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Prices over the business cycle: micro-level evidence from scanner data

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Abstract

A controversy has recently developed surrounding the extent to which prices are influenced by the business cycle. We provide some micro-level evidence on this issue using a large US scanner data set. Our model identifies the business cycle effect by looking at variation in unemployment and house price growth across US regions and compares this with individual price movements based upon a general hedonic formulation. We find little support for goods prices moving in response to fluctuations in the unemployment rate or house prices.

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1. Introduction

The movement of prices over the business cycle remains a contentious issue. Prior research focused on analyzing US macroeconomic data has generally found little change in prices due to the state of the economy (Gali and Gertler, 1999). The cyclicality, or otherwise, of prices is important. It influences the evolution of real wages and hence how deep or prolonged a recession may be. It also feeds into discussion about the extent of markup compression during recessions—a key driver of the business cycle in New Keynesian models (Nekarda and Ramey, 2013).

Recently there has been a revival of interest in examining the nature of pricing because of the availability of a new data source; supermarket scanner data. This records the prices and quantities of purchases made by shoppers in a given store over some time period. This data has provided a new means by which to explore issues such as the extent of price stickiness. Indeed, the high frequency of sales and other price changes has shown that in many ways prices are more flexible than previously thought (Nakamura and Steinsson, 2008). It seems likely then that large demand-side shocks—such as increases in the unemployment rate or falls in house prices—will impact adversely on goods prices. The advent of scanner data, in conjunction with regional unemployment and house price data, has enabled a new test of this hypothesis. Rather than trying to tease out the impact of the business cycle on prices using time series data, scanner data enables us to identify business cycle impacts by comparing how prices have evolved across regions which have experienced different economic developments.

Coibion, Gorodnichenko and Hong (2015) recently undertook such an exercise by constructing price indexes using scanner data for a number of cities in the US. These were then compared with changes in the unemployment rate in these cities. Interestingly, they found that while consumers tend to shop at less expensive stores during weak economic times the prices posted by retailers do not appear to be influenced by the unemployment rate. In related work, using the same scanner data set, Stroebel and Vavra (2014) undertake a similar exercise but instead focus on how house prices influence goods prices. They find significant impacts with cities which had more rapid rises in house prices having higher rates of inflation. Similarly, Beraja, Hurst and Ospina (2016), who used a broader scanner data set covering more regions and product categories, find strong evidence of procyclical pricing. They construct price indexes for each state—comparing price changes from 2007 to 2010—and find that states where the unemployment rate rose the most had the weakest inflation.

These various results leave the primary question of interest—whether prices respond to the state of the business cycle—somewhat unresolved. In examining this issue we take a different approach than that taken by previous researchers. While we use the same data as Coibion, Gorodnichenko and Hong (2015) and Stroebel and Vavra (2014) we adopt a purely micro-level approach. We consider a general model of prices for individual products and use differencing to isolate the effect of interest. That is, rather than first aggregating prices and then comparing these indexes with the macroeconomic data we do the comparison directly on the micro data. This avoids the possibility that an aggregate measure of price change may be contaminated by changes in product or store weights over time. This is potentially important because the weighting structures used to construct price indexes using scanner data remain contentious and are the subject of ongoing debate in the literature (Ivancic, Diewert and Fox, 2011; Melser, forthcoming). When we apply our approach to the data we find very little evidence of pure price changes in response to business cycle developments. We conclude that prices are essentially acyclical.

In the next section we discuss the model used to identify the effects of the business cycle on prices. Section 3 outlines the empirical investigation undertaken and discusses the results.

2. Isolating the Business Cycle's Effect on Prices

Suppose the price of a product $i = 1, 2, \ldots, I$ (a UPC or unique barcode in our data), in category $k = 1, 2, \ldots, K$ (e.g. beer, coffee, soup, etc.), in store $s = 1, 2, \ldots, S$, in region $r = 1, 2, \ldots, R$, in time $t = 1, 2, \ldots, T$, is generated from the following hedonic model,

$$\ln p_{iksrt} = \delta_{ikt} + \gamma_{iks} + \beta_k x_{rt} + \epsilon_{iksrt} \tag{1}$$

The δ_{ikt} is a product-category-time fixed effect which allows for each product, in each category, to follow a unique price path over time. This gives a very general model of price developments for each UPC. In addition we also allow for store-category-product effects, γ_{iks}. That is, each store may charge a particular premium/discount for a certain product. Finally, we include the effect of some business cycle variable, x_{rt}, on price. This variable varies across regions and time periods and we suppose its coefficient varies across categories. The hedonic function shown in equation (1) provides a very general model of the price generation process.

