The Timing of Purchases, Market Power, and Economic Fluctuations*

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Abstract

This paper analyzes a market in which sellers have market power and set price taking into account the ability of buyers to time their purchases. I demonstrate that expected fluctuations in demand are inherently fluctuations in the elasticity of demand, leading to smaller markups on the up-side of booms. Buyer intertemporal optimization opposes this force, generating real price stickiness and smoothing prices over time. These mechanisms produce prices which are less variable than quantitites, countercyclical markups, and greater persistence of demand shocks. Using industry data, I demonstrate that consumer goods for which timing is likely to be important do exhibit less real price response to demand-driven movements in sales.

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1. Introduction

All transactions are discrete– they occur at certain instants in time. Yet in most economic models, agents transact in every period or continuously, and do not choose the timing of discrete transactions.[1] This simplification leads to powerful insights, but it also obscures characteristics of markets in which the timing of transactions is important. Business cycles can be viewed as resulting from the temporal clustering of largely discrete decisions such as layoffs, purchases of durables, new product introductions, and plant retooling. Many recent models that explicitly allow agents to time transactions give new insights into business cycle phenomena.[2]

This paper analyzes a market with three characteristics. Sellers have market power, so that changes in the effective elasticity of demand can lead to changes in markups. Second, buyers choose when to make discrete, lumpy purchases. The combination of these two features separates the current model from both previous models of industry markup dynamics and models with fixed adjustment costs. Finally, the number of consumers who would like to purchase in each period fluctuates exogenously and predictably though time.

This structure captures realistic features of much of the economy. Most vendors have some discretion in setting price and demand does change in predictable ways. Every expenditure occurs at an instant in time, and all expenditures yield some lasting utility or service flow– consumers do not continuously purchase airline tickets, stereo components, clothes, haircuts, or even caffeinated beverages.

The dynamics of this market structure are unlike those which arise when markets are competitive, and also unlike those which arise when the timing of transactions is ignored. More generally, the focus on the timing of purchases has interesting implications for macroeconomic fluctuations.

First, fluctuations in the distribution of buyers waiting to buy represent changes in the elasticity of demand and thus lead to price variation. A firm considering decreasing its price weighs the lost profits on those buyers who would have purchased from it without the price change against the gain in sales made by encouraging more consumers to buy in the current period. The relative strength of the second effect at a given price is larger the faster demand is increasing. Thus when demand starts to rise, prices fall and sales are made sooner than if prices had not moved. These price movements increase sales and decrease markups at the beginnings of booms, while decreasing sales and increasing markups at the starts of slumps.

Second, the ability of buyers to delay or accelerate their purchases smooths prices. Sellers cannot raise prices relative to surrounding periods without losing sales. This "real price stickiness" arises because timing and durability amplify

[1] While many macroeconomic models, such as q-theory or consumption theory, focus on the optimal intertemporal allocation of purchases, every agent in such models transacts in every period or at every instant.

[2] See, for example, Caballero and Hammour (1994), Caballero, Engel and Haltiwanger (1995), Mortensen (1994), and Diamond (1994).

effective intertemporal substitution by buyers.[3] With increasing marginal costs, real price stickiness leads naturally to a countercyclical markup.

Third, this model offers an explanation for why quantities rather than prices seem to adjust over the business cycle. Time periods are not separate markets, each clearing independently. High prices in one period cause buyers to move transactions to nearby periods, so that the elasticity of demand is highly dependent on local price variation. On the other side of the market, sellers may choose not to decrease their prices much when demand is low because to do so would steal from their own future sales relative to a market in which timing is not a choice. Both buyer and seller behavior stop price variation from damping quantity fluctuations.

Finally, the price fluctuation that does occur reduces the volatility of sales relative to the fluctuations which a constant price would induce.[4] The timing of transactions thus creates a natural propagation mechanism. In a transitory boom, prices increase slightly and many buyers postpone purchases, increasing demand in later periods. Thus a shock in a single period is spread out over several periods.

After presenting a formal dynamic model, I demonstrate that industry pricing behavior is consistent with the model's implications. Measures of the frequency at which households purchase good are obtained for a subset of four-digit manufacturing industries which correspond well to specific consumer goods. Using the NBER productivity database and demand instruments, the following implication of the model is confirmed. Demand-driven increases in sales cause smaller real price increases for those goods which are purchased less frequently– that is, for which the timing of purchases is more important. In addition to smaller price responses to demand fluctuations, the model predicts that markups vary more countercyclically in industries where the timing of purchases is more important. Analysis of industry-level markups, however, is not informative due to large standard errors and unstable coefficients.

The balance of the paper is laid out as follows. In the next section, I present a model in which buyers are price-takers and optimally time their purchases of a lumpy good. Optimal seller and buyer strategies are studied when the market structure is monopolistically competitive and when it is monopolistic (under collusion). Sections 3 and 4 characterize the dynamics of prices, costs, and sales when there are fluctuations in the distribution of consumers. In section 5, I relate this theory of countercyclical markups to competing theories. Section 6 turns to industry-level data and tests the basic implications of the theory against other theories. The final section concludes and appendixes contain proofs and additional information on the data.

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[3] As will be discussed later, real price stickiness has very different implications from either real price rigidity, which occurs when firms' objective functions are flat-topped, or price stickiness, which occurs when nominal prices cannot adjust.

[4] As noted by Caballero (1993) and Bils and Klenow (1995) durable goods indeed seem to fluctuate less than would be predicted based on changes in nondurable consumption; however both of these papers interpret this as due solely to adjustment costs.

2. The Market Structure

This section presents the buyer and seller optimization problems, and discusses the necessary conditions for equilibrium. In the model, a large number of consumers search over the prices offered by a large number of sellers. Search by consumers generates market power, in a similar manner to the steady state analysis in Diamond (1971).

2.1. Consumers

The demand side of the market consists of a large number of potential buyers or consumers.[5] Each consumer has some amount of a good which depreciates deterministically through time. The good is lumpy, and consumers decide *when* to buy, not *how much* to buy. The good provides lasting utility or profit flow because it is a durable good or capital investment, because it must be bought "bundled" in a fixed quantity and is storable (like table salt), or because its consumption yields a stock which depreciates through time and gives a flow of utility (like expenditures on entertainment).

Consumers are price takers and decide when to purchase a single new good. After purchasing the good, consumers leave the market. There are large transactions costs: a buyer who upgrades to a new good gets nothing for its old good.[6] Consumers are differentiated by their individual stocks in any period, denoted k_{it}, that depreciate deterministically according to:[7]

$$k_{it} = (1 - \tilde{\delta})k_{it-1}. \tag{2.1}$$

The money-metric utility (or profit) flow from the stock of the good is logarithmic and additively separable from other goods,

$$u_{it} = \frac{1}{\lambda}\ln(k_{it}), \tag{2.2}$$

where λ is the marginal utility of wealth.[8] An individual's utility flow evolves according to:

$$u_{it+1} = u_{it} - \delta \tag{2.3}$$

where $\delta = -\frac{1}{\lambda}\ln(1 - \tilde{\delta}) \simeq \frac{\tilde{\delta}}{\lambda}$.

[5] Although I use the term consumers, the potential buyers may be firms considering purchasing new investment goods as well as households seeking to purchase consumer goods.

[6] This assumption can be relaxed without changing the substance of the results.

[7] I denote an individual consumer's or seller's stock, price, or sales using lower case letters, and market prices and quantities using capitals.

[8] The model can be generalized by using a constant relative risk aversion utility function at significant cost in tractibility. Similarly, deterministic decline in the marginal utility of wealth changes none of the main implications.

In every period, each consumer, i, observes the price of one randomly drawn seller, j, but does not automatically observe the price of any other seller. The consumer then chooses among the following three options. First, it can purchase the good at the posted price. In this case the consumer pays p_{jt} and receives v, which represents the dollar-denominated expected present discounted value of holding a new good.[9] Second, the consumer can choose to do nothing, in which case it receives the benefits of its current stock, and, in the next period, faces the same decision with the price of a new randomly drawn seller. Finally, it can pay a search cost c, and observe the price of a new randomly drawn seller.[10] It then faces the same decision again in the current period: purchase, wait, or continue searching.[11]

Each period thus consists of an infinite number of instants in which consumers can choose to search over prices/goods. If a buyer is intent on purchasing in a given period, it can visit as many sellers (and pay as much in search costs) as it wishes within a single period.

Prior to searching, consumers know the distribution of prices posted by sellers, and the payment of search costs yields only information about a specific seller's price. Thus, if a consumer ever prefers searching to delaying, it searches in the current period until it finds an acceptable price and purchases.[12] Consequently, once any potential buyer chooses to search, the problem is a stationary search problem and consumers search across firms until they find a price below their reservation price. The value to a buyer of having found price p_{jt} can be written recursively as:

$$V^s(p_{jt}) = Max\{v - p_{jt}\ , E_t[V^s(p_{kt})] - c\}. \tag{2.4}$$

The value to searching is the maximum of the value of buying at the current price, or paying c and going to a new seller and discovering its price.

The value of a consumer with a utility flow of u who sees a price offer of p_{jt}

[9] An earlier version of this paper explicitly included a stochastic, match-specific value of a new good, v_{ij}. In this case, some buyers search across goods in each period and the model exhibits the same set of implications as those presented here.

One might more realistically motivate a constant v by arguing that buyers actually return to the market (at the top of their adjustment bands in an (s, S) type model) but that all buyers have an expected holding time and future purchase prices which are independent of the current state of the system. This assumption would be close to true with a significant amount of individual uncertainty and little predictable variation in price at long horizons.

[10] Search costs correspond to the costs a consumer incurs in test-driving an automobile or in going to a store and pricing its goods; similarly a firm incurs a cost when it evaluates how well a given seller's equipment meshes with its other capital goods and its employees' skills and needs.

[11] Since all heterogeneity in firms occurs in their effective price, I am implicitly assuming that whatever differences there are in match quality are compensated through price adjustment. So, for example, if a firm chooses to produce tractors of low quality, consumers compensate by purchasing warranties, or paying for additional features or equipment which make these tractors equivalent to those of other firms.

[12] That is, if the value of searching exceeds the value of delaying, it does so after one round of search or any number, since search costs paid while searching are sunk.

can now be written recursively as:

$$V_t(u, p_{jt}) = Max\{v - p_{jt} \ , u + \beta E_t[V_{t+1}(u - \delta, p_{kt+1})] \ , E_t[V^s(p_{kt})] - c\} \tag{2.5}$$

where β is the consumer's discount factor. Equation (2.5) says that the value of having utility flow u in period t, and seeing the price of one good, p_{jt}, is equal to the maximum of 1) the value of purchasing at the observed price, 2) the expected value of delaying the decision by one period, and 3) the expected value of deciding to purchase in t, but doing some searching over prices first. Since consumers always end search by purchasing, henceforth entering the search mode is called purchasing.

