An Article Submitted to

The B.E. Journals in Macroeconomics

Manuscript 1420

Search, Costly Price Adjustment and the Frequency of Price Changes – Theory and Evidence

Jerzy D. Konieczny* Andrzej Skrzypacz†

*Wilfrid Laurier University, jkoniecz@wlu.ca

†Stanford Graduate School of Business, andy@gsb.stanford.edu

Search, Costly Price Adjustment and the Frequency of Price Changes – Theory and Evidence

Jerzy D. Konieczny and Andrzej Skrzypacz

Abstract

We establish a new empirical finding that the propensity to search for the best price affects the frequency of nominal price changes. This relationship holds in very different economies and for various proxies for propensity to search. We derive this relationship from a model of monopolistically competitive firms that face menu costs of changing nominal prices and heterogeneous consumers who search for the best price. We discuss alternative explanations and argue that they do not explain the observed correlations. Our results establish new, endogenous source of variation in pricing policies in the cross-section. This may be an important feature missing in many macroeconomic models based on nominal rigidities with exogenous frequency of price changes.

KEYWORDS: nominal rigidity, search, price adjustment

1. Introduction.

The goal of the paper is to provide a better understanding of nominal rigidities by analyzing micro-level pricing decisions. We establish a new empirical finding that the intensity of consumer search for the best price affects the frequency of price adjustment: price changes are more frequent and smaller in markets in which search is more intense. The relationship we document is both statistically and economically significant. We analyze an equilibrium model that explains the relationship. In our model, which is related to Bénabou (1992), customers are heterogeneous and search for the best price. We define the *propensity to search* as the expected return to search for a given relative price dispersion in the market. Competing firms face costs to adjust nominal prices. We show that equilibrium pricing strategies are affected by market characteristics related to consumer search and that the model predicts the patterns observed in the data.

The empirical relationship we discover holds in two very different data sets. The first data set consists of store-level, actual transactions prices for 55 products and services in Poland, each observed monthly in up to 47 stores, over 1992-96. Following the classic Stigler (1961) paper, we proxy the propensity to search with the value of purchases, the good's importance in household expenditure (conditional on the household buying the good) and the frequency of purchases. The second data set (Bils and Klenow (2004)), consists of prices collected by the Bureau of Labor Statistics in 1995-7; these prices cover 70% of US CPI. The data are grouped into 350 ELIs (Entry Level Items); for each ELI we have the average monthly probability of price changes in a given month. We proxy the propensity to search for goods grouped in a given ELI with its weight in CPI expenditure. Despite the very different environments (for example, the average CPI inflation is about 30% in Poland and is below 3% in the US), we find strong support for the predictions of the model in both data sets.

We consider several alternative explanations of the observed correlations: Taylor-Calvo's time-contingent model, Kashyap's (1995) price-contingent model, Diamond's (1993) sticker price model as well as temporary sales and argue that they cannot explain the patterns in the data. We also discuss Rotemberg's (2002) customer resistance model. This model has the potential to fit the data under two additional assumptions: that consumer resistance leads to smaller and more frequent price changes and that it is stronger in markets we identify as characterized by higher propensity to search. If so, more research on the effects of aggregate variables is needed to differentiate the two models.

Our search-based explanation of the cross-sectional heterogeneity is consistent with large, and remarkably consistent across countries, differences in the frequency of price changes across broad good categories. In both the Polish and the US data we find that the price changes are least frequent for services, followed by manufactured products and durable foodstuffs and are the most frequent for perishable foodstuffs. The same differences hold in recently obtained, extensive data sets for several European countries. Notably, differences across goods greatly exceed differences across countries. Furthermore, Bils and Klenow (2004) report that price changes are less frequent for processed than for raw goods. We attribute these differences to heterogeneity within broad good categories. The propensity to search for the best price is likely to be affected by non-price differences between goods (for example quality differences across different sellers). The larger are non-price differences, the smaller is the propensity to search for the best price (for given price differences) and so, according to our model, the less frequent are price adjustments. On the average, services are the most heterogeneous, followed by manufactured goods, durable foodstuffs and perishable foodstuffs. Similarly, processed goods are more heterogeneous than raw products.

We begin by presenting the model in the next section. Empirical evidence is in Section 3. In Section 4 we discuss alternative explanations of the patterns in the data. In Section 5 we provide a simple extension of the model which can account for the large observed differences in the average frequency of price changes between broad good categories. The last section concludes.

2. Menu Costs, Search and Price Changes.

In this section we develop an equilibrium model of search for the best price in the presence of menu costs and inflation. The model, closely related to Bénabou (1992), is a blend of the MacMinn (1980) and Carlson and McAfee (1983) models of costly search with heterogeneous consumers and the Sheshinski and Weiss (1977) and Caplin and Spulber (1987) models of costly price adjustment.

We consider a market for a single good produced by a continuum (of mass normalized to one) of long-lived firms. Given that there is a mass of firms, one firm's decisions do not affect the price distribution (or prices of other firms), so we can treat each firm as monopolistically competitive. All variables are expressed in real terms. All firms have the same constant marginal cost, MC, of supplying the good. They set nominal prices so as to maximize profits. Nominal prices are eroded at the constant (expected) inflation rate g. Each nominal price change entails a fixed cost m, the same for all firms. We assume that the sellers satisfy demand at the posted prices.

Each period a new cohort of consumers arrives at the market. Their number (mass) is v so that v is the relative measure of the number of consumers to the number of firms. Each consumer buys 0 or k units of the good and then exits the market. This is the main difference from Bénabou (1992) who assumes that individual demand is a smooth function of price. The simplification allows us to show below that the equilibrium is unique and establish comparative statics.

As prices of the good differ across firms, consumers search for the best price. Consumers are heterogeneous with respect to the search cost, c, which is distributed in each cohort uniformly over the range $[0,C]$. Each consumer chooses his search strategy to minimize the expected purchase cost, $E[kP+Nc]$, where P is the price paid and N is the total number of searches conducted. We assume that the value of the good to every consumer is high enough so that all buy k units of the product in equilibrium. Implicitly we make the standard assumption that search is instantaneous and consumption cannot be postponed.[1] Consumers form their search rules based on the expected (equilibrium) distribution of prices $f(P)$. Their search behavior yields a demand function for all producers, $q(P)$.

2.1. The Consumer's Problem and Demand.

Suppose that equilibrium prices are distributed according to a pdf f. Let type c denote a consumer whose search cost is c. Consider type c who finds a price quotation P. He has to decide whether to accept it or to search for a lower price in a different store. He is indifferent if:

$$c = k\int_0^P (P-x)\,f(x)dx \tag{1}$$

Denote by $P^*(c)$ the price that solves this equation. As is standard in search models, the optimal search rule takes the form of a reservation price: type c continues to search for a lower price until he finds a quote not higher than $P^*(c)$. Using the implicit function theorem we get:

$$\frac{dP^*(c)}{dc} = \frac{1}{kF(P^*(c))} > 0 \tag{2}$$

[1] See Bénabou (1992) for more discussion.

so higher prices are rejected by more customers. Denote by $c^*(P)$ the inverse of $P^*(c)$. Aggregating over consumers allows us to derive the expected demand of a firm that charges price P (assuming that all firms sell in equilibrium):

$$q(P) = \frac{vk}{C} \int_{c^*(P)}^{C} \frac{1}{F(P^*(c))} dc \tag{3}$$

The intuition is as follows. The density of consumers per unit of search costs is v/C. A firm charging price P sells k units of the good to all customers sampling its price whose search cost exceeds $c^*(P)$. Conversely, a customer who has a search cost c can buy the good from $F(P^*(c))$ firms (recall the number of firms is normalized at one). The term under the integral is each firm's share of type c consumers.

Using equations (2) and (3) we simplify the demand to:

$$q(P) = \frac{vk^2}{C} \int_{P}^{P^*(C)} dx = \frac{vk^2}{C}(P^*(C) - P)$$

where $P^*(C)$ is the reservation price of the buyer with the highest cost of search – the largest willingness to pay. From the definition (1) we obtain $P^*(C) = C/k + E[P]$, where $E[P]$ is the average price in the market. To simplify notation denote $A \equiv P^*(C),\ b \equiv vk^2/C.$ The demand function can be rewritten as:

$$q(P) = \frac{vk^2}{C}(C/k + E[P] - P) = b(A - P) \tag{4}$$

The demand faced by firms depends on how much search the buyers perform in equilibrium and on the total demand vk. The propensity to search depends on the exogenous, market-specific cost of search per unit bought, c/k (measured in the whole market by C/k), and on the (endogenous) average price on the market. In other words, the probability that a random consumer arriving to a store with a price x% higher than the market average is going to walk away and search for a lower price is a function of C/k and $E[P]$.

2.2. The Firm's Problem.

Sheshinski and Weiss (1977) showed that, if price setters are monopolistic or monopolistically competitive, menu costs are lump-sum, demand is stationary and the inflation rate is constant, the optimal pricing policy is of the (s,S) type: the firm waits until the real price P depreciates to s and then raises the nominal price so that P equals S. Assume, for simplicity, that the real discount rate is zero. At the time of the first price change the firm maximizes the average level of profits over the time period to the next price change:

$$\bar{\pi} \equiv \frac{1}{T}\left[\int_0^T \pi(Se^{-gt})dt - m\right] = \frac{1}{\ln(S/s)}\left[\int_s^S \frac{\pi(P)}{P}dP - gm\right] \tag{5}$$

where $\pi(P) = q(P)(P - MC)$ is the momentary real profit function and $T = \ln(S/s)/g$ is the time between price changes. The optimal pricing policy implies:

$$\begin{aligned} \pi(s) &= \pi(S) \\ \pi(S) &= \bar{\pi} \end{aligned} \tag{6}$$

2.3 Equilibrium.

We define a **(stationary) equilibrium** as a pair (*s, S*) specifying each firm's pricing rule which is optimal given the demand it faces; the (stationary) distribution of prices given by the policy rule; and the search strategy of each consumer that is optimal given the distribution of prices.[2] As shown in Caplin and Spulber (1987) and Bénabou (1988), the only time-invariant distribution of prices is log-uniform. This distribution of prices arises if the dates of the most recent price adjustment are distributed uniformly across firms over [-*T*, 0). Hence we consider staggered rather than synchronized price policies. The log-uniform distribution of price changes generates stationary demands and validates our analysis of the firm's problem.

Under uniform staggering of price changes the *pdf* of prices is:

$$f(P) = \frac{1}{P\ln(S/s)} \tag{7}$$

and the average price is:

$$E[P] = \int_s^S Pf(P)dP = \frac{(S-s)}{\ln(S/s)} \tag{8}$$

Following our previous discussion, the equilibrium is characterized by (*s, S*) that satisfy the two conditions for firm's optimality (6) and the aggregate condition that the average market

[2] As Bénabou (1988) argues there are three reasons to focus on stationary equilibria: optimality, macroeconomic consistency and stability. First, with any other distribution, search and demand are non-stationary, which makes the (s, S) rule suboptimal. Second, other distributions of prices result in the average price level not increasing smoothly at the rate g. Finally, if the bounds (s, S) differ slightly between firms (Caplin and Spulber 1987) or firms follow a randomized (s, S) strategy to limit storage by speculators (Bénabou 1989), then any initial distribution of real prices converges to this steady-state distribution.

price is consistent with firms' strategies, (8). Expanding equations (6) (and dividing by b) we can describe the equilibrium by the following system of equations:

$$(A-S)(S-MC)=(A-s)(s-MC) \tag{9a}$$

$$(A-S)(S-MC)=\frac{1}{\ln(S/s)}\left(\int_s^S \frac{(A-P)(P-MC)}{P}dP-\frac{gm}{b}\right) \tag{9b}$$

$$A-C/k=E[P]=\frac{S-s}{\ln(S/s)} \tag{9c}$$

Equation (9a) can be rewritten as:

$$s = A + MC - S \tag{10}$$

As we are interested mainly in how the frequency and size of price changes varies with the parameters of the model, we define $\sigma = S/s$; σ is the ratio of the initial to terminal real price. Using equation (10) and the definition of σ, we obtain the following simple expressions for the price bounds:

$$S=\frac{\sigma}{1+\sigma}(A+MC); \qquad s=\frac{1}{1+\sigma}(A+MC) \tag{11a}$$

Substituting (11a) into (9b) and (9c) and integrating we get:

$$\frac{(\sigma A-MC)(A-\sigma MC)}{(1+\sigma)^2}=\frac{(A+MC)^2}{2\ln\sigma}\frac{\sigma-1}{1+\sigma}-A\cdot MC-\frac{gm}{b\ln\sigma} \tag{11b}$$

$$E[P]=\frac{\sigma-1}{(1+\sigma)\ln\sigma+1-\sigma}\left(C/k+MC\right) \tag{11c}$$

We first prove that, for any given $E[P]$ (high enough so that it is possible for the firms to earn nonnegative profits), the firm's problem has a unique solution. All proofs are in Appendix A.

