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MARKET STRUCTURE, INFLATION, AND PRICE DISPERSION

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Market Structure, Inflation, and Price Dispersion

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Abstract. In this paper, we investigate the impact of market structure on the relationship between inflation and price dispersion. We first propose a new empirical model of the relationship between inflation and dispersion with firmer theoretical foundations, and then extend the basic model to incorporate the potential effects of market structure. We estimate the basic and market structure specifications using a unique micro-level data set from Istanbul, which consists of monthly price observations from three different store types: convenience stores, open-air markets, and supermarkets. Our empirical findings support almost all of the basic and market structure predictions.

Keywords: inflation, market structure, menu cost models, micro panel data, price dispersion

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1. Introduction

The relationship between inflation and price dispersion has been the focus of an extensive empirical and theoretical literature, which contributes to our understanding of the transaction costs of inflation, as well as the influence of macroeconomic activity on industry performance. The empirical literature includes Domberger (1987), Van Hoomissen (1988), Lach and Tsiddon (1992), Tommasi (1993), and Parsley (1996), among others.[1] With some notable exceptions, including Reinsdorf (1994), the consensus seems to be that there is a positive association between inflation and dispersion.

The theoretical literature consists of static equilibrium search models, menu cost models, signal extraction models, and the information investment model. Static equilibrium search models, such as Reinganum (1979), assume that consumers have imperfect information about prices and therefore engage in costly search. In the menu cost literature, including Sheshinski and Weiss (1977, 1983) and Bénabou (1988, 1992), an increase in *anticipated* inflation increases dispersion when there are non-zero costs of adjusting nominal prices (menu costs). In the signal extraction literature, including Bénabou and Gertner (1993) and Dana (1994), an increase in *unanticipated* inflation increases dispersion by reducing the informational content of observed prices. Finally, in the information investment model sketched in Van Hoomissen (1988), an increase in *anticipated* inflation increases dispersion by increasing the depreciation rate on information. Furthermore, current dispersion depends on lagged dispersion, since the latter reflects the pre-search stock of information.

In this paper, we investigate the impact of market structure on the relationship between inflation and dispersion.[2] We begin by establishing the market structure

[1] In this paper, we focus exclusively on *intra-market* relative price variability; i.e., price dispersion for an essentially homogeneous good. There is also a substantial literature on *inter-market* relative price variability, including Vining and Elwertowski (1976), Parks (1978), and Debelle and Lamont (1997).

[2] "Market structure" refers to differences in market power; fixed, menu, and search costs; and

predictions of static equilibrium search models, menu cost models, and signal extraction models. Static equilibrium search models predict that dispersion should be greater in markets involving higher search costs and more inelastic demand, where the latter result has an obvious interpretation in terms of market power. According to menu cost models, the relationship between dispersion and anticipated inflation depends on fixed and transaction (menu and search) costs, as well as other parameters. Finally, the Bénabou and Gertner (1993) signal extraction model derives a relationship between dispersion and unanticipated inflation which differs across markets with different search costs.

We test these predictions using a unique micro-level data set, consisting of monthly price observations collected in Istanbul over the period 1992:10-2000:06. Each observation corresponds to one of three distinct market structures: *bakkals* (convenience stores), *pazars* (open-air markets), and Western-style supermarkets. Crucially, these three store types can be plausibly ranked pazars < bakkals < supermarkets with respect to market power, and fixed, menu, and search costs, which permits an unambiguous mapping from the theoretical predictions to the data.

Before analyzing the impact of market structure on the relationship between inflation and dispersion, we address some fundamental specification issues. In particular, menu cost models, signal extraction models, and the information investment model predict different inflation-dispersion relationships, involving different inflation variables, whereas empirical specifications of that relationship typically include just one or two inflation variables. Specifically, menu cost models refer to anticipated *aggregate* inflation, signal extraction models to unanticipated *product-specific* (PS) inflation (i.e., the inflation rate for that particular product), while the information investment model identifies lagged dispersion, anticipated PS inflation, and unanticipated PS inflation as important explanatory variables. A well-specified empirical model must therefore include all of these explanatory variables in the

other characteristics across different markets.

same regression. To demonstrate the potential for misspecification bias, we use our data set to estimate a standard empirical model similar to that in Reinsdorf (1994). We then show that adding theoretically important explanatory variables (specifically, lagged dispersion) produces qualitatively different results. These findings cast substantial doubt on previous empirical results.

Having established an empirical specification which more accurately reflects the theoretical literature, we proceed to test the above market structure predictions. Our findings support all of those predictions except possibly those derived from menu cost models. First, we find significant store-type fixed effects on dispersion levels, with supermarkets exhibiting the greatest dispersion, followed by bakkals, then pazars. The ranking pazars $<$ bakkals $<$ supermarkets in terms of dispersion levels is consistent with static equilibrium search models, since the same ranking should also hold with respect to market power and search costs. We also find significant differences across store types in the relationship between dispersion and unanticipated inflation, as predicted by signal extraction models. Finally, we find that supermarket dispersion is reduced during seasonal sales periods, whereas bakkal and pazar dispersion is unaffected, which we explain in terms of the erosion of supermarkets' market power during such periods. However, our results may be inconsistent with menu cost models, since there are no significant differences across store types in the relationship between dispersion and anticipated inflation.

The rest of the paper is organized as follows. In section 2, we discuss the theoretical literatures on static equilibrium search models, menu cost models, signal extraction models, and the information investment model. In section 3, we describe the data and define the relevant variables. Section 4 demonstrates the potential for misspecification bias when theoretically important explanatory variables are neglected. In section 5, we propose a new empirical specification of the relationship between inflation and dispersion and estimate it using our data set. In section 6, we investigate the impact of market structure on that relationship. Section 7 concludes.

2. Theoretical Foundations

In this section, we discuss the theoretical literatures on static equilibrium search models, menu cost models, signal extraction models, and the information investment model.

Static Equilibrium Search Models

In static equilibrium search models, for example Reinganum (1979), consumers have imperfect information about prices and engage in costly search. An equilibrium price distribution simultaneously supports optimal consumer search and is induced by the profit-maximizing prices set by firms, which take as given the distribution of consumers' reservation levels. In these models, dispersion is increasing in consumers' search costs and decreasing in the price elasticity of demand.[3] The latter result can be interpreted in terms of firms' market power: an increase in market power increases dispersion.

Menu Cost Models

The menu cost literature includes, among others, Sheshinski and Weiss (1977, 1983) and Bénabou (1988, 1992). In these models, inflation is constant and fully anticipated and firms follow optimal (S, s) pricing policies because of non-zero menu costs. An increase in anticipated inflation induces firms to widen their (S, s) bands in order to conserve on menu costs, thereby increasing dispersion. During deflationary periods, the model works in reverse. Menu cost models therefore predict a V-shaped relationship between dispersion and expected inflation; i.e., dispersion increases when either expected inflation or expected deflation increases.[4]

[3] For example, consider the Reinganum (1979) equilibrium search model. If the demand function is $q(p) = p^e$ and firms' costs are uniformly distributed on $[0, 1]$, then for elasticities $-2 < e < -1$, the equilibrium price distribution is uniform on $[0, p_r]$ with an atom of firms charging the reservation level p_r. A reduction in market power (more negative e) induces firms to lower their prices, so p_r falls, the atom there grows, and dispersion is reduced. Of course, if demand is perfectly elastic, the Law of One Price obtains.

