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THE RESPONSES OF INTERNET RETAIL PRICES TO AGGREGATE SHOCKS: A HIGH-FREQUENCY APPROACH *

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Abstract: Using a unique dataset of daily price listings and the associated number of clicks for precisely defined goods from a major shopping platform, we examine whether internet prices respond to aggregate shocks at a high frequency. Despite internet retailers' unique position to exercise dynamic pricing due to low costs of nominal price adjustment, we find little evidence that online prices respond promptly to unanticipated announcements about macroeconomic activity. Shopping activity also appears unresponsive to aggregate shocks, suggesting that internet retailers may follow individual demand for their products more closely than aggregate demand.

Keywords: online markets, price stickiness, aggregate shocks, high-frequency approach
JEL Classification: E3

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1 Introduction

Internet retailers are uniquely positioned to adjust their prices every instant in response to changing business and economic conditions, a practice known as dynamic pricing. While some sectors such as air travel use dynamic pricing extensively (e.g., Bilotkach, Gorodnichenko, and Talavera 2010), little is known about whether online retailers adjust their prices at high frequencies in response to unanticipated changes in *macroeconomic* conditions. Yet, having estimates of these adjustment responses would be highly informative for understanding the nature of price setting from the macroeconomic perspective. Furthermore, looking at the response of online prices to aggregate shocks provides additional insights, as conventional explanations of price stickiness (e.g., menu costs and search costs) are less likely to be at play in online markets than in traditional brick-and-mortar stores.

In this paper, we use data from a leading online shopping platform to study whether prices respond to aggregate shocks at a high frequency. We measure aggregate shocks as a surprise component in macroeconomic announcements about aggregate statistics. We estimate the response of the frequency and size of price changes on the day of an announcement and within a subsequent 14 day period. We find little evidence that online prices respond to macroeconomic shocks at high frequencies. The lack of response is documented not only for regular prices (i.e., prices that exclude temporary discounts) but also for the frequency and size of temporary discounts.

In addition to high-frequency measurements of price quotes, we also have access to high-frequency information about the volume of demand. Specifically, consumer activity is measured by the total number of clicks on the links available on the shopping platform. We find that, like prices, the demand for goods does not respond to aggregate conditions. Having data on clicks also allows us to focus on prices that matter most to consumers (transaction prices) and to aggregate individual price series into an online price index.

Our previous work (Gorodnichenko, Sheremirov, and Talavera 2017) documents that online prices do not respond to predictable changes in demand conditions at a micro level. This paper instead focuses on *unanticipated* changes in aggregate demand. We also contribute to the literature focusing on the frequency and size of price changes (e.g., Bils and Klenow 2004, Cavallo 2015, Gorodnichenko and Talavera 2017) by examining the response of these aggregate statistics to macroeconomic shocks.

2 Data

We rely on two datasets used in the literature to study (separately) online prices and the effects of aggregate shocks. For daily internet prices (net of taxes and shipping costs) and clicks, we use proprietary data from a leading global online shopping platform on more than 50,000 goods in 22 broadly-defined consumer categories between May 2010 and February 2012. A detailed description of these data and their advantages for our analyses are provided by Gorodnichenko, Sheremirov, and Talavera (2017).

To measure aggregate shocks, we use real-time data from Informa Global Markets (IGM), which reports the actual release and median forecast of measures of economic activity such as capacity utilization, consumer confidence, core CPI, the employment cost index, GDP, initial claims, the manufacturing composite index, new home sales, nonfarm sales, PPI, retail sales (total and excluding motor vehicles), and unemployment—14 series overall. This dataset has been used to identify aggregate shocks, among others, by Andersen et al. (2003), wherein a detailed description of the data is provided.

3 A Measure of Aggregate Shocks

We construct a *daily* shock for each series i as

$$\text{Shock}_t^i = \text{Actual Realization}_t^i - \text{Median Forecast}_t^i, \tag{1}$$

where t indexes days. To make units comparable across shocks, we standardize each shock series to have zero mean and unit standard deviation.

While macroeconomic announcements are not synchronized, each shock series has nonmissing values only 12 or fewer days per year (only initial claims are weekly and thus have about 50 nonmissing values per year). To enhance the statistical power of our analysis, we construct a composite shock series. Specifically, we estimate the loadings of these shocks on the change in consumption using the *monthly* data for the 1995–2012 period:

$$\Delta \log C_m = \alpha + \sum_{i=1}^{14} \beta_i \cdot \text{Shock}_m^i + \varepsilon_m, \tag{2}$$

where m indexes months and $\Delta \log C_m$ is the log change of monthly real personal consumption expenditures (FRED® code: PCEC96). The R^2 in this regression is 0.47, so the shocks account for a considerable part of variation in the monthly consumption growth rate. We then compute the composite shock as the *daily* predicted values of the consumption growth rate, $\widehat{\Delta \log C}_t = \hat{\alpha} + \sum_{i=1}^{14} \hat{\beta}_i \cdot \text{Shock}_t^i$.

