

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

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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 show that it can be derived from a simple model of monopolistically competitive firms that face menu costs of changing nominal prices and heterogeneous consumers who search for the best price. We discuss several alternative explanations and argue that, with one exception, they cannot explain the observed correlations. The implied cross-sectional test of the menu cost model provides a potential explanation of the rejections of the menu cost model in some time-series tests. Our results imply that in macroeconomic, general equilibrium models, in which nominal rigidity is based on the Calvo-Taylor framework, the frequency of price changes should be treated as an endogenous parameter.

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1. Introduction.

With the exception of auction markets, nominal prices change infrequently. The determinants of the frequency of price changes are not only of intrinsic interest but also have implications for general equilibrium modeling of the effects of nominal changes on real variables, which is often based on the assumption that the (estimated) frequency is fixed. In this paper we establish a new empirical finding that search for the best price affects the frequency of nominal price changes at the level of individual goods. We find that price changes are more frequent and smaller in markets with more intense search for the best price. The effect is both statistically and economically significant. It holds in very different environments. One data set, from 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 probability of price change and the weight in US CPI, which we treat as a proxy for search intensity. The second data set consists of store-level, actual transactions prices for 55 products and services in Poland, each observed in up to 47 stores, over 1990-96. We divide goods into groups based on various search characteristics. Our finding is robust with respect to the choice of measures of search intensity.

We derive the relationship between search intensity and the frequency of price changes from a simple model in which firms face costs of changing nominal prices and consumers search for the best price. Our model is similar to Bénabou (1988) and (1992). The main difference from Bénabou (1988) is that consumers are heterogeneous in terms of search costs and there is active search in equilibrium. On the other hand, the model is a special case of Bénabou (1992). The main simplification is that we assume that each consumer buys a fixed amount of the good. This allows us to describe conditions under which the equilibrium is unique and derive cross-sectional predictions of the model.

In our model, the combination of inflation and costly price adjustment leads, in the usual way, to dispersion of prices across stores. Buyers know the overall price distribution but checking prices at individual stores is costly. The intensity of search for the best price depends on characteristics of the good. Following the classic Stigler (1961) paper, search intensity is assumed to depend on the value of purchases, the good's importance in household expenditure and the frequency of search for the best price.

The concentration on market heterogeneity allows us to develop cross-sectional predictions of the model. We show that price behaviour in the (unique) equilibrium depends on

determinants of search intensity in a given market: more intensive search leads to more frequent, and smaller, price changes. Empirical results, using the two data sets, provide strong support for the model.

The intuition for the theoretical result is that more intensive search leads to a more elastic demand and profits more concave as a function of real price. Hence profits decline faster as the real price varies from its profit-maximizing value and firms prefer to pay the menu cost more often to keep their prices within tighter bounds.

Using direct information on menu costs from Levy et. al. (1997), we calibrate the model to fit the 1992-96 average in the Polish data. We then compute the relationship between inflation and the frequency of price changes for individual years in the Polish data as well as for inflation rates in other empirical studies. Despite its simplicity, the model does a good job at replicating the relationship between inflation and the frequency of price changes in high-inflation environments, but it does a poor job for data from low-inflation countries. This is broadly consistent with the recent related work by Golosov and Lucas (2003), who stress the importance of relative shocks for price adjustment in low-inflation environments.

We discuss 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, temporary sales and Rotemberg's (2002) customer reluctance model. With the exception of the last model, they cannot explain patterns in the data.

Although it is perhaps not widely perceived, there exists a conflict between the menu cost model and some time-series evidence. Sheshinski and Weiss (1977) showed that, when changing prices is costly, higher (expected) inflation leads to larger and more frequent price changes (if the profit function is strictly concave in the log of the real price¹). Yet Lach and Tsiddon (1992) and Kashyap (1995) find several instances when price changes become smaller as inflation rises.² Using the Polish data we show that for many pairs of individual goods we observe behaviour that is inconsistent with the cross-sectional predictions of the menu cost model. We argue that the reason for the rejections is that individual pricing policies are highly idiosyncratic. Indeed, while we find strong support for the model using the average behaviour within groups, pairwise comparisons lead to frequent rejections of our model. This means that within-group variation is

¹ They call it the *monotonicity* condition.

² Furthermore, Cecchetti (1986) and Dahlby (1992) report no significant relationship between adjustment size and inflation.

often larger than the across-group variation, but the idiosyncrasies average out over several goods and, in the aggregate, across-group differences are significant.

The plan of the paper is as follows. For clarity of exposition we begin by presenting the model in the next section. The data are described in section 3. In Section 4 we present a simple calibration. Empirical results are in Section 5. In Section 6 we discuss alternative explanations of the patterns in the data. In Section 7 we suggest an explanation for the earlier rejections of the menu cost model. Conclusions are in the last section.

2. Menu Costs, Search Intensity and Price Changes.

In this section we develop a simple 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.³ The geographical 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. As discussed in the Introduction, it is a special case of Bénabou (1992).

³ 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.

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 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 the whole demand at the posted prices.