Lemma. For any given $E[P]\geq 0$, if there exist pricing strategies that yield nonnegative profits and $MC>\sqrt{2gm/b}-C/k$, then the firm's problem has a unique solution. Furthermore, for a given $E[P]>C/k - MC$, the optimal σ is decreasing in k, v and MC and increasing in C.

We can now address the question of existence and uniqueness of equilibrium.[3]

Proposition 1:

If $MC > \sqrt{2gm/b} - C/k$, then there exists a unique equilibrium.

The final step is to show the relationship between model parameters and the equilibrium size and frequency of price changes. Proposition 2 is the main result of this section: in markets in which consumers have a high propensity to search (because they have low search costs per unit bought, *C/k*, or because goods are expensive, due to high *MC*) or with a large volume of sales, *vk,* price changes are small and frequent. Also, the higher is the equilibrium relative price dispersion (measured by the coefficient of variation), the less frequent are price changes.

Additionally, according to Proposition 2, the explicit consideration of search does not alter the effects of inflation on the optimal pricing policy from those in the basic Sheshinski and Weiss (1977) model. As the inflation rate increases, price changes become larger and, given the form of the profit function, more frequent.[4]

Proposition 2:

(a) Assume $MC > \sqrt{2gm/b} - C/k$. The equilibrium size of price changes, σ , is increasing in the inflation rate, *g,* and in the size of the menu costs, *m*; it is decreasing in the marginal cost, *MC,* the density of customers, *v,* and in the size of purchases, *k.* Furthermore, if *MC>C/k,* the equilibrium σ is also increasing in search costs, represented by their maximum value, *C.*

(b) The frequency of price changes is decreasing in *m* and increasing in *g, MC, v* and *k.* If *MC>C/k* then the frequency is decreasing in *C.*

[3] A necessary condition for the existence of equilibrium is that the model parameters: *k, v, C* and *MC* are such that the firms profits are nonnegative. From (6) profits are nonnegative if and only if $s \geq MC$. Using (11a) and (11c) this is equivalent to: $C/k \geq MC \cdot [1-\sigma(1-\ln\sigma)]/\ln\sigma$, where σ is the equilibrium value found by solving (11b) and (11c). We assume that this condition is met.

[4] Also, firms with larger menu cost change prices less often and by larger amounts.

(c) Define the coefficient of variation as: $CV = STD[P]/E[P] = \sqrt{E[(P-EP)^2]}/E[P]$. For any changes of the model parameters (*C, k*, *MC*, *v*), the frequency of price changes is negatively correlated with *CV*.

The detailed proof is in the Appendix, but we provide intuition here. What is responsible for the differences in the frequency of price changes across firms and markets? The optimal frequency of price changes depends on the curvature of the profit function. If profits decline fast as the real price varies from its momentary profit-maximizing value, firms prefer to keep their prices within tighter bounds and pay the menu cost more often. In our case the real profit function is:

$$\pi(P) = (vk^2/C)\left(C/k + E[P] - P\right)\left(P - MC\right)$$

When price is *x* (percent) away from its momentary profit-maximizing value, profits are lower by $x^2 v \cdot [C + k(E[P] + MC)]^2 / 4C$, which is increasing in *v*, *k*, *MC*, and, as long as $C/k<E[P]+MC$, is decreasing in *C*. Note that this reasoning is not a full equilibrium argument since the shape of the profit function depends on the endogenous average market price.

Although this is not the focus of our empirical investigation, interestingly the model yields an ambiguous relationship between adjustment frequency and firm size. Intuition suggests that large firms should change prices more often since, for such firms, the cost of price changes are less important (Buckley and Carlson, 2000). But while, *ceteris paribus,* smaller menu costs mean more frequent price changes, the relationship between adjustment frequency and firm size depends on why the firm is large. By Proposition 2, efficient firms with low marginal costs change prices infrequently (and sell more units).

3. Empirical Results.

We now turn to testing the main prediction of our model: that goods on which customers spend more (relative to search costs) have a higher equilibrium frequency of price changes. The model predicts such a relationship because customers search more for a lower price for any *given* relative (percentage) price dispersion if *k* is higher, *C* is lower or the average price is higher. We refer to the expected return to search for any given price dispersion as the *propensity to search* and we treat it as exogenous. In equilibrium firms react to higher propensity to search by changing prices more frequently.[5]

Ideally, testing our model would require data that consist of detailed price information for individual goods in individual stores as well as information on search patterns of customers who buy these goods in these particular locations. Such data are not available. Hence we resort to data with detailed price information and use various proxies for the propensity to search. In particular, we try to proxy for k/C and for the average price, so our tests should be treated as joint tests of the model and the validity of our proxies.

We use two data sets. The first is a proprietary Polish data set. It consists of actual prices at the level of individual goods/stores. To proxy for the propensity to search we use the classification we created for an earlier paper (Konieczny and Skrzypacz, 2000) where we analyzed the effect of search on the dispersion of price level across stores. That classification follows Stigler's (1961) suggestions and looks at various aspects of search: expenditure on a given good (conditional on the household buying it), the value of a single purchase and the frequency of purchases.

The second data set consists of BLS data in Bils and Klenow (2004). These data, collected by the Bureau of Labour Statistics, cover almost 70% of US CPI. While the data are much more comprehensive than the Polish data, they do not contain the probabilities of price change for individual products but only for BLS-defined groups of goods (the so called ELIs – Entry Level Items). We use the share of expenditure of a given ELI in US households expenditures as a proxy for k and for the average price. It is difficult to disentangle whether a higher expenditure on a given good is caused by customers spending a lot rarely, or little but often. Fortunately, in either case, we expect customers to have a higher propensity to search for a lower price for any given price dispersion.

Before we present the results, we note a general problem in using prices which are not continuously observed to analyze price changes. We call it the *infrequent observations bias.*

Testing the model involves the analysis of differences in the probability and size of price changes across goods or groups of goods. When prices are not observed continuously (as is the case with essentially all existing data sets, and in particular with both the Polish and the BLS

[5] Of course, prices are endogenous in our model, but the large price differences across goods in our data correspond mainly to large differences in costs (MC in the model), so the endogeneity is a second-order issue. Our proxies for average prices should be treated as originating from the underlying differences in costs.

data), these differences are biased downward. Assume prices are observed once per period and let P_{ijt} denote the price of good *i* in store *j* in period *t*. Whenever $0 < P_{ijt-1} < P_{ijt}$ is observed, it is assumed that there was a single change of the price of good *i* in store *j* in period *t*. If there are instances of multiple price changes between *t*-1 and *t*, the sample frequency is lower than in the true data.

Assume (reasonably) that the higher is the sample frequency of price changes, the larger is the incidence of multiple adjustments during a given period. This means that the downward bias of sample frequency is bigger for goods that change prices often. Hence the cross-sectional variation of the probability of the price changes is smaller in the sample than in the true data. This biases the estimated coefficients towards zero.

On the other hand, infrequent observations need not lead to a reduction in the cross sectional variability of the size of price changes. If we observe $0< P_{ijt-1} < P_{ijt}$, we compute the size of adjustment as $(P_{ijt-1} - P_{ijt})/ P_{ijt-1.}$ This formula yields incorrect results whenever there are multiple price changes during month *t*. The cross-sectional variation of adjustment size will be underestimated if price changes in month *t* are all increases, or all decreases. Underestimation need not happen if the price changes are in the opposite direction.

3.1. Polish Data.

The first source of evidence is a proprietary data set on several goods and services in Poland. The data are a subset of the price information which the Polish Central Statistical Office (GUS) collects in order to calculate the CPI. GUS compiles price information on 1500-1800 products in 307 districts. For each good, the price is checked in one store in each district (Bauc et al, 1996, p. 55). Out of this set we obtained, for the period 1990-96, data on prices of 55 goods, each in 47 stores (districts). The 47 districts consist the complete set for four out of 49 Polish administrative regions, called voivodships. We selected voivodships with the largest number of districts.

These data were collected to analyze the effects of search for the best price on price behaviour, in particular on the dispersion of prices of identical products across stores, which is the focus of our earlier paper (Konieczny and Skrzypacz, 2000, hereafter KS1). The main criterion for including a good in our subsample was that it be precisely defined and remain unchanged throughout the studied period (excluding, for example, “a microwave oven” which may be a different good in different stores or time periods). 78 goods and services in the GUS data met this criterion. Of these we eliminated goods sold in packages of different size or whose packaging has changed during the study period, goods with regulated prices, and goods with many missing observations. Out of the 55 remaining goods, 38 are groceries (20 perishable and 18 durable), 4 are sold in cafeterias/cafes, 10 are nongrocery items and 3 are services. Summary statistics on the probability and the size of price changes are in Table 1. The list of the goods and various classifications are in Appendix B.

Table 1

Inflation, Probability and the Size of Price Changes

		All goods	Services	Manuf. goods	Foodstuffs	
					durable	perishable
		Polish data				
CPI Inflation rate (% per year)		29.9				
Probability of price change, %		32.2	18.3	24.2	33.1	40.2
Standard deviation		10.9	11.8	4.7	5.3	9.3
Probability of price:	increase, %	26.0	14.5	20.7	26.7	31.9
	decrease, %	6.2	3.8	3.4	6.3	8.3
Average size of: increase, %	increase, %	11.0	22.0	11.8	10.5	7.2
	decrease, %	8.4	15.4	8.8	8.0	6.2
		US data				
CPI Inflation rate (% per year)		2.7				
Probability of price change, %		23.3	11.8	23.6	24.7	38.3
Standard deviation		15.0	12.6	13.6	6.2	11.6

For a subset of goods, prices were checked several times a month in each store. To assure uniformity, we use the first observation in each month. Each month the maximum number of observations in our dataset is 2585. The actual number is smaller as data from some stores are missing; the proportion of missing data is about 20%.

As some data are missing, we compute the monthly probability of price changes by dividing the number of price changes by the number of observations in which we could have observed a price change, i.e. the number of cases when we have two consecutive price observations. This measure is an unbiased estimator of the probability of price change as long as the process generating missing data is independent of the pricing policies of the stores. There are 37817 price changes (30493 increases and 7324 decreases) and 115914 cases with two consecutive observations. The average monthly probability of price changes is about 1/3 (the values range from 0.38 in 1992 to 0.28 in 1996). As can be seen in Table 1, the probability is the lowest for services (18.2%), followed by manufactured goods (24.3%), durable foodstuffs (33.1%) and is the highest for perishable foodstuffs (40.2%). As we discuss at length below, this ranking of the probability of price changes across broad good categories is remarkably consistent across countries. The picture for the probability of price increases and decreases is similar. The probability of price changes for individual goods is in Appendix B.[6]

Table 1 also shows the size of price changes. The average price increase (the values for decreases are in brackets) is 11.0% (8.4%, respectively). Price increases (decreases) are the largest for services: 22% (15%), followed by manufactured products: 12% (9%), durable foodstuffs: 11% (8%) and perishable foodstuffs: 7% (6%). Information on individual goods is in Appendix B.

