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

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First Draft: February 2001
This Draft: February 21, 2006.

JEL E31, E52. Keywords: Nominal rigidity, search, price adjustment

Abstract

We establish a new empirical finding that the intensity of search for the best price affects the frequency of nominal price changes. This relationship holds in very different economies and for various proxies for search intensity. 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 that pricing policies differ endogenously 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.

*We would like to thank participants of the Conference on Price Stability at the Federal Reserve Bank of Chicago, and in particular the discussant, John Leahy, for very helpful comments. We also thank Mario Bonomo, Mathias Dewatripoint, Jordi Galí, Paul Romer and Julio Rotemberg for insightful comments and suggestions and Andrei Chernyak and Michelle Lin for excellent research assistance. The first author would like to thank the European Center of Advanced Research in Economics and Statistics (ECARES), Université Libre, Brussels, Belgium, where part of this work was done, for its hospitality and acknowledges financial support from Social Sciences and Humanities Research Council of Canada, grant # 410-96-0245. An earlier draft of this paper was titled "A New Test of the Menu Cost Model".

1. Introduction.

Rigidity of nominal prices is a fact of life. With the exception of auction markets (for example, financial markets), prices change infrequently. The average frequency of price changes is about four times a year in the US (Bils and Klenow, 2004) and less than twice a year in Europe (Dhyne et al, 2005). The frequency differs greatly over individual goods and over broad good categories. The properties of these discontinuous price strategies of individual price setters are not only of intrinsic interest but also have crucial implications for the consequences of monetary policies. In the vast literature based on the Taylor (1980) and Calvo (1983) frameworks[1], infrequent individual price changes (which are often treated as exogenous) are the main microfoundation of aggregate nominal rigidity and the reason monetary policy has real effects.

It is difficult to distinguish between various theories of nominal rigidity using macro models. Our goal is to provide a better understanding of the nominal rigidity by looking at individual pricing decisions. . We establish a new empirical finding and analyze an equilibrium model that explains it. We find 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. In our model, which is related to Bénabou (1992), customers are heterogeneous and search for the best price.[2] Competing firms face costs to adjust nominal prices. We show that equilibrium pricing strategies are affected by market characteristics related to the intensity of 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 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 divided in 350 groups; for each group we have the average monthly probability of price changes in a given month. We proxy search intensity with the group's weight in CPI expenditure. The second 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 search intensity depends on the value of purchases, the good’s importance in household expenditure (conditional

[1] Yun (1996), Gali and Gertler (1999), Chari, Kehoe and McGrattan (2000), Sbordone (2002), Christiano, Eichenbaum, and Evans (2005) are some examples of this large and expanding literature.

[2] The main difference between our model and Bénabou (1992) is that we assume that each consumer buys a fixed amount of the good, while in Bénabou (1992) each customer has a downward-sloping demand. This simplification allows us to establish analytically the uniqueness of equilibrium and derive comparative statics results.

on the household buying the good) and the frequency of purchases. Despite the very different environments (for example, the average CPI inflation is below 3% in the US and about 30% in Poland), we find strong support for the predictions of the model in both data sets.

We calibrate the model using direct information on menu costs from Levy et. al. (1997), to fit the 1992-96 average frequency of price changes in the Polish data. The model is able to fit the data quantitatively for high-inflation economies. For low-inflation countries it fits the data qualitatively but does a poor job quantitatively. This is broadly consistent with Golosov and Lucas (2003), who stress the importance of real shocks in low-inflation environment.

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: consumer resistance leads to smaller and more frequent price changes and it is stronger in markets we identify as having more intensive customer search. If so, more research on the effects of aggregate variables is needed to differentiate the two models.

The effects of nominal shocks and welfare consequences of alternative monetary policies are directly related to the frequency of individual price adjustment and the causes of nominal rigidity. Our results point out that the underlying assumptions in the Taylor-Calvo frameworks may be too restrictive. Aggregate models based on the Taylor-Calvo framework use the average frequency of price changes obtained from the data as an exogenous parameter underlying the behaviour of homogenous price setters. Firms are usually ex-ante identical and heterogeneity is ignored. But, as argued by Carvalho (2005), dynamic properties of aggregate models are affected by ex-ante heterogeneity.[3]

Data show large, and remarkably consistent across countries, differences in the frequency of price changes across broad good categories. Bils and Klenow (2004) report that price changes are more frequent for raw than for processed goods. In both the US and Polish data we find that the price changes are most frequent for unprocessed food, followed by processed food, manufactured products and services. The same differences hold in recently obtained,

[3] Similarly, Caballero and Engle (1991, 1993) find that aggregate behaviour of economies with state-contingent pricing is affected by firm heterogeneity.

extensive data sets for several European countries.[4] Notably, differences across goods greatly exceed differences across countries. 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. Our search-based explanation of the cross-sectional heterogeneity is consistent with these empirical observations. Intensity of 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 effect of given price differences on the search for the best price and so our model implies less frequent price adjustments.

Finally, our results show that pricing policies differ endogenously in the cross-section. This, together with the accounting for the substantial cross-sectional heterogeneity, may be an important feature missing in many macroeconomic models based on nominal rigidities with exogenous, homogeneous frequency of price changes.

There are several empirical studies of the cross-sectional variation. Carlton (1986), Caucutt, Gosh and Kelton (1999) and Bils and Klenow (2004) study the effects of market concentration. The hypothesis is that demand is more elastic in more competitive markets and hence, plausibly, firms change nominal prices more frequently. Empirical evidence is consistent with this hypothesis; however, Bils and Klenow (2004) find that it is not robust. Caucutt, Gosh and Kelton (1999) find that prices of durable goods change less often. Dhyne et al (2005) regress the probability of price changes on several variables and find that it is lower for firms which tend to charge “attractive” prices (prices that are round or end with a nine), for firms with regulated prices and in smaller shops than in supermarkets. Finally, Levy et al (1997), Owen and Trzepacz (2002) and Levy et al (2005) find that firms with higher price adjustment costs change prices less often. Except for the last relationship, which follows from Sheshinski and Weiss (1977) theoretical explanations of these relationships remain to be developed.

We begin by presenting the model in the next section. Empirical evidence is in Section 3. In Section 4 we provide a simple extension of the model which can account for the large

[4] The data sets consist of CPI source data and cover between 65% and 100% of the CPI: Álvarez and Hernando (2004) for Spain, Aucremanne and Dhyne (2004) for Belgium, Baudry et al (2004) for France, Baugartner et al (2005) for Austria, Dias et al (2004) for Portugal and Vilmunen and Laakonen (2004) for Finland. In addition, Hoffmann and KurzKim (2005), Jonker et al (2004), Lünnemann and Mathä (2005) and Veronese et al (2005) analyze smaller data sets for Germany, Holland, Luxemburg and Italy, respectlively. In all these studies the ranking of frequencies across broad good categories is the same as in the US and in the Polish data; see Dhyne et al (2005), table 3.

observed differences in the average frequency of price changes between groups of goods. In Section 5 we discuss alternative explanations of the patterns in the data. Last section concludes.

