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"Price Adjustment, Pass-Through and Monetary Policy"

presented by ***Emi Nakamura***

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Price Adjustment, Pass-Through and Monetary Policy

A dissertation presented

by

Emi Nakamura

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Price Adjustment, Pass-Through and Monetary Policy

ABSTRACT

My thesis focuses on the question of how firms adjust prices in reponse to changing economic conditions. In the first chapter, written jointly with Jón Steinsson, I use the price micro-data underlying the U.S. consumer and producer price indexes to document new facts about price adjustment in the U.S. The consumer price data set contains millions of observations on prices spanning the entire range of U.S. consumer products. We constructed a new data set on producer prices from the raw micro-data underlying the U.S. producer price index. We find that a substantial fraction of the flexibility documented by earlier studies for U.S. consumer prices is associated with transitory retail sales. We also document a substantial amount of price rigidity in producer prices.

In the second chapter of my thesis, I study the pass-through of imported costs into consumer prices in the coffee industry. Pass-through has been studied extensively in international economics since it plays a key role in understanding fluctuations in the real exchange rate. The coffee market provides a useful laboratory for pass-through since commodity costs account for a large fraction of marginal costs. I document both delayed and incomplete pass-through. Coffee roasters such as Folgers and Maxwell House adjust their prices infrequently– about 1.3 times per year. Almost all of the delays in pass-through occur at the wholesale level, so to the extent that price rigidity contributes to delayed pass-through it is wholesale prices that matter. I develop and estimate a structural model of pass-through with adjustment costs in prices for manufacturers. The model provides a quantitative explanation for both delayed and incomplete pass-through in this industry.

In the third chapter of my thesis, written jointly with Jón Steinsson, I study the implications of price rigidity for monetary non-neutrality. Most of the existing work on the implications of rigid prices for monetary policy analyzes models with identical firms. In this paper, we develop a multi-sector menu cost model and calibrate it to evidence from the BLS data set on the behavior of prices across sectors. We find that heterogeneity has first-order

implications for the effects of monetary policy. We also consider the effects of allowing for intermediate inputs. Together, these factors raise the economy's response to monetary shocks by an order of magnitude, helping to reconcile the micro-evidence on price rigidity with the large estimated responses of real output to monetary shocks.

TABLE OF CONTENTS

To my parents, who inspire me beyond words in research and in life.

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1. FIVE FACTS ABOUT PRICES: A REEVALUATION OF MENU COST MODELS

*with Jón Steinsson**

1.1 Introduction

The nature of price setting has important implications for a range of issues in macroeconomics including the welfare consequences of business cycles, the behavior of real exchange rates and optimal monetary policy. For this reason, macroeconomists have had a persistent interest in micro-level empirical evidence about the behavior of prices. We use BLS microdata underlying the consumer and producer price indices to document five basic features of price adjustment. We interpret this evidence through the lens of a benchmark menu cost model.

We begin by estimating the frequency of price change. Until recently, the best sources of information on U.S. pricing behavior were studies of price adjustment for particular products (Cecchetti, 1986; Kashyap, 1995), broader surveys of firm managers (Blinder et al., 1998), and evidence on the dynamics of industrial prices (Carlton, 1986). The conventional wisdom from this literature was that prices adjusted on average once a year. Bils and Klenow (2004) dramatically altered this conventional wisdom by showing that the median frequency of price change for non-shelter consumer prices in 1995-1997 was 21%, implying a median duration of 4.3 months.

We use a substantially more detailed dataset than Bils and Klenow (2004) that contains

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the micro-level price data underlying the non-shelter component of the consumer price index.[1] This dataset has been used by Klenow and Kryvtsov (2005) to analyze price adjustment behavior. We find that temporary sales play an important role in generating price flexibility for retail prices in categories that account for about 40% of non-shelter consumer expenditures. While the median frequency of price change including sales is 19-21% per month, we find that the median frequency of non-sale price change is only 9-12% per month depending on the time period and how we treat non-sale price changes over the course of sales and stockouts. These frequency estimates imply an uncensored duration of regular prices of between 8 and 11 months. If we include price changes associated with product substitutions, the frequency of price change increases by between 1 and 2 percentage points.

The importance of temporary sales in generating price flexibility draws attention to the question of how sales should be viewed when thinking about the macroeconomic implications of price rigidity.[2] Are the macroeconomic implications of sales the same as those of other price changes? Or are they different? The theoretical literature on price adjustment clearly indicates that different types of price adjustments can have very different macroeconomic implications. For example, the Calvo (1983) model and the Caplin and Spulber (1987) model have very different macroeconomic implications for the same frequency of price change.

We document several important empirical differences between sale price changes and other types of price adjustments. The most important differences are: 1) Sale price changes appear to be much more transient than other types of price changes. In most cases where a price is observed before and after a sale, the price returns to its original level following the sale. 2) Sales price changes are more than twice as large as other price changes on average. 3) The frequency and size of sales have a very different relationship to aggregate variables than regular price changes. 4) The hazard function of price change including sales is very different from that excluding sales. This last feature is a direct consequence of the transient nature of

[1] Bils and Klenow (2004) used the BLS Commodities and Services Substitution Rate Table for 1995-1997. This data set contains average frequencies of price changes and substitutions by disaggregated product categories over the 1995-1997 period. In contrast, the CPI research database contains the actual data series on prices underlying the consumer price index for the 1988-2005 period. See section 1.2 for a more detailed discussion of the data.

[2] A number of recent theoretical studies base their analysis on statistics for data where sales have been excluded (e.g., Golosov and Lucas, 2006; and Midrigan, 2005).

sales—the hazard function of price change including sales reflects the presence of a greater number of short price spells.

There are a number of reasons why it may be important to distinguish between sale and non-sale price changes. First, the transience of price adjustment associated with sales implies that a given number of price changes due to sales yield much less aggregate price adjustment than the same number of regular price changes (Kehoe and Midrigan, 2007). Second, some types of sales may be orthogonal to macroeconomic conditions. Third, transitory sales are a much more pervasive phenomenon in retail prices than in wholesale prices.

Our frequency of price change measures are for identical items. Product turnover is another source of price flexibility that plays an important role in truncating price spells, particularly in durable goods categories such as automobiles and apparel. The median frequency of product substitution over the period 1998-2005 in transportation goods and apparel was 10.2% and 9.9% per month, respectively. As with sales, it is important to distinguish between price changes due to product turnover and price changes for identical items. Many factors other than a firm's desire to change its price influence its decision to introduce a new product. The theoretical literature suggests that it is crucial to distinguish between price adjustments that are motivated primarily by a large difference between a firm's current price and its desired price and those that are motivated by other factors.[3]

We also present the first broad-based evidence on U.S. price dynamics at the producer level. Price rigidity at the producer level is potentially important because even if retail prices are perfectly flexible, price rigidity of producer prices could imply that shocks to production costs are not immediately passed through to consumer prices. In order to study this issue, we created a new data set on producer prices from the production files used by the BLS to construct the Producer Price Index. The median frequency of price change for finished goods producer prices was 10.8% in 1998-2005; it was 13.3% for intermediate goods producer prices; and it was 98.9% for crude materials. Price rigidity in finished goods producer prices thus seems comparable to the rigidity of consumer prices excluding sales but substantially more than the rigidity of consumer prices including sales.

[3] In chapter 3, we analyze a menu cost model in which product introduction represents a random opportunity to set a new price. We show that increasing the frequency of product introduction lowers monetary non-neutrality by about 5 times less than an equal increase in the frequency of regular price changes.

There is a tremendous amount of heterogeneity across sectors in both the frequency of price change and the importance of temporary sales. Different summary statistics on price flexibility therefore give very different answers regarding the degree of price flexibility in the U.S. economy. Following Bils and Klenow (2004), we focus on the weighted median frequency of price adjustment across categories. Excluding sales lowers the median frequency of price change of consumer prices by over 50%, while it lowers the mean frequency of price change by only about 20%. This is due to the fact that sales are concentrated in sectors of the economy—such as food and apparel—that have a frequency of price change close to the median frequency of price change across sectors.

There is no model-free way of selecting what is the appropriate summary statistic to describe the degree of monetary non-neutrality in an economy with heterogeneous price rigidity. In chapter 3, we calibrate a multi-sector menu cost model to the sectoral distribution of the frequency and absolute size of price changes excluding sales. The degree of monetary non-neutrality implied by this multi-sector model is triple that implied by a single-sector model calibrated to the mean frequency of price change of all firms but similar to that implied by a single-sector model calibrated to the median frequency of price change. Bils and Klenow (2002) and Carvalho (2006) study the effect of heterogeneous price rigidity in time-dependent models.

The second feature of price change that we investigate is the fraction of price changes that are price decreases. We find this fraction to be roughly one-third in both consumer prices excluding sales and finished goods producer prices. We present a benchmark menu cost model along the lines of Golosov and Lucas (2006) and show that the fraction of price changes that are decreases helps pin down the key parameters of this model. Building on the insights in Golosov and Lucas (2006), we find that the combination of the fact that 1/3 of price changes are price decreases and the fact that the average absolute size of price changes is large favors a model in which large but relatively transient idiosyncratic shocks to firms are an important driving force behind most price changes.

The third feature of price change that we investigate is how the frequency and size of price changes covary with variations in the inflation rate. We find that the frequency of price increases covaries quite strongly with the rate of inflation, while the frequency of price decreases and the size of price increases and decreases do not. This fact provides a natural test for our calibrated benchmark menu cost model. We find that the model matches the data well along this dimension. The frequency of price increases covaries much more with inflation than the other three components in the model as in the data.

The fourth feature of price change that we investigate is the extent of seasonal synchronization of price changes. We find that price rigidity is highly seasonal both for consumer and producer prices. Prices are substantially more likely to change in the first quarter than in other quarters—the difference is particularly large for producer prices. For consumer prices, we furthermore find a consistent pattern within quarter. The frequency of price change is highest in the first month of each quarter and falls monotonically across months within the quarter. This feature of price change does not arise in our benchmark menu cost model. It could arise in a menu cost model in which firms face seasonal variation in marginal costs or demand; or it may be evidence of a time-dependent element of the pricing decisions of firms.

The fifth and final issue that we investigate is the hazard function of price change. We are primarily interested in the slope of the hazard function. Menu cost models can give rise to a wide variety of hazard functions depending on the specification of marginal costs. The hazard function implied by our calibrated benchmark menu cost model is sharply upward sloping for the first few months. This implies that prices are unlikely to change again in the month immediately following a price change.

The main empirical challenge in estimating the hazard function of price change is the fact that heterogeneity in the level of the hazard function across products—if not properly accounted for—leads to a downward bias in the slope of the hazard function. We use the empirical model of Meyer (1990) to account for heterogeneity. The estimated hazard function of price change for both consumer prices excluding sales and producer prices is slightly downward sloping for the first few months and then mostly flat. The only substantial deviation from a flat hazard after the first few months is a large spike in the hazard at 12 months for services and producer prices. We also estimate the hazard of price changes for consumer prices including sales. It is much more sharply downward sloping for categories with frequent sales.[4]

[4] Earlier empirical work on the hazard function of price changes includes Cecchetti (1986), Campbell and

An important body of work on the nature of price adjustment in the European context has been carried out by the Inflation Persistence Network (IPN) of the European Central Bank. Álvarez et al. (2005b) and Dhyne et al. (2006) summarize the conclusions of a number of papers on the frequency of price adjustment in consumer prices for the countries of the Euro Area. Vermeulen et al. (2006) summarizes analogous studies on producer prices in the Euro Area. Fabiani et al. (2004) summarizes the conclusions of a set of papers that analyze survey evidence on price adjustment in the Euro Area. A number of other recent papers have studied the size and frequency of price changes using disaggregated price data, including Lach and Tsiddon (1992), Konieczny and Skrzypacz (2005), Baharad and Eden (2004), Kackmeister (2005), Gopinath and Rigobon (2006), Hobijn et al. (2006) and Midrigan (2005). Hosken and Reiffen (2004) use CPI data to analyze the ability of industrial organization models to explain the sales observed in consumer prices, concluding that none of the existing models are particularly successful.

The paper is organized as follows. In section 1.2, we describe the data. In section 1.3, we present evidence on the frequency of price change, the fraction of price changes that are price increases, the frequency of product turnover, the absolute size of price changes and temporary sales. In section 1.4, we present and calibrate a benchmark menu cost model. In section 1.5, we present evidence on how the frequency and size of price changes vary with inflation. In section 1.6, we present evidence on the seasonality of price changes and sales. In section 1.7, we present our estimates of the hazard function of price change. Section 1.8 concludes.

1.2 The Data

We use two data sets gathered by the Bureau of Labor Statistics (BLS) in this paper. The first is the CPI Research Database. This is a confidential data set that contains product level price data used to construct the Consumer Price Index (CPI). The second is an analogous

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Eden (2004), Baumgartner et al. (2005), Álvarez et al. (2005a), Jenker et al. (2004), Dias et al. (2005), Fougere et al. (2005), Goette et al. (2005) and Gagnon (2005). The evidence on the shape of the hazard function from these papers is mixed. Most of the papers in this literature do not account for unobserved heterogeneity at the good level. However, several of them use the conditional logit specification to account for unobserved heterogeneity. Unfortunately, this specification yields inconsistent estimates of the shape of the hazard function, as discussed in Willis (2006).

data set of producer prices that we have created from the production files underlying the Producer Price Index (PPI). We will refer to this data set as the PPI Research Database. The CPI Research Database has been used by Klenow and Kryvtsov (2005).[5] The PPI Research Database has not been used before.

1.2.1 The CPI Research Database

Each month the BLS collects prices of thousands of individual goods and services for the purpose of constructing the CPI. The CPI Research Database contains the non-shelter component of this data set from 1988 to the present. The goods and services included in the CPI Research Database constitute about 70% of consumer expenditures. Prices are sampled in 87 geographical areas across the United States. Prices of all items are collected monthly in the three most populous locations (New York, Los Angeles and Chicago). Prices of food and energy are collected monthly in all other locations as well. Prices of other items are collected bimonthly. In most of our analysis, we use only monthly observations.

The CPI Research Database identifies products at an extremely detailed level. In general, two products are considered different products in the database if they carry different bar codes. In addition, the same product at two different outlets are considered different products in the database. An example of a product in the database is a 2 liter bottle of Diet Coke sold at a particular supermarket in New York. The database reports whether or not a product was "on sale" when its price was sampled in a particular month.[6] We use this sales flag to calculate statistics about the frequency and size of price change excluding sales. We also

[5] Bils and Klenow (2004) used the BLS Commodities and Services Substitution Rate Table for 1995-1997. The Substitution Rate Table contains the average frequency of price change including product substitutions and imputed missing values for all products in the CPI.

[6] BLS field agents are instructed to mark a price as a sale price if it is considered by the outlet to be lower than the regular selling price, temporarily, and is available to all consumers. In practice, the BLS sales flag corresponds roughly to whether there is a "sale" sign next to the price when it is collected. If an outlet never sells a product at its "regular" price—i.e. the product is always on sale—the BLS field agent is directed not to label it as a sale price. Sales available to customers with savings or discount cards are reported as sales only if the outlet confirms that more than 50% of its customers use these cards. Bonus items may be reported as sales, as long as they satisfy the normal criteria for sales described above. Three categories in which the sale flag is never used by design are new and used cars and airfares. The approach that is used to collect price data for these categories is quite different from the procedure used to collect price data for other categories. The price series for new cars combines data on list prices with data on average "deals" obtained by consumers. The used car data is based on an index of used car prices. The data on airline tickets is based on a sample of tickets from the U.S. Department of Transportation data bank. Chapter 10 of the unpublished BLS manual Price Reporting Rules contains a more detailed description of the definition of sales used by the BLS.

consider identifying sales based on a "sales filter" in section 1.3.8. Some prices in the database are derived from the price of other products rather than being based on a collected price. We drop all such observations.[7]

We present results for consumer prices at three levels of aggregation. First, we report statistics that are calculated using the entire cross section of goods. Second, we break the data set into 11 "Major Groups" (see table 1.3). Third, we report results for so called Entry Level Items (ELIs). Examples of ELIs are "Bread", "Carbonated Drinks", "Washers & Driers", "Woman's Outerwear" and "Funeral Expenses". Before 1998, the BLS divided the data set into roughly 360 ELIs. In 1998, the BLS revised the ELI structure of the data set. Since then, it has divided the data set into roughly 270 ELIs. The revision in the ELI structure of the data set in 1998 implies that in many cases we must report separate estimates for the periods 1988-1997 and 1998-2005. Most of our results are similar for the two sample periods. For concreteness, we will refer to the estimates for the latter period in the text unless we indicate otherwise.

In all of the statistics we present on the frequency and size of price changes, we focus on weighted medians across ELIs. The weights we use are CPI expenditure weights from 1990 for the period 1988-1997 and from 2000 for the period 1998-2005. The statistics at the ELI level are unweighted averages within the ELI.

1.2.2 The PPI Research Database

The PPI Research Database contains an unbalanced panel of raw data from the productions files used to construct the PPI. The earliest prices in the database are from the late 1970's. For most categories, however, the sample period begins some time during the early to mid 1980's. Throughout the sample period a number of categories are discontinued and others appear. To a large extent this "churning" reflects, on the one hand, ongoing modernization of the data set, and on the other hand, the expansion of the data set into new sectors. For the period 1988-2005—which we focus on in most of our analysis—the PPI Research Database contains data for categories that constitute well in excess of 90% of the

[7] Chapter 17 of the BLS Handbook of Methods (U.S. Department of Labor, 1997) contains a far more detailed description of the consumer price data collected by the BLS.

value weight for the Finished Goods PPI.[8]

An important difference between the CPI and the PPI is that the PPI is collected by BLS through a survey of firms. This methodology introduces greater concerns about data quality than in the CPI where BLS agents actually observe prices of products "on the shelf". Stigler and Kindahl (1970) criticized the methodology used to gather the PPI data because it relied on "list" prices rather than transaction prices. Since then the BLS has revamped its data collection methodology to focus expressly on collecting actual transaction prices. Specifically, the BLS requests the price of actual shipments transacted within a particular time frame.[9] It is important to note that many of the transactions for which prices are collected as part of the PPI are a part of implicit or explicit long-term contracts between firms and their suppliers. The presence of such long-term contracts makes interpreting the PPI data more complicates than interpreting CPI data as we discuss further in section 1.3.4.

Another difference between the consumer and producer price data is that the definition of a good in the PPI Research Database typically includes information about the buyer of the product as well as a detailed set of product and transaction characteristics. The definition is meant to capture all "price-determining variables". In its Handbook of Methods, the BLS says: "For example, if a company charges more for a red widget than a white one, color is one of the price-determining variables." Price-determining variables may include the buyer, the quantity being bought, the method of shipment, the transactions terms, the day of the month on which the transaction takes place as well as product characteristics. This implies that if a seller charges a different price to different customers, the BLS will collect prices for a transaction involving the same customer month after month.

The price data in the PPI are collected in two steps. When a product is first introduced into the dataset or when an industry is resampled, the BLS collects "checklist" information by conducting a personal visit to the firm. The checklist contains information on characteristics of the product, buyer and seller as well as the terms and date of the transaction. The checklist also contains information on various types of addendums to the standard price: for example,

[8] The weights referred to here are the post-1997 value weights used to construct the Finished Goods PPI.

[9] See Chapter 14 of the BLS Handbook of Methods (U.S. Department of Labor, 1997) for a more detailed description of BLS procedures.

whether the price may involve a trade or quantity discount or other type of discounts or surcharges. Once the product is initiated, price information is collected using a repricing form. The repricing forms are mailed or faxed to the respondent. If the form is not returned, a BLS Industry Analyst will call the firm or establishment to collect information over the phone. The checklist information is updated when an industry is resampled every five to seven years.

An important concern with the methods used to collect the PPI data is that the repricing form used to update prices in the PPI first asks whether the price has changed relative to the previous month and then asks the respondent to report a new price if the price did change. This structure of the repricing form may introduce a bias toward no change into the data. In order to evaluate sensitivity of the price data to the method used to collect prices, we compared the behavior of prices during the anthrax scare of 2001 to the behavior of prices during other time periods.[10] In October and November 2001, all mail to government agencies was rerouted and PPI collected all prices by a phone survey. Controlling for the relationship between the frequency of price change and inflation, we found no significant differences in the frequency of price change in 2001 versus other years. Another feature of the data that suggests that the producer price data contain meaningful information is the high correlation between the frequency of price change for manufacturer prices and consumer prices excluding sales documented in section 1.3.5.

The BLS publishes producer price indexes based on several different classification systems. The most important classification systems are industry classifications and stage of processing classifications. Indexes in all classification systems are based on the same pool of price information. We use the stage of processing classification system. This classification system groups goods according to the class of buyer and the amount of physical processing or assembly the products have undergone. The BLS constructs indexes for three different stages of processing: finished goods, intermediate goods and crude material. We focus attention on finished goods, but also report basic results for intermediate goods and crude materials. As with the consumer price data, we present results at three different levels of aggregation. First, we present results that are based on the entire cross section of goods. Second, we present

[10] We thank Roberto Rigobon for suggesting this robustness check.

results for 15 Major Groups. These Major Groups are the two digit stage of processing groupings used by the BLS. Third, we present results based on a matching between more disaggregated stage of processing groupings and CPI ELIs.

Our method for calculating statistics at various levels of aggregation in the PPI is somewhat more complicated than in the CPI. The most detailed grouping in the PPI research database is the cell code. We do not attempt to construct value weights at this level, since there is a substantial amount of churning in the cell codes used in the PPI from year to year. We instead obtain value weights for the PPI at the 4-digit commodity code level. We then construct statistics on the frequency of price change at the 4-digit commodity code level in the following way. First, we calculate the unweighted average frequency of price change within cell codes. Next, we calculate the unweighted median frequency of price change across cell codes within the 4-digit commodity code. Finally, we construct aggregate statistics by taking value weighted medians over the median price change frequencies at the 4-digit commodity code level. For the purpose of matching PPI categories with CPI ELIs, we also construct statistics at the 6-digit and 8-digit level. These statistics are unweighted medians analogous to the statistics we calculate at the 4-digit level.

1.3 How Often and How Much Do Prices Change?

In this section, we present statistics on the frequency and size of price changes in the U.S. economy. An important lesson from the theoretical literature on price adjustment is that different types of price adjustments can have very different macroeconomic implications. The menu cost model has the strong prediction that the products "selected" to change their prices in response to an expansionary monetary shock disproportionately have prices that are far below their current optimum level. As a consequence of this selection effect, the price level responds relatively rapidly to the shock and the effects of the shock on aggregate output are relatively transient (Caplin and Spulber, 1987; Golosov and Lucas, 2006). In contrast, if the timing of most price changes is random—as in the Calvo (1983) model—monetary shocks have significantly more persistent effects on output.

Motivated by this theoretical literature, we distinguish between three broad classes of price changes and present statistics on these different types of price changes separately. We distinguish between price changes for identical items and price changes that occur due to product turnover. We also distinguish between changes in the regular price of a product and price changes associated with temporary sales.

The literature on price rigidity has focused primarily on modeling and measuring the frequency of price change for identical items. However, in sectors such as apparel, the primary mode of price adjustment is not price changes for identical products; it is product turnover. While the notion that prices adjust when they are far from the firm's desired price is intuitive in the case of price changes for identical items, the timing of product turnover in sectors such as apparel is primarily motivated by other factors such as seasonal demand variation and fashion. This implies that the selection effect associated with price changes due to product turnover may be weaker than for price changes for identical items. Price changes due to product turnover would then imply less aggregate price flexibility than the same number of price changes for identical items.

Most macro models of price adjustment abstract from temporary sales. Yet, temporary sales represent a large fraction of price changes in certain categories of retail products, such as grocery products and apparel. Like price changes due to product introduction, sales have quite distinct empirical characteristics from regular price changes. In particular, most sales are highly transient. When a product goes on sale, its price drops by a large amount. However, when the sale ends, the price typically returns to its original level. This is very different from regular price changes, which typically represent a quite persistent change in the price of a product. Kehoe and Midrigan (2007) analyze a model in which firms can make permanent and transitory price changes. They argue that temporary sales imply much less aggregate price adjustment than the same number of regular price changes.

1.3.1 The Frequency of Price Change: Consumer Prices

Table 1.1 reports estimates of the median frequency of price change for non-shelter goods and services in the CPI. These statistics are estimated by first calculating the mean frequency of price change for each ELI and then taking a weighted median across ELIs. In principle, calculating the frequency of price change is straightforward. It simply involves creating an indicator variable of when prices change and calculating the average of this variable. This procedure is complicated by three features of our retail price data. First, the data contain missing values as a consequence of stockouts. Second, products in the CPI research database are sometimes substituted out of the database and new products introduced in their stead. Third, we would like to construct statistics for price changes both including and excluding retail sales.[11]

We present several measures of the frequency of price change based on different procedures for addressing these complications. The simplest procedure we use is to calculate the frequency of price change based only on contiguous price observations (Bils and Klenow, 2004). According to this procedure, if a product's price is observed in two consecutive months, and the price differs between the two months, we define this as a price change; if the price is the same in the two months, we define this as no change. However, if either the current price or the price in the previous month are missing, we record a missing value in our price change indicator variable. In order to calculate the frequency of non-sale price change—which we refer to as the frequency of regular price change—we treat sales as missing observations and calculate the frequency of price change on contiguous non-sale price observations.[12]

Figure 1.1 graphically illustrates this simple procedure. The two panels in the figure report the first 10 observations for two hypothetical products. At the top of each panel, we record whether each observation is a sale or a regular price. The letter "R" denotes "regular price" while the letter "S" denotes "sale". Below the sale flag is a graph of the evolution of the price of the product for these 10 observations. At the bottom of each panel, are two indicator variables that record price changes and regular price changes, respectively. First, notice that the price change variable and the regular price change variable are missing for the first observation. This is because the price in the previous month is not observed. Second, notice that the fifth price observation is missing. This yields two missing values in the price change variables. Third, notice that for the 8th observation the sale flag indicates that this

[11] In order to identify temporary sales in the CPI data, we make use of the BLS sale flag. See section 1.2 for a discussion of this variable.

[12] In all of these estimates we completely discard all the bimonthly observations in the data set. As a robustness test, we have compared the bimonthly frequency of price change in the portion of our dataset that is sampled bimonthly to the bimonthly frequency of price change in the portion of our dataset that is sampled monthly. The bimonthly frequency of price change is slightly lower in the bimonthly data than the monthly data.

Table 1.1: Median Frequency of Price Change of Consumer Prices

	Median Frequency 88-97	Median Frequency 98-05	Median Implied Duration 88-97	Median Implied Duration 98-05
	%		Months	
Panel A: Including Sales				
1. Excluding Substitutions	20.3	19.4	4.4	4.6
2. Including Substitititions	21.7	20.5	4.1	4.4
Panel B: Excluding Sales and Substitutions				
3. Contiguous observations	11.1	8.7	8.5	11.0
4. Carry regular price forward during sales and stockouts	11.2	9.0	8.4	10.6
5. Estimate freq. of price change during sales	11.5	9.6	8.2	9.9
6. Estimate freq. of price change during sales and stockouts	11.9	9.9	7.9	9.6
Panel C: Excluding Sales, Including Substitutions				
7. Contiguous observations	12.7	10.9	7.4	8.7
8. Carry regular price forward during sales and stockouts	12.3	10.6	7.6	8.9
9. Estimate freq. of price change during sales	12.8	11.3	7.3	8.3
10. Estimate freq. of price change during sales and stockouts	13.0	11.8	7.2	8.0

All frequencies are reported in percent per month. Implied durations are reported in months. "Median Freq." denotes the weighted median frequency of price change. It is calculated by first calculating the mean frequency of price change for each ELI and then taking a weighted median across ELI's within the Major Group using CPI expenditure weights. The implied duration is equal to -1/ln(1-f), where f is the median frequency of price change.

price observation is a sale. In both panels, the sale yields two price changes in the "raw" price change variable. However, dropping the sale observation from the data set yields two missing observations for the regular price change variable.

The key difference between the two panels is that in panel B a regular price change occurs during the sale. It may at first seem that the procedure based only on contiguous observations necessarily underestimates the frequency of regular price change because it does not count regular price changes during sales. In this regard, it is important to notice that while using only contiguous observations leads one to drop a price change in the situation depicted in panel B, it also causes one to drop a no change in the situation depicted in panel A. If sales occur randomly, we are simply randomly dropping a small fraction of the observations in the data set.

The median frequency of price change including sales in 1998-2005 measured based on contiguous observations was 19.4%, while it was 20.3% in 1988-1997. We define the corre-

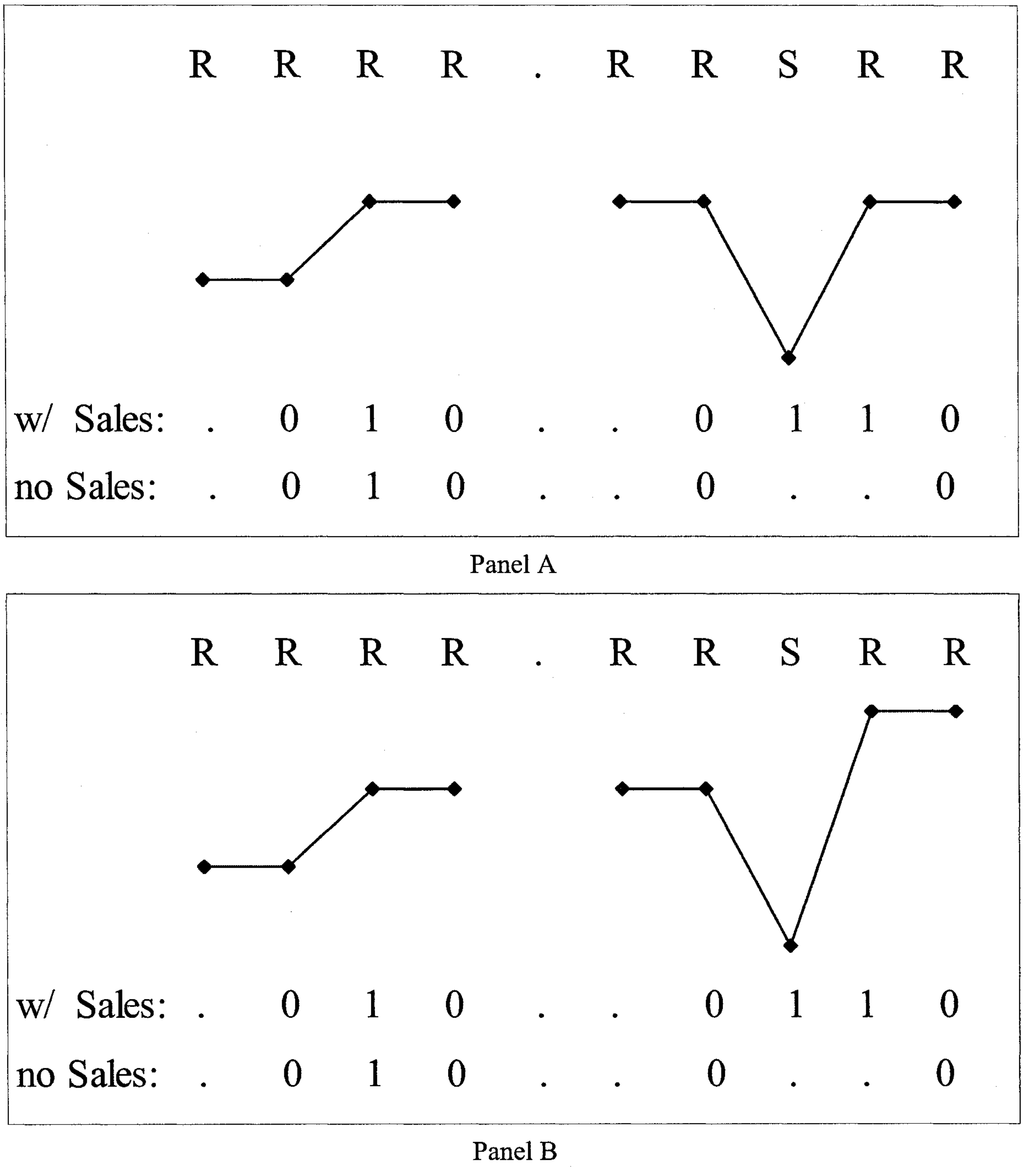

Figure 1.1: Construction of Price Change Variables With and Without Sales
Each panel reports the first 10 observations for a hypothetical price series. The top row of each panel records the values of the sales flag for the 10 observations. The letter "R" denotes "regular price" while the letter "S" denotes "sales". Below the flag is a graph of the evolution of the price of the product. At the bottom of each panel are two indicator variables. The first records price changes, while the second records regular price changes.

sponding median implied duration to be $d = -1/\ln(1-f)$, where f is the median frequency.[13] Measured in this way, the median implied duration of raw prices in 1998-2005 was 4.6 months, while it was 4.4 months in 1988-1997. Including substitutions raises the median frequency by about 1% in each period. This estimator for the case including sales and substitutions is very similar to the procedure used by Bils and Klenow (2004).

We present four procedures for excluding sales. The first procedure estimates the frequency of regular price change off of contiguous non-sale observations as described above. This method yields a median frequency of price change excluding sales in 1998-2005 equal to 8.7%. The corresponding median implied duration is 11 months. The second procedure, calculates the frequency of regular price change by carrying forward the last observed regular price through sale and stockout periods that are followed by another regular price within 5 months.[14] This method yields a median frequency of regular price change in 1998-2005 equal to 9.0%, which implies a median duration of 10.6 months.

The third and fourth procedures make use of direct measures of the frequency of regular price change during sale and stockout periods. Specifically, the third procedure is based on the following weighted average: $(1-s)f + sf'$, where f is the measure of the frequency of price change based on contiguous non-sale, non-stockout observation, f' is a direct estimate of the frequency of regular price change during one and two month sales and s is the fraction of price change observations corresponding to sales. The fourth procedure is analogous to the third procedure except that it allows the frequency of regular price change to differ during stockouts as well as sales.[15]

[13] A constant hazard λ of price changes implies a monthly probability of a price change equal to $f = 1 - e^{-\lambda}$. This implies $\lambda = -\ln(1-f)$ and $d = 1/\lambda = -1/\ln(1-f)$. In the case of statistics where substitutions are excluded, the implied duration is an estimate of the duration for the case where product exit is viewed as a censoring event. In other words, it is a measure of the median uncensored duration.

[14] This procedure is analogous to the procedure used by Klenow and Kryvtsov (2005). In practice, the estimates based on this procedure are not sensitive to the duration of sale or missing spells that we fill in since the majority of these spells last for one or two periods.

[15] We calculate $f' = \omega_1 f_1' + (1-\omega_1) f_2'$, where f_1' and f_2' are the monthly frequency of regular price change during one period sales and two periods sales respectively. They are estimated using the method described in section 1.3.3. ω_1 is the fraction of sales that are one period sales. This procedure yields an upward biased estimate of the probability of price change during sale and missing periods due to Jensen's inequality. The choice of how to weight the probability that a price returns to the original price for spells of different lengths make little difference in practice. Using the empirical frequency of price change during sales of all different lengths yields virtually identical results. We only make use of cases where a price is observed before and after the event in calculating the probability of price change over the course of sales and stockouts. In particular,

The third and fourth procedures yield estimates of the median frequency of regular price change for 1998-2005 of 9.6% and 9.9%, respectively. The corresponding median implied durations are 9.9 and 9.6 months. If the frequency of price change was the same during sale and stockout periods as during non-sale, non-stockout periods, these procedures would yield the same estimate as the procedure based only on contiguous non-sale, non-stockout observations. The fact that they yield higher estimates is because the frequency of regular price changes over the course of sales and stockouts is on average about 2 percentage points higher than during other periods.

Our results on the median frequency of regular price change are roughly in line with recent evidence on the frequency of price change in Europe based on CPI micro-data (Dhyne et al., 2006). The frequency of price change estimates in Dhyne et al. (2006) vary in their treatment of sales. However, Dhyne et al. report that in cases where sales could be identified they had little impact on the frequency of price change suggesting that sales are less important in Europe than in the U.S.

In summary, the median frequency of regular price change for 1998-2005 based on these four different procedures was 9-12% while the median frequency of price change including sales was 20%. Adjusting for sales makes such a large difference not only because sales are common in the data—21.5% of price changes are due to sales (table 1.2)—but also because of the uneven distribution of sales across goods. Table 1.3 reports the fraction of price change due to sales by Major Group. There is a huge amount of heterogeneity across Major Groups regarding the prevalence of sales. On the one extreme, 87.1% of price changes in Apparel and 66.8% of price changes in Household Furnishings are due to sales. On the other, virtually no price changes in Utilities and Vehicle Fuel are due to sales and only 3.1% of price changes in Services—a category that has an expenditure weight of 38.5%—are due to sales.

The sectors that have relatively few sales tend to be the sectors with either very high (Utilities, Vehicle Fuel and Travel) or very low (Services) unadjusted frequencies of price change. The sales adjustment is therefore concentrated in sectors that start off with a frequency of price change that is relatively close to the median frequency of price change. This heterogeneity in the prevalence of sales implies that the median frequency of price change

clearance sales do not contribute to these statistics.

Table 1.2: Frequency of Sales

	1988-1997	1998-2005
Expenditure weighted:		
Fraction of Price Changes Due to Sales	21.2	21.5
Fraction of Price Quotes with Sales	6.6	7.4
Weighted by Number of Observations:		
Fraction of Price Quotes with Sales	10.3	12.1

All statistics are reported as percentages. For the statistics in the first row, we first calculate the fraction of price changes due to sales for each ELI and then take an expenditure weighted mean across ELIs. The same procedure is used in the second row to calculate the expenditure weighted fraction of price quotes with sales. In the last row, we apply the same procedure as in the second row except that values for each ELI are weighted by the number of price observations for that ELI.

drops by 55% when sales are excluded, rather than 21.5%.

To see more clearly how heterogeneity in the prevalence of sales across sectors can lead to a large adjustment in the median frequency of price change, consider the three sector example presented in table 1.4. Suppose the three sectors in the economy are services, food and gasoline. Each has an expenditure weight of 1/3. Prices of services change once a year and have no sales. Prices of food change every other month, but 3/4 of these price changes are sales. The price of gasoline changes every month and gasoline never goes on sale. In this example—as in our data—sales are concentrated in the sector that is in the middle of the distribution of price change frequency. Adjusting for sales sector by sector yields a median frequency of regular price change of 1/8 and a median duration of 8 months.[16] However, a researcher that only knew that the overall fraction of price changes due to sales in the entire economy is 3/12 and adjusted the frequency of price change in all sectors using this number would conclude that the median frequency of price change is 3/8 and the median duration is 2.67 months.

There is a huge amount of heterogeneity in the frequency of regular price change across sectors in the U.S. economy (table 1.3). Furthermore, the distribution of the frequency of regular price change is very right-skewed. Most of the mass of the distribution lies below a frequency of regular price change of 12%, while categories such as vehicle fuel have a frequency

[16] For simplicity, we assume that only one price change can occur per month in this example.

Table 1.3: Frequency of Price Change by Major Group in 1998-2005

		Regular Prices				Prices				Sales	
		Median		Mean	Frac.	Median		Mean	Frac.	Frac.	Frac.
Major Group	Weight	Freq.	Impl.Dur.	Freq.	Up	Freq.	Impl.Dur.	Freq.	Up	Price Ch.	Obs.
Processed Food	8.2	10.5	9.0	10.6	65.4	25.9	3.3	25.5	54.7	57.9	16.6
Unprocessed Food	5.9	25.0	3.5	25.4	61.2	37.3	2.1	39.5	53.3	37.9	17.1
Household Furnishing	5.0	6.0	16.1	6.5	62.9	19.4	4.6	20.6	49.0	66.8	21.2
Apparel	6.5	3.6	27.3	3.6	57.1	31.0	2.7	30.1	36.1	87.1	34.5
Transportation Goods	8.3	31.3	2.7	21.3	45.9	31.3	2.7	22.2	44.0	8.0	2.7
Recreation Goods	3.6	6.0	16.3	6.1	62.0	11.9	7.9	13.7	51.3	49.1	10.9
Other Goods	5.4	15.0	6.1	13.9	73.7	15.5	5.9	20.6	61.3	32.6	15.3
Utilities	5.3	38.1	2.1	49.4	53.1	38.1	2.1	49.4	53.1	0.0	0.0
Vehicle Fuel	5.1	87.6	0.5	87.4	53.5	87.6	0.5	87.5	53.4	0.0	0.3
Travel	5.5	41.7	1.9	43.7	52.8	42.8	1.8	44.4	52.2	1.5	2.1
Services (excl. Travel)	38.5	6.1	15.8	8.8	79.0	6.6	14.6	9.1	76.8	3.1	0.5
All Sectors	100.0	8.7	11.0	21.1	64.8	19.4	4.6	26.5	57.1	21.5	7.4

All frequencies are reported in percent per month. Durations are reported in months. Fractions are reported as percentages. Regular prices denote prices excluding sales. "Weight" denotes the CPI expenditure weight of the Major Group. "# Obs." denotes the number of price observations for each Major Group. "Median Freq." denotes the weighted median frequency of price change. It is calculated by first calculating the mean frequency of price change for each ELI and then taking a weighted median across ELI's within the Major Group using CPI expenditure weights. The other median statistics in this table are calculated in an analogous manner. "Median Dur." is equal to -1/ln(1-f), where f is the median frequency of price change. "Median Ch.+Sub." denotes the median of the frequency of price change including price changes associated with substitutions. "Mean Freq." denotes the expenditure weighted mean frequency of price change. "Frac. Up" denotes the median fraction of price changes that are price increases. "Frac. Price Ch." and "Frac. Obs." denote the expenditure weighted mean fraction of price changes that are due to sales and fraction of observations that are sales.

Table 1.4: Sales Adjustment when Sales Are Concentrated in Certain Sectors

	Services	Food	Gasoline
Expenditure Weight	1/3	1/3	1/3
Frequency of Price Change	1/12	1/2	1
Implied Duration of Price Spells	12 months	2 months	1 month
Fraction of Price Changes Due to Sales	0	3/4	0
Frequency of Regular Price Change	1/12	1/8	1
Implied Duration of Regular Price Spells	12 months	8 months	1 month
Assuming a Constant Fraction of Price Changes Due to Sales:			
Frequency of Regular Price Change	1/16	3/8	9/12
Implied Duration of Regular Price Spells	16 months	2.66 months	1.33 months

In this example the expenditure weighted fraction of price changes due to sales is 3/12. Assuming that the fraction of price changes due to sales is the same across sectors, the frequency of regular price change equals the frequency of price change multiplied by 1-3/12=9/12. For simplicity, we assume that only one price change can occur per month in this example.

of price change substantially higher than 50%. As a consequence, the mean frequency of regular price change is almost twice the median frequency of regular price change. Table 1.5 shows that the weighted mean frequency of price change in the 1998-2005 period is 26-28% including sales and 21-22% excluding sales. These estimates are consistent with the estimates of Klenow and Kryvtsov (2005).

The large difference between the mean and median frequency of regular price change raises the question of which statistic is most informative about the degree of monetary non-neutrality in the economy. This question does not have a model free answer. In chapter 3, we show that a multi-sector menu cost model calibrated to the cross-sectional distribution of the frequency of price change excluding sales yields a degree of monetary non-neutrality that is similar to that of a single sector model calibrated to the median frequency of regular price change but much greater than that of a single sector model calibrated to the mean frequency of regular price change.[17] Carvalho (2006) argues that in a multi-sector Calvo model the mean duration provides a good approximation to the overall degree of monetary non-neutrality in the economy. Table 1.5 also reports the weighted mean implied durations

[17] In chapter 3, we also calibrate the multi-sector model to the sectoral distribution of the frequency of price change including sales, i.e., we treat sales are if they are the same as regular price changes. The degree of monetary non-neutrality implied by the calibration including and excluding sales differ by a factor between 1.5 and 2.

Table 1.5: Mean Frequency of Price Change in the CPI

	Mean Frequency 88-97	Mean Frequency 98-05	Mean Implied Duration 88-97	Mean Implied Duration 98-05
Panel A: Including Sales	%		Months	
1. Excluding Substitutions	23.9	26.5	8.3	9.0
2. Including Substititutions	25.2	27.7	7.5	7.7
Panel B: Excluding Sales and Substitutions				
3. Contiguous observations	18.7	21.1	11.6	13.0
4. Carry regular price forward during sales and stockouts	18.6	20.9	11.0	12.3
5. Estimate freq. of price change during sales	19.0	21.3	11.2	12.5
6. Estimate freq. of price change during sales and stockouts	18.9	21.5	10.8	11.7
Panel C: Excluding Sales, Including Substitutions				
7. Contiguous observations	20.4	22.8	9.3	9.8
8. Carry regular price forward during sales and stockouts	19.7	22.0	9.6	10.4
9. Estimate freq. of price change during sales	20.8	22.8	9.2	9.8
10. Estimate freq. of price change during sales and stockouts	20.7	23.1	9.0	9.3

All frequencies are reported in percent per month. Implied durations are reported in months. "Mean Frequency" denotes the weighted mean frequency of price change. It is calculated by first calculating the mean frequency of price change for each ELI and then taking a weighted mean across ELI's using CPI expenditure weights. "Mean Implied Duration" denotes the weighted implied duration of price change. It is calculated by first calculating the implied duration for each ELI as $-1/\ln(1-f)$, where f is the frequency of price change for a particular ELI and then taking a weighted mean across ELI's using CPI expenditure weights.

for the various alternative procedures for calculating the frequency of price change. Jensen's inequality implies that the mean implied duration is not the same as the implied duration for a product with the mean frequency of price change. Our estimates of the mean implied duration lie between 9 and 13 months.

