The Law of One Price and the Role of Market Structure

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Abstract

This paper examines the role of market structure on the persistence of price deviations from the LOP using monthly actual product prices of 47 items collected from three different types of markets in Istanbul over 1993:01-2008:12. After showing the importance of market structure on the distribution of relative prices, we implement threshold autoregressive models. We find significant differences in average threshold estimates across markets which we explain referring to differing menu costs in each market. Yet, we find no differences in average half-life estimates across markets. We argue that this is due to low search costs in Istanbul. Robustness checks verify our findings.

Keywords: Law of one price; Nonlinearity; TAR models; Market segmentation; Menu and search costs.

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1 Introduction

The law of one price (LOP) states that prices of homogeneous goods across different locations can at most differ by transaction costs or other impediments of arbitrage. Although the idea of LOP seems reasonable, empirical research shows that there are sizeable and persistent price differentials in the short run. For instance, Rogoff (1996) points out that the half-life of purchasing power parity (PPP) deviations are estimated to be around three to five years. Subsequent research, depending on the data or the methodology used, show that the half-life estimates fall somewhere between 1 to 6 years.[1] However, researchers point out that these estimates are too long even when the law of one price is viewed as a long run phenomena.

Testing the validity of the LOP is not a trivial task. It involves getting accurate data on individual prices as well as considering various forces that may affect the behavior of prices. In fact, there are several pitfalls in constructing such a dataset and carrying out the empirical investigation; even fairly homogeneous goods differ significantly across cities and countries, and it may be too difficult to control for some of the forces that may affect equalization of prices.[2] Nevertheless, testing the validity of LOP is of great interest to economists as its failure constitutes "a prime suspect in the failure of purchasing power parity" (Engel and Rogers (2001), p. 5) which is considered as one of the most important theoretical concepts in international economics (see for instance Frankel and Rose, (1996) among others). Indeed, over the last decade, researchers have achieved reasonable success in providing support for the LOP (PPP) by refining the datasets and the empirical methodology that they implement in their investigation. In particular, the use of product level data and the acknowledgement of the nonlinear nature of the adjustment process have helped researchers to expand our understanding of the factors that affect the speed at which adjustments occurs.

In this study we examine the persistence of deviations of prices from the LOP as we focus

[1] See, among others, Frankel and Rose (1996), Murray and Papell (2005) and Choi et al (2006).

[2] For instance taste of coffee differs even across different shops let alone across countries as there are different varieties of the same product. Furthermore, cost of some transactions, which impede equalization of prices including distribution or networking costs, may be too hard to get a handle on.

exclusively on actual prices of food and non-food items collected from the largest metropolitan city in Turkey, Istanbul. Using this unique dataset, different from the available literature, we specifically investigate the role of market segmentation, the importance of menu and search costs on the LOP as the data are collected from three different types of markets and 15 different neighborhoods in Istanbul.[3] Furthermore, examining the LOP deviation of prices concentrating on data collected from a large city such as Istanbul also allows us to overcome several hurdles that researchers have shown to affect results. Within the context of our study some of the hurdles that we can abstract from are the effects of trade barriers, exchange rate volatility, distance and other differences across cities, regions or countries which may prevent traders from taking arbitrage opportunities when cross country or cross city data used. At this point it is also useful to note that, although Istanbul is a large metropolis, the city is compact and public transportation means can take someone from any part of the city to another for less than a US dollar. Hence, one can travel from point A to point B cheaply to take advantage of price differentials between different neighborhoods or markets limiting the deviation of product prices from the average prices in Istanbul. In that sense residents of Istanbul can shop at different markets in their own or adjacent neighborhoods in search of lower prices, which as a consequence limit price deviations across locations.

We start our investigation by inspecting the data visually to verify the role of market structure on the deviation of product prices from the Istanbul average. We then implement threshold autoregressive (TAR) models and examine the key parameters (the threshold and half-life estimates) of the model. An examination of the LOP deviation of prices within the context of TAR models is appealing because this approach not only allows the researcher to study the behavior of LOP deviations within a nonlinear context but it also captures the Heckscher's idea of commodity points: that due to lack of perfect arbitrage opportunities prices would have no tendency to equalize within the inner regime; a band of inaction.[4] In this set up the inner regime captures the episodes when price deviations from the LOP are

[3] We use market or seller type while referring to market segmentation.
[4] See Obstfeld and Taylor (1997).

relatively small so that within this band no arbitrage opportunities arise for the traders. In contrast, the outer regime corresponds to episodes when price differentials from the LOP exceed the transaction costs inducing arbitrageurs to take profit opportunities. Thus, we expect that the price deviations from the LOP would exhibit unit root characteristics within the inner band and mean reverting behavior otherwise.

In our investigation, different from the literature, we focus on the importance of market segmentation, menu and search costs in evaluating the validity of the LOP as we investigate the estimated key parameters of the TAR model. We can do so because our dataset provides us with individual product price data collected from three distinct markets as we indicated earlier: Bakkals (small convenience stores), pazars (bazaars), and Western-style supermarkets, which exhibit significant differences in terms of menu costs, search costs, and other important parameters identified by the relevant theoretical literatures. Given the differences across markets, we conjecture that the estimated threshold values would differ across market types if market segmentation as well as menu and search costs should make a difference. We also expect that the half life estimates for each of these markets should not statistically differ and convergence should be rather quick *should* relative LOP hold.

An investigation of LOP using data from Istanbul brings along several additional advantages. A review of the earlier literature provides evidence that the purchasing power parity holds reasonably well for high-inflationary countries in contrast to low inflationary countries.[5] To that end our dataset presents a natural environment for such an investigation as the average annual inflation rate for the full sample has been around 40%; a rate considerably higher than the available studies which have mainly used data from developed economies. Another advantage of using this dataset relates to the relative similarity (consistency) of the consumption patters of the residents of Istanbul. Although Istanbul is a metropolis with a population over ten million people, it is a rather compact city whose inhabitants across the neighborhoods are more homogeneous when compared to cities of similar size around the world such

[5] See, for instance, Cheung and Lai, (2000) and Frenkel, (1978).

as London or New York.[6] Thus, issues such as taste differences that may affect the general consumption patterns or transportation costs which could prohibit arbitrage opportunities would not affect our investigation regarding the validity of LOP (or PPP) as much as in the earlier work that used commodity prices collected from different cities. Last but not least, our investigation does not suffer from measurement errors as surveyors recorded the price of the same product (brand, packaging and weight) across all store types in all boroughs and visited the same seller unless the seller went out of business.

We start our analysis by displaying the differences in the distribution of product price deviations from the Istanbul average for bakkals, pazars and supermarkets. Equipped with this *prima facia* evidence that there are significant differences in product prices across different seller types, we then begin our examination of the behavior of relative prices implementing TAR models. Using prices of 47 products from three different type of sellers in fifteen neighborhoods covering the period over 1993:01–2008:12, we estimate and verify more than fifteen hundred TAR models. We report summary information on the key parameters which represent the extent of barriers to arbitrage and discuss the role of market structure on the behavior of relative price deviations. Last but not least we carry out robustness checks to verify that our findings is not an artifact of the data and changes in the monetary policy in Turkey.