Prices are bounded below so that the value function is bounded above for a positive depreciation rate and discount rate less than one.[13] Further, the value function is decreasing in its first argument, which decreases through time. Thus, provided the first term is always positive, a finite purchase time is optimal. Note that the value function is a function of time– the buyer's optimal purchase date depends on the price path that it faces. The time-path of prices in turn depends on the true state of the system: the entire distribution of consumers over utility flows. In solving the model below, I look at cyclical equilibria, so that there are a finite number of value functions to solve.

In every period, each firm is randomly matched with a slice of consumers distributed according to $f_t(u)$. Let u_t^+ denote the utility flow of the buyer with the least amount of the good in the market at the beginning of period t. The function $f_0(u)$ is assumed to be continuous, atomless, bounded above, and strictly positive over $[u_t^+, \bar{u}]$. The distribution evolution according to:

$$f_t(u) = \begin{pmatrix} f_{t-1}(u + \delta t) + g_t(u) & \bar{u} \geq u \geq u_t^+ \\ 0 & \text{otherwise} \end{pmatrix} \tag{2.6}$$

where $g_t(u)$ is deterministic and strictly positive only over $[\bar{u} - \delta, \bar{u}]$.[14]

The evolution of u_t^+ follows from consumer optimization.

2.2. Sellers

There are an infinite number of identical sellers along the unit interval. Each seller posts a price in each period and sells to those consumers who arrive and have reservation prices above the seller's posted price. I restrict attention to symmetric Nash equilibria, so that each firm takes the market price as given. The search process gives each seller some market power. That there are an infinite number of

[13] Marginal costs are assumed to be weakly increasing so that prices are bounded below by marginal cost when producing the first increment of output. The facts that utility flow depreciates linearly and firms discount future profits exponentially are sufficient but far from necessary to generate bounded returns in this setup.

[14] In reality, these fluctuations are likely to be driven partly by the history of the market. The function $g_t(u)$ provides a boundary condition for the distribution.

sellers means that each one ignores the impact of its own price setting on its future sales. That is, there is a problem of the commons. Like competition for a natural resource, seller competition leads to rapid depletion of potential consumers. If firms colluded, they would choose to have higher prices and sell to all consumers at later dates. Since the dynamic implications differ, an analysis of equilibria in which firms collude is presented in section 4.

Sellers choose a sequence of prices, $\{p_{js}\}$, to maximize:

$$\sum_{s=t}^{\infty} R^{t-s} E_t \left[p_{js} q_s(p_{js}, P_s) - c_1 q_s(p_{js}, P_s) - \frac{1}{2} c_2 q_s(p_{js}, P_s)^2 \right] \tag{2.7}$$

taking the market price, P_s, as given. The function $q_s(p, P)$ is the amount of sales that a seller charging p makes in period s when the market price is P. This function is determined by the distribution of potential consumers and their optimal strategies. c_1 and c_2 represent quadratic costs of production, both of which are weakly positive.[15] Equation (2.7) reduces to a sequence of static problems in which sellers choose individual prices, taking present, past, and future market prices as given. The first order condition can be written as an inverse elasticity pricing rule:

$$\frac{p_{js} - c_1 - c_2 q_s(p_{js}, P_s)}{p_{js}} = \frac{1}{\epsilon_s^d(p_{js}, P_s)}, \tag{2.8}$$

where $\epsilon_s^d(p_{js}, P_s) \equiv -\frac{\partial q_s(p_{js}, P_s)}{\partial p_{js}} \frac{p_{js}}{q_s(p_{js}, P_s)}$, the elasticity of firm demand given the market price.

2.3. Market Equilibrium

Finding an equilibrium amounts to finding the series of functions $q_t(p, P)$ which follows from buyer optimization given rational price expectations. This is done based on a series of lemmas.

Define u_t^* as the utility flow of the buyer with the smallest stock of the good after sales have been made in period t. Then by equation (2.3)

$$u_{t+1}^+ = u_t^* - \delta. \tag{2.9}$$

Lemma 1. *No search. In a symmetric equilibrium, no consumers search and*

$$V_t(u, p_{jt}) = Max\{u + \beta E_t[V_{t+1}(u - \delta, P_{t+1})] \ , v - p_{jt}\} \tag{2.10}$$

The proofs of all lemmas are contained in Appendix A. Since in every period all firms charge the same price, any search has a total expected gain of minus the search cost. Define T_{tj} as the expected purchase date of consumer j conditional on information available at time t.

[15] The problem could also contain fixed costs to entry and fixed costs in each period, both of which would determine market size and ensure that sellers not make net profits in excess of the usual rate of return. These costs are not relevant to the analysis at hand and are ignored.

Lemma 2. *Skimming property.* $u_{ti} > u_{tj}$ *implies* $T_{ti} \leq T_{tj}$.

This lemma follows from a revealed preference argument, which demonstrates that the value function is weakly increasing in its first argument. Lemma 2 implies that sales in any period can be calculated by finding the buyer who is indifferent between purchasing and waiting, and then summing over consumers with lower utility flows.

Lemma 3. u_t^* *evolution. Provided that sellers sell to some consumers in every period,* u_t^* *is defined by*

$$u_t^* = (1-\beta)v + \beta E_t\left[P_{t+1}\right] - P_t \tag{2.11}$$

Equation (2.11) is derived from equation (2.10) by noting that the marginal consumers today will buy tomorrow, and, therefore, that their expected value to delaying is the expected utility of purchasing in the next period.

Lemma 4. *Positive sales. If* $q_0 > 0$*, and* $p_t \geq c_1\ \forall t$*, then* $q_t > 0\ \forall t$.

Weak conditions are needed to imply positive sales and to insure that equation (2.11) holds in all periods. Lemmas 3 and 4 together imply that equation (2.11) gives u_t^* and allow derivation of $q_t(p_t, P_t)$.

First, if all sellers are charging P_t, then, for every seller the quantity of sales is the integral of the buyer distribution from u_t^+ to u_t^*:

$$Q_t(P_t) \equiv \int_{u_t^+}^{(1-\beta)v+\beta E_t[P_{t+1}]-P_t} f_t(u)du. \tag{2.12}$$

Now consider a seller who deviates from the market price. If the seller cuts price, then it sells to a larger share of the consumers who see its price in the current period. However, it gains no sales from other sellers since no consumer finds it worth searching across such a large number of sellers when it knows only one seller has cut its price. Thus for all price cuts:

$$q_{jt}(p_{jt}, P_t) \equiv \int_{u_t^+}^{(1-\beta)v+\beta E_t[P_{t+1}]-p_{jt}} f_t(u)du. \tag{2.13}$$

For price increases, the seller may lose some of its customers. However, as long as the price increase is smaller than c, no one leaves the seller to search, although some consumers may decide to delay purchase rather than buy or search. Thus, equation (2.13) determines demand for $p_{jt} \in [c_1, P_t + c)$; for higher prices, demand is zero. Note that $q_{jt}(P_t, P_t) = Q_t(P_t)$.

Given a set $\left(f_0(u),\ u_0^+,\ \{g_s(u)\}_{t=0}^{\infty}\right)$, an equilibrium is a series $\{P_s, u_s^+\}_{t=0}^{\infty}$ which satisfies the following.

1. Consumers choose optimally whether to search and when to buy, so combining equations (2.9) and (2.11) yields:

$$u_t^+ = (1-\beta)v + \beta E_t\left[P_{t+1}\right] - P_t - \delta. \tag{2.14}$$

2. The forcing term evolves according to equation (2.6).
3. P_t represents a global profit maximum for each firm.
4. $E_{t-s}[P_t] = P_t$ for all $s \geq 0$.
5. Each seller optimizes, so that its first-order condition, which is the following nonlinear difference equation in prices, is satisfied:

$$P_t - c_1 - c_2 \int_{u_t^+}^{(1-\beta)v+\beta E_t[P_{t+1}]-P_t} f_t(u)du = \frac{\int_{u_t^+}^{(1-\beta)v+\beta E_t[P_{t+1}]-P_t} f_t(u)du}{f_t((1-\beta)v + \beta E_t\left[P_{t+1}\right] - P_t)}. \tag{2.15}$$

In equation (2.15), the integral terms are the market quantity sold in period t, and the right-hand-side is the negative inverse of the elasticity of demand. Note that, in choosing prices, firms take taking u_t^+, P_t , and $E_t\left[P_{t+1}\right]$ as given, and that the first-order condition is evaluated at the market price. Together conditions $1-5$ are necessary and sufficient for a sequence of prices and lowest utility flows (u^+) to constitute an equilibrium.

Two main features of the equilibrium conditions drive interesting market dynamics. First, in equation (2.15), given a quantity of sales in t, the higher the density of consumers who are indifferent between purchasing in t and $t+1$ (the denominator of the right-hand side), the lower is the markup. That is, when the distribution of consumers is increasing, the markup is likely to be lower, and consumers will purchase sooner than if markup were held constant. Second, the quantity of sales is determined relative to the expected market price in the next period. Sellers are unable to sell if today's price is set much above future prices. Nor is it feasible to plan to price well below future prices since, given such a planned future price, consumers who might choose to buy in $t+1$ instead buy in t. In this case, sellers would end up having to cut future prices to satisfy their first order conditions and to sell to any consumers in $t+1$.

3. Properties of Dynamic Equilibria

3.1. The Steady State

The steady state of the system is defined as those constant quantities and prices that solve conditions 1 through 5 when the distribution of consumers over stocks is flat and evolves deterministically. Let α be the height of the distribution of consumers over utility flows, i.e. $f_t(u) = \alpha\ \forall t$.

Lemma 5. *Steady state equilibrium.* The steady state is uniquely determined by:

$$\begin{aligned} P_{ss} &= c_1 + c_2\alpha\delta + \delta \\ u^+_{ss} &= (1-\beta)(v - P_{ss}) - \delta \\ Q_{ss} &= \alpha\delta. \end{aligned} \tag{3.1}$$

The steady state quantity sold depends solely on the number of consumers at each point in the distribution and the speed at which consumers' utility flows depreciate. Note that the equilibrium markup rises with the depreciation rate.