This model is fundamentally similar in structure to the so-called 'country-product-dummy' approach initially proposed in Summers (1973). This approach is now widely used in constructing spatial and temporal price indexes (see for example, Silver (2009) and the references included). The model we propose is, however, much more general in allowing for product-specific inflation, store-product effects and the incorporation of the cyclical variable. The primary effect of interest to us in (1) is the value of β_k. This is identified by double-differencing. First, we difference each observation with respect to the average log-price of each product across regions for a given time period. This yields,

$$y_{iksrt} = \ln p_{iksrt} - \overline{\ln p_{ikt}} = \gamma_{iks} - \bar{\gamma}_{ik} + \beta_k \left(x_{rt} - \bar{x}_t\right) + e_{iksrt} \tag{2}$$

This removes the δ_{ikt} effect. Second, we first difference this expression over time to remove γ_{iks}, which yields,

$$\Delta y_{iksrt} = \Delta(\ln p_{iksrt} - \overline{\ln p_{ikt}}) = \beta_k \left[(x_{rt} - \bar{x}_t) - (x_{rt-1} - \bar{x}_{t-1})\right] + u_{iksrt} \tag{3}$$

This expression provides a readily implementable micro-level test of the existence of business cycle effects in prices based upon a flexible model of pricing behaviour. In essence it involves a double difference transformation. Note that we may rewrite the dependent variable as, $(\ln p_{iksrt} - \ln p_{iksrt-1}) - (\overline{\ln p_{ikt}} - \overline{\ln p_{ikt-1}})$, and the independent variable as, $(x_{rt} - x_{rt-1}) - (\bar{x}_t - \bar{x}_{t-1})$. Thus the β_k represents the extent to which price movements over time are higher or lower relative to the average movement and whether this is explainable by changes in the macro variable relative to its average change.

3. Data and Empirical Results

To apply this model we make use of the IRI scanner data (Bronnenberg, Kruger and Mela, 2008). This is the same data as was used by Coibion, Gorodnichenko and Hong (2015) and Stroebel and Vavra (2014). It contains price and quantities at a weekly frequency for 31 product categories over 46 cities or regions with which we can match regional economic data.[1] The data stretches from 2001 to 2012. In each case we construct the measure of price as the unit value over the aggregation period (a month or a quarter); that is the total value of sales divided by the number of units sold for each product. The use of unit values is standard in the price measurement literature and was also used by Coibion, Gorodnichenko and Hong (2015).

We investigate the influence of both the unemployment rate and house prices on goods prices. The unemployment rate data is available from the BLS at a monthly frequency for each of the metropolitan areas listed in footnote 1 and is seasonally adjusted. We source regional house price data from the FHFA where it is available at a quarterly frequency for each of the metropolitan areas in footnote 1. The 'All Transactions Index' is used which is seasonally unadjusted. In the models we use the unemployment rate and log of the house price index as the macroeconomic variables. Hence in the former case the β_k denotes the marginal effect on log prices of a 1 percentage point increase in the unemployment rate. For house prices the β_k denotes an elasticity.

For both model-types we construct our differenced prices in equation (3) at the requisite frequency. Our models are estimated separately for each of the product categories. A full listing of the categories is given in Table 1. We estimate each model for two samples; (a) the full sample, from 2001-12, and (b) roughly the period of the recession, when the unemployment rate was rising across the US, from 2007-10. This latter period is the time-span considered by Beraja, Hurst and Ospina (2016).

Because the error in equation (3) is likely to be heteroscedastic we estimate the standard deviation of β_k under a range of assumptions. The results presented in Table 1 use Driscoll and Kraay (1998) standard errors where a possible lag of up to a year is assumed. These standard errors are robust under quite general specifications and tend to produce the largest (and hence most conservative) standard errors of the various approaches, including clustered standard errors, that we considered.