The Polish price data have several desirable features. The first is the absence of temporary sales (i.e. price reductions which are followed by a return of the price to the previous level). Such sales are common in other data sets. For example, for the US Kackmeister (2002) reports that about 22% of all price changes are due to temporary sales; see also Chevalier, Kashyap and Rossi (2003). Also, the data consist of actual transaction prices, since quantity discounts or coupons were rare or nonexistent during the study period. Promotional packaging (i.e. 120g for the price of 100g) was virtually unknown.

The goods included in the data are precisely defined (for example, product 53 is a car wash of a specific car model), which is an important feature in a study of search. Furthermore, the environment, we believe, is characterized by active search for the best price. Prior to 1990 Poland was a planned economy and prices were identical in all stores. Shortages were common, especially at the end of the 1980s. This led Polish shoppers to become expert searchers for the availability of goods. The big-bang market reforms in January 1990 freed most prices from

[6] Note that, to avoid the effect of the uneven number of observations on the averages, the numbers in Table 1 are computed with equal weight attached to each good and each month. For example the average probability of price change in 1992-96 is computed as $\text{Prob} = (\sum_{T=1992}^{1996} \sum_{t=1}^{12} \sum_{i=1}^{55} \text{Prob}_{itT}) / N_{itT}$, where Prob_{itT} is the probability of price change for good i in month t in year T and $N_{itT} = 5*12*55$ is the number of values of Prob_{itT} in the summation. The average size of price changes is computed in the same manner.

government control.[7] Stores were allowed to set prices of goods they sell and shortages quickly disappeared.[8] In the new environment goods were available but prices differed across stores. Casual evidence suggests that the experienced searchers quickly switched from search for availability to search for the best price. In KS1 we find that, consistent with Stigler (1961), search determines the level of price dispersion for homogenous goods; we provide more details below. Therefore we concluded that the data are well suited for a test of the model.

The data set is potentially unusual as Poland switched to a market economy in 1990. In two companion papers (KS1 and Konieczny and Skrzypacz, 2005, hereafter KS2) we analyzed various aspects of individual price behaviour. We found that the initial behaviour was different than in later years. This initial transition period was brief: using the definition employed in KS1[9], it lasted longer than a year for only 6 out of the 55 goods. We concluded that transition was definitely over by the end of 1991. Therefore we restrict our analysis to the 1992-96 period.[10]

Some price changes in our sample may be caused by changes in the store being sampled. GUS price inspectors were instructed to collect price quotations for the same good in the same store, or in a nearby store when the good is temporarily unavailable, but changes in stores were not recorded. Additionally, during the period of the study the retail sector in Poland underwent significant transformation, in particular with respect to store ownership and the appearance of substitutes. Most of these changes took place in the 1990-91 period, which is excluded from our empirical analysis. In most cases, the goods in our sample remained the basic staple and new substitutes were significantly more expensive. So it is unlikely many of the price changes we analyze were the result of changes in the retail sector.

The Polish data provide an idea about the issues created by the infrequent observations bias. For a subset of goods in the Polish data set (goods 1-38 – foodstuffs and goods 49-52 – café and cafeteria items) there are three observations a month in 1991-96. There are between 13% (in 1995) and 26% (1991) more price changes in the high-frequency data. Multiple price changes do not alter the cross-sectional picture of the frequency of price changes or their size: across goods,

---

[7] Some prices were freed in September 1989. As of January 1990, prices of over 90% of goods and services were set by market forces. Regulated prices included rent, utilities, electricity, gasoline, domestic cigarettes and some alcohols. The share of administered prices in CPI was between 10.6 and 12 % from 1990 on (EBRD Transition Report, 1999).

[8] See Sachs (1993) for a description and discussion of Polish reforms.

[9] We analyzed the behaviour of price dispersion across stores for individual goods. It is, initially, high but falls rapidly. Transition is assumed to end in the month in which the dispersion falls below its average value in the next three, six and twelve months.

[10] The results for the entire period are, in fact, very similar.

the coefficient of correlation between the probability of price changes in monthly and in high frequency data is over 0.95 in each year, and the correlation for adjustment size is over 0.96 in each year. We conclude that, while the consequence of infrequent observations is to bias the estimated coefficient towards zero, it is unlikely to affect the qualitative nature of the results.

Before we turn to empirical results, we calibrate the model to ask whether it can generate the price behaviour observed in the Polish data with reasonable parameter values.

In order to pin down the parameters of the model, we use data from Levy et al (1997), who provide direct information on menu costs. They estimate the size of menu costs on the basis of direct observation of the price changing process in several large US grocery chains. They report that the average cost of price change is \$0.52. The yearly cost of price change is \$4.23 per product; it is \$0.0119 per item sold (see their Table 4), which implies the average monthly volume of sales (vk in our model) is 30. The gross margin is 25% and the total menu cost is 0.7% of all revenues and 2.8% of the gross margin. Using this information to calibrate the model is somewhat arbitrary as various crucial parameters are probably different in Poland. For example Polish stores are smaller, competition and search incentives may differ, real wages are lower, the inflation rate is much higher than in Levy et al (1997) etc. Hence this exercise is just a back-of-the-envelope illustration of the model.

We set MC=1, so that all reported values are in the units of the good. We chose k=1 and v=30. We then computed the values of the menu cost, m, and the maximum search cost, C, so that gross margin is 25%, total menu cost is 0.7% of all revenues and the probability of price change is 0.32 when the inflation rate is 2.23% per month – the average values for 1992-96 in the Polish data (see Table 1). The resulting numbers are m=0.4155 and C=0.334. With these numbers the average cost of search for the best price is 16.7% of the average cost of a unit purchased, the price bounds are s=1.287, S=1.381, the average price in the market, $E[P]$, is 1.333 and the average percentage price change is 7.3%.[11] These numbers appear reasonable and we conclude that, despite its simplicity, the model is able to capture some of the most relevant aspects of the data.

Next, we ask whether our model can replicate the empirical relationship between inflation and the frequency of price changes. To do this we compute the predicted probability of price change for individual years in the data, using the calibrated parameter values and that

[11] This number is equal to the average price change in our data. However, unlike in the model, we also observe price decreases (19% of price changes). The average price increase in our data is 11% - see Table 1 for more details.

year's inflation rate. The results of this exercise are in Table 2. It is clear that the model does a good job qualitatively matching the relationship between inflation and frequency of price changes in the Polish data. Quantitatively, the empirical relationship between inflation and adjustment frequency is flatter than predicted by the model: while the probability of price changes is monotonically related to inflation, between 1992 and 1996 it falls from 38% to 28% per month while the model predicts decline from 39% to 23%.

Table 2
Predicted vs. actual probability of price changes

Period	Inflation rate, % per year	Monthly probability of price change		Percentage difference predicted-actual
		actual	predicted	
1992-96	30	0.32	0.32	0%
1990	95	0.60	0.59	-1%
1991	60	0.43	0.47	8%
1992	44	0.38	0.39	3%
1993	38	0.34	0.36	7%
1994	30	0.31	0.31	1%
1995	22	0.30	0.26	-13%
1996	19	0.28	0.23	-17%

3.2. Proxies for the Propensity to Search in Polish Data.

As mentioned above, we use proxies for propensity to search developed in KS1. We divided the goods on the basis of three characteristics: (a) the amount spent on a single purchase, (b) the frequency of purchases, (c) the weight of the given good in household expenditure, conditional on the household buying the good. They correspond to the model parameters as follows:

- A good with high amount spent on a single purchase constitutes a large portion of expenditure of a household who buys it in a given month (for example good 41 – a bicycle). This corresponds to a high value of k or a high average price.[12]

[12] Recall that, for a given frequency of price changes, our model implies consumers search more if the average price is higher. Large differences in average prices come in our data from differences in cost of goods sold, which corresponds to a higher MC in the model. Hence we treat the proxies for the average price as exogenous.

- If a good is purchased frequently, a possible strategy for a consumer is to continue purchasing at the same store, once a sufficiently low price is found.[13] Hence one search may lead to several purchases and the average cost of search per shopping trip is low. This corresponds to a low value of C/k. For example, the average cost of search for bread (goods 18-20) is lower than the cost of search for vinegar (good 36).
- If a good constitutes a large share of expenditure, it is bought frequently (low C/k) or/and the amount spent on a single purchase is large (high k or average price).

We also divided the goods on the basis of a summary statistic (d) that measures the overall propensity to search (for a given relative price dispersion). It aims at dividing the goods based on how much for a given relative price dispersion customers would (in our opinion) search for a lower price. It is based on our judgment about the relative importance of the first three measures as well as possibly some omitted factors.[14]

As we did not have direct information on these characteristics our classification is subjective. We divided the goods independently into categories within each characteristic and reconciled the rankings. To minimize arbitrariness, within each characteristic the goods were divided into only three categories: high, medium and low. The categories capture different characteristics of the goods: the correlation coefficients between different characteristics vary from –0.19 (between the value of a single purchase and purchase frequency) and 0.86 (between the weight in expenditure on a given good and the value of a single purchase). Our treatment of the characteristic (c) avoids the mismeasurement of the importance of household expenditure of goods bought by few households (for example, good 21: baby formula is important for households with babies, but its weight in aggregate expenditure is small).[15]

The classification of products into these categories is in Appendix B. The method of ranking the goods may seem arbitrary so we urge the Reader to examine Appendix B and compare a few goods with different rankings.

We used this classification in KS1 to analyze the effect of search on the differences between price levels for the same good sold by different stores. We expect price differences to be, on the average, smaller for goods in the high category in each characteristic than in the

[13] As argued by Stigler (1961) this requires that prices in stores be positively correlated over time. In our data the rank correlations between successive prices in a given store is in the range 0.8-0.98.
[14] For example, live carp is usually bought for Christmas or Easter holidays; its weight in expenditures, the frequency of purchases and the amount spent on a single purchase are low, but we expect a high propensity to search mainly because the search is so concentrated and search costs are low thanks to the word of mouth.
[15] This mismeasurement is a problem whenever weights in expenditure are used, as discussed below for the US data.

medium and in the low categories, and for the medium than for the low category. Our empirical results in KS1 are clear-cut. Depending on the comparison, between 80% and 100% of differences are as expected. These results indicate that search matters in the Polish data and that our classification is a good proxy for the propensity to search for the best price.