Our empirical findings can be summarized as follows. When we examine the deviation of relative prices from the product specific average Istanbul prices, we find that the mean threshold estimate for the full sample is 3.9%. This implies that within a band of 7.8% there are no forces in action to pull the relative prices back to their mean as price deviations from the LOP exhibit unit root behavior. However, once price deviations exceed the upper or lower threshold bounds, prices are quickly pushed back towards the band of inaction. In fact we find that the average half-life estimate is in the order of 2.7 months; that is, when

[6] Also, we must note that there are no large ethnic groups in Istanbul who had arrived from many different parts of the world residing in certain parts of the city as one can see in metropolises such as London and New York.

the LOP deviation of product prices exceed the threshold levels, it takes less than 3 months for the impact of the shock to decay by half. We next turn our attention to examine the role of market structure on the average threshold and half-life estimates. Controlling for the product and region effects, we find that the average threshold is almost 2.8% for bakkals and that it is around 3.7% for supermarkets, where this difference is statistically significant. We claim that the significant difference in the average thresholds for bakkal and supermarket estimates can be explained referring to the presence of menu costs across different market types. Our investigation does not provide evidence for any significant difference between pazar and bakkal average threshold estimates though. When we turn to investigate the average half-life estimates, we find that the average half-life estimate for bakkals is about 1.3 months (i.e. just about 5 weeks) where this estimate does not significantly differ from that of supermarkets and pazars.[7] That is, once LOP deviation of prices exceed the band of inaction, it takes on average 5 weeks for the impact of the shock to decay by half in all market segments. We attribute this high speed of convergence to low search costs as traveling is rather cheap within the city as well as to the low opportunity cost of time for many of the residents in Istanbul (due to low wages and high unemployment) which induce consumers to visit different markets before completing their shopping for the week.

For robustness purposes, we carry out three additional sets of TAR models. In the first set we split the data into two sub-periods; pre- and post-2002. The choice of year to split the data as of 2002 is based on the observation that the Central Bank of Turkey moved into inflation targeting in January 2002. Therefore, it is important to reassess the behavior of relative prices for the period before and after this cut-off year to guard against the possibility that the changes in monetary policy might have different effects on the LOP deviation of relative prices between these two periods. Our investigation shows that results from each period provide similar observations with respect to our original findings. The next robustness check questions our sample choice. While our main results are based on a broad set of 47

[7]To our knowledge an average half-life of 1.3 months is the fastest convergence rate so far reported in the literature.

commodities, we do not observe price data for all of the 47 commodities in each market type at each point in time. That is our original dataset is unbalanced as price information for some products is missing for one or two markets. Hence, to examine whether our main results are driven by the choice of commodities in our dataset, we focus on a balanced dataset comprised of 14 products for which we have price quotations from each market type. Our final robustness check involves assessing the results after eliminating the pazar data for one may claim that product prices collected from pazars may be contaminated due to haggling. Results from all three cases are similar to our original findings.

The paper is structured as follows. Section 2 briefly surveys the literature on the law of one price. Section 3 informs about the seller types (bakkal, supermarket and pazar) in Istanbul that we explore. After explaining the computation regarding the relative product prices, the section lays out the econometric methodology that we follow. Section 4 presents the main results as well as the robustness checks. Section 5 concludes.

2 A Brief Literature Review

One of the major pillars of the economics of exchange rates and open economy macroeconomic models is the assumption of the law of one price (or its aggregate version—the purchasing power parity) which suggest that prices of homogeneous goods sold in separate locations can differ at most by the impediments of arbitrage. However, despite all efforts, empirical researchers have found little support for the LOP (and the PPP) in the short run. The estimated half lives for deviations of prices, depending on the data and the methodology used, span a range between one to six years, which is long even when LOP is considered as a long-run concept.

There are several potential explanations for the failure of LOP. Some researchers attribute this failure to the existence of transaction costs which may arise from various reasons including tariff and non-tariff barriers, the failure of nominal exchange rates to adjust to relative price shocks, segmented markets, sticky nominal prices and transportation costs. To assess the importance of some of these factors, a strand of literature examines the behavior of prices across cities within a country or a region. For instance, Parsley and Wei (1996) use absolute level of prices collected from several US cities and find that the convergence rate is much faster (half-lives estimated to be around four to five quarters) than that obtained from international data. Engel and Rogers (2001) examine the proportional law of one price across cities in the US and conclude that both transportation costs and sticky nominal prices explain the deviation of prices from the equilibrium. Ceccheti et al. (2002) estimate the half-life of convergence around nine years and rationalize slow convergence referring to the presence of transportation costs, differential speeds of adjustments to small and large shocks and the inclusion of traded goods prices. More recently, Goldberg and Verboven (2005) find strong evidence of convergence towards LOP using a panel data set of car prices for the case of European market integration. Crucini and Shintani (2008) using a micro-panel of goods prices collected from major cities in 63 countries and 13 major US cities present evidence that the average half-life of deviations from the LOP is about one year. Crucini et al. (2010) focus on data from cities in Japan and show that price stickiness and distance play an important role to explain the deviations from the LOP. Yazgan and Yilmazkuday (2011) reconsider price-level convergence investigating 48 final goods and service prices obtained for 52 U.S. cities. They report quicker convergence than those of previous studies.

Several other researchers attribute the failure of LOP to the presence of nonlinearities in the data. A number of theoretical studies including Dumas (1992), Sercu et al. (1995), O'Connell (1998) argue that the persistence of deviations from the LOP depends on whether prices exceed transaction costs. In this framework if the deviation of prices from the LOP is less than the transaction costs then there would be no reason for the prices to move back to equilibrium as there would be no arbitrage opportunities. In contrast, if the deviation of prices from LOP are more than the transaction costs then prices would revert back to equilibrium as traders take advantage of the arbitrage opportunities. Given this basic prediction of the model, several researchers estimated threshold autoregressive models using intra-country price data to show that prices quickly adjust in one regime while there is very slow adjustment or no response in the other regime. For instance, Obstfeld and Taylor (1997) implementing TAR models on aggregate data show that the half-lives of deviations of international prices are even less than a year once non-linearity in the adjustment process is allowed for.[8] O'Connell and Wei (2002), using a nonlinear framework, model price adjustments in the presence of transportation costs and confirm that prices adjust very rapidly outside the band. Ceglowski (2003) finds relatively fast convergence for Canada where the average estimated half-life is slightly less than a year. Ratfai (2006), using data from Hungary shows that the median half-life price differentials is about four months. Yet, Cheung and Fujii (2008), using product specific data from Japan, present evidence that the LOP deviations are persistent and follow a non-linear trend.