Following Bils and Klenow (2004) and Dhyne et al. (2006), we have adopted a frequency based approach to estimating the median duration of price changes. A more direct approach would be to record the duration of each price spell and then find the weighted median duration across all price spells. However, the presence of a large number of censored price spells complicates this approach. To account for right-censoring, one must estimate a hazard model. This is complicated by the presence of heterogeneity. Left censoring is particularly problematic in applications with heterogeneity. The standard practice in the duration literature is to drop left-censored spells. This introduces an initial conditions problem that biases the estimated duration downward in the presence of heterogeneity (Heckman and Singer, 1986). Intuitively, longer spells are more likely to be left-censored.

Klenow and Kryvtsov (2005) present estimates of the median length of price spells based on duration data in footnote 3 of their paper. They do not present an estimate of the median duration of regular prices that adjusts for right and left censoring. The estimates in this footnote are therefore not comparable to our estimates. Klenow and Kryvtsov (2005) also present frequency based estimates of the mean frequency of price change that are similar to the estimates we present in table 1.5.[18]

One issue that arises in considering the macroeconomic implications of sales is that the quantity sold on sale is likely to be disproportionately large relative to fraction of time the product is on sale. In the extreme, suppose all of the volume for a particular product is sold on sale. In this case, does the rigidity of the regular price influence real quantities? The answer to this question depends on whether sale prices are set entirely independently from non-sale prices or sales prices are partially set relative to a product's regular price. In the second case, even if all products are sold on sale the rigidity of the regular price still influences real quantities through the sales prices.

Bils and Klenow (2004) also present a statistic on the frequency of price change adjusted for sales. Because of data limitations, they were not able to adjust for sales at the good level. Instead, they adjusted the median frequency of price change by the fraction of price changes due to sales in the entire data set. This procedure yields an estimate of the sales adjusted median duration of 5.5 months. It is a valid adjustment for sales under the assumption that sales account for the same fraction of price changes in all sectors. As we discuss above, this assumption is dramatically at odds with the data.

1.3.2 Product Turnover

Table 1.6 reports information on product turnover for consumer products. Since product introductions involve pricing decisions, the frequency of product introduction would be the ideal measure of product turnover for the purpose of measuring price flexibility. The CPI research database provides an imperfect measure of product introduction by providing an

[18] Klenow and Kryvtsov's estimate of the mean frequency of price change is slightly higher than our estimate because they treat price changes over multiple periods for seasonal items the same as price changes over a single period. Our estimate of the mean frequency of price change is virtually identical to the corresponding estimate in Klenow and Willis (2006), where price changes over multiple periods for seasonal items are not included.

Table 1.6: Frequency of Substitution and Price Change by Category

Major Group	weight	Subs. Freq.	Pr.Ch. + Prod. Intro. Freq. Reg.	Pr.Ch. + Prod. Intro. Freq.	Price Change Freq. Reg.	Price Change Freq.
Processed Food	8.2	1.3	11.1	26.6	10.5	25.9
Unprocessed Food	5.9	1.2	25.6	37.9	25.0	37.3
Household Furnishing	5.0	5.0	9.3	23.1	6.0	19.4
Apparel	6.5	9.9	10.7	36.9	3.6	31.0
Transportation Goods	8.3	10.2	36.6	36.6	31.3	31.3
Recreation Goods	3.6	6.3	9.5	16.7	6.0	11.9
Other Goods	5.4	1.0	15.6	17.1	15.0	15.5
Utilities	5.3	0.6	38.4	38.4	38.1	38.1
Vehicle Fuel	5.1	0.2	87.6	87.6	87.6	87.6
Travel	5.5	1.9	42.6	43.6	41.7	42.8
Services (excl. Travel)	38.5	0.9	7.5	7.5	6.1	6.6

The sample period is 1998-2005. "Subs. Freq." gives the median average monthly frequency of price changes associated with forced item substitutions in the consumer price index as a fraction of all months in which the product is available, as well as intermediate periods of 5 months or less when the product is unavailable at the time of sampling but subsequently becomes available. "Pr. Ch. + Prod. Intro." indicates the median average monthly frequency of price change adjusted for product turnover according to the formula (1-f)(1-pc) where $f=0.75f_{sub}$ and f_{sub} is the frequency of product substitution discussed above and the formula relating f and f_{sub} is discussed in the text. "Price Change" indicates the median monthly frequency of price change. The median statistics are calculated by first calculating the mean frequency of price change or substitutions within ELI's and then calculating the expenditure-weighted median across ELI's. "Weight" denotes the expenditure weight of the ELI. "CDF" denotes the cumulative distribution function of the frequency of regular price change.

indicator for whether a product undergoes a "forced substitution". A forced substitution occurs if the BLS is forced to stop sampling a product because it becomes permanently unavailable.[19]

The main complication that arises in trying to relate the frequency of substitutions to the frequency of product introduction is that the CPI research database does not follow products over their entire lifetime. Following a substitution, BLS procedure for choosing a new product to sample tends to lead to the selection of products that have existed for some time.[20] Despite this caveat, the frequency of substitutions provides useful information on the frequency product turnover. We measure the frequency of substitutions as a fraction of the

[19] Moulton and Moses (1997) show that price changes that are concurrent with product substitutions play a disproportionate role in explaining steady state aggregate inflation. This effect is particularly strong in apparel where "clearance sales" are common just before product substitutions.

[20] Specifically, when a product in the dataset becomes unavailable, BLS pricing agents are instructed to substitute to the most similar available product. In sectors where fashion is important, this is likely to be an older product. If older products are more likely to become permanently unavailable than new ones, then the average frequency of forced product substitution is an upward biased measure of the average frequency of product introduction. For example, Lancaster (1990) shows that if all products have a fixed lifetime, then the average time until a product exits is only half of its expected lifetime of the product.

total product lifetime.[21]

The frequency of substitutions varies a great deal across difference Major Groups. Substitutions are much more common in durable goods categories than they are in other categories. In apparel, we estimate the frequency of substitutions to be 9.9%. Many clothes categories undergo substitutions twice a year at the beginning of the spring and fall seasons. For some clothes—such as women's dresses—substitutions are even more common. Substitutions are also common in transportation goods. In this category, the monthly rate of substitutions is 10.2%. This high rate of substitutions is driven by the introduction of the new model-year in cars each fall. Household furnishings and recreation goods also have high rates of substitution, 5.0% and 6.3%, respectively. Other product categories have a rate of substitutions close to 1%.[22]

1.3.3 The Behavior of Prices During and After Sales

Most of the existing literature on menu cost models does not attempt to fit the behavior of retail sales. Rather, this literature seeks to fit the behavior of prices excluding sales (see, e.g., Golosov and Lucas, 2006; and Midrigan, 2005). Explanations for sales in the industrial organization literature may be grouped into two categories. First, some sales arise due to intertemporal price discrimination of retail outlets (Varian, 1980; Sobel 1984). Price changes due to this type of sales may be largely orthogonal to macroeconomic aggregates. Second, sales are also used as a method for inventory management (Lazear, 1986; Aguirregabiria, 1999). Sales of this type are related to the macroeconomy to the extent that inventory is cyclical. Not all clearance sales are due to variation in aggregate demand. In some products—such as apparel—clearance sales may occur due to unpredictable shifts in tastes rather than

[21] We define a product's lifetime as the total time the product is priced and available, where we also include periods where the product is temporarily unavailable for 5 months or less. This definition is meant to capture the idea that permanent product exits are likely to be followed by new product introductions; but a new product introduction is less likely to occur when the product is only temporarily absent. In this definition, we do not include any time periods after the last period when the product is priced and available. This measure differs from the measure used in Bils and Klenow (2004). They define the frequency of substitutions as a fraction of the total number of prices collected. We do not include product substitutions for which the price of the new product is observed in the months immediately after the substitution and is the same as the price of the old product.

[22] See the "Supplementary Material" to this paper for a detailed analysis of the frequency of product substitutions in different sectors of the U.S. economy.

shifts in aggregate demand (Pashigian, 1988). Pashigian and Bowen (1991) argue that price discrimination and clearance sales due to uncertainty about tastes account for most sales. Hosken and Reiffen (2001) document that sales are uncorrelated across retail outlets. They interpret this as evidence that retail sales are not primarily driven by changes in wholesale prices.

Sales are different from regular prices along important dimensions. Some features of sales seem inconsistent with the standard menu cost model. Table 1.7 documents a feature of sales that is particularly difficult to reconcile with the standard menu cost model, namely, the fact that the price of a product usually returns to its original regular price following a sale. The table presents statistics on sales for the 4 Major Groups for which sales are most important. For these 4 Major Groups, prices return to their original regular price between 60.0% and 86.3% of the time after a one period sale.[23] This fraction is highly negatively correlated with the frequency of regular price change. The fact that prices of Unprocessed Foods return to their original level after sales only 60.0% of the time may seem low. However, given that the frequency of regular price change in Unprocessed Food is 25.0%, for one period sales the probability that the regular price does not change between the month before the sale and the month after the sale is 56.2%.[24]

We use these statistics to compare the frequency of regular price change during sales and the frequency of regular price change during non-sale periods. We calculate the fraction of one-period sales that have a different regular price immediately following the sale than immediately preceding the sale. From this number we calculate the monthly frequency of price change under the assumption that the hazard of price change was constant during this two month period. The resulting statistic is reported in column 2 of table 1.7. We find that the frequency of regular price change is similar during sale periods as during other periods in processed and unprocessed food but quite a bit higher in household furnishings and apparel. The simple average of the difference across these 4 Major Groups is 1.8 percentage points.

[23] These statistics are based on sales for which a regular price for the product is observed after the sale ends. Clearance sales are therefore not included when these statistics are calculated.

[24] These statistics probably underestimate the fraction of sales that return to the regular price since they are based on monthly statistics. Sales shorter than one month may revert to the original price, and then experience a regular price change.

Table 1.7: Sales and Prices During Sales

	Freq. Reg. Price Ch.	Freq. Price Ch. During One Period Sales	Frac. Return After One Period Sales	Frac. of Sales that Last One Period	Freq. Price Ch. Dur. One Period Sales/Missing
Processed Food	10.5	11.4	78.5	64.7	11.1
Unprocessed Food	25.0	22.5	60.0	63.2	22.1
Household Furnishings	6.0	11.6	78.2	43.3	9.4
Apparel	3.6	7.1	86.3	35.8	5.9

The sample period is 1998-2005. "Freq. Reg. Price Ch." denotes the median frequency of price changes excluding sales. "Freq. Price Ch. During One Period Sales" denotes the median monthly frequency of regular price change during sales that last one month. The monthly frequency is calculated as $1-(1-f)^{0.5}$ where f is the frequency of regular price changes during one month sales. "Frac. Return After One Period Sales" denotes the median fraction of prices that return to their original level after one period sales. "Frac. of Sales that Last One Period" denotes the median fraction of sales that last one month. In calculating this statistic we drop left censored sale spells. Medians are calculated by first calculating an average within each ELI and then calculating an expenditure weighted median across ELIs within the Major Group. "Freq. Price Ch. During One Period Sales/Missing" denotes the median monthly frequency of regular price change during sales or missing periods that last one month, calculated in the manner described above for sales.

1.3.4 Frequency of Price Change: Producer Prices

Table 1.8 presents statistics on the median frequency of price change for producer prices at three different stages of processing: finished goods, intermediate goods and crude materials. The median frequency of price change of finished producer goods in 1998-2005 was 10.8%. The corresponding median implied duration is 8.7 months. The median frequency of price change of intermediate goods in 1998-2005 was 13.3% and the corresponding median implied duration is 7.0 months. In contrast to finished goods and intermediate goods, crude materials seem to have almost completely flexible prices. The median frequency of price change of crude materials in 1998-2005 was 98.9% and corresponding median implied duration is 0.2 months. Sales do not appear to be common in our producer price data set.[25] We therefore make no adjustment for sales when analyzing producer prices.

Table 1.9 reports results on the frequency of price change of producer prices by two digit Major Groups. As in the case of consumer prices, there is a large amount of heterogeneity across sectors. Table 1.9 also reports the frequency of product substitution for these two digit Major Groups. The frequency of product substitution is close to 2% for all the Major Groups.

[25] The PPI database does not include a sales flag. We used the sales filters described in section 1.3.8 to assess the importance of sales in the producer price data. These sales filters identified very few sales.

Table 1.8: Frequency of Price Change for Producer Prices

	Finished Goods		Intermediate Goods		Crude Materials	
	88-97	98-05	88-97	98-05	88-97	98-05
Median Freq. of Change	10.6	10.8	11.4	13.3	73.5	98.9
Median Implied Duration	8.9	8.7	8.3	7.0	0.8	0.2
Median Frac. of Increases	65.3	60.6	61.1	58.4	48.4	56.1
Mean Freq. of Change	25.2	24.7	21.7	26.7	78.0	86.0

Frequencies are reported in percent per month. Implied durations are reported in months. Fractions are reported in percentages. The median frequency of price change is calculated by first calculating the mean frequency of price change for each cell code, then taking an unweighted median within 4-digit commodity code and then taking a value weighted median across 4-digit commodity codes. The median implied duration is -1/ln(1-f), where f is the median frequency of price change. The mean frequency of price change is a value weighted mean across the 4-digit commodity code statistics discussed above. "88-97" and "98-05" denote the time periods 1988-1997 and 1998-2005, respectively.

In the PPI, a relatively small (value-weighted) fraction of the categories have a frequency of price change close to the median. Most of the categories with frequencies of price change above the median, have frequencies of price change substantially higher than 10%. As a consequence, the 55th percentile is 18.7% for 1998-2005, while the median is 10.8%. In contrast, for the CPI the 55th percentile is 10.1% for 1998-2005, while the median is 8.7%.

The finding that finished goods producer prices exhibit a substantial degree of rigidity confirms for a broader set of products the results of a number of previous studies. Blinder et al. (1998) surveyed firm managers about their pricing practices and found that prices changed on average once a year. Carlton (1986) estimated the rigidity of prices in the Stigler-Kindhal data set. He also found a substantial degree of price rigidity. Most of the prices analyzed in these studies were producer prices.

Interpreting this evidence is, however, more complicated than interpreting evidence on consumer prices. Buyers and sellers often enter into long-term relationships in wholesale markets. It is therefore possible that buyers and sellers enter into long-term "implicit contracts" in which observed transaction prices are essentially payments on a "running tab" that the buyer has with the seller (Barro, 1977). In such cases, the buyer would perceive a marginal cost equal to the shadow effect of purchasing the product on the total amount he would eventually pay the seller. But this shadow price would be unobserved. Of course, it is not

Table 1.9: Frequency of Price Change by Major Group for the Finished Goods PPI

Category Name	Weight	Med. Freq. Price Ch.	Med. Freq. Substitions	Frac. Up
Farm Products	1.6	87.5	2.2	48.6
Processed Foods and Feeds	22.4	26.3	2.6	57.8
Textile Products and Apparel	3.6	2.3	2.9	49.7
Hides, Skins, Leather, and Related Products	0.3	3.8	2.9	80.0
Fuels and Related Products and Power	20.8	48.7	2.3	54.1
Chemicals and Allied Products	2.8	6.1	2.9	61.6
Rubber and Plastic Products	1.8	3.2	2.9	83.8
Lumber and Wood Products	0.1	1.3	3.0	86.6
Pulp, Paper and Allied Products	3.0	4.4	2.5	74.9
Metals and Metal Products	1.1	3.8	2.5	72.2
Machinery and Equipment	13.0	3.7	2.7	71.0
Furniture and Household Durables	5.6	5.1	2.4	78.6
Nonmetallic Mineral Products	0.1	4.1	2.3	67.0
Transportation Equipment	16.8	27.3	3.0	53.7
Miscellaneous Products	6.9	16.5	1.8	81.3

The sample period is 1998-2005. Frequencies are reported in percent per month. Fractions are reported in percentages. "Weight" denotes the post-1997 final goods value weight of the Major Groups. "Med. Freq. Price Ch." denotes the median frequency of price change. It is calculated by first calculating the mean frequency of price change for each cell code, then taking an unweighted median within 4-digit commodity code and then taking a value weighted median across 4-digit commodity codes within the Major Group. "Frac Up" denotes the median fraction of price increases. It is calculated in an analogous manner to the median frequency of price change.

clear why buyers or sellers would choose to enter into such implicit contracts, or how and why they then choose to subsequently uphold them. In this type of situation retail prices would react to changes in manufacturer price even if wholesale prices did not change. Another complication in wholesale markets is that sellers may choose to vary quality margins—such as delivery lags—rather than varying the price (Carlton, 1979).

1.3.5 *Frequency of Price Change: CPI vs. PPI*

In order to compare price flexibility at the consumer and producer levels, we matched 153 ELI's from the CPI with product codes from the PPI.[26] Table 1.10 presents comparisons between the frequency of price change at the consumer and producer level for the Major Groups in which a substantial number of matches were found. In all the Major Groups

[26] 42 ELI's were matched to PPI categories at the 8 digit product-code level, 71 ELI's were matched to PPI categories at the 6 digit product-code level and 40 ELI's were matched to PPI categories at the 4 digit product-code level. When an ELI was matched to a PPI category at, for example, the 6 digit product code level, the unweighted median of the mean frequency of price change of item codes within that 6 digit product code was used.

Table 1.10: Frequency of Price Change: Comparison of CPI and PPI Categories

Category	Num. of Matches	Frequency CPI w/ sales	Frequency CPI non-sale	Frequency PPI	Implied Duration CPI w/ sales	Implied Duration CPI non-sale	Implied Duration PPI
Processed Food	32	26.1	10.5	7.2	3.3	9.0	13.4
Unprocessed Food	24	37.3	25.9	67.9	2.1	3.3	0.9
Household Furnishings	27	23.0	6.5	5.6	3.8	14.9	17.3
Apparel	32	31.0	3.6	2.7	2.7	27.3	36.3
Recreation Goods	16	14.5	6.8	6.1	6.4	14.2	15.9
Other Goods	13	33.6	23.2	17.1	2.4	3.8	5.3

CPI regular prices denote consumer prices excluding sales. "Num. of Matches" denotes the number of ELIs matched to 4, 6 or 8-digit commodity codes within the PPI in the Major Group. "Frequency" denotes the median frequency of price change. "Implied Duration" denotes -1/ln(1-f), where f is the median frequency of price change. Medians for the consumer price data are are calculated by first calculating an average within each ELI and then calculating an expenditure weighted median across ELIs within the Major Group. Medians for the producer price data are calculated by first calculating the mean frequency of price change for each cell code, then taking an unweighted median within 4-digit commodity code and then taking a value weighted median across 4-digit commodity codes. All statistics are for the period 1998-2005.

except Unprocessed Food, the median frequency of price change for producer prices is similar to that for consumer prices excluding sales, but substantially lower than the median frequency of price change of consumer prices including sales. For example, for Processed Food, we find that the median frequency of price change is 7.2% for producer prices, 10.5% for regular consumer prices and 26.1% for consumer prices including sales. Similarly, for Household Furnishings, we find that the median frequency of price change is 5.6% for producer prices, 6.5% for regular consumer prices but 23.0% for consumer prices including sales. For all 153 matches, the correlation between the frequency of price change for producer prices and regular consumer prices is 0.83, while the correlation for producer prices and raw consumer prices is 0.64.

1.3.6 The Relative Frequency of Price Increases and Price Decreases

Most models of price rigidity make the simplifying assumption that price changes occur only in response to aggregate shocks.[27] With even a modest amount of inflation, these models imply that almost all price changes are price increases. Table 1.3 shows that this assumption is far from being realistic. The weighted median fraction of regular price changes in consumer

[27] Examples include, Taylor (1980), Calvo (1983), Caplin and Spulber (1987), Dotsey et al. (1999) and Mankiw and Reis (2002). A notable exception is Golosov and Lucas (2006).

prices that are price increases is 64.8%, while the weighted median fraction of price changes including sales that are increases is 57.1%.[28] Table 1.8 shows that the same pattern emerges for producer prices. The fraction of price changes in producer prices are increases is 60.6%. This result has important implications for the calibration of models of price rigidity. Along with the large average size of price changes—emphasized by Golosov and Lucas (2006)—it provides strong evidence for the hypothesis that idiosyncratic shocks are an important driving force of price changes.

1.3.7 The Size of Price Changes

Price adjustment seems lumpy not only because prices often remain unchanged for substantial periods of time but also because prices change by large amounts when they do change. Table 1.11 reports the median absolute size of log changes in consumer prices. For consumer prices excluding sales, the median absolute size of price changes is 8.5%.[29] This table also reports the absolute size of price change by Major Group. Price changes that are due to sales are on average much larger than regular price changes. Table 1.11 reports that the median absolute size of price changes due to sales is 29.5%, more than three times the size of regular prices. We have also calculated the size of price changes for finished goods producer prices. The median absolute size of log changes for finished goods producer prices is 7.7%.

Another result that emerges from table 1.11 is that the median size of price decreases is 3.2 percentage points larger than the median size price increases. For finished goods producer prices this difference is 1 percentage points. The median size of price decreases is larger than that of price increases for 10 of 11 Major Groups for consumer price and 11 of 15 Major Groups for producer prices.

1.3.8 Alternative Measures of Sales

Up until now we have used the BLS sale flag to identify sales. In doing so, we follow a number of previous papers (Bils and Klenow, 2004; Klenow and Kryvtsov, 2005). An

[28] These statistics are calculated as follows. First, we calculate the fraction of price changes that are increases by ELI. Then, we calculate the weighted median of these statistics across ELI.

[29] This statistic is calculated by finding the average log change in price by ELI and then taking the weighted median across ELI's.

Table 1.11: Absolute Size of Changes

		Regular Prices			Sales			All Prices
		Median	Median	Median	Median	Median	Frac.	Median
Major Group	Weight	Change	Increase	Decrease	Change	Ratio	Price Ch.	Change
Processed Food	8.2	13.2	11.5	17.6	33.1	2.6	57.9	26.5
Unprocessed Food	5.9	14.2	13.9	15.0	35.1	2.5	37.9	27.1
Household Furnishings	5.0	8.7	8.0	9.8	28.0	2.8	66.8	20.8
Apparel	6.5	11.5	10.0	13.3	37.1	3.1	87.1	30.2
Transportation Goods	8.3	6.1	5.9	6.2	14.1	0.9	8.0	6.1
Recreation Goods	3.6	10.1	8.7	12.0	32.9	3.1	49.1	18.9
Other Goods	5.4	7.3	7.2	9.2	26.5	2.9	32.6	10.0
Utilities	5.3	6.3	6.2	6.4	12.6	1.6	0.0	6.3
Vehicle Fuel	5.1	6.4	6.8	5.9	11.7	1.8	0.0	6.4
Travel	5.5	21.6	20.9	22.4	29.3	1.4	1.5	21.9
Services (excl. Travel)	38.5	7.1	6.5	9.5	29.5	2.9	3.1	7.3
All Sectors	100.0	8.5	7.3	10.5	29.5	2.6	21.5	10.7

The sample period is 1998-2005. "Regular prices" denote prices excluding sales. "Weight" denotes the CPI expenditure weight of the Major Group. "Median Change", "Median Increase" and "Median Decrease" refer to the weighted median absolute size of log price changes, increases and decreases, respectively. The median absolute size of log price changes is calculated by first calculating the mean absolute size of log price changes for each ELI and then taking a weighted median across ELIs using CPI expenditure weights. Other median statistics are calculated in an analogous manner. "Median Ratio" denotes the weighted median ratio of the mean absolute size of log price changes due to sales to the absolute size of log regular price changes within ELIs. For each ELI the mean size of sales is calculated for all price changes at the beginning and end of sales. "Frac. Price Ch." denotes the mean fraction of price changes that are due to sales.

alternative (and complementary) approach to identifying sales is to look for "V-shaped" patterns in the data and identify these patterns as sales. An important conceptual difference between this "sales filter" approach and our previous approach is that clearance sales are not defined as "sales" according to this approach.

There are two main empirical drawbacks of the sale filter approach as a mechanism for identifying V-shaped sales. First, since prices are observed at a monthly frequency, a simple sale filter that excludes only V-shaped sales would not be able to identify V-shaped sales that are followed by a regular price change within the same month. For example, consider a good that goes on sale for one week, reverts to the original price following the sale, but subsequently experiences a regular price change before the BLS price collector returns to the store. The simple sale filter would not identify this price pattern as a "sale", even though the true pattern of prices (unobserved in monthly data) exhibited a V-shaped pattern. Another type of event that would not be captured by a V-shaped filter is if the good is on sale twice in a row when the BLS price collector samples it but at a different sale price—say a 30%

Table 1.12: Frequency of Price Change for Sales Filters 1998-2005

	No Substitutions		w/ Substitutions	
	A	B	A	B
Window:				
1 month	13.3	15.3	14.7	16.4
2 months	12.5	14.2	14.7	15.5
3 months	11.9	13.4	14.1	15.1
4 months	11.4	12.5	13.6	14.7
5 months	11.4	12.5	13.3	14.6
Price Changes	19.4		20.5	
Reg. Price Changes	8.7		10.9	
Reg. Price Ch. + Clear	10.7		13.0	

This table gives the weighted median frequency of price change for alternative procedures for filtering out "V-shaped" sales. Frequencies are reported in percent per month. The median frequency is calculated by first calculating the mean frequency of price change for each ELI and then taking an expenditure-weighted median across ELI's using CPI expenditure weights. In all cases, clearance sales are not removed. Sale Filter B removes only symmetric "V-shaped" sales while Sale Filter A also allows for regular price changes immediately preceding or following sales or asymmetric V's. We consider sale filters with a "window" for return to the original price of betwen 1 and 5 months. See appendix A for a detailed description of the sale filter algorithm.

discount and then a 50% discount.

Second, in some categories with highly volatile prices, such as gasoline, sale filters may identify sales even when there are none. In these categories, sale filters may identify "V-shaped" price patterns simply because prices tend to chance by discrete amounts—e.g., from \$2.49 to \$2.59. For this reason, sales filters will indicate that gasoline is on sale a significant fraction of the time, while the BLS sale flag indicates that there are virtually no sales in the gasoline category.

The sale filter approach nevertheless provides useful information about both the nature of price adjustment as well as the definition of the "sale flag" variable. Table 1.12 reports results for two types of sales filters, which we refer to as sales filter A and B. Sale filter B removes price patterns in which the price returns to the original price within a set number of months without going above the original price. Sales filter A is designed to also remove price patterns in which a sale is followed by a change in the regular price, i.e., asymmetric V's. These procedures are described in detail in the "Supplementary Material" for this paper. For each type of filter we consider different windows between 1 and 5 months. For example, for the 2 month case, we require that the price return to a regular price in the first two months after the price decline occurs.

The median frequency of price change based on the sale filter B with a window of 5 months is 12.3% for the 1998-2005 period. The median frequency of price change based on the more complex sale filter A is 11.0% over this period. This statistic is similar to the weighted median frequency of price change that uses the sales flag to exclude all sales except for clearance sales. However, depending on how one parameterizes the sale filter, and depending on whether product substitutions are included as price changes, one can get substantially different answers for the median frequency of price change. In particular, if one assumes a window of one month and includes substitutions as price changes, the frequency of price change rises to 16.4%. For alternative choices of the window and the decision of whether to include substitutions, one can obtain a variety of intermediate values between 11.4% and 16.4%.

1.4 A Benchmark Menu Cost Model

The facts we have established can help distinguish between different models of price setting behavior. We focus on a benchmark version of the menu cost model developed by Barro (1972), Sheshinski and Weiss (1977) and Golosov and Lucas (2006). We analyze whether the facts established in the preceding section are consistent with this model and what they imply about the values of its key parameters.

Consider the pricing decision of a single firm. This firm produces a good using a linear technology

$$y_t(z) = A_t(z)L_t(z), \tag{1.1}$$

where $y_t(z)$ denotes the output of the firm in period t, $A_t(z)$ denotes the productivity of the firm's labor force in period t and $L_t(z)$ denotes the quantity of labor hired by the firm for production purposes in period t. Assume that demand for the firm's good is

$$c_t(z) = C\left(\frac{p_t(z)}{P_t}\right)^{-\theta}, \tag{1.2}$$

where $c_t(z)$ denotes the quantity demanded of the firm's good in period t, $p_t(z)$ denotes the nominal price the firm charges in period t, P_t denotes the price level in period t and C is a constant which determines the "size of the market" for the firm's good. In order to generate price rigidity, we assume that the firm must hire an extra K units of labor in order to change its price.

For simplicity, we assume that the real wage rate in the economy is constant and equal to

$$\frac{W_t}{P_t} = \frac{\theta - 1}{\theta}, \tag{1.3}$$

where W_t denotes nominal wage rate in the economy at time t.[30]

Using equations (1.1), (1.2), (1.3) and the fact that markets clear we can write real profits as

$$\Pi_t(z) = C\left(\frac{p_t(z)}{P_t}\right)^{-\theta}\left(\frac{p_t(z)}{P_t} - \frac{\theta-1}{\theta}\frac{1}{A_t(z)}\right) - \frac{\theta-1}{\theta}KI_t(z), \tag{1.4}$$

Assume that the logarithm of productivity of the firm's labor force follows an AR(1) process:

$$\log(A_t(z)) = \rho\log(A_{t-1}(z)) + \epsilon_t(z), \tag{1.5}$$

where $\epsilon_t(z) \sim \mathrm{N}(0, \sigma_\epsilon^2)$ is an idiosyncratic productivity shock.

Assume that the logarithm of the price level fluctuates around a trend:

$$\log P_t = \mu + \log P_{t-1} + \eta_t, \tag{1.6}$$

where $\eta_t \sim \mathrm{N}(0, \sigma_\eta^2)$.

The firm maximizes profits discounted at a constant rate β. The value function of the firm is given by the solution to

$$V(p_{t-1}(z)/P_t, A_t(z)) = \max_{p_t(z)}\left[\Pi_t(z) + \beta E_t V(p_t(z)/P_{t+1}, A_{t+1}(z))\right],$$

where E_t denotes the expectations operator conditional on information known at time t. We

[30] In a general equilibrium model with linear disutility of labor and constant aggregate consumption, the real wage would be equal to $W_t/P_t = \alpha U_C(C)$, where α is the marginal disutility of labor. Under the additional assumption that prices are flexible, $W_t/P_t = (\theta-1)/\theta$. More generally, if the degree of monetary non-neutrality is small, variation in C_t will be small and the real wage will be approximately constant.

solve the firm's problem by Value Function Iteration on a grid. We approximate the processes for $A_t(z)$ and P_t using the method proposed by Tauchen (1986).

The solution to the firm's problem depends on the parameters of the model: β, θ, K/C, μ, ρ, σ_ϵ and σ_η. We set the monthly discount factor equal to $\beta = 0.96^{1/12}$. We choose $\theta = 4$ to roughly match estimates from the industrial organizations literature on markups of price over marginal costs.[31] We estimate $\mu = 0.0021$ and $\sigma_\eta = 0.0032$ from data on the CPI from 1998-2005. This sample period was chosen to correspond to the more recent sample period for which we report result from the CPI Research Database.

We choose the remaining three parameters to match our estimates of the frequency of regular price change, the fraction of regular price changes that are price increases and the size of regular price changes in 1998-2005. The parameter values that imply that the model matches the data along these three dimensions are $K/C = 0.0245$, $\rho = 0.660$, $\sigma_\epsilon = 0.0428$.[32] The model does not generate sale-like behavior for prices. We calibrate the model to match statistics for regular price changes and investigate whether it provides a good positive model of regular price adjustments. The simultaneous existence of rigid regular prices and frequent sales is an important challenge for the theoretical literature on monetary non-neutrality. We minimize the squared deviations of the model implied values of these moments from their estimated values in the data. Using this loss function, the parameters are well identified. Since we are able to exactly match all three parameters, the relative weights on different parameters in the loss function do not matter.

We can now test the model calibrated in this way by seeing how well it can account for other empirical features of price change. In the next three sections, we present several new empirical facts about price change and consider how well they line up with the implications of the model presented above.

[31] Berry et al. (1995) and Nevo (2001) find that markups vary a great deal across firms. The value of θ we choose implies a markup similar to the mean markup estimated by Berry et al. (1995) but slightly below the median markup found by Nevo (2001). Broda and Weinstein (2006) estimate elasticities of demand for a large array of disaggregated products using trade data. They report a median elasticity of demand below 3. Midrigan (2005) uses $\theta = 3$ while Golosov and Lucas (2006) use $\theta = 7$. The value of θ is not important for the points we make in this paper.

[32] Were we to assume $\theta = 10$, our estimate of K/C would rise to 0.07. All other results would be essentially unaffected.

1.5 *Inflation and the Frequency of Price Change*

The frequency of price change is not constant over time. As the rate of inflation varied over the period 1988-2005, the frequency of price change varied systematically along with it. This empirical result, which we document in this section, provides a natural test for our menu cost model. We analyze the evolution of four components of aggregate inflation: the median frequency of price increases, the median frequency of price decreases, the median absolute size of price increases and the median absolute size of price decreases.[33] Figures 1.2 and 1.3 plot the annual evolution of these four series for consumer prices along with the evolution of CPI inflation.[34] Of these four components of aggregate inflation, only the frequency of price increases displays a strong relationship with inflation. In contrast, the frequency of price decreases and the size of price increases and price decreases covary much less with inflation.

The correlation between the frequency of price increases and inflation is 0.81. Furthermore, a regression of the median frequency of price increases on aggregate inflation over the period 1988-2005 indicates that a 1 percentage point increase in the inflation rate is associated with approximately a 1 percentage point increase in the median frequency of price increases. A back-of-the-envelope calculation indicates that the variation in the frequency of price increases is large enough to account for most of the variation in aggregate inflation. A 1 percentage point increase in the monthly frequency of price increases, is associated with an increase of 0.1 percentage points in monthly inflation (since the average size of price increases is approximately 10%). This corresponds to approximately a 1 percentage point increase in annual inflation.

Table 1.13 conveys through regressions what figures 1.2 and 1.3 convey graphically. We regress the four components at the ELI-level on the aggregate CPI inflation rate. The regressions include ELI fixed effects and a time trend. We run such regressions both including and excluding sales and separately for 1988-1997 and 1998-2005. The regression coefficient on the

[33] Gagnon (2005) has emphasized the importance of distinguishing between price increases and price decreases in this context. Analyzing disaggregated Mexican consumer price data, he found that at low levels of inflation (<10% per year) the overall frequency of price change covaries little with inflation because movements in the frequency of price decreases partly offset movements in the frequency of price increases.

[34] As in section 1.3, these statistics are calculated by first calculating the mean frequency (size) within each ELI and then finding the weighted median across ELIs.

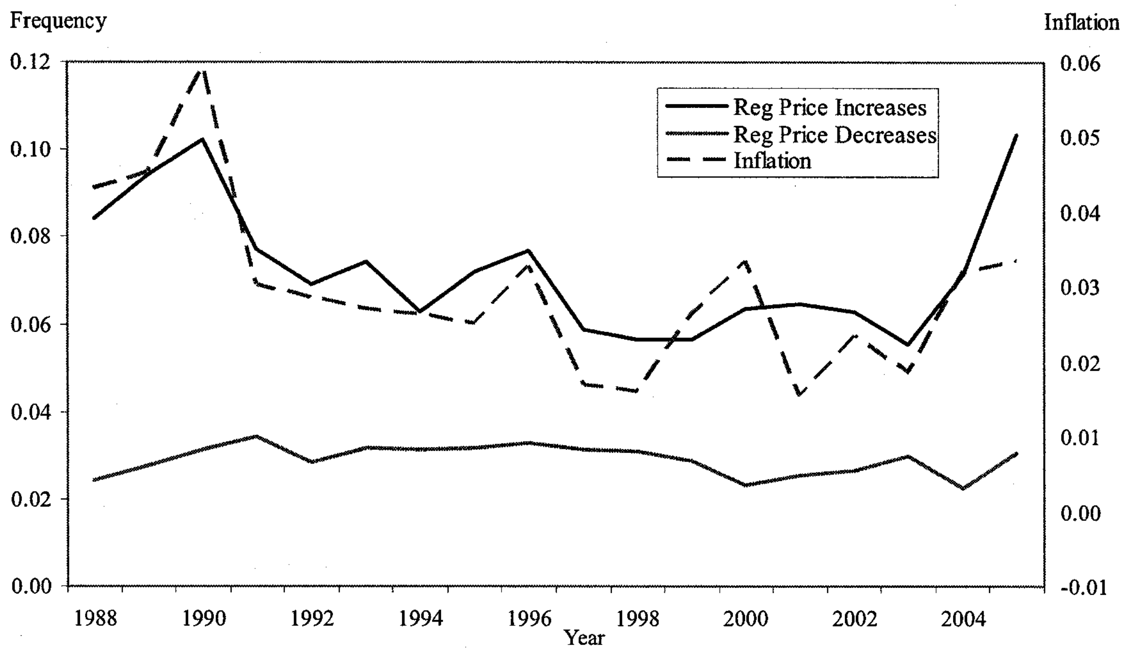

Figure 1.2: Inflation and the Frequency of Regular Price Change for Consumer Prices
The figure plots the annual evolution of the weighted median frequency of regular price increases and decreases along with the CPI inflation rate.

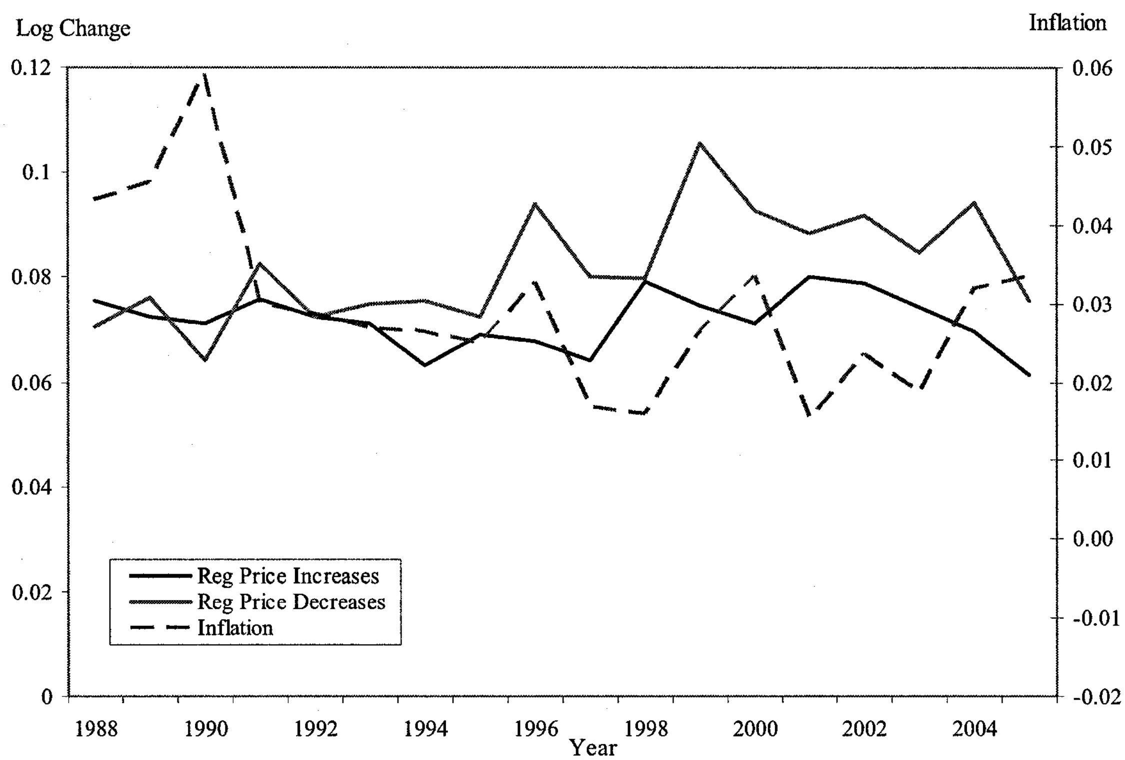

Figure 1.3: Inflation and the Size of Regular Price Changes for Consumer Prices
The figure plots the annual evolution of the weighted median absolute size of log regular price increases and decreases along with the CPI inflation rate.

Table 1.13: Regressions of Frequency and Size of Consumer Price Changes on Inflation

	Regular Prices		Prices	
Dependent Variable	1988-1997	1998-2005	1988-1997	1998-2005
Consumer Price ELI Level:				
Frequency of Price Increase	0.96*	0.56*	0.77*	0.70*
	(0.09)	(0.26)	(0.10)	(0.22)
Frequency of Price Decrease	-0.22*	-0.36*	-0.22	-0.41
	(0.10)	(0.08)	(0.13)	(0.13)
Size of Price Increase	0.17	-0.48	-0.06	-0.58
	(0.18)	(0.45)	(0.09)	(0.40)
Size of Price Decrease	-0.11	-0.43	0.08	0.24
	(0.37)	(0.24)	(0.24)	(0.14)
Frequency of Price Change	0.74*	0.37	0.56*	0.41
	(0.18)	(0.43)	(0.21)	(0.34)
Size of Price Change	0.52*	0.49	0.17	0.59
	(0.12)	(0.35)	(0.10)	(0.56)

The table reports the results of regressions of the median frequency and absolute size of log price increases and decreases at the ELI level on the aggregate CPI inflation rate (log change over 12 months). For example, the number in the table in the first row of numbers and first column of numbers (i.e. 0.96) refers to the regression coefficient on CPI inflation in a regression where the dependent variable is the frequency of regular price increases in 1988-1997. Each observation is for a particular ELI in a particular year. All regressions include ELI-level fixed effects and ELI-level time trends. Standard errors are in parentheses. The standard errors are cluster-robust standard errors calculated according to the method described in Arellano (1987), where the standard errors are clustered by year. A star denotes significance at the 5% level.

frequency of price increases is always positive and statistically significant. The coefficient on price decreases is always negative and statistically significant for regular price decreases. In contrast, the coefficients on the absolute size of price increases and decreases are inconsistent and never significantly different from zero. It is important to note that the results for the 1988-1997 period, which are most pronounced, are heavily influenced by the behavior of inflation and the frequency of price change in 1990; and more generally that these results should be interpreted with caution given the small amount of inflation variability over the period we consider.[35] Yet, as we discuss below, the empirical behavior of the frequency of price change appears to be broadly consistent with the simple menu cost model.

Figures 1.4 and 1.5 compare the evolution of these variables in the model to their evolution

[35] The year 1990 is an outlier in terms of both the frequency of price change and the inflation rate and therefore contributes disproportionately to the statistical significance and magnitude of the regression coefficients. We also considered specifications where we include a dummy variable for the year 1990. In these specifications, the coefficient fell to 0.68 (0.36) for the frequency of price change and was virtually unchanged at 0.97 (0.18) for the frequency of price increases, in the regressions for the 1988-1997 period.

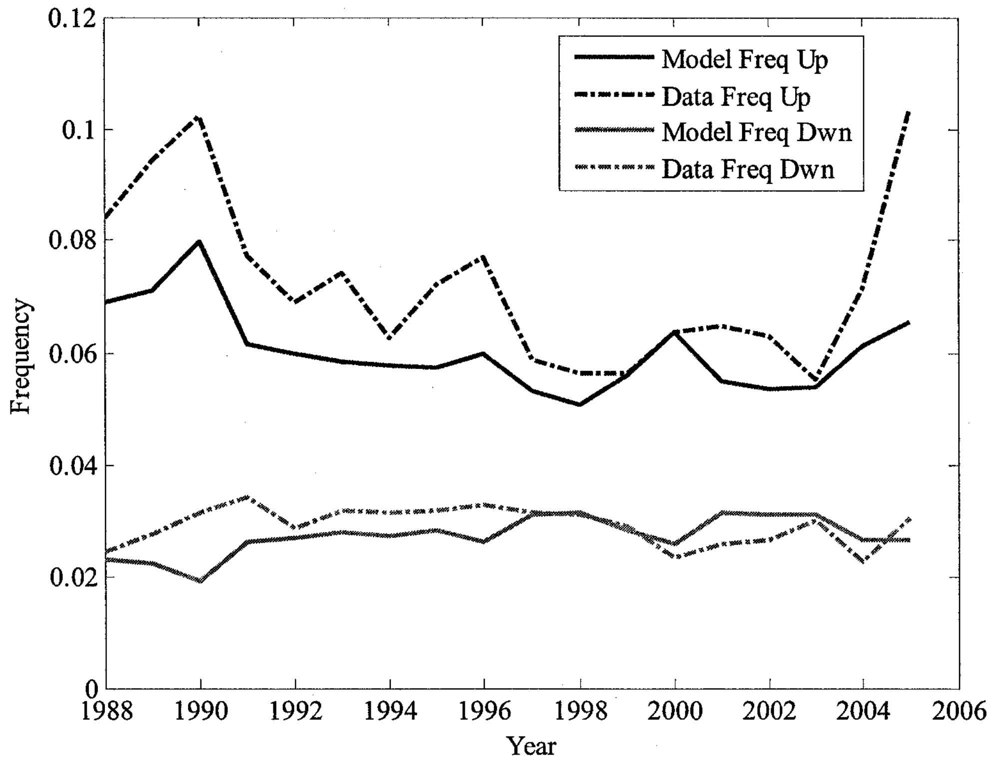

Figure 1.4: Evolution of the Frequency of Price Increases and Decreases in the Data and the Model

in the data. We simulated the model 100,000 times for the actual evolution of the CPI over 1988-2005 and calculated the average frequency and size of price increases and decreases by year. Just as in the data, the frequency of price increases in the model covaries much more strongly with inflation than the frequency of price decreases and the size of price increases and price decreases. For robustness, we also carry out this exercise in the general equilibrium model presented in chapter 3 and get virtually identical results.