Next, we estimate the effect of our shock measures on the cross-sectional frequency and size of price changes and shopping intensity (number of clicks). Let f_t^{b} be the between-good, click-weighted frequency of price adjustment on day t computed as in Gorodnichenko, Sheremirov, and Talavera (2017). To allow for a delayed response to shocks, we also construct $\tilde{f}_t^{\mathrm{b}} = \sum_{\tau=0}^{13} f_{t+\tau}^{\mathrm{b}}/14$, the average weighted frequency of price adjustment within 14 days since day t. In a similar spirit, let $\overline{|\Delta \log p|}_t^{\mathrm{w}}$ be the between-good, click-weighted average price change on day t and $\widetilde{|\Delta \log p|}_t^{\mathrm{b}}$ the average value of the size of price changes between t and $t+14$. Since we expect a given shock to move prices in a certain direction, we consider price increases and decreases separately. We reach the same conclusion when we use the absolute value, rather than the level, of a shock. Finally, Q_t is the total number of clicks on day t and $\tilde{Q}_t$ the average number of daily clicks between t and $t+14$.

We project each moment at a daily frequency on a set of dummy variables to remove the predictable variation of the moment across days of the week and days of the month. Then, we regress the residual from this projection on each individual shock separately and on the composite shock. Since we have relatively few nonmissing observations for each shock, we use bootstrap to calculate standard errors.

4 High-Frequency Responses of Online Prices

While Andersen et al. (2003) and many others show that the surprise component in macroeconomic announcements moves asset prices at high frequencies, we find little evidence that the shocks have a consistently discernible effect on the moments on impact or within 14 days after a shock (Table 1). In columns (1)–(4), we show the response of the *cross-sectional* frequency and size of regular price increases and decreases to realized shocks *on the day of an announcement about variables in rows*. In columns (5)–(6), we show the response of the frequency and absolute size of temporary price discounts ("sales"). The vast majority of the estimates are not statistically or economically significant. None of the shocks moves the number of clicks, our proxy for demand (column 7). The composite shock, which has the largest number of nonmissing observations, does not have any significant estimates (last row). The lack of response is also observed two weeks after the announcements (columns 8–14). Our conclusions remain unchanged when we do not use clicks as weights or when we condition responses on the sign of a shock.

In Table 2, we estimate the effect of our shock measures on the aggregate price index. We construct the aggregate price index in two ways. First, we take the click-weighted average price across all sellers and goods on a given day. Second, we compute the weighted average price at the broad category level, and then extract the first principal component from the category-level price series. The results confirm our main finding that at high frequencies, sellers do not reset their prices in response to macroeconomic shocks. Hence, the conventionally emphasized frictions of nominal price adjustment (e.g., menu costs, search costs) could play a minor role in the observed price stickiness.

5 Conclusions

Using unique daily data on prices and clicks from a large online shopping platform, this paper documents that online prices do not exhibit a significant response to unanticipated changes in aggregate economic conditions. This result is consistent with models in which firms are inattentive to changes in aggregate conditions but respond promptly to idiosyncratic shocks, a strategy that may lead to a combination of a relatively high frequency of price changes and monetary non-neutrality (e.g., Boivin, Giannoni, and Mihov 2009, Maćkowiak and Wiederholt 2009). Future research focusing on understanding the response of online prices to idiosyncratic changes in demand conditions and to sectoral shocks may therefore be useful to discriminate among alternative theories.

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Table 1. Effects of Macroeconomic Shocks on Pricing