Given the state of the literature, empirical research that concentrated on price data gathered from cities has helped us to understand the factors that affect LOP deviation of prices. However, researchers have been silent about the role of market segmentation on the validity of LOP. Likewise, although the theoretical literature has shown that menu and search costs affect the behavior of prices, the presumption that the LOP deviation of prices may be affected by these costs differently depending on the composition of the market (i.e. the type of sellers that operate in the market) has not been explored. Last, earlier research mainly focused on data from countries where inflation was subdued but not on those where the rate of inflation varied over time. Accordingly, using actual price data gathered from Istanbul, we investigate the importance of all these issues (market segmentation, menu costs, search costs, the underlying inflation) on the LOP deviation of prices.

[8] Also see Michael et al. (1997), Taylor and Sarno (1998), Taylor (2000), Baum et al. (2001) and Juvenal and Taylor (2008), among others, who also implement TAR models to test for PPP.

3 Preliminaries

3.1 Data

Our dataset consist of monthly price observations for individual products sold by individual markets in Istanbul and cover the period 1993:01–2008:12. The data are collected by the Istanbul Chamber of Commerce in order to construct a broad-based Cost of Living index for wage earners in the city.[9] The data, overall, does not suffer from measurement errors. To achieve consistency the surveyors visited the same stores approximately at the same day of the week to record prices of various products (same brand, quantity/weight, and other characteristics) across sellers, unless the seller went out of business.

While there are around 250 items in the original dataset, some of these items have a single quotation per month (e.g. price of electricity, taxi fares etc.) or some are collected from a single store (e.g. clothing items, durable goods etc.) or some items have price quotations on a seasonal basis (specifically for fresh produce). Since we like to achieve a wide coverage in terms of price data availability across store types and over time as well as to have definitional consistency of commodities we have chosen 47 distinct products to examine in this study. The price quotations for these 47 products are collected from fifteen different boroughs and three distinct store types (bakkal, pazar, or supermarket) each month. We should note that, for some products the dataset presents us only two quotations per neighborhood, where one quotation is always from a bakkal, the other is either collected from a supermarket or a pazar. In two boroughs pazar prices are not available altogether. Of these 47 products, which are commonly consumed by all households, eight items are non-food products and the rest are food products. These 47 products are staple items which consumers regularly purchase, unlike big-ticket items that are purchased on an infrequent or a one-off basis. Appendix A provides a list of the products that we use in our investigation.

[9] As a pre-condition for its use, the authors signed a confidentiality agreement with the Chamber that restricts the dissemination of the data, yet aggregated data for verification purposes can be provided upon request.

3.1.1 Market Types in Istanbul

There are three basic market types in Istanbul, namely Pazars, Bakkals and Supermarkets. These market types are available in each neighborhood and each of them have distinct characteristics as we discuss below.

Pazars in the classic sense are open-air markets for fresh produce and small consumer items. There is one main pazar in each neighborhood which stays open one day a week. These markets approach the perfectly competitive ideal: there are several individual sellers in a pazar each selling a small number of fresh produce or small consumer items. Furthermore, each product generally has several sellers within a small geographical area (a large pazar covers about two to three acres). Given their high spatial density, we expect that competition should be relatively intense in pazars. The search cost in a pazar which incorporates the cost of obtaining another price quote for a product should be very low as there are several similar sellers of the same product. We also expect the menu cost to be small as the seller has only a few products to sell.

Bakkals are small convenience stores, almost always family-owned and operated and located in residential areas. They are also important social institutions, where one typically buys one or two items and exchanges news and gossip with the owner and his family. The nearest competitor is usually another bakkal a few blocks away. Bakkals tend to have a very loyal customer base, so this market structure is reminiscent of monopolistic competition based on spatial and "product" differentiation in the social dimension. For this type of market structure, although we would expect the search cost for the consumer to be higher than that in a pazar, it should not be prohibitively high as the next bakkal is only a few minutes away on foot around the next block. We should expect that the menu cost should be higher than that of Pazars as a Bakkal sells several goods.

Like their Western counterparts, *supermarkets* in Istanbul are large and stock a wide variety of distinct products and brands. They are also corporate-owned and are generally located away from potential competitors. Given its relative isolation from the nearest supermarket or bakkal, obtaining another price quote generally entails a trip by car or public transportation. An ordinary shopper who commits herself to a particular supermarket would normally complete all her shopping in one attempt and would not visit another supermarket as such a visit entails another trip by car or public transportation means which is quite costly in terms of the time spent on the road in addition to the financial cost. Since supermarkets stock a variety of products and brands than bakkals, menu costs for supermarkets can be substantial in comparison to bakkals and pazars.

Note that all of these market types are major institutions where customers shop for various products, so our results are not biased due to lack of consumers for some store type. However, given these basic differences across the three market types, we have good reasons to expect that the threshold estimates will significantly differ across markets although the speed of price adjustments may not.

3.2 Basic Definitions

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

$$q_{i,b,s,t} = p_{i,b,s,t} - \frac{1}{N} \sum_{b=1}^{B_{i,j}} \sum_{s=1}^{S_{i,b}} p_{i,b,s,t} \qquad (1)$$

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; i.e the average product price in Istanbul. $B_{i,j}$ is the number of boroughs and $S_{i,b}$ is the number of store type in a borough for which data are available. N is the number of stores/sellers ($N = B_{i,j} \times S_{i,b}$) for which we have a price quote every month.

To give an overall view of the distribution of relative prices (i.e. the deviation of prices from the average product prices) in Table 1 we present the mean, median and the standard deviation of relative prices as well as a set of select percentiles evaluated at the 5, 25, 50, 75 and 95 levels. Overall looking at the Table one gains the impression that the data are distributed evenly around the mean/median. However, the information in Table 1 is rather dull as it is hard to visualize the information. To have a visual perception of the relative prices, we plot the empirical kernel density estimates of $q_{i,b,s,t}$ in Figure 1. As it is clear from the Figure we observe a quite sizeable deviation of the relative prices from the mean: within a 90% band around the mean, depicted as the area between the vertical lines, prices deviate from the mean by approximately 40%. This is a rather wide range.

Given that we are using relative product prices of several homogeneous goods which are collected from neighborhoods within a single city, one would not expect to observe permanent differences in relative prices. If this were the case, what we see in Figure 1 should be an artifact of outliers which would wash out once the time effect is removed out, unless stores have some monopoly power. We, therefore, compute the time average of the relative product prices, $\bar{q}_{i,b,s} = \frac{1}{T}\sum_{t=1}^{T} q_{i,b,s,t}$ and plot the empirical kernel density estimates of the average long-run relative prices in Figure 2, i.e. the long run deviation of product prices from the Istanbul average product prices. Looking at the figure, we observe that long-run prices deviate by approximately 33% from the mean within a 90% interval as captured between the vertical lines. Although smaller than what we observe in Figure 1, this is still a sizeable variation. To yield the distribution shown in Figure 2, it must be the case that some product/store/borough prices should be consistently above or below the average. To push the investigation further, although we argued that the distance between neighborhoods as well as product types should not affect our findings, we remove these effects from the long-run relative prices by regressing $\bar{q}_{i,b,s}$ on borough and product dummies and examine the residuals. In this case, too, we see a sizeable price deviation of about 29%, when we construct a 90% band around the mean.[10] Given these observations, we argue that the dispersion in long-run relative prices should be related to market segmentation and other forces which affect behavior of relative prices in each market type including menu and search costs.