The greater covariance of the frequency of price increases than the frequency of price decreases is a consequence of the fact that the price level is drifting upward. Positive inflation implies that the distribution of relative prices is asymmetric with many more prices bunched towards the lower sS bound than the upper sS bound. The bunching toward the lower sS bound implies that the frequency of price increases covaries more than the frequency of price decreases with shocks to the price level.

Figure 1.5 shows that the model also matches the fact that the median size of price decreases is larger than that for price increases. Ellingsen et al. (2006) show that this asymmetry can arise because the firm's profit function is asymmetric when the elasticity of

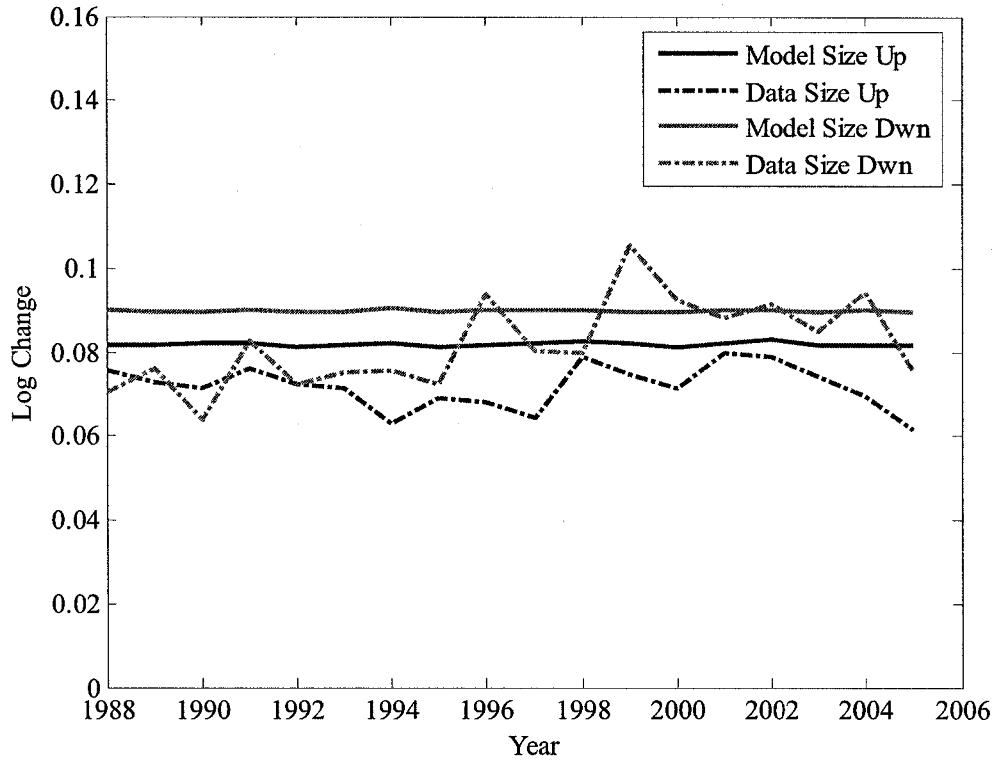

Figure 1.5: Evolution of the Size of Price Increases and Decreases in the Data and the Model

demand for it product is constant. The relative size of price increases and price decreases also depends on the steady state rate of inflation. As the steady state rate of inflation rises the size of price increases eventually becomes larger than the size of price decreases.[36]

If new technologies cause the fixed costs of changing prices to fall, the frequency of price change should be increasing over time, other things equal. Figure 1.4 shows that for the economy as a whole we do not find evidence of this phenomenon. To the contrary, our menu cost model with a constant menu cost is able to roughly match the evolution of the frequency of regular price change over the period 1988-2005 when we take into account the evolution of inflation.[37]

The finding that the frequency of price change covaries more with variation in the inflation rate than the size of price changes is consistent with a number of previous empirical

[36] A alternative explanation for the fact that price decreases are larger than price increases in the data is that we may have failed to filter out all sales.

[37] There are two sectors that do not follow this general pattern. These are vehicle fuel and travel services. The frequency of price change for vehicle fuel rose essentially monotonically from approximately 60% in 1988 to approximately 95% in 2005; while the frequency of price change for travel services rose again monotonically from approximately 20% in 1988 to 50% in 2005.

studies. Vilmunen and Laakkonen (2004) and Gagnon (2005) provide direct evidence for this phenomenon. Lach and Tsiddon (1992), Cecchetti (1986), Kashyap (1995), and Goette et al. (2005) all find that inflation has a substantial effect on the frequency of price change, but a much weaker effect on the absolute size of price changes.

Klenow and Kryvtsov (2005) find that most of the variation of aggregate inflation stems from variation in the average size of price changes. At first glance, our results may seem to contradict their results. Notice, however, that the average size of price change may be decomposed as $s_{all} = f_u s_u - f_d s_d$, where f_u and f_d denote the frequency of price increases and price decreases, respectively, and s_u and s_d denote the size of price increases and price decreases, respectively. We find that the frequency of price increases f_u is an important driving force behind variation in the average size of price changes.

The response of producer prices to variation in inflation is similar to the response of consumer prices excluding sales. We regress the frequency of price increases and decreases and the size of price increases and decreases for producer prices on CPI and PPI inflation separately at the four digit level for the period 1988-2005. The regressions include product fixed effects and a time trend. The frequency of price increases is highly correlated with both inflation rates. The size of price increases is also significantly correlated with both inflation rates. However, the frequency and size of price decreases are not related to inflation in a statistically significant way.

The evolution of sales in consumer prices over the past two decades has been entirely different from the variation in the frequency of regular price changes. Figure 1.6 shows the annual evolution over the period 1988-2005 of the median fraction of price quotes that are sales for the four Major Groups for which sales are most important. There has been a remarkable increase in the frequency of sales over this period. The frequency of sales increases substantially in all four categories, doubling in both processed food and apparel.[38] The average size of sales has also increased substantially over the sample period in all of the categories except for household furnishings. The increase is most dramatic in processed

[38] The size of a sale is measured as the absolute change in prices at the start of a sale (when the sale flag switches from "R" to "S") or at the end of a sale (when the sale flag switches from "S" to "R"). Only sales in which prices before or after the sale are observed are included in this calculation. We found no significant difference between the size of the price decrease at the beginning of sales and the size of the price increase at the end of sales.

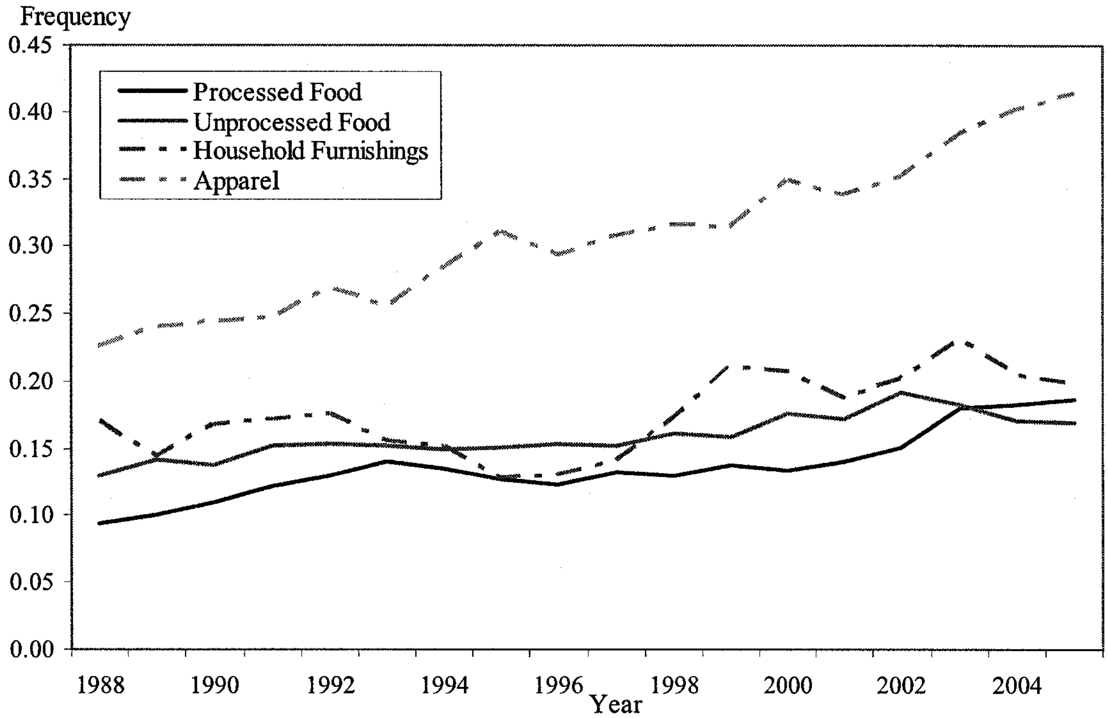

Figure 1.6: Evolution of the Frequency of Sales
The figure plots the weighted median fraction of observations that are sales by quarter for the four Major Groups for which sales are most prevalent.

food, where the size of sales has nearly doubled from about 20% to almost 40%. These facts extend the results of Pashigian (1988), who documents a trend in the frequency and size of sales beginning in the 1960's.

Table 1.14 presents the results of regressions of the frequency and size of sales on CPI inflation, ELI fixed effects and a time trend. We do not find robust evidence of a relationship between either the size or frequency of sales and aggregate variables. For both 1988-1997 and 1998-2005, we find a negative coefficient on the inflation rate, but neither coefficient is statistically significant at the 5% level. This suggests that a small effect may exist, but greater variation in desired prices than is generated by the variation in aggregate inflation over our sample period may be necessary to identify it.

1.6 *Seasonality of Price Changes*

The synchronization or staggering of price change is an important determinant of the size and persistence of business cycles in models with price rigidity. One form of synchronization

Table 1.14: Regressions of Frequency and Size of Sales on Inflation

Dependent Variable	1988-1997	1998-2005
Consumer Price ELI Level:		
Frequency of Sales	-0.34	-0.24
	(0.17)	(0.20)
Size of Sales	-0.19	0.45
	(0.44)	(0.43)

The table reports the results of regressions of the frequency and absolute size of sales at the ELI level on the aggregate CPI inflation rate (log change over 12 months). Each observation is for a particular ELI in a particular year. All regressions include ELI-level fixed effects and ELI-level time trends. Standard errors are in parentheses. The standard errors are cluster-robust standard errors calculated according to the method described in Arellano (1987), where the standard errors are clustered by year. A star denotes significance at the 5% level.

of price change is seasonality. Analyses of price change behavior often discuss the existence of a "pricing season". Yet the magnitude of this phenomenon, and the extent to which pricing seasons are coordinated across firms, have not previously been documented for the U.S. economy. We find a substantial seasonal component of price changes for the U.S. economy, for both consumer and producer goods.

Figure 1.7 presents the weighted median frequency of price increases and decreases by month for consumer prices excluding sales over the period 1988-2005. Three results emerge. First, the frequency of regular price change declines monotonically over the four quarters. It is 11.1% in the first quarter, 10.0% in the second quarter, 9.8% in the third quarter and only 8.4% in the forth quarter. Second, in all four quarters, the frequency of price change is largest in the first month of the quarter and declines monotonically within the quarter. This gives rise to the pattern of local peaks in the frequency of price change in January, April, July and October. Third, price increases play a disproportionate role in generating seasonality in price changes. The decline in the frequency of price increases between the first and fourth quarter is 1.9 percentage points, or 25%. In contrast, price decreases decline by 0.6 percentage point, or 18%, between the first and last quarter.[39]

The quarterly seasonal pattern in producer prices mirrors the seasonal patters in consumer prices qualitatively, but is substantially larger. For producer prices, the frequency of price change is 15.9% in the first quarter, 9.4% in the second quarter, 8.9% in the thrid quarter

[39] Álvarez et al. (2005b) find that prices are significantly more likely to change in January in the Euro Area.

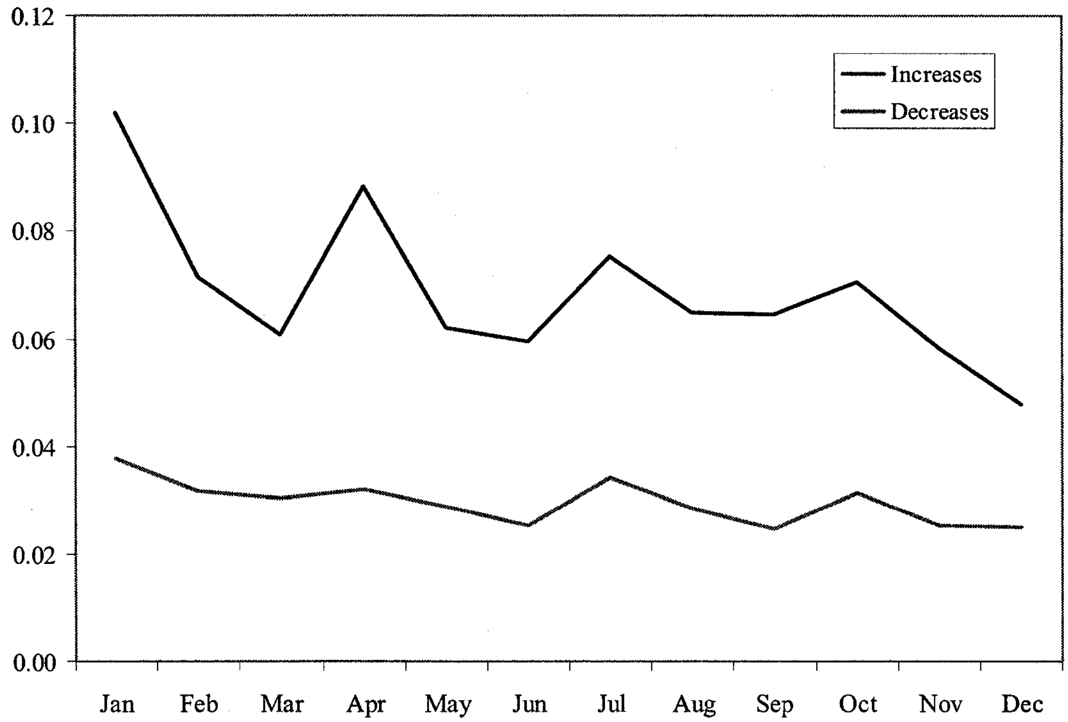

Figure 1.7: Frequency of Regular Price Increases and Decreases by Month in Consumer Prices
The figure plots the weighted median frequency of regular price increase and decrease by month.

and only 8.2% in the fourth quarter. Most of the seasonality in the frequency of price change in producer prices is due to the fact that producer prices are more than twice as likely to change in January than on average in other months of the year. As in consumer prices, most of the seasonality in the frequency price change comes from the frequency of price increases.

Olivei and Tenreyro (2005) show that the real effects of monetary policy shocks differ depending on the quarter of the year in which the shock hits. They argue that seasonality in the flexibility of wages can explain their empirical findings. Our finding that a disproportionate number of price changes are recorded in January provides an alternative potential explanation for their findings. Of course, seasonality in price-setting may simply be evidence of an allocative effect of seasonality in wage setting or other components of costs.

The seasonal pattern in sales is very different from the seasonal pattern in regular price changes. Figure 1.8 plots the fraction of price quotes that are sales by month for the four Major Groups for with sales are most important. The Major Group with by far the most seasonal variation in sales is Apparel. The frequency of sales is about 10 percentage points higher in Apparel in December, January and June than in the months with the least sales.

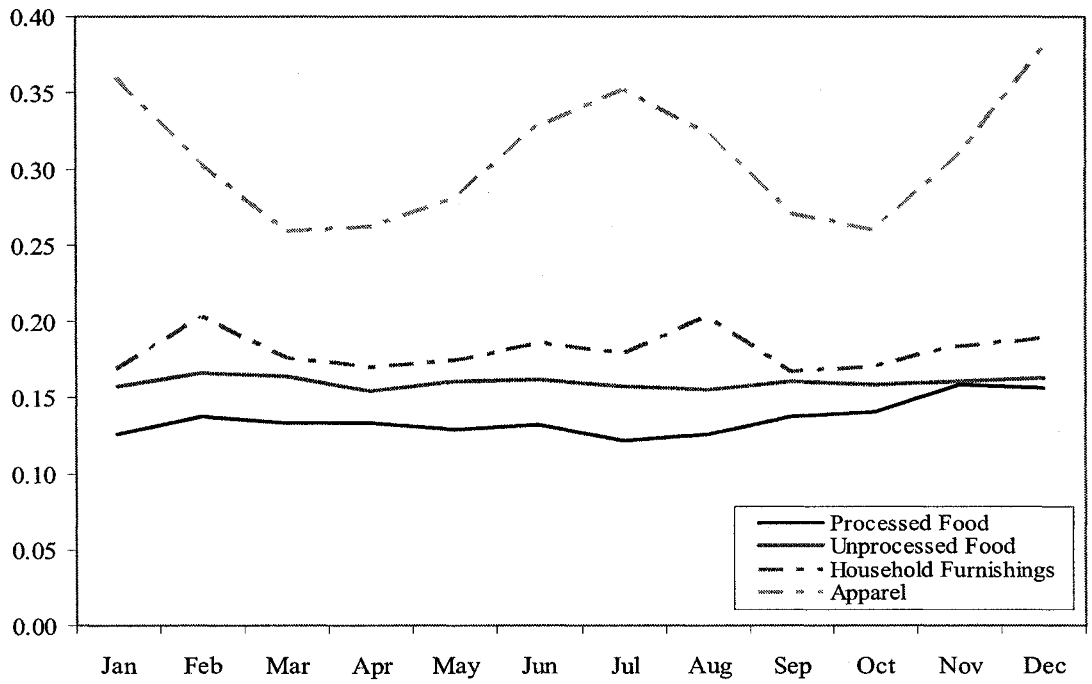

Figure 1.8: Seasonality in the Frequency of Sales
The figure plots the weighted median fraction of observations that are sales by quarter for the four Major Groups for which sales are most prevalent.

However, even in these other months, more than 25% of price quotes are sales in Apparel. The yearly winter and summer sales are clearly not the only sales in Apparel. This pattern has remained roughly unchanged between 1988-1997 and 1998-2005 while the overall level of sales in Apparel has increased dramatically. We find much less seasonality in sales in other Major Groups.

1.7 The Hazard of Price Change

Are prices that have recently changed more likely than others to change again? Or is it the case that prices become more likely to change the longer they have remained unchanged? These questions are essentially questions about the shape of the hazard function of price change. Let T be a random variable that denotes the duration of a generic price spell. In discrete time, the hazard function is defined as $\lambda(t) = \mathrm{P}(T = t | T \geq t)$. In other words, the hazard of a price change at time t is the probability that the price will change after t periods given that it has survived for t periods. If prices become more likely to change the longer they have remained unchanged, the hazard function of price change is upward sloping.

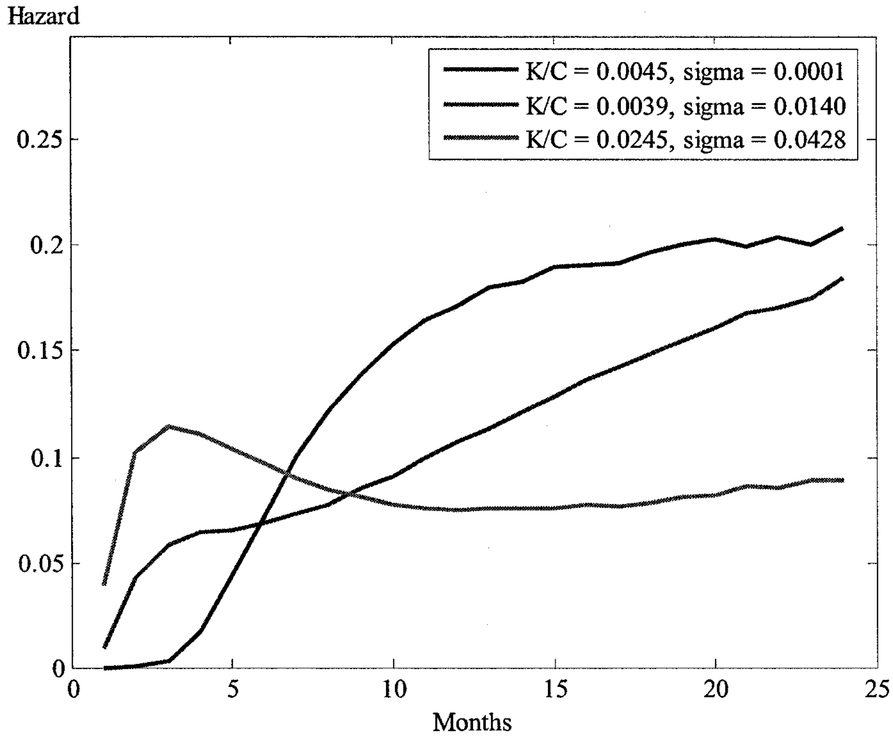

Figure 1.9: Hazard Function for Menu Cost Model with Varying Levels of Volatility of Idiosyncratic Shocks. In all cases $\rho = 0.66$ and the frequency of price change is 8.7%.

Menu cost models can give rise to a multitude of different shapes for the hazard function of price change. If marginal costs follow a random walk, the hazard function will be upward sloping. More generally, the shape of the hazard function is influenced by the relative size of transient and permanent shocks to marginal costs. Non-stationarity in marginal costs—e.g. due to inflation—tends to yield an upward sloping hazard function, while transient shocks tend to flatten the hazard function and can even yield a downward sloping hazard. Figure 1.9 illustrates how the shape of the hazard function in our benchmark menu cost model is affected by idiosyncratic shocks to marginal costs. As the variance of idiosyncratic shocks rises relative to the rate of inflation, the hazard function flattens out at longer durations but remains steeply upward sloping in the first few months.[40] In contrast, the Calvo model assumes a flat hazard function of price change.

[40] The reason why idiosyncratic shocks flatten the hazard function is that they give rise to temporary price changes that are quickly reversed. Such price changes occur when the idiosyncratic shock is large enough that it is worthwhile for the firm to change its price temporarily to an "abnormal" level even though it realizes that it will soon have to change it back. For calibrations of the model with very large idiosyncratic shocks—much too large to be realistic—the model even generates a downward sloping hazard in the first few months.

We estimate the hazard function of price change for consumer and producer prices and investigate how it lines up with the implications of our calibrated menu cost model. The main empirical challenge we face in doing this is to account for heterogeneity across products. It is well known in the literature on duration models that estimates of hazard functions based on pooled data from many heterogeneous products leads to a downward bias in the estimated slope of the hazard function. Even if the hazard functions of all the goods are flat or upward sloping, heterogeneity in the level of the hazard function of different products can cause the estimated hazard function to be downward sloping.[41]

We account for heterogeneity in two ways. First, we divide the products in our data set into groups and estimate hazard functions separately for each group. Second, within each group we estimate the empirical model proposed by Lancaster (1979) and analyzed in detail by Meyer (1986, 1990).[42] This model allows for multiplicative unobserved heterogeneity in the level of the hazard function at the product level, while estimating the slope of the hazard function non-parametrically. Specifically, we assume that the hazard function is

$$\lambda_i(t|x_{i,j}) = \nu_i \lambda_0(t) \exp(x_{i,j}\beta) \tag{1.7}$$

where i indexes products, j indexes observations, ν_i is a product specific random variable that reflects unobserved heterogeneity in the level of the hazard, $\lambda_0(t)$ is a non-parametric baseline hazard function with dummies for each month, $x_{i,j}$ is a vector of covariates for the jth observation of products i and β is a vector of parameters.[43] We assume that $\nu_i \sim \text{Gamma}(1, \sigma_\nu^2)$.[44] An important advantage of our data is that we observe multiple price spells for the same product. This fact substantially enhances our ability to identify the distribution of ν_i.[45] We estimate the model by maximum likelihood. We truncate the price spells at 18

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[41] See Kiefer (1988) for a survey of hazard function estimation.

[42] An example of a "product" is 16oz Kraft Singles sold at a particular supermarket in New York.

[43] The only covariates we consider are seasonal month dummies.

[44] We have estimated the model with $\nu_i \sim \text{N}(1, \sigma_\nu^2)$. The results are virtually identical.

[45] See Honore (1993) for a discussion of identification results for multiple spell duration models.

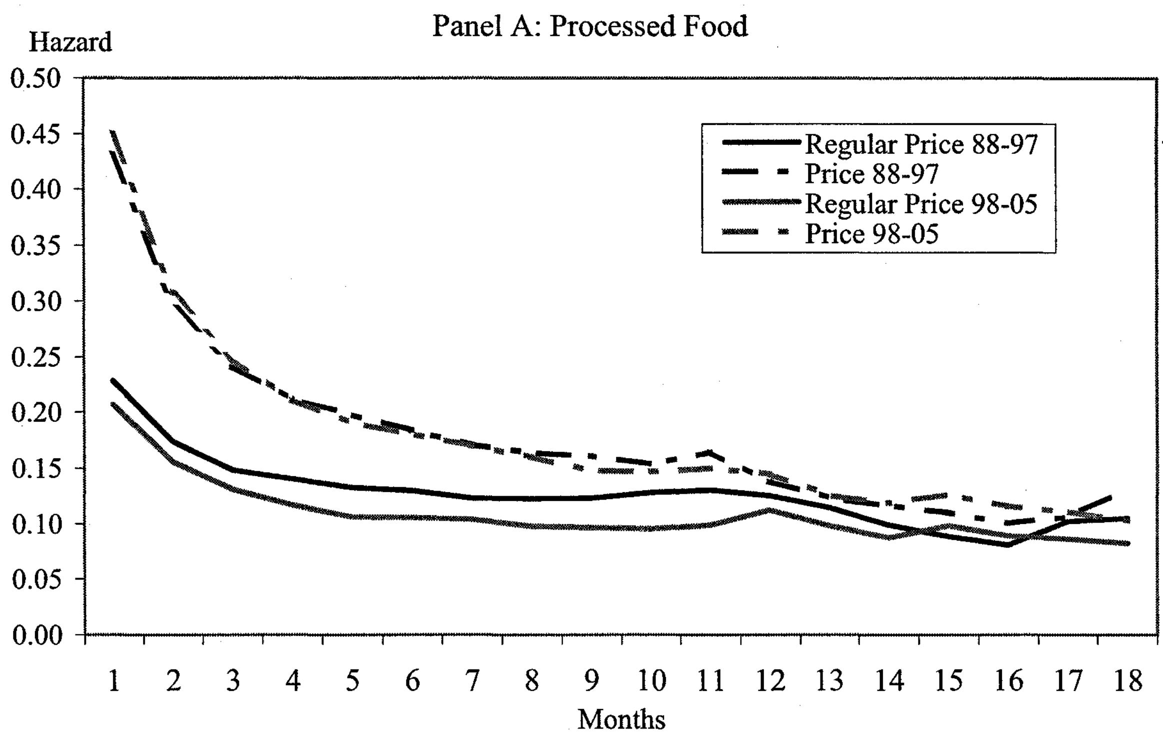
months and drop left censored spells.[46]

For consumer prices, we have approximately 2.75 million price spell observations after dropping left-censored spells. When we exclude sales as well, we are left with 1.65 million observations. We divide the data set into groups at the level of Major Groups. Figure 1.10 plots the baseline hazard function from the model described by equation (1.7) for Processed Food and Services.[47] Each panel plots the hazard function separately for prices with and without sales and separately for 1988-1997 and 1998-2005. The shape of the hazard function for Processed Food is representative of the shape of the hazard function for many of the Major Groups. The hazard function of regular prices is somewhat downward sloping for the first few months and then mostly flat after that. We do not find any evidence of upward sloping hazard functions for the Major Groups. This pattern holds even when we estimate our hazard model separately at the ELI level or when we sort products in each Major Group by their frequency of price change into 8 subgroups. For the major groups in which sales occur frequently (i.e., Processed and Unprocessed Food, Household Furnishings and Apparel), the hazard function including sales is much more steeply downward sloping than the hazard function of regular prices. Models of price change designed to match the behavior of prices including sales must generate this steeply downward sloping hazard function. For Services, we estimate a large spike in the hazard function at 12 months. This spike is perhaps most naturally interpreted as an element of time-dependence in firms' pricing decisions but may alternatively arise because of seasonality in costs or demand. Interestingly, such a 12 month spike is completely absent in most other Major Groups. We do not include information about the standard errors of our estimates in figure 1.10 because the standard errors are very small in most cases due to the large number of observations.

For producer prices, we have 1.95 million price spells after dropping left-censored spells. We estimate the model described by equation (1.7) separately for the 15 two digit Major Groups. The main stylized facts about the shape of the hazard function are similar for

[46] In the presence of heterogeneity, discarding left-censored spells leads us to disproportionately drop price spells arising from subjects with low values of ν_i, since long spells are disproportionately censored (Heckman and Singer, 1986). This does not bias our results about the shape of the hazard function under the proportional hazards assumption, though it does affect the estimated level of the hazard function.

[47] The extented version of this paper—available on our websites—reports plots of the hazard function of eight Major Groups for consumer prices and another eight Major Groups for producer prices.



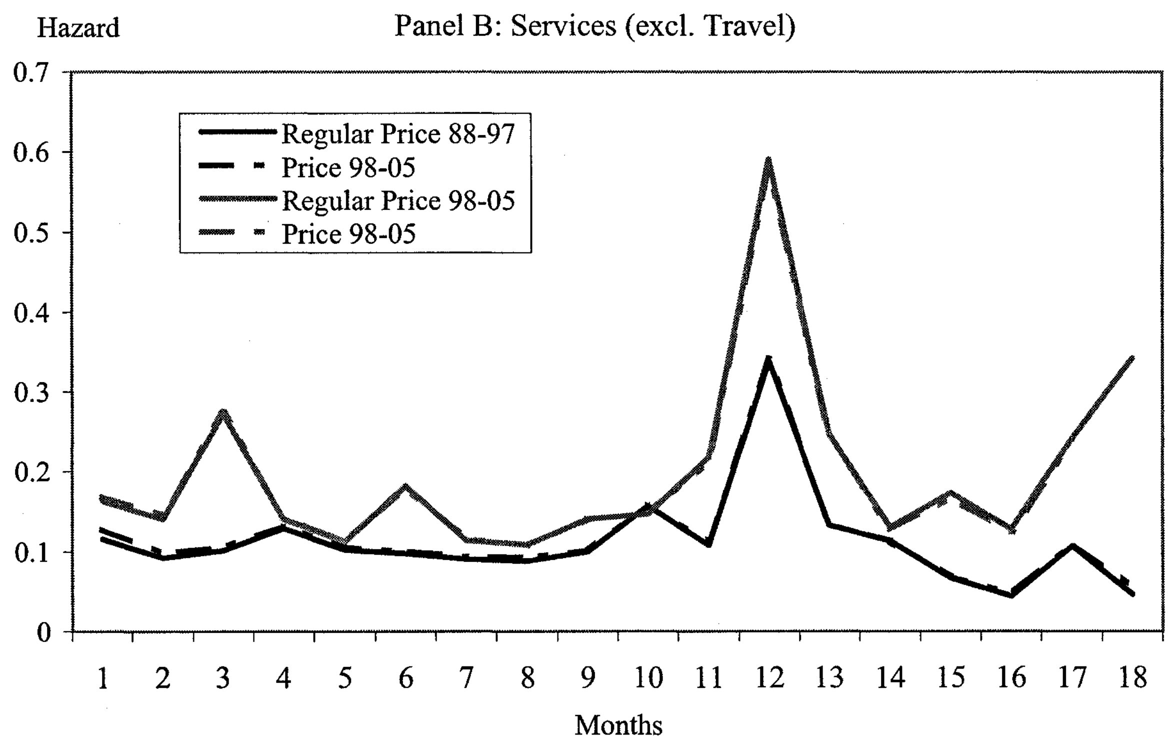


Figure 1.10: Hazard Functions for Consumer Prices

producer prices as they are for consumer prices. The hazard functions are downward sloping for the first few months, then mostly flat except for a large 12 month spike in all Major Groups. Accounting for heterogeneity leads to a substantial flattening of the hazard functions and a large increase in the size of the spike at 12 months. Interestingly, the 12 month spike in the hazard function is a much more pervasive phenomena in producer prices than in consumer prices.

The existing evidence on the shape of the hazard function is mixed. Empirical support for upward sloping hazard functions appears to arise mostly in studies in which almost all price changes are increases, indicating few idiosyncratic shocks (Goette et al. 2005; and Cecchetti, 1986), or in periods of very high inflation (Gagnon, 2005).[48] These facts line up well with the basic intuitions about the shape of the hazard function that arise from the menu cost model.

The main difference between the hazard function generated by our benchmark menu cost model and the hazard functions we estimate from the data is the behavior of the hazard in the first few months. In the data the hazard is large and falling while in the model it is small and rising sharply. We have considered an extension of our benchmark model with heteroskedastic shocks to marginal costs. This model generates a downward sloping hazard function in the first few months that lines up with the data. In a general equilibrium setting, the model with heteroskedastic shocks to marginal costs yields similar behavior for macroeconomic aggregates as the model with homoskedastic shocks to marginal costs. Another way to generate a downward sloping hazard function is time variation in the cost of changing prices. This type of model generates substantially more monetary non-neutrality than a general equilibrium model we analyze in chapter 3. Finally, sufficiently large and transient shocks to marginal costs can generate a downward sloping hazard function.

1.8 Conclusion

In this paper, we present new evidence on price adjustment in the U.S. economy. Using BLS micro-data we document that the median frequency of non-sale price change is 9-12% per month, roughly half of what it is including sales. This implies an uncensored median duration

[48] The results from some of these studies are hard to interpret since they use the conditional logit formulation. This formulation is biased in this application (see Willis, 2006).

of regular prices of 8-11 months. Product turnover plays an important role in truncating price spells in durable goods. The median frequency of price change for finished goods producer prices is roughly 11% per month. We argue that it is important to analyze regular price changes, price changes due to product introduction and temporary sales separately since these three types of price changes have quite distinct empirical features and are likely to have different macroeconomic implications. We show that one third of price changes are price decreases. Combined with the large average absolute size of price changes, the large number of price decreases observed in the data provides clear evidence that idiosyncratic shocks are an important source of price changes.

We find that the frequency of price increases covaries strongly with inflation while the frequency of price decreases and the size of price increases and price decreases do not. We show that this pattern is consistent with the implications of a benchmark menu cost model. We document a dramatic secular rise in the frequency and size of sales in several sectors of the U.S. economy. We do not find robust evidence that sales respond to aggregate variables. We find that the frequency of price change is highly seasonal. It is highest in the 1st quarter and lowest in the 4th quarter. Furthermore, in consumer prices the frequency of price change is highest in the first month of each quarter and falls monotonically within quarter.

Finally, we estimate the hazard function of price change for consumer and producer prices accounting for heterogeneity at the product level. We find that this hazard function is slightly downward sloping for the first few months and then flat (except for a large spike at 12 months in consumer services and all producer prices). This pattern is not consistent with our benchmark menu cost model. The calibrated benchmark model yields a hazard function that is sharply upward sloping in the first few months and does not imply a spike at 12 months. The spike at 12 months may be evidence of a time-dependent element of price setting. The fact that the empirical hazard is large and falling in the first few months may be evidence of heteroskedasticity in marginal costs or time variation in the cost of adjusting prices.

2. ACCOUNTING FOR INCOMPLETE PASS-THROUGH

2.1 Introduction

A substantial body of empirical work documents that exchange rate pass-through to prices is delayed and incomplete (Engel, 1999; Parsley and Wei, 2001; Goldberg and Campa, 2006).* These studies show that the prices of tradable goods respond sluggishly and incompletely to variations in the nominal exchange rate. An increase in the exchange rate leads to a substantially less than proportional increase in traded goods prices; and much of the price response occurs with a substantial delay.[1]

Recent theoretical work has suggested a number of potentially important factors in explaining incomplete pass-through. First, in oligopolistic markets, the response of prices to changes in costs depends both on the curvature of demand and the market structure (Dornbusch, 1987; Knetter, 1989; Bergin and Feenstra, 2001). Second, local costs may play an important role in determining pass-through (Sanyal and Jones, 1982; Burstein, Neves and Rebelo, 2003; Corsetti and Dedola, 2004). Local costs drive a wedge between prices and imported costs that remains fixed when the exchange rate changes. As a consequence, if local costs are large, even a substantial increase in the price of an imported factor of production may have little impact on marginal costs. Third, menu costs or other dynamic factors have the potential to contribute to incomplete pass-through (Giovannini, 1988; Kasa, 1992; Devereux and Engel, 2002; Bacchetta and van Wincoop, 2003).

I study pass-through in the coffee industry. Coffee is the world's second most traded

* I would like to thank Ariel Pakes and Kenneth Rogoff for invaluable advice and encouragement. I am grateful to Ulrich Dorazelski, Gita Gopinath, Joseph Harrington, Elhanan Helpman, David Laibson, Ephraim Leibtag, Julie Mortimer, Roberto Rigobon, Julio Rotemberg, Jón Steinsson, seminar participants at Harvard University and the Federal Reserve Board for helpful comments and suggestions. I am especially grateful to Dawit Zerom for jointly developing the numerical algorithm and computer code. I also thank the US Department of Agriculture for funding.

[1] See also Frankel, Parsley, and Wei (2005) and Parsley and Popper (2006).

commodity after oil. Over the past decade, coffee commodity prices have exhibited a remarkable amount of volatility. However, retail and wholesale coffee prices have responded sluggishly and incompletely to changes in imported commodity costs– an important feature of the aggregate evidence.[2] By wholesale prices, I mean the prices charged by coffee roasters like Folgers and Maxwell House, which I also refer to as manufacturer prices. For both retail and wholesale prices, a one percent increase in coffee commodity costs leads to an increase in prices of approximately a third of a percent over the subsequent 6 quarters (I refer to this as long-run pass-through). More than half of the price adjustment occurs with a delay of one quarter or more.[3]

Reduced form regressions indicate that delayed pass-through in this industry occurs almost entirely at the wholesale level. This evidence suggests that, to the extent that barriers to price adjustment contribute to delayed pass-through in this industry, it is wholesale price rigidity that matters. Goldberg and Hellerstein (2007) find similar results for the beer market using data from a large US supermarket chain. I document substantial rigidity in coffee prices at both the wholesale and retail level: over the time period I consider, manufacturer prices of ground coffee adjust on average 1.3 times per year, while retail prices excluding sales adjust on average 1.5 times per year over the same time period. The frequency of wholesale price adjustment is highly correlated with commodity cost volatility: wholesale prices adjust substantially more frequently during periods of high commodity cost volatility. Retailers play an important role in determining long-run pass-through since retail markups insert an additional wedge between imported costs and prices.[4]

A key question in interpreting the evidence on wholesale price rigidity is whether rigid wholesale prices actually determine the retail prices faced by consumers. Since manufacturers and retailers interact repeatedly, the observed rigid prices may not be "allocative" (Barro,

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[2] This has generated considerable public interest in coffee markets. In 1955, 1977 and 1987, the US Congress launched inquiries into the pricing practices of coffee manufacturers.

[3] An important strand of the international economics literature seeks to understand incomplete pass-through to the prices of imported inputs "at the dock" (though national statistics on imported prices sometimes reflect "c.i.f." prices including delivery charges). In the coffee market, pass-through "at the dock" is complete since the imported input, green bean coffee, is a publicly traded commodity. I focus instead on incomplete pass-through at the manufacturer and retail level.

[4] The role of retail behavior in determining pricing behavior is analyzed in detail by Hellerstein (2005) and Villas-Boas (2007).

1977). In particular, retail prices may react to cost shocks even when wholesale prices do not. I find little evidence of this phenomenon in the coffee market: conditional on wholesale prices, retail prices do not appear to react to changes in commodity prices.

I build a structural model of the coffee industry and investigate its success in explaining the facts about pass-through. I begin by estimating a model of demand for the coffee market. The coffee market, like most markets, is best described as a differentiated products market. The main difficulty of estimating demand curves in a differentiated products industry is that an unrestricted specification of the dependence of aggregate demand on prices leads to an extremely large number of free parameters. It is therefore useful to put some structure on the nature of demand. I do this by specifying a discrete choice model of demand (McFadden, 1974). This type of structural model places restrictions on the cross-price elasticities by assuming utility maximizing behavior resulting in a substantially more parsimonious model. I follow Berry, Levinsohn, and Pakes (1995b) in estimating a random coefficients model with unobserved product characteristics. An advantage of the coffee industry in estimating the demand system is that coffee prices are buffeted by large exogenous shocks to supply in the form of weather shocks to coffee producing countries. I use these weather shocks as instruments to identify the price elasticity of demand.

I combine this demand model with a structural model of the supply side of the coffee industry. I fix the number of firms and the products produced by the firms to match the observed industry structure. I use this model to estimate the "local costs of production". I account for the observed degree of price rigidity by assuming that firms must pay a menu cost in order to adjust their prices. I then analyze the equilibrium response of prices to costs in a Markov perfect equilibrium of this model. In my baseline estimation procedure, I use local costs estimated from a static model in order to avoid the problem of searching over a large number of parameters in the dynamic estimation procedure. I also consider an alternative procedure in which I estimate a common component in marginal costs as part of the dynamic estimation procedure.

The estimated model matches a number of features of pass-through in the coffee industry. As in the data, the model implies that a one percent increase in coffee commodity costs leads to a "long-run" pass-through into prices of approximately a third of a percent over the subsequent 6 quarters. The model also matches the extent of delayed pass-through observed in the data. In particular, in the model as in the data, more than half of the pass-through occurs in the quarters following the initial cost shock. This extent of delayed pass-through depends on the estimated degree of price rigidity: greater barriers to price adjustment imply slower adjustment. Despite a substantial amount of price rigidity (prices adjust on average 1.3 times a year) pass-through is relatively rapid because these price adjustments occur in periods when the incentive to adjust is high.

I also study the extent to which the model fits the timing of price adjustments. The main prediction of the menu cost model in this respect is that price adjustments occur more frequently in periods when marginal costs change substantially. This prediction of the model is borne out by the data. There is a strong positive relationship between the frequency of price change in a given year and the amount of turbulence in the coffee commodity market over that year.[5] It is important to note that neither the model's fit to the dynamics of pass-through nor its fit to the timing of price adjustments are "guaranteed" by the estimation procedure: the estimation procedure fits the level of prices and the overall average frequency of price change to the data, as well as fitting the demand data, but this estimation procedure does not make use of the model's implications for pass-through or the timing of price adjustments.

I compare the benchmark dynamic model to successively simpler models to determine how much local costs, markup adjustment and menu costs contribute to pass-through. I find that local costs and markup adjustment explain the bulk of incomplete pass-through: 78% of incomplete long-run pass-through is explained by local costs, about 20% is explained by oligopolistic markup adjustment, and about 2% is explained by menu costs.[6] Menu costs nevertheless play an important role in explaining pricing dynamics. The barriers to price adjustment generate a delayed response of prices to costs.[7]

The predictions of this type of model depend on a number of factors, only some of which

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[5] Similarly, Davis and Hamilton (2004) find that a monopolistic competition model with menu costs is broadly successful in explaining the timing of price adjustments in the wholesale gasoline market.

[6] These results echo the findings of Goldberg and Verboven (2001) for the European car market, as well as the findings of Burstein, Eichenbaum, and Rebelo (2005) for the behavior of tradable goods prices following large devaluations.

