Price dynamics and market segmentation

Price Dynamics and Market Segmentation

Mustafa Caglayan
Heriot-Watt University, UK

Alpay Filiztekin*
Sabanci University, Turkey

Abstract

Scrutinizing hundreds of TAR models, we examine the persistence of price dynamics across market segments. Using a unique dataset of monthly actual product prices of 47 items collected from three different market segments in Istanbul over 1993:01-2008:12, we provide evidence that the extent of price persistence differs across market segments while the half-life estimates do not.

Keywords: Persistence; Nonlinearity; TAR models; Market segmentation.
JEL Codes: E31; C23; F30

*Corresponding author. Sabanci University Faculty of Arts and Social Sciences Orhanli 34956 Tuzla Istanbul Turkey. e-mail: alpayf@sabanciuniv.edu; Tel ++90 216 483 92 65; Fax ++90 216 483 92 50.

1 Introduction

There is a significant effort to understand product price dynamics as this information contributes to our understanding of the effectiveness of monetary policy in stabilizing the economy. Although several researchers have examined the behavior of prices,[1] research on actual price dynamics across different market segments is scarce.[2] In this paper, we investigate the persistence of price dynamics using actual product prices collected from different market segments. In particular, we implement hundreds of TAR models to examine whether the key parameter (threshold and half-life) estimates vary between market segments.

The analysis employs a unique dataset from Istanbul, Turkey, which provides the actual monthly prices of 47 food and non-food items collected from 15 neighborhoods and 3 different market segments. Controlling for product and neighborhood effects, we find that the average threshold estimates differ between market segments while the average half-life estimates do not. We conjecture that the former observation is due to differing menu costs between market segments and that the latter observation is due to low search costs. Robustness checks verify our findings.

2 Empirical Analysis

2.1 Data

Our dataset provides monthly prices of 47 products sold in distinct market segments (bakkal, pazar, or supermarket) over the period 1993:01–2008:12.[3] *Pazars* are open-air markets for fresh produce and small consumer items. *Bakkals* are small convenience stores, almost always

[1] For example see Bils and Klenow (2004), Clark (2006), de Graeve and Walentin (2011).

[2] To our knowledge only three papers have examined product prices across different market segments: i) Asplund and Friberg (2002) study food prices in Sweden across different markets; ii) Caglayan et al. (2008) examine price variability across market segments in Istanbul and iii) Lira et al. (2012) examine prices across Chilean supermarkets

[3] Appendix A lists the products and the market segments included in our dataset.

family-owned and operated and located in residential areas. Like their Western counterparts, *supermarkets* in Istanbul are large and stock a wide variety of distinct products and brands.

The data are collected by the Istanbul Chamber of Commerce to construct a broad-based Cost of Living index for wage earners in the city which comprise almost 25% of the entire index. To achieve consistency, surveyors visit the same stores approximately at the same day of the week to record product prices across sellers. These records note brand, quantity/weight, and other product specific characteristics. Given that different field surveyors visit different regions and shops, measurement errors are unlikely to be correlated across quotes.

To conduct the analysis, we construct the relative price of each commodity with respect to the city average by computing the deviation of product prices from the average product price in Istanbul:

$$q_{i,b,s,t} = p_{i,b,s,t} - \frac{1}{N}\sum_{b=1}^{B_i}\sum_{s=1}^{S_{i,b}} p_{i,b,s,t} \tag{1}$$

where $p_{i,b,s,t}$ is the log price of good i sold in store type (seller) s in borough b at time t. The second term in equation (1) is the average product price across all boroughs and stores. B_i, $S_{i,b}$ and N denote the number of boroughs, the number of store type in a borough and the number of sellers, respectively.

2.2 The Model

We examine the persistence of price dynamics and the duration of shocks to prices using band-TAR models. Prior to estimating the TAR model we implement Hansen (1997) test based on 1000 bootstraps and find that the TAR model is rejected for 1% of the cases against the

linear autoregressive framework. Discarding these series, we estimate the following model:[4]

$$\Delta q_{i,b,s,t} = \begin{cases} \rho(q_{i,b,s,t-1} - c) + \sum_{p=2}^{P} \beta_p q_{i,b,s,t-p} + \epsilon_t & \text{if } q_{i,b,s,t-d} > c \\ \rho_0 q_{i,b,s,t-1} + \sum_{p=1}^{P-1} \beta_p^{in} \Delta q_{i,b,s,t-p} + \epsilon_t & \text{if } |q_{i,b,s,t-d}| < c \\ \rho(q_{i,b,s,t-1} + c) + \sum_{p=2}^{P} \beta_p q_{i,b,s,t-p} + \epsilon_t & \text{if } q_{i,b,s,t-d} < c, \end{cases} \tag{2}$$

