IQR $p_{75\%}-p_{25\%}$ (4)	Range $p_{max}-p_1$ (5)	Gap p_2-p_1 (6)
No	21.5	23.6	24.4	34.6	40.7	27.6
W	21.4	22.9	23.3	32.0	40.7	27.6
B	19.9	20.3	24.8	26.1	50.1	21.1

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Less mass around the min. price

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			Actual prices, P_{ist}			
No	21.5	23.6	24.4	34.6	40.7	27.6
W	21.4	22.9	23.3	32.0	40.7	27.6
B	19.9	20.3	24.8	26.1	50.1	21.1
			Prices net of seller fixed effects, ε_{ist}			
No		21.2	18.3	31.2	36.8	25.1
W		20.7	17.5	28.9	36.8	25.1
B		17.5	18.6	22.5	43.8	18.8

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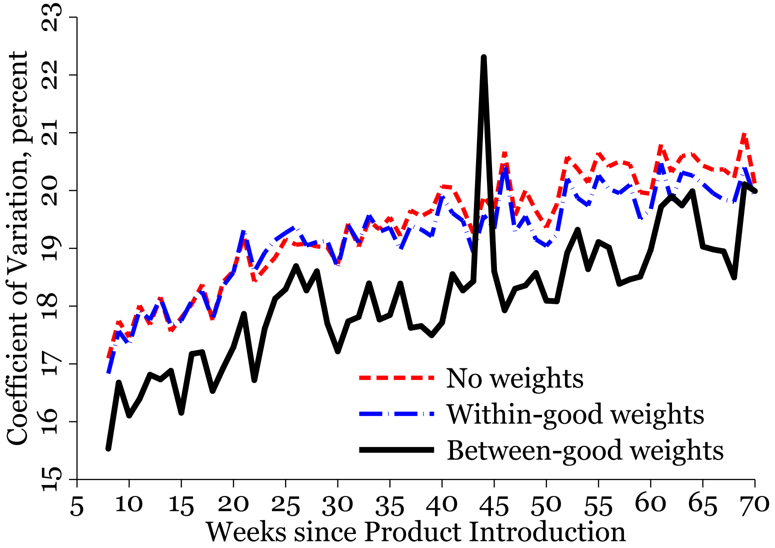
Less mass around the min. price

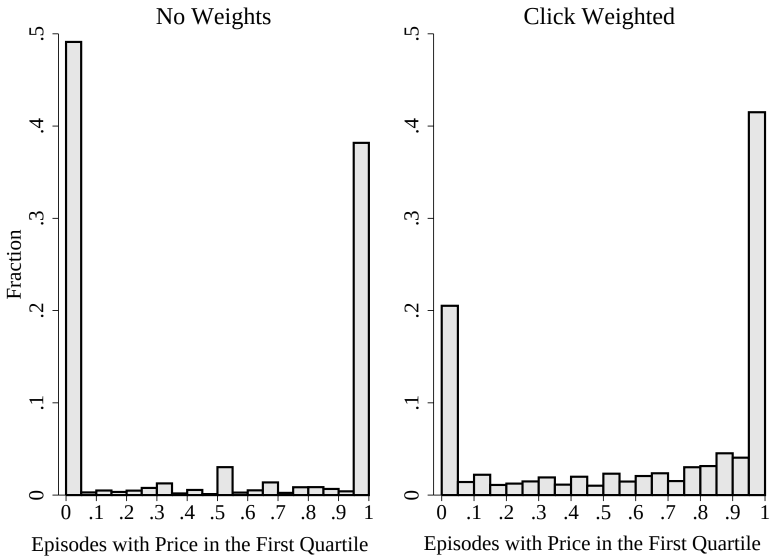
Seller FE control for delivery, return, customer experience, etc.

$\log P_{ist} = \alpha_i + \gamma_s + \varepsilon_{ist}$

Price Dispersion since Product Introduction



Spatial vs Temporal Price Dispersion



Do online retailers use dynamic pricing?