[7] For other interesting attempts to distinguish between markup adjustment and price rigidity in explaining exchange rate pass-through see Giovannini (1988) and Marston (1990).

arise in a static context. Since firms consider not only current but future costs in making pricing decisions, pass-through also depends on the dynamics of marginal costs. In the case of a monopolistic competition model with a symmetric profit function, it is clear by symmetry that if marginal costs follow a unit root then prices adjust to the static optimum conditional on adjusting (Dixit, 1991). This intuition essentially goes through in the present model as well—implying that menu costs have little impact on long-run pass-through in the unit root case. This case is relevant for the coffee market since I cannot reject the hypothesis that coffee commodity costs are a unit root. I investigate quantitatively how pass-through varies depending on the persistence of costs, the degree of consumer heterogeneity and the model of price adjustment behavior (i.e. menu cost vs. Calvo). I also study how the extent of price rigidity implied by a particular magnitude of menu costs depend on the dynamics of marginal costs and the extent of forward-looking behavior. Less persistent marginal costs imply a greater role for menu costs in explaining long-run pass-through, through both the frequency of price adjustment and the magnitude of price changes conditional on adjustment.

The basic approach I use to study pass-through in this industry builds on recent work by Goldberg and Verboven (2001) and Hellerstein (2005). These papers provide a detailed models of pricing in particular industries, and analyze their models' implications for pass-through. In particular, Hellerstein (2005) introduces a novel decomposition of the sources of incomplete pass-through into non-traded costs and markup adjustment. These analyses have focused on the contemporaneous response of prices to changes in costs. Yet, the delayed response of prices to costs suggests that dynamic factors are also important in explaining cost pass-through. This paper extends these models to incorporate additional empirical facts about delayed and incomplete pass-through. Goldberg and Hellerstein (2007) carry out a closely related study of the role of price rigidity in pass-through in the beer market, but approximate the firms' pricing policies using a static model. In contrast, I study the firms' pricing policies in a dynamic framework. The menu cost pricing model in this paper builds on Slade (1998, 1999) and Aguirregabiria (1999) who incorporate menu costs into industrial organization models of price adjustment in order to estimate the barriers to price adjustment.[8] More broadly, this paper is related to a large empirical literature on cost

[8] See also Gross and Schmitt (2000) for an alternative explanation of delayed pass-through.

pass-through as well as a growling literature on state-dependent pricing models solved using numerical methods.[9] Bettendorf and Verboven (2000) study the relationship between Dutch coffee prices and commodity costs using a structural model and find similar results on the magnitude of non-coffee bean costs.

Clearly, one issue that arises in this type of analysis based on a particular industry is the extent to which conclusions based on one particular industry can be extended to understand pricing dynamics in other industries. One conclusion of my analysis is that delays in wholesale price adjustments almost entirely explain the delayed response of prices to costs. It is therefore crucial to distinguish between retail and wholesale prices in understanding the link between price rigidity and the response of prices to costs. Retailers play an important role in numerous sectors of the US economy, particularly food, clothing and household furnishings which account for more than 30% of US consumption. A second conclusion of my analysis is that a simple menu cost model can provide a good explanation of the dynamics of price adjustment, but menu costs play almost no role in explaining "long-run" pass-through over a horizon of 6 quarters. This conclusion depends on the persistence of coffee commodity costs, but is likely to also be relevant to pass-through of other highly persistent series such as exchange rates and wages. Two features of the results that are likely to be sensitive to the choice of the coffee industry are the extent of local costs and markup adjustment. Coffee beans are likely to represent a disproportionate share of marginal costs compared to imported inputs in other industries. In addition, coffee costs are highly correlated across firms. The fact that some firms face marginal cost shocks due to imported inputs while other firms do not may be an important motive for pricing to market in other industries.

The paper proceeds as follows. Section 2.2 provides an overview of the data used in the paper. Section 2.3 presents stylized facts about price adjustment in the coffee industry. Section 2.4 describes the estimation of the demand model. Section 2.5 applies the demand model to estimate markups and local costs. Section 2.6 presents the menu cost oligopoly model and the computational algorithm used to solve for the equilibrium of this model,

[9] In the cost pass-through literature, see Kadiyali (1997), Gron and Swenson (2000) and Levy et al. (2002). See also Bettendorf and Verboven (2000) and the references therein for specific analyses of coffee prices in various countries. A recent example of a numerical state dependent pricing model in the international economics literature is Floden and Wilander (2004).

and establishes the basic features of firm equilibrium behavior in the model. Section 2.7 establishes the predictions of the model for incomplete pass-through, and documents the relative importance of markup adjustment, local costs and menu costs. Section 2.7 also investigates the role of the persistence and volatility of costs in determining pass-through. Section 2.8 concludes.

2.2 Data on Prices and Costs

I pull together a number of sources of data on prices and costs from a number of sources to develop the model of the coffee industry. I use data on prices and sales from two industry sources. My source for retail price and sales data is monthly AC Nielsen data. These data are market-level average prices and sales for the period 2000-2004. I use these data to construct series on retail prices and market shares.[10] The advertising variable I use in estimating demand is brand-level monthly national total advertising dollars per brand from the AdDollars database.

I also obtained wholesale price data from the PromoData company. Promodata collects data on manufacturer prices for packaged foods from grocery wholesalers. Promodata collects its information from the largest grocery wholesaler in a given market but does not identify the wholesaler for confidentiality reasons. These data provide the price per case charged by the manufacturer to the wholesaler for a particular UPC in a particular week. Because Promodata surveys a much less complete array of markets and wholesalers than AC Nielsen, the wholesale price data covers a substantially less complete array of markets, time periods and products than the retail data, though the actual coverage varies by market. However, the wholesale price data also have some features not available in the retail data. In particular, since the wholesale data are actually prices for individual products from particular manufacturers to a particular wholesaler in a particular week, I can also use these data to analyze price rigidity. In a recent report by the Brazil Information Center (Brazil-Information-Center-Inc., 2002), about half of 20 large US retailers interviewed reported using grocery wholesalers, though

[10] AC Nielsen collects prices from cooperating supermarkets, with at least $2 million in sales. Sales by super-centers, such as Walmart and Target, are not covered in the data. The 50 AC Nielsen markets span almost the entire continental United States. AC Nielsen markets are generally considerably larger than cities.

the fraction was lower among the largest supermarkets in this group. In general, the price quoted to a grocery wholesaler is non-negotiable, and the product is delivered directly to the wholesaler's warehouse. The grocery wholesaler may then resell the product to a supermarket. The wholesale price data contain information on both base prices and "trade deals". Trade deals are discounts offered to the grocery wholesalers to encourage promotions. For some types of trade deals, manufacturers require proof that a promotion has been carried out in order to redeem the discount though this is not always the case. According to a former grocery wholesale executive, since advertising is often carried out collectively by grocery stores associated with a particular wholesaler, in many cases, the funds associated with the trade deal are used by a grocery collective for promotional purposes rather than being passed on to individual stores. The cost pass-through regressions I present are for prices including trade deals. For both the retail and wholesale pass-through regressions, I only include the prices of ground caffeinated coffee, since decaffeinated coffee has a substantially different (and more complicated) production process.

The commodity price data are based on commodity prices on the New York Physicals market collected by the International Coffee Organization (ICO). I focus on price responses to a "composite commodity index" that I construct in the following way. I construct the commodity price index as a weighted average of the commodity prices for Colombian Mild Arabicas, Other Mild Arabicas, Brazilian and Other Natural Arabicas, and Robustas. I weight the commodity prices for the different varieties based on the average composition of U.S. coffee consumption from Lewin, Giovannucci, and Varangis (2004) over the years 1993-2002. These weights have remained relatively stable over the sample period. For example, the fraction of Robustas varied between 23.7% and 26.7% over the period 1993-2002. I also adjust the commodity price for the fact that roasted green coffee beans lose about 19% of their weight during the roasting process.

Finally, in order to construct the graphs of aggregate series in section 2.3, I make use of retail and wholesale price indexes from the Bureau of Labor Statistics. In particular, I make use of the "ground coffee" retail price index and the "roasted coffee" wholesale price index downloaded from the Bureau of Labor Statistics webpage.

In principle, it would be preferable to analyze the responses of coffee prices separately to movements in different types of coffee.[11] Unfortunately, reliable estimates of the composition of different brands of coffee by coffee bean type are not available. However, the effect of analyzing responses to the coffee commodity index rather than individual coffee types is likely to be small for two reasons. First, the prices for different types of green bean coffee covary strongly. Second, as I note above, the consumption weights of the different types of coffee for the U.S. as a whole have changed little over the sample period.

2.3 Cost Pass-Through Regressions

Let us begin by looking at the relative movements of coffee prices and costs over the past decade.[12] Figure 2.1 presents a graph of average retail, wholesale and commodity prices in US dollars per ounce.[13] To be clear about terminology, I shall refer to the price charged by supermarkets to consumers as the *retail* price, the price charged by coffee roasters such as Folgers and Maxwell House to grocery wholesalers as the *wholesale* price, and the price of green bean coffee on the New York market as the *commodity* cost.

The vast majority of coffee sold in the U.S. is imported in the form of green bean coffee (the largest coffee producing countries are Brazil, Colombia and Vietnam). Coffee manufacturers such as Folgers and Maxwell House roast, grind, package and deliver the coffee to the American market. While packaged coffee is typically viewed as a tradable good, the dominant trade in coffee is therefore trade in a "middle" good which is then combined in fixed proportions with inputs in the domestic market (Sanyal and Jones, 1982).[14] Green bean coffee prices were highly volatile over this period, losing almost two thirds of their value between 1997 and 2002. Most of the volatility in commodity costs arises from weather conditions in coffee producing countries, planting cycles and new players in the coffee market. Since coffee commodity prices are quoted in U.S. dollars, commodity prices have also been affected by

[11] In some industries, shifting input composition plays an important role in determining cost pass-through. See Gron and Swenson (2000).

[12] This section draws heavily on the analysis in Leibtag et al. (2005).

[13] These graphs are based on indexes of retail roasted coffee prices and wholesale ground coffee prices downloaded from the Bureau of Labor Statistics website.

[14] In order to manufacture one ounce of ground roasted coffee, 1.19 ounces of green bean coffee are required. In 1997, the U.S. imported over 20 million bags of green bean (unprocessed) coffee in 1999 (2.5 billion dollars), but only about 0.7 million bags of roasted coffee.

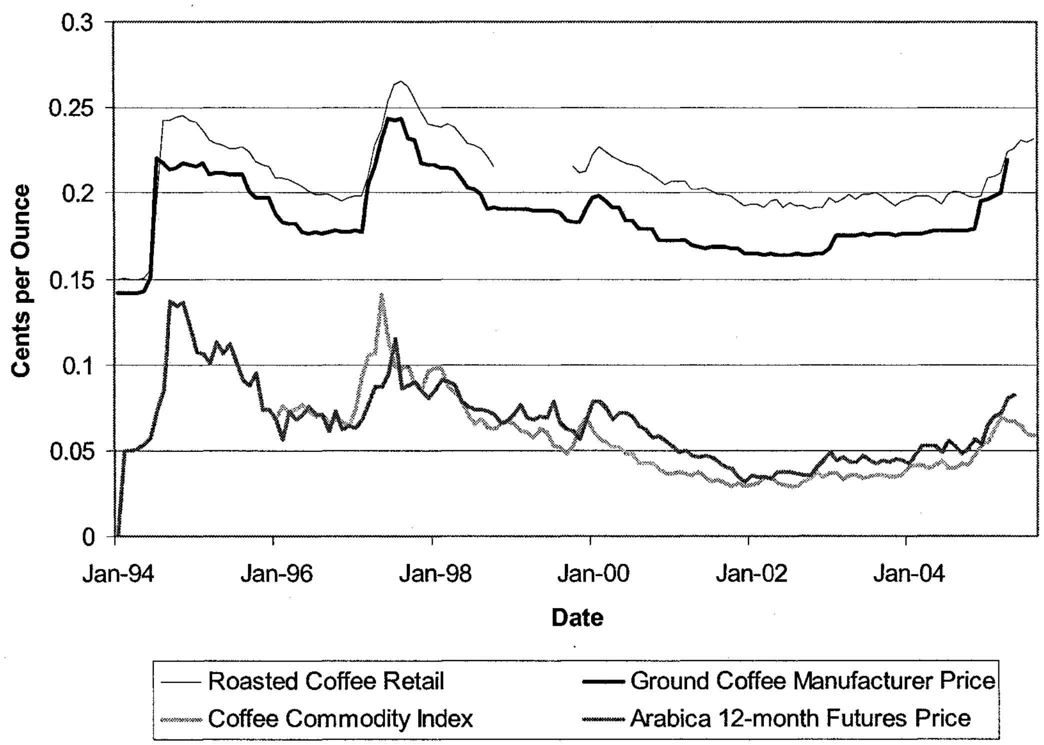

Figure 2.1: Retail, Wholesale and Commodity Prices

The roasted coffee retail and ground coffee manufacturer prices are average prices from the Bureau of Labor Statistics database on consumer and producer prices. The Arabica 12 month futures price is from the New York Board of Trade. The coffee commodity index is a weighted average of the prices of different types of green bean coffee.

the rise and fall of the U.S. exchange rate.

Figure 2.1 shows that retail and wholesale prices tracked commodity prices closely over this period. The close relationship between prices and commodity costs is not surprising given the large role of green bean coffee in ground coffee production. Industry estimates suggest that green bean coffee accounts for more than half of the marginal costs of coffee production.[15] To quantify this relationship, I estimate the following standard pass-through regression,

$$\Delta \log p_{jmt}^{l} = a + \sum_{k=1}^{6} b_k \Delta \log C_{t-k} + \sum_{k=1}^{4} d_k q_k + \epsilon, \tag{2.1}$$

where $l = r, w$, $\Delta \log p_{jmt}^{r}$ is the log retail price change of product j in market m, $\Delta \log p_{jmt}^{w}$ is the corresponding log wholesale price change, $\Delta \log C_{t-k}$ is the log commodity cost index, q_t is a quarter of the year dummy, a, b_k and d_k are parameters and ϵ is a mean zero error term. The wholesale price series include trade deals; the results excluding trade deals are extremely similar.[16] The coefficients b_k may be interpreted as the percentage change in prices associated with a given percentage change in commodity costs k quarters ago. The empirical model follows the approach of Goldberg and Campa (2006). The model is motivated by the fact that, as in Goldberg and Campa (2006), the regressor is highly persistent: a Dickey-Fuller test for the hypothesis of a unit root in commodity prices cannot be rejected at a 5% significance level.[17] Goldberg and Campa (2006) define the long-run rate of pass-through in this model as the sum of the coefficients $\sum_{k=1}^{6} b_k$. I selected the number of lags included in the regression such that adding additional lags does not change the estimated long-run rate of pass-through. I estimated the model using the retail and wholesale price data described

[15] For example, a major producer estimated in 1976 that green bean coffee accounted for 82% of marginal costs (Yip and Williams, 1985). Industry estimates suggest, however, that the fraction of marginal costs accounted for by commodity costs have since fallen with the price of green bean coffee.

[16] Trade deals are more common when commodity costs are low. Numerically, however, the effect is small: an increase in green bean coffee costs by 1 cent lowers the frequency of trade deals by a statistically significant amount of about 0.2 percentage points; the size of trade deals are not correlated in a statistically significant way with commodity costs.

[17] An alternative approach would be to estimate a panel error correction model. I cannot reject the null of no cointegration of coffee prices and coffee bean costs in aggregate data over the time period I consider. Syed (2005) analyzes a vector error correction model for the coffee market with aggregate data, yielding very similar results for both long-term pass-through and dynamics to the present analysis.

in Section 2.2, for quarterly changes in prices and costs over the 2000-2005 period.[18]

The first panel of table 2.1 presents the results of the pass-through regression for retail and wholesale prices. Table 2.1 documents a substantial amount of incomplete pass-through in percentage terms. The estimated long-run pass-through elasticity is 0.252 for retail prices and 0.262 for wholesale prices. In other words a one percent increase in commodity costs eventually leads to only about a quarter of a percent increase in coffee prices.[19] Table 2.1 also documents that there is a substantial delay in the response of prices to commodity costs. For both retail and wholesale prices, more than half of the adjustment to a change in costs occurs in the period *after* the cost shock. Similar patterns of delayed and incomplete pass-through are found for the coffee market by Syed (2005) and the UK Competition Commission (1991). One advantage of this type of detailed industry setting is that it minimizes measurement error in foreign costs, which are typically approximated using foreign price indexes.

I also consider an alternative specification of the pass-through regression. The second panel of table 2.1 presents the results of the pass-through regression (2.1) in levels rather than logs. This specification cannot typically be estimated using aggregate indexes on exchange rates and inflation since it requires information on the absolute level of prices and costs. For this specification, the long-run pass-through of retail prices to commodity costs is 0.916, while the long-run pass-through to wholesale prices is 0.852. Thus, a one cent increase in commodity prices leads to slightly less than a one cent increase in prices. The difference between the regressions in levels and logs is explained by the substantial wedge between observed prices and costs, which implies that a one cent change corresponds to a substantially smaller percentage change in prices than costs.[20] I find similar results for long-run pass-through when I estimate these regressions using the weather instruments discussed in section

[18] The standard errors for all of the regressions in this section are clustered by unique product and market to allow for arbitrary serial correlation in the error term for a given product. See, for example, Wooldridge (2002) for a discussion of this procedure.

[19] I do not find evidence that prices systematically react asymmetrically to price increases or decreases.

[20] These statistics are for retail prices including temporary sales. A 1 cent per ounce increase in commodity costs is associated with a 0.03 cent decrease in the difference between base prices (excluding sales) and net prices (including sales)—about 3% of the overall pass-through, based on a fixed effects regression of the difference between base and net prices on commodity costs and quarter dummies. In terms of the effect on average prices, retail prices contribute little to overall pass-through, though it is unclear how to interpret this fact given the complex dynamic response of demand to retail sales.

Table 2.1: Pass-Through Regressions

Variable	Log Specification		Levels Specification	
	Retail	Wholesale	Retail	Wholesale
Δ Commodity Cost (t)	0.063	0.115	0.142	0.218
	(0.013)	(0.018)	(0.040)	(0.061)
Δ Commodity Cost (t-1)	0.104	0.169	0.446	0.520
	(0.008)	(0.013)	(0.024)	(0.043)
Δ Commodity Cost (t-2)	0.013	-0.010	0.016	0.029
	(0.007)	(0.010)	(0.019)	(0.028)
Δ Commodity Cost (t-3)	0.031	-0.016	0.080	0.004
	(0.006)	(0.009)	(0.018)	(0.026)
Δ Commodity Cost (t-4)	0.048	0.007	0.144	0.023
	(0.007)	(0.013)	(0.018)	(0.030)
Δ Commodity Cost (t-5)	0.007	0.025	0.070	0.067
	(0.006)	(0.011)	(0.017)	(0.031)
Δ Commodity Cost (t-6)	-0.015	-0.026	0.017	-0.009
	(0.008)	(0.012)	(0.021)	(0.029)
Constant	0.033	-0.004	0.007	0.001
	(0.003)	(0.003)	(0.0004)	(0.0005)
Long-run Pass-through	0.252	0.262	0.916	0.852
	(0.007)	(0.018)	(0.023)	(0.052)
Number of observations	40129	2867	40129	2867
R squared	0.079	0.141	0.088	0.134

The retail price variable is the change in the UPC-level retail price per ounce in a particular US market over a quarter. The wholesale price variable is the change in the wholesale price per ounce (including trade deals) of a particular UPC in a particular US market over a quarter. The standard errors are clustered by unique product and market to allow for arbitrary serial correlation in the error term for a given product. The data cover the period 2000-2005.

2.4.[21]

This alternative specification of the pass-through regression begs the question of whether it might be more relevant to consider cent-for-cent pass-through as a benchmark for "complete" pass-through as opposed to a pass-through elasticity of 1. One reason why a pass-through elasticity of 1 is an interesting benchmark is that this is an implication of the workhouse Dixit-Stiglitz model with no local costs of production. Also, at a practical level, the empirical literature has focused on pass-through elasticities (rather than pass-through in levels) because only percentage changes (i.e. elasticities) are meaningful for price indexes for aggregate data.

I next consider to what extent delays in pass-through occur at the wholesale versus the retail level. This issue matters both for how we model price adjustment behavior, and what data is most relevant for parameterizing the model. In order to analyze this issue, I consider the following regression of retail prices on wholesale prices,

$$\Delta p^r_{jmt} = \alpha^r + \sum_{k=0}^{2} \beta^r_k \Delta p^w_{jmt-k} + \sum_{k=1}^{4} \gamma^r_k q_k + \epsilon, \tag{2.2}$$

where α^r, β^r_k and γ^r_k are parameters, and ϵ is a mean zero error term. The wholesale price data are likely to be a noisy proxy for the wholesale costs faced by any particular retailer. To avoid attenuation bias, I estimate this equation by instrumental variables regression with commodity costs as instruments.[22] Table 2.2 reports the results of this regression. The estimated pass-through coefficient on contemporaneous changes in wholesale prices is 0.958, with small and insignificant coefficients on the lagged wholesale price changes. This regression indicates that retail prices respond immediately and approximately cent-for-cent to changes in wholesale prices associated with cost shocks, indicating that almost all of the delays in pass-through in this market may be explained by delays at the wholesale level. This result motivates a focus on both documenting and explaining price adjustment at the wholesale level.

Finally, I document the extent of price rigidity in manufacturer prices in the coffee in-

[21] I considered instrumental variables estimates of the pass-through regressions in levels, using the weather in Brazil and Colombia as instruments as discussed in section 2.4. The resulting estimates of long-run pass-through are 0.968 for retail prices and 0.960 for wholesale prices.

[22] The instruments I use are current changes in the commodity cost index and 12 month Arabica futures prices as well as 6 lags of these variables.

Table 2.2: IV Regression of Retail Prices on Wholesale Prices

	Retail Prices
Δ Wholesale Price(t)	0.958
	(0.131)
Δ Wholesale Price (t-1)	-0.050
	(0.180)
Δ Wholesale Price (t-2)	-0.027
	(0.129)
Constant	0.005
	(0.001)
Quarter Dummies	YES
Number of observations	2792
Instruments	Commodity Costs

The dependent variable is the change in the UPC-level monthly average of the retail price per ounce in a particular US market over a quarter. The wholesale price variable is the change in the wholesale price per ounce (including trade deals) of a particular UPC in a particular US market over a quarter. The standard errors are clustered by unique product and market to allow for arbitrary serial correlation in the error term. The data cover the period 2000-2005. Wholesale prices are instrumented for by current changes in commodity costs and Arabica futures as well as 6 lags of these variables.

dustry. Figure 2.2 presents a typical wholesale price series for coffee. The figure shows that wholesale coffee prices have sometimes remained unchanged for substantial periods of time. Since 1997, Proctor and Gamble (P&G), the maker of Folgers coffee has announced three major price increases and eight major price decreases.[23] P&G commented to reporters in conjunction with its 2004 price increase that P&G "increases product prices when it is apparent that commodity price increases will be sustained". (Associated Press, Dec. 10 2004). Table 2.3 presents the statistics on the annual evolution of the frequency of price adjustment for wholesale and retail prices, where the frequency of price adjustment of retail prices is based on data from the consumer price index database analyzed in chapter 1. The average frequency of wholesale price adjustment is 1.3 over the 1997-2005 period while the average frequency of retail price adjustment excluding retail sales is 1.5.

There is a strong and statistically significant relationship between commodity cost volatility and the frequency of price change. Table 2.4 presents statistics on the average number of wholesale price adjustments per year over the period 1997-2003. Over the years 1997 to 2005, the average number of price changes in a year varied between 0.2 and 4.3 for wholesale price changes not including trade deals. Figure 2.3 plots the relationship between the average

[23] This statistic is based on price change announcements reported in the Lexis Nexus news archive.

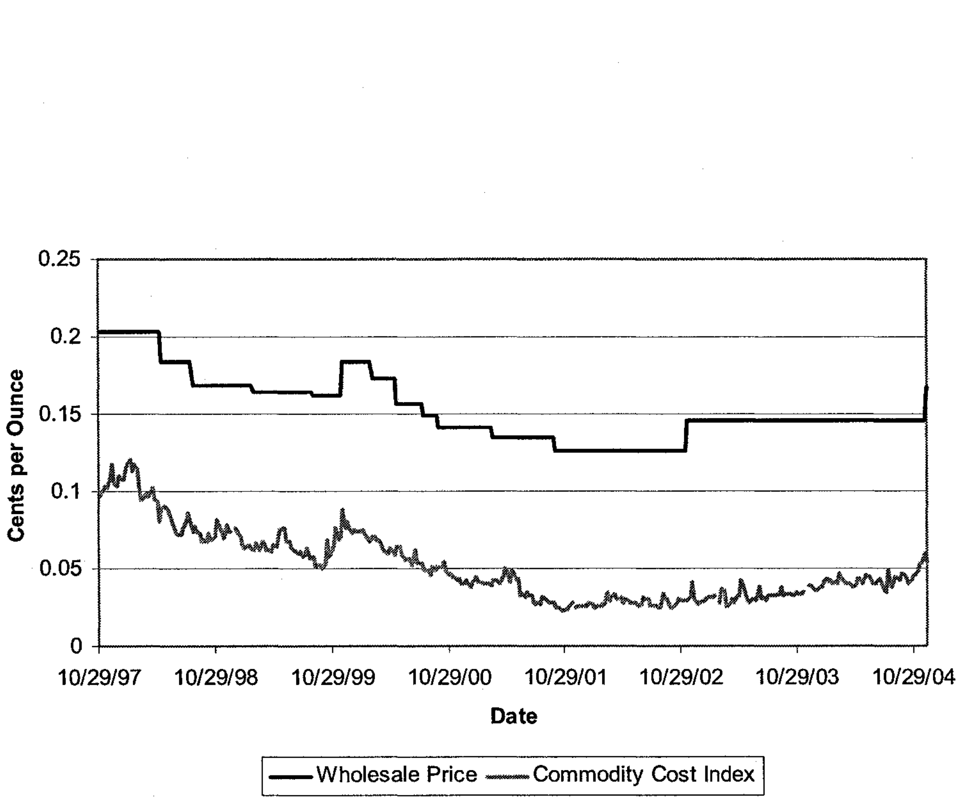

Figure 2.2: A Typical Wholesale Price Series
The gross wholesale price of a leading coffee brand. The coffee commodity price is a weighted average of the prices of different types of coffee on the New York Board of Trade.

Table 2.3: Annual Frequency of Price Change

Wholesale Prices	Retail Prices	
	Without Retail Sales	With Retail Sales
1.3	1.5	3.1

The wholesale price statistics are based on weekly wholesale price data for the period 1997-2004. The first column presents the statistics for regular prices (excluding trade deals). The observations are weighted by average retail revenue over the period 2000-2004. The second and third columns of present statistics on the frequency of price change for retail prices of ground coffee from chapter 1 based on monthly data from the CPI research database collected by the Bureau of Labor Statistics.

Table 2.4: Frequency of Price Change and Commodity Cost Volatility

Year	Average Number of Price changes	Standard Deviation of Commodity Cost index
1997	4.3	2.1
1998	1.7	1.6
1999	1.7	0.8
2000	3.0	0.9
2001	1.0	0.4
2002	0.4	0.3
2003	0.2	0.1
2004	0.6	0.5

The second column gives a size-weighted average of the annual frequency of wholesale price change, not including trade deals. These statistics are based on weekly wholesale price data for the period 1997-2004. The observations are weighted by average retail revenue over the period 2000-2004 (the period covered by the retail data). The third column gives the standard deviation of the coffee commodity index in units of cents per ounce.

frequency of wholesale price changes and the annual volatility of the monthly commodity cost index for the years 1997-2005, illustrating a strong positive relationship.

The relationship between commodity cost volatility and the frequency of price change reflects a large amount of co-ordination in price-setting across coffee manufacturers. If pricing were perfectly staggered, the frequency of price change would be constant over the sample period; in contrast, if pricing were perfectly synchronized, the frequency of price change would be one or zero in every time period. For the overall dataset of wholesale prices over the 1997-2005 period, I find that there are many time periods in which either a very high or a very low fraction of firms adjust their prices. Specifically, in the quartile with the lowest frequency of price change, less than 4.5% of products adjust their prices; while in the quartile with the highest frequency of price change, more than 65% of products adjust their prices.

There are two types of concerns one might have about my approach to analyzing pass-through associated with the idea that certain parties are not engaging in spot transactions, but rather involved in long-term contracts. First, a key question in interpreting the evidence on wholesale price rigidity is whether rigid wholesale prices actually determine the retail prices faced by consumers. Since manufacturers and retailers interact repeatedly, the observed rigid prices may not be "allocative" (Barro, 1977). This question can be reformulated as asking whether retail prices respond to commodity costs even conditional on wholesale prices. Table

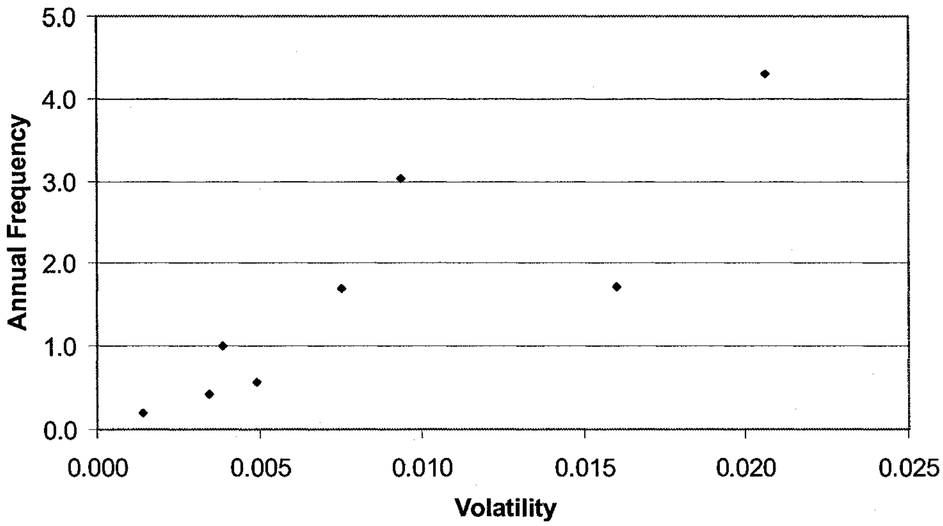

Figure 2.3: Price Change Frequency Versus Commodity Cost Volatility
This figure plots the average annual frequency of price change for the wholesale price (not including trade deals) vs. the volatility of the commodity cost index for each of the years 1997-2004. These statistics are based on weekly wholesale price data for the period 1997-2004. The observations are weighted by average retail revenue over the period 2000-2004 (the period covered by the retail data).

2.5 presents the results of the regression,

$$\Delta \log p^r_{jmt} = \eta^0 + \sum_{k=0}^{1} \eta^C_k \Delta \log C_{t-k} + \sum_{k=0}^{1} \eta^r_k \Delta \log p^w_{jmt-k} + \sum_{k=1}^{4} \gamma^r_k q_k + \epsilon, \tag{2.3}$$

where η^r_k, η^C_k and η^0 are parameters. Again, I estimate this equation by instrumental variables regression with the same instruments used above. The standard errors are clustered by unique product and market. Table 2.5 shows that there is little evidence for the view that retail prices respond to commodity costs independent of wholesale prices: the current wholesale price p^w_{jmt} has a coefficient of 1.001 while the remaining coefficients are statistically insignificant at standard confidence levels.

Second, one might be concerned that since manufacturers enter into long-term contracts for coffee or purchase hedging contracts that insure them against cost shocks, the commodity cost index is a poor indicator of the costs they face. However, this concern ignores the fact that in an economic model, firms' prices respond to marginal costs rather than accounting costs. While hedging contracts affect the firm's total costs, they do not affect its marginal costs.[24]

[24] This argument requires the simplifying assumption that transaction costs are small.

Table 2.5: Regression of Retail Prices on Wholesale Prices and Commodity Costs

	Retail Prices
Δ Wholesale Price(t)	1.001
	(0.337)
Δ Wholesale Price (t-1)	-0.053
	(0.164)
Δ Commodity Cost (t)	-0.208
	(0.123)
Δ Commodity Cost (t-1)	0.089
	(0.223)
Constant	0.005
	(0.001)
Quarter Dummies	YES
Number of observations	2831

The dependent variable is the change in the UPC-level monthly average of the retail price per ounce in a particular US market over a quarter. The change in wholesale prices is the change in the wholesale price per ounce (including trade deals) of a particular UPC in a particular US market over a quarter. The change in commodity costs is the change in the commodity cost index over the quarter. The standard errors are clustered by unique product and market to allow for arbitrary serial correlation in the error term. The data cover the period 2000-2005. Wholesale prices are instrumented for by current changes in commodity costs and Arabica futures as well as 6 lags of these variables.

2.4 *Consumer Demand*

The first building block of my structural model of the coffee industry is a model of consumer demand. I estimate a random coefficients discrete choice model for demand (Berry, Levinsohn and Pakes, 1995).[25] In this model, the consumer is assumed to select the product that yields the highest level of utility, where the indirect utility of individual i from purchasing product j takes the form,

$$U_{ijmt} = \alpha_i^0 + \alpha_i^p(y_i - p_{jmt}^r) + x_j\beta^x + \xi_{jmt} + \epsilon_{ijmt}, \tag{2.4}$$

where α_i^p is the parameter governing the individual-specific marginal utility of income, y_i is income, p_{jmt} is the price in market m at time t, x_j is a vector of product characteristics, β^x is a vector of parameters, and ξ_{jt} is an unobserved demand shifter that varies across products

[25] Discrete choice models have been applied widely in the empirical organization literature. Other applications include shopping destination choice (McFadden, 1974), cereal (Nevo, 2001) and yogurt (Villas-Boas, 2004). See Anderson, Palma, and Thisse (1992) for an overview of this class of models.

and regions.[26] I also allow the consumer to select the outside option of not purchasing ground caffeinated coffee. Since the mean utility from the outside option is not separately identified, I normalize $\xi_{0mt} = 0$ implying that the utility from the outside option is given by $U_{i0mt} = \alpha_i^p y_i + \epsilon_{i0mt}$. For computational tractability, the idiosyncratic error term ϵ_{ijmt} is assumed to be distributed according to the extreme value distribution. Demand is then given by the market share s_{jmt}, the fraction of consumers for whom product j yields the highest value of utility, multiplied by the size of the market M.

The key advantage of this type of structural model relative to an unrestricted model of demand is that it allows for a substantial reduction in the number of parameters that must be estimated in a differentiated products market relative to an unrestricted model of aggregate demand, while still allowing for a substantial amount of flexibility in substitution patterns. To build intuition, I begin by estimating the logit model, a simplified version of the model in which $\alpha_i^p = \alpha^p$ and $\alpha_i^0 = \alpha^0$ for all i. In this case, the model implies the following equation for aggregate shares,

$$\log s_{jmt} - \log s_0 = \alpha^0 - \alpha^p p^r_{jmt} + x_j\beta + \xi_{jmt} + \epsilon_{ijmt}, \tag{2.5}$$

where α_0 is a constant. I estimate the model on monthly price and market share data for ground, caffeinated coffee for 50 US markets as defined by AC Nielsen, where the prices and market shares are averages by market, brand, time period and size. The model is estimated using the top 15 products by volume sold nationally over the 5 year sample period 2000-2004. These products account for 74% of the total AC Nielsen ground coffee sales over this period. To estimate the model, it is necessary to define the total potential market M. I define the relevant market as two cups of caffeinated coffee (made from ground coffee purchased at supermarkets) for every individual 18 or over in a given market area per day.[27]

[26] This expression for indirect utility may be derived from a quasi-linear utility function. One way of interpreting this model is to view the consumer's decision of what to consume as a discrete choice at each "consumption occasion". Given micro-level data on consumers' purchases, an alternative approach would be to estimate an explicit model of multiple discrete choices as in e.g. Hendel (1999).

[27] AC Nielsen market areas are somewhat larger than cities. The adult population in a market area is determined by multiplying the total population in a given area (provided by AC Nielsen) by the fraction of adults in a given area, calculated using the Current Population Survey. This specification implies that, depending on the market and time period, the market share of the outside option is between 21% and 89% with a median value of 74%.

The classic econometric problem in demand estimation is the endogeneity of prices. Firms are likely to set high prices for products with high values of the omitted characteristic ξ_{jmt}. This will bias price elasticity estimates toward zero. Intuitively, the price elasticities are biased downward because the model does not account for the fact that high priced products are also likely to be particularly desirable. The first column of table 2.6 presents estimates of equation (2.5) where x_j includes only advertising, a dummy for product size, dummy variables for years, as well as a dummy variable for December to account for demand fluctuations associated with Christmas. This specification yields an inelastic demand curve for the majority of products and time periods: the median price elasticity is 0.54.[28] An obvious potential explanation is the endogeneity problem described above.

The panel structure of the data implies that I can account for fixed differences in ξ_{jmt} in a flexible manner by introducing dummy variables (Nevo, 2001). These dummy variables allow for constant differences in utility across products, as well as regional differences in the mean utility of products. The second column of Table 2.6 presents estimates for the logit model including brand-region fixed effects.[29] Including fixed effects dramatically increases the estimated price elasticity: the median price elasticity for the logit model including brand-region fixed effects is 1.96.

The inclusion of brand-region fixed effects does not, however, fully alleviate the endogeneity problem since demand shocks may be correlated with prices over time. I compare the implications of a number of alternative approaches for instrumenting for prices and advertising. In the third column, I instrument for prices and advertising using current and lagged average prices of the same product in another market within the same census division, an instrumentation strategy that is reasonable if demand shocks are uncorrelated across markets within a census division (Hausman, 1996; Nevo, 2001). The median price elasticity estimate given this instrumentation strategy is considerably higher than the OLS estimates: it is 3.02. The fourth column presents the results of using commodity costs as instruments. This ap-

[28] In all of the regression estimates, I cluster the standard errors by unique product and market to allow for unrestricted time series correlation in the error term. See, for example, Wooldridge (2002) for a discussion of this procedure.

[29] I divide the U.S. into four regions: Northeast, Midwest, South and West using the suggested divisions in the CPS.

Table 2.6: Demand Estimates

	Logit					Random Coefficients
	OLS1	OLS2	IV1	IV2	IV3	IV
Price	2.92	10.59	16.36	14.60	17.29	17.76
	(0.37)	(1.05)	(1.54)	(1.17)	(1.33)	(0.78)
Random Coefficients:						
π_{y0}						-1.03
						(1.31)
π_{yp}						-3.24
						(0.09)
Large size (>24 ounces)	0.47	0.12	-0.16	-0.08	-0.21	-0.28
	(0.13)	(0.10)	(0.11)	(0.10)	(0.10)	(0.08)
Total advertising (1000's, quarterly)	0.45	0.05	0.19	0.13	0.20	0.20
	(0.02)	(0.004)	(0.20)	(0.02)	(0.01)	(0.02)
Year dummies	YES	YES	YES	YES	YES	YES
Christmas dummy	YES	YES	YES	YES	YES	YES
Brand x Region dummies	NO	YES	YES	YES	YES	YES
Instrument			Hausman	Commodity Cost	Weather	Weather
Median Price Elasticity	0.54	1.96	3.02	2.69	3.20	3.46*
						[2.59 4.48]
Number of Observations	22411	22411	22411	22411	22411	22411

The demand system is estimated using monthly averages of UPC-level retail prices per ounce in US markets. The IV specifications use instruments for both prices and advertising. Commodity cost instruments: the commodity cost index, current, one and three lags. Hausman instruments: average price of product within the census division, current and lagged. Weather instruments: lagged minimum and maximum temperatures for the Sao Paulo / Congonhas (Brazil) and the Cali / Alfonso Bonill (Colombia) weather stations. The standard errors are clustered by unique product and market to allow for arbitrary serial correlation in the error term. *The 95% confidence interval is constructed using a parametric bootstrap. I draw from a joint normal distribution representing the joint distribution of the coefficients.

proach yields a median price elasticity estimate of 2.69, a strategy that seems more robust, though it requires that commodity costs are not influenced by trends in demand for coffee in the U.S. market.

The fifth column presents the results of the most robust instrumentation strategy, which uses lagged minimum and maximum temperatures for the Sao Paulo-Congonhas (Brazil) and the Cali-Alfonso Bonill (Colombia) weather stations as instruments. I chose these weather stations because Colombia and Brazil are two of the largest exporters of green bean coffee and because they are located at high elevations where coffee is typically grown. The weather instruments have an adjusted R^2 of 37% in explaining variation in the commodity cost index over the past 5 years. This approach yields a price elasticity of 3.2. This is the instrumentation strategy I use in the random coefficients estimates below.

A disadvantage of the logit model noted by many authors is that it implies unrealistic substitution patterns. In particular, the substitution patterns implied by the logit model satisfy the "independence from irrelevant alternatives" property that the odds of choosing one alternative over another are independent of the remaining alternatives. One implication of this fact is that if the price of a "premium" product increases, there is no tendency for demand to shift to other premium products rather than to other less similar products. As Berry, Levinsohn, and Pakes (1995b) discuss, one way of generalizing the model is to allow for heterogeneity in individual preferences. This seems appropriate for the coffee industry given that there is a substantial amount of variation in the demographic profiles of consumers of different types of coffee. Over 50% of Starbucks' customers have household incomes of over $100 000 whereas this fraction is only about 25% for other major coffee brands.[30] I estimate a simple version of the random coefficients model—equation (2.4)—in which an individual's price sensitivity as well as the mean utility of purchasing coffee is allowed to vary with his or her household income.

$$\alpha_i = \alpha + \Pi \tilde{y}_i, \tag{2.6}$$

where $\alpha_i = [\alpha_i^0, \alpha_i^p]'$, $\Pi = [\Pi_{y0}, \Pi_{yp}]'$ and $\tilde{y}_i$ is household income normalized, for ease of interpretation, to have mean zero and variance of one across all markets that I consider. I

[30] These statistics are from Leibtag et al. (2005).

assume that $\tilde{y}_i$ has a log-normal distribution within markets, where the parameters of this distribution are chosen to match the observed distribution of household income within each market for individuals over 18 in the March Supplement of the 2000 Current Population Survey (CPS) after trimming the bottom 2.5% of the sample (which includes negative and zero income observations).[31] Thus, the model allows for both heterogeneity in income within individual markets and variation in the mean and variance of the income distribution across markets.

It will be useful in describing the estimation procedure below to rewrite the indirect utility as $U_{ijmt} = \delta_{jmt} + \mu_{ijmt} + \epsilon_{ijmt}$ where δ_{jmt} captures the component of utility common to all consumers and μ_{ijmt} is a mean-zero heteroskedastic term μ_{ijmt} that reflects individual deviations from this mean.[32] Given this decomposition, the aggregate market shares may be written as a function of the mean utility and the heterogeneity parameter, i.e. $s_{jmt}(\delta_{jmt}, \Pi_y)$.

The vector of parameters Π govern the effect of consumer heterogeneity on demand. When consumer heterogeneity is absent i.e. $\Pi = 0$, the model reduces to the logit demand model discussed above. A positive value for Π_{yp} indicates that higher income consumers are less responsive to prices. This parameter plays an important role in determining pass-through since it governs how the price elasticity faced by a firm varies with its prices. If Π_{yp} is positive, then as a firm raises its price, its consumer base is increasingly dominated by households with a low price elasticity of demand. This effect lowers the price elasticity faced by the firm as it raises its prices, leading to greater pass-through of costs into prices.

The basic estimation approach of Berry, Levinsohn, and Pakes (1995b) relies on two sets of moments. The first set of moments equates the aggregate market shares implied by the model to those observed in the data,

$$s_{jmt}(\delta_{jmt}, \Pi_y) - \hat{s}_{jmt} = 0, \tag{2.7}$$

for all j, m, t where $\hat{s}_{jmt}$ are the empirical market shares. Given a parameter Π_y, this equation

[31] I matched the CPS demographic data to the ACN market areas using the MSA and county code information in the CPS and information provided by AC Nielsen on market coverage.

[32] In particular, the mean utility and individual component are given by $\delta_{jmt} = \alpha^0 - \alpha^p p^r_{jmt} + x_j\beta^x + \xi_{jmt}$ and $\mu_{ijmt} = -\Pi_y \tilde{y}_i p^r_{jmt}$.

may be solved for a vector of mean utilities δ_{jmt}. Berry, Levinsohn, and Pakes (1995b) show how to solve for δ_{jmt} numerically using a contraction mapping property. The second set of moments requires that the instruments z_{jmt} be orthogonal to the aggregate demand shocks ξ_{jmt},

$$E(\xi_{jmt} z_{jmt}) = 0, \tag{2.8}$$

where in this application z_{jmt} are the weather instruments described above.

A common difficulty with estimating the random coefficients model using the aggregate moments alone is that the income heterogeneity parameter Π_y is not well identified. I follow Petrin (2002a) in incorporating an additional set of moments that makes use of the model's predictions about market shares for particular income groups to help identify the income heterogeneity parameters Π_{yp} and Π_{y0}. This set of moments fits the model's predictions about market shares *within* income groups to the observed market shares,

$$E(s_{jkmt}(\delta_{jmt}, \Pi_y) - \hat{s}_{jkmt} | d_j) = 0, \tag{2.9}$$

where d_j is a dummy variable for brand j and k is an income group. The basic idea of this set of moments is to match the model's predictions for market shares *within* particular income groups to the market shares observed in the data. The market share for an individual income group k can be derived by numerical methods as a function of the parameters as $s_{jkmt}(\delta_{jmt}, \Pi_y)$. The empirical brand shares by demographic group $\hat{s}_{jkmt}$ are national averages of the market shares of coffee brands for 5 different household income classes.[33]

How do these additional moment conditions help to identify the income heterogeneity parameters? Without consumer heterogeneity, the brand shares of high income consumers are identical to those of low income consumers. As Π_y^p rises, the purchases of high income consumers are increasingly dominated by premium products. The moment condition (2.9) matches the predictions of the model along this dimension to the data.