where Δ is the difference operator, c is the threshold parameter and d is the delay parameter. P is the autoregressive order (to determine the order, we use the Akaike information criterion), and ρ is the adjustment coefficient. The model assumes that the thresholds are symmetric and that the price dynamics are persistent within the band so that ρ_0 is equal to zero.[5] We set the delay parameter (d) to one for the data are extracted from a highly inflationary period.[6] With these assumptions, we estimate TAR(P,2,1). To estimate the threshold, $\hat{c}$, we carry out a grid search.

2.3 Empirical Results

We estimate 1554 TAR models and collect the resulting threshold and half-life estimates for each product. We discard 36 models due to non-convergence and remove the top 1 percentile of the data for which half-life estimates were more than 18 months.[7] Using the estimated parameters we find that the average half-life is in the order of 2.63 months (11 weeks) and that the mean threshold is 3.84%. This implies that the price dynamics are persistent as long as prices are contained within the band and that the impact of shocks that push the prices above this band dissipate by half on average in about 11 weeks.[8]

[4] In an earlier version we estimated the model for all series. Results from this set were similar to those we present here.

[5] See for instance Obstfeld and Taylor (1997).

[6] We also estimate the model setting d=2. Results from this experiment, which are similar to those reported here, are available upon request.

[7] In a highly inflationary environment, 18 months is a too long period as a half-life estimate for perishable products. However, in a separate exercise, we estimated these discarded series setting $d = 2$. Incorporating the key parameters of the model from this exercise to our main data did not lead to different conclusions.

[8] Fast half-life estimates can be explained by fact that the inflation rate in Turkey was rather high during the period of investigation.

Next, we scrutinize the role of market segmentation on threshold and half-life estimates by examining the following equations:

$$\hat{c}_i = \alpha + \beta_1 Market + \beta_2 Pazar + \beta_3 Borough_i + \beta_4 product_i + \epsilon_i \quad (3)$$

$$\hat{T}_i = \alpha + \beta_1 Market + \beta_2 Pazar + \beta_3 Borough_i + \beta_4 product_i + \epsilon_i \quad (4)$$

where $\hat{c}_i$ denotes the threshold and $\hat{T}_i$ denotes half-life estimate for product i that we estimated from model (2) above. $Market$ and $Pazar$ dummy variables are set to one if the product price is collected from a supermarket or a pazar, respectively, and zero otherwise. Equations 3 and 4 also incorporate *product* and *borough* dummies to account for the fixed effects which may potentially emanate from these sources. Observing $\hat{\beta}_1$ and $\hat{\beta}_2$ for each equation we can determine if product price dynamics in pazars and supermarkets differ from that of bakkals.

Table 1 shows that the average threshold level for supermarkets is significantly greater than that of bakkals (by about 1%). The average threshold estimate for pazar, however, does not significantly differ from that of bakkals. We conjecture that the difference in threshold estimate between supermarkets and bakkals (and pazars) is due to the presence of differing menu cost across market segments. For instance Anderson et al. (2011) argue that menu costs matter in pricing and that price of goods sold in bigger markets are stickier not only because of the variety of products at work, but also due to the associations between products, which require simultaneous price changes. Hence, menu costs should be higher for supermarkets than bakkals, while pazar vendors are expected to have the lowest menu cost. The threshold estimates we present here support this view and show that the extent of price persistence differs across market segments: prices are sticky within a wider band for supermarkets than that for bakkals (and pazars).

The last column of the table shows that the half-life of a shock is similar across markets.[9] Similar half-life estimates across market segments can be explained referring to low search

[9] As noted earlier, the average half life estimate for our sample is around 11 weeks.

costs within and across markets allowing consumers to visit different market segments in the same or adjacent neighborhoods before completing their purchases. Low search costs overcome informational problems so that the impact of shocks disappear quickly.[10]

2.4 Robustness

We examine the data from three different perspectives as detailed below to check for the robustness of our findings.