3.2. Equilibrium and the Coase Conjecture

In this model, as the length of a time period goes to zero, the markup goes to zero (in equation (3.1), this amounts to letting δ go to zero).[16] This result follows from the same intuition as the well-known Coase (1972) conjecture.[17] Sellers cannot commit to keeping price high, so that as time periods become shorter, and follow one another more quickly, firms eventually sell to customers so rapidly that they run out of customers to sell to in any given interval of real time, and price falls to marginal cost.[18] However, this feature of the model results from assumptions made to preserve the tractability of the dynamic solutions rather then from the economics of the problem. More specifically, either a model in continuous time with a matching function or one in which search, rather than costing c, took a fixed amount of real time, would preserve the dynamics of interest and be immune to a Coase critique.

3.3. Demand Fluctuations with Constant Marginal Cost

For general sequences of $\{g_t(u)\}$ the solutions to the difference equations (2.6), (2.14) and (2.15) are difficult to characterize even numerically. Moreover, the system may exhibit multiple solutions to these conditions.[19] While there may be

[16] Despite the fact that the size of the markup goes to zero as the length of a period goes to zero, the percent fluctuation in the markup over the cycle remains constant.

[17] See Bulow (1982)and Stokey (1981) for proofs and discussion of the robustness of the Coase conjecture. Depreciation can eliminate this result, see Hamilton (1996).

[18] Another way of looking at this thought experiment is that as the length of a time period goes to zero, fewer and fewer buyers purchase in any given period, so that sellers no longer worry about losing profits on their inframarginal customers. It is the presence of inframarginal customers which generates markups.

[19] This possibility arises from the complexity of the nonlinear difference equations being solved (in addition to being nonlinear, equation (2.15) contains values of the state variable inside the forcing function) and from the lack of restriction on the demand curve in each period. The latter difficulty is endemic to market analysis, and most research eliminates the possibility by assuming a nice functional form for the demand curve. Since the demand curve in the current work depends crucially on past actions as well as the input specification, the more flexible approach of examining each case is chosen.

interesting economic implications of multiple equilibria in this dynamic system, this is left to later research. For now, to characterize the interesting features of equilibrium market dynamics, a solution to conditions $1 - 5$ is found for a distribution of utility flows over consumers, $f_t(u)$, that has infinitely repeating, deterministic cycles. That is, in solving the model, $f_0(u)$ is chosen to be periodic, and equilibrium price and quantity dynamics are found with the same period. I use a multiple shooting technique to find a series of prices and cutoff utility flows that satisfy the equilibrium conditions, taking the steady-state values as the starting points for this search process.[20] The distribution of consumers over stocks is taken to be a square wave. When interpreting the cycles, one must keep in mind that since these solutions assume certainty, one should only extrapolate to implications for expected economic fluctuations.

Figures $1A$, $1B$, and $1C$ display the results of a typical simulation when firms have constant marginal costs.[21] The figures demonstrate that price is set in part according to the change in the height of the distribution. That is, when a large "lump" of consumers gets near to buying, price declines and quantity sold increases. This effect causes a reduced markup on the up-side of booms.[22] Further, notice that this effect also drives down the price and quantity immediately before the boom. Consumers know that the price will fall in period 2, so they substitute towards that period; sellers respond by cutting price in period 1. Thus consumer optimization smooths price. Here, the sharp change in elasticity caused by the fluctuation in the distribution fights the price-smoothing effect of buyer intertemporal optimization. The upshot is that immediately before the boom, there is a "recession amplifier" as consumers delay purchasing to take advantage of the lower prices at the beginning of the boom.

A similar set of factors act at the end of the boom to amplify the end of the boom, as consumers substitute away from the high prices that occur at the beginning of the recession. After the recession begins, consumers have just been waiting to purchase and many have low stocks (Figure $1C$). Thus price declines only slowly due to the presence of fewer inframarginal consumers at the start of the low-demand time.

3.4. Demand Fluctuations with Increasing Marginal Cost

The second simulation employs the same cycling distribution of consumers over utility flows, but now considers sellers with increasing marginal costs. Figures $2A$ through $2D$ display the results of a typical simulation.

[20] See Judd (1993) for description of multiple shooting techniques. The program checks that all local optima for sellers are global optima, and also, for robustness, that quantity is weakly positive in every period.

[21] Due to the stylized nature of the model, the model is not calibrated beyond setting the parameters so price exceeds marginal cost by 15 to 20 percent in all of the simulations.

[22] I would argue that it is exactly this effect which leads retailers to offer pre-season sales on seasonal items, such as clothing.

Three points can be taken from this experiment. First, the price-smoothing effect of consumer intertemporal optimization is much more powerful than the price responses of firms to changes in the height of the distribution. The price changes analyzed above are still present, however, and are visible in the asymmetry of the figures. Thus, in this case, sharp swings in the distribution are not necessary to get significant changes in markups and the timing of sales.

Second, the main effect of increasing marginal cost is to increase price in booms and therefore decrease quantity and smooth sales over the cycle. This effect generates propagation of increases in demand. All buyers postpone (or accelerate) purchase slightly so as to move towards lower-price periods.

Third, intertemporal substitution by consumers robs firms of their market power during booms. Buyers are less willing to purchase because past and future prices are lower. This substitution by consumers causes a reduction in the markup when sales are high.[23] Figure $2C$, shows u^+, the utility flow for the buyer with the lowest utility flow. Immediately before the boom, u^+ rises as consumers buy earlier than they would have if prices had stayed constant. Thus when the boom begins, sellers find themselves facing consumers who have higher amounts of their old goods left. In competing to sell to these consumers, firms lower their markups. Sellers only slowly increase their prices once in the boom, as u^+ falls towards its equilibrium level. Inversely, at the end of the boom, consumers delay their purchases, and this decreases prices before the end of the boom and smooths the price and quantity fluctuation on the downside.

To summarize the implications of these two computational experiments, in markets in which the timing of purchases is important: 1) when marginal costs are flat, prices and markups should be low when quantity increases at the beginning of booms; 2) when marginal costs are increasing, booms should be smoothed and markups should be countercyclical.

4. Properties of Dynamic Collusive Equilibria

4.1. Sellers

When sellers are able to collude, total profits are maximized by the sequence of prices which would be chosen by a monopolist who owned all the firms.[24] One can write this recursively as:

[23] Because the costs of production are quadratic, the ratio of price to marginal cost declines in steady state with increases in the height of the distribution. Since this is not novel nor the interesting source of markup cyclicality in this paper, I report price less marginal cost as the markup.

[24] I continue to assume that the colluding firms or monopolist take $E_t[P_{t+1}]$ as given when choosing P_t, as is standard. See for example Bils (1989). However, using a self-punishment scheme, it may be possible for firms to rationally internalize the effects of changes in today's price on consumer expectations of tomorrow's price. See Hamilton (1996).

$$V_t(u_t^+) \equiv \max_{\{P_t\}} \left(P_t q_t(P_t, P_t) - c_1 q_t(P_t, P_t) - \frac{1}{2} c_2 q_t(P_t, P_t)^2 + R^{-1} E_t \left[V_{t+1}(u_{t+1}^+) \right] \right). \tag{4.1}$$

However, it may not be possible to maintain this optimal level of collusion.[25] If a firm deviates from the prescribed price sequence, it will cut price and try to steal consumers from the future demand of all firms. The usual punishment strategy involves all other firms setting prices to punish the defector in the subsequent period. Here however the optimal collusive arrangement can be maintained by subsequent pricing that makes the one-period payoff to defecting zero in the period of defection. After seeing any price below the collusive price, all firms choose the largest price that makes any consumers who purchased from the defector wish that they had not. In equilibrium, these consumers therefore would not. Subsequently, the firms all return to collusion.[26] As long as periods are not so far apart that these prices must be very different, collusion can be maintained.[27]

Using the first-order condition and the envelope condition yields the following intertemporal Euler equation which is satisfied in the collusive equilibrium:

$$q_t(P_t, P_t) + R^{-1} E_t \left[(P_{t+1} - c_1 - c_2 q_{t+1}(P_{t+1}, P_{t+1})) \frac{dq_{t+1}}{dP_t} \right] = (P_t - c_1 - c_2 q_t(P_t, P_t)) \frac{-dq_t}{dP_t}.$$

When the firms consider a price increase they balance the additional return on the inframarginal buyers, $q_t(P_t, P_t)$ and the gain in profits on increased sales in $t+1$ against the decrease in profit from lost sales in the current period.

4.2. Market Equilibrium

Lemmas $1-3$ still apply when firms are colluding, but firms may choose sales equal to zero.[28] Rather than keep track of these corner solutions, attention is restricted to fluctuations in demand that generate positive sales in every period.

Equation (2.12) determines quantity, so that the firm's first-order conditions can be rewritten to replace condition 5 as:

$$\begin{aligned} -R^{-1} \left[E_t[P_{t+1}] - c_1 - c_2 E_t[Q_{t+1}(P_{t+1})] \right] & + \left[P_t - c_1 - c_2 Q_t(P_t) \right] \\ &= \frac{Q_t(P_t)}{f_t((1-\beta)v + \beta E_t \left[P_{t+1} \right] - P_t)}, \end{aligned} \tag{4.2}$$

[25] Indeed, Rotemberg and Saloner (1986) argue that difficulty in maintaining collusion during booms causes prices to fall from monopolistic levels and leads to countercyclical markups.

[26] Note that this equilibrium is not renegotiation-proof.

[27] I would argue that this is why collusion is possible in industries like the airline industry where the timing of purchases is important.

[28] While existence is still assured, the firm first-order condition does not hold in periods of zero sales.

which uses the fact that:

$$\frac{dQ_t(P_t)}{dP_t} = -f_t(u_t^*) = -f_{t+1}(u_t^* - \delta) = -f_{t+1}(u_{t+1}^+) = -\frac{dQ_{t+1}}{dP_t}. \tag{4.3}$$

The first equality comes from equation (2.12), the second from equation (2.6), the third from equation (2.9), the final one from equation (2.12).

4.3. The Steady State

When sellers are colluding the steady state price, quantity and cutoff utility flow are:[29]

$$\begin{aligned} P_{ss} &= c_1 + c_2\alpha\delta + \frac{\delta}{1 - R^{-1}} \\ u_{ss}^+ &= (1-\beta)(v - P_{ss}) - \delta \\ Q_{ss} &= \alpha\delta. \end{aligned} \tag{4.4}$$

As in the noncollusive case, the steady-state markup would go to zero if time periods were made infinitely fine.[30]

When firms collude and have constant marginal cost, prices are almost constant in the face of demand fluctuations. Colluding firms internalize the effect of price changes today on sales tomorrow. Firms do not have an incentive to cut prices to steal sales from their competitors' pool of potential future sales. Thus both firms and consumers seek to smooth prices, so that prices are effectively flat in this scenario.[31]

4.4. Demand Fluctuations with Increasing Marginal Cost

Figures $3A$ to $3D$ display the results of a typical simulation when colluding firms have increasing marginal costs.[32] In this case, buyer intertemporal optimization acts to smooth price and quantity fluctuations. Sellers, on the other hand, try to keep markups roughly constant. They are willing to cut margins at the beginning

[29] As in Lemma 5, the steady state is unique. The proof follows exactly that of Lemma 5.