Dynamic Pricing

Warner and Barsky's (1995):
firms permanently reset prices during high demand episodes

Uneven price staggering may affect the timing of monetary policy
—similar to Olivei and Tenreyro's (2007) argument

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- We find confirmation for WB at low frequencies
  (around sales seasons: Thanksgiving or Christmas)
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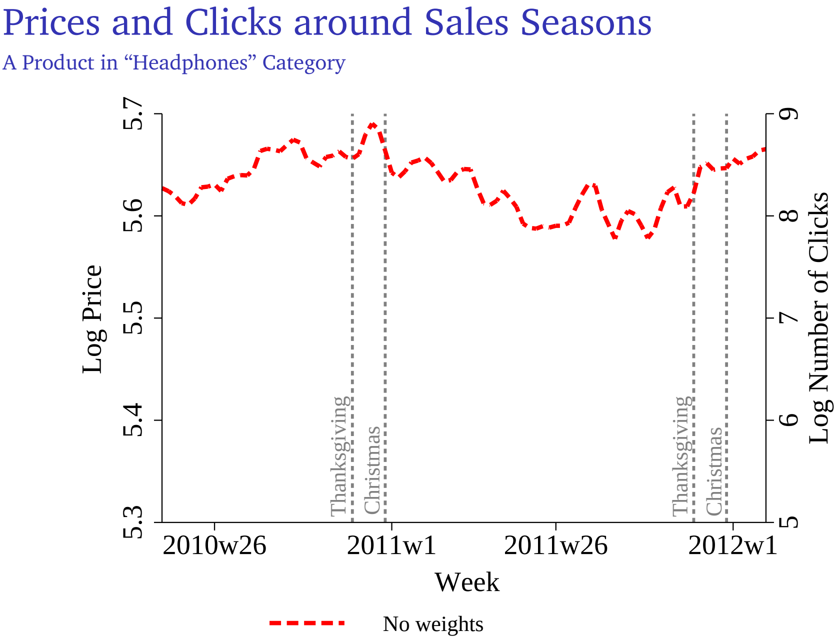
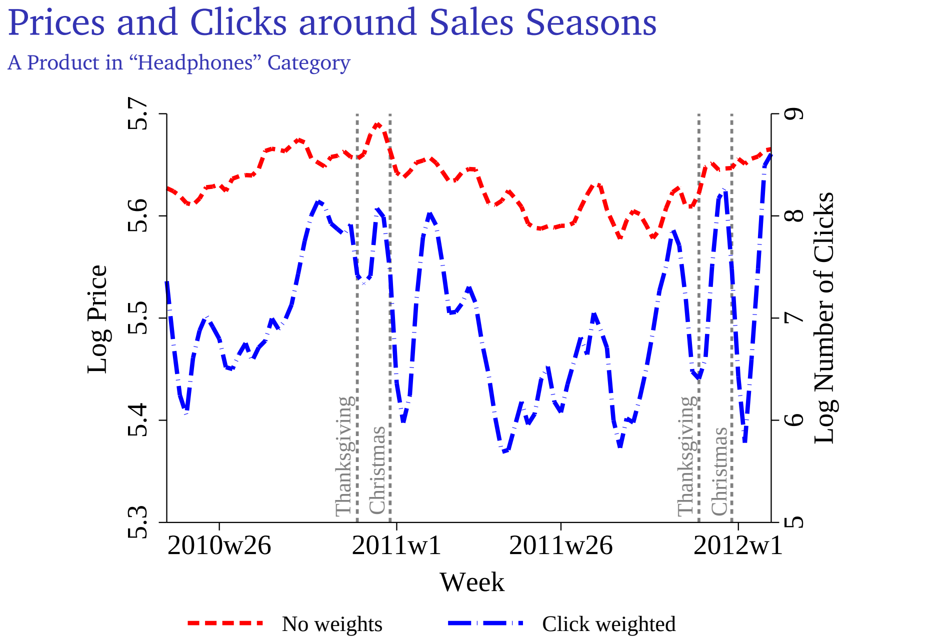
—similar to Olivei and Tenreyro's (2007) argument

- We find confirmation for WB at low frequencies
  (around sales seasons: Thanksgiving or Christmas)
  - clicks ↑, prices permanently ↓
- No confirmation at higher frequencies
  (days of the week or month)
  - Consumers shop online at the beginning of the week or month
  - No evidence firms adjust their prices more often


Prices and Clicks around Sales Seasons
A Product in “Headphones” Category
Log Price
5.7
5.6
5.5
5.4
5.3
Log Number of Clicks
9
8
7
6
5
Thanksgiving
Christmas
Thanksgiving
Christmas
2010w26
2011w1
2011w26
2012w1
Week
No weights



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A Product in “Headphones” Category
Log Price
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5.3
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2011w1
2011w26
2012w1
Week
No weights
Click weighted