2. Menu Costs, Search Intensity 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. In a seminal paper, Stigler (1961) argued that the amount of search depends on (a) the fraction of the buyer's expenditure on the commodity, (b) the fraction of repetitive (experienced) buyers in the market (provided the correlation between successive prices in a given store is positive), (c) the fraction of repetitive sellers and (d) the geographical size of the market. The importance of the first three factors is mostly due to the effect of repeated purchases on the ratio of search costs to expenditure on the good. If the good is purchased rarely (relative to the frequency of price changes) or if sellers stay in the market for a short time, price information obtained in the previous search is of no use to the buyer and each purchase requires bearing the full search cost. On the other hand, if purchases are repetitive and buying from the same store again is possible then, once a store with low prices has been identified, the buyer may continue to patronize the store and save on search costs.[5] The geographic size of the market (more precisely, store density) affects the cost of a single search. The expenditure on a good matters either in case of frequent, small purchases (for example bread) or rare but high value purchases (for example a TV set).

The exact implementation of all these considerations in an equilibrium search model with costly price adjustment is beyond the scope of this paper. Instead, we proxy these factors with several variables which affect the intensity of search in a clear manner.

The model 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) model of costly price adjustment.

We consider a market for a single good produced by a continuum of long-lived firms and purchased by a continuum of short-lived consumers. We first characterize the equilibrium with a fixed number of firms and then allow for free entry and exit to determine it endogenously. In the model without entry we normalize the measure of firms to 1. All variables are expressed in real

[5] Another way of saving search cost, mentioned by Stigler (1961, p. 219) is pooling of information when buyers compare prices. Search cost may also be reduced by checking out several prices during one shopping trip, for example prices of several kinds of groceries during one visit to a store.

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 is *v* so, in the absence of entry, *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 the 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. 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*).[6]

2.1. The Consumer's Problem.

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 (see, for example, Carlson and McAfee (1983) or Tommasi (1994)), 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:

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

[6] Implicitly we make the standard assumption that the search is instantaneous and consumption cannot be postponed. See Bénabou (1992) for more discussion.

so firms with lower prices face higher demand. Denote by $c^*(P)$ the inverse of $P^*(c)$. The expected quantity sold by a firm that charges price P is (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 obtain demand:

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

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

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

The three market-specific variables: the number of units bought by each consumer, k, the size of search costs (measured by their range, $[0,C]$) and the number of consumers, v, affect search intensity for the best price as perceived by the firm. C and k impact search intensity of each customer, by changing the search cost per unit purchased. The effect of v is less direct. Changes in v affect search intensity as perceived by the firm: as is the case with changes in C and in k, they affect the responsiveness of demand to the difference between a firm's price and the average price in the market.

2.2. The Firm's Problem.

Given that there is a mass of firms, one firm's decisions do not affect the price distribution or prices of the remaining firms, so we can treat each firm as monopolistically competitive. Sheshinski and Weiss (1977) showed that, if 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.

Clearly, the optimal pricing rules depend on demand, which in turns depends on E[P]. If all firms follow the same (s,S) policy, the distribution of prices depends on whether price changes are staggered or synchronized. As shown in Caplin and Spulber (1987) and Bénabou (1988), the only time-invariant distribution of prices is log-uniform:

Lemma (Bénabou 1988):

If a continuum of price setters follow identical (s, S) rules with respect to some index inflating at a constant rate g, the only cross-sectional distribution of their real prices which is invariant over time is log-uniform over $(s, S]$. Under this invariant distribution, the average price in the market grows at the rate g.

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. This assumption generates stationary demands and validates our analysis of the firm's problem. As Bénabou (1988) argues there are three reasons why this assumption is justified: 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.

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:

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

This allows us to define equilibrium in the market:

A (stationary) equilibrium is a pair (*s, S*) specifying each firm's pricing rule which is optimal given the demand it faces; the (stationary) log-uniform distribution of prices given by the policy rule; and the search strategy of each consumer that is optimal given the distribution of prices.

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 price is consistent with firms' strategies, (8). Expanding equations (6) we obtain that the equilibrium is described by the following system of equations:

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

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

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

Equation (9a) can be rewritten as:

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

As we are interested mainly in how the frequency 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:

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

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

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 $E\left[P\right]\geq 0$, if there exist pricing strategies that yield nonnegative profits and $MC > \sqrt{2gm/b} - \frac{C}{k}$, 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. 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: $\frac{C}{k} \geq \frac{1-\sigma(1-\ln\sigma)}{\ln\sigma} MC$, where σ is the equilibrium value found by solving (11b) and (11c). For the rest of this section we assume that this condition is met.

Proposition 1:

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

The final step is to show the relationship between model parameters, the equilibrium σ and the frequency of price changes.

Proposition 2:

(a) Assume $MC > \sqrt{2gm/b} - \frac{C}{k}$. The equilibrium size of price changes, σ, is increasing in *g* and *m* and decreasing in *MC, v* and *k*. Furthermore, if *MC>C/k,* the equilibrium σ is also increasing in *C*.

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

(c) Define the coefficient of variation as: $CV = STD[P]/E[P] = \sqrt{E[(P-EP)^2]}/E[P]$. *CV* is increasing in the frequency of price changes.

2.4. Entry and Exit.

When there is free entry and exit, the number of firms (measured in the model by v) will adjust until the average profits per unit of time are zero: $\overline{\pi} = 0$. If the fixed cost of production and the cost of entry are zero, the solution to the model must meet s=MC (see equation (6)). This implies, using (11a) and (11c), that:

$$\frac{C}{k} = \frac{1-\sigma(1-\ln\sigma)}{\ln\sigma}MC \tag{12}$$

By Proposition 1, there exists a unique value of σ as a function of the parameters of the model, in particular as a function of v. From Appendix equation (A5) which determines the equilibrium, after some straightforward algebra we obtain that the relationship between g, m and v in equilibrium is:

$$\left[\left(h(\sigma)+1\right)/H(\sigma)\right]\left[(C/k+MC)^2/(Ck^2)\right] = mg/v \tag{13}$$

where the functions $h(\sigma)$ and $H(\sigma)$ are defined in the Appendix A. By equation (12), in a free-entry equilibrium the left side of (13) is independent of the parameters on the right hand side. Therefore changes in the inflation rate and in price adjustment costs affect the number of firms in equilibrium. The higher is inflation and/or the higher is the price adjustment cost in a given market, the smaller is the number of firms in the industry. Inflation and/or adjustment costs affect the frequency of price changes but, unlike in the absence of entry, has no effect on price bounds and on the size of adjustment.

Equations (12) and (13), together with Proposition 2, imply the following comparative statics in free-entry equilibrium:

Proposition 2a:

If the equilibrium number of firms is determined by free entry, then the size of price changes, σ, is not affected by m and g, is increasing in C and decreasing in k and MC. The frequency of price changes is not affected by m, increasing in g, k and MC and decreasing in C.