I estimate the model using a two-stage GMM estimation procedure. Stacking the moment conditions (2.7)-(2.9) yields the vector of moment conditions $G(\theta)$ where θ are the parameters

[33] The income classes are: under 30k, 30-50k, 50-70k, 70-100k and >100k. The demographic statistics are from Leibtag et al. (2005) based on AC Nielsen scanner panel data for the period 1998-2003.

to be estimated, $E[G(\theta^0)] = 0$ and θ^0 denotes the true value of these parameters. The GMM estimator is,

$$\hat{\theta} = \text{argmin}_\theta G(\theta)'WG(\theta), \tag{2.10}$$

where W is the optimal weighting matrix given by the inverse of the asymptotic variance-covariance matrix of the moments $G(\theta)$, constructed using a preliminary consistent estimator of the parameters.[34] The market shares implied by the model in (2.7) and (2.9) are simulated using 250 draws of income y_i. The standard errors for the coefficients are based on standard GMM formulas (Hansen, 1982) where I have "clustered" the standard errors by unique product and market, allowing for an arbitrary correlation between observations in different years for the same unique product and market.[35]

The estimated coefficients for the random coefficients model are presented in the last column of Table 2.6. The median price elasticity estimate for this model is 3.46, which is slightly higher than the corresponding estimate for the logit model. The standard error for this estimate is calculated using a parametric bootstrap.[36] This price elasticity estimate is very similar to the estimate obtained in Foster, Haltiwanger, and Syverson (2005)—3.65—despite the fact that these two estimates are obtained using entirely different estimation strategies.[37] These estimates are slightly higher than the median estimates of price elasticities obtained by Broda and Weinstein (2006) for a broad range of products. The main advantage of my estimation procedure compared to Broda and Weinstein (2006) is that, because I focus a particular industry, I am able to account for potential time series endogeneity of prices using weather instruments. More generally, the price elasticity estimates I obtain are not unusual compared to demand elasticity estimates for other consumer packaged goods. For example,

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[34] The asymptotic variance-covariance matrix of $G(\theta)$ is block-diagonal since the sources of error from the two moments are independent. The part of the variance-covariance matrix associated with the demographic moments is calculated using the procedure described in Appendix B.1 of Petrin (2002b). I used first-stage estimates of the parameters to calculate the part of the variance-covariance matrix associated with the mean utilities using the standard GMM formulas.

[35] I do this by viewing all of the observations associated with a unique product-market as a single "observation" (e.g. See Berry, Levinsohn and Pakes, 1995; Petrin, 2002).

[36] I calculated the standard error by drawing multiple values of the coefficients from the joint distribution of the parameters implied by the estimates of the asymptotic variance-covariance matrix.

[37] Foster, Haltiwanger, and Syverson (2005) also compute price elasticity estimates for the ground coffee market for a linear demand model, using plant-level productivity as instruments.

Nevo (2001) finds a median price elasticity of 2.9 for breakfast cereals, and Villas-Boas (2007) finds price elasticities between 3 and 4 for yogurt.

The differentiated product demand system implies a particular model of markup adjustment in which consumer heterogeneity plays an important role. I estimate a moderate degree of heterogeneity in the price elasticity parameter. The estimated value of Π_{yp} is -3.24, indicating that high income households have moderately lower price elasticities than low income consumers. A household with an income one standard deviation above the mean has a price elasticity about 20% below the price elasticity of the median consumer. The income heterogeneity parameter Π_{yp} plays an important role in determining pass-through since it governs how the price elasticity faced by a firm changes as the firm raises its prices. The point estimate of heterogeneity in the mean utility of coffee Π_{y0} is negative (-1.03) indicating that higher income consumers have a slightly lower utility for ground coffee—as opposed to not purchasing coffee at all, or purchasing pre-made coffee at a cafe. However, this parameter is not statistically signficantly different from zero at standard confidence levels.

2.5 Local Costs

In modeling the response of prices to costs in the coffee industry, an important consideration is that only some fraction of marginal costs are accounted for by coffee beans. The remaining "local costs" of production play an important role in determining pass-through behavior since they drive a wedge between fluctuations in imported costs and the marginal cost of production (Sanyal and Jones, 1982; Burstein, Neves and Rebelo, 2003; Corsetti and Dedola, 2004). If local costs are large, even a substantial increase in the price of an imported factor of production may increase marginal costs by only a small fraction.

The magnitude of the local costs cannot be observed directly. The oligopolistic structure of the market implies that the difference between prices and commodity costs reflects a combination of marginal costs and oligopolistic markups.[38] Given a particular model of the supply side of the industry, it is possible to infer the markup by "inverting" the demand system to find the vector of marginal costs that rationalizes firms' observed pricing behavior.

[38] Such markups are consistent with zero economic profit. For example, they may reflect substantial fixed and sunk costs of entry in the coffee industry.

Since I know exactly how many ounces of green bean coffee are used to produce a given quantity of ground coffee, I can then obtain estimates of the local costs of production by subtracting commodity costs from the inferred marginal costs.[39]

I will ultimately be interested in a dynamic model of pricing that allows for price rigidity. I begin, however, by inferring markups for a static Nash-Bertrand equilibrium (Bresnahan, 1987; Berry, Levinsohn and Pakes, 1995). I extend this model to allow for adjustment costs in prices in section 2.6. In order to avoid searching over a large parameter space as part of the dynamic estimation procedure, I use the estimates of local costs from the static model in the baseline parameterization of the dynamic model. In order to gauge how different this approach is from estimating local costs as part of the dynamic estimation procedure, I also consider an alternative approach in section 2.6 in which I estimate a common component local costs as part of the dynamic estimation procedure.

The supply side of the model consists of J multi-product firms that each produce some subset of the products. I fix the number of firms and the products produced by the firms to match the observed industry structure. In particular, Folgers and Maxwell House dominate the market for ground roasted coffee with a combined market share by volume of over 65% in many U.S. cities. Firm j's per-period profits π_{jmt} in a market m at time t may be written,

$$\pi_{jmt} = \sum_{k \in \Upsilon_j} (p^w_{kmt} - mc_{kmt}) M s_{kmt} - F_{km}, \tag{2.11}$$

where mc_{kmt} is the marginal cost of producing the product, F_{km} a fixed cost, Υ_j is the set of products produced by firm j. I assume a reduced form model of retailer behavior: retail prices p^r_{kmt} depend on wholesale prices such that $\partial p^r(p^w_{kmt})/\partial p^w_{kmt} = 1$. This assumption is consistent with the fact that the empirical response of retail prices to wholesale price changes documented in section 2.3.[40]

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[39] The simple (and known) production relationship between green bean coffee and ground coffee is an advantage of studying the coffee market. In other markets it is necessary to estimate a production function to determine the contribution of imported inputs to production costs (see e.g. Goldberg and Verboven's (2001) analysis of the auto industry).

[40] This assumption could be micro-founded, for example, by assuming that retailers face demand given by a logit demand model. This reduced-form approach to modeling retail behavior abstracts from an important aspect of pricing (see e.g. Hellerstein (2005) and Villas-Boas (2007)). However, the lack of detailed information on competition at the retail level make these issues challenging to analyze in my data.

I assume that firms set wholesale prices to maximize the profits associated with their products in a Bertrand-Nash fashion. The optimizing firms' prices satisfy the first-order conditions,

$$s_{kmt} + \sum_{k \in F_f} (p^w_{kmt} - mc_{kmt}) \frac{\partial s_{kmt}}{\partial p^r_{kmt}} = 0. \tag{2.12}$$

Let us define the matrix Φ such that the element Φ_{kj} is defined $-\partial s_{kmt}/\partial p^r_{jmt}$ for $k, j = 1, ..., J$, and the matrix $\hat{\Omega}$ as a matrix such that the element $\hat{\Omega}_{kj}$ equals 1 for k, j such that the same firm owns both products, and equals 0 otherwise. Finally, let us define $\Omega = \Phi \cdot \hat{\Omega}$. The first order conditions may then be written in matrix form as,

$$s_{mt} - \Omega(p^w_{mt} - mc_{mt}) = 0, \tag{2.13}$$

where s_{mt}, p^w_{mt} , mc_{mt} and ξ_{mt} are vectors consisting of s_{kmt}, p^w_{kmt}, mc_{kmt}, and ξ_{kmt} for $k = 1, ..., K$ respectively. This equation may be inverted to give the following expression for the markup of wholesale prices over marginal costs,

$$p^w_{mt} - mc_{mt} = \Omega^{-1} s_{mt}. \tag{2.14}$$

The markup implied by this equation depends on the estimated demand system through Φ, as well as the assumed oligopolistic market structure through $\hat{\Omega}$. For example, a higher elasticity estimate yields a lower markup based on equation (2.14) while a more concentrated market structure implies a higher markup.

I use equation (2.14) to derive markups based on the observed wholesale prices and the random coefficients discrete choice demand system estimated in section 2.4. Table 2.7 presents summary statistics on the percentage markup of price over marginal cost implied by this procedure. The median percentage markup of price over marginal cost is 58.3%. These estimates of the percentage markup are not unusual for consumer packaged goods industries. For example, Nevo (2001) estimates a median markup of about 67% for the ready-to-eat cereal industry. Villas-Boas (2007) estimates wholesale markups in the range of $25 - 100\%$ for yogurt.[41]

[41] As a check on whether the estimates are reasonable, I also investigated the fraction of implied marginal

Table 2.7: Markup and Local Costs

Median Implied Markup	Median Fraction of Costs Accounted for By Coffee
58.3%	44.7%

The first statistic gives the median percentage markup of prices over marginal costs. The second column gives the median fraction of marginal costs accounted for by green bean coffee. These statistics are calculated from the static pricing model.

In order to obtain estimates of the local costs of production, I simply subtract coffee commodity costs from the total marginal cost (which can be obtained by "inverting" the markup). A small estimated markup therefore implies that local costs must be large to rationalize the observed prices and vice versa. Table 2.7 presents statistics on the role of coffee beans in marginal costs. On average, coffee beans account for almost half of marginal costs. This fraction is roughly consistent with industry estimates of the magnitude of non-coffee costs reported in Yip and Williams (1985) and the Survey of Manufacturers. These estimates are also similar to Bettendorf and Verboven's (2000) results for the Dutch coffee market. Since the inputs used to produce an ounce of coffee are relatively stable, the fraction of marginal costs accounted for by coffee beans tends to rise with the commodity cost of coffee. According to the census of manufacturers, green bean coffee accounted for 75% of non-capital costs in 1997 when commodity costs were at a high, but the proportion fell to 43% by 2002 when commodity costs were at a low.

2.6 A Menu Cost Model of an Oligopoly

The standard static pricing model discussed in the previous section does not account for the infrequent price adjustments or delayed price responses documented in section 2.3. In this section, I therefore extend the model to allow for adjustment costs in price-setting. The model I present is based on the dynamic model developed in Nakamura and Zerom (2006). The model builds on previous menu cost estimated using dynamic methods by Slade (1998, 1999) and Aguirregabiria (1999). I allow for small random costs of adjustment, as for example in Dotsey, King, and Wolman (1999). While the distribution of these costs is known,

costs that are negative: I find that negative implied marginal costs occur extremely infrequently—less than 0.2% of the time.

the realization of the menu cost is private information. Incorporating menu costs into the firm's pricing problem makes the pricing problem fundamentally dynamic. If a cost change is expected to persist for many periods, a forward-looking firm may choose to adjust its prices even if the current benefit from doing so is quite small. Moreover, given the oligopoly setting, the firm recognizes that its competitors may respond in the future to its current pricing decisions.

The model is formally related to the dynamic oligopoly model studied by Pakes and McGuire (1994).[42] It is not possible to solve analytically for the Markov perfect equilibrium of the model. Therefore, I adopt methods from this literature (e.g. Benkard (2004)) to numerically solve for the equilibrium pricing policies of the firms. The equilibrium concept that I adopt is Markov perfect Nash equilibrium, where the strategy space consists of firms' prices (Maskin and Tirole, 1988). This equilibrium concept restricts attention to pay-off relevant state variables, thus focusing attention away from the large number of other subgame perfect equilibria that exist in this type of model.

I use value function iteration to solve for the policies of the individual firms and then use an iterative algorithm to update the firms' policy functions until a fixed point is achieved. I assume that demand is given by the demand system estimated in section 2.4. As in the case of the Pakes-McGuire algorithm, there is no guarantee that this algorithm converges.[43]

2.6.1 Model

The model consists of a small number of oligopolistic firms. Firm j seeks to maximize the discounted expected sum of future profits,

$$E_0 \sum_{t=0}^{\infty} \beta^t \left[\pi_{jmt}(p^w_{mt}, C_t) - \gamma_{jmt} 1(\Delta p^w_{jmt} \neq 0) \right], \tag{2.15}$$

[42] As in the dynamic oligopoly literature, the assumption that the menu cost is random and private information is helpful from a computational perspective since it implies that firms choose their actions in response to the expected policies of their competitors, which helps to smooth their responses. Doraszelski and Pakes (2006) provide a detailed overview of these models.

[43] I am not aware of theoretical work guaranteeing the existence or uniqueness of a pure strategy equilibrium in this type of oligopoly model. Indeed, there is no proof of uniqueness even for the static oligopoly model with demand given by the discrete choice random coefficients model. I dealt with this issue by doing a numerical search for other equilibria by starting the computational algorithm at alternative initial values. This approach always yielded a unique equilibrium.

where p^w_{mt} the vector of wholesale prices in market m at time t, π_{jmt} is the firm's per-period profit, C_t is the commodity cost, β is the firm's discount factor, γ_{jmt} is a random menu cost the firm pays if it changes its prices, $1(\Delta p^w_{jmt} \neq 0)$ is an indicator function that equals one when the firm changes its price. I assume that $\beta = 0.99$. The firm's profits $\pi_{jmt}(p^w_{mt}, C_t)$ are given by expression (2.11) above, where the relationship between retail and wholesale prices is discussed below. The firm's profits depend both on its own prices and the prices of its competitors.

The menu cost γ_{jmt} is independent and identically distributed with an exponential distribution i.e. $F(\gamma_{jmt}) = 1 - \exp\left(-\frac{1}{\sigma}\gamma_{jmt}\right)$. The firm's draw of the menu cost γ_{jmt} is private information. In every period, the pricing game has the following structure:

1. Firms observe the commodity cost C_t and their own draws of the menu cost γ_{jmt}.
2. Firms choose wholesale prices p^w_{jmt} simultaneously (*without* observing other firm's draws of γ_{jmt}).

The Bellman equation for firm j's dynamic pricing problem is thus,

$$V_j(p^w_{mt-1}, C_t) = \max_{p^w_{jmt}} E_t\left[\pi_{jmt}(p^w_{mt}, C_t) - \gamma_{jmt}1(\Delta p^w_{jmt} \neq 0) + \beta V_j(p^w_{mt}, C_{t+1})\right]. \qquad (2.16)$$

The expectation in equation (2.16) is taken over two sources of uncertainty: uncertainty about the future commodity cost C_{t+1} and uncertainty about competitors' prices given that γ_{jmt} is private information. Notice that a given firm's profits and value function depend on the entire vector of wholesale prices in the market at a given time. From the perspective of a firm's competitors, each firm's strategy will have two parts. First, a pricing rule $p^w_j(p^w_{mt-1}, C_t)$ for all firms $j = 1, ..., B$ that gives the firm's price *if* it decides to change its price. Second, a probability function $\mathrm{pr}_j(p^w_{mt-1}, C_t)$ that gives the probability that the firm changes its price at every state.

An equilibrium is defined as a situation where the firm chooses optimal policies (i.e. the Bellman equation (2.16) is satisfied), and the firms' expectations are consistent with the equilibrium behavior of the firm's competitors. As I note above, the firm's strategy is restricted to be Markov i.e. to depend only on the payoff-relevant state.

In order to make the problem computationally tractable, I make the following simplifying assumptions. First, I assume that the prices for different sizes of the same brand move together. (i.e. If the per-ounce price of Folgers 16 ounce coffee increases by 10 cents then the same thing happens to the per-ounce price of Folgers 40 ounce coffee).

$$p^w_{kmt} = p^w_{jmt} + \alpha_k, \tag{2.17}$$

for all $k \in F_j$, where α_k is a known parameter. This assumption is motivated by the fact that empirically, the timing of price changes is often coordinated across products from the same brand. Second, I assume that retail prices equal wholesale prices plus a known constant margin ξ_k,

$$p^r_{kmt} = \xi_k + p^w_{kmt}. \tag{2.18}$$

Marginal cost is modeled as the sum of a product-specific constant μ_k and the commodity cost,

$$mc_{kmt} = \mu_k + C_t. \tag{2.19}$$

This specification is meant to capture the idea that non-coffee costs are several times less variable than coffee commodity costs. By adopting this specification, I also assume that the firm faces constant returns to scale in production.[44]

Uncertainty about future costs takes the form,

$$C_t = a_0 + \rho_C C_{t-1} + \epsilon_C, \tag{2.20}$$

where ϵ_C is distributed $N(0, \sigma^2_C)$ and σ^2_C, a_0 and ρ_C are known coefficients. Since a unit root in commodity costs cannot be rejected at standard confidence levels, I model commodity costs as a random walk i.e. $a_0 = 0$ and $\rho_C = 1$. For computational reasons, I assume that commodity costs follow a random walk so long as costs lie between the bounds C^H and C^L, but are bounded within this region. Firms' perceptions about the stochastic process of costs play a key role in determining pass-through as I discuss in section 2.7. The assumption that

[44] This specification is consistent with the fact that green bean coffee rises as a share of total variable costs, as reported in the Annual Survey of manufacturers, when green bean coffee prices are high. If marginal costs are increasing in output, this would provide an additional explanation for incomplete pass-through of commodity costs or exchange rates to prices (see Goldberg and Knetter (1997) for a discussion of this issue).

commodity costs are a unit root is consistent with the fact that the premium of 12-month Arabica futures over spot Arabica prices does not vary greatly over this time period.

The firm's decision about whether to adjust its price depends on the difference between its payoffs when it adjusts and when it does not adjust,

$$\Delta W = W_{ch} - W_{nch}, \tag{2.21}$$

where W_{ch} is the firm's payoff from adjusting its price, and W_{nch} is its payoff from maintaining a fixed price. Given the pricing policies of its competitors, the firm adjusts its price if the benefits of doing so outweigh the costs. The firm's pricing policy is given by the following policy rule,

$$p_{jmt} = \begin{cases} p^w_{jmt-1} & \text{if } \Delta W > \gamma_{jmt} \\ p^{w*}_{jmt} & \text{otherwise} \end{cases} \tag{2.22}$$

where the firm's price conditional on adjustment is given by,

$$p^{w*}_{jmt} = \arg\max_{p^w_{jmt}} E_t\left[\pi_{jmt}(p^w_{mt}, C_t) + \beta V_j(p^w_{mt}, C_{t+1})\right]. \tag{2.23}$$

In an equilibrium, all firms set their prices according to the decision rule implied by equations (2.22) and (2.23). Solving for the firms' optimal policy functions is complicated, as in Pakes and McGuire (1994), by the fact that the firms' incentives to adjust their prices depend, in turn, on the prices of the other firms.

I solve the model numerically using the computational algorithm described in appendix A. The computational algorithm is conceptually straightforward but computationally intensive. I begin with some initial values of the firms' pricing policies. For a given firm, say Firm 1, I solve for the optimal dynamic pricing policy conditional on the initial pricing policies of its competitors by value function iteration. I use the solution to this problem to update the assumed pricing policy for Firm 1. Next, I solve for Firm 2's optimal dynamic pricing policy, conditioning on the updated pricing policy for Firm 1. I repeat this exercise until the maximum differences the firms' pricing policies between successive iterations are sufficiently small.

2.6.2 Parameters

Given the computationally intensive nature of the iterative procedure, it is not possible to separately analyze the implications for all possible markets. I focus on a representative market: the Syracuse market. The Syracuse market has a representative market structure dominated by P&G (Folgers), Kraft (Maxwell House) and Sara Lee (Hills Brothers). The average annual revenue in the Syracuse market is approximately 3 million dollars, which is close to the median across markets in my sample. Each brand produces two different products according to the definition discussed in section 2.4 leading to two products per firm and 6 products in total.

I parameterize the demand curve according to the random coefficients discrete choice model estimated in Section 2.4. I also estimates of the constant non-coffee cost μ_k from the marginal costs implied by the static pricing model described in section 2.5. Specifically, I take μ_k to be the average non-coffee costs,

$$\mu_{km} = \frac{1}{T}\sum_{t=1}^{T}\left[\hat{p}^{w}_{kmt} - \Omega^{-1}\hat{s}_{kmt} - C_t\right]. \tag{2.24}$$

In simple models with quadratic loss functions (e.g. Dixit, 1991), symmetry implies that the average price in the dynamic model equals the average price in the static model. This property does not hold in the present model because of asymmetries in the profit function and strategic interactions. Essentially, "risk-aversion" type effects may lead to higher prices in the dynamic model. I consider an alternative procedure where I estimate a common component in marginal costs as part of the dynamic estimation procedure below. I find that these effects are small. I parameterize the retail margin ξ_k as the average difference between retail and wholesale prices for a particular market and brand. Moreover, I parameterize the constant difference in prices produced by the same manufacturer α_k as the average difference between the retail prices for those products. I also condition on the observed value of wholesale prices in the period before the simulations begin (1999 Q4). I set the standard deviation of shocks to commodity costs equal to the observed standard deviation of commodity costs σ_C over the sample period.

The remaining parameter is the mean of the menu cost distribution, σ. I estimate this parameter to match the observed frequency of wholesale price change using the indirect estimation approach of Gourieroux, Monfort, and Renault (1993) for dynamic models. In particular, I use the following procedure in selecting this parameter. For different values of the menu cost, I simulate the model for the actual observed values of the commodity cost index over the 2000-2005 period. I then carry out a grid search over alternative possible values of the menu cost. The menu cost estimate is chosen to minimize the loss function,

$$L = (f - \hat{f})^2, \tag{2.25}$$

where f is the frequency of price change predicted by the model, conditional on the actual sequence of observed commodity costs, and $\hat{f}$ is the actual average frequency of price change excluding trade deals over the 2000-2005 period.[45] The average frequency of price change excluding trade deals over this period was 1.3 times per year or a monthly frequency of price change of about 11%.[46] Figure 2.4 presents a diagram of L for different values of σ, where σ is presented as a fraction of average annual revenue of coffee manufacturers in the Syracuse market over the period 2000-2005 is about 3.07 million dollars. Figure 2.4 shows that the frequency of price changes is monotonically decreasing in the menu cost. The frequency of price changes is monotonically decreasing in the menu cost over these parameter values. Thus, the loss function has a clear minimum in the range of parameters I consider. Table 2.8 presents the results of this estimation procedure. The value of σ that best matches the frequency of price change implied by the model to the observed frequency of price change is 0.23% of average annual revenues per firm. Since the firm disproportionately adjusts its price when it draws a low value of the menu cost, the average menu cost actually paid by the firm is substantially lower: 0.18% of average annual revenues.

The standard error of this estimate may be calculated using the formulas presented in

[45] Gourieroux, Monfort, and Renault (1993) do not formally extend their analysis to the case of dynamic models with discontinuities in the sample moment. However, Dridi (1999) argues that the technical apparatus used to analyze this case for static models may be extended to dynamic models. Magnac, Robin, and Visser (1995) find that this estimator performs well in a dynamic model in Monte Carlo simulations.

[46] A limitation of this model is that it does not explain trade deals. In a model with trade deals, one would expect pass-through to increase, since trade deals provide an additional mechanism for transmitting cost shocks. In the present application, this effect may be small. As I discuss in section 2.3, trade deals relatively unimportant in explaining cost pass-through in this market.

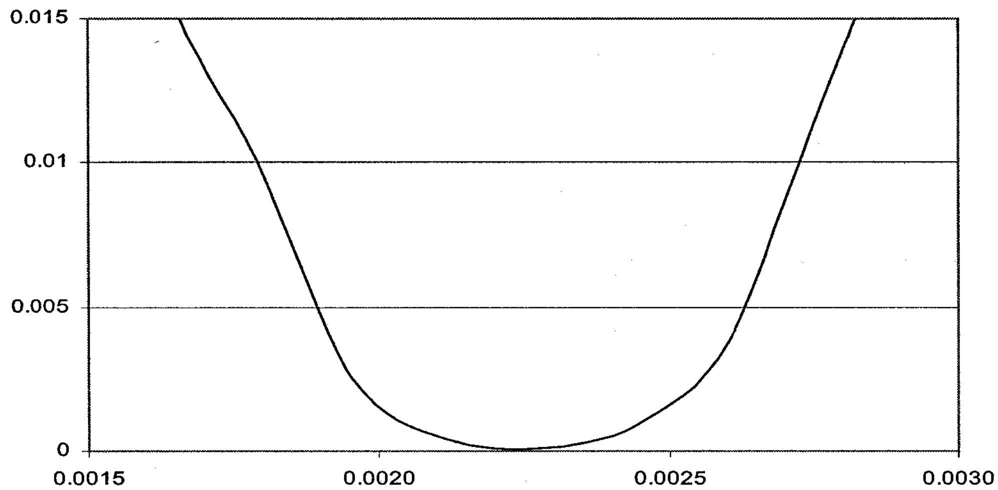

Figure 2.4: Squared Deviation Between Observed and Predicted Price Change Frequency
This figure plots the squared deviation between the average observed frequency of price change over the 2000-2005 period and the frequency of price change predicted by the menu cost oligopoly model as a function of the menu cost. The menu cost is reported as a fraction of average annual retail revenue per firm over the 2000-2005 period.

Gourieroux, Monfort, and Renault (1993) for the case of static moments in dynamic models. In evaluating this formula, I use a numerical estimate of the derivative of the loss function with respect to the parameter estimate. I estimate the variance of the sample moment using a parametric bootstrap.[47] This procedure yields a standard error of 0.09% for menu costs as a fraction of average annual revenues, implying an upper bound for the 95% confidence interval of the estimator of 0.33%. Even this upper bound implies costs of adjustment well below the direct estimates of menu costs in Zbaracki et al. (2004), who estimate that costs of price adjustment account for 1.22% of annual revenue in a large industrial firm.

In order to gauge how different this approach is from estimating local costs as part of the dynamic estimation procedure, I also consider the following alternative approach. This approach is meant to account for the fact that the dynamic model may imply higher or lower prices on average for a given level of marginal costs—leading to different estimates of local costs than in the static model presented in section 2.5. I find, however, that these effects are numerically small. The dynamic model implies average wholesale prices of 14.3 cents per ounce versus 14.4 cents per ounce in the static model. The alternative estimation procedure

[47] Specifically, I evaluate the sample moment for alternative draws of costs from the assumed Markov process for costs. I calculate the variance of the sample moment based on these draws. This approach takes into consideration sampling error in the menu cost as well as commodity costs, but not parameter uncertainty arising from the estimation of the demand system.

Table 2.8: Menu Cost Estimate

Absolute Size	As a Fraction of Average Annual Firm Revenue
7000	0.22%
(2806)	(0.09)

The table presents menu cost estimates in dollars and as a fraction of average annual firm revenue in the Syracuse market. The standard error is in parentheses and is calculated from standard asymptotic formulas for the simulated method of moments estimator, where the variance of the sample moment is calculated by a parametric bootstrap. The standard error takes into consideration sampling error associated with random variation in the costs and the menu cost draw, but not sampling error in the estimated demand parameters.

is presented in appendix B. This procedure yields almost identical estimates of local costs to the estimates based on the static model described above.

2.6.3 Equilibrium Pricing Policies

The equilibrium consists of pricing policies for all firms. Recall that the pricing policy defines for each state 1) what price the firm adjusts to conditional on adjusting and 2) the probability of adjustment. The state variables in the model are the previous value of the commodity cost, a firm's own past price, and its competitors' prices. The probability of adjustment depends on a firm's past price since firms are more likely to adjust if there is a large difference between the firm's past price and its current desired price. Figure 2.5 plots an example (for a particular firm and time period) of a firm's probability of adjustment in period t as a function of its period $t-1$ price. This figure gives the expected probability of adjustment, where the expectation is taken over different values of the random menu cost γ_{jmt}. In this example, the optimal dynamic price occurs at \$0.138 per ounce. At this price, the probability of adjustment is zero. The probability that the firm will adjust its price increases monotonically in the distance from the dynamic optimal price.

A firm's optimal pricing policy also depends on its competitors' prices. The demand model described in section 2.4 implies that prices may be either strategic complements or substitutes. For the estimated parameter values, prices are in general strategic complements. Figure 2.6 plots an example of a Firm 3's probability of adjustment as a function of its competitors' previous prices, all else constant. In this example, Firm 3 has, for the most part, a higher probability of raising its price given higher values of its competitors' past prices. As

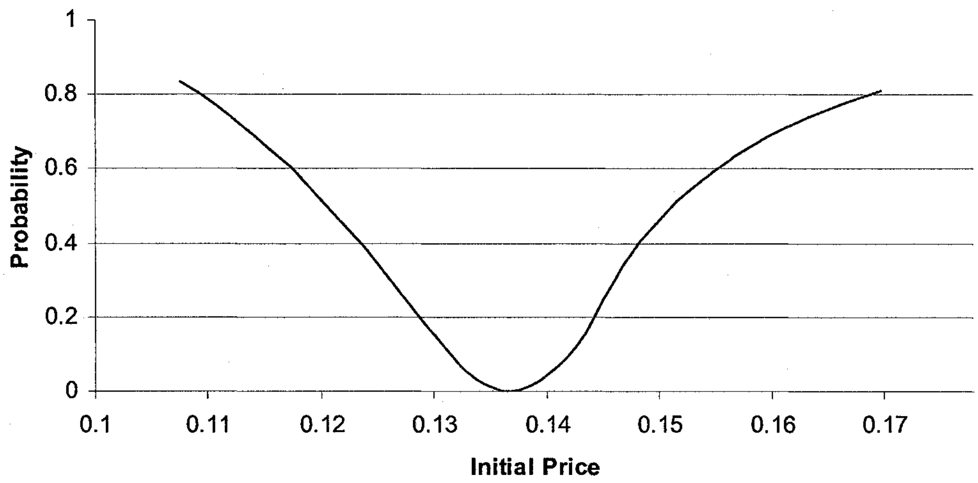

Figure 2.5: Probability of Adjustment Versus Initial Price
This figure plots an example of the relationship between the probability of adjustment and the initial price in the menu cost model.

Figure 2.6 shows, however, the probability of adjustment is not monotonically increasing in competitors' prices. The intuition for the non-monotonic relationship is the following. As a competitors' time $t-1$ prices rise it becomes increasingly likely that competitor will readjust its prices downward in period t—and this, in turn, lessens Firm 3's incentive to raise its prices.

2.7 Results

I begin by showing that the model provides quantitatively realistic predictions for the timing of price adjustments. To investigate model's predictions for the timing of price adjustments, I simulate the model for the actual sequence of costs over the 2000-2004 period based on the equilibrium policy rules. For each simulation, I draw new values of the firms' menu costs. I then calculate the average frequency of price change by year across the simulations. I assume that the stochastic process generating costs (2.20)—which determines the firms' perceptions about the cost process—is fixed over the sample period. All of the variation in costs therefore arises from random variation in the shocks to this process ϵ_C.

Figure 2.7 plots the annual frequency of price adjustment for the model versus the data. The menu cost model explains much of the variation in the frequency of price change: as in the data, the minimum average frequency of price adjustment in both the model and the data

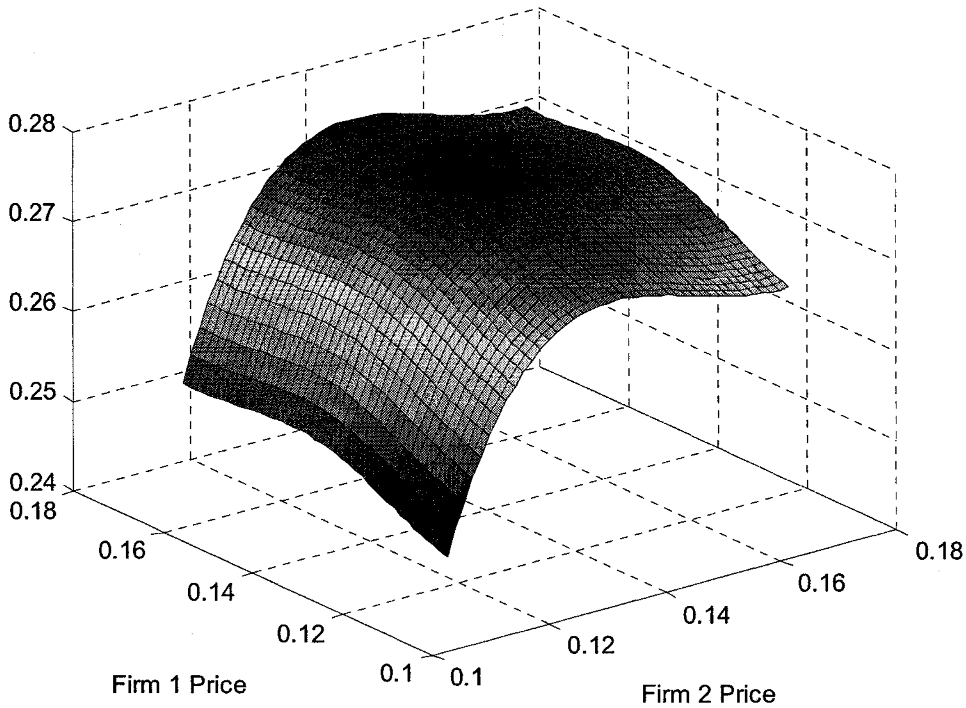

Figure 2.6: Probability of Adjustment as a Function of Competitors' Prices
This figure plots an example of the probability of adjustment as a function of competitors' prices in the menu cost model.

occurs in 2003, while the maximum occurs in 2000. In the model, as in the data, the frequency of wholesale price change is strongly positively related to the volatility of commodity costs. The variation in the expected frequency of price adjustment is, however, somewhat smaller than the observed variation in the frequency of price change over this period.[48]

The model also yields quantitatively realistic implications for pass-through. I document this feature of the model by estimating a pass-through regression, of the form of equation (2.1) for the simulated data. The last column of Table 2.9 presents the results of this regression. The table shows that long-run pass-through generated by the model is 0.269, compared to 0.247 in the data.

The model's predictions for delayed pass-through are also quantitatively realistic: as in the data, less than half of the long-run pass-through occurs in the quarter of the shock, but most of the pass-through occurs within the first 3 quarters after the shock. The intuition for

[48] This may indicate that the assumed distribution of menu costs (exponential) is more dispersed than in the actual distribution. A more dispersed distribution of menu costs generates less variation in the frequency of price change over time since there are more "randomly timed" adjustments in prices.

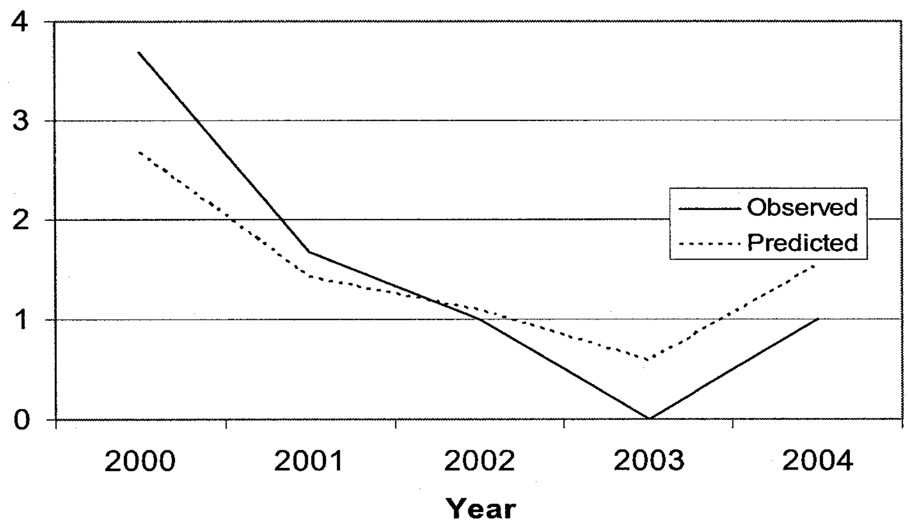

Figure 2.7: Predicted and Observed Frequency of Price Change for Dynamic Model
This figure plots predicted annual frequency of price change for the dynamic model over the years 2000-2005 as well as the observed average frequency of price change for the Syracuse market over this period.

the delayed pass-through in the menu cost model is the following. Because of the barriers to price adjustment, firms have a low probability of adjusting immediately in response to a change in costs. As shocks accumulate in the same direction, however, the firm's probability of adjusting grows. This generates delayed pass-through.

I next investigate the determinants of pass-through in the menu cost model. The first question I ask is how pass-through depends on the persistence of marginal costs. I consider counterfactual experiments where I hold fixed the *actual* sequence of costs faced by the firms, but make different assumptions about what firms believe regarding the stochastic process generating marginal costs (i.e. equation (2.20)). The menu cost is adjusted to hold fixed the frequency of price change in each simulation equal to the observed frequency of price change.

Table 2.10 (columns 3-4) presents pass-through regressions for cases where $\rho_C = 0.9$ and $\rho_C = 0.5$. The variance and constant term in the alternative cost processes are chosen to match the corresponding unconditional statistics in the data. Quantitatively, the persistence of marginal costs has a substantial role in determining long-run pass-through. As we move from the baseline specification with a unit root cost process to the case with $\rho_C = 0.5$, the long-run pass-through drops from 0.269 (the baseline case) to 0.161. Even for the case with $\rho_C = 0.9$ the pass-through is 0.210, substantially lower than in the baseline specification. Intuitively, firms adjust incompletely to changes in costs even over the longer horizon because

Table 2.9: Pass-Through Regressions for Simulated Data

Variable	Dixit-Stiglitz (no local costs)	Dixit-Stiglitz (local costs)	Static Discrete Choice	Dynamic Discrete Choice
Δ Commodity Cost (t)	1	0.398	0.198	0.100
Δ Commodity Cost (t-1)	0	0.035	0.068	0.112
Δ Commodity Cost (t-2)	0	-0.002	0.026	0.034
Δ Commodity Cost (t-3)	0	-0.018	0.001	-0.01
Δ Commodity Cost (t-4)	0	-0.018	-0.030	-0.007
Δ Commodity Cost (t-5)	0	0.021	-0.005	0.021
Δ Commodity Cost (t-6)	0	0.011	0.027	0.019
Constant	0	0.011	0.012	-0.004
Long-run Pass-through	1	0.426	0.284	0.269

The dependent variable in all of the specifications is the simulated retail price per ounce in a particular market and quarter. The price and cost variables are in logs. The second column gives the implications of a Dixit-Stiglitz model. The third column gives the implications of a Dixit-Stiglitz model modified to allowing for local costs. The fourth column gives the implications of the static discrete choice model, allowing for local costs and markup adjustment. The fifth column gives the implications of the dynamic discrete choice model allowing for local costs, markup adjustment and menu costs.

they expect costs to revert to some "normal" level. This effect does not arise in the case where marginal costs follow a unit root. The role of persistence in determining pass-through has also been discussed in somewhat different models by Taylor (2000) and Kasa (1992).

Second, I consider how the timing of price changes implied by the menu cost model affects pass-through. I compare pass-through in the menu cost model to pass-through in the Calvo (1983) model in which the timing of price changes is selected randomly. The Calvo model is a workhorse of the macroeconomics and international economics literatures. In the Calvo specification, I assume that instead of facing a menu cost as in the model in section 2.6, firms are randomly selected to adjust their prices with probability α_{calvo}. I choose α_{calvo} to fit the observed frequency of price change as in the other simulations. Otherwise, the model is unchanged, and has the same parameterization as the baseline model.

Table 2.10 (columns 5-6) presents the results of pass-through regressions for the Calvo model. The baseline Calvo model implies substantially more delayed pass-through than the menu cost model: only about 25% of pass-through occurs in the first quarter on average compared to an average of 40% in the menu cost model. This difference arises because, in the menu cost model, prices adjust rapidly to large and persistent cost shocks. Table 2.10 also

Table 2.10: Rass-Through Regressions for Simulated Data (Counterfactual Parameters)

		Alternative Persistence Parameters		Calvo		High Heterogeneity
Variable	Baseline (Unit Root)	Persistence =0.5	Persistence =0.9	Baseline (Unit Root)	Persistence =0.9	
Δ Commodity Cost (t)	0.100	0.118	0.089	0.066	0.072	0.104
Δ Commodity Cost (t-1)	0.112	0.085	0.097	0.098	0.103	0.117
Δ Commodity Cost (t-2)	0.034	0.001	0.021	0.042	0.015	0.079
Δ Commodity Cost (t-3)	-0.01	-0.044	-0.013	0.009	-0.015	0.017
Δ Commodity Cost (t-4)	-0.007	-0.016	-0.013	0.000	-0.020	-0.013
Δ Commodity Cost (t-5)	0.021	0.017	0.013	0.017	0.010	0.014
Δ Commodity Cost (t-6)	0.019	0.000	0.014	0.016	-0.003	0.036
Constant	-0.004	-0.009	0.001	-0.004	-0.010	0.013
Long-run Pass-through	0.269	0.161	0.210	0.249	0.162	0.353

The dependent variable in all of the specifications is the simulated retail price per ounce. The price and cost variables are in logs. The second column repeats the results for the baseline model. Columns 3-4 present pass-through regressions for the cases where ρ_C=0.5 and 0.9 respectively. Columns 5-6 present results for the Calvo model for the cases where ρ_C=1 and 0.9 respectively. Column 7 presents results for the case where consumer heterogeneity is 350% what it is in the baseline parameterization.

presents results for the Calvo model with $\rho_C = 0.9$. Lowering the persistence of costs has an even greater effect on the results for the Calvo model than for the menu cost model: the long-run pass-through falls from 0.249 in the baseline specification to 0.162 in the specification with lower persistence.

Third, I ask how pass-through depends on the degree of consumer heterogeneity in demand. The literature on differentiated products demand systems with consumer heterogeneity (e.g. Berry, Levinsohn and Pakes, 1995) has emphasized that consumer heterogeneity can lead to higher markups for higher priced items since these items tend to appeal to consumers who are price insensitive. In the time series, this feature of the model implies that if consumers are very heterogeneous in their degree of price sensitivity, a firm has an incentive to raise its markup as costs rise since its products increasingly appeal to less price sensitive consumers. In order to illustrate this effect, the last column of table 2.10 presents the results of a pass-through regression for a case where heterogeneity is 350% larger than in the baseline case, i.e. where I raise the standard deviation of heterogeneity in price sensitivity Π_{yp} by 350%. In the "high heterogeneity" specification of the model, long-run pass-through is about 1/3 greater than in the baseline case.

Table 2.11: Menu Cost Estimates (Counterfactual Parameters)

	Baseline (Unit Root)	Alternative Persistence Parameters: Persistence =0.5	Alternative Persistence Parameters: Persistence =0.9	Alternative Volatility Parameters: Low Volatility	Alternative Volatility Parameters: High Volatility	Static Model Discount Factor =0
Menu Cost Estimate	0.22%	0.049%	0.11%	0.33%	0.13%	0.065%

The table presents menu cost estimates as a fraction of average annual firm revenue in the Syracuse market. The first column repeats the baseline results. Columns 3-7 present results for counterfactual parameter values. Columns 3-4 present results for the cases where ρ_C=0.5 and 0.9 respectively. Columns 5-6 present results for the low and high volatility cases described in the text. Column 7 presents results for a case where β=0 i.e. no forward-looking behavior.

The dynamics of marginal costs also have substantial effects on the magnitude of menu costs required to explain a given level of price rigidity. Table 2.11 (columns 3-4) presents menu cost estimates for the cases where $\rho_C = 0.5$ and $\rho_C = 0.9$ discussed above. Lower persistence of costs is associated with lower menu cost estimates since firms realize that current changes in costs are likely to be only temporary. The perceived persistence of cost shocks has a huge effect on the menu costs required to sustain the frequency of price change observed in the data. The specification with $\rho_C = 0.5$ implies that the menu costs required to sustain the price rigidity observed in the data are about 1/5 what they are in the unit root case. Even in the case with $\rho_C = 0.9$ the menu costs required to sustain the level of price rigidity are 1/2 what they are in the unit root case.