To determine whether the cause of this wide variation in long-run relative prices are due

[10]The data and the corresponding figure are available upon request.

to market segmentation, we provide summary statistics of the long-run relative prices across market types in Table 2, while Figure 3 depicts the corresponding distribution, $\bar{q}_{i,b,s}$. We see that the mean long-run relative prices for each market type, after controlling for product and borough effects, are statistically different from one another. In particular, we observe that the mean is highest for bakkal and that for pazar is the lowest.[11] The reason as to why there are significant differences in product prices across market types can be attributable to the characteristic of each market type.[12] Bakkals are located within residential areas and hence customers have the convenience to shop from a bakkal as they arrive home from work or at any time of the day. But this convenience gives a bakkal the monopoly power to charge higher prices on average to a customer as the decision to go to a supermarket entails a trip often by car (or by bus). The difference in prices between bakkals and pazars arise due to the fact that pazars are set once a week rendering it inconvenient for a customer to shop at a pazar any time she needs an item. In contrast, supermarkets provide a different kind of convenience to the consumers in that they offer a wider variety of products, enabling them to charge higher prices than their marginal costs in comparison to pazars but lower than bakkals. Finally, while there is higher competition within a pazar, every stall-owner is also aware that the price they offer to customers is only for the particular day of the pazar as consumers do not have an option to purchase products from a seller in the local pazar on another day of the week. Thus, sellers at pazar have limited power to charge prices higher than the marginal cost. Hence, similar to O'Connell and Wei (2002) we do not find support for absolute version of LOP and, it appears that long-run deviations of prices can be explained by market segmentation.[13]

[11]See Caglayan et al. (2008) who show the importance of market structure on the association between inflation and price variability.

[12]We are not, by any ways, suggesting that each store type has fixed customers segments. In Istanbul and in Turkey it is generally the case that each consumer visits a portfolio of stores and shop at a particular store type at different times.

[13]Clearly, some portion of price dispersion can be attributable to subtle differences among the services offered by competing stores. A product purchased at a store where one can have a friendly chat with the seller, like in most bakkals and pazars, or in a pleasant environment, like in supermarkets, is not the same product purchased elsewhere. However, we agree with Stigler that "... [while] a portion of the observed dispersion is presumably attributable to such differences...it would be metaphysical, and fruitless, to assert

3.3 Empirical Model

To examine the relative short-run deviation of prices from the LOP, we implement threshold autoregressive models. This class of models are attractive because it allows the researcher to entertain the behavior of LOP deviations within a nonlinear context while capturing the theoretical underpinnings that market frictions generate a band of inaction within which price differentials are not arbitraged away until the marginal benefit of rebalancing price differentials exceeds the cost. Only when price differentials exceed the transaction costs, entrepreneurs arbitrage away the differences pushing the prices back into the band of inaction. In this study, we implement a Band-TAR model which takes the following general form:[14]

$$\Delta q_{i,b,s,t} = \begin{cases} \rho_1(q_{i,b,s,t-1} - c) + \sum_{p=2}^{P} \beta_p q_{i,b,s,t-p} + \epsilon_t & \text{if } c < q_{i,b,s,t-d} \\ \rho_0 q_{i,b,s,t-1} + \sum_{p=1}^{P-1} \beta_p^{in} \Delta q_{i,b,s,t-p} + \epsilon_t & \text{if } |q_{i,b,s,t-d}| < c \\ \rho_1(q_{i,b,s,t-1} + c) + \sum_{p=2}^{P} \beta_p q_{i,b,s,t-p} + \epsilon_t & \text{if } q_{i,b,s,t-d} > c, \end{cases} \tag{2}$$

where Δ is the difference operator, c is the threshold parameter, d is the delay parameter, P is the autoregressive order which we select using the Akaike criterion, ρ_0 and ρ_1 are the adjustment coefficients.

Similar to the earlier literature (see for instance Obstfeld and Taylor (1997) and Juvenal and Taylor (2008)) our model assumes that the thresholds are symmetric and that arbitrage forces operate in a similar way whether deviations occur above or below the threshold band. Following this literature, we also allow for the deviations from the LOP to be persistent within the band and assume that ρ_0 is equal to zero. With this assumption, relative prices are restricted to follow a unit root process within the band. This is sensible because within the band arbitrage opportunities are not available and therefore prices are not expected to exhibit any tendency to revert back towards the equilibrium if the disturbance is small. In contrast,

that all dispersion is due to heterogeneity." (Stigler, 1961, p. 215). We interpret bakkals having consistently higher and pazars having consistently lower prices as strong indication of market segmentation.

[14]Smooth threshold autoregressive models (STAR) are generally used to investigate the behavior of real exchange rates whereas TAR models are suitable to investigate that of disaggregated product prices.

when prices are higher (or lower) than the threshold level, arbitrageurs take advantage of the profit opportunities rendering relative product prices to follow an autoregressive process and converge to the *edge* of the band as long as $\sum_{p=1}^{P} \beta_p < 1$.

In our empirical implementation, given that the delay parameter captures the reaction of agents to deviations from the LOP, we set it to one as the data are extracted from a highly inflationary period. Our reasoning is simple: unlike the case when a researcher studies LOP or PPP using data across a number of cities (or countries) where the rate of inflation is low, it would be hard to conceive that sellers in Istanbul who are facing approximately 40 percent annual inflation would wait to react to deviations in prices from the LOP longer than a month as real profits quickly fall rendering the seller to experience a loss. Hence, we do not carry out a grid search to estimate the delay parameter.

With these assumptions, we estimate TAR(P,2,1) where P is the autoregressive lag, 2 stands for the number of thresholds and 1 is the delay parameter. The thresholds of the model are symmetric and the dynamics on either end are identical. We assume that the error term is identically and independently distributed and has the form $\epsilon \sim N(0, \sigma^2)$. To estimate the threshold, $\hat{c}$, we carry out a grid search such that the sum of squared residuals of equation (2) is minimized using the least squares approach. We estimate the model for the demeaned series.

4 Empirical Results

4.1 Preliminaries

We should note that prior to running the TAR model in equation (2), we investigate the presence of unit root in the series. Results from this procedure informs us whether any of our series has a tendency to return to its long-run equilibrium when it is perturbed by a shock. In particular we implement the Dickey-Fuller test and the Enders and Granger (1998) threshold unit root test. As one can expect the results obtained from the Enders and

Granger test yields more rejection of the unit root null than that from the Dickey Fuller test.[15] However, given the low power of both tests for highly persistent series we assume that the series under investigation are nonlinear which exhibit stationarity in the outer regime and unit root properties in the inner regime and proceed with the Band-TAR model.