Each period a new cohort of consumers arrives at the market. Their number is ν so, in the absence of entry, ν 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. 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, $q(P)$.⁴

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:

$$c = k \int_0^P (P - x) f(x) dx \quad (1)$$

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:

⁴ Implicitly we make the standard assumption that the search is instantaneous and consumption cannot be postponed. See Bénabou (1992) for more discussion.

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

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):

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

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 $A \equiv P^*(C)$, $b \equiv vk^2/C$. The demand function can be rewritten as:⁵

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

The three market-specific variables: the number of consumers, v , the number of units bought by each consumer, k , and the size of search costs (measured by their range, $[0, C]$) affect firms' incentives to change price. The higher is the number of consumers and/or the number of units bought and the lower are search costs, the more responsive is 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

⁵ Note that, b depends only on the parameters of the model. In contrast the maximum willingness to pay, A , is determined endogenously, as it depends also on the expected price in the market.

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:

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

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:

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

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:

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

and the average price is:

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

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:

$$(A-S)(S-MC) = (A-s)(s-MC) \quad (9a)$$

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

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

Equation (9a) can be rewritten as:

$$s = A + MC - S \quad (10)$$

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:

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

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

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

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

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

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

We can now address the question of existence and uniqueness of equilibrium. 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. For the rest of this section we assume that this condition is met.⁶

Proposition 1:

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

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

Proposition 2:

(a) Assume $MC > \sqrt{2gm/b} - C/k$. 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 .

⁶ 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).

(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: $\bar{\pi} = 0$. 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:

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

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:

$$G(\sigma)(C/k + MC)^2 / (Ck^2) = mg / v \quad (13)$$

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/or adjustment costs affect the number of firms in equilibrium and do not affect the pricing policies of the active firms. The higher is inflation and/or the higher are adjustment costs in a given market, the more concentrated is the industry.

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:

$$\pi(s) = F \ln(\sigma) / g \quad (14)$$

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 4, 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 change the effects of inflation and menu costs on the optimal pricing policy from those in the basic Sheshinski and Weiss (1977) model. Firms with larger menu cost change prices less often and by larger amounts. As the inflation rate increases, price changes become larger and (since the profit function meets their sufficient condition) more frequent. In addition, the higher is marginal cost, the more frequent and larger are price changes.

More importantly for our empirical results, the effect of the three market-specific variables on the size and frequency of price changes is unambiguous. The model predicts that in markets in which search is intensive (due to low search costs, or large customer's purchases, k), or in which demand is more elastic due to a large number of customers, ν , price changes are small and frequent.

The intuition for this result is as follows. When prices are costly to change, a firm changes prices infrequently to save on adjustment costs. The optimal policy equates the marginal gain from the reduction in adjustment costs to the marginal loss from not charging the profit-maximizing price. For a given frequency of adjustment, the loss depends on how fast profits fall as price departs from its profit-maximizing value. In our model the profit function is:

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

and the more intensive is search (due to higher k or lower C), the more rapidly profits deteriorate as price departs from the optimal one.⁷ Hence in markets with more intensive search firms change prices more frequently and by smaller amounts. In equilibrium the demand is additionally affected (through $E[P]$ and, in markets with free entry through ν) by the behavior of other firms, but the intuition remains valid.

In Figure 1 we show the effects of changes in the inflation rate, g , the maximum (and the average, $C/2$) search cost, C , and in the number of customers, ν . Note that changes in C affect

⁷ For a single firm with a quadratic profit function, Bénabou and Koniczny (1994) show that the optimal size of adjustment is: $\sigma = \exp[-12gm / F''(P^m)] / 3 = \exp[6gmC / \nu k^2] / 3$, where P^m denotes the profit maximizing real price (see their equations (7)-(8)).

both price bounds in the same direction. Higher search costs reduce the competitiveness of the market and raise monopolistic markups. As a result both price bounds increase but the probability of price change falls and the size of adjustment rises.⁸

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).

3. The Data.

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 US consumer expenditure. They are grouped into the so – called *entry level items* (ELI). For years 1995-97, Table 1 in Bils and Klenow (2004) provides the probability of price changes and weight in US CPI for each of the 350 ELIs.

The second source of evidence, which we describe in more detail, is a data set consisting of unpublished store-level price information on selected products and services in Poland. The data start at the beginning of the big-bang transition to market economy in 1990⁹ and cover a period of seven years. The environment is particularly suitable to test our model, as the average annual CPI inflation rate was on the order of magnitude higher than in the US data and hence a larger share of price changes is likely to be caused by nominal shocks.

While the source of the data is 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.¹⁰ Stores were allowed to set prices of goods they sell and shortages quickly disappeared. 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.

⁸ The effects of 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.

⁹ See Sachs (1993) for a description and discussion of Polish reforms.

¹⁰ 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).

The data were collected by the Polish Central Statistical Office (GUS) in order to calculate the Consumer Price Index. 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 data on prices of 55 goods. We selected the goods on the basis of several criteria. In order to minimize the number of spurious price changes, the good had to be precisely defined and remain unchanged during the study period (excluding, for example, "a man's suit"). We eliminated goods sold in packages of different size as well as goods whose packaging has changed during the study period. We excluded goods with regulated prices, and with many missing observations. Out of the 55 goods, 38 are groceries (20 perishable and 18 storable), 4 are sold in cafeterias/cafes, 10 are nongrocery items and 3 are services. The list of the goods and various classifications are in Appendix B.