[30] In the context of this analysis, depreciation is proportional to the product of real economic depreciation and the magnitude of the per-period utility flow. Letting ∂t be the length of a period, real economic depreciation, $\widetilde{\delta}$, goes to zero at the same rate as ∂t. The foregone utility flow from delaying purchase for a period, which is proportional to utility flow, u, goes to zero at the same rate as ∂t. The second effect is the essence of the Coase conjecture, and without it, price would exceed marginal cost in the limit. As it is however, $\frac{\delta}{1-R^{-1}} = \frac{\delta}{r}(1+r) \to 0$ at rate ∂t, since $r \to 0$ at rate ∂t and $\delta \to 0$ at rate $(\partial t)^2$.

[31] Colluding firms seek to shift sales forward because sales today are worth more than future sales, and, if demand is increasing, because inframarginal sales are less important than marginal sales. This does lead to some small price variation over a cycle, but it is more than an order of magnitude smaller than that of the other simulations.

[32] Domowitz, Hubbard and Petersen (1987) also examine this case and argue that it implies a countercyclical markup.

of the boom, however, since getting buyers to buy early helps to keep costs lower. Firms also raise prices at the end of the boom because losing some buyers to the future helps to keep costs low. Thus, this market structure predicts that markups should be lowest at the start of booms, when demand is increasing, as in the first case analyzed. Price and quantity dynamics mimic the dynamics of the noncollusive case with increasing marginal costs: prices rise in booms and quantity fluctuations are smoothed and propagated.

5. Related Models of Markups and Durable Goods

Both Conlisk, Gerstner and Sobel (1984) and Domowitz et al. (1987) present models similar in spirit to the current model in that demand is shifted and markups are countercyclical. In Conlisk et al. (1984), however, demand cannot be shifted forward and firms do not compete for sales. Rather two sorts of consumers enter the market every period. A monopolist sells to desperate consumers in every period, by never lowering price too fast. Then, every so often, price gets down to the reservation price of the low-demand consumers, who have been piling up unsatiated in the market, and all consumers buy. In the next period, price jumps up to the reservation price of the desperate consumers and sales are only to the desperate consumers as price slowly declines again. This model thus has endogenous cycles, countercyclical markups, and the shifting of sales, but through a monopolist's optimal strategy rather than intertemporal competition for consumers.

Domowitz et al. (1987) explore similar issues in the context of a two-period model of a monopolist. In their model, markups are countercyclical because the monopolist does not want to cut prices when demand is low, since it can make the sales later. This dynamic is most similar to the price smoothing case examined in the previous section.

Before moving to testing the importance of this model for price and markup dynamics I contrast its predictions with the four main alternative models of countercyclical markups. First, and most closely related are customer market models, as in Phelps and Winter (1970) and Bils (1989). In such models, firms have repeat customers, for whom interfirm competition is weak, and potential new customers, for whom interfirm competition is strong. When new customers are relatively more important than repeat customers— that is when demand is increasing— markups are low. This pricing behavior does not shift demand. Chevalier and Scharfstein (1994) analyze a variant of this model in which firms also face cash constraints and thus increase margins when cash flow is low. Markups are high when demand is low, and, again, the timing of demand fluctuations is unchanged. Thus, the basic predictions for the dynamics of sales and markups in the customer market are the same as for the timing model. However, the key difference is that the customer market story should apply to markets in which repeat purchases and switching costs are important, such as in the supermarket industry which Chevalier and

Scharfstein (1994) analyze. The timing model predicts these dynamics in markets in which timing is key.

Second, Rotemberg and Saloner (1986) and Rotemberg and Woodford (1991) argue that implicit collusion among firms becomes more difficult when the size of profits in the present are greater than profits in the future. In order to maintain cooperation among firms, margins are therefore lowest when demand is decreasing. This model has the opposite implication from the timing model, and is more likely to apply to highly concentrated markets.

Third, Bils (1991) models a market for durables in which high-income consumers are the marginal consumers deciding whether to purchase the good in recessions, while middle-income consumers are the marginal consumers in booms. Since there are far more middle-income consumers, the elasticity of demand is higher in booms, and therefore markups lower. While this model predicts that durable goods should have more countercyclical markups, it does not incorporate the effect of durability on the consumer side of the market. Further, there are many degrees of luxuriousness in durables and the relative importance of marginal purchasers may well be reversed for goods besides the most luxurious.

Finally, perhaps the most widespread theory of countercyclical markups comes from models of *nominal* price stickiness. In these models prices do not increase when demand increases due to costs of changing nominal prices. Such models generally require real rigidities– small profit losses to small deviations of price from its optimal level– and nominal rigidities– small costs of changing prices. Considering timing makes the *real* price sticky. That is, if firms were to charge prices much above expected future prices, buyers would delay purchases. Small deviations of prices from expected future prices can be very costly. Thus the real price is tightly constrained and will not be allowed to stray far from its optimal level. That is, real price *rigidity* is reduced by real price *stickiness*. With cyclical changes in the general price level, if the timing model applies to an industry, small costs of changing prices are less likely to have real effects and cause countercyclical markups.

6. Empirical Evidence

In this section, I quantify the importance of the dynamics derived from the theoretical model. Using industry data on prices, sales, and markups, I test the three main hypotheses taken from the model simulations. In industries that sell goods for which the ability of buyers to time their purchases is important: 1) price reactions to demand fluctuations are small (since buyer intertemporal optimization smooths prices); 2) when sales are increasing, prices and markups should be low (according to the first and third simulations); 3) markups should be countercyclical (when marginal costs are increasing).

6.1. The Data

The main dataset employed is the National Bureau of Economic Research (NBER) productivity database, which contains annual data on industry inputs, sales, and prices at the level of the four-digit SIC code. The dataset covers 450 industries from 1958 to 1991. Its strength is careful attention to temporal consistency of industry and variable definitions. It includes measures of industry sales and inputs– including intermediate goods and raw materials– and price deflators for all inputs except the capital stock, where instead the database includes a deflator for new industry investment. Labor input is decomposed into production worker hours and nonproduction worker employment. Appendix B contains further details on the data.

The second set of data comes from Bils and Klenow (1995). They report durability measures taken from the Bureau of Economic Analysis (BEA) and insurance company estimates which can be easily matched to the output of industries classified by four-digit SIC. This measure of durability is an imperfect measure of the concept of interest: how easily consumers can shift the purchase of a good through time. Bils and Klenow (1995) also use the Consumer Expenditure Survey (CEX) to construct Engel curves by good/industry for the same industries. However, they have difficulties with missing data, because many households in the data do not purchase every good. They report these fractions, which for their work represent a nuisance. For the present tests however these data are another imperfect measure of the concept of interest. From the reported statistics, I construct a variable that represents the percent of households which do not purchase a given good during a one year period.[33] There is a high correlation between these two measures. For example, motorcycles are not purchased by 99 percent of households, refrigerators and freezers by 92 percent, and blinds and shades by 91 percent. Tables **??** and B.2 in Appendix B give the industry names, SIC codes, frequency of purchase and durability measures.

After eliminating industries for which frequency and durability data are not available, there are 109 industries.[34] Due to a large number of outliers in the first year, I use data from 1959 to 1991 on each industry, leaving a total of 3597 observations.

Third, measures of industry four-firm concentration ratios are used to capture differences in cyclicality which are due to market power. Rotemberg and Saloner (1986), as discussed, argue that collusion plays an important role in price smoothing. The data are at the 2-digit SIC level and are based on 1967 data, which is roughly the middle of the sample. The data, taken from Rotemberg and Woodford (1991), are reported in Appendix B.

[33] I set the number to 0 for all nondurable industries (and also use a 0 for the measure of durability).

[34] These industries include all subindustries of SIC codes 20 and 21, which are nondurable industries, and those set of industries employed by Bils and Klenow (1995).

Finally, in order to capture the demand-driven fluctuations in sales, I use the now standard Hall-Ramey instruments: a dummy for the political party of the U.S. President, real Federal government defense spending, and the price of oil deflated by the GDP deflator. As discussed subsequently, I use these instruments interacted with the cross-industry measure of durability.

6.2. Testing Price Smoothness and Dynamics

In order to be able test whether prices are lower when demand is high, all regressions are performed in levels after log-detrending each time-varying series separately for each industry.[35] This procedure also has the advantage of removing fixed industry effects which might be correlated with the dependent variables. Since there is substantial industry-level serial correlation, all standard errors are calculated so as to be consistent in the presence of arbitrary serial correlation as:

$$(X'X)^{-1}(\sum_{j=1}^{J} X_j' e_j e_j' X_j)(X'X)^{-1} \quad \text{and}$$
$$(\hat{X}'\hat{X})^{-1}(\sum_{j=1}^{J} \hat{X}_j' e_j e_j' \hat{X}_j)(\hat{X}'\hat{X})^{-1}$$

for ordinary least squares and two-stage least squares respectively.[36] The letter j indexes industries and $e_j \equiv Y_j - X_j\hat{\beta}$, a $T = 33$ by 1 vector.

The first row of Table 6.1 shows the results of the regressing the real price of final sales[37] on real final sales, the percent of households who purchase the good, these two variables interacted, a constant, and a time trend.[38] A one percent increase in sales for a typical nondurable or frequently purchased good is associated with a 0.13 percent decrease in the real price of that good. A good purchased by only half of households in a year sees a typical decline in price of 0.08 percent. The negative relationship between sales and price represents the fact that some output increases are driven by supply-side factors such as increases in productivity and decreases in the cost of factor inputs. Note also that since I am using a subset of

[35] That is, I regress the logarithm of the variable in question on a constant and a time trend and then treat the residual as the datum. This procedure is done to make the regressions compatible with the markup regressions. One of the standard methods used to construct markups involves creating a log-detrended series. That industries may have a stochastic trend does not present a problem for the current estimation since asymptotic properties are derived from the number of industries going to infinity rather than the time dimension.

[36] Consistency follows as $J \to \infty$. In practice, correcting for serial correlation has a large impact, decreasing estimated standard errors on average by a factor of 3 to 4.

[37] The price deflator for final shipments divided by the consumer price index (then log-detrended).

[38] The time trend and constant are included because the first observation has been dropped. No substantive results change when these two variables are omitted. If time dummies are included instead of a time trend similar conclusions concerning statistical significance of the interaction terms are reached, although magnitudes vary somewhat.