When the fixed costs of production per unit of time, F, are positive, the free-entry condition becomes:

$$\pi(s) = F\ln(\sigma)/g \tag{14}$$

The explicit characterization of the equilibrium in this case is tedious. Numerical calculations suggest that comparative statics like in Proposition 2 continue to hold for parameter values close to the ones calibrated in Section 2.6, with the exception of *k*, which has a non-monotonic effect.

2.5. Summary and Intuition.

We now summarize the implications of the model. 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 (except in the free entry case). As the inflation rate increases, price changes become larger and, given the form of the profit function, more frequent. Firms with larger menu cost change prices less often and by larger amounts. In addition, the higher is the marginal cost, the more frequent and larger are price changes.

The main results concern the effects of the three search-related variables on the size and frequency of price changes. These effects are unambiguous. The model predicts that, in markets in which search is intensive (due to low search costs, large customer's purchases, or a large number of customers), price changes are small and frequent.

In Figure 1we show the effects of changes in the inflation rate, search cost, *C*, and in the number of customers on the equilibrium values of the price bounds and of the probability and size of price changes. The effect of inflation is shown in the top panels of Figure 1. With higher inflation the price bounds move further apart, and both the size and the probability of adjustment increase. The effects of changes in the search cost, are shown in the middle panels of Figure 1. Higher search costs reduce the competitiveness of the market and raise monopolistic markups, increasing both price bounds. The probability of price changes falls and the size of adjustment rises. Finally, in the bottom panels we show the effect of the changes in the number of customers. With more customers the price bounds move closer together, price changes become smaller and the probability of adjustment increases.[7]

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:

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

[7] The effects of changes in *k* are more complex. Higher *k* simultaneously reduces the cost of search per unit and shifts out the demand function; the net effect is to reduce both price bounds, raise the frequency and reduce the size of price changes.

For a quadratic profit function $\pi(P) = a+bP+cP^2$, when price is x percent away from the optimum, the profits are lower by $-x^2b^2/4c$. For our profit function $-b^2/4c$ is $v \cdot [C + k(E[P] + MC)]^2 / 4C$, which is increasing in v, k, MC, and is decreasing in C (assuming that C/k is less than $E[P] + MC$). Of course that alone allows only for a partial equilibrium argument about the relationship between the frequency of price changes and the parameters as some of the parameters of the profit function depend also on the strategies of other firms, via the average market price and, in the model with free entry, also via v.

Interestingly, the relationship between adjustment frequency and firm size is ambiguous. 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.

Finally, it is worth noting that the equilibrium with entry is consistent with empirical studies, which find a positive correlation between inflation and the frequency of price changes, but are mixed on the effect of inflation on the size of price adjustment (see Proposition 2a).

2.6. Calibration.

We now turn to calibrating the model to address three questions. We begin by asking whether our model can generate price behavior observed in the data with reasonable parameter values. We then use the initial calibrated values and check whether the response of frequency of price changes to inflation is similar in the model to that in data taken from a single source. Finally, we ask whether a single calibration can account for observations from different countries. The answers are yes, yes and no.

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, which equals 31% of the average cost of an item (\$1.70). 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.

We use this information to calibrate the model to the adjustment probability and the inflation rate in our proprietary, Polish data set (this data set allows us to answer the second question). The calibration is a somewhat arbitrary exercise as various crucial parameters may be different in these data; for example Polish stores are smaller, competition and search incentives may differ, the inflation rate is much higher than in Levy et al (1997) etc. Hence it should be understood as an illustration of the model.

To fit these numbers 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%, the menu cost is 31% of the average price in the market 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 percentage price change is 7.3%.[8] 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.

The next issue concerns the dynamic properties of our model. We ask whether it 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 year's inflation rate. The results of this exercise are in the top part of Table 2 and in the upper panel of Figure 2. It is clear that the model does a good job matching the relationship between inflation and frequency of price changes in the Polish data.

Finally, we compute the predicted frequency of price changes for data from other countries, using the calibrated parameter values and the relevant inflation rates. They are divided into two parts: high inflation (which includes studies using Argentinean[9], Hungarian, Israeli and Polish data) and low inflation (Austrian, Belgian, Canadian, Finnish, French, Portuguese, Spanish, US and Internet data). For each data set, Table 2 shows the yearly inflation rate, the

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[8] 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.

[9] The data in Tommasi (1993, in his Table 3) cover 45 weeks. We restricted the comparison to the last 35 weeks, when the inflation rate is relatively stable (between –6% and +10% per week; excluding the two extreme values it is between –2% and 5% per week). In the first 10 weeks the inflation rate is between –5% and +38% per week.

actual and the predicted frequencies of price change as well as the prediction error, measured as the percentage difference between the predicted and actual values. For convenience we illustrate the data in Figure 2, which shows the actual frequency of price changes for various studies as well as the predicted relationship between the inflation rate and the frequency.

Despite the heroic assumption that the different economies have similar underlying parameters, the model does a reasonable job for high-inflation environments. Except for two extreme values, the predicted value is within 20% of the actual value. Both extreme values are likely due to the coverage of products in the data. Sheshinski, Tishler and Weiss (1981) data are for regulated products. Ratfai's (2001) data are mostly for unprocessed meats and, as discussed below, price changes are more frequent for raw products and for perishable foodstuffs than for other goods.

On the other hand, the same calibration cannot account for the relationship in low-inflation environments. Prediction errors are between –95% (for Levy et al, 1997) and 780% (for the maximum duration reported by Cecchetti, 1986). With the exception of Kashyap's (1995) and Álvarez and Hernando (2004) data, they are all much larger, often by order of magnitude, than in high inflation countries. Nor can the errors be explained by good types. The frequencies of price changes in the seven comprehensive data sets (Bils and Klenow, 2004, Álvarez and Hernando, 2004, Aucremanne and Dhyne, 2004, Baugartner et al 2005, Beaudry et al, 2004, Dias, Dias and Neves, 2004 and Vilmunen and Laakonen, 2004, all of which cover over 65% of consumer expenditure in the respective country) are much higher than predicted by the model calibrated to the Polish, i.e. high inflation, data (see the lower panel of Figure 2).[10]

3. Empirical Results.

Empirical testing of our model requires data that, ideally, 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 proxies for consumer search. Our tests, therefore, are joint tests of whether menu costs and consumer search can explain the probability of price changes, and whether the proxy we use is an adequate measure of search behaviour. We

[10] The first four studies for low-inflation countires reported in Table 2 present a bit different picture, but we believe that this is caused by a small number of markets studied. Dahlby (1992) and Kashyap (1995) study markets in which there are obstacles to price changes (regulated car insurance and catalogue products, respectively). Fisher and Konieczny (2004) and Cecchetti (1986) analyze prices of newspapers and magazines; for reasons that are not immediately apparent these do not change often. Chakrabarti and Scholnick (2001) study prices on the internet, where the cost of price adjustment is lower than in traditional stores.

use two data sets. The first consists of BLS data in Bils and Klenow (2004). These data are comprehensive, covering almost 70% of US CPI. They contain the probabilities of price change for groups of goods, rather than for individual products. We use the share of expenditure as a proxy for the importance of the good in household expenditure and so for search intensity. As discussed below, there are significant problems with this proxy. Nonetheless, when we control for the differences between broad good categories, there is a strong positive association between the weight and the frequency of price changes that is both statistically, and economically, significant. The second data set is a proprietary Polish data set. While it is much less comprehensive than the BLS data, it consists of actual prices at the level of individual goods/stores. To measure search intensity we use the classification we created for an earlier paper (Konieczny and Skrzypacz, 2000) where we analyzed the effect of search intensity on the dispersion of price level across stores. That classification follows Stigler's (1961) suggestions more closely and look at various aspects of search: expenditure on a given good (conditional on the household buying it), the size of individual purchase and the frequency of purchases. It also allows us to test model implications on the relationship between search intensity and the size of price changes. As with the US data, despite problems with search proxies, we find strong support for the model.

