Economics Letters 116 (2012) 460–464

Contents lists available at SciVerse ScienceDirect

Economics Letters

journal homepage: www.elsevier.com/locate/ecolet

Durable goods and sticky prices: Industry-level evidence

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ARTICLE INFO

Article history:
Received 23 June 2010
Received in revised form
26 March 2012
Accepted 16 April 2012
Available online 23 April 2012

JEL classification:
E30
L16

Keywords:
Sticky prices
Durable goods
New Keynesian Phillips curve

ABSTRACT

We employ industry data to examine price stickiness of durables versus non-durables to evaluate Barsky et al. (2007) proposal that stickiness of durables' prices influences aggregate dynamics. Policy impacts from impulse responses accord with sticky-price frameworks even though non-durables' prices are relatively flexible.

1. Introduction

Barksy, House, and Kimball (BHK, 2007) theorize that stickiness in the shadow value of durable goods makes behavior of aggregate output and the price level dependent upon the flexibility of durable goods' prices. They note "lack of direct empirical evidence of price rigidity for long-lived durables" and suggest that "it is important to investigate whether substantial price rigidity exists for these goods". We estimate price-adjustment intervals using quarterly 1966–2007 data for 254 US 6-digit North American Industrial Classification System (NAICS) industries. Our results support BHK's predictions from simulations with sticky-price durable goods and flexible-price non-durable goods: Inflation measures respond to a 1-percentage-point money shock faster than predicted by sticky-price models; non-durable goods prices exhibit larger and faster responses than durable goods prices; and economy-wide output responds by 0.4% point before returning to steady state.

The next section explains how we classify industries according to goods durability and degree of price stickiness. Section 3 provides estimated impulse responses. Section 4 concludes.

2. Sticky-price analysis

To gauge aggregate, sectoral, and industry-level degrees of price stickiness, we employ Gali and Gertler's (1999) hybrid New Keynesian framework. (Results are similar with a forward-looking framework.) The estimation equation is $E_t[\{\pi_t - \frac{(1-\omega)(1-\theta)(1-\beta\theta)}{\phi} mc_t - \frac{\theta\beta}{\phi}\pi_{t+1} - \frac{\omega}{\phi}\pi_{t-1}\}z_t] = 0$, where π_t is inflation, mc_t is real marginal cost, $(1-\theta)$ is the probability of price adjustment, β is the discount factor, z_t is a vector of instrumental variables dated time $t-1$ or before, and $(1-\omega)$ is the fraction of forward-looking firms, with $\phi = \theta + \omega[1-\theta(1-\beta)]$. We employ Generalized Method of Moments (GMM) and instrumental variables including four lags of the rate of change of price, marginal cost, the output gap, the long–short interest rate spread, and wage and commodity price inflation.

Specification (1) in Table 1 follows Gali–Gertler by using US Bureau of Economic Analysis (BEA) GDP data and US Bureau of Labor Statistics (BLS) productivity and cost data. (An appendix available upon request details the data sources.) Specification (3) follows Gwin and VanHoose (2008a) by substituting the rate of change in the BLS All Commodities Except Farm producer price index (PPI) for GDP-deflator inflation.

There are adequate BLS sectoral price data to apply the model to manufacturing (including both durable and non-durable goods) as a benchmark and to sectoral data for durable goods and non-durable goods manufacturing. BLS sectoral productivity and cost

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doi:10.1016/j.econlet.2012.04.038

Table 1
GMM estimates, new Keynesian Phillips curve hybrid model.

Specification	Price index	Marginal cost proxy	Constant	ω	β	θ	Sig. of J	Price duration (quarters)
(1)	GDP deflator	ULC	−2.55 (1.20)	0.16 (0.09)	0.89 (0.07)	0.87 (0.03)	0.32	7.7
(2)	GDP deflator	AVC	−0.002 (0.03)	0.16 (0.09)	0.94 (0.07)	0.80 (0.06)	0.63	5.0
(3)	All commodities except farm	ULC	−10.47 (3.44)	0.10 (0.08)	0.91 (0.11)	0.69 (0.06)	0.12	3.2
(4)	All commodities except farm	AVC	−0.02 (0.07)	0.18 (0.07)	0.65 (0.17)	0.60 (0.04)	0.03	2.5
(5)	Manufacturing	AVC	0.02 (0.07)	0.15 (0.08)	0.60 (0.18)	0.63 (0.05)	0.44	2.7
(6)	Durable goods	AVC	0.003 (0.04)	0.25 (0.06)	0.28 (0.13)	0.64 (0.04)	0.51	2.8
(7)	Non-durable goods	AVC	0.10 (0.08)	0.07 (0.05)	0.13 (0.14)	0.57 (0.03)	0.24	2.3

Standard errors are in parentheses.
Lags = 0 for serial correlation in calculating the weighting matrix Eichenbaum and Fisher (2003).

data misrepresent costs as flat or even declining costs over time, so we follow Gwin and VanHoose (2008b) by employing Standard & Poor's *Compustat* database to estimate percentage changes in industry-level average variable costs.