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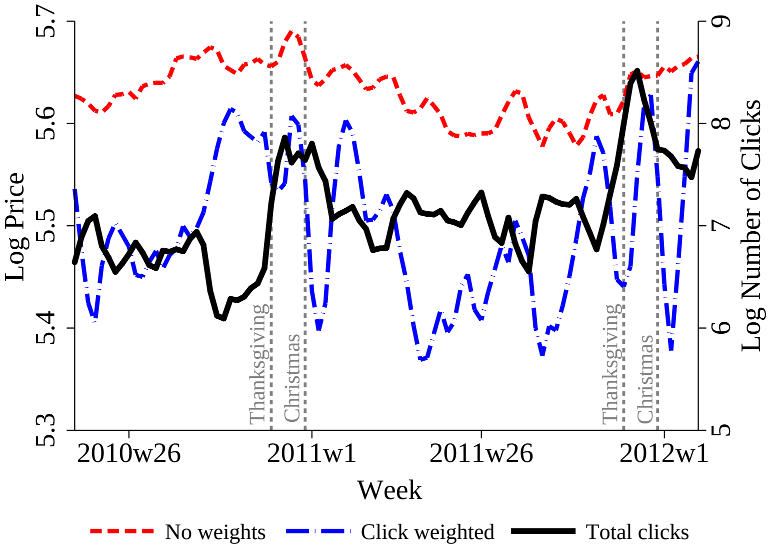


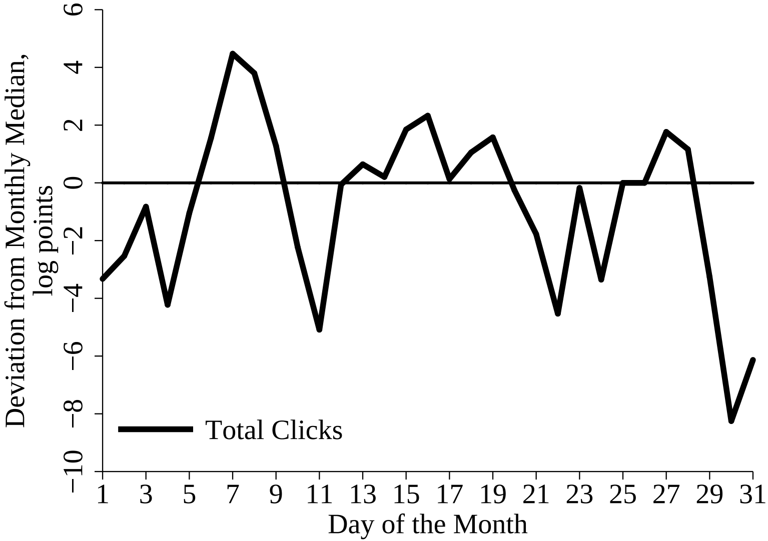
Prices and Clicks by Day of the Week

	Click Share, *percent* (1)	Log Deviation from Weekly Median, *log points*: Total Clicks (2)
Monday	16.2	10.0
Tuesday	15.5	6.4
Wednesday	14.8	3.8
Thursday	14.3	0.0
Friday	13.3	−6.6
Saturday	12.1	−16.0
Sunday	13.8	−4.4

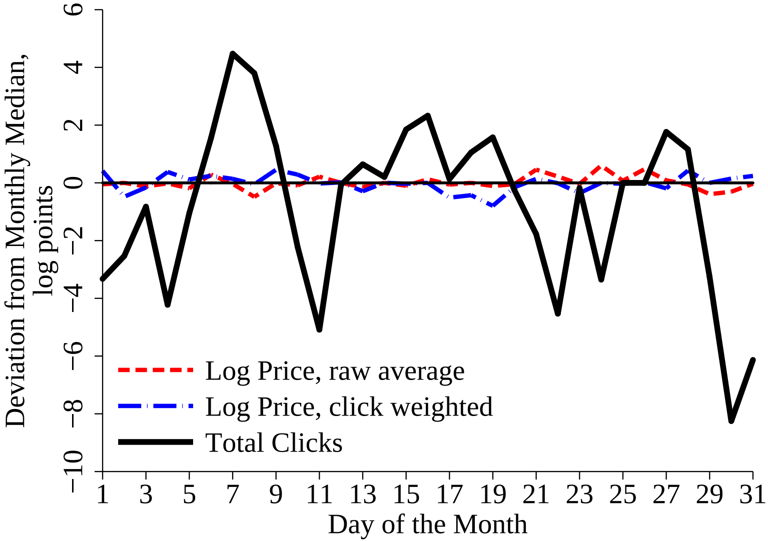
Prices and Clicks by Day of the Week

		Log Deviation from Weekly Median, *log points*		
	Click Share, *percent* (1)	Total Clicks (2)	Mean Price (3)	Weighted Mean Price (4)
Monday	16.2	10.0	−0.1	0.0
Tuesday	15.5	6.4	0.2	0.0
Wednesday	14.8	3.8	0.5	0.0
Thursday	14.3	0.0	1.4	0.1
Friday	13.3	−6.6	2.0	2.8
Saturday	12.1	−16.0	−3.0	−0.8
Sunday	13.8	−4.4	−5.4	−1.9

Prices and Clicks by Day of the Month



Prices and Clicks by Day of the Month



Do prices respond to aggregate shocks at high frequencies?