Infrequent Observations Bias.

Testing the model involves the analysis of differences in the probability 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 BLS and the Polish data), these differences are biased downward. We call it the *infrequent observation bias.*

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 stronger 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.[11]

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

The first 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 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 ¼. The probability depends on good type. It is much lower for services (1/9), similar to the average for manufactured goods and for durable foodstuffs, and much higher for perishable foodstuffs (2/5).[12]

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 search intensity, of the goods included in a given ELI. In our model it corresponds to a high value of *k*.

There are a couple of problems with using CPI expenditure weights as a proxy for search intensity. First, 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 search intensity, and in particular with different weight in consumer expenditure. 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 search to be much more intensive for the first ELI, since hearing aids tend to be expensive items bought by few households and constitute a much larger portion of expenditure than microwaves for households that buy them. This problem applies, in general, to all goods and services and so would be present even if expenditure data for individual products were available.

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[11] As reported below, the infrequent observation bias is unlikely to affect the qualitative results.
[12] The classification of ELIs into types is available on request.

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 search to be more intensive 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 is subject to intensive search for the best price. Therefore we expect a positive correlation between the probability of price adjustment for goods included in a given ELI and its weight in CPI.

3.2. Regression Results for U.S. Data.

We first regress the probability of price changes on the expenditure weights. All regressions are by OLS; t-statistics are in the brackets.We obtain:

$$Prob_i = \underset{\substack{22.47 \\ (24.81)}}{\alpha_0} + \underset{\substack{4.12 \\ (1.89)}}{\alpha_1} \cdot w_t + \varepsilon_t \tag{15}$$

where $Prob_i$ is the average monthly probability of price change and w_i is the weight in expenditure of a given ELI, i=1…350. ε_t represents unobserved heterogeneity across goods. t-statistics are shown in brackets. The coefficient on ELI weight has the expected sign and is significant at the 10% level; we comment on the economic significance below.

Intensity of search for the best price may be affected by non-price differences between goods (like quality differences across different sellers) and hence good type may be correlated with the frequency of price changes. On the average, services are the most heterogeneous, followed by manufactured goods and durable foodstuffs; perishable foodstuffs are the most homogeneous.[13] Furthermore, these types are correlated with the weight in expenditure: the average weight is the highest for the service-type ELI and the lowest for the perishable foodstuffs. This may lead to a significant ommited variable bias in regression (15).

[13] Bils and Klenow (2004) find that the probability of price change is three times larger for raw goods than for processed goods (see their Table 2). Raw goods are, on the average, more homogeneous than processed goods and, for given price differences, are subject to more intensive search. We discuss this issue below.

To account for this heterogeneity we introduce good type dummies. The resulting regression is:

$$\underset{}{Prob_i} = \underset{(23.40)}{\underset{37.04}{\alpha_0}} + \underset{(5.83)}{\underset{10.62}{\alpha_1 \cdot w_t}} + \underset{(-5.36)}{\underset{-13.70}{\beta_1 \cdot d}} + \underset{(-8.25)}{\underset{-14.97}{\beta_2 \cdot m}} + \underset{(-14.00)}{\underset{-29.33}{\beta_3 \cdot s}} + \varepsilon_t \qquad (16)$$

where *d, m* and *s* are dummy variables for durable foodstuffs, manufactured goods and services, respectively (the omitted group is perishable foodstuffs). The results confirm the effect of non-price heterogeneity and the possible bias: with dummies for good type included, the effect of the weight in expenditure on the probability of price changes is more than twice as large and is statistically significant at the 1% level.

The estimated coefficient means that goods with a 0.1% higher weight in expenditure have about 1% higher frequency of price changes, which is clearly economically significant.[14] Also, it means that an increase in the weight in expenditure by 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 of the top 15 ELIs is 25%, of the bottom 15 ELIs it is 0.07% of expenditure. 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 (16) 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. [15]

Overall these results provide strong support for 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 intensity.

[14] Note that due to the infrequent observation bias, the estimated coefficient on ELI weight is biased towards zero.

[15] 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 exaplains the high standard error).

3.3. Polish Data and Further Empirical Evidence.

We now turn to the second source of empirical evidence – a proprietary data set on several goods and services in Poland. While it is much less comprehensive than the BLS data, it consists of actual prices at the level of individual goods/stores. These data were collected to analyse 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). For that analysis we created classifications of goods by search characteristics; we use the same classifications here. They follow Stigler's (1961) suggestions more closely and look at various aspects of search: expenditure on a given good, the size of individual purchase and the frequency of purchases. In addition we can test model predictions on the relationship between search and adjustment size. The CPI inflation rate is much higher in this sample, so price changes are more likely caused by monetary shocks than in the US data.

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. 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 storable), 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.

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 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 probability ranges from 0.38 in 1992 to 0.28 in 1996. Note that, to avoid the effect of the uneven number of observations on the averages, the numbers in Tables 1 and 2 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.

The average probability of price changes is about 1/3. It is not much higher than in the US data despite the fact that the inflation rate is an order of magnitude greater. As can be seen in Table 1, the ranking of good types by the probability of adjustment is identical to that in the US data: the probability is the highest for perishable foodstuffs, followed by durable foodstuffs, manufactured goods and services. The picture for the probability of price increases and decreases is similar. The probability of price changes for individual goods is in Appendix B; a comparison with other studies is in Table 2.

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.

Data Issues.

While the Polish data set is much less comprehensive than Bils and Klenow (2004) data, it has several advantages. The data are for individual items rather than for groups of goods. An important feature 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 Kackmeister (2002) reports that about 22% of all price changes are due to temporary sales; see also Chevalier, Kashyap and Rossi (2003). 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.

Polish Transition.

The data set is potentially unusual as Poland switched to a market economy in 1990. In two companion papers (Konieczny and Skrzypacz, 2000, 2005, hereafter KS1 and KS2, respectively) 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[16], 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. The results for the entire period are, virtually, identical.

Importance of Search for the Best Price.