It should be noted that, while the dispersion of prices across stores, and the average frequency of price changes are closely related in our model, in empirical applications these issues are quite different. In the model we assume that the only source of heterogeneity in a given market is the timing of price changes. The average price in every store is the same and so the larger is the dispersion of prices, the lower is the frequency of price changes. In our data, however, the average price levels differ across regions (voivodships). For the typical good, prices across regions vary more than prices across stores.[16]

3.3. Results for Polish data.

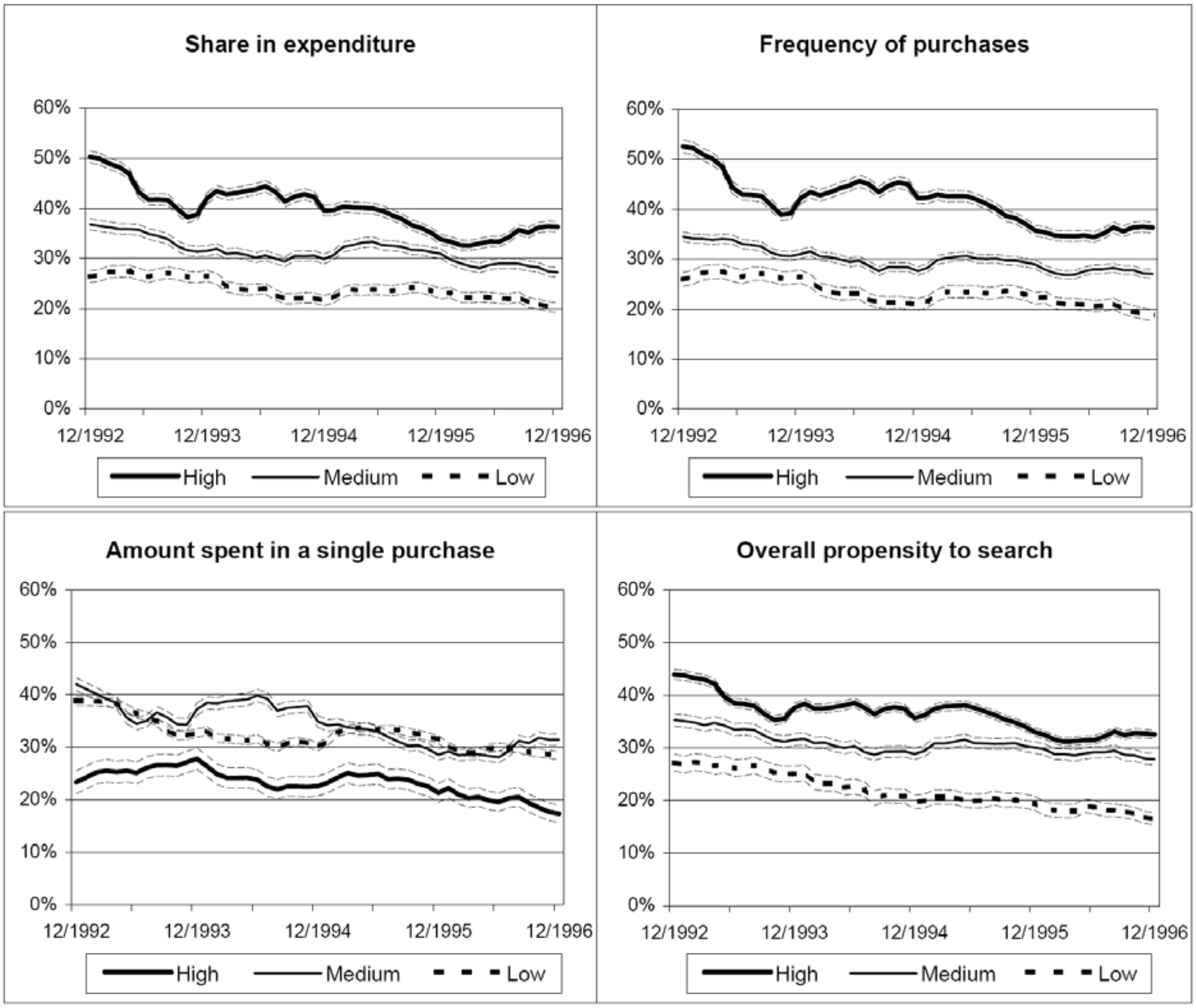
In Figure 1a we plot the computed probability of a price change, as well as 95% confidence intervals, for each category in the four characteristics Since some goods are seasonal and monthly probabilities are quite volatile, the values are 12-month averages. For example, the value in December 1992 is computed as the number of price changes in 1-12/1992, divided by the number of two consecutive observations. In Figure 1b we plot the average absolute size of price changes computed the same way (the pictures for increases and decreases for both the probability and the size of adjustment are similar).

Based on the model, we expect the probability to be the highest, and size of change to be the smallest in categories marked as *h* (highest propensity to search). The probability is expected to be the lowest, and the size of adjustment the largest, in categories marked as *l* (lowest propensity to search). It is clear from Figure 1 that the results are as predicted for the share in expenditure, frequency of purchases and the summary propensity to search characteristics. The only exception is the highest category in the "amount spent" characteristic, where price changes are rare and large. (The multivariate regression below shows that this is due to the omission of other variables).

[16] The coefficient of variation of the average voivodship prices is of similar size to the coefficient of variation of the price level across stores within a voivodship. The average voivodship prices are computed from between three and seventeen individual observations.

Figure 1a

Monthly Probability of Price Change by Search Categories*#

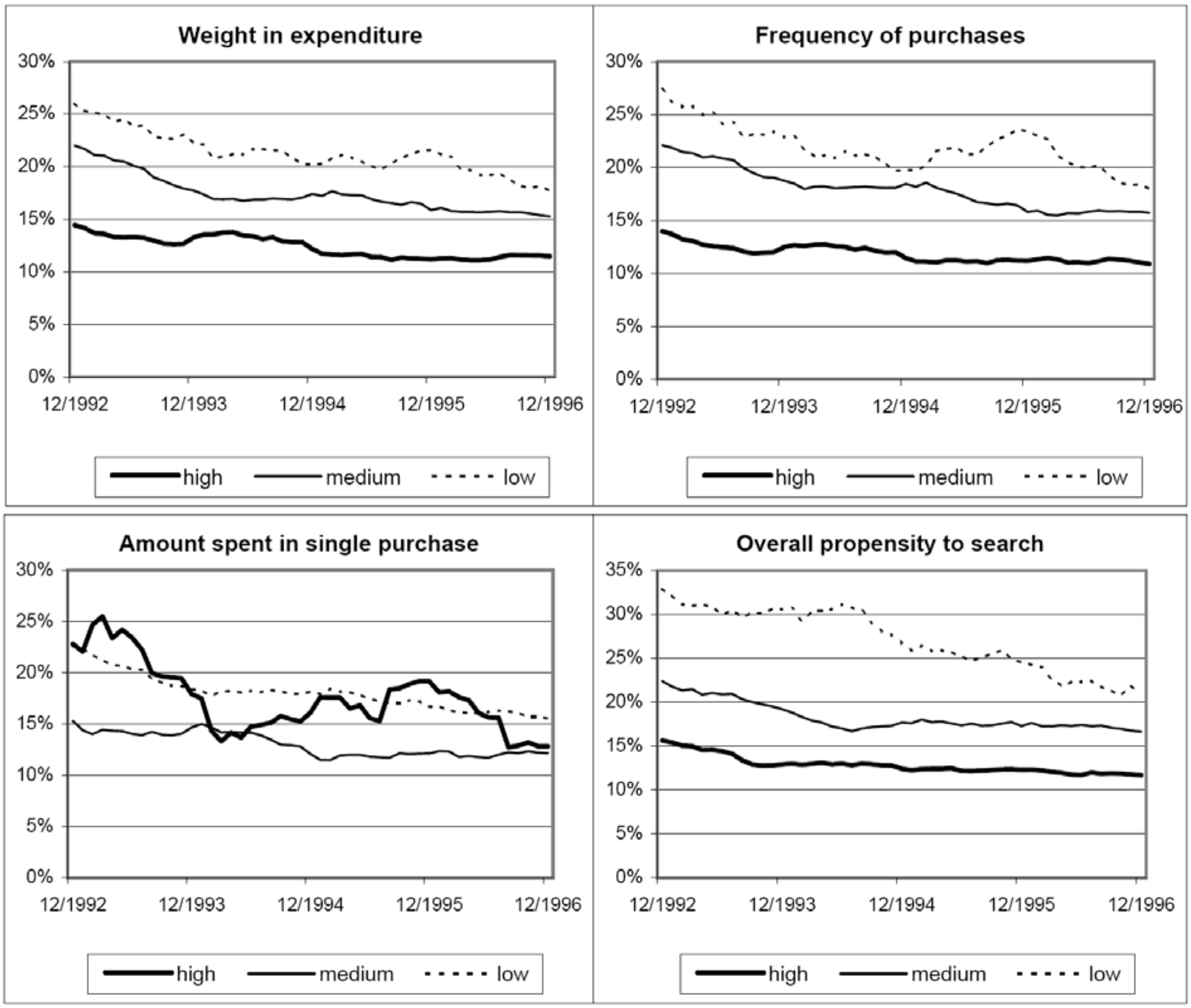


* Figures show 12 month averages ending in:

Dashed lines are denote 95% cofidence intervals

Figure 1b

Size of absolute price changes by search categories*



* Figures show 12 month averages ending in the month indicated on the horizontal axis

To analyze the relationship more formally, we regress the probability of price changes on category dummies, own inflation rate (i.e. rate of change of the nation-wide average price of the good), good type dummies and time dummies. In estimating Model 1 we use the overall propensity to search separately from the other classifications as it summarizes all factors relevant to search. We obtain:[17]

[17] The number of observations used to calculate the dependent variables differs across goods. Therefore in all regressions we have corrected for heteroscedasticity by multiplying the variables by the square root of the number of observations used to calculate the dependent variable.

$$Prob_{it} = \underset{(12.02)}{95.7} + \underset{(13.85)}{11.06}S^h + \underset{(7.84)}{6.63}S^m + \underset{(23.81)}{1.86}\, INF_{it} - \underset{(-5.70)}{3.55}\, df - \underset{(-16.01)}{11.6}\, mg - \underset{(-19.06)}{22.74}\, sv + \vec{\gamma}\cdot\vec{T} + \varepsilon_{it} \quad (12)$$

where $Prob_{it}$ is the probability of price change for good i in month t, expressed in percent. The data used in the regressions are monthly, unlike the data plotted in Figure 1 (which are 12-month averages). S^h and S^m are dummy variables, equal 1 for the high and medium propensity to search categories, respectively, and zero otherwise; *INF* is the nationwide inflation rate for good i in month t (also expressed in percent); *df, mg* and *sv* are dummies for durable foodstuffs, manufactured goods and services, respectively (the omitted type is perishable foodstuffs) and $\vec{T}$ is a vector of time dummies (total of 59, one for every month in the data). t values are in brackets.

INF is included on the right hand side to control for the effect of inflation on the frequency of price changes. It is better than alternative measures of inflation (for example CPI) as there are large relative price changes in the sample. We include dummies for broad good categories to control for the differences between the probability of price changes (see Table 1). Time dummies are included to allow for calendar/seasonal effects not captured by the inflation rate. They are jointly significant.

The results confirm predictions of the model. The probability of price change is the highest in the high propensity to search category and the lowest in the low, omitted category; all the differences between categories are significant at the 5% level. Note that this is despite the fact that, due to the infrequent observation bias, the differences between categories are probably underestimated.

We also find that the probability of price changes increases with inflation and that, controlling for inflation and search categories, prices of perishable foodstuffs change most often, followed by prices of durable foodstuffs and manufactured products; prices of services change least frequently. All the differences between the broad good categories are significant at the 5% level.

All results are highly significant, both economically and statistically. The difference in the probability of price change between the high and the low propensity to search categories is a bit larger than the standard deviation of the average frequencies for different goods (see Table 1). It is equivalent to about 6% higher average monthly inflation rate.

Model 2 involves estimating the same equation, but we replace the overall propensity to search dummies with dummies for the other three classifications. The results are:

$$\begin{aligned} Prob_{it} = & \underset{(8.67)}{71.75} + \underset{(1.88)}{2.91}\,E^h + \underset{(2.73)}{3.51}\,E^m + \underset{(6.7)}{15.3}\,F^h + \underset{(2.86)}{3.45}\,F^m + \underset{(4.98)}{5.7}\,A^h + \underset{(4.35)}{2.93}\,A^m \\ & + \underset{(23.96)}{1.85}\,INF_{it} + \underset{(3.32)}{4.7}\,df - \underset{(-1.89)}{2.35}\,mg - \underset{(-10.51)}{17.09}\,sv + \vec{\gamma}\cdot\vec{T} + \varepsilon_{it} \end{aligned} \tag{13}$$

where *E, F* and *A* denote the share in expenditure, frequency of purchases and amount spent on a single purchase, respectively. The results are, again, consistent with the predictions of the model. All the differences are as expected; all are significant at the 5% level, with the exception of the coefficient on the high category in the classification by share in expenditure, which is significant at the 10% level and is lower than the coefficient in the medium category. Note that, unlike suggested by Figure 1 (in which search category is the only explanatory variable) the probability of price change in the "high expenditure on a single purchase" characteristic is, as predicted by the model, higher than in the medium category.[18]

In columns 1 and 2 of Table 3 we repeat the tests with the probability of price increase as the dependent variable. The results are virtually identical to those obtained for the probability of price change. Finally, in the last two columns of Table 3, we report the results for Models 1 and 2 with the percentage price increase as the dependent variable. The results for Model 1 are consistent with our predictions. In Model 2 however, price changes for high frequency of purchases category are larger than for the other categories, and some results are not statistically significant. Price increases are the smallest for durable foodstuffs and the largest for services.