I also investigate the role of the volatility of cost shocks in determining the magnitude of menu costs required to sustain the observed frequency of price change. Higher volatility reduces the firm's incentive to adjust because it increases the "option value" from waiting to see what costs will be in the next period (Dixit, 1991). Columns 5-6 present the menu costs required to sustain the observed price rigidity for cases where the standard deviation of cost shocks σ_C^2 is assumed to be higher or lower than in the baseline case. Quantitatively, the option value effects are substantial. Lowering the standard deviation of costs to half the baseline case implies that the required menu costs are 150% what they are in the baseline case; while raising the standard deviation to twice what it is in the baseline case implies menu costs that are about 50% of the baseline value.

One approximation that has sometimes been used in the industrial organization and international economics literatures to evaluate the magnitude of barriers to price adjustment is to compare the profits from a case where prices are assumed to be constant to the case where prices are set optimally in a time-varying manner (e.g. Leslie, 2004; Goldberg and Hellerstein, 2007). One can evaluate the effects of this type of approximation by considering a static version of the model with the discount factor β set to zero. In this case, the firm simply compares the static profits from adjusting to the menu cost in each period in deciding whether to adjust. The last column of Table 2.11 shows that this procedure yields a menu cost estimate that is only 30% of what it is in the dynamic model with forward-looking behavior. The static procedure underestimates the magnitude of menu costs because it overlooks the fact that in deciding whether to adjust, the firm not only considers benefits today but also benefits in the future. These benefits are substantial when costs are persistent. Thus, menu cost estimates based on static procedures are likely to be substantially lower than estimates from dynamic models when costs are persistent.[49]

Finally, I use the dynamic model to investigate the sources of incomplete pass-through. In order to do this, I successively introduce markup adjustment, local costs, and barriers to price adjustment into a benchmark Dixit-Stiglitz pricing model to determine the role of these factors in incomplete pass-through. Table 2.9 presents estimated pass-through regressions for simulated data from four alternative pricing models. The first specification is the standard monopolistic-competition Dixit-Stiglitz model. As is well-known, this specification of demand implies a constant markup pricing rule and pass-through equal to one. The second specification introduces local costs. Again, I assume the Dixit-Stiglitz model, but I allow for local costs parameterized according to (2.19) and a retail margin parameterized by equation (2.18).[50] This specification implies a long-run pass-through of 0.427.

The third specification incorporates markup adjustment as well as local costs. I do this

[49] The menu cost estimate for $\beta = 0$ is much more similar to the menu cost estimate for $\rho_C = 0.5$ than to the estimate for the baseline case with unit root costs. This arises since the future benefits of adjustment are smaller when costs are less persistent. The menu cost estimate for $\rho_C = 0$ is actually lower than the estimate for $\beta = 0$. This difference arises because the static analysis also abstracts from the "option value" associated with not adjusting.

[50] I estimate the Dixit-Stiglitz model using the same data and instruments used to estimate the random coefficients discrete choice model. The resulting demand curve is $y_{jmt} = C_t \left(p^r_{jmt}/P_t\right)^{-\theta}$, where the estimated elasticity of substitution is $\theta = 2.92$.

by replacing the constant elasticity of substitution demand model with the static random coefficients discrete choice model examined in section 2.5.[51] This specification yields a long-run pass-through of 0.284. Pass-through falls substantially in the discrete choice model relative to the constant elasticity of substitution model.[52] The fourth column adds pricing dynamics in the form of the menu cost model presented in section 2.6, implying a long-run pass-through of 0.269.

This set of comparisons implies that local costs account for 78% of the incomplete long-run pass-through; markup adjustment accounts for 20%, and menu costs account for the remaining 2%. Menu costs therefore have little impact on long-run pass-through in this framework. As I discuss above, the role of menu costs in explaining long-run pass-through depends crucially on the persistence of marginal costs. Menu costs nevertheless play an important role in explaining pricing dynamics since they provide an explanation for the delayed response of prices to costs.

2.8 Conclusion

A large literature in international economics studies the response of domestic prices to fluctuations in imported costs. I use data on coffee prices at the retail, wholesale and commodity cost levels to study how variations in the price of an imported input translate into changes in prices. For both retail and wholesale prices, I find that pass-through is delayed and incomplete: a one percent increase in coffee commodity costs leads to a long-run increase in prices (over 6 quarters) of approximately a third of a percent. More than half of the price adjustment occurs in the quarters *after* the change in cost.

Reduced-form regressions indicate the delayed response of wholesale prices to costs in this industry occurs almost entirely at the wholesale level. I also document substantial rigidity in manufacturer coffee prices: over the time period I consider, manufacturer prices of ground

[51] Since the solution method for this model is standard, I discuss it in Appendix C (see e.g. Berry, Levinsohn and Pakes, 1995; Petrin, 2001 for a detailed discussion). Note that this model is not identical to the dynamic model with no menu costs since it does not assume asymmetric information.

[52] In order to build intuition, it is useful to consider pass-through in a logit model with symmetric firms. In this case, it is possible to solve analytically for the pricing equilibrium. This model implies cent-for-cent pass-through generating substantial markup adjustment when markups are large (Anderson, Palma and Thisse, 1992). In contrast, in the random coefficients model, the estimates of consumer heterogeneity play an important role in determining pass-through, as I discuss above.

coffee adjust on average 1.3 times per year, while retail prices excluding sales adjust on average 1.5 times per year over the same time period. I also show that wholesale prices adjust substantially more frequently during periods of high commodity cost volatility.

I develop an oligopoly menu cost model of pricing for the coffee industry, where the barriers to price adjustment are calibrated to match the frequency of wholesale price adjustment in this industry. I estimate the menu cost in the model to match the observed frequency of wholesale price adjustment. The model provides quantitatively realistic implications for long-run and short-run pass-through. The model also explains the strong tendency of prices to adjust more frequently in periods when commodity costs experience large changes. I investigate how pass-through in the model varies depending on the persistence of costs, the degree of consumer heterogeneity and the model of price adjustment behavior (i.e. menu cost vs. Calvo). I also find that menu cost estimates based on static procedures are likely to be substantially different from estimates from dynamic models when costs are persistent.

I use the model to analyze the role of markup adjustment, local costs, and barriers to price adjustment in determining incomplete pass-through. I successively introduce these features into a benchmark Dixit-Stiglitz pricing model to determine their role in incomplete pass-through. I find that local costs explain about 78% of incomplete long-run pass-through, oligopolistic markup adjustment explains about 20%, and menu costs explain only 2%. Nevertheless, menu costs play an important role in pricing dynamics since they explain the delayed response of prices to costs. Quantitatively, the persistence of costs is particularly important both in determining the role of price rigidity in pass-through and in determining the magnitude of menu costs required to support a particular level of price rigidity. In particular, the persistent swings in commodity costs imply that menu costs play a small role in explaining long-run incomplete pass-through in this market.

3. MONETARY NON-NEUTRALITY IN A MULTI-SECTOR MENU COST MODEL

*with Jón Steinsson**

3.1 Introduction

Menu costs are a simple way of explaining the empirical fact that prices adjust infrequently. Menu costs were first studied in a partial equilibrium setting (Barro, 1972; Sheshinski and Weiss, 1977; Mankiw, 1985; Akerlof and Yellen, 1985). General equilibrium analysis of menu cost models has long been restricted to relatively special cases (Caplin and Spulber, 1987; Caballero and Engel, 1991 and 1993; Caplin and Leahy, 1991 and 1997; Danziger, 1999; Dotsey et al., 1999). However, recently it has become feasible to solve much more general and quantitatively realistic menu cost models using numerical methods. Golosov and Lucas (2006) advanced the literature on menu cost models substantially by quantitatively analyzing a model rich enough to match micro-level evidence on both the frequency and absolute size of price changes.

It has been common practice in this literature to assume that all firms in the economy are identical.[1] Recent comprehensive studies of micro-level price setting behavior have, however, found a massive amount of heterogeneity across sectors in the frequency of price change (Bils and Klenow, 2004; Dhyne et al., 2006; Chapter 1). Table 3.1 reports the monthly frequency of price change excluding sales for a decomposition of U.S. consumer prices into 11 sectors

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[1] Exceptions to this include Caballero and Engel (1991, 1993).

Table 3.1: Frequency of Price Change Excluding Sales by CPI Major Group 1998-2005

Major Group	Weight	Median Freq.	Mean Freq.	Frac. Up	Median Abs. Size
	(%)	(%)	(%)	(%)	(%)
Processed Food	8.2	10.5	10.6	65.4	13.2
Unprocessed Food	5.9	25.0	25.4	61.2	14.2
Household Furnishing	5.0	6.0	6.5	62.9	8.7
Apparel	6.5	3.6	3.6	57.1	11.5
Transportation Goods	8.3	31.3	21.3	45.9	6.1
Recreation Goods	3.6	6.0	6.1	62.0	10.1
Other Goods	5.4	15.0	13.9	73.7	7.3
Utilities	5.3	38.1	49.4	53.1	6.3
Vehicle Fuel	5.1	87.6	87.4	53.5	6.4
Travel	5.5	41.7	43.7	52.8	21.6
Services (excl. Travel)	38.5	6.1	8.8	79.0	7.1
All Goods	100.0	8.7	21.1	64.8	8.5

This table presents the weighted mean and median frequencies of non-sale price change within Major Groups for the U.S. consumer price index (CPI). These statistics are from chapter 1. The weighted mean and median are calculated across "entry level items" in the CPI using CPI expenditure weights. The "weight" is the CPI expenditure weight. "Frac. Up" is the fraction of non-sale price changes that are price increases. "Median Abs. Size" is the median absolute size of log price changes. See chapter 1 for more detail on how these statistics are constructed.

for 1998-2005 taken from chapter 1. Figure 3.1 plots a finer decomposition. The frequency of price change ranges from 1% all the way to 100%. Most goods have a frequency of price change between 1% and 20%, but the distribution is highly asymmetric with a very long right tail.

The asymmetry of the distribution of the frequency of price change implies that the mean frequency of price change is much higher than the median frequency of price change. Table 3.2 reports the expenditure weighted mean and median frequency of price change of consumer prices excluding sales in the U.S. The mean monthly frequency is 21.1%, while the median is only 8.7%. Producer prices display a similarly large difference between the mean and median frequency of price change. Table 3.2 reports that the mean frequency of price change for finished producer goods is 24.7% while the median is only 10.8%.[2]

What implications does this heterogeneity have for the degree of monetary non-neutrality generated by a menu cost model? Does a single-sector menu cost model calibrated to match

[2] Most of the difference between the mean and the median arises from heterogeneity across sectors. The mean frequencies of price change for gasoline, utilities, and used cars was 87.6%, 38.1% and 100% respectively over the 1998-2005 period. Excluding these product categories (which account for about 13% of the total expenditure weight) causes the mean frequency of non-sale price changes to fall from 21% to 13%, while the median falls only from 8.7% to 7.7%.

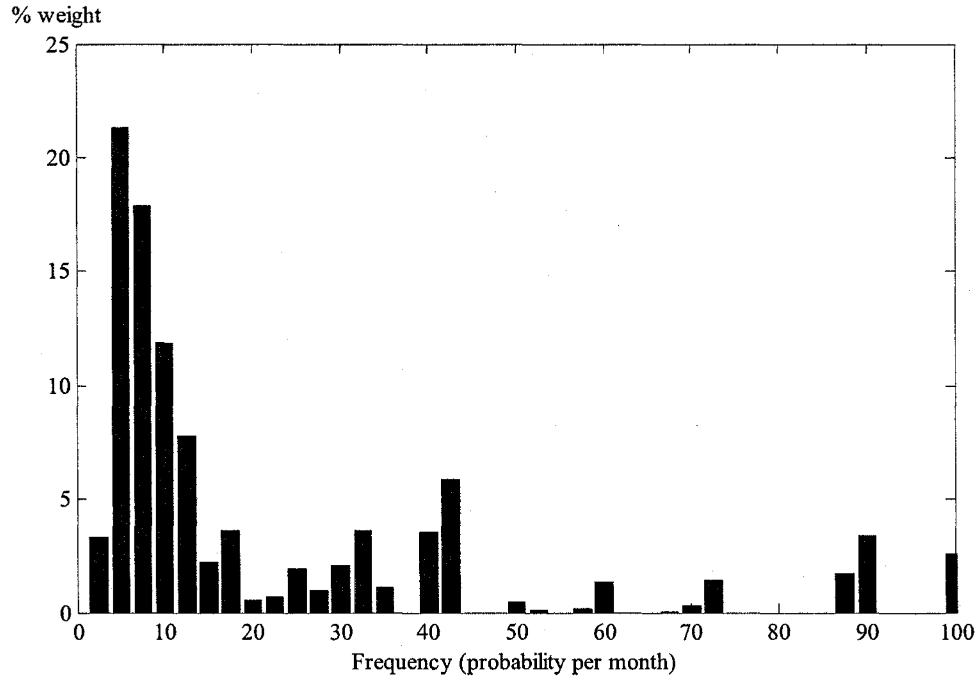


Figure 3.1: The Distribution of the Frequency of Price Change for U.S. Consumer Prices
This figure presents a histogram of the cross-sectional distribution of the frequency of non-sale price changes in U.S. consumer prices for the period 1998-2005 (percent per month). The figure is based on the statistics from chapter 1. It is based on the individual price quotes underlying the US CPI. The figure shows the expenditure weighted distribution of the frequency of price changes across entry level items (ELI's) in the CPI.

the average frequency of price change provide a good measure of the degree of monetary non-neutrality in an economy with the huge amount of heterogeneity in price rigidity we observe in the U.S. economy? In other words, how does the distribution of price changes across firms affect the degree of monetary non-neutrality in the economy? To address these questions, we develop a multi-sector menu cost model. We calibrate the model to match the distribution of price rigidity across sectors in the U.S. economy. We find that the monetary non-neutrality implied by our multi-sector model is triple that implied by a single-sector model calibrated to the mean frequency of price change.

To understand the effect that heterogeneity has on the degree of monetary non-neutrality, assume for simplicity that the pricing decisions of different firms are independent of one another. This implies that the degree of monetary non-neutrality in the economy is approximately a weighted average of the monetary non-neutrality in each sector. In this case, heterogeneity in the frequency of price change across sectors increases the overall degree of monetary non-neutrality in the economy if the degree of monetary non-neutrality in differ-

Table 3.2: Frequency and Size of Price Changes 1998-2005

	CPI	PPI	
		Finished Goods	Intermed. Goods
	(%)	(%)	(%)
Median Freq. Price Change	8.7	10.8	14.3
Mean Freq. Price Change	21.1	24.7	26.7
Median Frac. Increases	64.8	65.7	57.1
Median Abs. Size Price Changes	8.5	7.7	7.5

This table presents statistics on micro-level price changes for US consumer and producer prices over the 1998-2005 period. These statistics are from chapter 1. The weighted mean and median frequency of price change are calculated using CPI expenditure weights for consumer prices and PPI Finished Goods and Intermetiate Goods value weights for producer prices. The third and fourth rows of the table present the median fraction price changes that are price increases, and the median absolute size of log price changes. The CPI statistics refer to non-sale price changes. See chapter 1 for more details on how these statistics are constructed.

ent sectors of the economy is a convex function of each sector's frequency of price change (Jensen's inequality).

Consider the response of the economy to a permanent shock to nominal aggregate demand. In the Calvo model, the effect of the shock on output at any given point in time after the shock is inversely proportional to the fraction of firms that have changed their price at least once since the shock occurred. If some firms have vastly higher frequencies of price change than others, they will change their prices several times before the other firms change their prices once. But all price changes after the first one for a particular firm do not affect output on average since the firm has already adjusted to the shock. Since a marginal price change is more likely to fall on a firm that has not already adjusted in a sector with a low frequency of price change, the degree of monetary non-neutrality in the Calvo model is convex in the frequency of price change (Carvalho, 2006).

The relationship between the frequency of price change and the degree of monetary non-neutrality is more complicated in a menu cost model. Firms are not selected at random to change their price. Rather the firms that change their prices are the firms whose prices are furthest from their desired prices (Caplin and Spulber, 1987; Golosov and Lucas, 2006). This "selection effect" greatly diminishes the degree of monetary non-neutrality in a menu cost model relative to the Calvo model. It also affects the relationship between the frequency of price change and the degree of monetary non-neutrality. Consider two sectors of the economy that are identical except that one faces larger menu costs than the other. The sector with larger menu costs will have fewer price changes. But the average absolute size of price changes in this sector will also be larger. While a lower frequency of price change tends to raise the degree of monetary non-neutrality, the larger size of price changes tends to lower the degree of monetary non-neutrality. The net effect depends on the strength of the selection effect. In the Caplin-Spulber model, the selection effect is strong enough that it yields complete monetary neutrality regardless of the frequency of price change.

The strength of the selection effect is determined by a number of characteristics of a firm's environment, including the level of the menu cost, the level and variance of the inflation rate in the economy and the variance and kurtosis of idiosyncratic shocks to the firm's marginal costs.[3] Because of the selection effect, menu cost models can generate a wide range of relationships between the frequency of price change and the degree of monetary non-neutrality depending on what causes the variation in the frequency of price change across firms. If the selection effect is strong enough, the relationship between the frequency of price change and the degree of monetary non-neutrality may be concave or even increasing.

Despite the complications introduced by the selection effect, we find that heterogeneity amplifies the degree of monetary non-neutrality by roughly a factor of 3 for our multi-sector menu cost model calibrated to data on the U.S. economy. The features of the U.S. data that drive this result are: 1) the low average level of inflation in the U.S. economy, and 2) the fact that the average size of price changes is large and a substantial fraction of price changes are price decreases.

Bils and Klenow (2002) and Carvalho (2006) investigate the effect of heterogeneity in the frequency of price change in multi-sector Taylor and Calvo models. Bils and Klenow (2002) analyze the Taylor model and find that heterogeneity amplifies the degree of monetary non-neutrality by a modest amount. Carvalho (2006) considers both the Taylor and Calvo model as well as several time-depentent sticky information models. He incorporates strategic complementarity into his model and considers a different shock process than Bils and Klenow (2002). He finds a larger effect of heterogeneity. Our results are quantitatively similar to the

[3] Midrigan (2005) shows how the strength of the selection effect at a given frequency of price change is affected by the kurtosis of idiosyncratic shocks marginal costs.

results he finds when he considers the same shock process as we do.

We incorporate intermediate inputs into our menu cost model, following Basu (1995). Intermediate inputs generate a substantial degree of strategic complementarity in the model. The degree of monetary non-neutrality generated by the model with intermediate inputs is roughly triple that of the model without intermediate inputs. Intuitively, in the model with intermediate inputs, firms that change their price soon after a shock to nominal aggregate demand choose to adjust less than they otherwise would because the price of many of their inputs have not yet responded to the shock. We find a similar affect of heterogeneity in both the model with and without intermediate inputs. The model with intermediate inputs generates positive comovement of output of different sectors, unlike a model with no real rigidities.[4]

Strategic complementarity has long been an important source of amplification of nominal rigidities (Ball and Romer, 1990; Woodford, 2003). However, recent work has cast doubt on this mechanism as a source of amplification in menu cost models with idiosyncratic shocks by showing that the introduction of certain sources of strategic complementarity implies that the models are unable to match the average size of micro-level price changes for plausible parameter values (Klenow and Willis, 2006; Golosov and Lucas, 2006). Following Ball and Romer (1990) and Kimball (1995), we divide sources of strategic complementarity into two classes—ω-type strategic complementarity and Ω-type strategic complementarity. We show that models with a large amount of ω-type strategic complementarity are unable to match the average size of price changes, while this problem does not afflict models with a large amount of Ω-type strategic complementarity. The introduction of intermediate inputs increases the amount of Ω-type strategic complementarity. It therefore does not affect the size of price changes or require unrealistic parameter values.

Finally, we compare the results of our menu cost model to a model in which price changes are largely time-dependent. The menu cost model abstracts completely from the idea that price reviews may require less resources in some periods than others. Such variation may arise due to, e.g., the introduction of new products or economies of scale in decision making.

[4] The lack of comovement of output across sectors in models with heterogeneity in the frequency of price change has been emphasized recently by Bils et al. (2003), Barsky et al. (2003) and Carlstrom and Fuerst (2006).

The Calvo model takes the opposite extreme position. It abstracts completely from selection by firms regarding the timing of price changes. This causes the Calvo model to have problems matching the micro-data on price setting. To capture the idea that price changes may require less resources in some periods than others but at the same time match the micro-level evidence on the frequency and absolute size of price changes, we develop an extension of the Calvo model in which firms face a high menu cost with probability α and a low menu cost with probability $1-\alpha$. We refer to this model as the CalvoPlus model. The CalvoPlus model has the appealing feature that it nests both the menu cost model and the Calvo model as special cases.[5]

In the Calvo limit—when all price changes occur in the low menu-cost state—monetary non-neutrality is six times what it is in the menu cost model. However, the degree of monetary non-neutrality drops rapidly as the fraction of price change in the low menu-cost state falls below 100%. When 85% of price changes occur in the low menu cost state, the CalvoPlus model generates half as much monetary non-neutrality as in the Calvo limit. When 50% of price changes occur in the low menu cost state the degree of monetary non-neutrality in the CalvoPlus model is close to identical to the value in the menu cost model. This suggests that the relatively large amount of monetary non-neutrality generated by the Calvo model is quite sensitive to even a modest amount of selection by firms regarding the timing of price changes.

Our analysis builds on the original work on menu cost models in partial equilibrium by Barro (1972), Sheshinski and Weiss (1977), Mankiw (1985), Akerlof and Yellen, 1985 and others. The implications of menu costs in general equilibrium have been analyzed analytically in simple models by Caplin and Spulber (1987), Caballero and Engel (1991, 1993), Caplin and Leahy (1991, 1997), Danziger (1999), Dotsey et al. (1999) and Gertler and Leahy (2006). Willis (2003), Burstein (2006), Golosov and Lucas (2006) and Midrigan (2005) analyze the implications of menu cost models in general equilibrium using numerical solution methods similar to ours. Finally, we build on a long literature in monetary economics on real rigidities

[5] Our CalvoPlus model is related to the random menu cost model analyzed by Dotsey et al. (1999), Klenow and Kryvtsov (2005) and Caballero and Engel (2006). The results we find regarding amplification of monetary non-neutrality in our CalvoPlus model relative to the Calvo model are consistent with the results of Caballero and Engel (2006).

by Ball and Romer (1990), Basu (1995), Kimball (1995), Woodford (2003) and others.

The paper proceeds as follows. Section 3.2 presents a single-sector menu cost model with intermediate inputs. The section shows how intermediate inputs amplify the degree of monetary non-neutrality in the model without affecting the size of price changes. Section 3.3 presents the CalvoPlus model and analyzes its behavior. Section 3.4 introduces the multi-sector version of the menu cost model and analyzes the effects of heterogeneity. Section 3.5 concludes.

3.2 A Single-Sector Menu Cost Model

We first present a single-sector general equilibrium model in which firms face menu costs. This model is a generalization of the model presented by Golosov and Lucas (2006).

3.2.1 Household Behavior

The households in the economy maximize discounted expected utility given by

$$E_t \sum_{j=0}^{\infty} \beta^j \left[\frac{1}{1-\gamma} C_{t+j}^{1-\gamma} - \frac{\omega}{\psi+1} L_{t+j}^{\psi+1} \right], \tag{3.1}$$

where E_t denotes the expectations operator conditional on information known at time t, C_t denotes household consumption of a composite consumption good and L_t denotes household supply of labor. Households discount future utility by a factor β per period; they have constant relative risk aversion equal to γ; the level and convexity of their disutility of labor are determined by the parameters ω and ψ, respectively.

Households consume a continuum of differentiated products indexed by z. The composite consumption good C_t is a Dixit-Stiglitz index of these differentiated goods:

$$C_t = \left[\int_0^1 c_t(z)^{\frac{\theta-1}{\theta}} dz \right]^{\frac{\theta}{\theta-1}}, \tag{3.2}$$

where $c_t(z)$ denotes household consumption of good z at time t and θ denotes the elasticity of substitution between the differentiated goods.

The households must decide each period how much to consume of each of the differentiated products. For any given level of spending in time t, the households choose the consumption bundle that yields the highest level of the consumption index C_t. This implies that household demand for differentiated good z is

$$c_t(z) = C_t \left(\frac{p_t(z)}{P_t} \right)^{-\theta} \tag{3.3}$$

where $p_t(z)$ denotes the price of good z in period t and P_t is the price level in period t given by

$$P_t = \left[\int_0^1 p_t(z)^{1-\theta} dz \right]^{\frac{1}{1-\theta}}. \tag{3.4}$$

The price level P_t has the property that $P_t C_t$ is the minimum cost for which the household can purchase the amount C_t of the composite consumption good.

A complete set of Arrow-Debreu contingent claims are traded in the economy. The budget constraint of the households may therefore be written as

$$P_t C_t + E_t[D_{t,t+1} B_{t+1}] \leq B_t + W_t L_t + \int_0^1 \Pi_t(z) dz, \tag{3.5}$$

where B_{t+1} is a random variable that denotes the state contingent payoffs of the portfolio of financial assets purchased by the households in period t and sold in period $t+1$, $D_{t,t+1}$ denotes the unique stochastic discount factor that prices these payoffs in period t, W_t denotes the wage rate in the economy at time t and $\Pi_t(z)$ denotes the profits of firm z in period t. To rule out "Ponzi schemes", we assume that household financial wealth must always be large enough that future income suffices to avert default.

The first order conditions of the household's maximization problem are

$$D_{t,T} = \beta^{T-t} \left(\frac{C_T}{C_t} \right)^{-\gamma} \frac{P_t}{P_T}, \tag{3.6}$$

$$\frac{W_t}{P_t} = \omega L_t^{\psi} C_t^{\gamma}, \tag{3.7}$$

and a transversality condition. Equation (3.6) describes the relationship between asset prices and the time path of consumption, while equation (3.7) describes labor supply.

3.2.2 Firm Behavior

There are a continuum of firms in the economy indexed by z. Each firm specializes in the production of a differentiated product. The production function of firm z is given by,

$$y_t(z) = A_t(z)L_t(z)^{1-s_m}M_t(z)^{s_m}, \tag{3.8}$$

where $y_t(z)$ denotes the output of firm z in period t, $L_t(z)$ denotes the quantity of labor firm z employs for production purposes in period t, $M_t(z)$ denotes an index of intermediate inputs used in the production of product z in period t, s_m denotes the materials share in production and $A_t(z)$ denotes the productivity of firm z at time t. The index of intermediate products is given by

$$M_t(z) = \left[\int_0^1 m_t(z,z')^{\frac{\theta-1}{\theta}}dz'\right]^{\frac{\theta}{\theta-1}},$$

where $m_t(z,z')$ denotes the quantity of the z'th intermediate input used by firm z.

Following Basu (1995), we assume that all products serve both as final output and inputs into the production of other products. This "round-about" production model reflects the complex input-output structure of a modern economy.[6] When the material share s_m is set to zero, the production function reduces to the linear production structure considered by Golosov and Lucas (2006). Basu shows that the combination of round-about production and price rigidity due to menu costs implies that the pricing decisions of firms are strategic complements. In this respect, the round-about production model differs substantially from the "in-line" production model considered, for example, by Blanchard (1983). The key difference is that in the round-about model there is no "first product" in the production chain that does not purchase inputs from other firms. The fact that empirically almost all industries purchase products from a wide variety of other industries lends support to the "round-about" view of production.[7]

[6] See Blanchard (1987) for an earlier discussion of a model with "horizontal" input supply relationships between firms.

[7] See Basu (1995) for a detailed discussion of this issue.

Firm z maximizes the value of its expected discounted profits

$$E_t \sum_{j=0}^{\infty} D_{t,t+j} \Pi_{t+j}(z), \tag{3.9}$$

where profits in period t are given by

$$\Pi_t(z) = p_t(z) y_t(z) - W_t L_t(z) - P_t M_t(z) - K W_t I_t(z). \tag{3.10}$$

Here $I_t(z)$ is an indicator variable equal to one if the firm changes its price in period t and zero otherwise. We assume that firm z must hire an additional K units of labor if it decides to change its price in period t. We refer to this fixed cost of price adjustment as a "menu cost".

Firm z must decide each period how much to purchase of each of the differentiated products it uses as inputs. Cost minimization implies that the firm z's demand for differentiated product z' is

$$m_t(z, z') = M_t(z) \left(\frac{p_t(z')}{P_t} \right)^{-\theta}. \tag{3.11}$$

Combining consumer demand—equation (3.3)—and input demand—equation (3.11)—yields total demand for good z:

$$y_t(z) = Y_t \left(\frac{p_t(z)}{P_t} \right)^{-\theta}, \tag{3.12}$$

where $Y_t = C_t + \int_0^1 M_t(z) dz$. It is important to recognize that C_t and Y_t do not have the same interpretations in our model as they do in models that abstract from intermediate inputs. The variable C_t reflects *value-added* output while Y_t reflects *gross* output. Since gross output is the sum of intermediate products and final products, it "double-counts" intermediate production and is thus larger than value-added output. GDP in the U.S. National Income and Product Accounts measures value-added output. The variable in our model that corresponds most closely to real GDP is therefore C_t.

The firm maximizes profits—equation (3.9)—subject to its production function—equation (3.8)—demand for its product—equation (3.12)—and the behavior of aggregate variables. We solve this problem by first writing it in recursive form and then by employing value function iteration. To do this, we must first specify the stochastic processes of all exogenous variables.

We assume that the log of firm z's productivity follows a mean-reverting process,

$$\log A_t(z) = \rho \log A_{t-1}(z) + \epsilon_t, \tag{3.13}$$

where ϵ_t is independent and identically distributed.

We assume that the monetary authority targets a path for nominal value-added output, $S_t = P_t C_t$. Specifically, the monetary authority acts so as to make nominal value-added output follow a random walk with drift in logs:

$$\log S_t = \mu + \log S_{t-1} + \eta_t \tag{3.14}$$

where η_t is independent and identically distributed. We will refer to S_t either as nominal value-added output or as nominal aggregate demand.[8]

The state space of the firm's problem is infinite dimensional since the evolution of the price level and other aggregate variables depend on the entire joint distribution of all firms' prices and productivity levels. Following Krusell and Smith (1998), we make the problem tractable by assuming that the firms perceive the evolution of the price level as being a function of a small number of moments of this distribution.[9] Specifically, we assume that firms perceive that

$$\frac{P_t}{P_{t-1}} = \Gamma\left(\frac{S_t}{P_{t-1}}\right). \tag{3.15}$$

Forecasting the price level based on this single variable turns out to be highly accurate. Figure 3.2 plots the actual log inflation rate as a function of $\log(S_t/P_t)$ over a 280 month simulation of the model using our benchmark calibration. A linear regression of log inflation on $\log(S_t/P_t)$ has an $R^2 = 0.989$. To allow for convenient aggregation, we also make use of log-linear approximations of the relationship between aggregate labor supply, aggregate intermediate product output and aggregate value-added output.

[8] This type of specification for nominal aggregate demand is common in the literature. It is often justified by a model of demand in which nominal aggregate demand is proportional to the money supply and the central bank follows a money growth rule. It can also be justified in a cashless economy (Woodford, 2003). In a cashless economy, the central bank can adjust nominal interest rates in such a way to achieve the target path for nominal aggregate demand.

[9] Willis (2003) and Midrigan (2005) make similar assumptions.

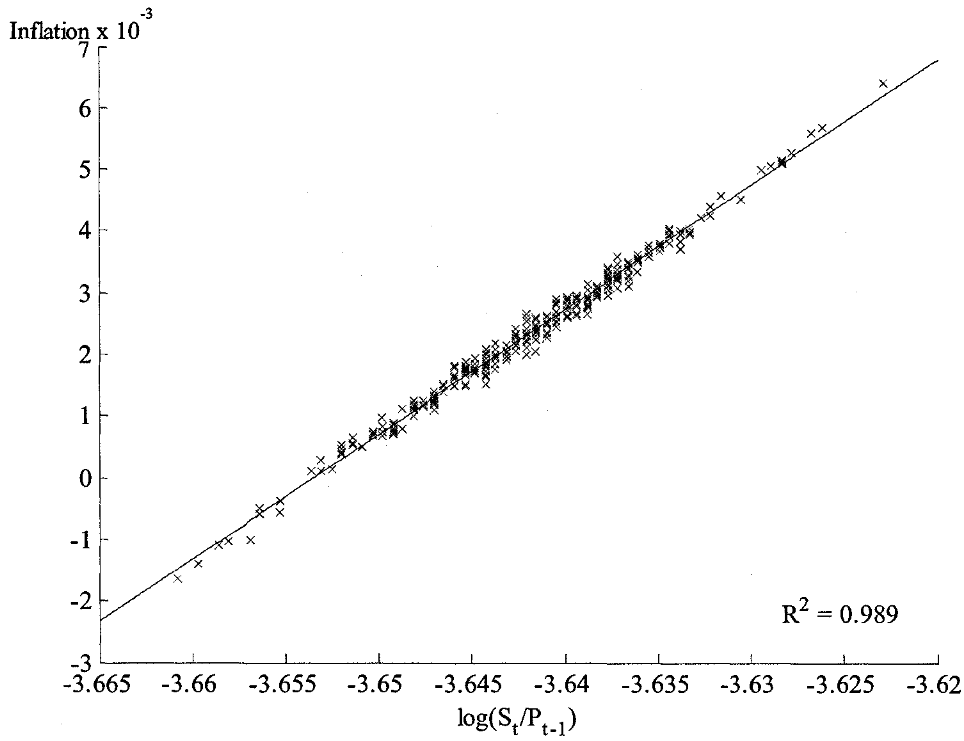


Figure 3.2: Log Inflation as a Function of $\log(S_t/P_{t-1})$ for the Single-Sector Model
This figure presents simulated log inflation as a function of $\log(S_t/P_{t-1})$ for the single-sector menu cost model with intermediate inputs. The figure is based on 280 simulated periods of data.

Given these assumptions, firm z's optimization problem may be written recursively in the form of the Bellman equation

$$V\left(A_t(z), \frac{p_{t-1}(z)}{P_t}, \frac{S_t}{P_t}\right) = \max_{p_t(z)} \left\{ \Pi_t^R(z) + E_t\left[D_{t,t+1} V\left(A_{t+1}(z), \frac{p_t(z)}{P_{t+1}}, \frac{S_{t+1}}{P_{t+1}}\right)\right]\right\}, \quad (3.16)$$

where $V(\cdot)$ is firm z's value function and $\Pi_t^R(z)$ denotes firm z's profits in real terms at time t.[10]

An equilibrium in this economy is a set of stochastic processes for the endogenous price and quantity variables discussed above that are consistent with household utility maximization, firm profit maximization, market clearing and the evolution of the exogenous variables $A_t(z)$ and S_t. We use the following iterative procedure to solve for the equilibrium: 1) We specify a finite grid of points for the state variables, $A_t(z)$, $p_{t-1}(z)/P_t$ and S_t/P_t. 2) We propose a function $\Gamma(S_t/P_{t-1})$ on the grid. 3) Given the proposed Γ, we solve for the firm's policy

[10] In appendix D, we show how the firm's real profits can be written as a function of $(A_t(z), p_{t-1}(z)/P_t, S_t/P_t)$ and $p_t(z)$.

function F by value function iteration on the grid. 4) We check whether Γ and F are consistent.[11] If so, we stop and use Γ and F to calculate other features of the equilibrium. If not, we update Γ and go back to step 3. We approximate the stochastic processes for $A_t(z)$ and S_t using the method proposed by Tauchen (1986).[12]

3.2.3 Calibration

We focus attention on the behavior of the economy for a specific set of parameter values (see table 3.3). We set the monthly discount factor equal to $\beta = 0.96^{1/12}$. We assume log-utility in consumption ($\gamma = 1$). Following Hansen (1985) and Rogerson (1988), we assume linear disutility of labor ($\psi = 0$). We set ω such that in the flexible price steady state labor supply is 1/3. We set $\theta = 4$ to roughly match estimates of the elasticity of demand from the industrial organization and international trade literatures.[13] Our choices of $\mu = 0.002$ and $\sigma_\eta = 0.0037$ are based on the behavior of U.S. nominal and real GDP during the period 1998-2005. Since our model does not incorporate a secular trend in economic activity, we set μ equal to the mean growth rate of nominal GDP less the mean growth rate of real GDP.

[11] We do this in the following way: First, we calculate the stationary distribution of the economy over $(A(z), p(z)/P, S/P)$ implied by Γ and F as described in appendix E. Second, we use the stationary distribution and equation (3.4) to calculate the price index implied by Γ—call it P_Γ—for each value of S/P. Third, we check whether $|P_\Gamma - P| < \xi$, where $|\cdot|$ denotes the sup-norm.

[12] A drawback of numerical methods of the type we employ in this paper is that it is difficult to prove uniqueness. The main feature of our model that potentially could generate non-uniqueness is the combination of strategic complementarity and menu costs (Ball and Romer, 1991). However, the large idiosyncratic shocks that we assume in our model significantly reduce the scope for multiplicity (Caballero and Engel, 1993). In particular, the type of multiplicity studied by Ball and Romer does not exist in our model since the large idiosyncratic shocks prevent sufficient synchronization across firms. In this respect our results are similar to John and Wolman (2004). It is also conceivable that our use of Krusell and Smith's approximation method could yield self-fulfilling approximate equilibria. There is, however, nothing in the economic link between agents beliefs and their pricing decision that suggests such self-fulfilling equilibria. In fact, the actual behavior of the price level in our model is quite insensitive to even relatively large changes in beliefs. The reason for this is that by far the most important factor in agent's decisions is movements in their idiosyncratic productivity levels as opposed to movements in aggregate variables. We solved our model with more sophisticated beliefs (additional moments) and starting our fixed point algorithm at various initial values. In all cases the resulting approximate fixed point is virtually identical.

[13] Berry et al. (1995) and Nevo (2001) find that markups vary a great deal across firms. The value of θ we choose implies a markup similar to the mean markup estimated by Berry et al. (1995) but slightly below the median markup found by Nevo (2001). Broda and Weinstein (2006) estimate elasticities of demand for a large array of disaggregated products using trade data. They report a median elasticity of demand below 3. Also, Burstein and Hellwig (2006) estimate an elasticity of demand near 5 using a menu cost model. Midrigan (2005) uses $\theta = 3$ while Golosov and Lucas (2006) use $\theta = 7$. The value of θ affects our calibration of the menu cost—a higher θ imply higher menu costs—and it affects our calibration of the intermediate input share—a higher θ implies lower values for s_m. Given the large size of price changes we observe, a high value of θ has extreme implications about quantity variation.

Table 3.3: Benchmark Parameters

Discount factor	$\beta = 0.96^{1/12}$
Coefficient of relative risk aversion	$\gamma = 1$
Inverse of Frisch elasticity of labor supply	$\psi = 0$
Elasticity of demand	$\theta = 4$
Steady state labor supply	$L = 1/3$
Intermediate inputs share in production	$s_m = 0.75$
Speed of mean reversion of idiosyncratic productivity	$\rho = 0.7$
Mean growth rate of nominal aggregate demand	$\mu = 0.002$
St. deviation of the growth rate of nominal aggregate demand	$\sigma_\eta = 0.0037$

We set σ_η equal to the standard deviation of nominal GDP growth.

The parameter s_m denotes the cost share of intermediate inputs in the model. Table 3.4 contains information from the 2002 U.S. Input-Output Table published by the Bureau Economic Analysis. The table provides information about both the share of intermediate inputs in the gross output of each sector (column 1) and about how intensively the output of each sector is used as an intermediate input in other sectors (column 2). The revenue share of intermediate inputs varies from about 1/3 to about 2/3. It is highest in manufacturing and lowest in utilities. The use of different sectors as intermediate inputs is closely related to their weight in gross output. The main deviations are that the output of manufacturing and services are used somewhat more intensively as intermediate inputs than their weight in gross output would suggest while the output of the government sector and the construction sector are used less.

The weighted average revenue share of intermediate inputs in the U.S. private sector using CPI expenditure weights was roughly 52% in 2002. The input-output table treats health insurance as employee compensation rather than as an intermediate input. But roughly 35% of health expenditures (roughly 5% of GDP) are paid by employers. For our purposes it seems appropriate to count these as intermediate inputs. This raises the share of intermediate inputs in revenue to roughly 56%. The cost share of intermediate inputs is equal to the revenue share times the markup. Our calibration of θ implies a markup of 1.33. Our estimate of the weighted average cost share of intermediate inputs is therefore roughly 75%.

This calibration depends on a number of assumptions. Alternative assumptions yield estimates of the intermediate inputs share that are either lower or higher. Above we employed

Table 3.4: Intermediate Inputs in the U.S. Economy in 2002

	% Int. Inputs	% Used	% Gross Y	% GDP	% CPI
Agriculture and Mining	55.1	5.5	2.4	1.9	0.0
Utilities	36.8	2.6	1.7	2.0	5.3
Construction	46.8	1.5	4.8	4.6	0.0
Manufacturing	64.9	28.8	20.5	12.9	51.2
Trade	31.7	6.2	10.4	12.8	0.0
Services	39.3	53.0	48.7	53.0	43.5
Government	37.9	0.9	11.5	12.8	0.0

These data (except the last column) are from the 2002 "Use" table of the U.S. Annual Input-Output Accounts published by the Bureau of Economic Analysis. The last column is taken from chapter 1. "% Int. Inputs" denotes the fraction of intermediate inputs in each sectors gross output. "% Used" denotes the fraction of all intermediate inputs in the economy that come from each sector. "% Gross Y" denotes each sector's weight in gross output. "% GDP" denotes each sector's weight in GDP. "% CPI" denotes each sector's weight in the CPI.

CPI weights as we do elsewhere in the paper. Using gross output weights would yield a slightly lower number (68% rather than 75%) since services have a higher weight in gross output than in the CPI. However, increasing the weight of services would also lower the mean frequency of price change and increase the skewness of the frequency distribution. A higher value for the elasticity of demand would also yield a lower intermediate input share. For example, Golosov and Lucas (2006) use $\theta = 7$. This would yield and intermediate input share equal to 65% rather than 75%. On the other hand, we have assumed that intermediate inputs make up the same fraction of marginal costs as they do average variable costs. With a more general production structure, this is not necessarily the case. Materials might be disporportionately important at the margin, in which case the share of intermediate inputs in marginal costs would be higher than we estimate. Also, intermediate input use is skewed toward the more flexible sectors of the economy (manufacturing as opposed to services) while the more sticky sectors make up most of the intermediate inputs (services rather than manufacturing). This should imply that marginal costs move more sluggishly than our simple model with complete symmetry suggests. Given the uncertainty associated with these factors, we report results for $s_m = 0.65$ and $s_m = 0.85$ as well as $s_m = 0.75$.[14]

[14] Basu (1995) argues for values of the parameter s_m between 0.8 and 0.9. Bergin and Feenstra (2000) also focus on values of s_m between 0.8 and 0.9. Other authors—e.g., Rotemberg and Woodford (1995), Chari et al. (1996) and Woodford (2003, ch. 3)—use values closer to $s_m = 0.5$. The lower values of s_m are based on much lower calibrations of the markup of prices over marginal costs than we use. These low markups are meant to match the fact that pure profits are a relatively small fraction of GDP in the U.S.. We base our calibration of the markup of prices over marginal costs on evidence from the industrial organization and international trade

Table 3.5: Frequency of Price Change: Comparison of CPI and PPI

Category	Num. of Matches	Frequency of Price Change CPI	PPI
Processed Food	32	10.5	7.2
Unprocessed Food	24	25.9	67.9
Household Furnishings	27	6.5	5.6
Apparel	32	3.6	2.7
Recreation Goods	16	6.8	6.1
Other Goods	13	23.2	17.1

This table presents a comparison between the frequency of price change for consumer prices excluding sales and producer prices over the 1998-2005 period. These statistics are from chapter 1. These statistics are constructed by matching Entry Level Items (ELI's) in the CPI to 4, 6 or 8-digit commodity codes within the PPI. "Num. of Matches" denotes the number of such matches that were possible within the Major Group. "Frequency of price change" denotes the median frequency across categories among the matches found. See chapter 1 for more details on how these statistics are constructed.

We set the menu cost K and the standard deviation of the idiosyncratic shocks σ_ϵ for each case we consider below to match moments of the distribution of the frequency and size of price changes reported in table 3.2. For computational reasons, we set the speed of mean reversion of the firm productivity process equal to $\rho = 0.7$. This value is close to the value we estimate for ρ in chapter 1.

The assumption of round-about production implicitly assumes that prices are rigid to both consumers and producers. Direct evidence on producer prices from Carlton's (1986) work on the Stigler-Kindahl dataset as well as Blinder et al.'s (1998) survey of firm managers supports the view that price rigidity is an important phenomenon at intermediate stages of production. Chapter 1 presents a more comprehensive analysis of producer prices based on the micro-data underlying the producer price index and find that the rigidity of producer prices is comparable to the rigidity of non-sale consumer prices. The median frequency of price change of finished goods and intermediate goods producer prices is 10.8% and 14.3%, respectively, while the median frequency of price change of consumer prices is 8.7% (see table 3.2). Moreover, table 3.5 shows that the frequency of non-sale consumer price changes is highly correlated across sectors with the frequency of producer price change in that same sector. We match detailed CPI categories with detailed PPI categories and compare the frequency of price change. Over the 153 matches, the correlation between the frequency of

literature. These high markups are consistent with small pure profits if firms have fixed costs and/or if firm entry involves sunk investment costs that must be recouped with flow profits post-entry (Dixit and Pindyck, 1994; Ryan, 2006).