While the data are from a relatively new market economy, we strongly believe they are well suited to analyze search. 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 government control.[17] Stores were allowed to set prices of goods they sell and shortages quickly disappeared.[18] 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.

Spurious Price Changes.

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

[16] 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.

[17] 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).

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

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 the empirical analysis. In most cases, the goods in our sample remained the basic staple and new substitutes were significantly more expensive. If, in the end, many price changes were caused by changes in the retail sector and those changes were more prevalent in markets with more intensive search, we may be detecting spurious correlations.

Infrequent Observation Bias.

As in the case of the US data, the cross-sectional differences in the probability of price changes are biased downwards. 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.

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, 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.

3.4. Proxies for Search Intensity in Polish Data.

We use the proxies for search intensity developed in KS1, where we analysed the impact of search on the differences in price levels across stores. For that analysis we divided the goods on the basis of three characteristics: (a) the weight of the given good in household expenditure, conditional on the household buying the good (b) the value of a single purchase, (c) the frequency of purchases and (d) a summary measure of total search intensity. The last characteristics tries to aggregate all factors relevant to search - the three above as well as omitted factors which do not fall neatly into any of the three other characteristics.[19] 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.

This approach to obtaining search proxies, which was dictated by the lack of non-price information in the data has, nonetheless, several adventages. It allows us to follow Stigler's (1961) suggestions more closely and look at various aspects of search. The characteristics do measure different aspects of search behaviour in the data: the coefficients of correlation 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 (a) 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).

We use this classification in KS1 to analyze the effect of search on the differences between price levels for the same good sold by different stores. Sorensen (2000) argues that the more active is search, the smaller are the differences between price levels across goods. This means that price differences should be, on the average, smaller for goods in the high category in each characteristic than in the 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 search intensity.

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,

[19] 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 search for the best price is intensive.

however, the average price levels differ across regions (voivodships). For the typical good, prices across regions vary more than prices across stores.[20]

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 use the same classifications here to analyze the relationship between search intensity and the size and frequency of price changes. The characteristics are related to the market-specific variables in our model as follows:

- A good with high amount spent in 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.
- 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.[21] 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.[22] For example, the average cost of search for inexpensive 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) or/and the amount spent on a single purchase is large (high k).
- Finally, while the total search intensity classification is not precisely defined and so cannot be directly attributed to any specific variables in our model, any of the market variables will do, as the effect of search variables on the size and frequency of price changes is unambiguous in our model.

3.5. Results for Polish data.

In Figure 3 we plot the computed probability of a price change, as well as 95% confidence intervals, for each category in the four characteristics (the picture for increases is virtually identical). 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

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

[21] 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.

[22] Our formal model assumes a single purchase by a short-lived household. A different way of treating frequent purchases is through a higher k, interpreted as a possibility of purchasing several units in a period of time which is short relative to the usual length of time between price adjustments.

number of price changes in 1-12/1992, divided by the number of two consecutive observations in 12/1991-12/1992.

We expect the probability to be the highest in categories marked as *h* (most active search) and the lowest in categories marked as *l* (least active search). It is clear from Figure 3 that the results are as predicted for the share in expenditure, frequency of purchases and search intensity characteristics. The only exception is the highest category in the "amount spent" category, where price changes are rare. Formal analysis below, however, shows that this is due to the omission of other variables.

To analyze the relationship more formally, we regress the probability of price changes on category dummies, own inflation rate, good type dummies and time dummies. Model 1 involves estimating the following regression: [23]

$$\begin{array}{l} Prob_{it} = \underset{\substack{95.70^{*} \\ (12.02)}}{\alpha_0} + \underset{\substack{11.06^{*+} \\ (13.85)}}{\alpha_1 \cdot I^h} + \underset{\substack{6.63^{*} \\ (7.84)}}{\alpha_2 \cdot I^m} + \underset{\substack{1.86^{*} \\ (23.81)}}{\beta \cdot INF} + \underset{\substack{-3.55^{*+} \\ (-5.70)}}{\delta_1 \cdot d} + \underset{\substack{-11.60^{*+} \\ (-16.01)}}{\delta_2 m} + \underset{\substack{-22.74^{*} \\ (-19.06)}}{\delta_3 s} + \vec{\gamma} \cdot \vec{T} + \varepsilon_{it} \end{array} \qquad (17)$$

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 3, which are 12-month averages. I^h and I^m are dummy variables, equal 1 for the high and medium search intensity categories, respectively, and zero otherwise; *INF* is the nationwide inflation rate for good *i* in month *t* (also expressed in percent); *d, m* and *s* are, as before, 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. A "*" following a coefficient estimate denotes it is significantly different from zero; a "+" following a coefficient estimate denotes that it is significantly higher than the coefficient on the next dummy, both at 5% level against a two-sided alternative. For example the coefficient on the high search intensity dummy, I^h, is significantly different from the coefficient on the medium search intensity dummy, I^m; both are significantly different from zero.

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. Time dummies are included to allow for calendar/seasonal effects not captured by the inflation rate. They are jointly significant.

[23] 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.

In estimating Model 1 we use search intensity separately from the other classifications as it summarizes all factors relevant to search. The results confirm predictions of the model. The coefficients on the high and medium search intensity dummies show the difference between adjustment probabilities relative to the omitted low category. The probability of price change is the highest in the high search intensity category and the lowest in the low category; all the differences 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 prices of perishable foodstuffs change most often, followed by prices of durable foodstuffs and manufactured products; prices of services change least frequently. All results are highly significant, both economically and statistically. The difference in the probability of price change between the high and low search intensity categories is a bit larger than the standard deviation of average frequencies for the different goods (see Table 1). It is also equivalent to about 6% higher average monthly inflation rate.

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

$$
\begin{aligned}
Prob_{it} = {} & \underset{\substack{71.75^{*} \\ (8.67)}}{\alpha_0} + \underset{\substack{2.91 \\ (1.88)}}{\alpha_1 \cdot E^h} + \underset{\substack{3.51^{*} \\ (2.73)}}{\alpha_2 \cdot E^m} + \underset{\substack{15.30^{*+} \\ (6.70)}}{\alpha_3 F^h} + \underset{\substack{3.45^{*} \\ (2.86)}}{\alpha_4 F^m} + \underset{\substack{5.70^{*+} \\ (4.98)}}{\alpha_5 A^h} + \underset{\substack{2.93^{*} \\ (4.35)}}{\alpha_6 A^m} + \\
& + \underset{\substack{1.85^{*} \\ (23.96)}}{\beta \cdot INF} + \underset{\substack{4.70^{*} \\ (3.32)}}{\delta_1 \cdot d} + \underset{\substack{-2.35^{+} \\ (-1.89)}}{\delta_2 m} + \underset{\substack{-17.09^{*+} \\ (-10.51)}}{\delta_3 s} + \vec{\gamma} \cdot \vec{T} + \varepsilon_{it}
\end{aligned}
\tag{18}
$$

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 high category in the classification by share in expenditure. Note that, unlike suggested by Figure 3 (in which good category is the only explanatory variable) the probability of price change in the "high expenditure on a single purchase" category is, as predicted by the model, higher than in the medium category.