We should note that although our objective is to work with Band-TAR models which we presume will fit the assumed data generating process well, we compare its performance with that of linear autoregressive (AR) class models.[16] To carry out this comparison, we generate the asymptotic distribution of the classic F-statistic implementing a bootstrap method as suggested in Hansen (1997) which shows that the distribution of $F_T(c,d)$ is central χ^2. Using the parameter values estimated from the TAR model and the corresponding autoregressive model we bootstrap the Hansen test based on 1000 replications for all models. Completing this exercise we observe that the linear model is rejected against the TAR alternative in more than 90% of the cases.

4.2 LOP deviations from average prices in Istanbul

To implement the TAR model given in equation (2) we choose the appropriate lag length by examining the Akaike information criterion. Once the lag length is determined, we carry out a grid search to compute the upper and lower threshold values of the TAR model ensuring that at least 15% of the observations reside in the upper, middle and lower regions. Overall we estimate 1570 models and compute the threshold and half-life estimates for each product. Out of these 1570 models, 36 models did not converge which we then discard. After compiling all the key parameters, we remove some of the threshold-half-life pairs from further investigation which yield extreme half-life values (the top 1 percentile) at or above 18 months. We believe that this screening is reasonable for 18 months is a too long period for sellers not to change prices of these products, which are mostly perishable, in a highly inflationary environment.

[15] The details are available from the authors upon request.

[16] It should be noted that the benchmark TAR and AR models are not necessarily nested. These two models are in fact nested within a broader class of TAR models. Hence one must be careful setting up the null. See Obstfeld and Taylor (1997) footnote 7 for more on this.

In Table 3 we provide the summary statistics of threshold and half life estimates including the mean standard deviation and a select case of percentiles computed at different levels. The first column of the table presents information on the average threshold estimates and the second column presents that on the half-life estimates. We see from the first column of the table that the mean threshold estimate for the full sample is 3.9%. Although within this band there are no forces in action to pull the relative prices back to their mean, once the price deviations exceed the threshold they are quickly pushed back towards the band of inaction. In fact column 2 of Table 3 displays that the average half-life estimate is in the order of 2.7 months with a standard deviation of 2.3 months. The statistics reported in the second column show that for some products the half life estimate can be much lower than one month, yet there are some other goods whose half life estimates can exceed 7 months. Nevertheless, the average convergence rate we present here is quite fast providing support for the validity for the LOP.

So far we provided some general information about the key parameter estimates for our model in Table 3. To investigate the role of market structure on these estimates, we next implement a simple OLS model that includes Supermarket and Pazar dummy variables. In this exercise, the estimated parameters associated with the Supermarket and Pazar dummy variables capture the difference in average threshold or half-life estimates associated with these market types in comparison to that of bakkals. The constant will provide us with the average threshold or half-life for the Bakkal as Bakkal is the omitted dummy variable. Our model also incorporates *product* and *Borough* dummies to take into account the fixed effects which may potentially emanate from these sources.[17] The models for the threshold and (monthly) half-life estimates take the following form:

$$c_i = \alpha + \beta_1 Market + \beta_2 Pazar + \beta_3 Borough_i + \beta_4 product_i + \epsilon \quad (3)$$

$$T_i = \alpha + \beta_1 Market + \beta_2 Pazar + \beta_3 Borough_i + \beta_4 product_i + \epsilon \quad (4)$$

[17]The data are gathered from 15 boroughs; Aksaray, Bahcelievler, Bakirkoy, Besiktas, Beyoglu, Eminonu, Eyup, Fatih, Kadikoy, Kartal, Kasimpasa, Levent, Pendik, Sariyer, Sisli.

where c_i denotes the threshold and T_i denotes half life for each product i. $Market$ and $Pazar$ are dummy variables set to one if the product price is collected from a supermarket or a pazar and zero otherwise, respectively.

Table 4 provides the results generated from these two models. Average threshold estimates for each market type is given in the first column and we see that it is about 2.8% for bakkals. The average threshold level for supermarkets is significantly greater than that of bakkals at about slightly less than 3.7% (β_1 is significantly different from zero). The table also shows that the threshold estimate for pazar does not differ from that of bakkals (β_2 is not significantly different from zero).

We conjecture that the differences in estimated threshold levels across the market types is due to the presence of menu costs. Although the empirical support regarding the importance of menu costs is scant, researchers motivate nominal price stickiness referring to the menu costs which cover physical costs of changing price tags, reprinting catalogues and other costs associated with price changes.[18] Hence, if indeed menu costs would cause price stickiness, then supermarkets must be affected more than bakkals and pazars. One reason why supermarkets should incur higher menu costs than bakkals and pazars is related to the variety of products available for consumers at any point in time in a supermarket. As a consequence, if the product variety were to play a role, then cost of changing price tags should be highest for supermarkets followed by bakkals. However, there are possibly other forces at work when it comes to changing price tags. According to Anderson et al (2011) menu costs matter in pricing and they suggest that price of goods sold in bigger markets are stickier as it is not only the variety of products at work, but also the associations between products which require simultaneous price changes. Hence, given that there are several products in a supermarket which are interrelated to one another, more so than that in a bakkal (or a pazar), menu costs can explain the difference between the threshold estimates for bakkals and supermarkets.[19]

[18]Levy, et al. (1997) show that menu costs constitute a non-trivial factor in the price-setting decision of firms.

[19]For instance, consider the number of seasonings that a large supermarket holds. When the price of one seasoning changes, usually the price of the remaining seasonings prices follow accord.

With this reasoning, we should expect to see the average pazar threshold to be lowest which turns out to be lower than that of supermarkets but same as that of bakkals. Nevertheless, the observation that the bakkal threshold estimate is lower than that of supermarkets provides support for the claim that menu costs could lead to difference with respect to threshold estimates across market types.

We next turn to inspect the average half-life estimates for each market type. The second column of Table 4 shows that the average half-life estimate for bakkals is 1.23 months. The point estimates are slightly higher for both supermarkets and pazars but the difference is not significantly different from that of bakkals. To our knowledge, an average half-life estimate at about a month and a week (5 weeks) is the lowest convergence rate reported in the literature. More concretely, our analysis provides evidence that all types of sellers adjust their prices in Istanbul quickly despite the presence of menu costs. What is behind the finding of low average half-life estimates? The standard answer is the actions of the arbitrageurs who seek to make profits due to the presence of price differentials across regions or markets. Arbitrageurs in our case are not only sellers who are moving products from market to market or neighborhood to neighborhood but also the inhabitants of the city who purchase these goods on a regular basis. To that end, it is important to recall that we are working with data collected from a city where cost of transportation from one neighborhood to another is relatively cheap. It is also the case that unemployment in Istanbul is high and the minimum wages are low. As a result, search cost must be low for most of the residents in Istanbul. Therefore, whenever price of a product deviates too far off the average, consumers visit nearby shops or shops in other neighborhoods driving the prices back within the threshold levels. In other words, whenever price differentials from the LOP exceed the transaction costs, arbitrageurs, including both sellers and consumers, take profit opportunities by either selling or purchasing these products in different shops and locations pushing the prices back towards the equilibrium.