[4] An increase in deflation refers to a more negative inflation rate.

Some empirical studies attempt to test the predictions of menu cost models using expected PS inflation, the expected component of the inflation rate of the specific product in question. However, in menu cost models PS inflation is an *endogenous* variable which is a consequence of firms' equilibrium pricing strategies. Instead, these models derive a theoretical relationship between dispersion and an expected *exogenous* inflation rate such as expected macroeconomic inflation in Sheshinski and Weiss (1977) or expected inflation in input prices in Bénabou (1988, 1992).[5] In this paper, we therefore test the predictions of menu cost models using a broad-based cost-of-living (COL) index for Istanbul. Since the COL index is specific to Istanbul, expected COL inflation should provide a good proxy for the expected aggregate inflation rate affecting local sellers.[6]

In the Bénabou (1988) menu cost model, the relationship between dispersion and anticipated inflation depends on fixed and transaction (menu and search) costs, as well as other parameters. Since the store types in our data set can be plausibly ranked pazars < bakkals < supermarkets with respect to fixed and transaction costs (see the next section for a description of these store types), one would expect the relationship between dispersion and expected inflation to differ across these market structures.[7] In this paper, we test for systematic differences in that relationship across store types by estimating a specification which allows the slope coefficients on expected COL inflation to differ across store types.

Signal Extraction Models

The literature on signal extraction with search frictions includes Bénabou and Gertner (1993) and Dana (1994). The former predicts a V-shaped relationship between

[5] In Bénabou (1988, 1992), PS inflation equals aggregate inflation in steady-state equilibrium, but this is unlikely to characterize real-world data sets or more general theoretical models.

[6] Using CPI inflation instead of COL inflation produced qualitatively similar empirical results.

[7] Indeed, preliminary simulations of the Bénabou (1988) menu cost model suggest that the ranking pazars < bakkals < supermarkets with respect to fixed and transaction costs should imply systematic differences in the slope coefficients on anticipated inflation across these market structures. The details of the simulations are available from the authors upon request.

dispersion and unexpected inflation, because an increase in the absolute value of unexpected inflation induces consumers to search less, by reducing the informational content of observed prices. Furthermore, the model also predicts that higher search costs will be associated with higher dispersion levels (as in static equilibrium search models and menu cost models) and differences in search costs will lead to differential changes in dispersion following an increase in unexpected inflation.[8]

Some empirical studies attempt to test the predictions of signal extraction models using unexpected aggregate inflation. However, in the absence of Lucas-type confusion, it is clear that signal extraction models refer to unexpected PS inflation, since unexpected aggregate inflation will reflect shocks to other industries. In other words, the search decisions of a rational, well-informed consumer shopping for good A should not be affected by unexpected shocks in the market for an unrelated good B. We will test this hypothesis by including both unexpected PS inflation and unexpected COL inflation in our empirical model.

Information Investment Model

In menu cost and signal extraction models, individual consumers only purchase the good once. In contrast, Van Hoomissen (1988) poses the repeat-purchase search problem as an optimal investment decision where search not only reduces the current purchase price, it also adds to the consumer's current stock of information. Information depreciates because it can be forgotten or become obsolete. In particular, an increase in expected (permanent) inflation increases the depreciation rate on information, inducing consumers to hold smaller information stocks (although search can go either way), which should increase dispersion in current and future periods. Dispersion should therefore show some persistence. Indeed, current dispersion depends on lagged dispersion, since the latter reflects the pre-search stock of information. As far as we know, this is the first paper to investigate the empirical

[8] These predictions are based on Tables 1-3 in Bénabou and Gertner (1993).

importance of lagged dispersion. Furthermore, a burst of unexpected inflation may increase dispersion in current and future periods while consumers replenish their information stocks. Again, in the absence of Lucas-type confusion, expected PS inflation is the appropriate proxy for the depreciation rate on information, since an increase in expected inflation for good A should not increase the depreciation rate on the consumer's stock of information for an unrelated good B.

Theoretical Conclusions

In summary, the theoretical literature makes two distinct sets of predictions about the relationship between inflation and dispersion. The first set of predictions, which we call the *basic predictions*, concerns the change in dispersion with respect to a change in one of the inflation variables. These are summarized in Table 1 below.

Table 1 At The Back Goes Here

The second set of predictions, the *market structure predictions*, concerns differences in the relationship between inflation and dispersion across markets which differ in terms of market power, fixed costs, and transaction costs. We test both sets of predictions in this paper.

3. Data and Definitions

Data

The data consist of monthly price observations for 58 distinct products, mostly foodstuffs, listed in appendix A. These observations span the period 1992:10 to 2000:06, during which the average inflation rate was high but relatively stable at about 60% per annum.[9] The Istanbul Chamber of Commerce collects this data to construct a

[9] The stability of inflation during the sample period may be significant, since Caglayan and Filiztekin (2003) have shown that the empirical link between inflation and dispersion can break down in the presence of large structural breaks.

broad-based COL index for wage earners in Istanbul, which we also use. The 58 products listed in appendix A comprise 25% of the entire COL index.[10] Whenever possible, the data collectors visited the same vendor to record price observations on the same product (same brand, quantity/weight, and other characteristics).

Each price entry p_{ijkt} in our data set is indexed by the product i, the neighborhood (borough) j in Istanbul where it was collected, the store type k, and the month t. Each entry corresponds to one of three distinct store types: bakkals, pazars, and supermarkets. *Bakkals* are small convenience stores which are almost always family-owned and operated. Each neighborhood has at least a dozen bakkals and usually many more. Bakkals are also local institutions with an important social dimension, as consumers tend to drop in to buy one or two items and exchange news and gossip with the owner. *Pazars* are open-air markets for fresh produce and small consumer items. These markets approach the perfectly competitive ideal, since sellers operate small stalls with 1-4 products each, and each product generally has several sellers. There is one main pazar in each neighborhood, open one day a week. Turkish supermarkets are similar to their Western counterparts. They are relatively large, corporate-owned, and stock a wide variety of distinct products and brands. There are typically 1-2 supermarkets per neighborhood, centrally located. Note that all of these store types are major institutions with many customers, so our results are not biased due to a lack of consumers for some store type.

We now characterize these three store types in terms of the parameters of the theoretical models discussed in the previous section. In terms of market power, one would expect the ranking pazars $<$ bakkals $<$ supermarkets to apply, with supermarkets having the greatest degree of market power and pazars very little. Bakkals may have some local market power, since people tend to patronize their "favorite" bakkal. With respect to menu costs, one would expect the same ranking

[10] The COL index includes the following categories: Food; Dwelling Expenses; Household Expenses; Clothing, Health, and Personal Care; Transportation and Communication; Culture, Education, and Entertainment; and Other.

to apply due to the relative sizes of these organizations. The same ranking should also hold in terms of their associated search costs, the opportunity cost of soliciting another price quote. Once inside the pazar, the search cost is very low, since there are many sellers selling essentially the same item within a small geographical area. The search costs associated with bakkals should also be fairly low, since these are convenience stores located mainly in residential areas, so the closest alternative is likely to be another bakkal, a short walk away. In contrast, supermarkets tend to be geographically isolated from other sellers, so obtaining another price quote generally entails a trip by car or public transportation. Finally, one would also expect the same ranking in terms of fixed costs. In particular, bakkals and supermarkets own or rent significant shopping space, whereas pazar sellers operate simple stalls.