Finally, to reflect the differential importance of the various stores and products, we weighted each observation in equation (3) by the expenditure share in period t

[1] The cities/regions are; Atlanta, Birmingham/Montgomery, Boston, Buffalo/Rochester, Charlotte, Chicago, Cleveland, Dallas, Des Moines, Detroit, Eau Claire, Grand Rapids, Green Bay, Harrisburg/Scranton, Hartford, Houston, Indianapolis, Kansas City, Knoxville, Los Angeles, Milwaukee, Minneapolis/St. Paul, New Orleans, New York, Oklahoma City, Omaha, Peoria/Springfield, Philadelphia, Phoenix, Pittsfield, Portland, Providence, Raleigh/Durham, Richmond/Norfolk, Roanoke, Sacramento, St. Louis, Salt Lake City, San Diego, San Francisco, Seattle/Tacoma, Spokane, Syracuse, Toledo, Tulsa, Washington DC.

Table 1: Estimated Parameters (Using Driscoll-Kraay Std. Err.)

Product Category	Unemployment Rate				Log House Price Index			
	No. Obs. (mil.)	Coef.	St. Err.	P-value	No. Obs. (mil.)	Coef.	St. Err.	P-value
	Full Sample: 2001-2012							
Beer	27.37	0.0005	0.0008	0.5829	8.90	-0.0313	0.0200	0.1240
Blades (for Razors)	7.74	0.0011	0.0009	0.2169	2.88	0.0205	0.0332	0.5402
Carbonated Drinks	44.51	0.0018	0.0027	0.5014	14.08	-0.0225	0.0472	0.6358
Cigarettes	19.49	0.0003	0.0017	0.8666	7.32	0.0258	0.0485	0.5980
Coffee	22.09	-0.0017	0.0014	0.2015	7.60	0.0352	0.0548	0.5239
Cold Cereal	33.99	0.0056	0.0014	0.0001 ***	10.91	-0.0216	0.0519	0.6796
Deodorant	25.99	0.0021	0.0010	0.0495 **	10.20	-0.0202	0.0675	0.7661
Diapers	8.49	-0.0009	0.0015	0.5719	3.09	-0.0200	0.0199	0.3186
Facial Tissues	4.15	0.0047	0.0024	0.0516 *	1.27	0.0608	0.1931	0.7542
Frozen Dinners & Entrees	49.64	0.0038	0.0018	0.0374 **	15.98	0.0183	0.0494	0.7122
Fozen Pizza	16.84	0.0034	0.0016	0.0388 **	5.50	0.0029	0.0532	0.9572
Cleaners	12.61	0.0033	0.0017	0.0620 *	4.15	0.0162	0.0405	0.6919
Hot Dog	5.92	-0.0002	0.0037	0.9618	1.84	-0.1280	0.1496	0.3966
Laundry Detergent	15.57	0.0022	0.0022	0.3224	5.07	-0.1451	0.0422	0.0013 ***
Margarine & Butter	8.74	0.0010	0.0014	0.4650	2.72	0.0957	0.0785	0.2288
Mayonnaise	6.01	0.0037	0.0029	0.1949	2.00	0.0219	0.0837	0.7949
Milk	10.11	-0.0023	0.0014	0.1110	3.10	-0.1581	0.1243	0.2100
Mustard & Ketchup	9.39	0.0025	0.0019	0.1764	3.27	0.0031	0.1151	0.9788
Paper Towels	3.91	0.0029	0.0030	0.3332	1.27	0.0390	0.0823	0.6378
Peanut Butter	6.61	-0.0001	0.0020	0.9665	2.10	-0.0830	0.0893	0.3580
Photographic Equipment	1.53	-0.0037	0.0025	0.1457	0.63	0.1601	0.0721	0.0315 **
Razors	1.32	-0.0010	0.0032	0.7515	0.54	-0.0135	0.0640	0.8337
Salty Snacks	37.41	0.0033	0.0014	0.0207 **	12.04	0.0013	0.0241	0.9569
Shampoo	23.13	-0.0020	0.0015	0.1639	9.20	-0.0402	0.0386	0.3026