It is worth noting that, while higher inflation is associated with larger price changes, the effect is smaller than for probability of price changes. A 1% higher value of INF raises the probability of a price increase (probability of price change) by about 3% (2%, respectively) while the size of price increase rises by 0.2%. Klenow and Kryvtsov (2005) report that, in the US data, inflation affects mostly the size and not the frequency of price changes. It appears that their finding is unique. With the exception of Jonker et al (2004), European studies (which all use data from low inflation) report that the frequency of price changes is affected by inflation. A potential explanation of the difference between Polish and US data is that at different levels of inflation

[18] The coefficient on the manufactured goods dummy is significantly greater than the coefficient on the services dummy.

pricing polices respond differently to changes of inflation. Such explanation is consistent with Gagnon (2006) who studies price setting in Mexico. He reports that inflation is correlated with the frequency of price changes when it is high (roughly, above 10%) but not when it is low. The inflation rate in our data is above 20%; furthermore, we do observe that, as the inflation rate falls, the frequency of price changes decreases slower than implied by our model (see Table 2).

Table 3

Dependent Variable:		Probability of price increase		Percentage price increase	
		Model 1	Model 2	Model 1	Model 2
Deg. of Freedom		3234	3230	3234	3230
	R^2	0.571	0.577	0.453	0.542
Independent Variables[1]					
Share in Expenditure	HIGH		0.035 *		-0.090 *
	t value		2.599		-17.360
	MEDIUM		0.028 *		-0.089 *
	t value		2.532		-20.456
Frequency of Search	HIGH		0.099 *+		0.110 *+
	t value		5.020		14.315
	MEDIUM		0.031 *		0.007
	t value		2.997		1.717
Amount spent on a single purchase	HIGH		0.061 *+		-0.077 *+
	t value		6.175		-20.077
	MEDIUM		0.017 *		0.000
	t value		2.989		0.144
Overall Propensity to search	HIGH	0.093 *+		-0.052 *+	
	t value	13.503		-18.090	
	MEDIUM	0.056 *		-0.045 *	
	t value	7.720		-14.587	
INF		2.977 *	2.969 *	0.168 *	0.141 *
	t value	44.274	44.351	5.920	5.445
durable food		-0.026 *	0.021	0.030 *	0.126 *
	t value	-4.927	1.682	13.327	26.461
manufactured		-0.077 *‡	-0.024 *‡	0.037 *‡	0.112 *‡
	t value	-12.357	-2.262	14.046	26.832
services		-0.164 *‡	-0.139 *‡	0.131 *‡	0.242 *‡
	t value	-16.006	-9.886	30.412	44.139

Notes:

In all regressions a constant and dummies for each period of observations have been included. To save space we do not report these parameters.

* denotes coefficient significantly different from zero (at 5% significance level against two-sided alternative)

+ denotes High coefficient significantly different from Medium coefficient (at 5% sig. level, two-sided alternative)

‡ denotes category dummy significantly different from the category above (at 5% sig. level, two-sided alternative)

Proposition 2 (c) provides an additional test of the model, not related to the division of goods by search characteristics. It implies a negative correlation between the coefficient of variation of price levels, CV= STD[P]/E[P], and the probability of price changes. The estimated equation is:

$$Prob_{it} = \underset{(11.6)}{103.17} - \underset{(-20.61)}{0.75}\, CV_{it} + \beta\vec{T} + \varepsilon_{it} \qquad (14)$$

The coefficient on CV means that an increase of coefficient of variation by 10% corresponds to a 7.5% drop in frequency of price changes.

To conclude, the results obtained with the Polish data support the joint hypothesis that, (i) as predicted by the menu cost model with consumer search, the higher is the propensity to search for the best price, the more frequent and smaller are price changes and (ii) that our classification adequately captures search incentives.

3.4. U.S. Data and the Search Proxy.

The second source of evidence is the data set used by Bils and Klenow (2004); they describe it in detail. It contains the pricing information Bureau of Labour Statistics collects in order to calculate CPI. The data cover almost 70% of U.S. consumer expenditure. They are grouped into the so – called *entry level items* (ELIs). For years 1995-97, Table 1 in Bils and Klenow (2004) provides the probability of price changes and the weight in CPI for each of the 350 ELIs. A summary of the probability of adjustment data is in Table 1. The average probability of price change is about 25%. The probability depends on good type. It is much lower for services (11%), similar to the average for manufactured goods and for durable foodstuffs, and much higher for perishable foodstuffs (40%).[19]

To test the hypothesis that more intensive search leads to higher frequency of price changes, we treat ELIs' weights in CPI as a proxy for the average importance in expenditure, and so for the propensity to search, of the goods included in a given ELI. In our model it corresponds to a high value of k or to a high average price (or both).

There are a couple of problems with using CPI expenditure weights as a proxy for the propensity to search. First, as already discussed, what matters for search is not the weight of a given good in total expenditure, but rather its importance for households *who actually buy it*. Second, CPI weights are affected by the construction of ELIs.

ELIs group together items BLS considers similar. BLS may include in a single ELI goods with different propensity to search, and in particular with different weights in the expenditure of

[19] The classification of ELIs into types is available on request.

households who buy them. Consider, for example, ELI 55034 (hearing aids – with 0.024% weight in US CPI) and ELI 30032 (microwave ovens – with 0.03% weight in US CPI). The weights in expenditure are similar, but we expect the propensity to search to be much greater for the first ELI, since hearing aids tend to be expensive items bought by few households and, for households that buy them, constitute a much larger portion of expenditure than microwaves. This problem applies, in general, to all goods and services and so would be present even if expenditure data for individual products were available.

Second, CPI weights are affected by the construction of ELIs, especially by the number and heterogeneity of goods in an ELI. An ELI with a large weight in CPI may consist of a small number of goods that are important in consumer expenditure, or it may consist of a larger number of less important goods. For example, we expect greater propensity to search for goods in ELI 9011 (fresh whole milk – with 0.201% weight in US CPI) than for goods in ELI 18031 (potato chips and snacks – with 0.212 weight in US CPI), since whole milk typically constitutes a larger portion of a household expenditure than a particular brand of snacks.

Despite these problems we assume that, for a given ELI, a high value of weight in expenditure in CPI means the average good included in the ELI constitutes a large portion of household expenditure for customers who buy it and so the propensity to search for the best price is high. Therefore we expect a positive correlation between the probability of price adjustment for goods included in a given ELI and its weight in CPI.

3.5. Regression Results for U.S. Data.

To test the model using the BLS data set we regress the probability of price change on the expenditure weights and good type dummies (as before, the omitted good type is perishable foodstuffs). We obtain:

$$Prob_i = \underset{(23.40)}{37.04} + \underset{(5.83)}{10.62}\, w_i - \underset{(-5.36)}{13.70}\, df - \underset{(-8.25)}{14.97}\, mg - \underset{(-14.00)}{29.33}\, sv + \varepsilon_t \tag{15}$$

The results for the U.S. data again confirm the predictions of the model. The coefficient on the ELI weight is highly significant, both statistically and economically: the estimated coefficient means that goods with a 0.1% higher weight in expenditure have about 1% higher frequency of price changes.[20, 21] Also, it means that an increase in the weight in expenditure by

[20] Note that due to the infrequent observation bias, the estimated coefficient on ELI weight is biased towards zero.
[21] The coefficient on the manufactured goods dummy is statistically greater than that on the services dummy.

one standard deviation is associated with an increase in the frequency of price changes by about a quarter of a standard deviation (across the ELIs, the standard deviation of the weights in expenditure is 0.37% and of the frequency of price changes it is 15%).

The weights in CPI expenditure vary greatly across ELIs. The combined weight in expenditure of the top 15 ELIs is 25% while of the bottom 15 ELIs it is only 0.07%. The probability of adjustment in some heavy-weight ELIs is high (the top 15 ELIs include three types of gasoline and airline fares), while in some it is low (local phone charges and physician's services). Hence the results may be driven by outliers. To check whether this is the case we run regression (15) on various subsamples, selected by excluding ELIs with the highest weights. For all subsamples the coefficient on expenditure weight is positive; for most it is significant at the 1% level.[22]

To summarize, while the proxy we use is not ideal, the problems are unrelated to search considerations (since they are the result of BLS classification choices) and so their effect on the results are to increase errors. It is therefore encouraging that, despite this problem, and the infrequent observation bias (which reduces the estimated coefficient), the coefficient on the weight in expenditure is economically and statistically significant. Overall, the results support the joint hypothesis that (i) the more intensive is search for the best price, the more often are prices changed and that (ii) ELIs' weights in CPI are a sufficient proxy for search the propensity to search for the best price.

4. Alternative Explanations.

In this section we consider alternative explanations of the relationship between search and the frequency of price changes reported here. Most of the discussion focuses on the Polish data which are more detailed and allow the testing of alternatives. Note that search, by itself, leads to real rigidities since firms target their relative prices. In our model we need menu costs to explain the rigidity of nominal prices. There are many real stickiness theories, for example coordination failures (Ball and Romer, 1991), market concentration or collusion or the recent costly information theories (Mankiw and Reis, 2002) which, potentially, could explain the

[22] For example, if we exclude the top 15 ELIs, the coefficient for expenditure weight is 15.1 and is significant at the 1% level, while if we exclude the top half, it is 64.6 and is significant at the 10% level (the large value of the coefficient is due to the reduced variation in the right-hand side variable, which also explains the high standard error).

relationship between the propensity to search and real rigidities. They cannot explain why firms do not change nominal prices in continuous fashion and so we do not consider them here.

Time-Contingent Policies.

One possibility is that firms follow time-contingent policies, i.e. change prices at regular intervals, and the intervals are, for some reason, shorter in markets in which search for the best price is more intensive. In the absence of priors it is, of course, difficult to rule out policies that have a mixture of time- and state-contingent components. Assume, for example, that, as long as inflation is below 30% per year, a store changes the price of eggs every 40 days and the price of bread every 65 days. Discovering such patterns in the data is not practical, especially given the fact that some observations are missing.

For constant, deterministic inflation our model is observationally equivalent to a time-contingent Calvo-Taylor type model. At the very least, our findings show that the frequency of price changes varies significantly with the propensity to search for the best price and with good characteristics. Furthermore, in regressions (12) and (13) (as well as in Table 3) we find significant effect of inflation on the frequency of price changes. So, if time-contingent considerations are present, they are of secondary importance in the Polish data. In the US data, even if firms follow time-contingent policies, they are affected by search considerations.

Price-Contingent Policies

Kashyap (1995) proposed an alternative explanation of nominal price rigidity. According to his theory, certain values of nominal prices are preferred, for example round prices or prices ending in a 9. With aggregate inflation, a firm delays nominal price adjustment until it is optimal to change price to the next pricing point. To make the terminology consistent, we will call such policies *price-contingent policies*. We call prices ending in 9, 99, etc *tantalizing* prices, while prices ending in a zero will be called *round prices.*

In the absence of priors we selected prices as being round on the basis of a simple criterion: consecutive round numbers were allowed to differ by between 2% and 5%.These values are smaller than the average size of price change and so the choice is not restrictive.

Tantalizing prices were defined as prices just below the corresponding round price.[23] In what follows we discuss the results for the proportion of prices that are either round or tantalizing; the latter prices are rare in the Polish data and so the results are identical if we look only at round prices.