A potential problem with the pazar data is that, although pazar operators are legally required to post explicit prices, the actual purchase price may be determined by haggling, whereas our data set only records the posted prices. Nevertheless, we believe the pazar data are useful, because the issues involved in setting the posted prices are similar to those in menu cost and signal extraction models. In particular, consumers will make signal extraction-type inferences based on the posted prices. Furthermore, if the posted price is too high, the seller will attract little consumer interest, and if the posted price is too low, the seller's profit margins will be negatively affected, since the actual price will not exceed the posted one. Hence, the posted prices should be useful for testing the predictions of menu cost and signal extraction models, *even if the actual and posted prices differ*. In fact, casual observation suggests that in the morning, which is when the Chamber inspectors collect the data, the bulk of the transactions occur at the posted price. Haggling is more important in the afternoon, when sellers are eager to get rid of their stocks. In Figure 1, we plot dispersion [defined in equation (3) below] across time for each store type.

Figure 1 Goes Here

For present purposes, we note that the dispersion series for pazars is similar to the others, suggesting that similar forces are at work determining all three. For the sceptical reader, in appendix B we report our findings following the same empirical analysis as in the text, except that only the bakkal and supermarket data are used (haggling is not a feature of these markets). The results are essentially the same. See tables B2-B4 in appendix B, which correspond to tables 2-4 in the text.

Definitions

We make the standard definition that the *relative price* of product i in neighborhood j sold by store type k in month t is defined by

$$R_{ijkt} = \ln(p_{ijkt}/p_{it}) \tag{1}$$

where

$$p_{it} = \frac{1}{J}\frac{1}{K}\sum_j \sum_k p_{ijkt} \tag{2}$$

is the average price of the product at date t, $J = 15$ is the number of neighborhoods, and $K = 3$ is the number of distinct store types. *Price dispersion* is defined by

$$V_{ikt} = \left[\frac{1}{J-1}\sum_j (R_{ijkt} - R_{ikt})^2\right]^{1/2} \tag{3}$$

where

$$R_{ikt} = \frac{1}{J}\sum_j R_{ijkt}. \tag{4}$$

Note that many empirical studies use relative price *change* variability to measure price dispersion as opposed to relative price *level* variability as defined in (3). However, as Lach and Tsiddon (1992, Section III) concede and Reinsdorf (1994, Section IV) emphasizes, the theoretical literature refers specifically to relative price level variability. Indeed, these two dispersion measures are not equivalent and may have different relationships with inflation, so in this paper we only refer to relative price level variability as defined in (3). The *product-specific (PS) inflation rate* for product i is defined as the average[11]

$$\mathrm{PS}_{it} = \frac{1}{J}\frac{1}{K}\sum_{j}\sum_{k}\pi_{ijkt} \tag{5}$$

where

$$\pi_{ijkt} = \ln(p_{ijkt}/p_{ijk(t-1)}). \tag{6}$$

Expected and Unexpected Inflation

To relate our empirical analysis to the theoretical models discussed in section 2, we need to decompose both COL and PS inflation into their expected (permanent) and unexpected (transitory) components. For purposes of comparison, we follow the same procedure used in Lach and Tsiddon (1992) and Reinsdorf (1994). According to this procedure, we regress PS_t against $\mathrm{PS}_{t-1}, \mathrm{PS}_{t-2}, \ldots$ up to six lags, past values of COL inflation up to three lags, and deterministic components including a constant, linear trend, and time dummies. For each product i, the appropriate lag length and the choice of which deterministic components to include is determined by the Schwarz Information Criteria. For each estimation, the residuals are tested for serial correlation and autoregressive conditional heteroskedasticity up to six lags. If the residuals are clean with respect to these anomalies at conventional significance levels, the fitted values are used as the expected inflation series EPS_t and the residuals are used as unexpected inflation UPS_t. If the serial correlation or ARCH tests failed, we used the second-best specification according to the Schwarz Information Criteria, and so on. The same procedure was used to decompose COL inflation into its expected ECOL_t and unexpected UCOL_t components except that

[11] Alternatively, one could define separate PS inflation rates for each store type. Although regressing store-type dispersion against store-type PS inflation seems more parsimonious than using overall PS inflation, there is no theoretical basis for using such narrow inflation variables. From the perspective of signal extraction models, using store-type PS inflation would imply, for example, that a consumer who observes high apple prices at the pazar would not use this information to make inferences about bakkal apple prices.

only past values of COL inflation were used, along with deterministic components including a constant, linear trend, and time dummies.[12]

Other Issues

In the empirical literature, inflation and price dispersion are calculated at the city-level, implicitly assuming that cities are markets. However, one may doubt that cities as large as New York and Istanbul can be usefully thought of as markets. Following Marshall, Stigler (1985, 1987) argues that markets tend to be fairly large, because buyers' small search radii overlap to such an extent as to bind the city together. Furthermore, the size of a market "will be at least as large as the larger of the areas of sellers' competition and buyers' competition, or the sum of the areas when they partially overlap." (1987, p. 78). He also discusses some evidence supporting this claim, including data on potato prices. It therefore seems that the relevant question is not whether Istanbul is too large to be considered a market, but rather that it might be too small.

Another feature of the empirical literature is that dispersion is calculated by product, rather than by seller, or even type of seller. The implicit assumption is that competition occurs at the product level, rather than the firm level. This is almost certainly invalid for supermarkets, which exploit the fact that their customers buy large baskets of items. However, this objection seems much less applicable to our data set, since it is clear that buyers in pazars shop for goods, not sellers. This is because each pazar operator only sells 1-4 items, and each of those typically has many other sellers. Hence, one may buy apples from one seller, and oranges from another. A similar comment applies to bakkals. One may enter a bakkal to buy bread, or a bottle of water, or some sweets, but not a large basket. So the ability of supermarkets to price baskets of items is disciplined by competition from bakkals and pazars. Note that the latter play a much larger role in the shopping patterns

[12] The details of the decomposition procedure are available from the authors upon request.

of Turkish consumers, compared with farmers' markets in North America, with supermarkets playing a smaller role in Turkey.

4. Common Specifications

We begin our empirical analysis with a very basic specification, which is common in the literature:

$$V_t = \alpha + \sum_i \lambda_i + \sum_{k \neq b} \theta_k + \sum_l \tau_l + \sum_n T_n + \beta \left| \mathrm{PS}_t \right| + u_t \tag{7}$$

where V_t is price dispersion as defined in (3), α is a constant, $|\mathrm{PS}_t|$ is the absolute value of PS inflation, and u_t is the regression error term. We take the absolute value of PS_t, since all the theoretical models discussed in section 2 predict a V-shaped relationship between dispersion and the relevant inflation variable. The model also includes dummy variables to control for fixed effects specific to particular products λ_i, store types θ_k (where $k = b, p, s$ for bakkal, pazar, and supermarket, respectively), months τ_l, and years T_n.

The estimates for this fixed-effects regression model are reported in Table 2, column 1.