Table 3.6: The Single-Sector Menu Cost Model

	Intermed. Share	Menu Cost	σ_ε	Freq. (%)	Abs. Size (%)	CIR (%)	Var(C) (10^{-4})
(1)	0.00	0.0090	0.0465	21.1	8.5	0.5	0.018
(2)	0.65	0.0027	0.0465	21.1	8.5	1.3	0.068
(3)	0.75	0.0030	0.0465	21.1	8.5	1.6	0.078
(4)	0.85	0.0048	0.0465	21.1	8.5	2.1	0.111
(5)	0.00	0.0203	0.0425	8.7	8.5	1.6	0.090
(6)	0.65	0.0048	0.0425	8.7	8.5	3.3	0.194
(7)	0.75	0.0067	0.0425	8.7	8.5	4.2	0.260
(8)	0.85	0.0103	0.0425	8.7	8.5	5.7	0.348

This table presents estimated parameter values, the cumulative impulse response (CIR) and the variance or real value-added output for the benchmark specification of the CalvoPlus model for several values of the intermediate inputs share (s_m). (See Section 2.4 for a discussion of the CIR). Specifications (1)-(4) are parameterized to match the weighted mean frequency of price change of 21.1%, while specifications (5)-(8) are parameterized to match the weighted median frequency of price change of 8.7%. The menu cost is presented as a fraction of steady state revenue: $(\theta-1)/\theta$ K/Y_{SS} where Y_{SS} is steady state output under flexible prices. σ_ε is the variance of shocks to the log of the idiosyncratic productivity shocks.

price change for producer prices and consumer prices excluding sales is 0.83.

3.2.4 Results

Table 3.6 presents results for several calibrations of our menu cost model. We present results for four different values of s_m. In rows (1) through (4), we choose the menu cost and the variance of the idiosyncratic shocks to match the mean frequency of price change of U.S. CPI prices reported in table 3.2, while in rows (5) through (8) we choose these parameters to match the median frequency of price change. For clarity, in all cases we calibrate the model to match the median size of price changes.

We report the menu cost as a fraction of steady state monthly revenues under flexible prices.[15] In all cases considered in table 3.6, the size of the menu cost is quite modest—0.3-2% of steady state monthly revenue. Since the firm only pays the menu cost every 5 to 10 months, the resources devoted to changing prices as a fraction of revenue over a typical year are about 0.2% in the model without intermediate inputs and 0.05% in the model with

[15] That is, the menu cost we report in table 3.6 is $((\theta-1)/\theta)(K/Y_{ss})$, where K is the menu cost in units of labor, $(\theta-1)/\theta$ is the steady state real wage under flexible prices and Y_{ss} denotes flexible price steady state gross output.

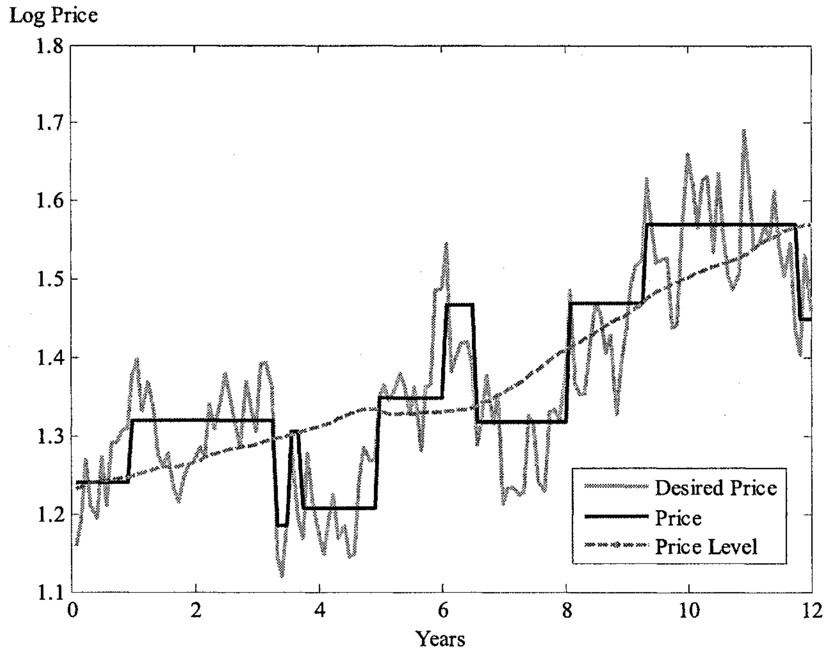


Figure 3.3: A Sample Path for the Single-Sector Model
This figure plots a sample path of the price for a single firm in the single-sector model with intermediate inputs calibrated to match the median frequency and size of price changes over a 12 year period. It also plots the price level and the desired price given by equation (17) for this simulation.

intermediate inputs ($s_m = 0.75$).[16]

Figure 3.3 plots a sample path for the model with intermediate inputs calibrated to the median frequency of price change. The variance of the idiosyncratic shocks is many times larger than the variance of the shocks to nominal aggregate demand. This is crucial for generating price changes sufficiently large to match the data, as well as the substantial number of price decreases observed in the data, a point emphasized by Golosov and Lucas (2006).

Our primary interest is the degree of monetary non-neutrality generated by the model. We report two measures of monetary non-neutrality. Our primary measure is the cumulative impulse response (CIR) of real value-added output to a permanent shock to nominal aggregate demand. More precisely, we consider the following experiment: Starting from steady state at time 0, the economy is hit by a nominal shock $\eta_0 = \delta$.[17] We assume that no subsequent

[16] Levy at al. (1997) estimate the menu costs of a large U.S. supermarket chain to be 0.7% of revenue.

[17] We set δ equal to the standard deviation of the change in nominal aggregate demand. We then normalize the CIR by multiplying it by $0.01/\delta$. If the model where exactly log-linear, the CIR number we report would therefore be equal to the cumulative output response to a one percent shock to nominal aggregate demand.

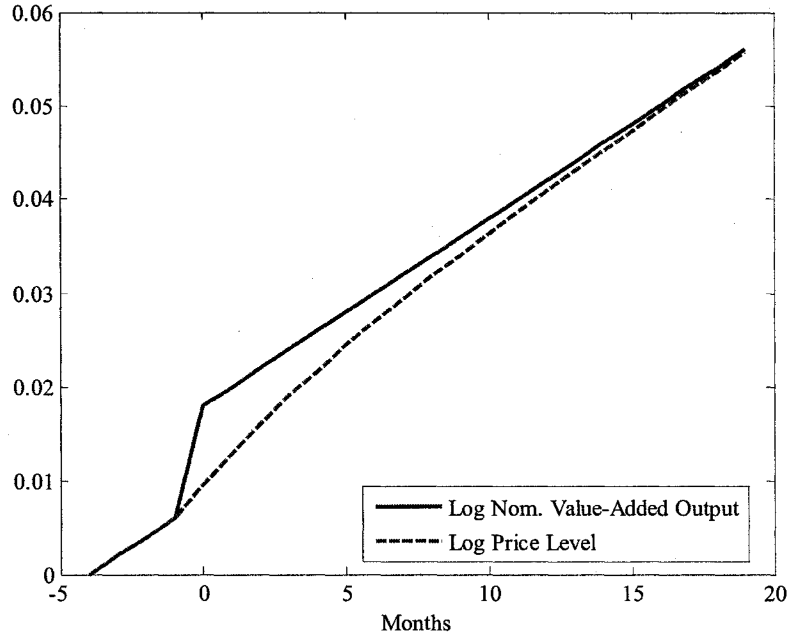


Figure 3.4: Price Level Response to Nominal Aggregate Demand Shock
This figure presents the impulse response of the price level in response to a 1% shock to nominal aggregate demand for the single-sector model with intermediate inputs calibrated to the weighted median frequency of non-sale price changes.

shocks occur and calculate the response of the price level and real value-added output to the shock. The response of these variables for our baseline model—the model with intermediate inputs and calibrated to the median frequency of price change—are shown in figures 3.4 and 3.5. Both the price level and real output converge monotonically to their steady state values with a half-life of between 4 and 5 months. The cumulative impulse response of real value-added output is equal to the cumulative difference between actual output and steady state output after the shock occurs (the area under the impulse response function in figure 3.5).[18]

While the CIR of real value-added output is convenient due to its simplicity and intuitive appeal, it is an imperfect measure of the degree of monetary non-neutrality if the relationship between inflation and real aggregate demand is non-linear in logs. This is due to the fact that the CIR measures the response of output for a shock of a particular size and it does not scale with the size of the shock unless the model is log-linear. Fortunately, the relationship between inflation and aggregate demand is close to being log-linear in our model. Figure

[18] The CIR has been used as a measure of monetary non-neutrality, e.g., by Christiano et al. (2005) and Carvalho (2006). Andrews and Chen (1994) argue that the CIR is a good measure of persistence in an AR(p) model.

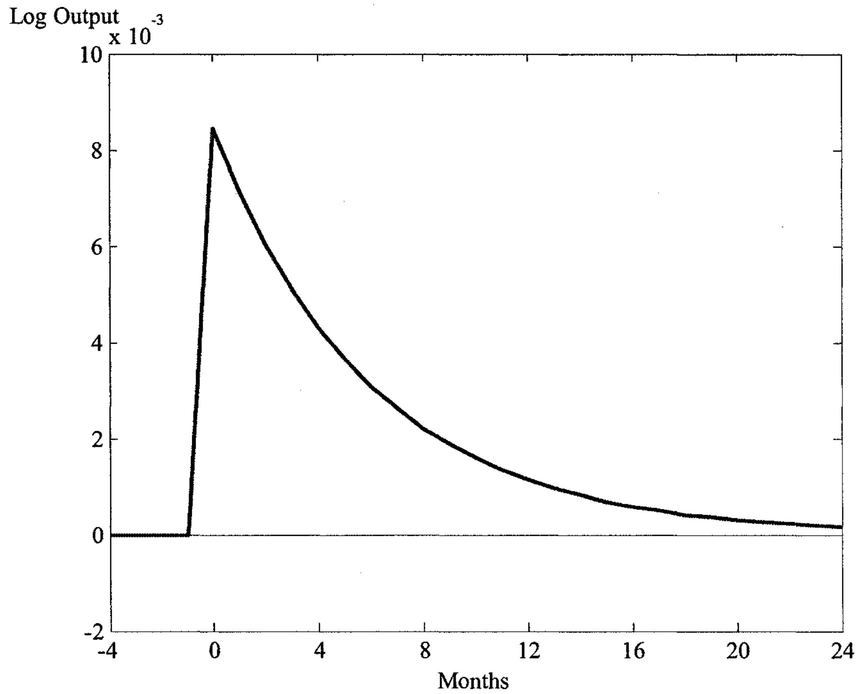


Figure 3.5: Output Response to Nominal Aggregate Demand Shock
This figure presents the response of real value-added output in response to a 1% shock to nominal aggregate demand for the single-sector model with intermediate inputs calibrated to the weighted median frequency of non-sale price changes.

3.2 illustrates this by plotting log inflation as a function of $\log(S_t/P_{t-1})$ for a 280 period simulation of our baseline case. The function $\Gamma(S_t/P_{t-1})$ is almost identical to the regression line plotted through these points. We however also report the variance of real value-added output as a alternative measure of monetary non-neutrality. In a linear AR(1) model, the CIR of output and the variance of output are proportional.

The last two columns of table 3.6 report the CIR and variance of real value-added output. Allowing for intermediate products ($s_m = 0.75$) raises the CIR by a factor of 2.6-3.2 depending on the frequency of price change. The variance of output is amplified by a slightly larger amount—a factor of between 2.9-4.0. This amplification of the monetary non-neutrality results from the fact that the pricing decisions of firms are strategic complements in the model with intermediate products.

The logic behind this amplification is simple to illustrate. Given our calibration of $\gamma = 1$ and $\psi = 0$, the labor supply curve is $W_t/P_t = \omega C_t$. Using $S_t = P_t C_t$, we can rewrite labor supply as $W_t = \omega S_t$. In other word, nominal wages are proportional to nominal value-added output. A firm with perfectly flexible prices would set its price equal to a constant markup over marginal costs. This "desired price" equals

$$\tilde{p}_t(z) = \frac{\kappa\theta}{\theta - 1}\frac{W_t^{1-s_m}P_t^{s_m}}{A_t(z)}. \tag{3.17}$$

Equation (3.17) implies that when $s_m = 0$ the firm's marginal costs are proportional to the nominal wage. A one percent rise in S_t therefore raises the firm's desired price by one percent if $s_m = 0$. In contrast, when the firm uses intermediate inputs, its marginal costs are proportional to a weighted average of the nominal wage and the price level with the weight on the price level being equal to s_m. Since the price level responds sluggishly to an increase in S_t when firms face menu costs, the firm's marginal costs rise by less then one-percent in response to a one-percent increase in S_t when $s_m > 0$. As a consequence, firms that change their price soon after a shock to S_t choose a lower price than they otherwise would because the price of many of their inputs have not yet responded to the shock.[19]

Recent work has cast doubt on strategic complementarity as a source of amplification in menu cost models with idiosyncratic shocks by showing that the introduction of strategic complementarity can make it difficult to match the large observed size of price changes for plausible values of the menu cost and the variance of the idiosyncratic shocks. Klenow and Willis (2006) show that a model with demand-side strategic complementarity of the type emphasized by Kimball (1995) requires massive idiosyncratic shocks and implausibly large menu costs to match the size of price changes observed in the data. Golosov and Lucas (2006) note that their model generates price changes that are much smaller than those observed in the data when they consider a production function with diminishing returns to scale due to a fixed factor of production. Burstein and Hellwig (2006) use supermarket scanner data to calibrate a model with a fixed factor of production and both demand and supply shocks. They find that even with large demand shocks, a substantial amount of strategic complementarity requires large menu costs to match the micro data on the size of price changes.

[19] The firm's profit function in our model simply implies that a fraction $1 - s_m$ of costs are proportional to S_t while a fraction s_m are proportional to P_t. In the derivation of this equation, we assume that the "flexible" input is labor and the "sluggish" input is intermediate inputs. However, this profit function is consistent with other models in which, e.g., wages are sluggish (Burstein and Hellwig, 2006) and perhaps some other input—such as a commodity—is flexible.

Table 3.7: The Single-Sector Model with Diminishing Returns to Scale

	θ	α	Menu Cost	σ_ε	Freq.	Frac.	Abs. Size	CIR
					(%)	(%)	(%)	(%)
(1)	7	1	0.0386	0.0415	8.7	66.6	8.5	1.5
(2)	7	2/3	0.0257	0.0415	8.7	85.4	3.2	3.5
(3)	7	2/3	0.1774	0.1250	8.7	67.4	8.5	3.4

This table presents the parameter values and cumulative impulse reponse (CIR) for the menu cost model both with and without diminishing returns to labor. (See Section 2.4 for a discussion of the CIR). All the specifications are parameterized to match the weighted median frequency of price change 8.7%. The parameter α is the coefficient on labor in the production function. Specification (1) presents the model without diminishing returns to labor where α=1. Specifications (2) and (3) present model with diminishing returns to labor where α=2/3. Specification (2) maintains the same variance of the idiosyncratic shock as specification (1), while specification (3) adjusts the variance of the idiosyncratic shock to match the weighted median size of price changes, 8.5%. The menu cost is presented as a fraction of steady state revenue: (θ-1)/θ K/Y_{SS} where Y_{SS} is steady state output under flexible prices. σ_ε is the variance of shocks to the log of the firms' idiosyncratic productivity levels.

Table 3.7 illustrates this point for a model with a fixed factor of production implying a production function $y_t(z) = A_t(z)L_t(z)^a$. The first row of the table presents results for this model with $a = 1$ as a benchmark.[20] In the second row of the table we hold the variance of the idiosyncratic shock constant but set $a = 2/3$ and vary the menu cost to match the frequency of price change. The average absolute size of price changes that results is less than half as large as in the data. In the third row, we match both the frequency and size of price changes in the data by recalibrating both the menu cost and the variance of the idiosyncratic shock. Matching the data requires extremely large shocks and menu costs.

In contrast, strategic complementarity caused by firms' use of intermediate inputs does not affect the size of price changes or require unrealistically large menu costs and idiosyncratic shocks. The reason for this difference can be illustrated using a dichotomy developed by Ball and Romer (1990) and Kimball (1995). A firm's period t profit function may be written as $\Pi(p_t/P_t, S_t/P_t, \tilde{A}_t)$, where p_t/P_t is the firm's relative price, S_t/P_t denotes real aggregate demand and $\tilde{A}_t$ denotes a vector of all other variables that enter the firms period t profit function. The firm's desired price under flexible prices is then given by $\Pi_1(p_t/P_t, S_t/P_t, \tilde{A}_t) =$

[20] In table 3.7 we set $\theta = 7$ for comparability with Golosov and Lucas (2006). In the fixed factor model, the degree of strategic complementarity is increasing in θ.

0, where the subscript on the function Π denotes a partial derivative. Notice that

$$\frac{\partial p_t}{\partial P_t} = 1 + \frac{\Pi_{12}}{\Pi_{11}}. \tag{3.18}$$

Pricing decisions are strategic complements if $\zeta = -\Pi_{12}/\Pi_{11} < 1$ and strategic substitutes otherwise.[21] Following Ball and Romer (1990), we can divide mechanisms for generating strategic complementarity into two classes: 1) those that raise $-\Pi_{11}$, and 2) those that lower Π_{12}. We refer to these two classes as ω-type strategic complementarity and Ω-type strategic complementarity, respectively.[22] Mechanisms that generate ω-type strategic complementarity include local labor markets, non-isoelastic demand and fixed factors of production. Mechanisms that generate Ω-type strategic complementarity include real wage rigidity and sticky intermediate inputs. Notice that $\partial p_t/\partial \tilde{A}_t = -\Pi_{13}/\Pi_{11}$. This implies that ω-type strategic complementarity mutes the response of the firm's desired price to other variables such as idiosyncratic shocks, while Ω-type strategic complementarity does not. Models with a large amount of ω-type strategic complementarity will therefore have trouble matching the large size of price changes seen in the micro-data, while this problem will not arise in models with a large amount of Ω-type strategic complementarity.

The key difference is that strategic complementarity due to intermediate inputs only affects the firm's response to aggregate shocks while strategic complementarity due to a fixed factor or non-isoelastic demand mutes the firm's response to both aggregate shocks and idiosyncratic shocks. In the model with a fixed factor, the firm's marginal product of labor increases as its level of production falls. The firm's marginal costs therefore fall as it raises its price in response to a fall in productivity, since a higher price leads to lower demand. This endogenous feedback of the firm's price on its marginal costs counteracts the original effect that the fall in productivity had on marginal costs and leads the firms desired price to rise by less than it otherwise would. In the model with intermediate inputs, the firm's marginal cost is not affected by its own pricing decision. The strategic complementarity in the model with intermediate inputs arises because of the rigidity of other firms' prices rather than because

[21] At the equilibrium $\Pi_{11} < 0$ and $\Pi_{12} > 0$.

[22] These names are based on the notation used by Kimball (1995).

of endogenous feedback on marginal costs from the firm's own pricing decision.

Gertler and Leahy (2006) explore an alternative menu cost model with strategic complementarity that does not affect the size of price changes. Their model has sector specific labor markets in which firms receive periodic idiosyncratic shocks. They assume that in each period firms in only a fraction of sectors receive idiosyncratic shocks. The resulting staggering of price changes across sectors generates strategic complementarity that amplifies the monetary non-neutrality in their model. The fact that the labor market is segmented at the sectoral level rather than the firm level avoids endogenous feedback on marginal costs from the firms' own pricing decisions and allows their model to match the size of price changes without resorting to large shocks or large menu costs.[23]

3.3 The CalvoPlus Model

In this section, we introduce a model in which price changes are largely time-dependent as a benchmark for comparision purposes. The model in section 3.2 makes the simplifying assumption that the menu cost K is constant. This assumption implies that a firm's decision about whether to change its price is based entirely on the external economic environment that the firm faces. There are however a number of factors that could generate variation in the costs of price adjustment including information acquisition by the firm that is undertaken for other reasons than to make pricing decisions, economies of scale in decision-making, product upgrades, the introduction of new products and variation in managerial workload. Blinder et al. (1998) report that managers in 60% of firms say they have "customary time intervals ... between price reviews". Zbaracki et al. (2004) discuss the existence of a "pricing season" at firms that occurs at regular intervals during the year. Recent empirical evidence has furthermore found support for some time-dependent elements in pricing. Bils and Klenow

[23] An important driving force behind the strategic complementarity in Gertler and Leahy's model is the assumption of staggering of price changes across sectors. If an equal fraction of firms in each sector received an idiosyncratic shock and changed their price in each period their model would not generate strategic complementarity. An alternative mechanism for generating strategic complementarity in a model with segmented labor markets is to allow for heterogeneity across sectors in the frequency of price change. We simulated a 6-sector menu cost model with sector specific labor markets in which the frequency and size of price change was calibrated to match the mean of these statistics in different of the U.S. economy. We found that this multi-sector menu cost model was not able to generate a quantitatively significant degree of strategic complementarity.

(2004) present evidence that product substitutions are frequent in many sectors of the U.S. economy. In chapter 1, we find evidence of a spike in the hazard function of price change at 12 months as well as evidence of seasonality in the frequency of price change for U.S. CPI and PPI prices.[24]

The goal of this section is to develop a model that captures the idea that repricing may be less costly at some points in time than others. The most widely used model with this feature is the model of Calvo (1983).[25] In this model, price changes are free with probability $(1-\alpha)$ but have infinite cost with probability α. These extreme assumptions make the Calvo model highly tractable. However, they also cause the model to run into severe trouble in the presence of large idiosyncratic shocks or a modest amount of steady state inflation.[26] The reason is that the firm's implicit desire to change its price can be very large and it frequently prefers to shut down rather than continue producing at its pre-set price. As we discuss below, the Calvo model is also unable to match the average size of price changes observed in the data for reasonable parameter values.

Rather than assuming that price changes are either free or infinitely costly, we assume that with probability $(1-\alpha)$ the firm faces a low menu cost K_l, while with probability α it faces a high menu cost K_h. These assumptions are meant to capture the idea that the timing of some price changes are largely orthogonal to the firm's desire to change its price in a more realistic way than the Calvo model does but at the same time to retain the tractability of the Calvo model. We refer to this model as the "CalvoPlus" model. The CalvoPlus model has the appealing feature that it nests both the Calvo model and the menu cost model as special cases.[27]

We can use the CalvoPlus model to illustrate the deficiencies of the Calvo model. The

[24] Baumgartner et al. (2005), Álvarez et al. (2005a), Jenker et al. (2004), Dias et al. (2005), Fougere et al. (2005), Álvarez et al. (2005b) and Dhyne et al. (2006) present analogous results for consumer prices in Europe.

[25] Examples of papers that use the Calvo model include Christiano et al. (2005) and Clarida et al. (1999). An alternative "time-dependent" price setting model was proposed by Taylor (1980). Examples of papers that have used the Taylor model include Chari et al. (2000).

[26] See Bakhshi et al. (2006) for an analysis of the latter issue.

[27] Caballero and Engel (2006) analyze a similar hybrid model. In their model, firms generally face a menu cost but randomly get an opportunity to change prices for free.

Table 3.8: Matching the Facts With the CalvoPlus Model

	Menu Cost			Frac.		Abs.		
	High	Low	σ_ε	Low Cost	Freq.	Size	CIR	Var(C)
				(%)	(%)	(%)	(%)	(10^{-4})
(1)	0.30	0	0.0425	99	8.7	2.8	9.9	0.659
(2)	1.50	0	0.1700	99	8.7	7.2	10.2	0.699
(3)	0.340	0.0010	0.1100	89	8.7	8.5	5.1	0.312
(4)	0.113	0.0025	0.0725	74	8.7	8.5	3.4	0.210
(5)	0.049	0.0050	0.0545	54	8.7	8.5	2.4	0.135

This table presents estimated parameter values, the cumulative impulse response (CIR) and the variance or real value-added output (Var(C)) for the benchmark specification of the CalvoPlus model for several values of the intermediate inputs share (sm). The first two columns present the menu cost in the "high" and "low" menu cost states respectively. The fraction of time spent in the "low menu cost" state is set at $1-\alpha = 0.087$ in all cases. The third column gives the variance of shocks to the log of the idiosyncratic productivity shocks σ_ε. The fourth column gives the fraction of price changes that occur in the low menu cost state. The fifth and six columns give the frequency and average absolute size of log price changes implied by the model. In all cases, the parameters are set to match the weighted median frequency of price change 8.7%. The share of intermediate inputs in the production function is set to $s_m = 0$ in all cases. The first two specifications imply that all price changes occur in the low menu cost state, while specifications (3)-(5) imply that some price changes occur in both the high and low menu cost states.

first two rows of table 3.8 present results for a calibration of the CalvoPlus model that closely approximates the Calvo model. We set $K_l = 0$, $\alpha = 1 - 0.087$ and K_h high enough that 99% of price changes occur in the low menu cost state. In the first row, we set the standard deviation of the idiosyncratic shocks σ_ϵ equal to the value we use for the menu cost model. To prevent the firm from changing prices in the high menu cost state, we must set the menu cost in the high menu cost state equal to 30% of monthly revenue. Also, the average size of price change is less than 1/3 the value observed in the data. In the second row, we quadruple the size of the idiosyncratic shocks. In this case, the menu cost in the high menu cost state must be truly huge—1.5 times monthly revenue—to prevent price changes in this state, but the average size of price changes is still considerably smaller than in the data.

Suppose instead that the menu cost in the low cost state is small but not zero. Rows 3 through 5 of table 3.8 present the implications of assuming that the menu cost in the low menu cost state is 0.001, 0.0025 and 0.005 of monthly revenue, respectively. In these cases, we calibrate K_h and σ_ϵ to match the frequency and size of price changes in the data. Even for these modest values of the menu cost in the low menu cost state, the behavior of the CalvoPlus model is dramatically different. The model is able to match the size of price changes in the data without resorting to implausibly high values of K_h and σ_ϵ. When the menu cost in the low menu cost state is 1/4% of monthly revenue, the CalvoPlus model matches the frequency and size of price changes in the data with a menu cost in the high state equal to 11.3% of monthly revenue and a standard deviation of idiosyncratic shocks equal to 7.25%.

We use the CalvoPlus model as a benchmark against which we compare the monetary non-neutrality in the menu cost model. Table 3.9 shows that the incorporation of intermediate goods has a similar effect in the CalvoPlus model as it does in the menu cost model considered in section 3.2. In this table, we assume that $K_l = K_h/40$. This calibration of the CalvoPlus model implies that roughly 75% of price changes occur in the low menu cost state. As in table 3.6, we consider four values for s_m—0, 0.65, 0.75 and 0.85—and we choose K_h and σ_ϵ to match either the mean or median frequency of price change as well as the median size of price changes. We set $(1-\alpha)$ equal to the frequency of price change, i.e., 8.7% or 21.1%. In all four cases, the CalvoPlus model calibrated in this way yields a CIR that is about twice the size of the CIR for the menu cost model in table 3.6. As with the menu cost model, the incorporation of intermediate inputs roughly triples the CIR for $s_m = 0.75$.

Golosov and Lucas (2006) emphasize the fact that in the menu cost model firms are not selected at random to change their prices. Rather the firms that change their prices are the firms that have the largest desire to change their price. Golosov and Lucas (2006) show that this "selection effect" reduces the degree of monetary non-neutrality generated by their menu cost model by a factor of 5 relative to the Calvo model. The CalvoPlus model provides a useful framework for analyzing the robustness of this conclusion. Is the degree of monetary non-neutrality in a model in which a modest fraction of price changes occur due to an exogenous opportunity to change prices rather than a large desire to change prices close to what it is in the Calvo model? Or is it closer to the degree of monetary non-neutrality in the menu cost model?

Figure 3.6 plots the CIR of real value-added output to a shock to nominal aggregate demand as the fraction of price changes in the low menu cost state varies from zero to one. In this experiment, we fix $\alpha = 1 - 0.087$ and $\sigma_\epsilon = 0.0425$ and vary K_h and K_l so that the model matches the median frequency of price changes in the data and a particular fraction

Table 3.9: CalvoPlus With and Without Intermediate Goods

	Intermediate Inputs Share	Menu Cost High	Menu Cost Low	σ_ε	Frac. Low Cost	Freq.	Abs. Size	CIR	Var(C)
					(%)	(%)	(%)	(%)	(10^{-4})
(1)	0	0.0525	0.0013	0.0665	77	21.1	8.5	1.2	0.058
(2)	0.65	0.0128	0.0003	0.0665	77	21.1	8.5	2.5	0.144
(3)	0.75	0.1730	0.0043	0.0665	77	21.1	8.5	3.1	0.185
(4)	0.85	0.0278	0.0007	0.0665	77	21.1	8.5	4.3	0.260
(5)	0	0.1095	0.0027	0.0725	73	8.7	8.5	3.3	0.195
(6)	0.65	0.0255	0.0006	0.0725	73	8.7	8.5	6.4	0.409
(7)	0.75	0.0356	0.0009	0.0725	73	8.7	8.5	7.9	0.496
(8)	0.85	0.0563	0.0014	0.0725	73	8.7	8.5	11.4	0.834

This table presents estimated parameter values, the cumulative impulse response (CIR) and the variance or real value-added output for the benchmark specification of the CalvoPlus model for several values of the intermediate inputs share (s_m). (See Section 2.4 for a discussion of the CIR). The first two columns present the menu cost in the "high" and "low" menu cost states respectively. The "low" menu cost K_L is set at 1/40 of the high menu cost K_H in all cases. Specifications (1)-(4) are parameterized to match the weighted mean frequency of price change of 21.1%, while specifications (5)-(8) are parameterized to match the weighted median frequency of price change of 8.7%. The fraction of time spent in the "low menu cost" state is set at $1-\alpha$ = freq. in all cases. The third column gives the variance of shocks to the log of the idiosyncratic productivity shocks σ_ε. The fifth column gives the fraction of price changes that occur in the low menu cost state. The sixth and seventh columns give the frequency of price changes and the average absolute size of price changes implied by the model.

of price changes in the low menu cost state. This figure shows that the degree of monetary non-neutrality drops off rapidly as the fraction of price changes in the low cost state falls below 100%. When 85% of price changes occur in the low menu cost state, the CIR is less than half of what it is when all of price changes occur in the low cost state. When 50% of price changes occur in the low menu cost state, the CIR is close to identical to the value in the constant menu cost model. Figure 3.6 therefore suggests that the relatively large amount of monetary non-neutrality generated by the Calvo model is quite sensitive to even a modest amount of selection by firms regarding the timing of price changes.

3.4 The Multi-Sector Model

How does the distribution of price changes across sectors in the economy affect the degree of monetary non-neutrality that results from price rigidity? To address this question, we analyze a multi-sector version of the model developed in section 3.2. The firms in different sectors of our multi-sector model differ in the size of their menu cost K and the variance

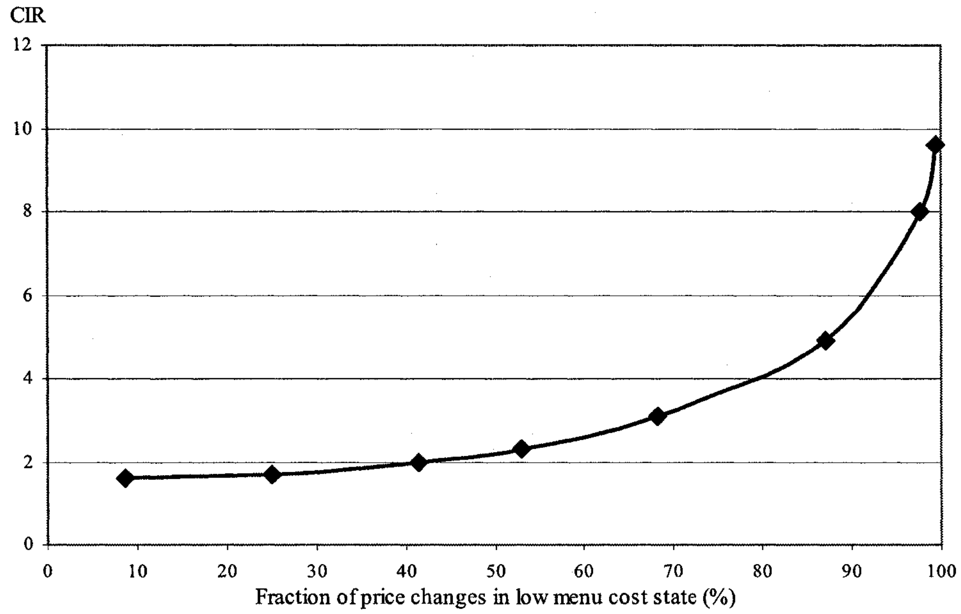


Figure 3.6: Monetary Non-Neutrality in the CalvoPlus Model
This figure presents the cumulative impulse response (CIR) of value-added output in the single-sector CalvoPlus model without intermediate inputs as a function of the fraction of price changes in the low menu cost state. The variance of the idiosyncratic shocks is fixed at $\sigma_\epsilon = 0.0425$ (the same value as in the single-sector menu cost model without intermediate goods). The menu costs in the high and low menu cost states are calibrated to match the weighted median frequency of price change 8.7% and the fraction of price changes in the low menu cost state. The fraction of time spent in the low cost state $1 - \alpha$=8.7%.

of their idiosyncratic productivity shock σ_ϵ. Otherwise, the model is identical to the single-sector model in section 3.2. In particular, we assume that consumption index—equation (3.2)—and the price index—equation (3.4)—are the same as in the single sector model.

We calibrate the sectors based on the empirical evidence on the frequency and size of price changes excluding sales in consumer prices across sectors of the U.S. economy presented in chapter 1.[28] We group goods with similar price change characteristics into 6 sectors, 9 sectors and 14 sector. Table 3.10 presents the mean frequency and mean absolute size of price changes for these sectors.[29] Both the frequency and size of price changes varies enormously across sectors. There is no simple relationship between the frequency of price change and the size of price changes. To the contrary, sectors with very similar frequencies of price change have

[28] We have also used the distribution of the frequency of price change including sales. We find that both of these distributions yield a similar results regarding amplification of monetary non-neutrality due to heterogeneity.

[29] To be able to aggregate the sectors easily, we calibrate the multi-sector models to the mean frequency and mean absolute size of price change at the sectoral level. The difference between the mean and median are small at this level of aggregation. See Table 3.1 for a comparison of means and medians at the sector level.

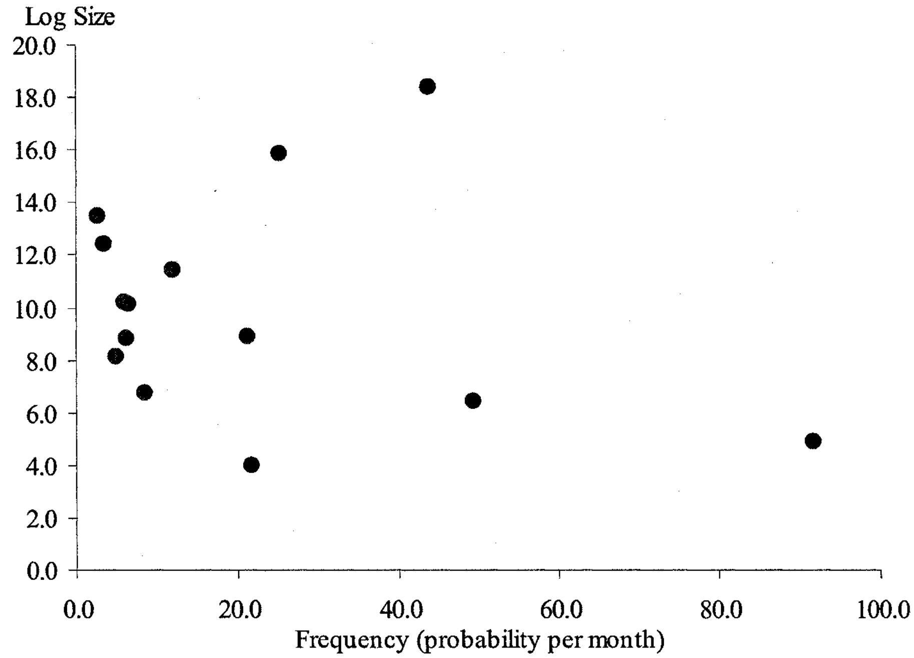


Figure 3.7: The Frequency and Size of Price Changes Across Different Sectors
The figure plots the average frequency and size of price changes for each sector in our 14 sector model. See table 10 for the underlying data.

very different average sizes and vice versa (see figure 3.7). The distribution of the frequency of price change is highly asymmetric. The right tail being much longer than the left tail. This is evident from the fact that the median frequency of price change in the economy is 8.7% while the mean is 21.1% (see table 3.2).

We parameterize the multi-sector model by minimizing the difference between the frequency and absolute size of price changes predicted by the model and the empirical statistics. Table 3.11 presents the parameterization of the menu cost and the variance of the idiosyncratic shocks at the sectoral level. As in the single sector model, the menu costs required to generate the observed size and frequency of price change are less than half as large when we allow for intermediate goods. Both versions of the model are able to match the observed size and frequency of price change in all sectors exactly. As in the single-sector model, we assume that the firms perceive inflation as being a function of only S_t/P_{t-1}. Figure 3.8 plots the actual log inflation rate as a function of $\log(S_t/P_t)$ over a 280 month simulation of the 6 sector model using our benchmark calibration. A linear regression of log inflation on $\log(S_t/P_t)$ has an $R^2 = 0.979$.

Table 3.12 presents our two measures of monetary non-neutrality for the multi-sector

Table 3.10: Sector Characteristics for the Multi-Sector Model

Name	Weight (%)	Freq. (%)	Abs. Size (%)	Subs (%)
Panel A: 6 Sector Model				
Vehicle Fuel, Used Cars	7.7	91.6	4.9	8.9
Transportation Goods, Utilities, Travel	19.1	35.5	10.9	4.5
Unprocessed Food	5.9	25.4	15.9	1.3
Processed Food, Other Goods	13.7	11.9	11.4	2.0
Services (excl. Travel)	38.5	8.8	8.3	2.0
Household Furnishings, Apparel, Recreation Goods	15.1	5.2	11.1	7.9
Panel B: 9 Sector Model				
Vehicle Fuel, Used Cars	7.7	91.6	4.9	8.9
Transportation Goods, Utilities, Travel	19.1	35.5	10.9	4.5
Unprocessed Food	5.9	25.4	15.9	1.3
Services(1)	9.2	19.7	4.6	2.1
Processed Food, Other Goods	13.7	11.9	11.4	2.0
Services(2)	9.6	7.6	7.2	3.7
Services(3)	10.0	5.5	8.1	1.3
Household Furnishings, Apparel, Recreation Goods	15.1	5.2	11.1	7.9
Services(4)	9.7	3.2	12.8	0.9
Panel C: 14 Sector Model				
Vehicle Fuel, Used Cars	7.7	91.6	4.9	8.9
Utilities	5.3	49.4	6.4	0.6
Travel	5.5	43.7	18.4	1.8
Unprocessed Food	5.9	25.4	15.9	1.3
Transportation Goods	8.3	21.3	8.9	8.8
Services (1)	7.7	21.7	4.0	2.2
Processed Food, Other Goods	13.7	11.9	11.4	2.0
Services (2)	7.5	8.4	6.7	4.4
Household Furnishing	5.0	6.5	10.1	5.0
Services (3)	7.8	6.2	8.8	1.7
Recreation Goods	3.6	6.1	10.2	5.9
Services (4)	7.6	4.9	8.1	0.9
Apparel	6.5	3.6	12.4	11.3
Services (5)	7.9	2.9	13.5	1.0

This table presents the weighted mean frequency and log absolute size of price changes as well as the frequency of product substitution for US consumer prices over the period 1998-2005 for divisions into 6, 9, and 14 sectors. These statistics are calculated using the methodology described in chapter 1. The weighted means are calculated using CPI expenditure weights for entry level items (ELI's). "Weight" gives the total expenditure weight for the category, "Freq." gives the weighted mean frequency of price change for the category, "Abs. Size" gives the weighted mean absolute size of log price changes for the category. "Subs" gives the weighted mean frequency of product substitution. See chapter 1 for more details on how these statistics are constructed. In the 9 and 14 sector models, the Service sector is divided equally into 4 and 5 groups respectively, where the ELI's are sorted into different groups according to the frequency of price change in the ELI.

Table 3.11: Parameter Values for Multi-Sector Model

	Menu Cost Model				CalvoPlus Model			
	$s_m = 0.75$		$s_m = 0$		$s_m = 0.75$		$s_m = 0$	
	K	σ_ε	K	σ_ε	K_h	σ_ε	K_h	σ_ε
	$x10^{-2}$	$x10^{-2}$	$x10^{-2}$	$x10^{-2}$	$x10^{-2}$	$x10^{-2}$	$x10^{-2}$	$x10^{-2}$
Panel A: 6 Sector Model								
Vehicle Fuel, Used Cars	0.003	5.10	0.006	5.00	0.03	5.00	0.12	5.99
Transp. Goods, Utilities, Travel	0.40	6.80	1.16	6.90	2.19	8.39	7.00	8.63
Unprocessed Food	1.18	9.00	3.45	9.10	6.38	12.41	21.40	12.40
Processed Food, Other Goods	1.22	5.80	3.60	5.70	5.73	8.69	20.40	9.20
Services (excl. Travel)	0.85	4.10	2.30	3.90	4.98	7.10	12.75	6.75
Hh. Furn., Apparel, Rec. Goods	1.32	4.00	6.47	5.46	9.01	9.00	35.70	9.85
Panel B: 9 Sector Model								
Vehicle Fuel, Used Cars	0.003	5.94	0.005	5.30	0.04	5.00	0.13	5.20
Transp. Goods, Utilities, Travel	0.35	6.45	1.15	6.90	2.33	8.70	6.91	8.63
Unprocessed Food	1.14	8.88	3.30	9.00	6.11	11.60	21.79	12.30
Services(1)	0.16	2.80	0.37	2.40	0.69	3.40	2.45	3.76
Processed Food, Other Goods	1.36	6.02	3.60	5.80	6.05	8.80	20.96	9.41
Services(2)	0.57	3.15	3.50	4.00	4.73	6.50	13.00	6.10
Services(3)	1.32	4.09	3.15	3.58	6.62	7.20	15.20	6.75
Hh. Furn., Apparel, Rec. Goods	1.94	5.09	6.35	5.55	10.21	9.50	34.00	9.77
Services(4)	3.91	6.39	11.50	6.19	17.01	11.60	53.00	11.31
Panel C: 14 Sector Model								
Vehicle Fuel, Used Cars	0.003	5.20	0.007	5.20	0.04	5.30	0.13	5.39
Utilities	0.10	4.80	0.28	4.65	0.52	5.30	1.55	5.28
Travel	0.78	12.00	1.95	11.10	5.04	14.00	14.00	14.00
Unprocessed Food	1.18	9.00	3.70	9.40	6.93	12.20	21.20	12.40
Transportation Goods	0.42	4.71	1.50	5.20	2.46	6.80	7.47	6.80
Services (1)	0.16	2.97	0.41	2.70	0.54	3.20	1.45	3.00
Processed Food, Other Goods	1.22	5.75	3.40	5.60	6.24	8.90	19.50	9.00
Services (2)	0.59	3.30	1.70	3.20	3.15	5.69	10.00	5.70
Household Furnishing	1.39	4.69	4.30	4.80	8.32	8.70	25.00	8.80
Services (3)	1.10	4.10	3.30	4.10	6.43	7.60	18.50	7.40
Recreation Goods	1.54	4.80	4.50	4.80	8.95	8.90	26.00	8.80
Services (4)	1.26	4.00	3.40	3.80	7.31	7.20	22.50	7.60
Apparel	3.23	5.99	9.52	6.05	15.44	10.54	40.00	10.50
Services (5)	4.96	6.82	15.58	7.01	21.11	12.00	60.00	11.50

This table presents the parameter values for the multi-sector menu cost model both with and without intermediate goods. The menu cost K is presented as a fraction of steady state revenue: $(\theta-1)/\theta$ K/Y_{SS} where Y_{SS} is steady state output under flexible prices. σ_ε is the variance of shocks to the log of the idiosyncratic productivity shocks. The first panel presents the parameters for the menu cost model both with and without intermediate goods; while the second panel presents the parameters for the CalvoPlus model with and without intermediate goods. s_m is the fraction of marginal costs accounted for by intermediate goods. In the CalvoPlus model, the fraction of time spent in the "low menu cost" state is set at $1-\alpha$ = freq. for each sector in all cases.