	On Impact							Two Weeks Ahead						
	Regular Price				Sales		Log Number of Clicks	Regular Price				Sales		Log Number of Clicks
	Frequency of		Absolute Size of					Frequency of		Absolute Size of				
	Increases	Decreases	Inc.	Dec.	Freq.	Abs. Size		Inc.	Dec.	Inc.	Dec.	Freq.	Abs. Size	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Capacity utilization	−0.05	−0.10	3.45	−0.91	−4.26	1.00	−0.10	−0.04	−0.23	0.49	−0.12	−0.68	−0.01	−0.08
	(0.48)	(0.53)	(1.22)	(1.47)	(3.32)	(2.63)	(0.12)	(0.28)	(0.29)	(0.75)	(0.92)	(2.10)	(0.32)	(0.13)
Consumer confidence	0.15	0.29	−4.36	0.16	0.00	0.21	0.11	0.40*	0.26	−0.62	−0.96	0.44	0.17*	0.05
	(0.54)	(0.49)	(3.98)	(1.14)	(1.82)	(0.29)	(0.12)	(0.24)	(0.26)	(0.65)	(0.85)	(1.17)	(0.10)	(0.11)
CPI, core	−0.67	−0.58	−1.00	3.38	−0.78	−3.50	0.11	−0.60	−0.58	0.24	−0.44	−0.81	−1.04	0.18
	(0.88)	(1.14)	(2.01)	(2.06)	(3.67)	(2.89)	(0.18)	(0.66)	(0.67)	(1.06)	(1.43)	(1.83)	(0.71)	(0.14)
Employment cost index	−0.02	0.25	−3.53	3.53	5.57	−0.56	0.01	0.06	0.06	−4.07**	−5.69*	1.14	−0.30	−0.15
	(1.67)	(1.43)	(3.06)	(3.83)	(5.08)	(3.95)	(0.24)	(0.84)	(0.73)	(1.73)	(3.07)	(2.66)	(0.36)	(0.18)
GDP	1.85	1.81	9.03	−22.89	−10.55	1.17	−0.24	−0.58	−0.22	10.70	14.97	−1.41	0.49	0.16
	(5.70)	(5.57)	(11.34)	(10.74)	(18.42)	(14.38)	(0.71)	(2.61)	(2.41)	(8.96)	(14.89)	(7.94)	(1.91)	(0.64)
Initial claims	−0.42	−0.29	0.67	−1.96	1.09	−0.52	−0.03	−0.27**	−0.28**	−0.10	−0.23	−0.65	−0.22*	−0.05
	(0.35)	(0.25)	(0.78)	(1.47)	(1.38)	(0.40)	(0.04)	(0.13)	(0.11)	(0.25)	(0.32)	(0.65)	(0.13)	(0.05)
ISM manufacturing index	0.14	0.00	−4.17	0.83	−1.60	0.74	0.10	0.13	0.14	−0.56	−0.65	2.38*	−0.08	0.09
	(0.35)	(0.45)	(4.33)	(2.29)	(3.40)	(0.78)	(0.13)	(0.19)	(0.20)	(0.54)	(0.81)	(1.42)	(0.31)	(0.11)
Leading indicators	−0.17	0.56	0.25	3.46	−3.09	3.34	0.09	0.40	0.15	0.22	0.00	1.02	0.10	0.09
	(0.55)	(0.64)	(1.37)	(1.40)	(2.31)	(4.13)	(0.11)	(0.39)	(0.28)	(0.70)	(1.05)	(1.24)	(0.40)	(0.14)
New home sales	−1.15	−0.46	−0.98	−7.03	5.76	−0.93	0.07	0.17	−0.12	−0.23	−0.86	1.28	−0.29	−0.04
	(1.56)	(1.24)	(0.84)	(11.38)	(4.24)	(0.66)	(0.28)	(0.60)	(0.55)	(0.94)	(1.06)	(2.06)	(0.31)	(0.26)
Nonfarm payrolls	0.85	1.09	−0.71	−0.48	−0.77	0.37	−0.11	0.18	0.26	−1.12*	−0.09	1.54	−0.33	−0.07
	(0.43)	(0.38)	(1.89)	(4.36)	(3.19)	(0.18)	(0.15)	(0.29)	(0.26)	(0.63)	(0.87)	(1.58)	(0.46)	(0.13)
PPI, core	−1.43*	−2.20	0.26	−0.76	−3.52	−0.19	0.01	−1.30***	−1.29***	0.04	−0.32	−0.65	−1.49**	−0.02
	(0.79)	(1.44)	(1.82)	(1.93)	(4.58)	(3.89)	(0.14)	(0.47)	(0.41)	(0.90)	(1.13)	(3.35)	(0.70)	(0.14)
Retail sales	0.27	0.65	−4.90	1.96	7.11	1.43	0.22	0.41	0.47	1.06	1.83*	1.60	1.45	0.24
	(1.33)	(1.56)	(2.47)	(1.82)	(4.55)	(2.38)	(0.29)	(0.86)	(0.86)	(0.80)	(1.03)	(2.52)	(1.51)	(0.25)
excluding motor vehicles	−0.16	−0.48	−2.51	1.89*	4.07	1.90	0.10	0.01	0.01	1.11***	1.50***	2.85	0.39	0.16
	(0.45)	(0.28)	(2.11)	(1.07)	(3.95)	(2.70)	(0.22)	(0.22)	(0.21)	(0.36)	(0.50)	(2.42)	(0.59)	(0.14)
Unemployment	0.11	0.25	−1.42	−3.93	1.55	−0.01	−0.06	−0.09	−0.11	−1.09**	−0.78	0.70	−0.05	−0.04
	(0.34)	(0.36)	(1.04)	(2.71)	(2.18)	(0.13)	(0.11)	(0.19)	(0.19)	(0.46)	(0.50)	(0.98)	(0.18)	(0.09)
Composite shock	***−0.17***	***−0.11***	***0.49***	***0.40***	***−0.57***	***−0.10***	***0.01***	***0.04***	***0.01***	***0.02***	***−0.26***	***−0.58***	***−0.01***	***−0.02***
	(0.19)	***(0.18)***	***(0.80)***	***(1.47)***	***(0.93)***	***(0.11)***	***(0.05)***	***(0.10)***	***(0.09)***	***(0.25)***	***(0.38)***	***(0.52)***	***(0.09)***	***(0.05)***