Price contingent policies are, in a sense, similar to time-contingent policies; it is the price, rather than time of adjustment, that is not chosen optimally. The loss from suboptimal price may be larger in markets where search is intensive, and so price-contingent policies can provide a potential explanation of the patterns in our data. Indeed, we find that the more intensive is search, the less frequent are pricing points. For example, for the overall propensity to search characteristic, the proportion of prices that are equal to pricing points is 0.355 for the high category, 0.504 for the medium category and 0.526 for the low category. Pricing points are the most common for services, followed by manufactured goods, and are the least common for perishable foodstuffs.[24]

To check whether the relationship between the propensity to search and the probability and the size of price changes is affected once we control for the proportion of pricing points we add the proportion of pricing points, PPP_{it}, to the right side of regression (12). We obtain:

$$Prob_{it} = \underset{(9.76)}{78.46} + \underset{(15.40)}{12.34} S^h + \underset{(7.58)}{6.32} S^m + \underset{(23.86)}{1.84} INF_{it} + \underset{(9.84)}{0.12} PPP_{it} + \vec{\gamma}\vec{T} + \vec{\delta}\vec{G} + \varepsilon_{it} \qquad (16)$$

where $\vec{G}$ =(df, mg, sv) is the vector of good types.

The addition of the proportion of pricing points as an explanatory variable has little effect on our previous results. The signs and the significance of the coefficients is not affected, and there is little effect on their size. While the proportion of pricing points is statistically significant, its economic significance is small. The standard deviation of the average proportion of pricing points for different goods is 17%, so a one standard-deviation increase in PPP corresponds to $Prob$ increasing only by 0.2 of the standard deviation. The results for the probability of price increases and for the size of price changes are similarly unaffected.

[23] The values of prices in the Polish data range from 0.0026 to 400 PLN (on January 1, 1995 the currency was redenominated at the rate 1PLN=10000zl; we use data denominated in the new currency, which explains the very low price). Round prices are defined as 10^{i-4} * {**x**}, i = 1,…,6; {**x**}={1.00,1.05,…,2.00,2.10,…,5.00,5.25,…,10.00}. The values of tantalizing prices are 10^{i-4} * {**y**}, i = 1,…,6; {**y**} = {{1.04-1.049}, {1.09-1.099},…,{1.94-1.949}, {1.95-1.999},{2.09-2.099},{2.19-2.199},…,{4.89-4.899},{4.95-4.999},{5.2-5.249},…,{9.7-9.749},{9.9-9.999}}

[24] Álvarez and Hernando (2004), Aucremanne and Dhyne (2004) and Baumgartner et al (2004) also find a negative correlation between the frequency of price changes and the proportion of pricing points.

Overall, we conclude that price-contingent policies cannot explain the patterns of price changes in the Polish data.

Temporary Sales.

Another possible explanation is that the observed frequency of price changes is generated by temporary sales. Chevalier, Kashyap and Rossi, (2003) analysed temporal patterns of price behaviour at the Dominic chain of grocery stores in Chicago. They find that the loss-leader model explains the behaviour of prices during demand peaks. Popular goods are often put on sale in order to attract customers to visit the store; the price is subsequently raised to the previous level. Using the same data set, Rotemberg (2002) illustrates the price behaviour of a particular product (Nabisco premium saltines) over a period of eight years (see his Figure 1). While price changes (down and up) are numerous, there are only five “regular” prices, defined as the price before and after a temporary sale. Temporary sales are frequent and the total number of price changes is an order of magnitude higher than the number of changes of the “regular” price. All changes in the “regular” price are increases. This illustrates the difficulty in analysing data collected with infrequent observations.

It is possible that, in the US data, the loss-leader approach to pricing leads to more frequent price changes for goods for which search for the best price is intensive. But temporary sales are very rare in the Polish data and so they cannot explain the patterns of price behaviour reported here.

Sticker-Price Model.

Diamond (1993) proposed a sticker price model as an explanation of nominal price rigidity. Whenever a good is delivered to a seller, a price sticker is attached to each item and the good is sold at the (constant) nominal price until old stock runs out. The price sticker is never changed. This is a potential explanation of the price pattern in our data. In markets in which search is intensive, the loss from having a suboptimal price is large. If a firm cannot change the price of a good already in inventory, it would order new stock in smaller batches and change prices more often.

If the Diamond (1993) model explains price behaviour, the effect of search on the frequency and size of price changes would hold only for goods with sticker prices. To check this we ran regressions (12) and (13) using data for goods priced without the use of stickers. These include goods sold by weight as well as services: goods 1-14, 18-20, 31, 35 and 49-55. Regression results, not reported here for brevity, are very similar to those obtained using the entire data set. In model 1 the coefficients on the overall propensity to search dummies are as predicted and the differences are significant at the 5% level. In model 2, the results for the share of expenditure, frequency of purchase, and the medium category in the amount spent classification are as predicted. The results are significant at the 5% level, except for the medium category in the share in expenditure classification. Overall, since the price behaviour is qualitatively the same for goods priced with, and without, stickers, the Diamond (1993) model does not explain the behaviour of prices in our data.

Customer Reluctance.

Rotemberg (2002) proposed recently an alternative explanation of nominal price stickiness. It is based on the idea that some price changes are perceived by customers as unfair, and so avoided by firms. As long as the new price is perceived as fair, customers accept it and do not react negatively by withdrawing purchases or switching to other suppliers. The implications of the model differ from those based on menu costs; in particular, adjustment frequency depends on observable economy-wide variables.

While Rotemberg's model is quite stylised, its implications are similar to those of our model provided that there are menu costs and consumer resistance leads to smaller and more frequent price changes. Buyers of frequently purchased goods are better informed and able to identify unfair price increases and so customer resistance is more relevant for these goods. Fairness is more relevant for goods which constitute a large portion of expenditure and for expensive goods. Therefore, for the three characteristics, Rotemberg's model also predicts smaller and more frequent price changes for the high groups. The main difference between the two models is in the effect of aggregate variables. In our model they affect the frequency of price changes indirectly, through their effect on the search process. In Rotemberg's model they have more direct effect, by affecting resistance to price changes (for example a depreciation of currency would make price increases more acceptable for goods with significant imported inputs). The best way to distinguish between our and Rotemberg's model is through careful analysis of the effect of aggregate variables on the size and frequency of price changes. Our data are not sufficient for such a test.

5. Potential Explanation of the Differences Across Broad Good Categories.

While our focus is on the analysis of pricing decision at the level of individual goods, in this section we consider the differences in the probability of price changes across broad good categories. These differences are striking and consistent across countries. In the eight comprehensive data sets (for U.S., Austria, Belgium, Finland, France, Luxemburg, Portugal and Spain)[25] as well as in the four smaller sets (for Poland, Germany, Holland and Italy)[26] the probability of price change is always the lowest for services, highest for perishable foodstuffs, followed by manufactured goods, durable foodstuffs and perishable foodstuffs. In the European studies, the probability of price changes for energy products is even higher than for perishable foodstuffs (except for Portugal, where energy prices are regulated). Furthermore, Bils and Klenow (2004) find that prices are changed more often for raw rather than manufactured products. Finally, price changes in Poland are the largest for services, and the smallest for perishable foodstuffs.[27]

We illustrate a potential explanation of these differences with a simple extension of our model, based on differentiation of goods within broad categories. Assume that, for each good, there are N varieties. Each store sells $M < N$ randomly chosen varieties. Consumer preferences are lexicographic: each consumer buys only one variety. Varieties are symmetric: each is sold by the same proportion of stores, and consumed by the same proportion of customers. This means that, when choosing a store at random, a consumer finds a variety she will buy with the probability M/N and so the expected cost of a single search is cN/M.

This extension of our model implies that the more differentiated are goods within a market (as measured by N/M), the greater are the (expected) search costs and so the less frequent, and bigger, are price changes. Although product heterogeneity is difficult to measure, our intuition is that it is the largest in services, followed by manufactured goods, durable foodstuffs, perishable foodstuffs and energy products, with large variations within these categories. Also,

[25] Bils and Klenow (2004), Baumgartner et al (2005), Aucremanne and Dhyne (2004), Vilmunen and Laakkonen (2004), Baudry et al (2004), Lünnemann and Mathä (2005), Dias et al (2004) and Álvarez and Hernando (2005), respectively.
[26] This paper, Stahl (2004), Jonker et al (2004) and Veronese et al (2005), respectively.
[27] See Table 1 above as well as Table 3 in Dhyne et al (2005).

product heterogeneity is larger for manufactured than for raw products. Hence our model potentially explains the observed differences between broad product groups. Of course, a proper test would require a way to measure, as well as new data on, the product heterogeneity across markets.

An alternative explanation of these differences is suggested by the observation in Bills and Klenow (2004) that prices of processed goods are changed less often than prices of raw goods. Prices of inputs are much more variable than wages, which tend to be quite sticky. Hence, the larger is the share of labor in the costs of production (which is correlated with how processed the good is), the lower is the variability of production costs. For example, cost shocks are more important for raw goods (energy and perishable foodstuffs) than for manufactured goods and services.

To check this alternative explanation we divided goods in the Polish data set into three categories according to the degree of processing (the division is in the Appendix B). We then added the processed dummy to regression (12). We obtained:

$$\begin{aligned} Prob_{it} = & \underset{(12.22)}{95.51} + \underset{(13.80)}{12.55} S^h + \underset{(8.28)}{7.85} S^m + \underset{(23.91)}{1.87} INF_{it} - \underset{(-5.98)}{3.82} df - \underset{(-4.27)}{6.37} mg - \underset{(-7.42)}{15.93} sv \\ & - \underset{(-4.49)}{7.24} PR^h - \underset{(-2.67)}{1.62} PR^m + \vec{\gamma}\vec{T} + \varepsilon_{it} \end{aligned} \tag{12a}$$

where PR^h and PR^m are the processed dummy variables, equal 1 for most and for medium processed goods, respectively.[28]

The addition of the processed dummy contributes a little towards explaining the differences in the probability of price changes across broad good categories. While the qualitative results in regression (12a) are the same as in regression (12), the coefficient on the manufactured good dummy falls by almost a half and the coefficient on the services dummy falls by almost 30%. The remaining coefficients change little, showing that search consideration matters when we control for the degree of processing. Of course these results are only indicative, as a better measure of variability of prices of inputs is necessary for a more thorough investigation.

[28] The differences between the coefficients on the S^h and S^m, as well as on the PR^h and PR^m, dummies are significant at the 5% level; also, the coefficient on the manufactured goods dummy is significantly greater than on the services dummy.

6. Conclusions.

In this paper we establish a new empirical finding: search for the best price affects the frequency of price changes at the level of individual goods. We show that the relationship between the propensity to search for the best price and adjustment frequency can be derived in a model in which firms face menu costs and heterogeneous customers search for the best price. These predictions are shown to hold in very different environments and for various measures of the propensity to search.

Our approach provides a cross-sectional test for the menu cost model. There are several advantages of looking at cross-sectional, rather than time-series, behaviour of prices. In the menu cost model, the optimal pricing policy depends on the expected rate of inflation. Our test avoids the difficulty of calculating the expected inflation rate in individual markets. It can be used when there is little variation in inflation rate over time, which makes it difficult to identify the time-series effects (as in, for example, Klenow and Kryvtsov, 2005). Finally, testing does not require long data series.

Further progress of this literature requires more empirical work using large, disaggregated data sets. The availability of such data has improved recently and provides an opportunity for such research. The Dominick data at Chicago GSB, the data sets used by Bils and Klenow (2004), Klenow and Kryvtsov (2005), the European data sets, scanner data as well as data from the Internet provide large, high quality data sets. However, the time series are short and the inflation rate is relatively stable, making it difficult to use the traditional test of the menu cost model. As our test does not require long data series or large variations in the inflation rate, it may be particularly suited for use with the new data sets.