In summary, using TAR models to study the LOP deviation of relative prices using a detailed product price data from Istanbul we observe that there is a different threshold for each market type. We argue that the difference in threshold estimates across market types is due to the presence of differing degrees of menu cost at work in each market type. Within the threshold bands price deviations from the LOP are relatively small so that within this band no arbitrage opportunities arise (for both consumers and sellers), rendering relative prices to exhibit unit root characteristics. However, once price deviations exceed the estimated thresholds, we show that relative prices are pushed back to equilibrium quickly—at around an average half-life of a month and a week (5 weeks)—due to the actions of arbitrageurs. In particular we suggest that the quick adjustment in prices is mainly due to low search costs within and across markets allowing consumers to visit different sellers in the same or adjacent neighborhoods before completing their weekly shopping. Hence, our results provide strong support for the validity of relative LOP.

4.3 Robustness

We pursue three additional sets of TAR models to check for the robustness of our findings. The first set uses the full dataset employed in the previous section while we carry out the analysis for the pre- and post-2002 periods separately. The reason why we choose 2002 to split the data is based on the observation that the Turkish Central bank begun to implement inflation targeting rules as of January 2002 to move the Turkish economy out of the inflationary cycle that the country experienced since mid 1970s. The average inflation rate (based on CPI) over the 1976-2002 period was generally around 50% with short spells of higher and sometimes lower inflation levels. With the implementation of monetary policy rules, we see that inflation drop rapidly to 20% at the end of the first year and settled around a rate slightly less than 10% as of 2004. Therefore, to guard against the possibility that a change in monetary policy might impact the LOP deviation of prices differently, we carry out the analysis separately for the pre- and post-2002 periods.

Table 5 provides the results with respect to periodization. The first two columns present the threshold estimates and the latter two columns provide the half life estimates for the pre- and post-2002 periods. The table shows that the pattern of the threshold estimates for the two periods is similar to that of the case when we use the full spell, although there are some interesting differences. In particular, we observe that the threshold estimate for bakkal is higher in the first sub-period but not significantly so than that in the second sub-period. The threshold estimate for supermarkets always exceed that of bakkals significantly for both periods, though half a percentage point more so in the second period. The interesting observation here is that the 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. However, in the post-2002 period there are no significant differences in the threshold estimates between bakkals and pazars.

The pattern of half-life estimates under periodization is similar to our main results, too. As in our main set of results, pazar and supermarket half-life estimates are not significantly different from that of bakkals. We interpret this observation same as before that search costs are low enough for shoppers in Istanbul so that the LOP deviation of prices are quickly driven back to equilibrium levels in both periods. It is also interesting to observe that the average half-life estimate is smaller for the pre-2002 sample in comparison to that for post-2002 sample. This observation suggests that in inflationary environments prices return back to equilibrium levels quicker than low inflationary periods. However, the difference between the pre- and post-2002 average half-life estimates is not statistically statistically significant.

The second set of robustness check questions whether the set of products that we use in our analysis has an effect our findings. The results reported in the main analysis and the first set of robustness check use the full dataset available to us (47 products given in Appendix A). However, because our main panel dataset is not balanced as some price quotes are not observed by one or the other market type, one may suspect that the results may depend on the nature of the dataset. Thus, we examine products for which data are available for all market types. This strategy leaves us with 14 products for which we carry out the full analysis.

In Table 6, we display our results for the balanced panel. The first column displays the average threshold estimates. As in the previous cases, results are similar to our original set of findings on threshold and half-life estimates. Same as before the bakkal threshold estimate is significant and it is not significantly different from that reported in Table 4. Also, the average threshold estimate for supermarkets is significantly higher than that of bakkals and that the threshold estimates for bakkal and pazar are not statistically different from each other. When we inspect the half-life estimates, we observe that it is about 3.5 weeks (less than a month) and similar with respect to all markets. Yet this figure is not significantly different from the average half-life estimates reported in Table 4. Given results in Table 6 we conclude that the choice of product set is not influential on our findings.[20]

The third and the last robustness test relates to the possibility that the actual purchase price of a product in pazars may be determined by haggling as we only observe the posted prices (sellers in the pazar are legally required to post product prices prices). Our own casual observation suggests that in the morning, when the Chamber inspectors collect the data, the bulk of transactions occur at the posted prices. Furthermore, the posted price set by the seller have to be competitive as there are several seller of the same product in a small area. If the price is too high, the seller will attract little consumer interest, and it cannot be set too low, because it will be extremely difficult for the seller to negotiate a price above the posted one. In fact, our observations suggest that actual purchase prices are usually fairly close to the posted ones. Yet, bargaining can be an issue in the afternoon when sellers are eager to get rid of their stocks. For instance Geertz (1978) points out that price negotiations at a pazar takes place to the right of the decimal point. However, to eliminate any doubt that may arise from inclusion of pazar data we report findings using data only from bakkals and supermarkets.[21] As it can be observed from Table 7, threshold and half-life estimates for bakkals and supermarkets, are essentially the same as in Table 4.

[20] Given we have used product dummies to generate results throughout the examination, results in Table 6 are not surprising.

[21] Haggling is not a feature of these markets.

5 Conclusion

In this paper we test the persistence of deviation of prices from the LOP using actual product prices of 47 items collected from three different types of markets (bakkals, supermarkets and pazars) in Istanbul, the largest city in Turkey. The data are collected from 15 neighborhoods in the city on a monthly basis between January 1993 and December 2008 and used by the Chamber of Commerce to compute the cost of living index in Istanbul. Using this dataset, we investigate the deviation of prices from the LOP. In doing so, we examine the importance of market segmentation and discuss the role of menu costs and search costs on the size of the band of inaction and the speed of convergence. One other advantage of using such a detailed dataset collected from Istanbul is to abstract from various factors such as the effects of trade barriers, exchange rate volatility, taste differences, and distance across regions that may affect our conclusions on the validity of the LOP.

We start our investigation by establishing the role of market structure on the LOP deviation of relative product prices from the Istanbul average. We then implement threshold autoregressive (TAR) models. Scrutinizing the threshold and half-life estimates gathered from our TAR model, we find that the mean threshold estimate for the full sample is 3.9% and the mean half-life estimate is in the order of 2.7 months. We next turn our attention to the role of market structure on the average threshold and half-life estimates controlling for the neighborhood and product effects. In this case we find that the average threshold is about 2.8% for bakkals. We also observe that the threshold estimates for supermarkets is significantly greater than that of bakkals at about 3.7%. Yet, we find no difference between pazar versus bakkal threshold estimates. We conjecture that the significant differences between bakkal and supermarket threshold estimates is due to differing menu costs across different market types. More interestingly, we find that the average half-life estimates for bakkals is about 1.2 months (i.e. five weeks) and this estimate does not significantly differ from that of supermarkets and pazars. This finding implies that once deviation of prices from the LOP exceed the threshold levels, within 5 weeks the impact of the shock decays by half as relative prices return towards the band of inaction. To our knowledge, this is the fastest rate of convergence reported in the literature. In this context although the actions of sellers is expected to be important in the behavior of relative prices, we mainly interpret the high speed of convergence in relative prices as a consequence of low search cost due to availability of relatively cheap transportation within the city along with the low opportunity cost of time for (many) residents of Istanbul.