For each good we obtained the complete data set for 4 out of 49 Polish administrative regions, called Voivodships. We selected Voivodships with the largest number of stores sampled. The frequency with which GUS inspectors collected prices varied over time and across goods, from four per month in each store (groceries in Jan-Nov 1990) to one per month in each store (nongrocery items, 1991-96). In order to make the data comparable across goods we use only the first observation each month. As a result, some multiple price changes within a month are missed. We discuss this issue in the next subsection. For each good, there are up to 47 price observations a month; the actual number is usually smaller as some data are missing.

Despite the care we took to select goods in the study, some price changes may be caused by changes in the store being sampled, management, ownership, competitive environment or by the appearance of substitutes. 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. During the period of the study the retail sector in Poland underwent significant transformation, in particular with respect to store ownership. We do not know the identity of the sampled stores but, as far as we know, multiple ownership changes were rare. On the other hand, store management, and pricing policy, may have changed more than once. The competitive environment may have been affected by entry of new stores. Finally, while we selected the goods that did not change during the seven years, in many cases market environment was affected by the appearance of substitutes (for example, we have data on the cost of washing a particular car model. The car was popular in 1990 but rare in 1996). New substitutes may have induced changes in the price of the incumbent product but, in most cases,

the goods in our sample remained the basic staple and new substitutes were significantly more expensive. As the goods in our sample were established, it is not likely that price changes were due to rapidly decreasing costs, common in case of new products.

The data set is potentially unusual as Poland switched to a market economy in 1990. In two companion papers (Konieczny and Skrzypacz, 2000, 2002, hereafter KS1 and KS2, respectively) we find, however, that there is nothing special about the behavior of prices and price changes. We analyze various aspects of firms' pricing policies and conclude that prices in Poland behaved as economic theory predicted they would. In particular, in KS1 we find that, consistent with Stigler (1961), search determines the level of price dispersion for homogenous goods. The comparison of the frequency of price changes in the Polish data with other studies (see Table 2) leads to the same conclusion.

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). Also, the data consist of actual transaction prices, since quantity discounts or coupons were rare or nonexistent during the study period. Promotional packaging (i.e. 120g for the price of 100g) was virtually unknown. The Polish data allow us to test the relationship between search intensity and the size of price changes and so provide further evidence on the validity of our model. Finally, inflation rate in the Polish data is much higher than in the US and so it is more likely that a large proportion of price changes is caused by nominal rather than real shocks (see Golosov and Lucas, 2003, for an analysis of the menu cost model in the presence of relative shocks).

3.1. Data Issues.

Initial Transition. The Polish data are somewhat unusual as in January 1990 the economic environment in Poland was dramatically altered. This resulted in a period of adjustment of all economic agents, including price setters and customers. In KS1 and KS2 we analyzed in detail the behaviour of prices over time. The initial behaviour was different than in later years; in particular, following the reforms the dispersion of price levels across stores declined rapidly.

This initial transition period was brief: using the definition employed in KS1¹¹, it lasted longer than a year for only 6 out of the 55 goods. We concluded that the initial period 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. Another reason we focus on this interval is that the expected inflation was much more stable than in the first two years (and the model assumes constant expected inflation).

Infrequent Observations Bias. Since we do not observe prices in a continuous fashion, the number of price changes is underestimated. Let P_{ijt} denote the price of good i in store j in month t . Whenever we observe $0 < P_{ijt-1} < P_{ijt}$, we assume that there was a single change of the price of good i in store j in month t and that the size of this single price change is equal to $P_{ijt} - P_{ijt-1}$. 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 month. 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.

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 $(P_{ijt} - P_{ijt-1}) / P_{ijt-1}$. 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.

Both data sets are affected by this bias. The Polish data are monthly; the US data are a combination of monthly and bimonthly observations (for the latter data Bils and Klenow derive monthly equivalents of the probability).

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. Comparing the monthly data with the data with these higher frequency observations provides an idea about the bias. There are between 13% (in 1995) and 26% (1991) more price changes in the high-

¹¹ We analyze 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.

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.

Missing data. The Polish data set is not complete. The proportion of missing observations varies between 26% in 1992 and 16% in 1995. Assuming that observations are missing randomly, breaks in the data make it less likely to observe long periods with unchanged prices. Calculating the average duration would underestimate the actual duration more severely in case of goods with long duration of constant prices. To avoid the problems caused by missing data, we calculate the monthly probability of price change by dividing the number of 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.

3.2. The Probability and Size of Price Changes.

Descriptive data information is in Table 1. The average probability of price changes is 0.26 in the US data and 0.32 in the Polish data.¹² As can be seen in Table 1, the probabilities depend on good type. It is the highest for perishable foodstuffs, followed by durable foodstuffs, manufactured goods and services.¹³ In the Polish data, the picture for the probability of price increases and decreases is similar. This relationship is not restricted to our data: Aucremanne and Dhyne (2004), as well as Dias, Dias and Neves (2004) report the same differences in probability of price change between good types. We discuss these differences in Section 5. The probabilities vary more in the US data than in the Polish data; this is, to some extent, the result of the much larger proportion of services in the first data set. The probability of price changes for individual goods in the Polish data is in Appendix B; a comparison with other studies is in Table 2.