We finish by posing a new question for empirical research on the determinants of nominal price rigidities at the micro level. We notice in the data striking, and remarkably consistent across countries, differences in the probability of price changes across broad good categories. The probability is the lowest for services, followed by manufactured goods, durable foodstuffs, perishable foodstuffs and energy products (for example gasoline).

One explanation of these differences is that they are caused by demand side differences, in particular by how the propensity to search varies with the heterogeneity of goods. The more differentiated are the goods within a market the greater are the (expected) costs of search for the best price and so our model implies that the less frequent (and bigger) are price changes. Services are the most heterogeneous, followed by manufactured goods, durable and perishable foodstuffs and energy products. Similarly, product heterogeneity is larger for processed than for raw products.

An alternative explanation is that the frequency of price changes is determined mostly by the behavior of prices of inputs. This explanation is suggested by the observation in Bills and Klenow (2004) that prices of processed goods are changed less often than prices of raw goods. Prices of inputs are much more variable than wages, which tend to be quite sticky. Hence, the larger is the share of labor in the costs of production (which is correlated with how processed the good is), the lower is the variability of production costs. For example, cost shocks are more important for raw goods (energy and perishable foodstuffs) than for manufactured goods and services. More research is needed to discriminate between these two explanations.

The observed heterogeneity across markets imply it is overly simplistic to view the economy as characterized by a single frequency of price changes. A better approach would be to consider the division of markets into categories (one such division was already proposed by Okun, 1981). Such division is important to understand the transmission channel of monetary policy, in particular because the (limited) evidence on producer prices suggests that prices of investment goods change least frequently.[29] We expect that both the supply-side and the demand-side explanations are relevant, but the relative importance of these two in the economy as a whole is an open question, the answer to which should inform us how we should model the division of the economy into submarkets.

---

[29] Álvarez, Burriel and Hernando (2004) for Spain, Dias, Dias and Neves (2004) for Portugal, Sabbatini, Fabiani, Gattulli and Veronese (2004) for Italy and Stahl (2004) for Germany. The evidence is summarized in Konieczny (2004).

Appendix A.

Proof of Lemma.

The solution to the firm's problem is characterized by equations (11). For a given value of $E[P]$, it is sufficient to show that (11b) has a unique solution. It can be simplified to:

$$(A+MC)^2(\sigma\ln\sigma-\frac{\sigma^2-1}{2})+\frac{gm}{b}(1+\sigma)^2=0 \tag{A1}$$

Note that, at $\sigma=1$, the left hand side of (A1) is positive. Its derivative with respect to σ has the same sign as:

$$\left(A+MC\right)^2\left(\frac{\ln\sigma+1-\sigma}{1+\sigma}\right)+2\frac{gm}{b}$$

At σ=1 the first term equals zero and so the derivative is positive. For σ>1 the expression with σ is negative and strictly decreasing, so the derivative changes sign from positive to negative at most once. This means the left hand side of (A1) is either monotonic or strictly quasiconcave. As $\lim_{\sigma\to\infty}[(\sigma\ln\sigma-(\sigma^2-1)/2)]/(1+\sigma)^2=-1/2$, the LHS of (A1) becomes negative if $\left(C/k+E[P]+MC\right)^2-2gm/b>0$. A sufficient condition is that $MC>\sqrt{2gm/b}-C/k$. So, indeed, (11b) has a unique solution.

For the second part of the lemma we use the implicit function theorem. Rewrite (11b) as: $F(\sigma,k)=0$. By the previous discussion, at the point where (11b) holds we have $\frac{\partial F(\sigma,k)}{\partial\sigma}<0$.

Taking the derivative of $F(\sigma,k)$ with respect to k and using that (11b) holds we obtain:

$$\frac{\partial F(\sigma,k)}{\partial k}=\frac{2gmC(\sigma+1)^2}{vk^3}\left(\frac{2C/k}{A+MC}-1\right) \tag{A2}$$

The term in brackets is positive by assumption. So $\frac{d\sigma}{dk}>0$. The proofs for the effect of v, C and MC on σ are analogous. QED.

Proof of Proposition 1.

Equation (A1) can be rewritten as:

$$E[P]=H(\sigma)\sqrt{gm/b}-\left(C/k+MC\right) \tag{A3}$$

where:

$$H(\sigma)=\frac{\sigma+1}{\sqrt{\frac{\sigma^2-1}{2}-\sigma\ln\sigma}} \tag{A4}$$

Define $h(\sigma)\equiv(\sigma-1)/[(1+\sigma)\ln\sigma+1-\sigma]$. $h(\sigma)$ is positive, strictly decreasing and $\lim_{\sigma\to1}h(\sigma)=1$, $\lim_{\sigma\to\infty}h(\sigma)=0$. From (11c) $E[P]=h(\sigma)(C/k+MC)$. Combining this with (A3) we obtain that the equilibrium is a solution to:

$$\frac{h(\sigma)+1}{H(\sigma)}=\frac{\sqrt{gm/b}}{C/k+MC}=\frac{\sqrt{Cgm/v}}{C+kMC} \tag{A5}$$

The LHS of (A5) is a function of σ which is strictly quasiconcave and $\lim_{\sigma\to 1}[h(\sigma)+1]/H(\sigma)=0$; $\lim_{\sigma\to\infty}[h(\sigma)+1]/H(\sigma)=\sqrt{2}/2$. So, if $\dfrac{\sqrt{gm/b}}{C/k+MC}<\dfrac{\sqrt{2}}{2}$, there is a solution and this solution is unique. That condition is equivalent to $MC>\sqrt{2gm/b}-C/k$. QED

Proof of Proposition 2.

(a) Notice that the solution to (A5) is on the upward sloping part of $G(\sigma)$. This implies that the solution increases as the RHS of (A5) rises. So the solution is increasing in *gm* and decreasing in *MC* and *b*; using $b=vk^2/C$ it is easy to see that the solution is decreasing in *v* and *k*. Finally, the derivative of the RHS of (A5) with respect to *C* has the same sign as (*MC*-*C/k*), which is positive by assumption and hence the equilibrium value of σ is increasing in *C*.

(b) The time between price changes is $T=\dfrac{\ln(S/s)}{g}=\dfrac{\ln\sigma}{g}$ and the frequency is $fr=\dfrac{1}{T}=\dfrac{g}{\ln\sigma}$.

As σ is increasing in *m* and *C* (if *MC*>*C/k*) and decreasing in *MC, v* and *k,* the frequency is decreasing in *m* and *C* and increasing in *MC, v* and *k*.

For the last claim note that *g* increases both the numerator and denominator of *fr*. The optimal price bounds *S,s* get further apart but, at the same time, the real price is eroded at a higher rate. To prove that the first effect dominates, solve (A5) for *g* and substitute it in the equation for the frequency:

$$fr=\frac{b(C/k+MC)^2}{m}\frac{(h(\sigma)+1)^2}{H^2(\sigma)\ln(\sigma)} \tag{A6}$$

Equation (A6) expresses frequency as a function of σ alone, and we know that σ increases in *g*. It turns out that, as long as $MC>/\sqrt{2gm/b}-C/k$, this function is increasing in σ over the interval in which (A5) has a solution, so we are in the range where *fr* is increasing in *g*.

The proof of part (c) is straightforward. The *CV* is invariant to changes in units. Hence dividing all prices by *S* does not change this measure of price dispersion. After such rescaling (for any parameter values) the distribution of prices is uniquely determined by s/*S* = 1/σ. The smaller is 1/σ the less frequent are price changes and the larger is the *CV* (as a smaller 1/σ implies both a larger standard deviation and a smaller average of the re-scaled prices). QED

Appendix B.

Good			**Search categories**				Raw/ Proc.	**Probability of price:**			**Size of price**		
Name	#	Type	E	F	A	S		change	incr.	decr.	change	incr.	decr.
Back bacon "Sopocka", 1 kg	1	p	h	h	m	h	m	0.40	0.32	0.08	0.06	0.05	0.04
Sausage "Krakowska sucha", 1kg	2	p	h	h	m	h	m	0.38	0.31	0.06	0.07	0.06	0.05
Sausage "Mysliwska sucha", 1kg	3	p	h	h	m	h	m	0.38	0.31	0.06	0.08	0.06	0.05
Sausage "Krakowska parzona", 1kg	4	p	h	h	m	h	m	0.39	0.33	0.06	0.08	0.06	0.05
Sausage "Zwyczajna", 1kg	5	p	h	h	m	h	m	0.43	0.34	0.09	0.08	0.06	0.05
Pork wieners, 1kg	6	p	h	h	m	h	m	0.41	0.32	0.09	0.09	0.06	0.05
Sausage "Torunska", 1kg	7	p	h	h	m	h	m	0.42	0.34	0.08	0.08	0.05	0.05
Sausage "Zywiecka", 1kg	8	p	h	h	m	h	m	0.38	0.32	0.06	0.07	0.05	0.04
Eggs, each	9	p	h	h	m	h	l	0.71	0.42	0.28	0.16	0.13	0.10
Carp, live, 1kg	10	p	l	l	l	m	l	0.36	0.26	0.10	0.12	0.11	0.07
Herring, salted, 1kg	11	p	l	m	m	m	l	0.28	0.23	0.05	0.11	0.08	0.07
Sprats, smoked, 1kg	12	p	l	m	m	m	l	0.28	0.23	0.05	0.09	0.08	0.08
Cheese "Gouda", 1kg	13	p	m	h	l	h	m	0.46	0.35	0.11	0.10	0.06	0.05
Cheese "Edamski", 1kg	14	p	m	h	l	h	m	0.46	0.36	0.11	0.09	0.06	0.05
Butter, 82.5% fat, 250g	15	p	h	h	l	h	l	0.50	0.35	0.15	0.11	0.06	0.05
Margarine "Palma", 250g	16	p	h	h	l	h	m	0.40	0.34	0.06	0.09	0.07	0.06
Veggie butter, 250g tub	17	p	h	h	l	h	m	0.43	0.36	0.07	0.08	0.07	0.06
Rye bread, 1kg	18	p	h	h	l	h	m	0.31	0.28	0.02	0.15	0.10	0.10
Bread "Baltonowski", 1kg	19	p	h	h	l	h	m	0.33	0.30	0.03	0.13	0.09	0.08
Bread "Wiejski", 1kg	20	p	h	h	l	h	m	0.33	0.29	0.03	0.12	0.10	0.10
Powdered baby formula, 500g	21	d	h	m	m	h	m	0.40	0.34	0.06	0.10	0.07	0.05
Flour "Tortowa", 1kg	22	d	m	m	l	h	l	0.35	0.29	0.06	0.11	0.08	0.05
Flour "Krupczatka", 1kg	23	d	m	m	l	h	l	0.29	0.25	0.04	0.12	0.09	0.05
Flour "Poznanska", 1kg	24	d	m	m	l	h	l	0.37	0.30	0.06	0.16	0.08	0.05
Pearl barley "Mazurska", 1kg	25	d	l	l	l	m	l	0.31	0.25	0.05	0.15	0.11	0.07
Sugar, 1kg	26	d	h	m	l	h	l	0.43	0.33	0.10	0.14	0.09	0.07
Plum butter, 460g jar	27	d	m	m	l	m	l	0.30	0.24	0.07	0.13	0.11	0.08
Jam, blackcurrant, 460g jar	28	d	m	m	l	m	l	0.33	0.25	0.08	0.12	0.11	0.08
Apple juice, 1 liter box	29	d	m	m	l	m	l	0.37	0.27	0.09	0.11	0.10	0.08
Pickled cucumbers, 900g	30	d	m	m	l	m	l	0.37	0.27	0.10	0.13	0.11	0.08
Candy "Krowka", 1kg	31	d	m	m	l	m	m	0.39	0.34	0.05	0.11	0.09	0.07
Cookies "Delicje szampanskie", 1kg	32	d	m	m	l	m	m	0.32	0.27	0.05	0.09	0.08	0.06
Cookies "Petit Beurre" type, 100g	33	d	m	m	l	m	m	0.32	0.27	0.05	0.14	0.11	0.10
Pretzel sticks, 100g	34	d	m	m	l	m	m	0.31	0.26	0.05	0.15	0.12	0.11
Halvah, 1kg	35	d	m	m	l	l	m	0.32	0.26	0.06	0.10	0.09	0.07