Table 2 Goes Here

The estimated coefficient on θ_s is positive and significant at the 1% level, indicating that supermarkets exhibit greater dispersion than bakkals, *ceteris paribus*. Similarly, the estimated coefficient on θ_p is negative and significant, indicating that pazars exhibit less dispersion than bakkals. These findings are consistent with most static equilibrium search models, since these store types can be plausibly ranked pazars < bakkals < supermarkets in terms of market power and search costs. These estimates also confirm the visual evidence in Figure 1. The coefficient β on $|\mathrm{PS}_t|$ characterizes the relationship between PS inflation and dispersion for this model. The estimate for β is positive and significant at the 1% level, which agrees with the usual finding that there is a V-shaped relationship between dispersion and PS inflation.

Asymmetric Impact of Inflation vs. Deflation

As Jaramillo (1999) demonstrates, conclusions about the empirical relationship between inflation and dispersion can hinge on the proper treatment of outliers, especially those corresponding to deflationary episodes. In order to properly account for these, we introduce a dummy variable $D_{<0}$ which equals 1 when PS inflation is negative (deflation) and zero otherwise:

$$V_t = \alpha + \sum_i \lambda_i + \sum_{k \neq b} \theta_k + \sum_l \tau_l + \sum_n T_n + \beta\,|\mathrm{PS}_t| + \gamma\, D_{<0}\,|\mathrm{PS}_t| + u_t. \qquad (8)$$

This model therefore allows for an asymmetric V-shaped relationship between dispersion and PS inflation.

The estimates are reported in Table 2, column 2. We observe that β and γ are positive and significant at the 5% level, indicating an asymmetric V-shaped relationship. Specifically, a unit increase in inflation increases dispersion by about $\beta = 0.043$, while a unit increase in deflation increases dispersion by about $\beta + \gamma = 0.06$. Similar asymmetries, involving a larger change in dispersion for increases in deflation, have been reported by Reinsdorf (1994) and Jamarillo (1999).

Note that menu cost models can explain such asymmetries with respect to *aggregate* inflation variables. As Bénabou (1992, p. 303) points out, menu costs include *all* costs of a nominal price change not captured by the model, not just the direct costs of changing sticker prices. For example, a firm which raises its price may lose some of its valuable reputation as a low-price firm. Similarly, if firms are colluding, then a firm which lowers its price runs the risk of sparking a damaging price war. Hence, the menu cost of raising price may differ from the menu cost of lowering price, which may lead to an asymmetric effect on dispersion depending on whether the inflationary episode is inflationary or deflationary.

Effects of Expected vs. Unexpected Inflation

We now estimate a specification similar to that in Lach and Tsiddon (1992, Table 2) and Reinsdorf (1994), which relates dispersion to expected and unexpected PS inflation:

$$V_t = \beta_1 \, |\mathrm{EPS}_t| + \beta_2 \, |\mathrm{UPS}_t| + \gamma_1 \, D_{<0} \, |\mathrm{EPS}_t| + \gamma_2 \, D_{<0} \, |\mathrm{UPS}_t| + u_t. \tag{9}$$

The decomposition of PS inflation into its expected and unexpected components is intended to separately test the predictions of menu cost and signal extraction models, respectively. We also allow for an asymmetric V-shaped relationship between dispersion and each of these inflation variables. Note that while an asymmetric V-shaped relationship between dispersion and expected inflation is consistent with menu cost models, signal extraction models do not suggest any reason for such asymmetries involving unexpected inflation. The regression also includes a constant as well as product, store-type, and time dummies, but for simplicity we do not display them.[13]

In Table 2, column 3, the estimates for β_1, β_2, and γ_1 are all positive and significant at the 5% level. We therefore find an asymmetric V-shaped relationship between dispersion and expected PS inflation, with a steeper slope for expected PS deflation. Momentarily suppressing our reservations about the relevance of expected PS inflation for menu cost models, this is consistent with greater menu costs of lowering price than raising price. We also find a symmetric V-shaped relationship between dispersion and unexpected PS inflation, which is consistent with signal extraction models. It is also consistent with the information investment model.

Lagged Dispersion

Our results thus far are similar to previous findings in the empirical literature. However, specifications (7)-(9) do not include any aggregate inflation variables and

[13] From now on, we refrain from displaying these variables, although they always enter the estimation procedure.

may therefore fail to adequately capture menu cost effects. Furthermore, PS inflation and expected PS inflation are endogenous variables, and should therefore be proxied by appropriate instrumental variables, which is rarely (if ever) done in the empirical literature. Finally, lagged dispersion is neglected, which is an important explanatory variable according to the information investment model. Indeed, inspection of Figure 1 above suggests that dispersion exhibits some persistence, so failing to include it may lead to biased and inconsistent estimates. As a first step, we therefore add V_{t-1} to the model in (9):

$$V_t = \beta_0 \, V_{t-1} + \beta_1 \, |\mathrm{EPS}_t| + \beta_2 \, |\mathrm{UPS}_t| + \gamma_1 \, D_{<0} \, |\mathrm{EPS}_t| + \gamma_2 \, D_{<0} \, |\mathrm{UPS}_t| + u_t. \quad (10)$$

The model now has a dynamic structure, and we use the one-step GMM estimation procedure for dynamic panels analyzed in Arellano and Bond (1991).[14]

In Table 3, column 1, we observe that β_0 is positive and significant at the 1% level, which is consistent with the information investment model.

Table 3 Goes Here

Interestingly, the coefficients β_1 and γ_1, which were positive and significant in Table 2, column 3 have now become insignificant with the inclusion of V_{t-1}. In other words, the empirical link between expected PS inflation and dispersion has completely disappeared. We conclude that either menu cost effects are absent from our data, or that expected PS inflation fails to adequately capture those effects. The result $\beta_1 = 0$ is also inconsistent with the prediction of the information investment model that an increase in expected PS inflation should increase current as well as

[14] Arellano and Bond (1991) report that the Sargan test has asymptotic chi-squre distribution only if the error terms are homoskedastic, and that it over-rejects the null hypothesis of valid instruments in the presence of heteroskedasticity, which seems likely for our sample. Furthermore, they recommend using one-step results for inference on coefficients, as the estimated standard errors from the two-step method would be downward biased. We adopt this suggestion, and present one-step estimation results while implementing the Huber-White robust standard error estimation procedure to control for possible heteroskedasticity. All computations were performed by STATA, where lagged values of the inflation variables and the lagged dependant variable were used as instruments.

future dispersion. A possible explanation for this finding could be that the effect of expected PS inflation on current dispersion is too small to detect, although the total effect on future dispersion is significant and is captured by the coefficient on lagged dispersion. Note that the results for β_2 and γ_2 are not qualitatively changed from Table 2, so the data continue to support the basic prediction of signal extraction models after lagged dispersion has been included. These results cast substantial doubt on findings obtained from specifications similar to that in (9), such as those in Reinsdorf (1994), which fail to include lagged dispersion. Furthermore, Reinsdorf's (1994) finding of a negative relationship between inflation and dispersion may not adequately account for menu cost effects, since aggregate inflation variables are not included in his study.