Table 6.1: Real Price Regressions

	Sales	Sales* %NotBuy	Sales* cr4	ΔSales	ΔSales* %NotBuy	ΔSales* cr4	N*T
OLS	-0.13	0.10					3597
	(0.03)	(0.03)					
IV	2.63	-3.19					3597
	(1.26)	(1.55)					
	2.53	-3.24	0.32				3465
	(1.33)	(1.72)	(0.41)				
	2.47	-2.99		-2.07	2.46		3597
	(0.73)	(0.90)		(1.77)	(2.16)		
	2.69	-3.63	0.44	-4.34	1.23	8.47	3465
	(0.99)	(1.40)	(0.55)	(3.68)	(2.49)	(9.65)	

All regressions also include a constant, a time trend, and the percent of households who do not purchase the good.

The instrument set for all regressions includes a time trend, the Hall-Ramey instruments, the durability of the industry's good, and the same interacted with the Hall-Ramey instruments. The instrument set for regressions with differenced right-hand-side variables also includes the Hall-Ramey instruments and interactions once lagged.

manufacturing industries and since industry output includes intermediate goods there is no reason for the average real price response to be zero.

To isolate the response of price to demand fluctuations, I instrument the measures of sales with the Hall-Ramey instruments.[39] For two distinct reasons, the instruments also include the interaction of durability and the Hall-Ramey series. First, an aggregate demand shock does not increase demand equally across all industries. Economic theory suggests that demand increases much more for more durable goods, as expenditures must move large amounts to adjust stocks. The interaction term increases the explanatory power of the instruments significantly. Second, the frequency of purchase is only an imperfect measure of the concept of interest. Using durability instead of the frequency of purchase in the instrument set eliminates the attenuation bias resulting from this mismeasurement of the true concept of interest.

The second row of Table 6.1 shows the results of two-stage least squares estima-

[39] The regressions were also conducted using the real aggregate personal consumption expenditures series from the NIPA. All conclusions are robust to using this alternative instrument.

tion. The typical frequently purchased good now sees a price rise of two and a half percent for each percentage increase in sales due to demand. For a good purchased by only half of households, this number falls to one percent, and the difference is statistically significant.[40] Including the measure of industry concentration ($CR4$) does not alter this conclusion, nor does including the first difference of sales and its interaction with the frequency of purchase measure. Thus the first implication of the theory is confirmed in the data: prices rise less in response to increases in demand for goods which are purchased less frequently.[41]

Rows 4 and 5 add the first difference of the sales variables to the regression in order to test whether, for infrequently purchased goods, prices are lower when quantities are increasing. Prices are lower when sales are increasing in general, and there is no statistically significant effect of frequency of purchase on this relationship.[42] Thus, the relationship predicted to hold for the subset of goods for which timing is important holds for all goods. It may well be that this additional general force which lowers prices when sales are increasing causes the price-smoothing effect to become the dominant difference between goods for which timing is important and those for which it is not. Thus, prices are smoother for this subset of goods rather than lower when sales are increasing.

While prices are smoother for goods for which timing is important, there remains the possibility that marginal costs are heterogeneous across industries in just such a way as to generate smoother prices for less frequently purchased goods. That is, some combination of higher returns to scale and more elastic factor supplies implies that marginal costs are flatter or even decreasing for those goods which I find have smoother prices. To rule out this possibility, I perform a similar set of regressions using markups as the dependent variable. In doing so, I also seek to quantify the contribution of consumer intertemporal substitution of purchases to the cyclicality of the markup and thus the cyclical variability of production and sales.

6.3. Constructing Markups

Measuring markups is a difficult and controversial undertaking. Three different constructed measures of markups are analyzed, each based on a slightly different set

[40] The large change in the coefficient on sales in the theoretically predicted direction is evidence of good instruments. Further, the fits of the first stages are good. In rows 2 and 3, %NotBuy is predicted with an R^2 of 0.74; sales with an R^2 of 0.09; sales interacted with %NotBuy with an R^2 of 0.12. First differenced sales are predicted with an R^2 of 0.04, and, when interacted with %NotBuy, with an R^2 of 0.05.

[41] Bils and Klenow (1995) do not include the interaction term and regress relative prices on relative labor-capital ratios in first differences and find insignificant and small relationships, even when they instrument. The main differences are that I am working in log-deviations from trend and more importantly that I use sales and an interaction term as the explanatory variables. A regression without the interaction term yields an insignificant coeficient on total sales.

[42] Similar results are obtained if the change in sales at $t+1$ is used instead of t (without a change in the timing of the instrument set).

of assumptions. The starting point for all of the measures is a standard production function in which real gross output is produced from labor input, capital, and intermediate goods:[43]

$$Y = AF(L, K, M). \tag{6.1}$$

Time and industry subscripts are omitted for notational simplicity. Assuming that firms are price takers in factor markets and that factors are freely variable, cost minimization implies:

$$\frac{F_J J}{Y} = \lambda \frac{P_J J}{PY}, \tag{6.2}$$

where P_J is the price of input J, λ is the Lagrange multiplier on the output constraint, and J is any factor for which the marginal product, F_J, is strictly positive and bounded for strictly positive and bounded levels of J. If this is true for all inputs, $\lambda = \mu$, the markup, defined as price divided by marginal cost. Then, the elasticity of output with respect to each factor input equals the markup times the ratio of the input's cost to total revenue.[44] Finally, define γ as the degree of returns to scale of the production function so that:

$$PY = \frac{\mu}{\gamma} \sum_J P_J J. \tag{6.3}$$

The first measure of markups considered is derived from three assumptions. First, γ is assumed constant across time for each industry. Second, on average there are no pure profits in each industry, so that revenues equal costs for each industry over the sample: $\frac{1}{T} \sum_t PY = \frac{1}{T} \sum_t \left(\sum_J P_J J \right)$. Finally, capital is assumed quasi-fixed. Rearranging equation (6.3) and taking log-deviations from trend, the first markup measure is:

$$\widehat{\mu 1} = \frac{PY - \overline{PY} - \left(P_L L - \overline{P_L L}\right) - \left(P_M M - \overline{P_M M}\right)}{\overline{PY}}, \tag{6.4}$$

where $\widehat{x} \equiv \frac{x - \bar{x}}{x}$ and $\bar{x}$ is the log-trend in x. While the assumption of capital fixity is rather crude, because the real capital stock does not move much over the cycle, the empirical effects of assuming fixity are small.[45]

[43] I experimented with including production and nonproduction workers as separate inputs. Conclusions reached throughout this alternative analysis were similar if not slightly more favorable to the theory being tested. I chose to report this method since the only measure of compensation of production workers is wages, which is likely significantly more cyclical than total compensation of production workers. Thus, I use total payroll for all workers to measure the cost of labor input.

[44] Hall (1988) originates the use of this methodology to estimate marginal costs (and thus markups). See Basu and Fernald (1995b) for a discussion of this general methodology and the importance of using gross output data.

[45] Basu and Fernald (1994) assumes freely variable capital and argue that the effects of fixity are likely small. The arguments apply here in reverse. Further, an alternative approach is to assume that capital is freely variable and construct the nominal cost of capital. This can be done rather crudely under the assumption that capital is freely variable, so that $(P_K K)_t = P^I_{t-1} K_{t-1} +$

The second measure of markups is constructed by adding the additional assumption that the marginal product of labor is proportional to the ratio of labor input to real output. This is true, for example, of a Cobb-Douglas production function. Substituting into equation (6.2) and taking log-deviations from trend yields:

$$\widehat{\mu 2} = \left(\widehat{\frac{PY}{P_L L}}\right), \tag{6.5}$$

Finally, I follow the method of Benabou (1992) that extends the procedure of Rotemberg and Woodford (1991) to include intermediate goods. First, one assumes that intermediate goods are used in strict proportion to output and that the production function exhibits constant returns to scale but there may be fixed costs. Therefore equation (6.2) applies only to capital and labor, $\lambda = \frac{\mu}{1-\mu S_M}$ where S_M is the share of intermediate goods costs in total revenue, and equation (6.3) has $\gamma = 1$. Next, one assumes that free entry leads to the elimination of pure profits, so that the average cost shares of each input for each industry sum to one. Finally, one assumes that the cost share of labor in value added is equal to one minus the cost share of capital in value added. This allows one to avoid having to calculate a cost of capital series, and this assumption can be justified by assuming that capital and labor are combined using a Cobb-Douglas technology. Taking log-deviations and rearranging (see Benabou (1992)), the third markup series is:

$$\widehat{\mu 3} = \frac{1}{1 + S_M(\frac{\mu}{1-S_M} - 1)} \left[-\widehat{S_H} - (1 - S_M - \mu)\left(S_H \widehat{H} + S_K \widehat{K} + S_M \widehat{S_M}\right)\right]. \tag{6.6}$$

As before, all hatted variables are log deviation from trend (for each industry), while variables without hats represent sample averages (again by industry). S_M, S_H, S_K represent the share of intermediate goods, labor, and capital in total revenue; and μ is the average markup. The only difference between this equation and equation (8) in Benabou (1992) is the term $\frac{\widehat{S_H}}{1-S_M}$ and using $\frac{\widehat{S_M}}{1-S_M}$ instead of the price series employed in Benabou (1992). The first is correcting a typo; the second substitution is taken because nominal shares are likely to be better measured than price deflators. Steady state and log-deviations can all be calculated from the NBER productivity database, except for the average markup which is set to 1.20 based on recent consensus.[46]

6.4. Testing Markup Dynamics

Table 6.2 presents the results of regressions in which the dependent variable is the markup of price over marginal costs. The three pairs of rows each contain

$P_t^I I_t - P_t^I K_t$ where P^I is the price deflator for new investment, and I is new investment. When tried, the results are similar to those reported for $\mu 1$, but with slightly larger standard errors, due most likely to the additional error that the noisy measure of the return to capital introduces.

[46] See for example Basu and Fernald (1994).

Table 6.2: Markup Regressions

Markup Series		Sales	Sales* %NotBuy	ΔSales	ΔSales* %NotBuy
$\mu 1$	OLS	-0.12	0.12		
		(0.39)	(0.63)		
	IV	0.31	0.29		
		(0.63)	(0.93)		
	IV	-0.23	0.23	1.78	-2.48
		(0.73)	(1.00)	(2.32)	(3.26)
$\mu 2$	OLS	0.14	-0.11		
		(0.02)	(0.03)		
	IV	0.86	-1.12		
		(0.43)	(0.54)		
	IV	0.74	-1.00	-1.63	2.03
		(0.42)	(0.53)	(1.05)	(1.27)
$\mu 3$	OLS	-0.04	0.01		
		(0.01)	(0.02)		
	IV	-0.98	1.14		
		(0.40)	(0.49)		
	IV	-0.96	1.11	0.02	0.08
		(0.25)	(0.31)	(0.47)	(0.56)

All regressions also include a constant, a time trend, and the percent of households who do not purchase the good.