*, **, and *** represent the 10, 5, and 1 percent significance level, respectively. Bootstrap standard errors are in parentheses.

Table 2. Effects of Macroeconomic Shocks on Aggregate Price Index

	On Impact				Two Weeks Ahead			
	Posted Price		Regular Price		Posted Price		Regular Price	
	Av. Price	Factor	Av. Price	Factor	Av. Price	Factor	Av. Price	Factor
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Capacity utilization	0.02	−0.12	0.02	−0.13	0.07*	−0.13	0.07*	−0.14
	(0.03)	(0.31)	(0.03)	(0.32)	(0.04)	(0.32)	(0.04)	(0.30)
Consumer confidence	−0.03	−0.06	−0.03	−0.07	−0.01	−0.08	−0.01	−0.09
	(0.03)	(0.23)	(0.03)	(0.22)	(0.03)	(0.23)	(0.03)	(0.23)
CPI, core	−0.03	−0.53	−0.03	−0.51	−0.02	−1.00**	−0.02	−0.98**
	(0.05)	(0.37)	(0.05)	(0.35)	(0.04)	(0.46)	(0.05)	(0.40)
Employment cost index	0.08	−0.36	0.08	−0.33	0.07	−0.21	0.07	−0.20
	(0.09)	(2.14)	(0.08)	(1.88)	(0.05)	(0.97)	(0.04)	(1.17)
GDP	−0.07	1.24	−0.09	1.11	−0.11	0.67	−0.11	0.61
	(0.27)	(3.71)	(0.28)	(4.01)	(0.16)	(3.44)	(0.14)	(3.55)
Initial claims	0.01	−0.14	0.01	−0.13	0.01	−0.09	0.01	−0.09
	(0.01)	(0.19)	(0.01)	(0.20)	(0.01)	(0.12)	(0.01)	(0.11)
ISM manufacturing index	−0.05	0.27	−0.05	0.25	−0.03	0.18	−0.03	0.18
	(0.04)	(0.32)	(0.04)	(0.32)	(0.03)	(0.25)	(0.03)	(0.20)
Leading indicators	−0.01	−0.23	−0.01	−0.24	0.03	−0.24	0.03	−0.25
	(0.04)	(0.34)	(0.04)	(0.38)	(0.05)	(0.35)	(0.05)	(0.30)
New home sales	−0.03	−0.27	−0.03	−0.23	0.04	−0.36	0.04	−0.35
	(0.08)	(1.43)	(0.09)	(1.15)	(0.08)	(0.75)	(0.07)	(0.70)
Nonfarm payrolls	−0.00	−0.10	−0.01	−0.15	0.01	−0.28	0.02	−0.29
	(0.04)	(0.36)	(0.04)	(0.34)	(0.04)	(0.43)	(0.04)	(0.43)
PPI, core	−0.00	0.14	−0.00	0.13	0.01	−0.75	0.01	−0.71*
	(0.04)	(0.47)	(0.04)	(0.43)	(0.06)	(0.50)	(0.05)	(0.41)
Retail sales	−0.06	0.33	−0.06	0.31	−0.07	1.38*	−0.08	1.34*
	(0.07)	(0.61)	(0.07)	(0.62)	(0.08)	(0.80)	(0.08)	(0.79)
excluding motor vehicles	−0.01	0.19	−0.01	0.18	−0.02	0.51	−0.02	0.51
	(0.07)	(0.27)	(0.06)	(0.33)	(0.07)	(0.48)	(0.07)	(0.44)
Unemployment	0.02	−0.00	0.02	0.01	0.02	0.01	0.02	0.01
	(0.03)	(0.22)	(0.03)	(0.21)	(0.03)	(0.20)	(0.03)	(0.18)
Composite shock	***−0.00***	***−0.04***	***−0.00***	***−0.04***	***0.00***	***−0.03***	***0.01***	***−0.03***
	(0.01)	***(0.09)***	***(0.02)***	***(0.09)***	***(0.01)***	***(0.10)***	***(0.01)***	***(0.10)***

*, **, and *** represent the 10, 5, and 1 percent significance level, respectively. Bootstrap standard errors are in parentheses.