5. A New Specification

Our findings in the previous section demonstrate the potential for misspecification bias when important theoretical explanatory variables are omitted. In this section, we therefore propose a new specification of the relationship between inflation and dispersion based on the theoretical conclusions in section 2:

$$
\begin{aligned}
V_t = {} & \beta_0\, V_{t-1} + \beta_1\, |\mathrm{EPS}_t| + \beta_2\, |\mathrm{UPS}_t| + \beta_3\, |\mathrm{ECOL}_t| + \beta_4\, |\mathrm{UCOL}_t| + \\
& \gamma_1\, D_{<0}\, |\mathrm{EPS}_t| + \gamma_2\, D_{<0}\, |\mathrm{UPS}_t| + \\
& \gamma_3\, D_{<0}\, |\mathrm{ECOL}_t| + \gamma_4\, D_{<0}\, |\mathrm{UCOL}_t| + u_t.
\end{aligned} \tag{11}
$$

As summarized in Table 1 above, this specification includes lagged dispersion and expected PS inflation to capture information investment effects, expected COL inflation for menu cost effects, and unexpected PS inflation for information investment and signal extraction effects. We also include unexpected COL inflation to test the hypothesis that consumers are not fooled by unexpected aggregate inflation. Finally, we allow for asymmetric V-shaped relationships between dispersion and each of the inflation variables.[15]

[15] We do not include lagged inflation variables in (11), since those effects should already be

In column 2 of Table 3, the estimates for β_0, β_1, β_2, γ_1, and γ_2 are qualitatively the same as in column 1 and require no further comment. Turning to the results for COL inflation, β_3 is positive and significant at the 1% level, indicating a V-shaped relationship between dispersion and expected COL inflation, as predicted by menu cost models. Note that our data set contains only two observations of expected COL deflation. As Jaramillo (1999) points out, testing for an asymmetric relationship is therefore equivalent to testing whether those two observations of expected COL deflation are influential outliers. Since γ_3 is positive and significant at the 1% level, this is indeed the case. It also hints that the V-shaped relationship between dispersion and expected COL inflation may be asymmetric, with a steeper slope for expected COL deflation. Note that Jaramillo, who had more deflationary observations to work with, found just such a relationship between dispersion and aggregate inflation. As for unexpected COL inflation, β_4 and γ_4 are both insignificant which suggests that, in the main, consumers are not fooled by unexpected changes in COL inflation. Except for expected PS inflation, these findings agree with the predictions in Table 1. The data therefore provide strong support for the *basic predictions* of menu cost and signal extraction models, with less support for the information investment model.

6. The Impact of Market Structure

We have now established an empirical specification (11) with firmer theoretical foundations compared with the existing empirical literature, and shown that our data support all but one of the *basic predictions* in Table 1. We now extend the basic model in (11) to incorporate the potential effects of market structure on the relationship between inflation and dispersion, and proceed to test the *market*

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captured by lagged dispersion. Indeed, V_{t-1} is the key theoretical lagged variable, since it proxies consumers' information stocks at date t, and may incorporate other factors besides inflation, such as the effects of supermarket advertising.

structure predictions. Specifically, we consider the model

$$
\begin{aligned}
V_t = &\beta_0 V_{t-1} + \beta_1 |\mathrm{EPS}_t| + \beta_2 \theta_p |\mathrm{EPS}_t| + \beta_3 \theta_s |\mathrm{EPS}_t| + \\
&\beta_4 |\mathrm{UPS}_t| + \beta_5 \theta_p |\mathrm{UPS}_t| + \beta_6 \theta_s |\mathrm{UPS}_t| + \\
&\beta_7 |\mathrm{ECOL}_t| + \beta_8 \theta_p |\mathrm{ECOL}_t| + \beta_9 \theta_s |\mathrm{ECOL}_t| + \\
&\beta_{10} |\mathrm{UCOL}_t| + \beta_{11} \theta_p |\mathrm{UCOL}_t| + \beta_{12} \theta_s |\mathrm{UCOL}_t| + \\
&\gamma_1 D_{<0} |\mathrm{EPS}_t| + \gamma_2 D_{<0} \theta_p |\mathrm{EPS}_t| + \gamma_3 D_{<0} \theta_s |\mathrm{EPS}_t| + \\
&\gamma_4 D_{<0} |\mathrm{UPS}_t| + \gamma_5 D_{<0} \theta_p |\mathrm{UPS}_t| + \gamma_6 D_{<0} \theta_s |\mathrm{UPS}_t| + \\
&\gamma_7 D_{<0} |\mathrm{ECOL}_t| + \gamma_8 D_{<0} \theta_p |\mathrm{ECOL}_t| + \gamma_9 D_{<0} \theta_s |\mathrm{ECOL}_t| + \\
&\gamma_{10} D_{<0} |\mathrm{UCOL}_t| + \gamma_{11} D_{<0} \theta_p |\mathrm{UCOL}_t| + \\
&\gamma_{12} D_{<0} \theta_s |\mathrm{UCOL}_t| + u_t. \qquad (12)
\end{aligned}
$$

This specification includes the same explanatory variables as (11), except that now the inflation variables enter in conjunction with the store-type dummies θ_p and θ_s, which allows for different slope coefficients across store types. The estimates are reported in Table 4.

Table 4 Goes Here

Expected PS Inflation

In Table 4, all the coefficients corresponding to expected PS inflation are insignificant except for γ_3, which is negative and significant at the 5% level. In other words, the only effect of expected PS inflation is that an increase in expected PS deflation reduces supermarket dispersion.

To investigate why expected PS deflation should be associated with lower dispersion for supermarkets, but not for bakkals or pazars, we study the pattern of PS deflation in our data. These observations correspond to falling nominal prices, which seem remarkable against the backdrop of 60% average inflation in Turkey. We note that there are 520 instances of PS deflation in our data set and 342 instances of expected PS deflation, so these are not rare occurrences.

In Figure 2, we plot the proportion of firms within each store type reducing nominal price at each date in the sample.

Figure 2 Goes Here

For present purposes, the most striking feature of Figure 2 is the seasonal price reductions, mainly by pazars, which occur every year during the warm months April-August, although the exact months vary from year to year. In other words, we seem to be observing annual summer sales.[16]

In Figure 3, we plot the distribution (relative frequency) of actual PS deflation and expected PS deflation across the months of the year.

Figure 3 Goes Here

We observe that the distribution for PS deflation peaks on April-July, which shows that the price cuts in Figure 2 tend to be associated with falling prices on average across all sellers, so these are market-wide sales. Furthermore, the distribution of expected PS deflation provides a relatively good, albeit imperfect, approximation to that for actual PS deflation, so the former variable should capture some of the effect of seasonal sales on dispersion.[17] Note that this is a consequence of the fact that Turkish inflation was relatively stable over the sample period. When inflation is volatile, expected inflation may be a poor predictor of actual inflation.

This suggests a straightforward explanation as to why expected PS deflation should be associated with lower dispersion for supermarkets, but not for bakkals or

[16] There may be other, smaller or less regular, annual sales periods. In particular, in Figures 2 and 3 there is some indication of a fall/winter sale centered on November which is also associated with PS and expected PS deflation.