Macro Announcement Surprises

Gurkaynak, Sack, and Swanson (2005):
macro announcement surprises move asset prices

Do macro announcement surprises also move online retail prices?

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DATA:
14 real-time series from Informa Global Markets
(CPI, GDP, unemployment, leading indicators, etc.)

$$\text{Shock}_t^i = \text{Actual Realization}_t^i - \text{Median Forecast}_t^i$$

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$$\text{Shock}_t^i = \text{Actual Realization}_t^i - \text{Median Forecast}_t^i$$

SPECIFICATION:

$$f_t^{\mathrm{b}} = \alpha + \beta \cdot \text{Shock}_t^i + \varepsilon_t^i$$

where f_t^b is a between-good, click-weighted measure of stickiness

Obs. are click-weighted; Shocks are normalized; S.E. are bootstrapped

Aggregate Shocks

We construct consumption shock series at the daily frequency

1. Estimate loadings of shocks on *monthly* real PCE growth rate
   1995–2012 sample ($R^2 = 0.47$):

$$\Delta \log C_m = \alpha + \sum_{i=1}^{14} \beta_i \cdot \text{Shock}_m^i + \varepsilon_m$$

2. Compute predicted values of *daily* real PCE growth rate:

$$\widehat{\Delta \log C_t} = \hat{\alpha} + \sum_{i=1}^{14} \hat{\beta}_i \cdot \text{Shock}_t^i$$

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2. Compute predicted values of *daily* real PCE growth rate:

$$\widehat{\Delta \log C_t} = \hat{\alpha} + \sum_{i=1}^{14} \hat{\beta}_i \cdot \text{Shock}_t^i$$

Allow for a delayed response to shocks:
$\tilde{f}_t^{\text{b}} = \sum_{\tau=0}^{13} f_{t+\tau}^{\text{b}} / 14$

Responses on Impact

	Regular Price				Sales		Log # of Clicks
	Frequency		Abs. Size				
	Inc	Dec	Inc	Dec	Freq.	Size	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Capacity utilization	−0.05	−0.10	3.45	−0.91	−4.26	1.00	−0.10
	(0.48)	(0.53)	(1.22)	(1.47)	(3.32)	(2.63)	(0.12)
Consumer confidence	0.15	0.29	−4.36	0.16	0.00	0.21	0.11
	(0.54)	(0.49)	(3.98)	(1.14)	(1.82)	(0.29)	(0.12)
CPI, core	−0.67	−0.58	−1.00	3.38	−0.78	−3.50	0.11
	(0.88)	(1.14)	(2.01)	(2.06)	(3.67)	(2.89)	(0.18)
Employment cost index	−0.02	0.25	−3.53	3.53	5.57	−0.56	0.01
	(1.67)	(1.43)	(3.06)	(3.83)	(5.08)	(3.95)	(0.24)
GDP	1.85	1.81	9.03	−22.89	−10.55	1.17	−0.24
	(5.70)	(5.57)	(11.34)	(10.74)	(18.42)	(14.38)	(0.71)
Initial claims	−0.42	−0.29	0.67	−1.96	1.09	−0.52	−0.03
	(0.35)	(0.25)	(0.78)	(1.47)	(1.38)	(0.40)	(0.04)
ISM manufacturing index	0.14	0.00	−4.17	0.83	−1.60	0.74	0.10
	(0.35)	(0.45)	(4.33)	(2.29)	(3.40)	(0.78)	(0.13)
Leading indicators	−0.17	0.56	0.25	3.46	−3.09	3.34	0.09
	(0.55)	(0.64)	(1.37)	(1.40)	(2.31)	(4.13)	(0.11)
New home sales	−1.15	−0.46	−0.98	−7.03	5.76	−0.93	0.07
	(1.56)	(1.24)	(0.84)	(11.38)	(4.24)	(0.66)	(0.28)
Nonfarm payrolls	0.85	1.09	−0.71	−0.48	−0.77	0.37	−0.11
	(0.43)	(0.38)	(1.89)	(4.36)	(3.19)	(0.18)	(0.15)
PPI, core	−1.43*	−2.20	0.26	−0.76	−3.52	−0.19	0.01
	(0.79)	(1.44)	(1.82)	(1.93)	(4.58)	(3.89)	(0.14)
Retail sales	0.27	0.65	−4.90	1.96	7.11	1.43	0.22
	(1.33)	(1.56)	(2.47)	(1.82)	(4.55)	(2.38)	(0.29)
excluding motor vehicles	−0.16	−0.48	−2.51	1.89*	4.07	1.90	0.10
	(0.45)	(0.28)	(2.11)	(1.07)	(3.95)	(2.70)	(0.22)
Unemployment	0.11	0.25	−1.42	−3.93	1.55	−0.01	−0.06
	(0.34)	(0.36)	(1.04)	(2.71)	(2.18)	(0.13)	(0.11)
Aggregate shock	***–0.17***	***–0.11***	***0.49***	***0.40***	***–0.57***	***–0.10***	***0.01***
	(0.19)	***(0.18)***	***(0.80)***	***(1.47)***	***(0.93)***	***(0.11)***	***(0.05)***