Soup	45.35	0.0003	0.0022	0.8737	15.21	0.0829	0.0972	0.3981
Spaghetti Sauce	18.20	0.0026	0.0024	0.2925	6.04	-0.1940	0.0779	0.0165 **
Sugar Substitute	3.85	0.0001	0.0008	0.9437	1.28	-0.0390	0.0362	0.2863
Toilet Tissue	5.73	0.0037	0.0019	0.0479 **	1.84	-0.0245	0.0645	0.7055
Tooth Brushes	12.50	0.0007	0.0016	0.6807	4.90	-0.0081	0.0443	0.8554
Toothpaste	18.43	0.0032	0.0023	0.1741	6.38	-0.0566	0.0781	0.4723
Yoghurt	26.80	0.0010	0.0016	0.5469	8.32	0.0687	0.0539	0.2094
	Recession Sample: 2007-2010							
Beer	10.28	-0.0016	0.0008	0.0563 *	3.42	-0.0502	0.0299	0.1142
Blades (for Razors)	2.60	0.0003	0.0016	0.8710	1.02	0.0203	0.0299	0.5083
Carbonated Drinks	15.27	0.0014	0.0023	0.5568	5.00	-0.0576	0.0454	0.2238
Cigarettes	5.56	-0.0042	0.0018	0.0225 **	2.17	-0.0151	0.0915	0.8712
Coffee	9.15	-0.0001	0.0010	0.9453	3.19	0.0581	0.0574	0.3278
Cold Cereal	11.88	0.0027	0.0019	0.1651	3.93	0.0310	0.0507	0.5495
Deodorant	8.53	0.0000	0.0018	0.9839	3.48	-0.0046	0.0869	0.9583
Diapers	3.51	-0.0041	0.0026	0.1165	1.31	-0.0113	0.0319	0.7278
Facial Tissues	1.49	0.0025	0.0036	0.5034	0.48	0.0392	0.3861	0.9205
Frozen Dinners & Entrees	21.95	0.0057	0.0022	0.0115 **	7.12	0.0682	0.0403	0.1116
Fozen Pizza	6.02	0.0023	0.0021	0.2861	2.03	-0.0487	0.0407	0.2503
Cleaners	6.77	0.0070	0.0046	0.1327	2.19	0.0088	0.0570	0.8798
Hot Dog	2.03	-0.0098	0.0034	0.0063 ***	0.66	0.0533	0.0640	0.4186
Laundry Detergent	5.72	0.0048	0.0037	0.1955	1.87	-0.1512	0.0591	0.0218 **
Margarine & Butter	2.96	0.0002	0.0024	0.9375	0.95	-0.1046	0.0484	0.0474 **
Mayonnaise	2.07	0.0087	0.0035	0.0166 **	0.69	-0.0220	0.0752	0.7735
Milk	3.67	-0.0039	0.0036	0.2892	1.14	-0.0151	0.1513	0.9221
Mustard & Ketchup	3.13	0.0014	0.0033	0.6714	1.14	0.0557	0.0683	0.4277
Paper Towels	1.28	0.0019	0.0044	0.6656	0.45	-0.1536	0.0497	0.0074 ***
Peanut Butter	2.33	0.0005	0.0032	0.8877	0.75	-0.2081	0.0938	0.0425 **
Photographic Equipment	0.34	-0.0075	0.0040	0.0689 *	0.15	0.2405	0.1306	0.0854 *
Razors	0.46	-0.0048	0.0043	0.2708	0.21	-0.0949	0.0758	0.2298
Salty Snacks	13.41	0.0000	0.0017	0.9798	4.45	-0.0048	0.0447	0.9166
Shampoo	8.08	-0.0061	0.0019	0.0019 ***	3.39	-0.0207	0.0573	0.7229
Soup	20.33	-0.0033	0.0031	0.2817	6.87	-0.0813	0.0813	0.3330
Spaghetti Sauce	6.35	0.0047	0.0055	0.3973	2.19	-0.0993	0.0685	0.1674
Sugar Substitute	1.43	-0.0029	0.0020	0.1606	0.49	-0.0238	0.0739	0.7521
Toilet Tissue	2.09	0.0068	0.0022	0.0030 ***	0.69	-0.1321	0.0414	0.0061 ***
Tooth Brushes	5.47	-0.0014	0.0014	0.3047	2.16	0.0060	0.0646	0.9277
Toothpaste	6.53	0.0035	0.0044	0.4288	2.38	-0.0152	0.1137	0.8953
Yoghurt	10.20	0.0026	0.0027	0.3504	3.21	0.0334	0.0654	0.6171