[17] Although monthly dummies were used, they may not adequately control for the effects of the sales periods on dispersion, since the sales periods vary from year to year in terms of their magnitude, duration, and the months in which they occur.

pazars. For most of the year, supermarkets possess a significant degree of market power, and the exercise of that power may partly explain why supermarkets exhibit the greatest level of dispersion. During seasonal sales periods, however, a substantial proportion of pazar sellers cut their prices, perhaps as a passive response to some major exogenous force such as the agricultural cycle. Given the character of pazar operators, their price-setting behavior is unlikely to be strategic. In the face of these price cuts, which correspond to falling prices on average across all sellers, supermarkets have little choice but to price their products more competitively, reducing price in some cases and restricting price increases in others. As a result of the erosion of their market power, supermarket dispersion is reduced. Since expected PS deflation is a good predictor of PS deflation, we find a negative relationship between the former and supermarket dispersion. In contrast, the effect on dispersion for bakkals and pazars is negligible since these firms have little or no market power.

Unexpected PS Inflation

We now turn to the results for unexpected PS inflation. The coefficient β_4 is positive and significant at the 5% level, while β_5, γ_4, and γ_5 are all insignificant. We therefore find a symmetric V-shaped relationship between dispersion and unexpected PS inflation which is identical for bakkals and pazars. This finding may be consistent with signal extraction models, since the search costs for bakkals and pazars should be relatively low, and the difference may be too small to detect any difference in the relationship. With respect to supermarkets, we would expect the relationship to be different from that for bakkals and pazars, since the search cost for supermarkets should be significantly higher. Indeed, β_6 is positive and significant at the 10% level, while γ_6 is negative and significant at the 5% level. If we accept the estimate for β_6, then the V-shaped relationship between supermarket dispersion and unexpected PS inflation has a slope of $\beta_4 + \beta_6 = 0.11$ on the positive side and a slope of

$\beta_4 + \beta_6 + \gamma_6 = 0.001$ on the negative (unexpected PS deflation) side.[18]

To explain these findings for supermarkets, we note that there are 2,960 instances of unexpected PS deflation in the data, so again these are not rare. These refer to *statistically* unexpected PS deflation, as determined by the procedure described in section 3, and not all of these will have been genuinely unanticipated by buyers and sellers in Istanbul. Hence, unexpected PS deflation captures two separate effects. First, the component of unexpected PS deflation genuinely unanticipated by buyers and sellers in Istanbul will have signal extraction effects, reducing the informational content of observed prices, leading to a symmetric V-shaped relationship between dispersion and unexpected PS inflation. Since search costs are higher for supermarkets, this relationship should be different from that for bakkals and pazars and, in fact, we find a steeper slope for supermarkets. Second, some component of actual PS deflation corresponding to seasonal sales will have been statistically unexpected, and therefore negatively correlated with supermarket dispersion. These two effects may largely cancel out, leaving a very flat slope on the deflation side for supermarkets.

Expected COL Inflation

In Table 4, β_7 is positive and significant at the 5% level, while β_8 and β_9 are insignificant, indicating a V-shaped relationship between dispersion and expected COL inflation which is identical for all three store types. The coefficients γ_7, γ_8, and γ_9 are all significant at conventional significance levels, so the two observations of expected COL deflation are again influential outliers.

As in Table 3 of the previous section, these findings support the basic prediction of menu cost models, that an increase in the absolute value of expected aggregate

[18] In Table B4 in appendix B, where only bakkal and supermarket data are used, there is a symmetric V-shaped relationship between dispersion and unexpected PS inflation for bakkals. For supermarkets, the slope on the positive side is the same as that for bakkals, while the slope on the negative side is positive. This is the only qualitative difference which arises when only bakkal and supermarket data are used.

inflation increases dispersion. However, the lack of any systematic differences in that relationship across store types may be inconsistent with menu cost models, since bakkals, pazars, and supermarkets should exhibit significant differences with respect to fixed and transaction costs, as well as other important parameters. It could be that real-world sellers follow (S, s) pricing strategies which take the form of rules-of-thumb (e.g., standard mark-ups), rather than the more sophisticated optimal (S, s) pricing strategies in menu cost models. This may lead to greater uniformity across store types than standard menu cost models would predict, which might explain our findings.

Unexpected COL Inflation

Finally, all the coefficients in Table 4 corresponding to unexpected COL inflation are insignificant except γ_{11}, which is positive and significant at the 10% level. With the possible exception of pazars, people are not fooled by unexpected changes in COL inflation. Since pazars are small businesses operated by independent local people, they (or their customers) may be less well-informed than bakkals and supermarkets, which might explain why unexpected COL inflation may have a non-zero impact on pazar dispersion.

7. Conclusions

The contributions of the paper are twofold. First, we established a new empirical specification of the relationship between dispersion and inflation, which more accurately reflects the relationship predicted by theory. To demonstrate the potential misspecification bias of existing empirical models, we estimated a common specification (9), similar to that in Reinsdorf (1994), which neglects lagged dispersion, an important theoretical explanatory variable according to the information investment model. We then showed that adding lagged dispersion produces qualitatively different results. In contrast, our findings using the new specification (11) provides support for all the basic predictions in Table 1, except that corresponding to expected PS inflation. In particular, the estimated coefficient on lagged dispersion is positive and highly significant, as predicted by the information investment model, identifying a new channel by which monetary policy can have dynamic real effects at the industry level.

We then extended the basic specification to incorporate the potential impact of market structure, and proceeded to test the market structure predictions using our data set, which is uniquely suited for that purpose, since it contains price observations from three distinct store types which should exhibit significant differences in market power, fixed and transaction costs, and other characteristics. Our empirical analysis revealed significant store-type fixed effects on dispersion, with supermarkets exhibiting the greatest level of dispersion, followed by bakkals, then pazars. We also found significant differences in the relationship between dispersion and unexpected PS inflation across store types, as predicted by signal extraction models. Furthermore, supermarket dispersion is reduced during seasonal sales periods, whereas bakkal and pazar dispersion levels are unaffected, which is consistent with the market power predictions of static equilibrium search models. However, there are no significant differences in the relationship between dispersion and expected COL inflation across store types, which seems inconsistent with menu cost models. Although the basic predictions of menu cost model are borne out by the data, the market structure predictions are not. Finally, we found that unexpected COL inflation has no significant effect on dispersion, except possibly in pazars, which suggests that most buyers and sellers are not fooled by unexpected changes in aggregate inflation.

It remains to be seen whether our findings carry over to other data sets. In particular, Reinsdorf (1994) found a negative relationship between dispersion and PS inflation, driven by the negative estimate for unexpected PS inflation, which he attributes to signal extraction effects. However, his specification neglects lagged dispersion and aggregate inflation variables, so his estimates may suffer from misspecification bias. Furthermore, expected PS inflation may not adequately capture menu cost effects, and the relationship between dispersion and *aggregate* inflation may turn out to be positive, even for his data set.

Finally, our work shows that it is misleading to talk about the effects of *the* inflation rate. While aggregate inflation drives menu cost models directly, its effects in signal extraction models are indirect, since shocks to other industries are filtered away by rational agents. This suggests that menu cost and signal extraction effects may be fundamentally different, with potentially different welfare implications.