¹² In the Polish data there are 115914 cases with two consecutive observations. There are 37817 price changes (30493 increases and 7324 decreases). 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 $N_{itT} = 5 \cdot 12 \cdot 55$ is the number of values of Prob_{itT} in the summation. The average size of price changes is computed in the same manner.

¹³ The classification of ELIs into types is available on request; the classification of goods in the Polish data is in Appendix B.

Table 1 also shows the size of price changes in Polish data. The average price increase (the values for decreases are in brackets) is 11.0% (8.4%, respectively). It falls from 13.1% (9.6%) in 1992 to 9.1% (7.1%) in 1996. 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.

It is interesting to note that, for goods with high average rates of own inflation¹⁴ price changes are large but, somewhat surprisingly, infrequent. For the 55 goods, the correlation between the average rate of own inflation and the average price increase (decrease) is 0.6 (0.53), respectively, but the correlation with the probability of price change (increase, decrease) is -0.31 (-0.3 , -0.29), respectively.

4. Calibration.

We now conduct a simple calibration to check how well our simple model can replicate the main empirical regularities in the Polish as well as in other data sets. Our model involves several parameters which are difficult to observe. To pin them down, we use information from Levy et al (1997), which is the best available source of information on menu costs. They estimate the size of menu costs on the basis of data obtained by direct observation of the price changing process in several large US grocery chains.¹⁵ The calibration is a somewhat arbitrary exercise as various crucial parameters may be different in our data set; for example Polish stores are smaller, competition and search incentives may differ etc. Hence it should be understood as an illustration of the model.

Levy et al. (1997) provide data from one chain located in a state that requires that the price must be placed on each item and four chains not subject to the item pricing law. As Polish stores were not required to attach prices to each item, we use the values they report for the four chains. The 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 of the stores is 25% and the total menu cost is 0.7% of all revenues and 2.8% of the gross margin.

To fit these numbers we set $MC=1$, which means all reported numbers are in the units of the good. We chose $k=1$ and $v=30$. We then compute the values of the menu cost, m , and the

¹⁴ We use the term own inflation as a rate of increase of nation-wide average price of the good and denote it by INF.

¹⁵ See Slade (1998), Aguirregabiria (1999) and Willis (2000) for econometric estimates of menu costs.

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. 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, $E[P]=1.333$ and the percentage size of price change, $\sigma-1=7.3\%$.¹⁶ 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 Polish data.

A different, and more interesting, issue concerns the dynamic properties of our model. We now ask whether it can replicate the relationship between inflation and the frequency of price changes in the Polish, US and other data. To do this we compute the predicted probability of price change for different inflation rates, using the calibrated parameter values. The results of this exercise are in Table 2 and Figure 2. Table 2 summarizes empirical evidence from several studies. It is divided into two parts: high inflation (which includes studies using Argentinean¹⁷, Hungarian, Israeli and Polish data) and low inflation (Belgian, Canadian, French, Portuguese, US and Internet data). For each set of data we specify the yearly inflation rate, actual and predicted frequencies of price change and the percentage difference between the predicted and actual values. For convenience we illustrate the data in Figure 2, where we show the actual frequency of price changes for various studies as well as the predicted relationship between inflation and the frequency.

In the first part of Table 2 we show the results for individual years in the Polish data set (together with the 1992-96 average which was used for calibration). It is clear that the model does a good job replicating the relationship between inflation and the frequency of price changes in the Polish data. The percentage difference between the predicted and actual values is between -17% and 8% . The largest differences are for 1995 and 1996, indicating the decline in adjustment frequency was smaller than implied by the drop in the inflation rate.

More generally, 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

¹⁶ 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.

¹⁷ 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.

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; as already discussed, price changes are more frequent for raw products and for perishable foodstuffs than for other goods

On the other hand, the model 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) data set, they are all much larger, often by order of magnitude, than in high inflation countries. Nor can the errors be explained by good types. We expect the probability of price changes in the first four studies to be low and for the Chakrabarti and Scholnick (2001) to be high¹⁸. But the frequency of price changes in the four comprehensive data sets (Bils and Klenow, 2004, Aucremanne and Dhyne, 2004, Beaudry et al, 2004 and Dias, Dias and Neves, 2004, all of which cover over 50% of consumer expenditure in the respective country) are much higher than predicted. We discuss this issue briefly in the conclusions.

5. Empirical Results.

We now turn to empirical testing of the relationship between search intensity and the size and frequency of price changes.

5.1. US Data.

We start by analysing the US data. To test the hypothesis that more intensive search leads to higher frequency of price changes, we treat the ELIs' weights in US CPI as a proxy for the average importance in expenditure, and so for search intensity, of the goods included in a given ELI.