We carry out three additional sets of TAR models to check for the robustness of our findings. In the first set we split the data into two periods; pre- and post-2002. The choice of year to split the data is based on the observation that the Central Bank of Turkey moved into inflation targeting as of January 2002. Therefore, we reassess the behavior of prices for the period before and after this cut-off year to guard against the possibility that the change in monetary policy might have different effects on the LOP deviation of prices. Our next robustness check relates to the unbalanced *versus* balanced nature of the dataset. In particular, while our main set of results are based on a broad set of commodities, not all of the 47 commodities are sold in each market type. Hence, to investigate the possibility that our original results could be driven by the choice of the product set, we focus on a balanced dataset comprised of 14 products for which we observe in each market type. The last set focuses on bakkal and supermarket data only as one can claim that product prices obtained from pazars might be contaminated due to haggling. Results from these there sets of TAR models provide similar observations to our original findings.

Our results show that i) the market structure affects the behavior prices up to a point where menu costs differs across different type of sellers; ii) the convergence of prices to their long run levels is related to search costs. Hence we conjecture that in environments where search cost is low the impact of shocks to relative prices quickly decay as the relative prices move back towards the equilibrium. Our results indirectly point out that the frictions we abstract from within the context our study play an important role in behavior of prices across cities or countries as we report fast decay of shocks to relative prices. Furthermore, given the quick adjustment of relative prices in all segments of the market our findings provide strong support for the validity of the LOP

Last but not least, although one may perceive that our results are peculiar to the market structure institutionalized in Istanbul, similar market types are in operation in many of the developed and developing countries around the world. For instance in the US, the UK and the continental Europe corner shops (or the so called mom-and-pop shops) do operate along with supermarkets. Farmer markets, although they may not be as institutionalized in Turkey, are set up on certain days of the week in cities or boroughs of many developed economies. In that sense, we believe that our results have wider implications which can improve our understanding on the behavior of prices. More research along these lines would further benefit our understanding.

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Table 1: Basic Statistics on Relative Prices ($q_{i,b,s,t}$)

Min	-1.176		
5%	-0.224		
25%	-0.080		
Median	0.004	Mean	0.000
75%	0.082	Std. Dev.	0.133
95%	0.210		
Max	1.087		
N.	301,440		

Table 2: Long-run Deviations of Relative Prices by Market Type ($q_{i,b,s,t}$)

store	N	mean	sd	p5	p50	p95
Bakkal	705	0.063	0.056	-0.020	0.055	0.163
Market	540	-0.016	0.058	-0.103	-0.020	0.093
Pazar	325	-0.111	0.058	-0.210	-0.108	-0.020
Total	1570	0.000	0.088	-0.155	0.008	0.134

Table 3: Average Threshold and Half-life Estimates

	Average Threshold	Average Half-life
mean	0.039	2.7
sd	0.029	2.3
p5	0.010	0.5
p25	0.017	1.1
p50	0.030	2.0
p75	0.054	3.4
p95	0.097	7.1

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

	Average Threshold	Average Half-life
Supermaket	0.0088***	0.0195
	(0.0016)	(0.1268)
Pazar	0.0009	0.1544
	(0.0017)	(0.1349)
Constant	0.0279***	1.2291***
	(0.0046)	(0.3051)
D_Borough F-stat	2.41	5.23
p_value	(0.003)	(0.000)
D_Product F-stat	7.01	14.33
p_value	(0.000)	(0.000)
Observations	1534	1534
R^2	0.2205	0.2758

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Robustness check: Periodization

	Pre 2002 Avg. Th.	Post 2002 Avg. Th.	Pre 2002 Avg. Hl.	Post 2002 Avg. Hl.
Supermarket	0.0049***	0.0111***	0.0901	-0.2038
	(0.0014)	(0.0017)	(0.0717)	(0.1881)
Pazar	-0.0043**	0.0011	-0.0294	0.2075
	(0.0016)	(0.0020)	(0.0783)	(0.1998)
Constant	0.0326***	0.0267***	0.6347**	1.0337***
	(0.0062)	(0.0050)	(0.1410)	(0.3212)
D_Borough F-stat	3.65	6.26	2.98	2.71
p_value	(0.000)	(0.000)	(0.000)	(0.000)
D_Product F-stat	5.88	5.52	14.83	13.22
p_value	(0.000)	(0.000)	(0.000)	(0.000)
Observations	1474	1471	1474	1471
R^2	0.1810	0.2007	0.2882	0.2564

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Robustness check: The 14 goods case

	Average Threshold	Average Half-life
Supermarket	0.0054**	0.1542
	(0.0026)	(0.2152)
Pazar	0.0031	0.3475
	(0.0024)	(0.2406)
Constant	0.0224***	0.8383**
	(0.0051)	(0.3832)
D_Borough F-stat	1.09	3.13
p_value	(0.364)	(0.000)
D_Product F-stat	9.20	13.49
p_value	(0.000)	(0.000)
Observations	591	591
R^2	0.1905	0.244

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Average Threshold and Half-life Estimates by Market Type

	Average Threshold	Average Half-life
Supermaket	0.0097***	0.0874
	(0.0017)	(0.135)
Constant	0.0279***	1.2291***
	(0.0051)	(0.506)
D_Borough F-stat	2.91	4.45
p_value	(0.000)	(0.000)
D_Product F-stat	7.23	6.65
p_value	(0.000)	(0.000)
Observations	1066	1066
R^2	0.2341	0.1778

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 1: Distribution of Price Deviations (q)