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Appendix A

Table A: Products

Product	Mean Inflation	stdev	Product	Mean Inflation	stdev
Rice	0.0486	0.0485	Roasted chick peas	0.0523	0.0496
Pasta	0.0457	0.0544	Walnuts	0.0564	0.0930
Flour	0.0452	0.0361	Raisins	0.0473	0.0451
Baklava	0.0508	0.0317	Apple	0.0509	0.1394
Cookies	0.0508	0.0317	Lemon	0.0453	0.1304
Flodough[a]	0.0472	0.0347	Tomato	0.0497	0.2703
Cracked wheat	0.0487	0.0304	Green peppers	0.0396	0.3354
Veal	0.0472	0.0386	Cucumbers	0.0409	0.2619
Chicken	0.0446	0.0818	Lettuce	0.0420	0.1472
Mutton	0.0472	0.0411	Zucchini	0.0395	0.2209
Fish	0.0545	0.1898	Scallion	0.0456	0.1722
Sucuk[b]	0.0489	0.0343	Olives	0.0488	0.0232
Offal[c]	0.0476	0.0448	Honey	0.0496	0.0344
Salami	0.0479	0.0319	Tomato paste	0.0464	0.0610
Sausage	0.0453	0.0283	Halvah[d]	0.0472	0.0482
Feta cheese	0.0464	0.0388	Jam	0.0469	0.0360
Margarine	0.0501	0.0519	Ready soup	0.0462	0.0300
Cooking oil	0.0485	0.0572	Broom	0.0505	0.0503
Eggs	0.0400	0.1307	Cleaning powder	0.0496	0.0344
Olive oil	0.0504	0.0579	Soap	0.0477	0.0477
Kasari cheese	0.0481	0.0555	Detergent	0.0451	0.0367
Potato	0.0474	0.1125	Bleach	0.0497	0.0316
Onion	0.0530	0.1695	Paper tissue	0.0501	0.0431
Lentils	0.0489	0.0527	Light bulbs	0.0390	0.0417
Chick peas	0.0541	0.0569	Plastic kitchenware	0.0495	0.0388
Dried beans	0.0525	0.0610	Toothpaste	0.0489	0.0404
Sunflower seeds	0.0460	0.0420	Toilet soap	0.0470	0.0468
Peanuts	0.0493	0.0470	Shampoo	0.0436	0.0532
Hazelnuts	0.0599	0.1127	Razor	0.0523	0.0579

a A very thin sheet of dough. *b* A type of sausage. *c* Sheep viscera. *d* A type of sweet.

Appendix B

Table B2: Panel data fixed effects estimation results

	(1) v1	(2) v1	(3) v1
dmrk	0.015	0.015	0.015
	[0.001]***	[0.001]***	[0.001]***
$\lvert PS\rvert$	0.058	0.051	
	[0.006]***	[0.006]***	
$D * \lvert PS\rvert$		0.031	
		[0.009]***	
$\lvert EPS\rvert$			0.047
			[0.010]***
$\lvert UPS\rvert$			0.047
			[0.009]***
$D * \lvert EPS\rvert$			0.053
			[0.018]***
$D * \lvert UPS\rvert$			0.000
			[0.011]
Constant	0.078	0.078	0.070
	[0.004]***	[0.004]***	[0.006]***
Observations	8464	8464	8207
R^2	0.37	0.37	0.37

Standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Variable definitions are given in the text.

Appendix B

Table B3: Panel data dynamic GMM estimation results

	(1)	(2)
	v1	v1
LD.	0.638	0.637
	[0.028]***	[0.028]***
$\lvert EPS \rvert$	-0.003	-0.007
	[0.017]	[0.018]
$\lvert UPS \rvert$	0.060	0.057
	[0.020]***	[0.019]***
$D * \lvert EPS \rvert$	0.020	0.024
	[0.036]	[0.035]
$D * \lvert UPS \rvert$	0.004	0.010
	[0.032]	[0.032]
$\lvert ECOL \rvert$		0.135
		[0.033]***
$\lvert UCOL \rvert$		0.009
		[0.018]
$D * \lvert ECOL \rvert$		0.463
		[0.309]
$D * \lvert UCOL \rvert$		-0.025
		[0.034]
Observations	8115	7952

Standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Variable definitions are given in the text.

The numbers in parentheses are robust standard errors from Arellano-Bond one-step GMM estimation.

Appendix B

Table B4: Panel data fixed effects estimation results

	(1)	(2) All	(3) Deviation of Supermarkets
LD.	0.636 [0.029]***		
$\vert EPS\vert$		-0.010 [0.021]	0.028 [0.042]
$\vert UPS\vert$		0.049 [0.020]**	0.066 [0.041]
$D * \vert EPS\vert$		0.034 [0.036]	-0.126 [0.045]***
$D * \vert UPS\vert$		-0.024 [0.033]	-0.122 [0.052]**
$\vert ECOL\vert$		0.115 [0.037]***	0.022 [0.044]
$\vert UCOL\vert$		0.009 [0.021]	-0.024 [0.034]
$D * \vert ECOL\vert$		1.161 [0.321]***	-1.917 [0.551]***
$D * \vert UCOL\vert$		-0.014 [0.033]	0.002 [0.042]
Observations	7952		

Robust standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Variable definitions are given in the text.

The numbers in parentheses are robust standard errors from Arellano-Bond one-step GMM estimation.

Table 1: Basic Predictions

	MenuCost	SignalExtraction	Information Investment
Lagged dispersion	n/a	n/a	positive
$\lvert ECOL \rvert$	positive	n/a	zero*
$\lvert UCOL \rvert$	n/a	zero*	zero*
$\lvert EPS \rvert$	n/a	n/a	positive
$\lvert UPS \rvert$	n/a	positive	positive

*Assuming no Lucas-type confusion.

Table 2: Panel data fixed effects estimation results.

Dependent variable:	The dispersion measure, V		
	Eq.(7)	Eq.(8)	Eq.(9)
dmrk	0.014	0.014	0.014
	[0.001]***	[0.001]***	[0.001]***
dpaz	-0.015	-0.015	-0.015
	[0.001]***	[0.001]***	[0.001]***
$\|PS\|$	0.047	0.043	
	[0.004]***	[0.005]***	
$D * \|PS\|$		0.017	
		[0.007]**	
$\|EPS\|$			0.036
			[0.008]***
$\|UPS\|$			0.043
			[0.007]***
$D * \|EPS\|$			0.026
			[0.012]**
$D * \|UPS\|$			-0.001
			[0.009]
Constant	0.089	0.089	0.088
	[0.002]***	[0.002]***	[0.002]***
Observations	10672	10672	10341
R^2	0.10	0.10	0.10

Standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Time and market type product dummies are included in all regressions.

Table 3: Panel data dynamic GMM estimation results.

Dependent variable: The dispersion measure, V		
	Eq.(9)	Eq.(10)
Lagged V	0.576	0.578
	[0.030]***	[0.031]***
$\lvert EPS \rvert$	0.009	0.010
	[0.013]	[0.013]
$\lvert UPS \rvert$	0.051	0.052
	[0.012]***	[0.012]***
$D * \lvert EPS \rvert$	0.017	0.014
	[0.024]	[0.024]
$D * \lvert UPS \rvert$	0.003	0.004
	[0.022]	[0.022]
$\lvert ECOL \rvert$		0.103
		[0.032]***
$\lvert UCOL \rvert$		-0.024
		[0.017]
$D * \lvert ECOL \rvert$		1.195
		[0.342]***
$D * \lvert UCOL \rvert$		-0.004
		[0.028]
Observations	10,225	10,022

Standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

The numbers in parentheses are robust standard errors from Arellano-Bond one-step GMM estimation.