The instrument set for all regressions includes a time trend, the Hall-Ramey instruments, the durability of the industry's good, and the same interacted with the Hall-Ramey instruments. The instrument set for regressions with differenced right-hand-side variables also includes the Hall-Ramey instruments and interactions once lagged.

Table 6.3: Markup Regressions on Subsample

Markup Series		Sales	Sales* %NotBuy	ΔSales	ΔSales* %NotBuy
$\mu 1$	IV	1.25	-1.41		
		(0.73)	(0.91)		
	IV	1.27	-1.42	0.09	-0.14
		(0.60)	(0.77)	(0.53)	(0.85)
$\mu 2$	IV	1.58	-1.49		
		(0.89)	(0.77)		
	IV	-1.52	1.61	-0.25	0.40
		(0.73)	(0.85)	(0.82)	(0.96)
$\mu 3$	IV	0.94	-1.06		
		(0.54)	(0.63)		
	IV	0.97	-1.10	0.23	-0.20
		(0.41)	(0.48)	(0.40)	(0.47)

All regressions also include a constant, a time trend, and the percent of households who do not purchase the good.

The instrument set for all regressions includes a time trend, the Hall-Ramey instruments, the durability of the industry's good, and the same interacted with the Hall-Ramey instruments. The instrument set for regressions with differenced right-hand-side variables also includes the Hall-Ramey instruments and interactions once lagged.

the results for one markup series. OLS regressions show markups to be roughly acyclical, falling between the findings of Domowitz, Hubbard and Petersen (1988) and Rotemberg and Woodford (1991).

Instrumental variables regressions capture the change in markups associated with demand-driven fluctuations. These regressions do not give clean answers about either markup hypothesis. First, markups seem slightly more countercyclical in response to demand fluctuations. Second, markups are more countercyclical for goods for which timing is more important only for the second markup measure. Evidence from the first markup series is inconclusive and evidence from the third shows less frequently purchased goods to have more procyclical markups. Third, the three series also give contradictory and weak evidence as to whether markups are lower when sales of infrequently purchased goods are increasing.[47]

[47] When the regressions include industry concentration interacted with the quantity dependent variable, and/or its first difference, these variables are never significant. As in the price regres-

Why are the results so unstable and inconclusive? One possibility is that differences in the construction of the three markup series generate different answers. However, it is also possible that the pattern of industry-specific returns to scale is confounding inference. In industries with short-run increasing returns to scale, real price stickiness may increase markups in booms. That is, as the theoretical sections discuss, the impact of frequency of purchase depends on the slope of the marginal cost curve. To test this, I reestimate the markup regressions on two subsamples of industries.

First, I use only those industries that are in 2-digit industries which Basu and Fernald (1995a) find have decreasing returns to scale. The results for this subsample of industries are similar to the results reported in Table 6.2. This is not wholly surprising given that returns to scale is only one component of marginal cost, and differences in factor elasticities may well be more important. Thus, as a second cut, I examine only the subsample of industries in which the instrumented correlation of sales and price is positive.[48] This leaves 1815 observations. As is shown in Table 6.3, there is evidence that markups are less procyclical for infrequently purchased goods.[49] There is little evidence, however, of a consistent relationship between markups and whether demand is increasing or decreasing.

In sum then, cross industry evidence suggests that prices are smoother in industries where the timing of purchases is important. However, the timing variable is potentially correlated with the industry-specific slope of marginal cost. Evidence on markups, which attempt to measure both marginal cost and price, is not conclusive.

7. Conclusion

This paper presents a model in which consumers' ability to time their purchases of goods amplifies their effective elasticity of intertemporal substitution. When firms have some market power, fluctuations in consumer demand are fluctuations in the elasticity of demand and lead to potentially important price dynamics. When marginal costs are increasing, the markup of price over marginal cost is countercyclical, and demand fluctuations are smoothed over time, or propagated.

Using industry data, I demonstrate that, as predicted by the model, the price responses to fluctuations in demand are smaller for those goods for which the timing of purchases is more important. But the evidence on the behavior of markups is less clear. Only a shred of evidence is found that markups are more countercyclical (or

sions, the addition of industry concentration variables does not alter the significance or magnitude of other coefficients.

[48] That is, for each industry separately and using the usual instruments, I run price on sales, a time trend, and the percent of households not buying the good. Then I use only those industries for which the coefficient on sales is positive.

[49] There remains one puzzle however, which is that the relationship between price smoothness and the timing variable is reversed in this subsample.

less procyclical) for those goods purchased most infrequently. In future empirical work, I plan to examine specific industries in which the timing of purchases is thought to be important and for which measures of marginal cost are simpler to come by.

Throughout the paper, I assume that the distribution of consumers over the old stocks is exogenous. However, relaxing this assumption, consider a market in which consumers follow (s,S) rules for discarding their old good and buying a new one. Let these consumers initially be distributed uniformly between their two bands of adjustment. Now, when the distribution of consumers is perturbed, the endogenous response of sellers with a constant or decreasing marginal cost technology amplifies the shock. The distribution of consumers is moved further from a uniform distribution. The next time this larger group prepares to purchase new goods, the producers' pricing strategies may add still more consumers to this group, so that the demand fluctuation grows. It is possible that if the amount of individual uncertainty is not too great, the market may exhibit stable repeating fluctuations. Under these circumstances, it would be surprising if we did not see demand-driven business cycles.

Future research will embed these timing considerations in a general equilibrium stochastic growth model. The structure may be able to address two shortcomings in current general equilibrium business cycle theory. First, consideration of optimal timing of sales provides a propagation mechanism that may significantly improve the empirical fit of the model. Second, this extension may provide a theoretical alternative for the *ad hoc* assumption common in the Real Business Cycle literature that technology shocks are highly serially correlated. Instead of serially correlated technology, timing considerations could cause a single, uncorrelated demand shock to generate changes in the markup lasting several periods. In the partial equilibrium model examined, a positive shock to demand is smoothed and a countercyclical markup arises. Thus, as the markup returns to normal and sales increase it might appear as if technology were improving in a highly serially correlated manner.

References

Ball, Lawrence and David Romer, "Real and Nominal Rigidities," American Economic Review, 1990, 45.

Bartelsman, Eric and Wayne Gray, "NBER Manufacturing Database," December 1994. NBER Manuscript.

Basu, Susanto and John G. Fernald, "Constant Returns and Small Markups in U.S. Manufacturing," September 1994. Board of Governors of the Federal Reserve System International Finance Division Paper No. 483.

__ and __ , "Aggregate Productivity and the Productivity of Aggregates," December 1995. NBER Working Paper 5382.

__ and __ , "Are Apparent Productivity Spillovers a Figment of Measurment Error?," Journal of Monetary Economics, December 1995, 36 (1), 165–88.

Benabou, Roland, "Inflation and Markups," European Economic Review, 1992, 36, 566–74.

Bils, Mark, "Pricing in a Customer Market," Quarterly Journal of Economics, November 1989, 104, 699–718.

__ , "Cyclical Pricing of Durable Goods," September 1991. University of Chicago GSB mimeo.

__ and Peter J. Klenow, "Uncovering Curvature– Tests of Competing Business Cycle Models," March 1995.

Bond, Eric W. and Larry Samuelson, "Durable Good Monopolies with Rational Expectations and Replacement Sales," Rand Journal of Economics, 1984, 15, 336–345.

__ and __ , "The Coase Conjecture Need not Hold for Durable Good Monopolies with Depreciation," Economic Letters, 1987, 24, 93–97.

Bulow, Jeremy, "Durable Goods Monopolists," Journal of Political Economy, 1982, 90, 314–32.

Caballero, Ricardo J., "Durable Goods: An explanation for Slow Adjustment," Journal of Political Economy, 1993.

__ and Mohamad L. Hammour, "The Cleansing Effect of Recessions," American Economic Review, December 1994, 84, 1350–68.

__ , Eduardo M. R. A. Engel, and John C. Haltiwanger, "Plant Level Adjustment and Aggregate Investment Dynamics," Brookings Papers on Economic Activity, 1995, 1, 1–39.

Chevalier, Judith and David Scharfstein, "Capital Market Imperfections and Countercyclical Markups: Theory and Evidence," Jan 1994. NBER Working Paper No. 4614.

Coase, Ronald, "Durability and Monopoly," Journal of Law and Economics, 1972, 15, 143–49.

Conlisk, John, Eitan Gerstner, and Joel Sobel, "Cyclic Pricing by a Durable Goods Monopolist," Quarterly Journal of Economics, August 1984, 99, 489–505.

Diamond, Peter A., “A Model of Price Adjustment,” Journal of Economic Theory, 1971, 3, 156–68.
__ , On Time, Cambridge, UK: Cambridge University Press, 1994.
Domowitz, Ian, R. Glenn Hubbard, and Bruce Petersen, “Market Structure, Durable Goods, and Cyclical Fluctuations in Markups,” June 1987. Mimeo, Northwestern University.
__ , __ , and __ , “Market Structure and Cyclical Fluctuations in U.S. Manufacturing,” Review of Economics and Statistics, February 1988, 70, 55–66.
Hall, Robert E., “The Rlation Between Price and Marginal Cost in U.S. Industry,” Journal of Political Economy, October 1988, 96, 921–47.
Hamilton, Bruce W., “The Coase Conjecture in Continuous Time: Imperfect Durability, Endogenous Durability, and Aftermarkets,” March 1996. Johns Hopkins University Working Papers in Economics No. 362.
Judd, Kenneth, “Numerical Methods in Economics,” 1993. manuscript, Hoover.
Mortensen, Dale T., “The Cyclical Behavior of Job and Worker Flows,” Journal of Economic Dynamics and Control, Nov 1994, 18 (6), 1121–42.
Phelps, Edmund S. and Sidney G. Jr. Winter, “Optimal Price Policy under Atomistic Competition,” in E.S. Phelps, ed., Foundations of Inflation and Employment Theory, New York, NY: Norton 1970.
Rotemberg, Julio and Garth Saloner, “A Supergame-Theoretic Model of Price Wars During Booms,” American Economic Review, June 1986, 76, 390–407.
__ and Michael Woodford, “Markups and the Business Cycle,” in Oliver Jean Blanchard and Stanley Fischer, eds., N.B.E.R. Macroeconomics Annual, 1991, Cambridge, MA: MIT Press 1991, pp. 63–129.
Stokey, Nancy, “Rational Expectations and Durable Goods Pricing,” Bell Journal of Economics, 1981, 12, 112–28.
Stokey, Nancy L., Robert E Lucas, and Edward Prescott, Recursive Methods in Economics Dynamics, Harvard University Press, Cambridge, MA., 1989.