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 smallest for perishable foodstuffs and largest for services.[24]

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:

$$Prob_{it} = \underset{\substack{103.17^{*} \\ (11.60)}}{\beta_0} + \underset{\substack{-0.75^{*} \\ (-20.61)}}{\beta_1} CV_{it} + \beta\vec{T} + \varepsilon_{it} \tag{19}$$

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, results obtained with the Polish data provide strong evidence for the joint hypothesis that, as predicted by the menu cost model with consumer search, the higher is search intensity the more frequent and smaller are price changes and that our classification adequately captures search incentives.

4. Potential Explantion of 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 seven comprehensive data sets (for U.S., Austria, Belgium, Finland, France, Portugal and Spain) as well as in the five smaller sets (for Poland, Germany, Holland, Italy and Luxemburg) the probability of price change is always the highest for perishable foodstuffs, followed by durable foodstuffs, manufactured goods and services. 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) – see Dhyne (2005), table 3. Furthermore, Bils and Klenow find that prices are changed more often for raw rather than manufactured products. Finally, price

[24] It is worth noting that, while higher inflation is associated with larger price changes, the effect is smaller than in the case of 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%. It is broadly consistent with our model – as Figure 1 shows for the calibrated parameters the effect of inflation on frequency is an order of magnitude larger than on size of price increases.

changes in Poland are the largest for services, and the smallest for perishable foodstuffs (see Table 3).

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 simple 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, 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.

5. Alternative Explanations.

In this section we consider alternative explanations of the price behaviour reported here. Most of the arguments are based on the Polish data, since they are more detailed and allow the testing of alternatives. Clearly, the data show inflexibility of nominal prices at the level of an individual seller. Any alternative theory must, therefore, explain why nominal prices do not adjust continuously. 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) but they cannot explain why firms do not change nominal prices in continuous fashion. Moreover, in the Polish data nominal price changes are large and infrequent even in 1990, when the new market environment is being established.[25] It is not likely that strategic considerations, long term relationships or imperfect information play important

[25] Despite rapid inflation and the need to adjust pricing structure to market forces, the average size of price change for the first 37 goods in 1990, for which we have weekly data, is over 10%. Except for January 1990, prices stay unchanged for well over a month.

roles in these circumstances. Therefore we concentrate on alternative theories of nominal rigidity.

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 prices of eggs every 40 days and 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 this frequency of price changes varies significantly with the intensity of customer search for the best price and other good characteristics. Furthermore, in regressions (17) and (18) (as well as in Table 3) we find that inflation affects the frequency and size of price changes, so that the pricing rules are not fully time contingent. 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 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.[26] In what

[26] 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 $10^{i-4} * \{\mathbf{x}\}$, $i = 1,\ldots,6$; $\{\mathbf{x}\}=\{1.00,1.05,\ldots,2.00,2.10,\ldots,5.00,5.25,\ldots,10.00\}$.

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 search intensity, 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 most common for services, followed by manufactured goods, and least common for perishable foodstuffs.[27]

To check whether the relationship between search intensity and the probability and the size of price changes is affected once we control for the proportion of pricing points we add PPP_{it} to the right side of regression (17)[28]

$$Prob_{it} = \underset{\substack{78.46^{*} \\ (9.76)}}{\alpha_0} + \underset{\substack{12.34^{*+} \\ (15.40)}}{\alpha_1 S^h} + \underset{\substack{6.32^{*} \\ (7.58)}}{\alpha_2 S^m} + \underset{\substack{1.84^{*} \\ (23.86)}}{\beta_1 INF_{it}} + \underset{\substack{0.12^{*} \\ (9.84)}}{\beta_2 PPP_{it}} + \vec{\gamma}\cdot\vec{T} + \vec{\delta}\cdot\vec{G} + \varepsilon_{it} \tag{20}$$

The addition of the proportion of pricing points as an explanatory variable has little effect on our previous results. While the value of some coefficient changes, their sign or significance is not affected. The proportion of pricing points has a strong positive effect on the frequency of price changes, significant at the 1% level. (The standard deviation of the average propotion of pricing points for different goods is 17%, so a one-standard-deviation increase in *PPP* corresponds to *Prob* increasing only by 0.2 standard deviation, so the effect is economically less significant than of the search categories). The results for the probability of price increase and the size of price changes are similarly unaffected.

Overall, we conclude that, while search intensity affects the proportion of pricing points, price-contingent policies cannot explain the patterns of price changes in the Polish data.

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}}

[27] 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.

[28] $\vec{G}$ is a vector of good types (d, m, s).

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 (17) and (18) 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 search intensity 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) 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 if 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.

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 search intensity and adjustment frequency can be derived in a simple 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 search intensity.

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, 2003). 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 (2003), 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.

Simulations of the model show that it does a reasonable job at tracing the relationship between inflation and the frequency of price changes for high-inflation economies, but greatly underestimates the frequency for low-inflation economies. These results are consistent with a related study by Golosov and Lucas (2003). There are three main differences between their model and ours. In their model, the environment is stochastic, there is no search, and firms face not only aggregate, but also relative shocks. They calibrate the model to reflect the inflation/probability relationship in Klenow and Kryvtsov's (2003) (low inflation) as well as in Lach and Tsiddon's (1992) (high inflation) data. Unlike ours, their model does a good job for both high and low inflation. They then redo the simulations assuming away relative shocks. This has little effect for the high inflation data but leads to significant underestimation of the frequency of price changes for low inflation data. They interpret the findings as suggesting that, in low-inflation economies, a vast majority of price adjustment is the result of relative rather than aggregate shocks. In our model there are no relative shocks and the frequency of price changes is underestimated in low inflation environments. Both studies suggest that, in the presence of menu costs, price adjustment at the individual level may be dominated by inflation when it is high, and by relative shocks when it is low. Our empirical results for the US data suggest that customer search for best price affects the frequency of price changes regardless of whether the nominal price is suboptimal because of real or nominal shocks.

Our results have important implications for general-equilibrium modeling of the effect of nominal rigidities on real variables. As state-contingent models are difficult to solve, researchers often adopt the Calvo-Taylor time-contingent approach. The probability of price changes is estimated from the data. The model is then calibrated under the assumption that the probability is fixed. Our results suggest that this procedure maybe ill-suited for policy prescriptions as the "Calvo probability" varies across markets depending on the search intensity (and other characteristics) and hence should be treated as an endogenous parameter.

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 $\sigma=1$ the first term equals zero and so the derivative is positive. For $\sigma>1$ 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 $\left(C/k+E\left[P\right]+MC\right)^2-2gm/b>0$. 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 the fact 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 identical. QED.

Proof of Proposition 1.