2.4.1 Sample Splits

We split the price data into pre- and post-2002 samples and investigate these samples separately for the former sample corresponds to a period of high inflation. Over the 1976-2002 period, the average inflation rate (based on CPI) was around 50%. As the central bank began targeting inflation, the inflation rate dropped to around 10-15% for the remainder of the sample. The first two columns of Table 2 provide the threshold estimates and the latter two columns provide the half-life estimates for the pre- and post-2002 data.

Although there are some differences between the two periods, the pattern of the average threshold estimates across market segments for the two sub-periods are similar to that presented in Table 1. The average threshold estimate for supermarkets significantly exceed that of bakkals in both samples. The interesting observation is that the average threshold estimate for pazars for the pre-2002 period is significantly lower than that of bakkals providing us the ranking we *a priori* expected to observe.[11] This feature disappears for the post-2002 period.

When we examine the pattern of the average half-life estimates for pazars and supermarkets we find that these estimates do not differ significantly from that of bakkals for either periods. As expected, when we compute the average half life estimate for the pre- and post-2002 periods, we find that it is lower during the pre-2002 period (1.63 *versus* 2.74 months).

[10] Also see Caglayan et al. (2008) who discuss price variability in market segments on the role of search.

[11] Prices are assumed to be least sticky in pazars for menu costs are expected to be lowest in this market segment.

This finding relates to the differing levels of inflation rate between the two periods.

2.4.2 Using a balanced dataset

To avoid any claim that the results may be driven due to the use of an unbalanced dataset, we carry out the analysis for those products which are available for all market types throughout the full sample period. This strategy leaves us with 14 products. The results which we report in Table 3 are similar to those in Table 1: i) the average threshold estimate for supermarkets is significantly higher than that of bakkals; ii) the average half-life estimates do not differ significantly across market segments.

2.4.3 Dropping pazar data

We carry out the analysis one last time for the full sample after dropping the price series collected from pazars for one may suggest that the actual purchase price of a product from a vendor in a pazar may be determined by haggling while we only observe the posted prices (sellers in a pazar are legally required to post product prices). Table 4 shows that the threshold estimate for supermarkets is significantly higher than that of bakkals while the half-life estimates are similar.

3 Conclusion

Using detailed data collected from 15 neighborhoods and three markets in Istanbul, we estimated TAR models to examine the persistence of price dynamics across market segments. After controlling for the role of product and neighborhood effects, we find that price persistence between market segments differs. We conjecture that differing menu costs between market segments play an important role in this observation. Second we find that the average half-life estimates across markets is similar. We base this observation on low search costs within and across market segments in Istanbul. Last but not the least we observe that the

half-life estimate for the high inflationary period is lower than that for the low inflationary period.

Given our finding that the threshold estimates differ across market segments and that the extent of thresholds may be associated with the presence of differing menu costs across markets, one can argue that the impact of monetary policy and its transmission would depend on the size of the market segments in an economy. As consumers from different income groups tend to shop from certain market segments, our findings also suggest that policy changes will have differing welfare implications on consumers with different levels of incomes. Our second observation on the similarity of half life estimates suggests that access to cheap transport, reducing information problems, may reduce price variability within and across market segments. Our findings may be useful in extending monetary search and signal extraction models.

References

[1] Asplund, M. and Friberg, R. (2002) Food prices and market structure in Sweden. *Scandinavian Journal of Economics*, 104, 547-66.

[2] Anderson, E., Jaimovic N. and Simester D., 2011. Menu costs and price rigidities: Micro evidence. *unpublished manuscript*.

[3] Bils, M. and Klenow, P. 2004. Some Evidence on the Importance of Sticky Prices. *Journal of Political Economy* 112, 947-985.

[4] Caglayan, M., Filiztekin, A. and Rauh, M.T., 2008. Inflation, price dispersion, and market structure. *European Economic Review* 52, 1187-1208.

[5] Clark, T, 2006. Disaggregate Evidence on the Persistence of Consumer Price Ination. *Journal of Applied Econometrics* 21, 563-587

[6] De Graeve, F., and Walentin, K., 2011. Stylized (Arte)Facts on Sectoral Inflation. Sveriges Riksbank Working Paper 254.

[7] Lira, L., Ugarte, M., and Vergara, R. 2012. Prices and market structure: an empirical analysis of the supermarket industry in Chile. *Applied Economics*, 44, 4731-4744.