While the extensive coverage of expenditure of the Bils and Klenow data set is an obvious advantage, the weight in US CPI may be a poor proxy for search-inducing importance in expenditure. This is because US CPI weights are affected by the construction of ELIs. An ELI with a large weight in expenditure may consist of a small number of goods that are important in consumer expenditure, or may consist of a larger number of unimportant goods. For example, we expect search to be much more intensive for ELI 9011 (fresh whole milk – with 0.201% weight

¹⁸ Dahlby (1992) and Kashyap (1995) study markets in which there are institutional 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 adjustment is lower than in brick-and-mortar stores.

in US CPI) than for goods in ELI 18031 (potato chips and snacks – with 0.212 weight in US CPI). Furthermore, what matters for search is not the weight in US CPI but the importance of a given good in the expenditure of households that actually buy it. For example, we expect search to be much more intensive for ELI 55034 (hearing aids – with 0.024% weight in US CPI) than for ELI 30032 (microwave ovens – with 0.03% weight in US CPI).¹⁹

Despite these potential problems assume that a high value of weight in expenditure for a given ELI in US CPI means the goods included in the ELI constitute a large portion of household expenditure for a household which buys them. In our model this corresponds to a high value of k . Therefore we expect a positive correlation between the probability of price adjustment for goods included in a given ELI and its weight in US CPI.

We first regress the probability of price changes on the expenditure weights.²⁰ We obtain:

$$Prob_i = \alpha_0 + \alpha_1 \cdot w_i + \varepsilon_i \quad (15)$$

α_0 α_1 ε_i
 22.47 4.12
 (24.81) (1.89)

where $Prob_i$ is the average monthly probability of price change and w_i is the weight in expenditure of a given ELI, $i=1 \dots 350$. t values are shown in brackets. The coefficient on group weight has the expected sign and is significant at the 10% level.

As already discussed, price change probabilities depend on good type. The differences are consistent with search for the best price. Within each ELI, non-price differences between goods affect the intensity to search for the best price. Consistent with this interpretation, Bills and Klenow find that the probability of price change is three times larger for raw goods than for processed goods (see their Table 2). On the average, services are most heterogeneous, followed by manufactured goods and durable foodstuffs; perishable foodstuffs are the most homogeneous.

We take account of this heterogeneity by adding good type dummies to the regression. The resulting regression is:

$$Prob_i = \alpha_0 + \alpha_1 \cdot w_i + \beta_1 \cdot d + \beta_2 \cdot m + \beta_3 \cdot s + \varepsilon_i \quad (16)$$

α_0 α_1 β_1 β_2 β_3 ε_i
 37.04 10.62 -13.70 -14.97 -29.33
 (23.40) (5.83) (-5.36) (-8.25) (-14.00)

¹⁹ There may be also problems with the way the probability of price change is calculated. It is the average probability of changes for all goods included in the group. Most ELIs consist of goods that are not homogenous and the frequency of observation may differ across goods in a given ELI. Hence the number of observations for each good may affect the computed value of the average probability of price changes.

²⁰ All regressions are by OLS; t-statistics are in the brackets.

where d , m and s are dummy variables for durable foodstuffs, manufactured goods and services, respectively (the omitted group is perishable foodstuffs). The relationship between weight in expenditure and the probability of price changes is as expected; it is 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.

Overall, despite the measurement issues noted above, these results support the joint hypothesis that (i) the more intensive is search for the best price, the more often are prices changed and that (ii) ELIs' weights in CPI are a good proxy for search intensity.

5.2. Polish Data.

While the Polish data are much less comprehensive than the US data, they consist of prices of individual goods and so the issues arising from the construction of the ELIs do not affect our proxies of search intensity. In order to avoid probability measures being affected by the number of observations we give equal weight to every good and every month in computing averages, as described in footnote 12. We also take into account the fact that not all goods are bought by all households in constructing our proxy for importance in expenditure. Finally, the high inflation rate in the Polish data increases the role of inflation-induced price changes compared to changes resulting from relative shocks.

Our approach is dictated by the data set, which consists solely of retail prices. In particular, we do not have any quantity information or measures of the average size of purchase, the number of customers per store, costs of search or wholesale prices. Therefore we base our tests on the classifications developed in a companion paper (KS1), where we analysed the impact of search intensity on differences in price levels across stores. We divided the goods on the basis of three market characteristics: (a) the portion of household expenditures spent on a given good (for households that buy the good), (b) the value of a single purchase and (c) the frequency of purchases. Our treatment of characteristic (a) avoids the mismeasurement of the importance of household expenditure of goods bought by few households (for example good 21 – baby formula).²¹ We also added a fourth measure of total search intensity, which tries to aggregate all factors relevant to search - the three discussed above as well as omitted factors which do not fall neatly into any of the three characteristics.²² It reflects our opinion about the total search

²¹ We were unable to obtain from GUS the information on the share of the goods in total household expenditures.

²² 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.

intensity. As we did not have direct information on these characteristics, our classification is subjective. We divided the goods independently into categories within each characteristic and reconciled the rankings. To minimize arbitrariness, within each characteristic the goods were divided into only three categories: high, medium and low. The classification of products into these categories is in Appendix B. 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 portion of expenditure spent on a given good and the value of a single purchase). 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.