Equation (A1) can be rewritten as:

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

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(σ) is positive, strictly decreasing and $\lim_{\sigma\to 1}h(\sigma)=1$, $\lim_{\sigma\to\infty}h(\sigma)=0$. 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 $\frac{\sqrt{gm/b}}{C/k+MC}<\frac{\sqrt{2}}{2}$, 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 $T=\frac{\ln(S/s)}{g}=\frac{\ln\sigma}{g}$ and the frequency is $fr=\frac{1}{T}=\frac{g}{\ln\sigma}$.

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. QED

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Appendix B

Classifications and statistics for Polish goods

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

Appendix B continued

Classifications and statistics for Polish goods

Good			Search categories				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	0.26	0.20	0.06	0.15	0.10	0.09
Citric acid, 10g bag	37	d	l	l	l	l	0.24	0.19	0.05	0.31	0.25	0.18
Tea "Madras", 100g	38	d	h	m	m	h	0.25	0.21	0.04	0.11	0.10	0.09
Vacuum cleaner, type 338,5	39	m	l	l	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	0.26	0.24	0.02	0.11	0.09	0.05
Folding bicycle “Wigry-3"	41	m	l	l	h	h	0.27	0.22	0.06	0.09	0.08	0.06
Radio receiver "Ania"	42	m	l	l	h	h	0.19	0.17	0.02	0.13	0.11	0.10
Razor blade "Polsilver", each	43	m	l	m	l	l	0.17	0.14	0.02	0.22	0.20	0.14
Toothpaste "Pollena", 98g	44	m	m	m	l	m	0.29	0.25	0.04	0.25	0.12	0.11
Shaving cream	45	m	l	m	l	m	0.28	0.24	0.05	0.29	0.12	0.13
Sanitary pads "Donna", box of 20	46	m	m	m	m	h	0.27	0.21	0.05	0.16	0.10	0.06
Paint thinner, 0.5l	47	m	l	l	l	l	0.23	0.19	0.04	0.17	0.13	0.10
Radiator coolant “Borygo” or “Petrygo”	48	m	l	l	l	l	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	0.14	0.11	0.03	0.27	0.26	0.15
Boiled egg in a cafeteria, each	50	s	m	m	l	l	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	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	0.23	0.19	0.04	0.16	0.16	0.10
Car-wash, of car: "FSO 1500"	53	s	m	m	m	m	0.12	0.12	0.01	0.27	0.23	0.15
Varnishing of hardwood floor, 1m^2	54	s	l	l	h	h	0.13	0.12	0.01	0.29	0.19	0.22
ECG test	55	s	l	l	m	l	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

Search characteristics:

E - by importance in expenditure, F - by search frequency,

A - by amount spent on a single purchase, S - by search intensity

Search categories within characteristics:

h - high, m - medium, l - low

Table 1

Inflation, Probability and the Size of Price Changes

	All goods	Services	Manuf. goods	Foodstuffs durable	Foodstuffs perishable
	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
	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, %	11.0	22.0	11.8	10.5	7.2
decrease, %	8.4	15.4	8.8	8.0	6.2

Table 2

Evidence on Inflation and the Frequency of Price Changes

Study	Country	Goods	Period	Inflation rate, % per year	Monthly probability of price change: actual	Monthly probability of price change: predicted	Percentage difference predicted-actual
High Inflation							
Konieczny and Skrzypacz	Poland	various	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%
Lach and Tsiddon	Israel	foodstuffs	1982	133	0.61	0.70	14%
Tomassi	Argentina	foodstuffs	1990	70	0.46	0.51	10%
Lach and Tsiddon	Israel	foodstuffs	1978-6/79	58	0.39	0.46	18%
Sheshinski, Tishler, Weiss	Israel	cofee (noodles)	1973-8	40	0.35 (0.27)	0.37	6%(37%)
Ratfai	Hungary	meats	1993-6	18	0.41	0.23	-44%
Low inflation							
Dahlby	Canada	car insurance	1974-82	8.6	0.08	0.14	88%
Fisher and Konieczny	Canada	newspapers	1976-89	6.1	0.02 (0.04)	0.12	480%(190%)
Kashyap	US	catalogue apparel	1953-87	4.1	0.07	0.09	34%
Cecchetti	US	magazines	1953-79	4.0	0.01-0.04	0.09	120%-780%
Chakrabarti and Scholnick		books	3/2000-4/01	3.1	0.17	0.07	-55%
Alvarez and Hernando	Spain	70% of CPI	1993-2001	3.4	0.13	0.08	-39%
Bills and Klenow	US	70% of CPI	1995-7	2.7	0.26	0.07	-73%
Dias, Dias and Neves	Portugal	95% of CPI	1997-2001	2.6	0.22	0.07	-70%
Aucremanne and Dhyne	Belgium	68% of CPI	1989-2001	2.2	0.17	0.06	-64%
Vilmunen and Laakonen	Finland	100% of CPI	1997-2003	1.8	0.20	0.05	-74%
Baumgartner et al	Austria	90% of CPI	1996-2003	1.6	0.15	0.05	-68%
Beaudry et al	France	65% of CPI	1994-2003	1.5	0.19	0.05	-76%
Levy et al	US	supermarket	1991-2	1.0	0.67	0.04	-95%

Notes:

Fisher and Konieczny: the first number is for single copy, the second for weekly delivery, respectively.

Chakrabarti and Scholnick - data are from Amazon.com and BarnesandNoble.com

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 Search Intensity	**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 we have included a constant and dummies for each period of observations, but to save space we do not report those parameters.