Quarterly individual-firm (i) revenue ($R_{i,t}$) and cost of goods sold ($VC_{i,t}$) for the time (t) period 1st Quarter 1966 to 2nd Quarter 2007 are available from the Standard & Poor's *Compustat* database. The BLS provides price data for six economic sectors including Mining; three sectors of Manufacturing; Transportation and Warehousing; and Information. The BLS collects data on 995 6-digit NAICS PPI series, but 1997 and 2002 NAICS reclassifications yielded insufficient data for 521 industries, sporadic data collection ruled out 12 others, and *Compustat* data could not be matched for 95 others. The combined BLS/S&P industry data series yielded fewer than 40 observations for 118 industries, and wage data (an instrument in the inflation specification) were not available for 4 more. Of the 292 remaining industries, 254 could be matched to US Census Bureau classifications of durable and non-durable goods.

For an N-firm industry, total revenue is $R_t = \sum_{i=1}^{N} R_{i,t}$, and total variable cost is $VC_t = \sum_{i=1}^{N} VC_{i,t}$, so average variable cost (AVC_t) is $P_t \frac{VC_t}{R_t} = P_t \frac{AVC_t \times Q_t}{P_t \times Q_t} = AVC_t$ where P_t is the BLS industry PPI. Similar measures of AVC are computed for groups comprised of (1) all *Compustat* firms satisfying matching criteria, (2) manufacturing firms, (3) durable goods firms, and (4) non-durable goods firms. Each sectoral AVC is calculated with the matching BLS sectoral PPI. The first AVC measure is applied to the GDP Deflator and All Commodities Except Food PPI measures to gauge its effectiveness as a marginal cost proxy. The second, third, and fourth measures of AVC are used to estimate price stickiness in total manufacturing as a benchmark and then for the durable goods and non-durable goods subsectors of manufacturing.

Specification (2) of Table 1 uses the rate of change in the GDP deflator for inflation and employs the AVC proxy, yielding results similar to Specification (1). Specification (4) also uses the AVC proxy but employs the rate of change in the All Commodities Except Food PPI for inflation. This yields results similar to specification (3), indicating that the AVC proxy is as informative as the ULC proxy. Specifications (5) for total manufacturing, (6) for durable goods manufacturing, and (7) for non-durable goods manufacturing utilize appropriate sectoral BLS PPIs and AVC proxies, yielding estimated durations inconsistent with a sticky-price economy.

We classify industries as sticky-price or flexible-price by applying the empirical model to each industry and partitioning the industry marginal cost coefficients into two distinct non-overlapping groups with Stata's kmedians cluster analysis. In an iterative process, each industry is assigned to the group whose median center is closest. Based on that categorization, new group centers are determined. These steps continue until no industries change groups. A median center provides a more stable measure of the group centers, a useful feature because the flexible-price coefficients are relatively large and statistically significant whereas the sticky-price coefficients are close to zero and statistically insignificant. The flexible-price industry group's durations range from 1.5 to 7.5 quarters. Durations for the sticky-price group are 7.8 quarters or higher, including cases in which the duration is indeterminately long, implying that prices do not respond to cost by any measure, a particularly meaningful cutoff since the GDP-deflator price duration is 7.7 quarters.

Table 2
Frequency and sales proportion of durable/non-durable goods and sticky/flexible-price industries.

		Sticky price	Flexible price
Durable good	No. of industries:	83	69
	Percent of sales:%	17.3	24.5
Non-durable good	No. of industries:	54	48
	Percent of sales:%	12.2	46

Table 2 shows the frequency and sales shares of durables-versus non-durables industries and sticky-versus flexible-price industries. (Specific industry information is in the appendix.) Consistent with BHK's models in which non-durable goods have flexible prices, the table indicates that flexible-price industries account for 72% of total non-durable goods sales.

3. Monetary policy

We utilize the VAR methodology of Balke and Wynne (2007) to evaluate price and output responses to a monetary policy shock. The VAR includes 12 lags of five variables: the industrial production index, personal-consumption-expenditure price index, a commodity price index, the federal funds rate, and the M2 measure of money supply; a constant; and seasonal dummies, with shocks orthogonalized in the aforementioned order using a Choleski decomposition. Following BHK, we utilize an orthogonal shock to M2 to represent an expansionary monetary shock but also consider a federal funds rate shock.

Fig. 1 presents cumulative orthogonalized impulse responses of various BLS measures of inflation to a positive money shock. In the BHK simulations, flexible prices allow for at least partial immediate responses, but actual data yield a lag in responses ranging from 4 to 8 quarters. Thus, comparisons of our impulse response functions to the predictions of BHK are based on the dynamics after each response has reached its peak.

Panels (a)–(c) of Fig. 1 indicate that the positive responses of economy-wide BLS measures of inflation to a money shock occur at a speed consistent with the BHK simulation based on