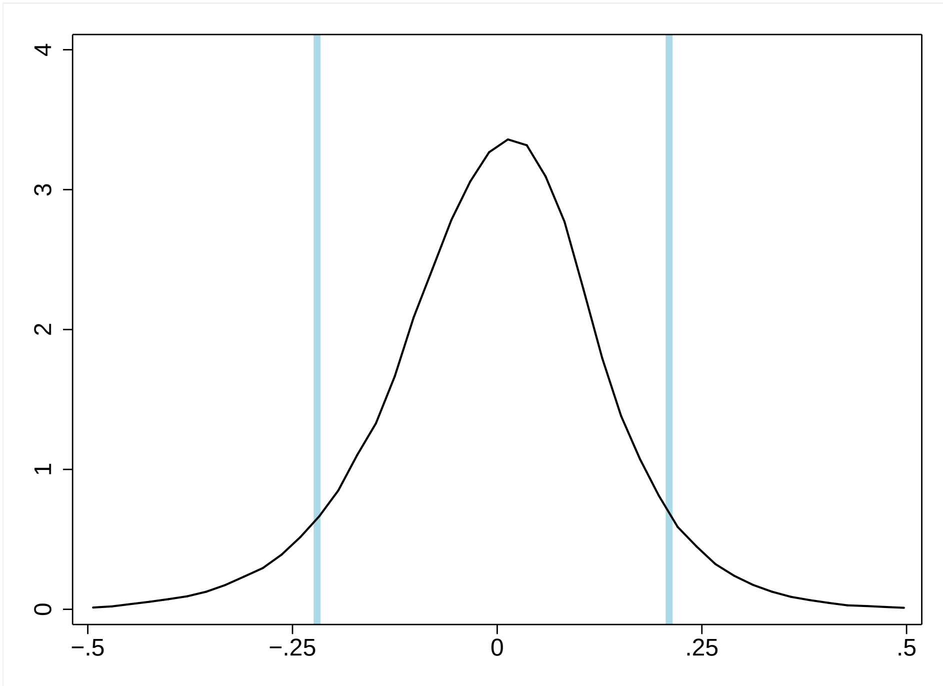


Figure 2: Distribution of Time Demeaned Price Deviations

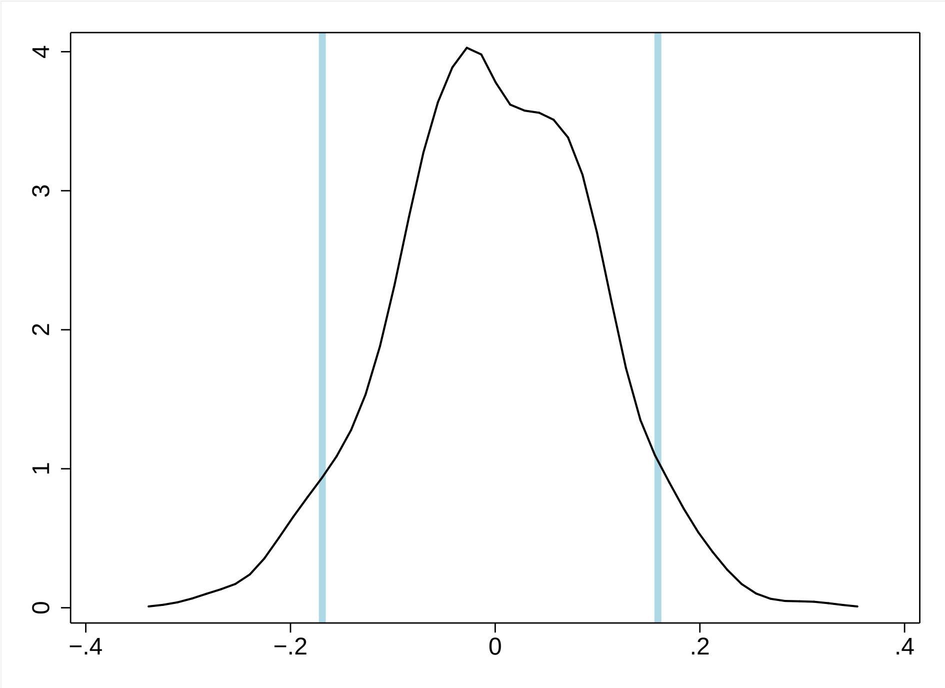
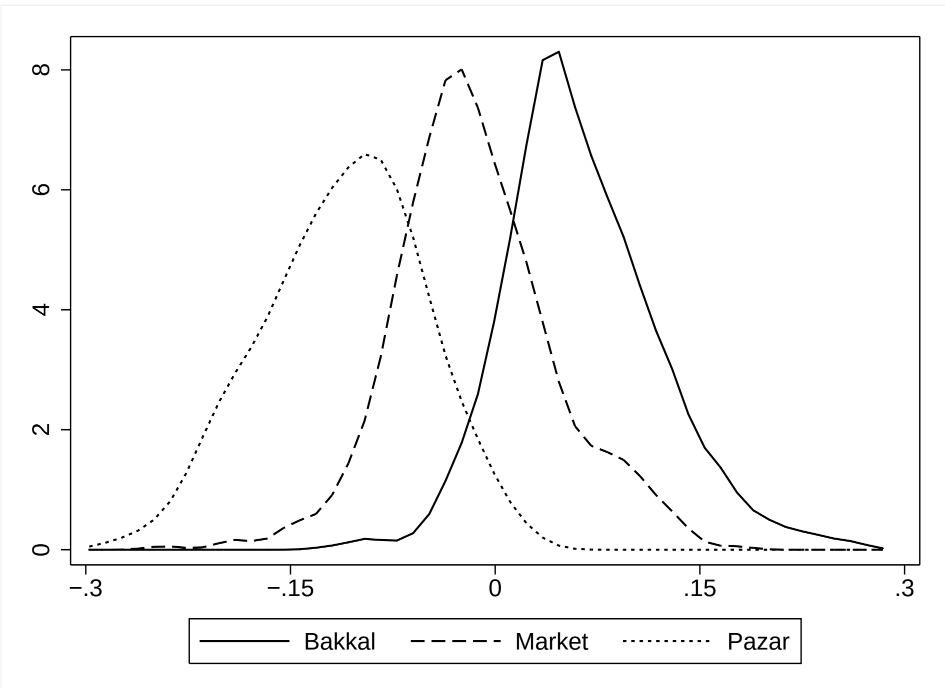


Figure 3: Distribution of Time Demeaned Price Deviations Across Markets Controlling for Regions and Products



Appendix A

List of products and availability of price quotes

Product	Bakkal	Pazar	Supermarket
Rice	1	1	1
Pasta	1	1	1
Flour	1	1	1
Filo Dough[a]	1	0	1
Cracked Wheat	1	1	1
Veal	1	0	1
Chicken	1	0	1
Mutton	1	0	1
Sucuk[b]	1	0	1
Salami	1	0	1
Sausage	1	0	1
Feta cheese	1	1	1
Kasseri cheese	1	0	1
Margarine	1	0	1
Eggs	1	1	1
Butter	1	0	1
Cooking oil	1	1	1
Olive Oil	1	1	1
Yoghurt	1	0	1
Potato	1	1	0
Onion	1	1	0
Lentils	1	1	1
Chickpeas	1	1	1
Beans	1	1	1
Apples	1	1	0
Lemon	1	1	0
Tomato	1	1	0
Green Peppers	1	1	0
Cucumbers	1	1	0
Lettuce	1	1	0
Zucchini	1	1	0
Scallion	1	1	0
Parsley	1	1	0
Olives	1	1	1
Honey	1	1	1

Appendix A: List of products and availability of price quotes (continued)

Product	**Bakkal**	**Pazar**	**Supermarket**
Tomato Paste	1	1	1
Halvah	1	0	1
Jam	1	0	1
Ready soup	1	0	1
Broom	1	0	1
Cleaning Powder	1	0	1
Soap	1	0	1
Detergent	1	0	1
Bleach	1	0	1
Paper	1	0	1
Lightbulbs	1	0	1
Plastic Kitchenware	1	0	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.