Note: *=significant at the 10% level, **=5%, ***=1%.

plus that in $t-1$. This is in line with the suggestions in Diewert (2005) in a related context.[2]

The results are shown in Table 1. The table reports the number of observations in each regression and the estimated value of β_k, its standard error and p-value for each

[2] We also explored using the sum of current and lagged expenditures as weights but this led to little difference in the results.

product category. This is reported for both the unemployment rate and log house prices as the cyclical regressor over the two samples. As can be seen the models are estimated across an enormous amount of data. For example, one of the models for the "Frozen Dinners & Entrees" category includes 49.64 million observations.

Turning now to the results. For the unemployment rate, if we tally the results in the full sample we find that only 8 of 31 product categories have an estimated β_k which is significant at the 10% level or less. But all of these have positive coefficients—implying that prices rise with the unemployment rate. For the recession sample there is somewhat more, though still minimal, evidence of procyclical movements in prices. Again there are 8 of 31 categories with significant coefficients at the 10% level but this time 5 exhibit a negative β_k.

For house prices in the full sample just 3 categories are significant at the 10% level or less. Only 1 of which has a positive sign, as would be expected if goods prices move procyclically with house prices. In the recession sample 6 categories are significant at the 10% level or less of which only 1 has a positive coefficient.

Taken as a whole these results provide very weak evidence for shifts in goods prices in response to business cycle developments. We find very few cases in which the coefficient on the unemployment rate and house prices are significant in the full sample or the sample focused around the recession years of 2007-10. Moreover, the sign of the effect does not appear to be either strongly positive or negative. Overall, our results are generally supportive of the conclusion that prices are acyclical.

References

Beraja, M., E. Hurst and J. Ospina (2016), "The Aggregate Implications of Regional Business Cycles," NBER Working Paper Series No. 21956.

Bronnenberg, B. J., M. Kruger and C. F. Mela (2008), "The IRI Marketing Data Set," *Marketing Science* 27(4), 745-748.

Coibion, O., Y. Gorodnichenko and G. H. Hong (2015), "The Cyclicality of Sales, Regular and Effective Prices: Business Cycle and Policy Implications," *American Economic Review* 105(3), 993-1029.

Diewert, W. E. (2005), "Weighted Country Product Dummy Variable Regressions and Index Number Formulae," *Review of Income and Wealth* 51(4), 561-571.

Driscoll, J. C. and A. C. Kraay (1998), "Consistent Covariance Matrix Estimation with Spatially Dependent Panel Data," *The Review of Economics and Statistics* 80(4), 549-560.

Gali, J. and M. Gertler (1999), "Inflation Dynamics: A Structural Econometric Analysis," *Journal of Monetary Economics* 44(2), 195-222.

Ivancic, L., E. W. Diewert and K. J. Fox (2011), "Scanner Data, Time Aggregation and the Construction of Price Indexes," *Journal of Econometrics* 161(1), 24-35.

Melser, D. (forthcoming), "Scanner Data Price Indexes: Addressing Some Unresolved Issues," *Journal Of Business & Economic Statistics*.

Nakamura, E. and J. Steinsson (2008), "Five Facts About Prices: A Reevaluation of Menu Cost Models," *Quarterly Journal of Economics*," 123(4), 1415-1464.

Nekarda, C. J. and V. A. Ramey (2013), "The Cyclical Behavior of the Price-Cost Markup," NBER Working Paper Series No. 19099.

Silver, M. (2009), "The Hedonic Country Product Dummy Method and Quality Adjustments for Purchasing Power Parity Calculations," *IMF Working Paper*.

Stroebel, J. and J. Vavra (2014), "House Prices, Local Demand, and Retail Prices," NBER Working Paper Series No. 20710.

Summers, R. (1973), "International Price Comparisons Based upon Incomplete Data," *Review of Income and Wealth* 19(1), 1-16.