Table 4: Panel data dynamic GMM estimation results by store type

Dependent variable: The dispersion measure, V		All	Deviation of Pazars	Deviation of Supermarkets
Lagged V	0.576			
	[0.031]***			
$\|EPS\|$		0.003	0.019	0.020
		[0.017]	[0.030]	[0.041]
$\|UPS\|$		0.048	0.000	0.062
		[0.020]**	[0.024]	[0.037]*
$D * \|EPS\|$		0.029	-0.030	-0.129
		[0.034]	[0.047]	[0.055]**
$D * \|UPS\|$		0.023	-0.032	-0.109
		[0.033]	[0.043]	[0.053]**
$\|ECOL\|$		0.087	-0.019	0.037
		[0.035]**	[0.045]	[0.040]
$\|UCOL\|$		-0.010	-0.051	-0.028
		[0.021]	[0.044]	[0.032]
$D * \|ECOL\|$		1.321	1.790	-1.727
		[0.333]***	[0.947]*	[0.560]***
$D * \|UCOL\|$		-0.008	0.087	-0.021
		[0.027]	[0.051]***	[0.040]
Observations	10,022			

Standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

The numbers in parentheses are robust standard errors from Arellano-Bond one-step GMM estimation.

Figure 1: Price dispersion by store type

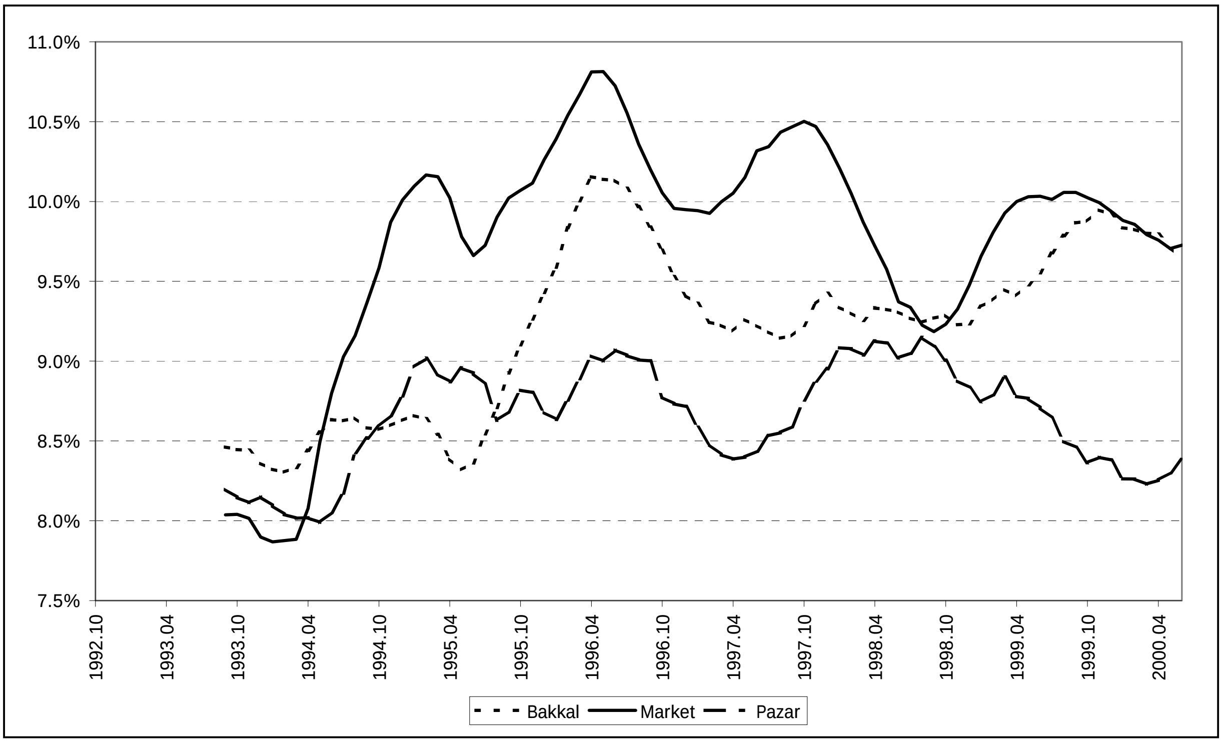

Figure 2: Percent of price reductions by store type

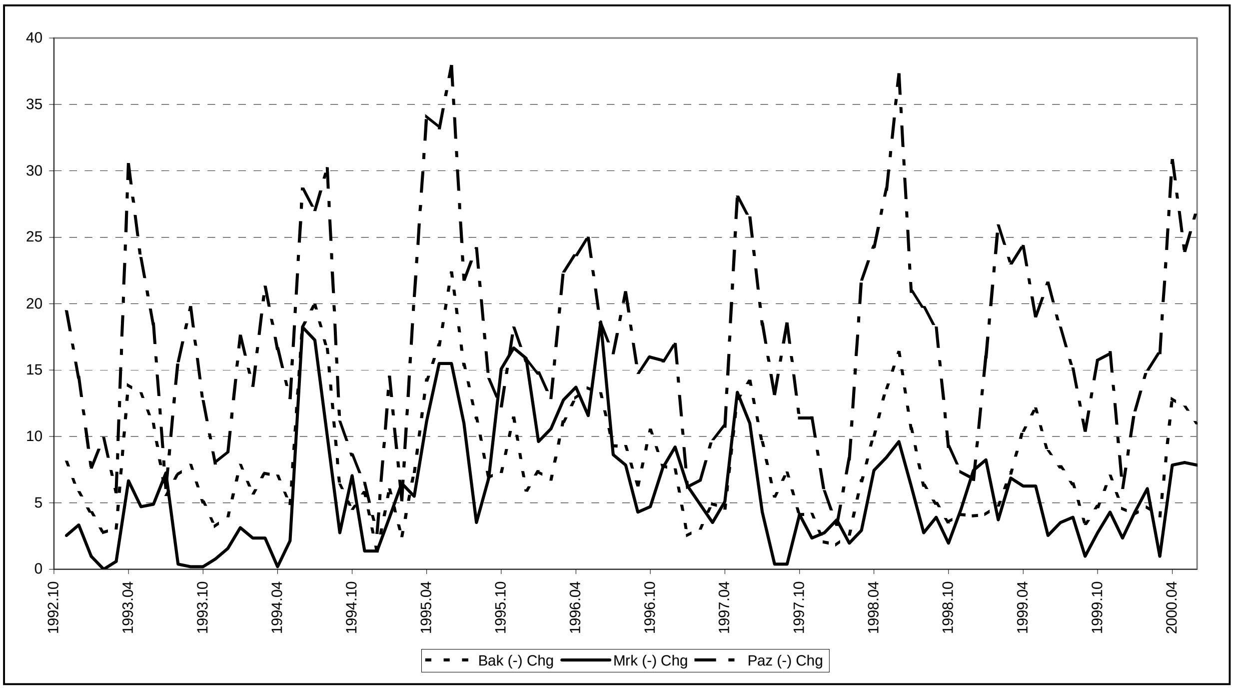

Figure 3: The distribution of PS deflation and expected PS deflation.