Responses within Two Weeks

	Regular Price				Sales		Log # of Clicks
	Frequency		Abs. Size				
	Inc	Dec	Inc	Dec	Freq.	Size	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Capacity utilization	−0.04	−0.23	0.49	−0.12	−0.68	−0.01	−0.08
	(0.28)	(0.29)	(0.75)	(0.92)	(2.10)	(0.32)	(0.13)
Consumer confidence	0.40*	0.26	−0.62	−0.96	0.44	0.17*	0.05
	(0.24)	(0.26)	(0.65)	(0.85)	(1.17)	(0.10)	(0.11)
CPI, core	−0.60	−0.58	0.24	−0.44	−0.81	−1.04	0.18
	(0.66)	(0.67)	(1.06)	(1.43)	(1.83)	(0.71)	(0.14)
Employment cost index	0.06	0.06	−4.07**	−5.69*	1.14	−0.30	−0.15
	(0.84)	(0.73)	(1.73)	(3.07)	(2.66)	(0.36)	(0.18)
GDP	−0.58	−0.22	10.70	14.97	−1.41	0.49	0.16
	(2.61)	(2.41)	(8.96)	(14.89)	(7.94)	(1.91)	(0.64)
Initial claims	−0.27**	−0.28**	−0.10	−0.23	−0.65	−0.22*	−0.05
	(0.13)	(0.11)	(0.25)	(0.32)	(0.65)	(0.13)	(0.05)
ISM manufacturing index	0.13	0.14	−0.56	−0.65	2.38*	−0.08	0.09
	(0.19)	(0.20)	(0.54)	(0.81)	(1.42)	(0.31)	(0.11)
Leading indicators	0.40	0.15	0.22	0.00	1.02	0.10	0.09
	(0.39)	(0.28)	(0.70)	(1.05)	(1.24)	(0.40)	(0.14)
New home sales	0.17	−0.12	−0.23	−0.86	1.28	−0.29	−0.04
	(0.60)	(0.55)	(0.94)	(1.06)	(2.06)	(0.31)	(0.26)
Nonfarm payrolls	0.18	0.26	−1.12*	−0.09	1.54	−0.33	−0.07
	(0.29)	(0.26)	(0.63)	(0.87)	(1.58)	(0.46)	(0.13)
PPI, core	−1.30***	−1.29***	0.04	−0.32	−0.65	−1.49**	−0.02
	(0.47)	(0.41)	(0.90)	(1.13)	(3.35)	(0.70)	(0.14)
Retail sales	0.41	0.47	1.06	1.83*	1.60	1.45	0.24
	(0.86)	(0.86)	(0.80)	(1.03)	(2.52)	(1.51)	(0.25)
excluding motor vehicles	0.01	0.01	1.11***	1.50***	2.85	0.39	0.16
	(0.22)	(0.21)	(0.36)	(0.50)	(2.42)	(0.59)	(0.14)
Unemployment	−0.09	−0.11	−1.09**	−0.78	0.70	−0.05	−0.04
	(0.19)	(0.19)	(0.46)	(0.50)	(0.98)	(0.18)	(0.09)
Aggregate shock	***0.04***	***0.01***	***0.02***	***–0.26***	***–0.58***	***–0.01***	***–0.02***
	(0.10)	***(0.09)***	***(0.25)***	***(0.38)***	***(0.52)***	***(0.09)***	***(0.05)***

Concluding Remarks

Summary:

- Online prices are more flexible than offline prices
- Still, there are significant frictions in online markets
- Data on quantity margin improves measurement

Implications:

- Price stickiness is unlikely to disappear due to e-commerce
- Online prices have special effects on aggregate price and inflation

Future research:

- Need for alternative mechanisms that generate price stickiness
- Sellers with online and offline presence
- Data on inventories and costs