[8] Obstfeld, M., Taylor, A., 1997. Nonlinear aspects of goods-market arbitrage and adjustment: Heckscher's commodity points revisited. *Journal of the Japanese and International Economies* 11, 441-479.

Table 1: Average Threshold and Half-life Estimates by Market Type

	Average Threshold	Average Half-life
Supermarket	0.0090***	0.0460
	(0.0016)	(0.1263)
Pazar	0.0011	0.1186
	(0.0018)	(0.1320)
Observations	1,518	1,518
R^2	0.2215	0.2750
Testing for fixed effects (F-stat, p-values are in parentheses)		
D_Borough	2.43	5.18
	(0.002)	(0.000)
D_Product	6.93	14.32
	(0.000)	(0.000)

Heteroscedasticity consistent standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2: Robustness check: Periodization

	Pre 2002 Avg. Th.	Post 2002 Avg. Th.	Pre 2002 Avg. Hl.	Post 2002 Avg. Hl.
Supermarket	0.0041***	0.0104***	0.0602	-0.1219
	(0.0014)	(0.0017)	(0.0671)	(0.1675)
Pazar	-0.0045***	0.0009	-0.0011	0.1759
	(0.0017)	(0.002)	(0.0747)	(0.1619)
Observations	1,450	1,338	1,450	1,338
R^2	0.1742	0.2118	0.287	0.2882
Testing for fixed effects (F-stat, p-values are in parentheses)				
D_Borough	3.81	5.93	2.63	2.91
	(0.000)	(0.000)	(0.000)	(0.000)
D_Product	5.61	5.11	14.52	12.42
	(0.000)	(0.000)	(0.000)	(0.000)

Heteroscedasticity consistent standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3: Robustness check: The 14 goods case

	Average Threshold	Average Half-life
Supermarket	0.0054**	0.1598
	(0.0026)	(0.1999)
Pazar	0.0032	0.3519
	(0.0025)	(0.2262)
Observations	582	582
R^2	0.1887	0.2444
Testing for fixed effects (F-stat, p-values are in parentheses)		
D_Borough	1.09	3.18
	(0.359)	(0.000)
D_Product	8.77	13.09
	(0.000)	(0.000)

Heteroscedasticity consistent standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Average Threshold and Half-life Estimates by Market Type

	Average Threshold	Average Half-life
Supermarket	0.0099***	0.0878
	(0.0017)	(0.1303)
Observations	1,209	1,209
R^2	0.2315	0.2366
Testing for fixed effects (F-stat, p-values are in parentheses)		
D_Borough F-stat	3.11	4.61
p_value	(0.000)	(0.000)
D_Product F-stat	6.01	11.50
p_value	(0.000)	(0.000)

Heteroscedasticity consistent standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix A

Table A.1: List of products and availability of price quotes

Product	**Bakkal**	**Pazar**	**Supermarket**	**Product**	**Bakkal**	**Pazar**	**Supermarket**
Rice	1	1	1	Apples	1	1	0
Pasta	1	1	1	Lemon	1	1	0
Flour	1	1	1	Tomato	1	1	0
Filo Dough	1	0	1	Green Pepper	1	1	0
Cracked Wheat	1	1	1	Cucumber	1	1	0
Veal	1	0	1	Lettuce	1	1	0
Chicken	1	0	1	Zucchini	1	1	0
Mutton	1	0	1	Scallion	1	1	0
Sucuki	1	0	1	Parsley	1	1	0
Salami	1	0	1	Olives	1	1	1
Sausage	1	0	1	Honey	1	1	1
Feta cheese	1	1	1	Tomato paste	1	1	1
Margarine	1	0	1	Halvah	1	0	1
Cooking Oil	1	1	1	Jam	1	0	1
Egg	1	1	1	Ready soup	1	0	1
Butter	1	0	1	Broom	1	0	1
Olive Oil	1	1	1	Cleaning powder	1	0	1
Kasseri cheese	1	0	1	Soap	1	0	1
Yoghurt	1	0	1	Detergent	1	0	1
Potato	1	1	0	Bleach	1	0	1
Onion	1	1	0	Paper	1	0	1
Lentils	1	1	1	Light bulb	1	0	1
Chickpeas	1	1	1	Plastic kitchenware	1	0	1
Beans	1	1	1				

1 indicates that price quotes is available in that particular store type.

[a] A very thin sheet of dough. [b] Type of sausage. [c] Sheep viscera.