Our findings in KS1 support the hypothesis that search for the best price determines the distributions of price levels across stores. Between 80% and 100% of comparisons across categories in a given characteristic are as expected: the more active is search, the smaller are price differences across stores, as measured by the coefficient of variation of price levels.

We use the same classifications here to analyze the relationship between search intensity and the size and frequency of price changes. The advantage of this approach is that, while the classification is subjective, it was created for a different purpose.

The characteristics are related to the market-specific variables in our model as follows:

- Goods with high amount spent in a single purchase constitute a large portion of expenditure of a household which 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.²³ 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 .²⁴ 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 constitute a large share of expenditure, it is bought frequently (low C) or/and the amount spent on a single purchase is large (high k).

²³ 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.

²⁴ A different way of modeling frequent purchases is through a higher k , interpreted as a possibility of purchasing more units in a short period of time (compared to the usual length of time between price adjustments).

- 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.

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). 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). Since some goods are seasonal and monthly probabilities are quite volatile, the values are 12-month averages. For example, the value in December 1992 is computed as the number of price changes in 1-12/1992, divided by the number of two consecutive observations in the same period.

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, inflation rate, good type dummies and time dummies. Model 1 involves estimating the following regression:²⁵

$$\begin{aligned}
 Prob_{it} = & \alpha_0 + \alpha_1 \cdot S^h + \alpha_2 \cdot S^m + \beta \cdot INF + \delta_1 \cdot D + \delta_2 M + \delta_3 R + \vec{\gamma} \cdot \vec{T} + \varepsilon_{it} \\
 & 0.967^* \quad 0.111^{*+} \quad 0.066^* \quad 1.863^* \quad -0.035^{*+} \quad -0.116^{*+} \quad -0.227^* \\
 & (12.020) \quad (13.848) \quad (7.844) \quad (23.810) \quad (-5.704) \quad (-16.006) \quad (-19.064)
 \end{aligned} \tag{17}$$

where $Prob_{it}$ is the probability of price change for good i in month t . The data used in the regressions are monthly, unlike the data plotted in Figure 3, which are 12-month averages. S^h and S^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 ; D , M and R are dummies for durable foodstuffs, manufactured goods and services, respectively (the omitted type is perishable foodstuffs) and \vec{T} is a vector of time dummies (total of 59, one for every month in the data). t values are in brackets. A “*” following a coefficient estimate denotes it is significantly different from zero at the 5% level, against a two-sided alternative; a “+”

²⁵ In the Polish data the number of observations we 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.

following a coefficient estimate denotes that it is significantly higher than the coefficient on the next dummy, at 5% level, against a two-sided alternative. For example the coefficient on the high search intensity dummy, S^h , is significantly different from the coefficient on the medium search intensity dummy, S^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.

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 bias discussed in subsection 3.1, the differences between categories are probably underestimated.

We also find that the probability of price changes increases with inflation and 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 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:

$$\begin{aligned}
 Prob_{it} = & \alpha_0 + \alpha_1 \cdot E^h + \alpha_2 \cdot E^m + \alpha_3 F^h + \alpha_4 F^m + \alpha_5 A^h + \alpha_6 A^m + \\
 & \begin{array}{ccccccc}
 0.71^* & 0.03 & 0.04^* & 0.15^{*+} & 0.03^* & 0.06^{*+} & 0.03^* \\
 (8.7) & (1.9) & (2.73) & (6.7) & (2.9) & (5.0) & (4.4)
 \end{array} \\
 & + \beta \cdot INF + \delta_1 \cdot D + \delta_2 M + \delta_3 R + \bar{\gamma} \cdot \bar{T} + \varepsilon_{it} \\
 & \begin{array}{ccccccc}
 1.85^* & 0.05^* & -0.024+ & -0.17^{*+} & & & \\
 (24.0) & (3.3) & (-1.9) & (-10.5) & & &
 \end{array}
 \end{aligned} \tag{18}$$

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 middle category.

In columns 1 and 2 of Table 4 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 4, 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.²⁶

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, $CV = \text{STD}[P]/E[P]$, and the probability of price changes. The estimated equation is:

$$Prob_{it} = \beta_0 + \beta_1 CV_{it} + \beta T + \varepsilon_{it} \quad (19)$$

$$\begin{array}{ccc} 1.03^* & -0.75^* & \\ (11.6) & (-20.6) & \end{array}$$

The coefficient -0.75 on CV means that a 10% increase of coefficient of variation corresponds to a 7.5% drop in frequency of price changes.

To conclude, results obtained with the Polish data set provide strong evidence that, as predicted by the menu cost model with consumer search, the higher is search intensity the more frequent and smaller are price changes.

6. Alternative Explanations.

In this section we turn our attention to alternative explanations of the price behaviour in our data. Most of the arguments are based on the Polish data as 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

²⁶ 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.

adjust continuously. There are many real stickiness theories, for example coordination failures (Ball and Romer, 1991) 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.²⁷ It is not likely that strategic considerations, long term relationships or imperfect information play important 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 Taylor model in which the frequency of price changes is chosen endogenously depending on the demand in a given market. 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. Finally, as the comparison of regressions for the frequency of price increases and for the size of price increases indicates, firms react to higher inflation mostly by more frequent price changes (and only a bit larger price increases). Therefore the time-contingent model does not describe the Polish data even approximately. This is in contrast to Klenow and Kryvtsov (2003) (who analyse the US data set) and find that firms react to higher inflation mostly by larger price changes rather than more frequent ones.