Figure 2A
Price over a Cycle

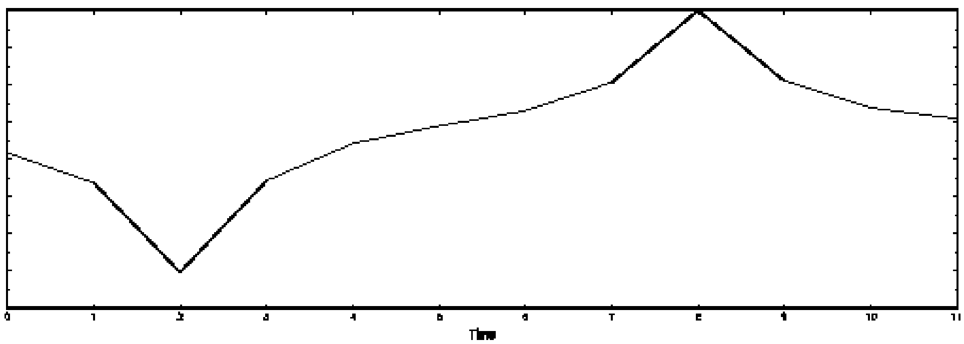


Figure 2B
Actual Sales and Sales at Steady-State Price

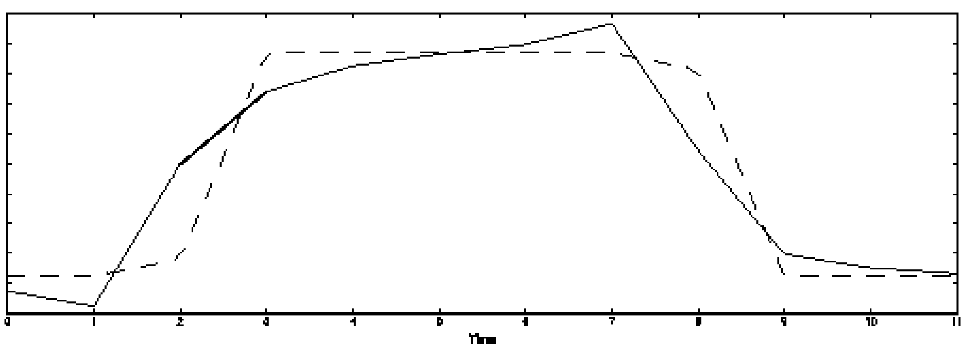
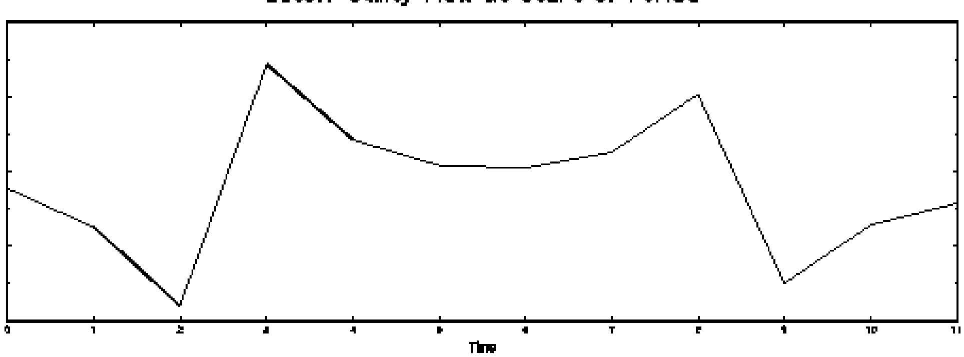
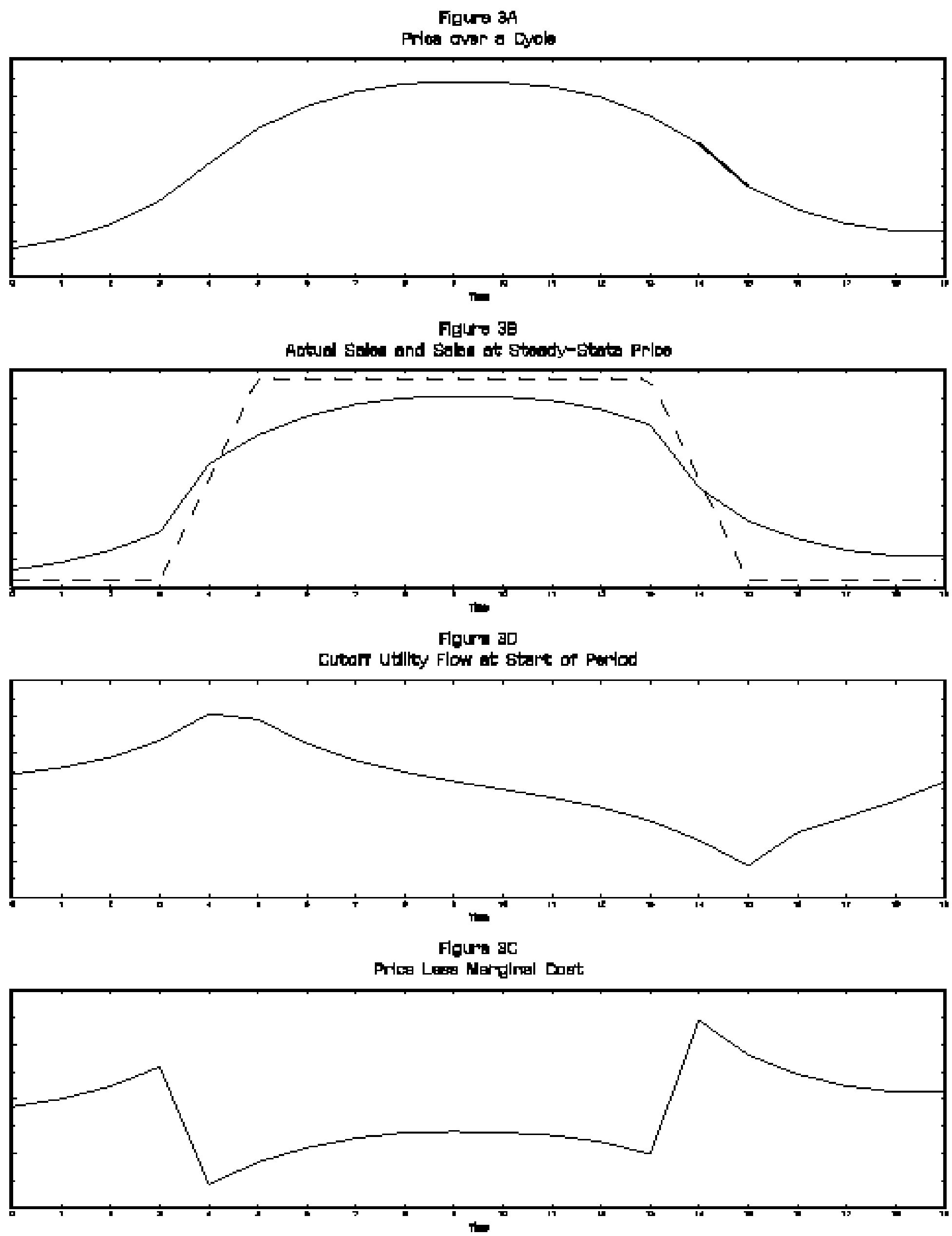


Figure 2C
Cutoff Utility Flow at Start of Period



Figures 1A, 1B, and 1C (Not Figure 2)



Figures 2A through 2D (Not Figure 3)

Figure 4A
Price over a Cycle

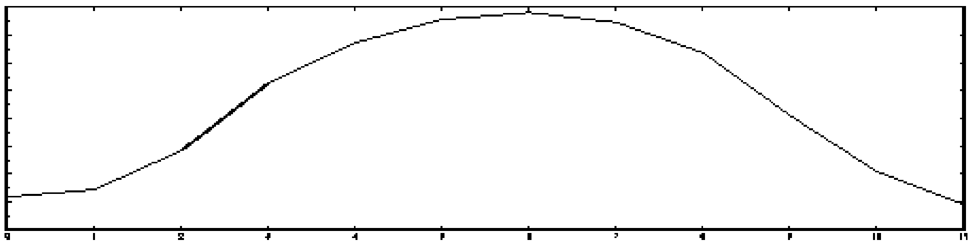


Figure 4B
Actual Sales and Sales at Steady-State Price

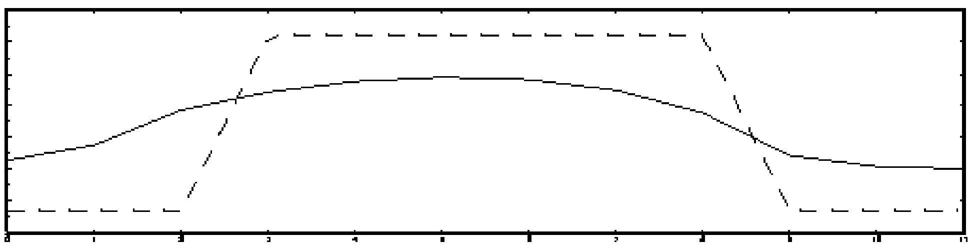


Figure 4C
Cutoff Utility Flow at Start of Period

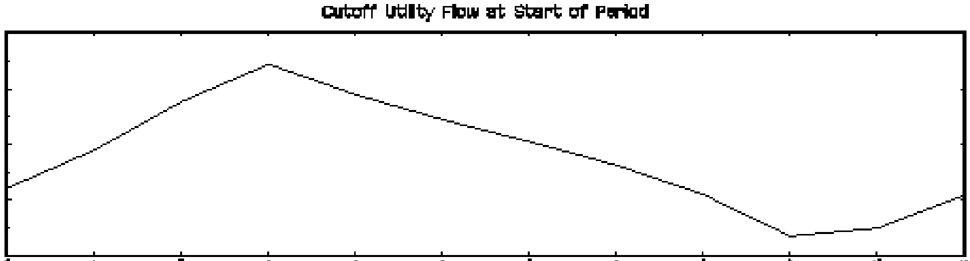


Figure 4D
Price Less Marginal Cost

Figures 3A through 3D (Not Figure 4)

Appendices

A. Proofs

In this appendix I restate and prove the lemmas in sections 2 and 3.