Good			Search categories				Raw/ Proc.	Probability of price:			Size of price		
Name	#	Type	E	F	A	S		change	incr.	decr.	change	incr.	decr.
Vinegar, 10%, 0.5l bottle	36	d	m	m	l	m	m	0.26	0.20	0.06	0.15	0.10	0.09
Citric acid, 10g bag	37	d	l	l	l	l	m	0.24	0.19	0.05	0.31	0.25	0.18
Tea "Madras", 100g	38	d	h	m	m	h	l	0.25	0.21	0.04	0.11	0.10	0.09
Vacuum cleaner, type 338,5	39	m	l	l	h	h	h	0.28	0.25	0.02	0.09	0.08	0.06
Kitchen mixer, type 175,5	40	m	l	l	h	h	h	0.26	0.24	0.02	0.11	0.09	0.05
Folding bicycle “Wigry-3"	41	m	l	l	h	h	h	0.27	0.22	0.06	0.09	0.08	0.06
Radio receiver "Ania"	42	m	l	l	h	h	h	0.19	0.17	0.02	0.13	0.11	0.10
Razor blade "Polsilver", each	43	m	l	m	l	l	h	0.17	0.14	0.02	0.22	0.20	0.14
Toothpaste "Pollena", 98g	44	m	m	m	l	m	h	0.29	0.25	0.04	0.25	0.12	0.11
Shaving cream	45	m	l	m	l	m	h	0.28	0.24	0.05	0.29	0.12	0.13
Sanitary pads "Donna", box of 20	46	m	m	m	m	h	h	0.27	0.21	0.05	0.16	0.10	0.06
Paint thinner, 0.5l	47	m	l	l	l	l	m	0.23	0.19	0.04	0.17	0.13	0.10
Radiator coolant “Borygo” or “Petrygo”	48	m	l	l	l	l	m	0.18	0.15	0.02	0.28	0.16	0.07
Mineral water in cafeteria, 0.33l bottle	49	s	m	m	l	l	h	0.14	0.11	0.03	0.27	0.26	0.15
Boiled egg in a cafeteria, each	50	s	m	m	l	l	h	0.43	0.27	0.16	0.20	0.16	0.11
Mineral water in a café, 0.33l bottle	51	s	m	m	l	l	h	0.16	0.13	0.02	0.32	0.25	0.17
Pastry "W-Z" in a café, each	52	s	m	m	l	l	h	0.23	0.19	0.04	0.16	0.16	0.10
Car-wash, of car: "FSO 1500"	53	s	m	m	m	m	h	0.12	0.12	0.01	0.27	0.23	0.15
Varnishing of hardwood floor, 1m^2	54	s	l	l	h	h	h	0.13	0.12	0.01	0.29	0.19	0.22
ECG test	55	s	l	l	m	l	h	0.08	0.07	0.00	0.35	0.29	0.18

Notes:

Good types:
p - perishable foodstuffs; d-durable foodstuffs, m - manufactured goods, s - services
Raw/Processed column: degree of processing
h - highest, m - medium, l - lowest
Search characteristics:
E - by importance in expenditure, F - by search frequency,
A - by amount spent on a single purchase, S - by overall propensity to search
Search categories within characteristics:
h - high, m - medium, l - low

Bibliography.

Álvarez, Luis J. and Ignacio Hernando (2005), Price Setting Behaviour in Spain. Stylised Facts Using Consumer Price Micro Data, European Central Bank Working Paper No. 538.

Álvarez, Luis J., Pablo Burriel and Ignacio Hernando (2005), Price Setting Behaviour in Spain: Evidence from Micro PPI Data, European Central Bank Working Paper No. 522.

Aucremanne, Luc and Emmanuel Dhyne (2004), How Frequently Do Prices Change? Evidence Based on the Micro Data Underlying the Belgian CPI, European Central Bank Working Paper No. 331.

Ball, Laurence and David Romer (1991), Sticky Prices as Coordination Failures, *American Economic Review*, 539-52.

Bauc, Jarosław, Marek Belka, Andrzej Czyżewski and Andrzej Wojtyna (1996), Inflacja w Polsce 1990-95 (Inflation in Poland 1990-95), Warsaw.

Baudry, L., Le Bihan, Hervé, Patrick Silvestre and S. Tarrieu (2004), Price Rigidity in France. Some Evidence from Consumer Price Micro-Data, European Central Bank Working Paper No. 384.

Baumgartner, Josef., Ernst Glatzer, Fabio Rumler and Alfred Stiglbauer (2005), How Frequently Do Consumer Prices Change in Austria? Evidence from Micro CPI Data, European Central Bank Working Paper No. 464.

Bils, Mark and Peter J. Klenow (2004), Some Evidence on the Importance of Sticky Prices, *Journal of Political Economy*, 947-85.

Bénabou, Roland (1988), Search, Price Setting and Inflation, *Review of Economic Studies*, 353-376.

Bénabou, Roland (1989), Optimal Search Dynamics and Speculation with a Storable Good, *Econometrica*, 41-81.

Bénabou, Roland (1992), Inflation and Efficiency in Search Markets, *The Review of Economic Studies*, 299-329.

Buckle, Robert A. and John A. Carlson (2000), Menu Costs, Firm Size and Price Rigidity *Economics Letters,* 59–63.

Calvo, G.A. (1983), Staggered Prices in a Utility-Maximizing Framework, *Journal of Monetary Economics*, 383-98.

Caplin, Andrew S. and Daniel F. Spulber (1987), Menu Costs and the Neutrality of Money, *Quarterly Journal of Economics*, 703-26.

Carlson, John A. and Preston McAfee (1983), Discrete Equilibrium Price Dispersion, *Journal of Political Economy*, 91, 480-93.

Cecchetti, Stephen G. (1986), The Frequency of Price Adjustment: A Study of the Newsstand Prices of Magazines, *Journal of Econometrics*, 255-74.

Chevalier, Judith, Anil Kashyap and Peter Rossi (2003), Why Don't Prices Rise During Periods of Peak Demand? Evidence from Scanner Data, *American Economic Review*, 15- 37.

Diamond, Peter (1993), Search, Sticky Prices and Inflation, *Review of Economic Studies,* 53-68.

Dias, Mónica, Daniel Dias and Pedro D. Neves (2004), Stylized Features of Price Setting Behaviour in Portugal: 1992-2001, ECB Working Paper No. 332.

Dhyne, Emmanuel, Luis J. Álvarez, Hervé Le Bihan, Giovanni Veronese, Daniel Dias, Johannes Hoffmann, Nicole Jonker, Patrick Lünnemann, Fabio Rumler and Jouko Vilmunen (2005), Price Setting in the Euro Area: Some Stylized Facts from Individual Consumer Price Data, European Central Bank, mimeo.

EBRD (1999), Transition Report. London.

Fisher, Timothy C.G. and Jerzy D. Konieczny (2004), Inflation and Price Adjustment: A Study of Canadian Newspaper Prices, *Journal of Money, Credit and Banking*, forthcoming.

Golosov, Mikhail and Robert E. Lucas Jr. (2003), Menu Costs and Phillips Curves, NBER Working Paper 10187.

Jonker, N., C. Folkertsma and H. Blijenberg (2004), An Empirical Analysis of Price Setting Behaviour in the Netherlands in the Period 1998-2003 Using Micro Data, ECB Working Paper No. 413.

Kackmeister, Alan (2001), Has Retail Price Behavior Changed since 1889? Evidence from Microdata, mimeo, University of California, Berkeley.

Kashyap, Anil K. (1995), Sticky Prices: New Evidence from Retail Catalogs, *Quarterly Journal of Economics*, 245-274.

Klenow, Peter J. and Oleksiy Kryvtsov (2005), State-Dependent or Time-Dependent Pricing: Does It Matter for Recent U.S. Inflation? Stanford University, mimeo.

Konieczny, Jerzy D. (2004), Discussion of Micro Producer Price Data, European Central Bank Conference on Inflation Persistence in the Euro Area, Frankfurt am Main, December. http://www.ecb.int/events/pdf/conferences/inflationpersistence/KoniecznyDiscussion.pdf

Konieczny, Jerzy D. and Andrzej Skrzypacz (2000), The Behavior of Price Dispersion in a Natural Experiment, Research Paper A741, Graduate School of Business, Stanford University.

Konieczny, Jerzy D. and Andrzej Skrzypacz (2005), Inflation and Price Setting: Evidence from a Natural Experiment, *Journal of Monetary Economics*, 621-32.

Lach, Saul and Daniel Tsiddon (1992), The Behavior of Prices and Inflation: An Empirical Analysis of Disaggregated Price Data, *Journal of Political Economy*, 349-89.

Levy, Daniel, Mark Bergen, Shantanu Dutta and Robert Venable (1997), The Magnitude of Menu Costs: Direct Evidence from Large U.S. Supermarket Chains, *Quarterly Journal of Economics,* 792-825.

Levy, Daniel, Georg Müller, Shantanu Dutta and Mark Bergen (2005), Holiday Price Rigidity and Cost of Price Adjustment, Bar-Ilan University, mimeo

Lucas, Robert.E.Jr. (1973), Some international evidence on output-unemployment tradeoff, *American Economic Review* 63, 326-34.

Lünnemann, P. and T. Mathä (2005), Consumer Price Behaviour in Luxembourg: Evidence From Micro CPI data, Banque Centrale du Luxembourg, European Central Bank Working Paper No.541.

MacMinn, Richard D. (1980), Search and Market Equilibrium, *Journal of Political Economy*, 308-27.

Mankiw, N. Gregory and Ricardo Reis (2002), Sticky Information Versus Sticky Prices: A Proposal to Replace the New Keynesian Phillips Curve, *Quarterly Journal of Economics,* 1295-1328.

Okun, Arthur (1981), *Prices and Quantities,* Brookings Institution, Washington, D.C.

Owen, Ann and David Trzepacz (2002), Menu Costs, Firm Strategy and Price Rigidity, *Economic Letters,* 345-9.

Rotemberg, Julio J. (2002), Customer Anger at Price Increases, Time Variation in the Frequency of Price Changes and Monetary Policy, NBER Working Paper 9320.

Sabbatini, Roberto, Silvia Fabiani, Angela Gattulli and Giovanni Veronese (2004), Producer Price Behaviour in Italy: Evidence from Micro PPI Data, Bank of Italy, mimeo.

Sachs Jeffrey D. (1993), Poland's Jump to the Market Economy, MIT Press.

Sheshinski, Eytan and Yoram Weiss (1977), Inflation and Costs of Price Adjustment, Review of Economic Studies, 287-303.

Sheshinski, Eytan, Tishler, A. and Yoram Weiss (1981), Inflation, Costs of Price Adjustment and Real Price Amplitude: An Empirical Study, in Development in an Inflationary World, M.J. Flanders and A. Razin, eds., Academic Press.

Stahl, Harald (2004), Price rigidity in German manufacturing, Deutsche Bundesbank, mimeo.

Stigler, George J. (1961), The Economics of Information, *Journal of Political Economy*, 213-25.

Taylor, John (1980), Aggregate Dynamics and Staggered Contracts, *Journal of Political Economy*, 1-23

Veronese, G, S. Fabiani, A. Gattulli. and R. Sabbatini (2005), Consumer Price Behaviour In Italy: Evidence From Micro CPI Data, ECB Working Paper No 449.

Vilmunen, Jouko and Halinä Laakkonen (2004), How Often Do Price Change in Finland? Evidence from Micro CPI Data", Suomen Pankki, mimeo.