²⁷ 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.

Summing up, in the Polish data if time-contingent considerations are present, they are of secondary importance. In the US data, at the very least the type of time-contingent policies the firms follow is affected by search considerations.

Price-Contingent Policies

Kashyap (1995) proposed pricing points as an alternative explanation of nominal price rigidity. According to this theory, certain values of nominal prices are preferred to other values, 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.²⁸ To make the terminology consistent, we will call them *price-contingent policies*. We will call prices ending in 9, 99, etc *tantalizing* prices, while prices ending in a zero will be called *round prices*.

The usual explanation of tantalizing prices, due to Basu (1997) and discussed extensively in Bergen, Chen and Levy (2003), is that buyers have limited information processing abilities and so ignore the last digit. It is then optimal for firms to set it equal to nine. An alternative explanation of the prevalence of both tantalizing and round prices is that, when exact optimisation is difficult and expensive, restricting the choice of prices to a subset of all numbers reduces decision costs.

The custom of firms to charge special prices differs across countries. Tantalizing prices are popular, for example, in North America while they are rare in, for example, Spain, where round prices are common. During the period in question pricing in Poland followed the Spanish pattern. 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.²⁹ In what follows we discuss the results for the proportion of prices that are either round or tantalizing; the latter prices are rare in the Polish data and so the results are identical if we look only at round prices.

²⁸ The recent introduction of the Euro raised interest in such policies. See Aucremanne and Cornille (2001), Folkerstma (2001) and National Bank of Belgium (2002) for an analysis of pricing points during change to Euro-denominated prices.

²⁹ 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=10000zł; we use data denominated in the new currency, what explains the very low price). Round prices are defined as $10^{i-4} * \{\mathbf{x}\}$, $i = 1, \dots, 6$; $\{\mathbf{x}\} = \{1.00, 1.05, \dots, 2.00, 2.10, \dots, 5.00, 5.25, \dots, 10.00\}$. The values of tantalizing prices are $10^{i-4} * \{\mathbf{y}\}$, $i = 1, \dots, 6$; $\{\mathbf{y}\} = \{\{1.04-1.049\}, \{1.09-1.099\}, \dots, \{1.94-1.949\}, \{1.95-1.999\}, \{2.09-2.099\}, \{2.19-2.199\}, \dots, \{4.89-4.899\}, \{4.95-4.999\}, \{5.2-5.249\}, \dots, \{9.7-9.749\}, \{9.9-9.999\}\}$

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 a model with pricing points can provide a potential explanation of the patterns in our data.

If we compare the frequency of pricing points between categories the picture is similar to that for the probability and for the size of price increases. 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.³⁰

This initial impression is not supported by formal analysis. We first estimate the following equation:

$$PPP_{it} = \alpha_0 + \alpha_1 S^h + \alpha_2 S^m + \alpha_3 INF_{it} + \bar{\gamma} \cdot \bar{T} + \bar{\delta} \cdot \bar{G} + \varepsilon_{it} \quad (20)$$

1.39	-0.1*	0.02*	0.18	
(12.7)	(-9.4)	(2.2)	(1.7)	

where PPP_{it} is the proportion of pricing points among recorded prices for good i at time t . This is the same regression as (17) but the dependent variable is the proportion of pricing points. For model 1, the proportion of pricing points is the lowest for high search intensity goods and lowest for middle search intensity goods; the results are significant at the 5% level. For model 2, the effect of search intensity is the same for the characteristics of share of expenditure and the high amount spent on a purchase, but is reversed for the frequency of purchases characteristic.³¹ A higher value of inflation, as measured by INF , increases the proportion of pricing points, but this effect is not significant at the 10% level. The explanatory power of regression (20) is about half of the explanatory power of regression (17). All in all, the relationship between search and the proportion of pricing points is weaker than between search and the probability of price changes.

A more important question, of course, is whether the relationship between search intensity and the probability and the size of price changes is affected if we control for the proportion of pricing points. To check this we add PPP_{it} to the right side of regression (17):

³⁰ Aucremanne and Dhyne (2004) also find a negative cross-sectional correlation between the frequency of price changes and the proportion of pricing points.

³¹ To conserve space, the regressions are not reported here. They are available from the authors on request.

$$\begin{aligned}
Prob_{it} = & \alpha_0 + \alpha_1 S^h + \alpha_2 S^m + \beta_1 INF_{it} + \beta_2 PPP_{it} + \bar{\gamma} \cdot \bar{T} + \bar{\delta} \cdot \bar{G} + \varepsilon_{it} \\
& 0.78^* \quad 0.12^{**} \quad 0.06^* \quad 1.84^* \quad 0.12^* \\
& (9.76) \quad (15.4) \quad (7.58) \quad (23.86) \quad (9.84)
\end{aligned} \tag{21}$$

The addition of the proportion of pricing points as an explanatory variable has little effect on the 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. But the explanatory power of the regressions is little changed (R^2 is 5% higher in regression (20) than in regression (17)). 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.