Lemma 1. *No search. In a symmetric equilibrium, no consumers search and*

$$V_t(u, p_{jt}) = Max\{u + \beta E_t[V_{t+1}(u - \delta, P_{t+1})]\ , v - p_{jt}\} \tag{A.1}$$

Proof. Since all firms charge the same price in every period, any search has a total expected gain of minus the search cost.⋄

Lemma 2. *Skimming property.* $u_{it} > u_{jt}$ *implies* $T_{ti} \leq T_{tj}$.

Proof. A buyer, i, with utility flow u_{it} can exactly imitate the strategy of a buyer, j, with a lower utility flow, in which case i receives the same return from purchasing but greater utility flow in every period before purchase. Thus $V_t(u, p_j)$ is weakly increasing in its first argument. Consider now the decision of each buyer as to whether to buy in t or wait, as captured by equation (A.1). Given that both u and $E_t[V_t(u - \delta, P_{t+1})]$ are greater for buyer i, the buyer with the lower utility flow, j, will always choose to purchase if buyer i does, and may choose to do so when buyer i does not.⋄

Lemma 3. u_t^* *evolution. Provided that sellers sell to some consumers in every period,* u_t^* *is defined by*

$$u_t^* = (1 - \beta)v + \beta E_t[P_{t+1}] - P_t \tag{A.2}$$

Proof. Consider consumers who are indifferent between purchasing in the current period and waiting. Allow the equilibrium to involve some of these indifferent consumers purchasing in the current period and some delaying their purchases.[50] Then it follows from Lemma (2), that all those with lower utility flows buy in the current period. Those with higher utility flows delay since $V_t(u, p_j)$ is increasing in u, $u + \beta E_t[V_{t+1}(u - \delta, P_{t+1})]$ is strictly increasing in u– the return to delaying is strictly increasing in u. If positive sales are made in every period, then those who are indifferent between purchasing and delaying in t will purchase in $t + 1$. u_t^* is then defined by indifference in equation (A.1) as

$$\begin{aligned} v - P_t &= u_t^* + \beta E_t[V_{t+1}(u_t^* - \delta)] \\ &= u_t^* + \beta(v -_t E[P_{t+1}]) \end{aligned} \tag{A.3}$$

Rearranging yields equation (A.2).⋄

[50] Since these consumers are measure zero to firms, whether they all purchase, wait, or mix is irrelevant for the equilibrium.

Lemma 4. *Positive sales. If $q_0 > 0$, and $p_t \geq c_1 \, \forall t$, then $q_t > 0 \, \forall t$.*

Proof. First suppose market price were such that no sales were being made in period t. Profits to all sellers are zero. Then any individual seller can choose a price an arbitrarily small distance above the marginal cost at zero sales, c_1, and, if it makes positive sales, make a profit in t. Since there are an infinite number of sellers, selling to some consumers does not reduce expected future profits noticeably. Thus, any supposed market price greater than c_1 cannot coexist with zero sales. Suppose sales are made in period t and in period $T > t+1$ and no sales are made between these dates. In period $T-1$, the highest utility flow buyer weakly refers buying in T:

$$v - P_{T-1} \leq u_{T-1}^{+} + \beta(v - P_T). \tag{A.4}$$

At the end of period t, the highest utility flow consumer weakly prefers purchasing in t to purchasing in all other periods including $t+1$:

$$v - P_t \geq u_t^{*} + \beta(v - P_{t+1}). \tag{A.5}$$

Since zero sales are made during the period between T and t, the highest utility flow individuals are the same and u evolves as: $u_s^{*} = u_s^{+} = u_{s-1}^{*} - \delta$. Using this to eliminate the utility flows from equations A.4 and A.5 yields:

$$v - P_{T-1} \leq -(T-1-t)\delta + (1-\beta)v + \beta P_{t+1} - P_t + \beta(v - P_T)$$

Note that in periods t and T sales are positive so that $P_t > c_1$, and $P_T > c_1$, while in periods $t+1$ and $T-1$, sales are zero so prices must be less than or equal to c_1. Making these substitutions preserves the inequality and yields:

$$0 \leq -(T-1-t)\delta, \tag{A.6}$$

which can only be true if $T = t+1$, that is if there is no intermediate period with no sales.$\diamond$

Lemma 5. *Steady state equilibrium. The steady state always exists is uniquely determined by*

$$\begin{aligned} P_{ss} &= c_1 + c_2\alpha\delta + \delta \\ u_{ss}^{+} &= (1-\beta)(v - P_{ss}) - \delta \\ Q_{ss} &= \alpha\delta \end{aligned}$$

Proof: In order for u_{ss}^{+} to remain constant, Q_{ss} must equal $\alpha\delta$. Plugging this and the distribution function into the seller first-order condition (2.15) yields a unique P_{ss}. Equation (2.14) then gives a unique u_{ss}^{+}. There is thus a unique candidate for a steady-state equilibrium. Existence then follows from the fact that the seller profit function is concave, a fact easily checked. The proof for the collusive/monopolist case is identical and omitted.$\diamond$

B. Data

A complete description of the NBER productivity database can be found in Bartelsman and Gray (1994). The database and Bartelsman and Gray (1994) can be downloaded currently from the \pub\productivity directory on nber.harvard.edu by anonymous ftp. The measure of sales covers all sales by firms within the SIC code. That is, sales includes sales of non-final goods. Buyers of the intermediate goods may have somewhat different abilities to time purchases than buyers of the final consumer goods, which generate the measures of durability and frequency of purchase. All SIC codes are based on the 1972 categorization, as used by the NBER productivity database. Gross nominal production is calculated as total revenue less change in nominal inventories. Nominal inventories in $t-1$ are multiplied by the current inventories price deflator and divided by the lagged inventories price deflator to make the nominal change consistent. These variables and nominal payments to labor and intermediate goods are included in the NBER database.

The measure of frequency of purchase represents the percent of households not reporting any consumption expenditures on items in this SIC code during a one-year period (1986). SIC codes defined as nondurable have these measures set to zero. These industries are all subindustries of 2-digit SIC code 20 and 21products and tobacco respectively. Tables **??** and B.2 list the measures of infrequency of purchase and the measures of durability. Durability measures are based on the life expectancy tables of a major U.S. insurance company. These life expectancies of goods are used by the company to adjust insurance claims for covered damages to these items and are weighted aggregates of slightly finer classifications. Durability measures for a subset of the industries (e.g. automobiles) are taken from Fixed Reproducable Tangible Wealth, 1925-89 by the Bureau of Economic Analysis. The reader is referred to Bils and Klenow (1995) for further details.

Industry concentration measures, taken from Rotemberg and Woodford (1991), estimate the share of total final sales accounted for by the four largest firms in 1967, roughly the midpoint of the sample. The concentration ratios are at the 2-digit level except motor vehicles and other transportation equipment which are split. They are as follows: SIC $20 : 0.345$, SIC $21 : 0.736$, SIC $22 : 0.341$, SIC $23 : 0.197$, SIC $25 : 0.216$, SIC $27 : 0.189$, SIC $28 : 0.499$; SIC $29 : 0.329$; SIC $30 : 0.691$, SIC $31 : 0.245$, SIC $32 : 0.374$, SIC $35 : 0.363$, SIC $36 : 0.450$, SIC $371 : 0.808$, SIC $372-9 : 0.501$; SIC $38 : 0.478$.

Table B.1: Durability and Infrequency of Purchase, Part I

SIC Code	Industry	Percent Not Buying	Durability (Years)
2251	Women's Hosiery	33.9	1.0
2252	Men's Hosiery	49.2	1.7
2271	Woven Carpets and Rugs	82.6	11.1
2272	Tufted Carpets and Rugs	82.6	11.1
2279	Carpets and Rugs, nec.	82.6	11.1
2311	Men's Suits and Coats	53.3	4.1
2321	Men's Shirts and Nightwear	34.9	2.7
2322	Men's Underwear	56.1	2.2
2327	Men's Trousers	34.6	2.7
2328	Men's Work Clothing	34.6	2.7
2331	Women's Blouses	36.6	2.3
2335	Women's Dresses	49.9	4.0
2337	Women's Coats	55.5	4.3
2341	Women's Underwear	32.7	1.8
2342	Brassiers, Girdles, etc.	32.7	1.8
2361	Girl's Dresses and Blouses	82.9	2.3
2391	Curtains and Drapes	82.9	4.2
2511	Wood Furniture	61.7	8.1
2512	Wood Furn. Upholstered	61.7	8.1
2514	Metal Furniture	61.7	8.1
2515	Mattresses and Beds	89.3	15.0
2591	Blinds and Shades	90.2	10.9
2711	Newspapers*	0.0	0.0
2721	Magazines*	0.0	0.0
2731	Books Publishing	44.5	11.0
2732	Books Printing	44.5	11.0
2834	Prescription Drugs	0.0	0.0
2911	Fuel Oil and Gasoline	0.0	0.0
2992	Motor Oil	0.0	0.0
3011	Tires	35.2	3.0
3143	Men's Footware	49.0	2.5
3144	Women's Footware	31.6	2.6

Source: Bils and Klenow (1995).

*These industries have their "percent not buying" measures set to zero since these goods are not purchased by everyone, yet they are nondurable in the sense that one chooses to buy the current issue or not at all. None of the results change significance or sign with this adjustment.

Table B.2: Durability and Infrequency of Purchase, Part II

SIC Code	Industry	Percent Not Buying	Durability (Years)
3161	Luggage	88.5	17.5
3229	Glassware	84.3	10.0
3262	China	84.1	17.5
3263	Cookware	79.4	17.5
3524	Lawnmowers	85.7	7.5
3631	Stoves and Ovens	88.3	14.1
3632	Refrigerators and Freezers	92.2	15.0
3633	Washers and Driers	91.9	11.0
3634	Portable Heaters	87.7	11.3
3635	Vacuum Cleaners	91.2	9.5
3645	Lamps	83.9	16.7
3651	TV's, VCR's, and Stereos	53.3	11.9
3652	Records and Tapes	49.7	5.0
3661	Telephones	80.7	7.1
3711	Automobiles	91.2	10.0
3713	Light Trucks and Vans	97.1	8.0
3732	Boats	99.1	10.0
3751	Motorcycles	90.2	8.6
3792	Trailers and Campers	98.6	8.0
3851	Eyeglasses and Contacts	68.3	10.0
3861	Film and Photo Equip.	39.2	6.7
3873	Clocks and Watches	64.1	15.5
3911	Jewelry	55.8	5.5
3914	Silverware	91.4	27.5
3931	Musical Instruments	91.5	13.0
3944	Games and Toys	41.9	5.0

Source: Bils and Klenow (1995).