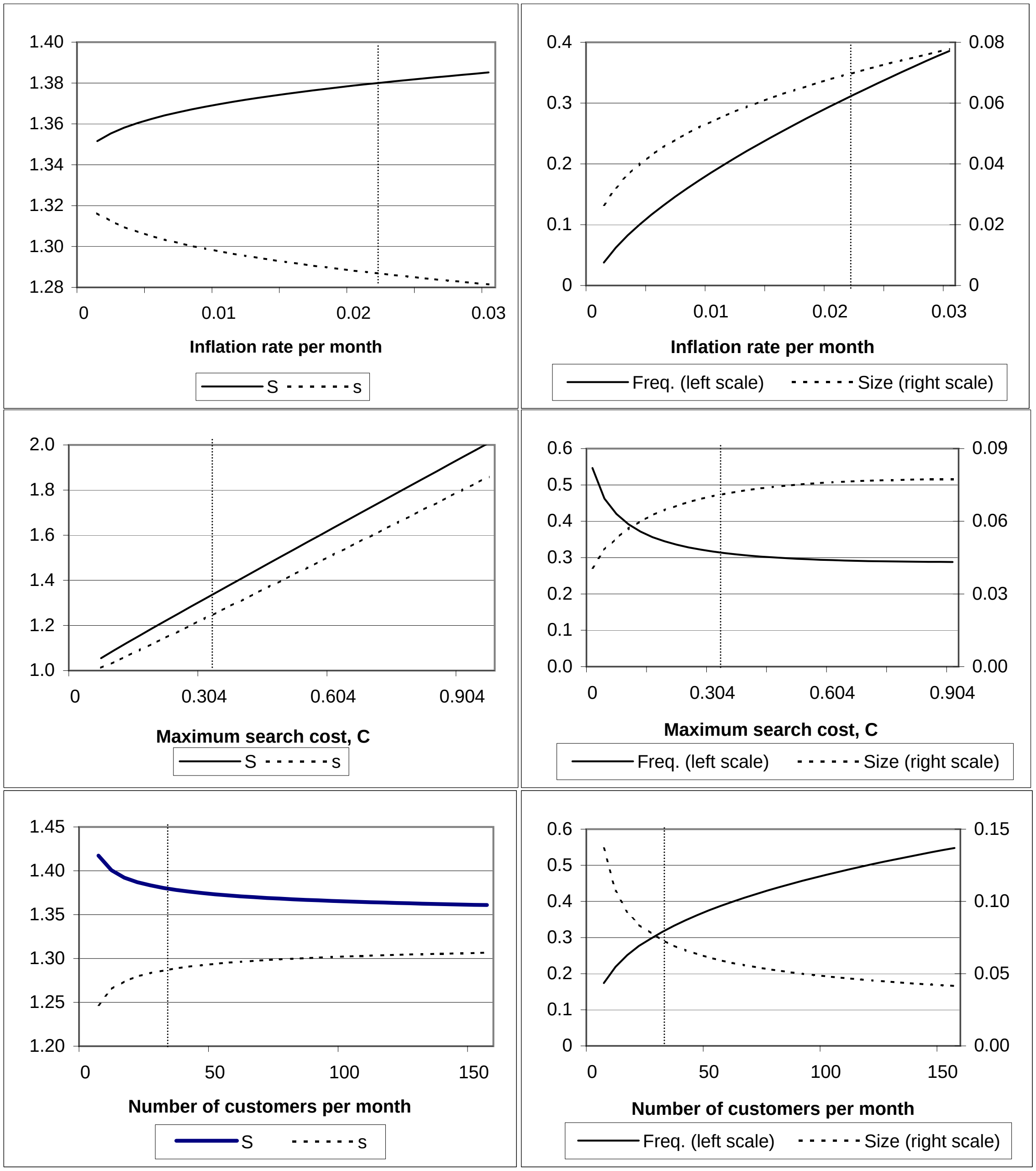
* denotes coefficient significantly different from zero (at 5% significance level against two-sided alternative)

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

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

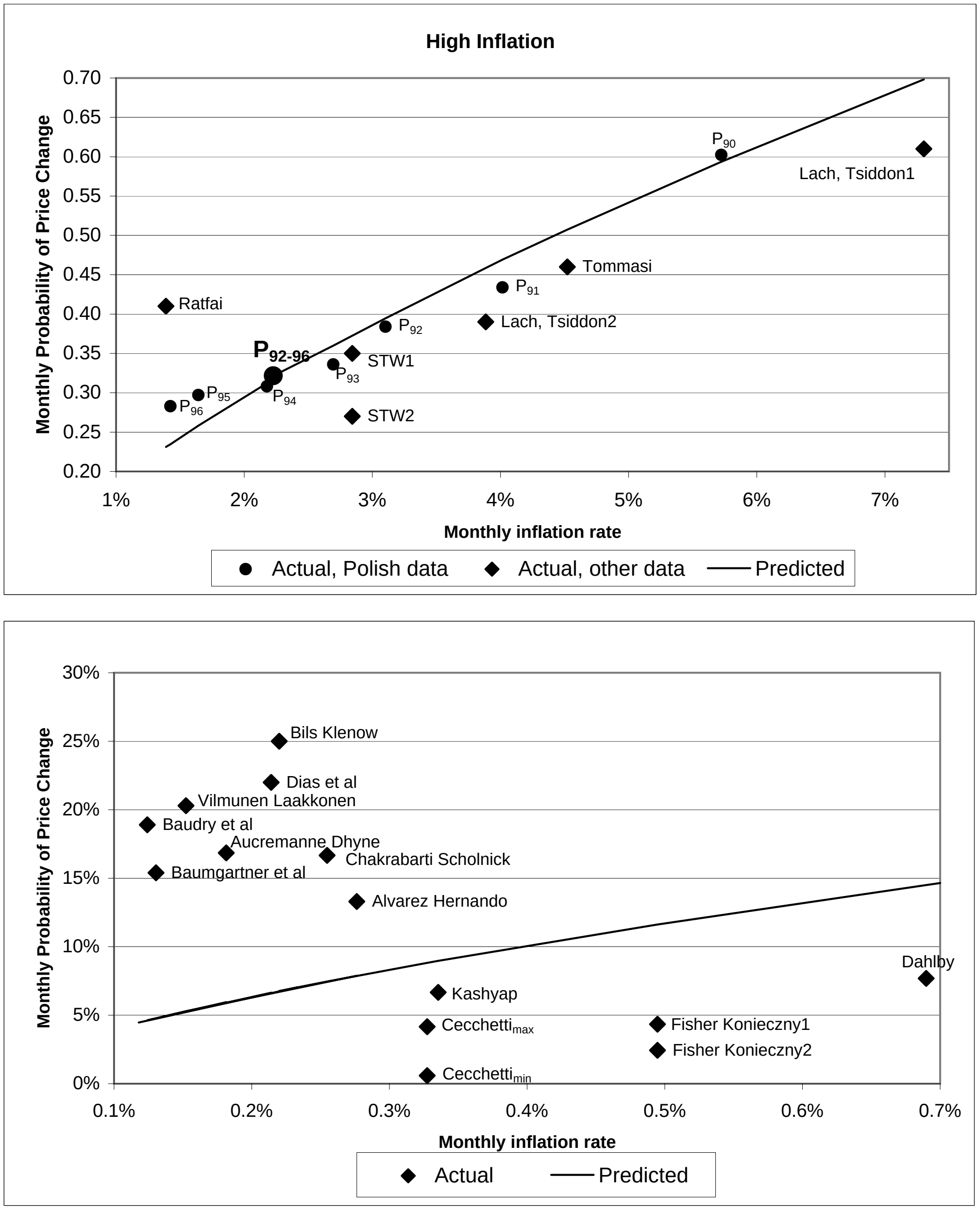
Figure 1

Effect of Changes in Parameter Values on the Price Bounds, on the Frequency of Price Changes and on Adjustment Size



Note: the dashed vertical lines denote the callibrated point: g = 2.23%, C =0.34 and v =30.

Figure 2



Notes:

Simulation parameters chosen to fit 1992-96 average in Polish data (P92-96).

Price change probability in Levy et al is 67%, inflation is 0.08%; it is omitted from the lower panel for clarity

Abbreviations:

P_i, i=90…96: Polish data 1990-96; STW1 (2): Sheshinski, Tishler and Weiss: cofee (noodles)

Lach and Tsiddon1(2): 1982 (6/1978-1979); Fisher and Konieczny1(2): weekly delivery (single copy)
Ceccetti$_{max}$ (Ceccetti$_{min}$): maximum (minimum) frequency in Cecchetti

Figure 3

Monthly Probability of Price Change by Search Categories