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 price data observed at regular intervals.

It is likely that 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 middle category in the amount spent classification are as predicted. The results are significant at the 5% level, except for the middle 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 consumer resistance leads to smaller and more frequent price changes. As buyers of frequently purchased goods are better informed and able to identify unfair price increases, customer resistance is more relevant for goods purchased frequently. 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.

7. An Explanation of Earlier Rejections.

The model in our paper is based on two elements: menu costs and search for the best price. Our test can therefore be viewed as a new, cross-sectional test of the menu cost model. Existing empirical studies are, almost exclusively, time-series tests of the relationship between inflation and the frequency and size of price changes.³² It is perhaps not widely perceived that some of these tests reject the menu cost model. Lach and Tsiddon (1992) analyze prices of several foodstuffs in Israel in 1978-79 and in 1982. The monthly inflation rate in the first period is 3.9%, in the second period is 7.3%, yet price changes become smaller in the latter period for four out of the 26 goods. Kashyap (1995) studies prices of catalogue items in the US over the period 1953-87. He divides the period into low inflation (pre-1968 and post-1982) and high inflation (1968-82). The average yearly inflation rate is 2.5% and 7.5%, respectively, yet for a majority of goods (6 out of 11) price changes are larger in the low inflation period.

The empirical results obtained from the cross-sectional analysis provide strong support for the menu cost model. As we argue in the Introduction, this may be due to the fact that pricing policies at the individual level are idiosyncratic but the differences average out over many goods. Figure 4 shows the average probability in 1992-96 of price changes for individual goods in each category, separately for each characteristic. It is clear that, on the average, the more active is search, the higher is the probability of price changes (with the exception of the "amount spent on single purchase" characteristic, discussed above). But this relationship is often reversed at the level of individual goods.

To test this more formally we consider the following experiment. Assume that a researcher has data for two randomly chosen goods. She then compares the frequency of price changes between goods in different search categories. In Table 5 we summarize the frequency with which this approach would lead to the rejection of our model at the standard 5% level, using a two-

³² Levy et al. (1997) and Owen and Trzepacz (2002) provide evidence on the effect on the frequency of price changes of differences in menu costs across firms, while Zbaracki et al. (2000) provide evidence on the effect of changes in menu costs over time.

sided test. We also provide the frequency with which the differences are not statistically significant. It is clear that rejections are frequent. For example there is a 20% chance that, for a randomly chosen good in the medium search intensity category significantly exceeds the probability for a randomly chosen good in the high search intensity category; the chance that the difference is not statistically significant is 26%.

Our results suggest that the within-category variation is larger than the across-category variation. As a result, while, in the aggregate, the data provide strong support for the model, its predictions are often rejected at the level of individual goods. This implies that tests of the menu-cost model when the data cover a single market (or a small number of markets) are not reliable and they should be done with large data sets.

8. 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, especially testing the cross-sectional predictions of our model. The Dominick data at Chicago GSB, the data sets used by Folkerstma (2001), Bils and Klenow (2004), Klenow and Kryvtsov (2003), Aucremanne and Dhyne (2004), Beaudry et al (2004) and Dias, Dias and Neves (2004), and 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.³³ 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, shown in Figure 2, demonstrate that it does a reasonable job at tracing the relationship between inflation and 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 and real, rather than aggregate and nominal 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.

Finally, 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 adopt the Calvo-Taylor time-contingent approach (see, for example, Chari, Kehoe and McGrattan, 2000 or Galí and Gertler, 1999). 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 is not justified and that the Calvo probability is an endogenous parameter.

³³ This problem may be the reason why Klenow and Kryvtsov (2003) are unable to identify state-contingent pricing policies in their data set.

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:

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

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

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

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 $\lim_{\sigma \rightarrow \infty} [(\sigma \ln \sigma - (\sigma^2 - 1)/2)] / (1 + \sigma)^2 = -1/2$, the LHS of (A1) becomes negative if

$(C/k + E[P] + MC)^2 - 2gm/b > 0$. 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:

$$F(\sigma, k) = 0. \text{ By the previous discussion, at the point where (11b) holds we have } \frac{\partial F(\sigma, k)}{\partial \sigma} < 0.$$

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

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

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:

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

where:

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

Define $h(\sigma) \equiv (\sigma - 1) / [(1 + \sigma) + 1 - \sigma]$. $h(\sigma)$ is positive, strictly decreasing and $\lim_{\sigma \rightarrow 1} h(\sigma) = 1$,

$\lim_{\sigma \rightarrow \infty} h(\sigma) = 0$. From (11c) $E[P] = h(\sigma)(C/k + MC)$. Combining this with (A3) we obtain that the equilibrium is a solution to:

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

The LHS of (A5) is a function of σ which is strictly quasiconcave and $\lim_{\sigma \rightarrow 1} [h(\sigma) + 1]/H(\sigma) = 0$;

$\lim_{\sigma \rightarrow \infty} [h(\sigma) + 1]/H(\sigma) = \sqrt{2}/2$. 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:

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

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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