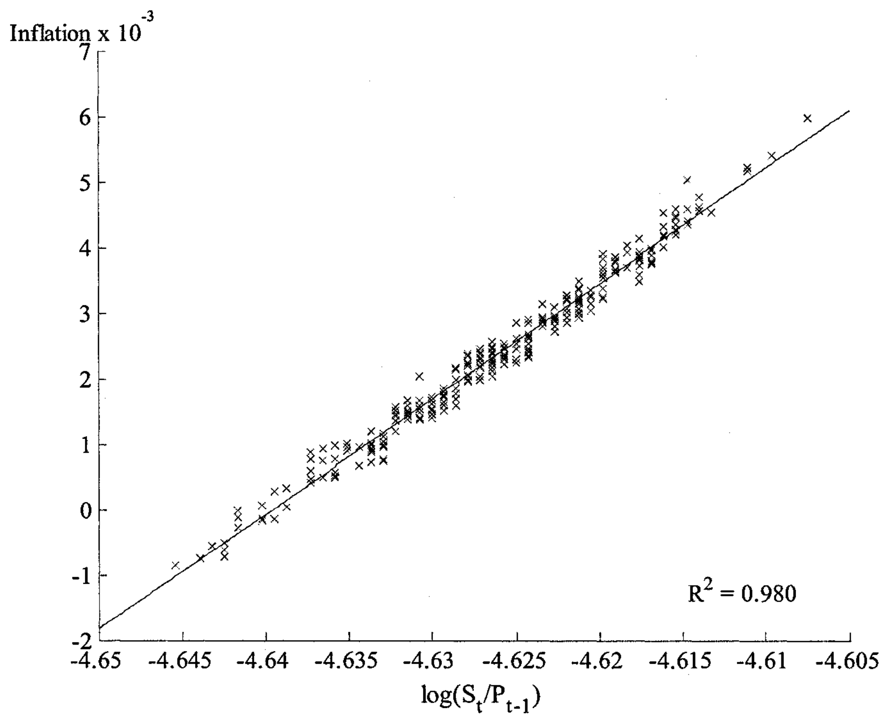


Figure 3.8: Log Inflation as a Function of $\log(S_t/P_{t-1})$ for the 6 Sector Model
This figure presents simulated log inflation as a function of $\log(S_t/P_{t-1})$ for the multi-sector menu cost model with intermediate inputs. The figure is based on 280 simulated periods of data.

model with and without idiosyncratic shocks. Panel A of table 3.12 presents the CIR of real value-added output to a shock to nominal aggregate demand, while panel B presents the variance of real value-added output. Both measures of monetary non-neutrality are increasing in the degree of heterogeneity. The 14-sector model with intermediate goods yields a CIR of 4.2%. This is slightly less than three times the CIR of the one sector model calibrated to the mean frequency of price change across all firms and roughly equal to the CIR of the one sector model calibrated to the median frequency of price change across all firms. For the model without strategic complementarity, the 14 sector model yields a CIR of 1.6%, also approximately triple the CIR of the one sector model calibrated to the mean. The degree of amplification due to heterogeneity is similar when it is measured using the variance real value-added output.

How important a role in economic fluctuations does our menu cost model suggest for monetary non-neutrality? The standard deviation of HP-filtered U.S. real GDP for 1960-2006 is 1.5%. The standard deviation of real output in a simulation of our multi-sector model with intermediate inputs is 0.5%. Our model therefore generates monetary non-neutrality

Table 3.12: Monetary Non-Neutrality in the Multi-Sector Models

	Menu Cost		CalvoPlus	
	$s_m = 0.75$	$s_m = 0$	$s_m = 0.75$	$s_m = 0$
Panel A: CIR				
1 Sector Model (Mean)	1.6	0.5	3.1	1.2
6 Sector Model	3.5	1.3	8.3	2.9
9 Sector Model	4.2	1.6	9.6	3.0
14 Sector Model	4.2	1.6	9.6	3.0
1 Sector Model (Median)	4.2	1.6	7.9	3.3
Panel B: Var(C_t)				
1 Sector Model (Mean)	0.080	0.018	0.185	0.058
6 Sector Model	0.200	0.050	0.527	0.130
9 Sector Model	0.237	0.058	0.610	0.129
14 Sector Model	0.244	0.058	0.613	0.133
1 Sector Model (Median)	0.260	0.090	0.496	0.195

This table presents estimates of the cumulative impulse response (CIR) and the variance or real value-added output for the multi-sector menu ocst model and the benchmark specification of the multi-sector CalvoPlus model for two values of the intermediate inputs share (s_m). The CIR is measured in percent. The variance of real value added output is multiplied by 10^4. The first two columns present results for the menu cost model. The third and fourth columns present results for the CalvoPlus model. See Table 11 for the menu cost and variance of idiosyncratic shocks assumed in these models. These statistics are presented for versions of the menu cost model with 1, 6, 9 and 14 sectors. In the CalvoPlus model, the fraction of time spent in the "low menu cost" state is set at 1-α = freq. for each sector in all cases. See Table 10 for the sectoral frequency and size of price changes used to parameterize these models.

that amounts to roughly 1/3 of the business cycle. In contrast, the standard devation of real output in a simulation of our single sector model without intermediate inputs is only 0.13%—less than 10% of the business cycle. Golosov and Lucas (2006) analyze a model that is virtually identical to this latter model and conclude that monetary non-neutrality "small and transient".[30]

We also consider multi-sector versions of the CalvoPlus model. In the multi-sector CalvoPlus model, we allow the probability of a low menu cost $1-\alpha$ to vary across sectors as well as the magnitude of the menu costs and the idiosyncratic shock. We set the probability of a low menu cost equal to the frequency of price change in each sector. We again set $K_l = K_h/40$. We then calibrate K_h and σ_ϵ to match the mean frequency and mean absolute size of price

[30] Evidence from structural VARs suggests that output responds with a lag to monetary distrubances and that the response of output is hump-shaped. While our model generates a substantial amount of monetary non-neutrality, it does not generate these features. A large recent literature has combined nominal price rigidities with a number of other frictions such as decision lags, nominal wage rigidity, habit formation and capital adjustment costs in order to match the response of the economy to monetary shocks (Rotemberg and Woodford, 1997; Christiano et al., 2005; Smets and Wouters, 2003). Introducing these types of frictions into a menu cost model of the type we study is a promising area for future research.

changes in each sector. The parameter values are presented in table 3.11. As in the multi-sector menu cost models, the multi-sector CalvoPlus models are able to exactly match these empirical moments.

Table 3.12 presents the results on monetary non-neutrality in the multi-sector CalvoPlus model. As in the menu cost model, we find that heterogeneity amplifies the degree of monetary non-neutrality by roughly a factor of three relative to the single sector model calibrated to the mean frequency of price change of all firms. The degree of amplification due to heterogeneity is somewhat larger in the CalvoPlus model with intermediate inputs than it is in the CalvoPlus model without intermediate inputs. This interaction between strategic complementarity and heterogeneity is consistent with the findings of Carvalho (2006). This interaction does not, however, exist in the pure menu cost model.

3.4.1 Understanding the Effect of Heterogeneity

To understand the effect of heterogeneity on the degree of monetary non-neutrality, it is useful to analyze the relationship between the frequency of price change and the CIR in the single-sector menu cost model. Figure 3.9 plots the CIR of the single-sector model as a function of the frequency of price change holding the average log absolute size of price changes constant at 8.5%. The CIR is highly convex as function of the frequency of price change.

With two simplifying assumptions, we can illustrate what drives the convexity of the CIR in figure 3.9. First, assume that the frequency of price change f_t in the menu cost model is constant at f. Panel A of figure 3.10 is a scatter plot of the frequency of price change as a function of $\log(S_t/P_{t-1})$ for a 800 period simulation of our menu cost model. The large variance of the idiosyncratic shocks in our model imply that the frequency of price change in fact does not vary greatly relative to its overall level. Second, assume that the average log size of price changes is linear in $\log(S_t/P_{t-1})$, i.e., $s_t = \nu \log(S_t/P_{t-1})$.[31] Panel B of figure 3.10 is a scatter plot of the average log size of price change as a function of real value-added output for a 800 period simulation of our menu cost model. The average log size of price

[31] Notice, that here we are making an assumption about the average size of price changes, not the average absolute size.

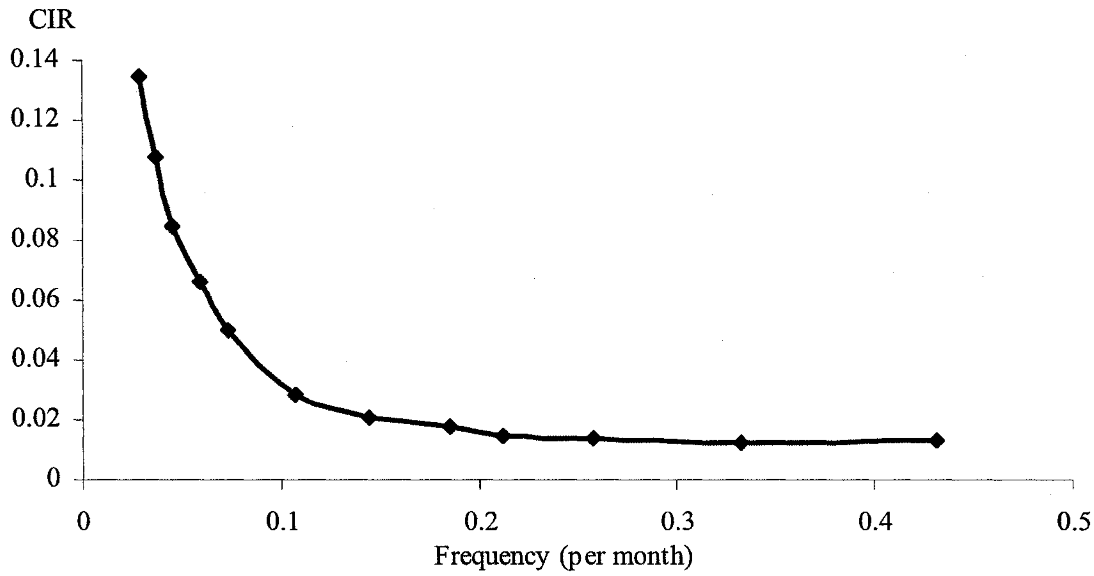


Figure 3.9: CIR as a Function of the Frequency of Price Change
This figure presents the cumulative impulse response (CIR) of real value-added output as a function of the frequency of price change in the single-sector menu cost model with intermediate inputs. The variance of the idiosyncratic shock is set equal to 0.0425 and the menu cost parameter is varied.

changes is in fact approximately linear in $\log(S_t/P_{t-1})$ in our model.

Given these assumptions, it is simple to calculate the CIR of real value-added output to a permanent increase in nominal aggregate demand that occurs in period 0 of size δ. For simplicity, we normalize $\log P_{-1} = 0$ and $\log C_{-1} = 0$. In period 0, $\log(S_0/P_{-1}) = \delta$. This implies that $\log P_0 = s_0 f = \nu\delta f$ and $\log C_0 = \delta - \log P_0 = (1-\nu f)\delta$. In period 1, $\log(S_1/P_0) = (1-\nu f)\delta$. This implies that $\log P_1 = s_1 f = (1-\nu f)\delta f$ and $\log C_1 = \delta - \log P_1 = \delta - (1-\nu f)\delta f = (1-\nu f)^2\delta$. Iterating this procedure yields

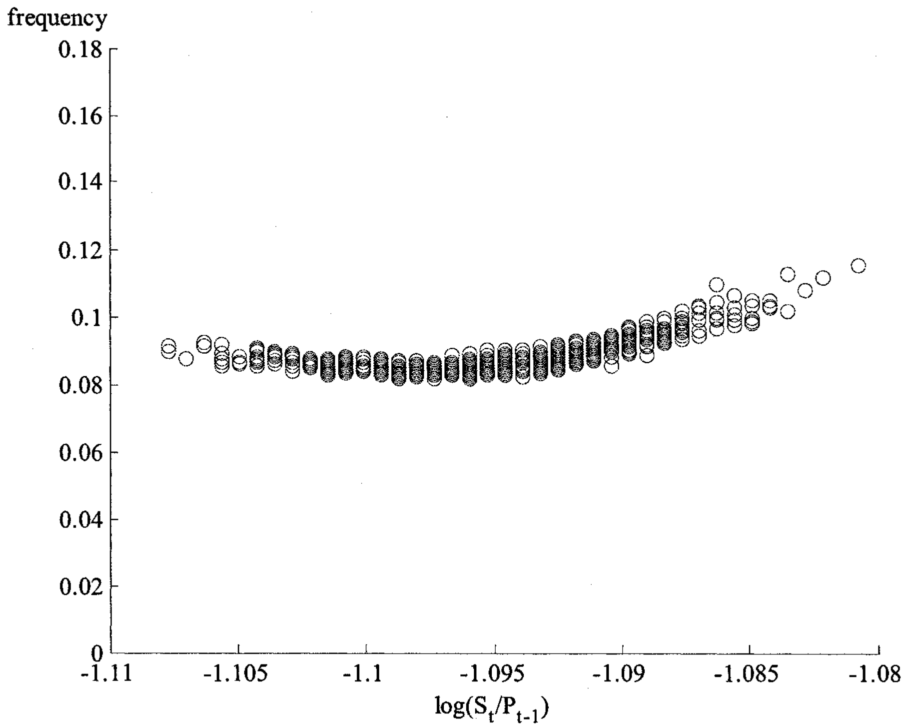
$$\log C_j = (1-\nu f)^{j+1}\delta.$$

This implies that

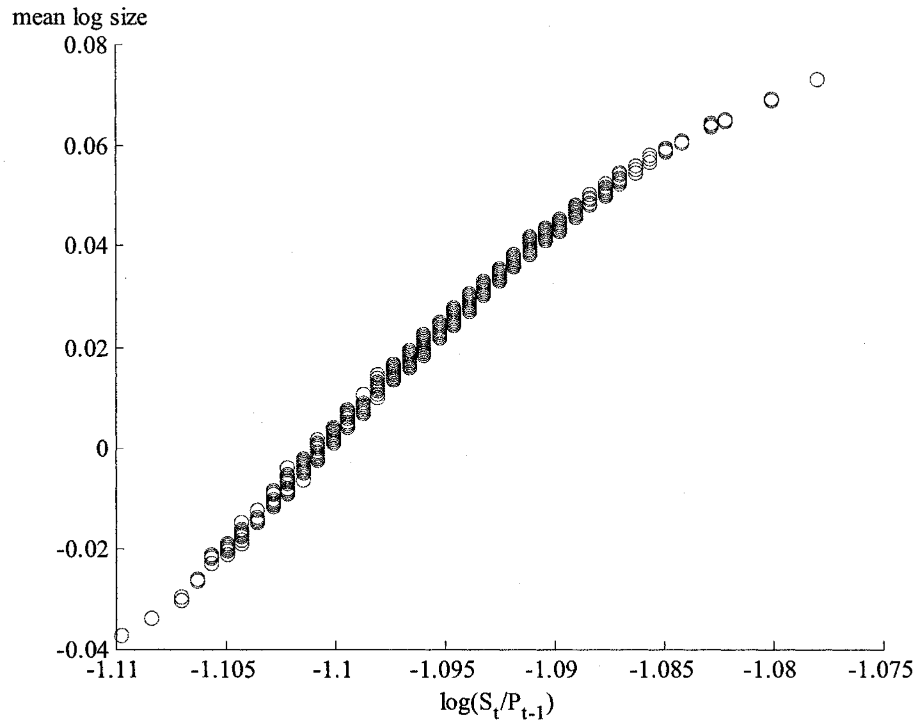
$$\text{CIR} = \sum_{j=0}^{\infty} \log C_j = \frac{1-\nu f}{\nu f}\delta$$

which is highly convex in the frequency of price change. Using the property of renewal processes that $E(d) = 1/f$, where $E(d)$ denotes the expected duration of price spells,[32] it

[32] This property does not rely on the assumption of a constant hazard. Theorem 1 in Chapter 5 of Lancaster (1990) states that for any renewal processes with constant expected duration and finite variance of durations, the frequency of price change converges to the reciprocal of the expected duration in a large sample.



Panel A



Panel B

Figure 3.10: Frequency and Average Log Size of Price Changes as a Function of $\log(S_t/P_{t-1})$
This figure plots the frequency (Panel A) and log average size (Panel B) of price changes as a function of real value-added output for an 800 period simulation of our single-sector menu cost model without intermediate inputs calibrated to match the median frequency of price change

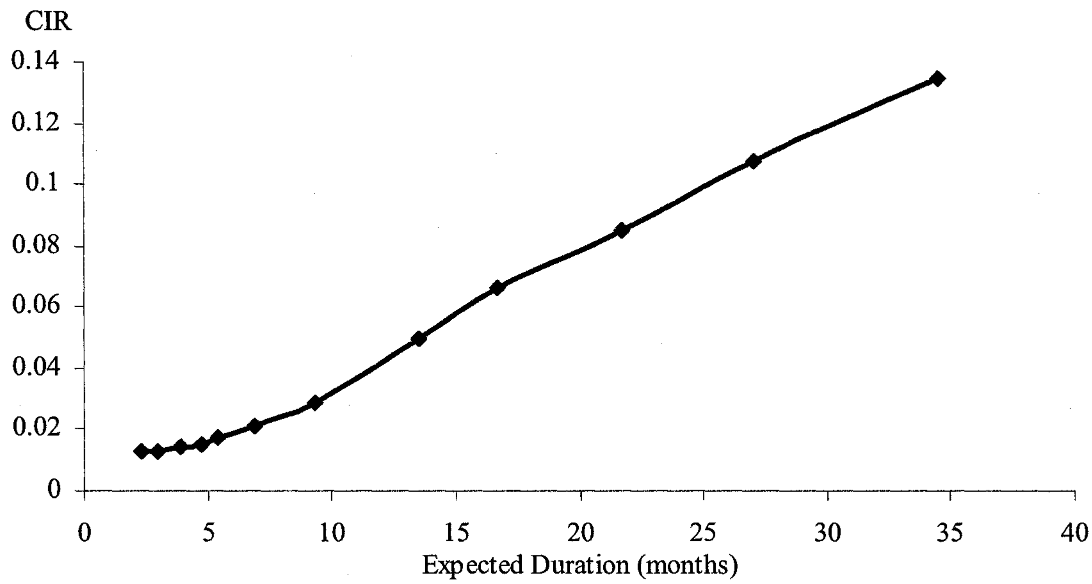


Figure 3.11: CIR as a Function of the Expected Duration of Price Spells
This figure presents the cumulative impulse response (CIR) of value-added output as a function of the expected duration of price spells in the single-sector menu cost model with intermediate inputs. The variance of the idiosyncratic shock is set equal to 0.0425 and the menu cost parameter is varied.

furthermore follows that

$$\text{CIR} = \frac{\delta}{\nu}E(d) - \delta. \tag{3.19}$$

Equation (3.19) shows that the CIR is linear in the expected duration of price changes given our two simplifying assumptions. Figure 3.11 plots the CIR for our single-sector menu cost model as a function the expected duration of price spells, holding constant the average absolute size of price changes. It shows that the CIR is indeed approximately linear in the expected duration of price spells.

Carvalho (2006) proves that a similar property holds up to a linear approximation in the Calvo model. A key difference between the Calvo model and the menu cost model is that $\nu = 1$ in the Calvo model whereas ν is substantially larger than one in the menu cost model. In the Calvo model, the firms that change their price are chosen randomly. This implies that the average size of price changes is equal to the average amount by which prices differ from their desired level. In other words, $\nu = 1$ in the Calvo model. In the menu cost model, however, the firms that change their prices in response to a positive shock to a nominal aggregate demand are disproportionately those that have the lowest real prices before the shock. This selection effect implies that the average size of price changes is larger than the

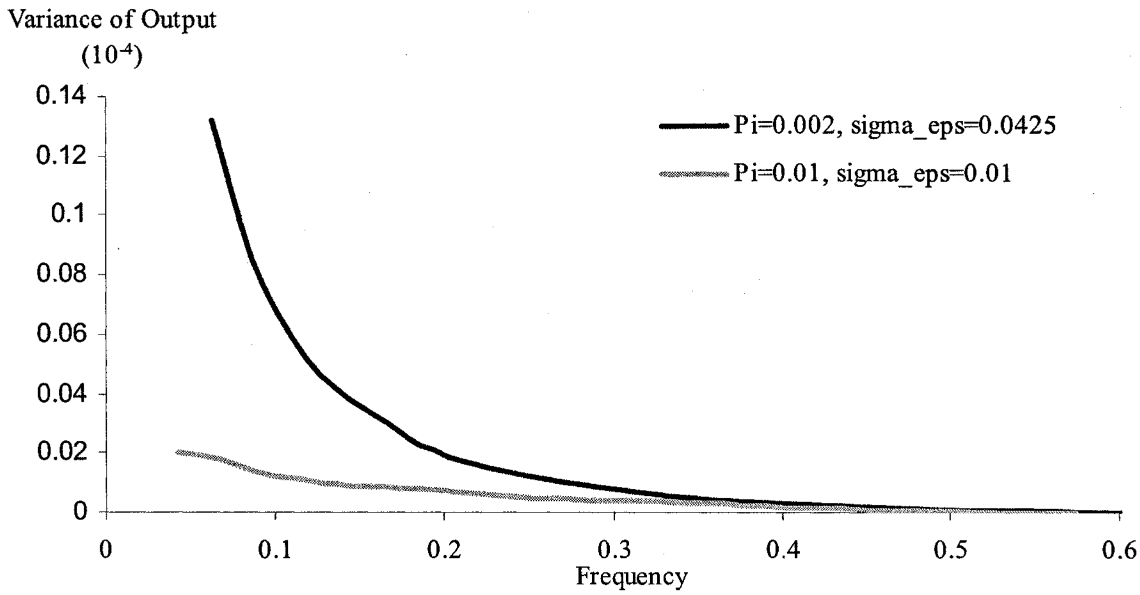


Figure 3.12: Variance of Output as a Function of the Frequency of Price Change
This figure plots the variance of value-added output as a function of the frequency of price change for two calibrations of our single sector model without intermediate inputs. First, we present our benchmark calibration of $\mu = 0.002$, $\sigma_\eta = 0.0037$ and $\sigma_\epsilon = 0.0425$. Second, we present a calibration in which $\mu = 0.01$, $\sigma_\eta = 0.0037$ and $\sigma_\epsilon = 0.01$.

average difference between the current prices and their desired levels, i.e., $\nu > 1$.

In general, menu cost models need not generate a convex relationship between the frequency of price change and the degree of monetary non-neutrality. This relationship can be linear or concave if the selection effect is strong enough. One way to increase the strength of the selection effect is to raise the average inflation rate and lower the variance of the idiosyncratic shocks. Intuitively, this moves the model closer to the assumptions in Caplin and Spulber (1987). Figure 3.12 plots the variance of value added output as a function of the frequency of price change for a high inflation/small idiosyncratic shocks case—specifically, $\mu = 0.01$ and $\sigma_\epsilon = 0.01$—as well as for our benchmark calibration—$\mu = 0.002$ and $\sigma_\epsilon = 0.0425$. In the high inflation/small idiosyncratic shocks case, the degree of monetary non-neutrality is smaller than in the benchmark calibration for each frequency of price change. Furthermore, the degree of monetary non-neutrality is much less convex in the frequency of price change than it is in our benchmark calibration.

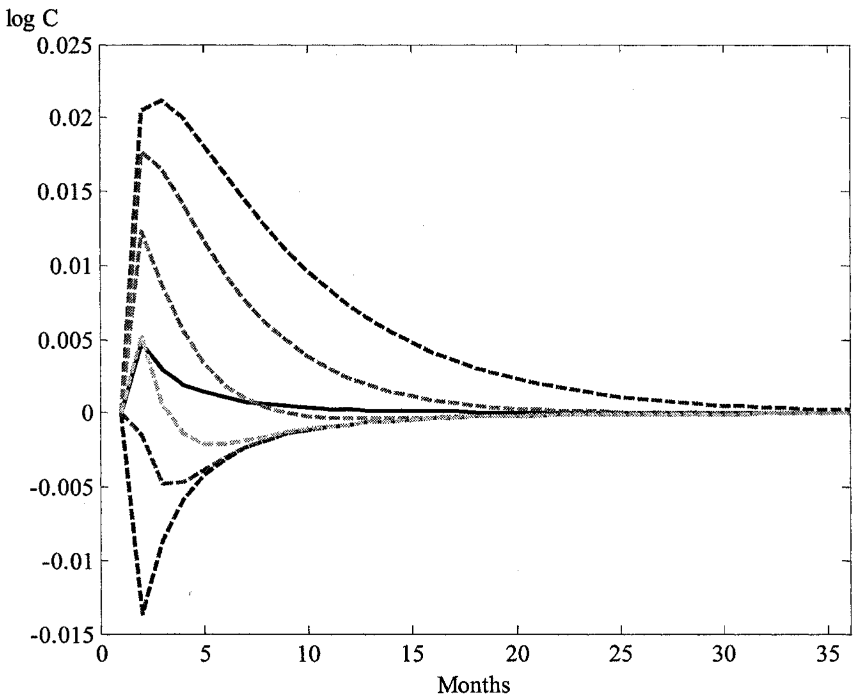


Figure 3.13: Sectoral Output Responses without Intermediate Inputs
This figure plots the response of aggregate real value-added output (solid line) and sectoral output for several sectors of the 14 sector model without intermediate inputs to a 1% permanent increase in nominal aggregate demand. From top to bottom the sectors that are plotted are: Services(5), Apparel, Services(3), Transportation Goods, Utilities and Vehicle Fuel and Used Cars.

3.4.2 Heterogeneity and Sectoral Output

The relatively modest response of aggregate value-added output to aggregate demand shocks in the model without intermediate inputs masks much larger responses of output in individual sectors. Figure 3.13 plots the response of aggregate output and sectoral output to an expansionary demand shock in our 14 sector model without intermediate inputs. The sectoral responses vary greatly. Output in the sectors with most price rigidity rises by several times as much as aggregate output, while output in the sectors with most price flexibility falls sharply.

In the model without intermediate inputs, the desired price of all firms rises approximately one-for-one in percentage terms with nominal aggregate demand and is approximately independent of the prices charged by other firms—equation (3.17) with $s_m = 0$. As a consequence, the sectoral price index in sectors with a high frequency of price change—such as gasoline—quickly rises proportionally to the shock, while the sectoral price index in sectors with more rigid prices adjusts more slowly. This causes the prices in the sectors with most flexible prices to rise sharply relative to the prices in the sectors with more rigid prices. This change in relative prices leads consumers to shift expenditures toward the sectors in which prices are more rigid. In the model without intermediate inputs, this expenditure switching effect is strong enough that output in the sectors with most flexible prices falls after the demand shock. We simulate the model for 600 periods and find that the heterogeneity in price flexibility implies that the correlation of output in different sectors with aggregate output ranges from -0.99 to 0.95, with output in the sticky price sectors being highly positively correlated with aggregate output while output in the flexible price sectors is highly negatively correlated with aggregate output.[33]

In contrast, in the model with intermediate goods, a firm's desired price is heavily dependent on the prices of other firms—equation (3.17) with $s_m = 0.75$. Since the prices of other firms make up a large component of the marginal costs of all firms, the higher are other firms' prices, the higher is any particular firm's desired price. This leads to a strikingly different response of sectoral output to aggregate demand shocks.

Figure 3.14 plots the response of aggregate output and sectoral output to an expansionary demand shock in our 14 sector model with intermediate inputs. Since each firm's desired price is heavily dependent on other firms' prices, even sectors with highly flexible prices do not raise their prices immediately by the full amount of the increase in nominal aggregate demand. Instead, they adjust their prices more gradually. This leads to far smaller differences in relative prices across sectors and far greater comovement in output across sectors. Figure 3.14 shows that output in all sectors rises sharply in response to an expansionary demand shock. As a consequence, in a 600 period simulation of the 14 sector model with intermediate inputs, the correlation of output in different sectors with aggregate output is positive for all sectors, ranging from 0.05 to 0.99.

A key characteristic of business cycles is that virtually all sectors of the economy comove strongly (Lucas, 1977; Stock and Watson, 1999). The lack of comovement across sectors in the multi-sector model without intermediate inputs is therefore grossly at odds with the

[33] The magnitude of the expenditure switching effect depends on the elasticity of substitution across sectors, which we assume is equal to 4. The effect would be smaller for a smaller assumed elasticity across sectors. Barsky et al. (2003) show that the expenditure switching effect can be large in the presence of durable goods even if the elasticity of substitution between sectors is small.

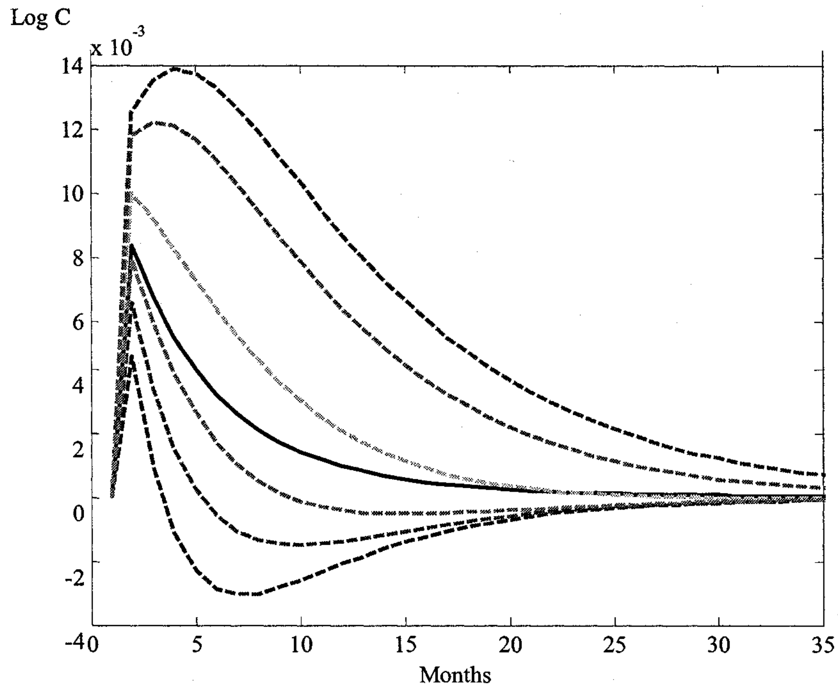


Figure 3.14: Sectoral Output Responses with Intermediate Inputs
This figure plots the response of aggregate real value-added output (solid line) and sectoral output for several sectors of the 14 sector model with intermediate inputs to a 1% permanent increase in nominal aggregate demand. From top to bottom the sectors that are plotted are: Services(5), Apparel, Services(3), Transportation Goods, Utilities and Vehicle Fuel and Used Cars.

data.[34] This lack of comovement across sectors in models with heterogeneity in the degree of price flexibility has been noted and analyzed by several recent papers including Bils et al. (2003), Barsky et al. (2003) and Carlstrom and Fuerst (2006). The discussion above shows that allowing for intermediate goods substantially increases the comovement between different sectors of the economy.[35] Barsky et al. (2003) present a number of alternative mechanisms for ameliorating this "comovement problem".

3.4.3 Product Introduction

The menu cost model we have been analyzing up until now in this paper implicitly assumes that products are infinitely lived. In fact, however, product turnover is quite rapid in certain sectors of the economy. When a firm introduces a new product, it must necessarily set a

[34] It is easy to show that aggregate productivity shocks lead to similar lack of comovement across sectors.

[35] Hornstein and Praschnik (1997), Dupor (1999) and Horvath (2000) discuss the effects of input-output linkages for comovement in a real business cycle framework.

new price for this product. Rapid product turnover can therefore affect the degree of price flexibility in the economy. Furthermore, since firms can often anticipate future product turnover—e.g., fall-spring turnover in apparel—they may decide not to incur the fixed cost needed to change the price of an existing product.

Table 3.10 reports the frequency of product substitution for the sectors in our multi-sector models.[36] Table 3.10 reveals that product substitution is a frequent occurrence in several categories of durable goods—Apparel, Transportation Goods (Cars), Household Furnishing and Recreation Goods—but less frequent for other products. A number of these categories—especially Apparel—have a very low frequency of price change. Since our results regarding amplification due to heterogeneity rely heavily outlying sectors such as Apparel, it is important to understand how accounting for product flexibility affects our results.

Many factors influence a firm's decision about the introduction of a new product. These include seasonality, development cycles, innovation and random shifts in consumer tastes. Figure 3.15 plots the frequency of product substitution across different months of the year for the four categories for which product substitution is most frequent. In Apparel, seasonal variation in tastes seems to be a dominant factor in the timing of product introduction. In the automobile industry, product introduction seems to be heavily influenced by a yearly development cycle with new models being introduced in the fall of each year.

This evidence suggests that product turnover may be largely orthogonal to a firm's desire to change its price and to macroeconomic conditions. A computationally tractable way of modelling this type of event is to consider a model in which new products arrive according to an exogenous Poisson process. This model is equivalent to the CalvoPlus model where $K_l = 0$ and $1 - \alpha$ in each sector is equal to the frequency of product substitution. The menu cost in the high cost state is calibrated so that the frequency of high cost price changes in the model matches the frequency of price change in the data for each sector.

Table 3.13 shows that product turnover associated with factors unrelated to the firms'

[36] Ideally we would have a measure of the rate of product introduction since pricing decisions are made when new products are introduced. However, the BLS does not tract the introduction of new products. When a product that the BLS has been tracking becomes permanently unavailable, the BLS agent is instructed to substitute to the most similar existing product. In most cases this product will have existed for some time. If the hazard of product exit is upward sloping, the frequency of product substitution is therefore an upward biased measure of the frequency of product introduction.

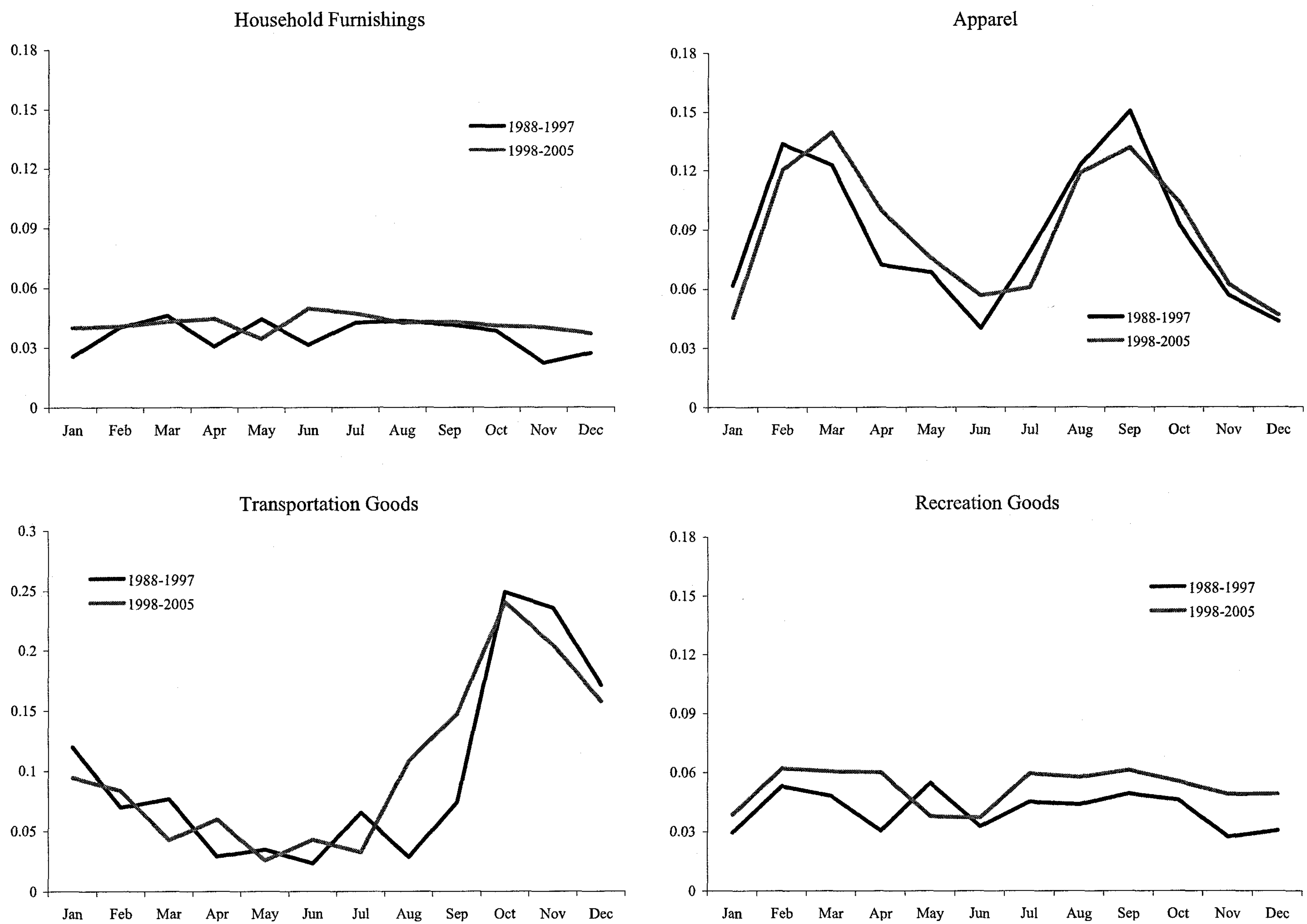


Figure 3.15: Seasonality of Product Substitution

Table 3.13: Multi-Sector Models with Products Flexibility

	Menu Cost		CalvoPlusSubs		Menu Cost Subs	
	$s_m = 0.75$	$s_m = 0$	$s_m = 0.75$	$s_m = 0$	$s_m = 0.75$	$s_m = 0$
Panel A: CIR						
1 Sector Model (Mean)	1.6	0.5	1.5	0.5	1.5	0.4
6 Sector Model	3.5	1.3	2.9	1.2	2.2	0.9
9 Sector Model	4.2	1.6	3.9	1.6	2.8	1.0
14 Sector Model	4.0	1.6	3.9	1.6	2.8	1.1
Panel B: Var(C_t)						
1 Sector Model (Mean)	0.080	0.018	0.072	0.015	0.063	0.012
6 Sector Model	0.200	0.050	0.168	0.044	0.125	0.030
9 Sector Model	0.237	0.058	0.219	0.053	0.151	0.033
14 Sector Model	0.244	0.056	0.221	0.054	0.152	0.035

This table presents estimates of the cumulative impulse response (CIR) and the variance or real value-added output for three calibrations of our multi-sector models and two values of the intermediate inputs share (sm). The CIR is measured in percent. The variance of real value added output is multiplied by 10^4. The first two columns present results for the menu cost model calibrated to match the frequency of price change across sectors. The third and fourth columns present results for the CalvoPlus model with $K_l = 0$, $1 - \alpha$ = freq. of substitutions and K_h calibrated so that that frequency of price change in the high cost state equals the frequency of price change in the data. The fifth and sixth columns present results for the menu cost model calibrated to match the frequency of price change plus the frequency of substitutions across sectors.

pricing decisions have little effect on the monetary non-neutrality implied by the model. This is because the "selection effect" applies only to the regular price changes. While new fashions are priced to keep up with inflation, they are not (in this model) introduced *because* the old fashions were mispriced. For comparison purposes, table 3.13 also presents results for a calibration of the menu cost model where we treat product introductions as if they were in the same as regular price changes. In this case, the shorter durations of prices associated with "product flexibility" would have a much larger effect on monetary non-neutrality. In either case, the inclusion of product substitutions in the model has little effect on the amplification effect associated with heterogeneity.

3.5 Conclusion

This paper analyzes the responsiveness of real output to monetary shocks in a multi-sector menu cost model that allows for intermediate goods. We calibrate the model to new evidence on the frequency of non-sale price changes from chapter 1. We find that heterogeneity across sectors approximately triples the monetary non-neutrality in the model relative to a one-sector model calibrated to the mean frequency of price change across all goods. Intuitively, the magnification arises because the degree of monetary non-neutrality in a one-sector model is a convex function of the frequency of price change, implying that greater heterogeneity increases the average degree of monetary non-neutrality. The degree of monetary non-neutrality in the multi-sector model with intermediate goods is comparable to the degree of monetary non-neutrality of a single-sector model calibrated to match the median frequency of price change.

Allowing for intermediate goods generates strategic complementarity in the menu cost model. The menu cost model with intermediate inputs generates three times as much monetary non-neutrality as a corresponding model without intermediate inputs. Incorporating strategic complementarities into menu cost models designed to fit the size and frequency of micro-level price changes has proven challenging. Standard sources of strategic complementarity—such as fixed factors of production and non-isoelastic demand curves—yield price changes that are much too small on average for reasonable parameter values. This is not the case for intermediate inputs. Allowing for intermediate goods generates strategic complementarities without requiring unrealistically large variation in marginal costs or menu costs.

We also develop an extension of the Calvo model designed to fit the microeconomic evidence on the size and frequency of price change, while still maintaining the idea that the timing of some price changes is random rather than occurring in response to changes in costs. We refer to this model as the CalvoPlus model. The effects of heterogeneity and intermediate goods on monetary non-neutrality in the CalvoPlus model are similar to the effects in the benchmark menu cost model. We show that the relatively large amount of monetary non-neutrality generated by the Calvo model is quite sensitive to even a modest amount of selection by firms regarding the timing of price changes. When 75% of price changes occur in the low menu cost state, the CalvoPlus model generates about double the amount of monetary non-neutrality generated by the menu cost model—about 1/3 of the monetary non-neutrality generated in the Calvo limit.

APPENDIX

A. COMPUTATIONAL ALGORITHM

I solve for equilibrium prices in the dynamic pricing model using the following iterative procedure. For expositional simplicity, I present the algorithm for the case of two firms $j = 1, 2$. It is, however, easy to see how the algorithm can be generalized to the case of n firms. I will begin by describing the value function iteration procedure used to solve each individual firm's dynamic pricing problem. Suppose we start with an initial value for the firm's expected value EV_j at time $t-1$,

$$EV_j(p_{1t-1}^w, p_{2t-1}^w, C_{t-1}) = E_{t-1}V_j(p_{1t-1}^w, p_{2t-1}^w, C_t). \tag{A.1}$$

The value function iteration procedes by iteratively updating EV_j until a fixed point is obtained. I next describe the procedure I use to update EV_j in the value function iteration. The first step is to calculate the value from different possible prices excluding the menu cost,

$$W'(p_{1t}^w, p_{2t}^w, c_t) = \pi_{jt}(p_{1t}^w, p_{2t}^w, c_t) + \beta EV_j(p_{1t}^w, p_{2t}^w, c_t). \tag{A.2}$$

This expression depends on the current prices of the firm's competitors as well as current costs.

The second step in updating the value function is to calculate the expectation of W' over competitors' prices. The menu cost model implies a simple structure for this expectation since firm j' has probability $1 - \mathrm{pr}_{j'}$ of maintaining its current price, and probability $\mathrm{pr}_{j'}$ of changing its price. Let us denote the firm's price conditional on adjusting by p_{jt}^{w*}. A given firm's pricing strategy depends on the entire vector of past prices (p_{1t-1}^w, p_{2t-1}^w). Denoting the expectation over competitors' prices as W'' we have,

$$W''(c_t, p_{1t}^w; p_{1t-1}^w, p_{2t-1}^w) = (1 - \mathrm{pr}_2)W'(p_{1t}^w, p_{2t-1}^w, c_t) + \mathrm{pr}_2 W'(p_{1t}^w, p_2^{w*}, c_t). \tag{A.3}$$

Third, we must calculate the firm's optimal pricing policy. There are two relevant cases. The expectation if the firm does not adjust its price is

$$W_{nch}(p^w_{1t-1}, p^w_{2t-1}, c_t) = W''(c_t, p^w_{1t-1}; p^w_{1t-1}, p^w_{2t-1}), \tag{A.4}$$

while the expectation if it does adjust its price is

$$W_{ch}(p^w_{1t-1}, p^w_{2t-1}, c_t) = \max_{p^w_{1t}} W''(c_t, p^w_{1t}; p^w_{1t-1}, p^w_{2t-1}). \tag{A.5}$$

The firm's decision about whether to adjust its price depends on the difference between its payoffs when it adjusts and when it does not adjust,

$$\Delta W = W_{ch}(p^w_{1t-1}, p^w_{2t-1}, c_t) - W_{nch}(p^w_{1t-1}, p^w_{2t-1}, c_t). \tag{A.6}$$

The firm adjusts its price when $\Delta W > \gamma_{jt}$ while it maintains a fixed price when $\Delta W <= \gamma_{jt}$. Recall that I assume that the menu cost γ_{jt} is independent and identically distributed with an exponential distribution i.e. $F(\gamma_{jt}) = 1 - \exp(-\frac{1}{\sigma}\gamma_{jt})$. The probability of price adjustment is therefore $Pr_{ch} = F(\Delta W)$, where $F(x) = 1 - \exp(-\frac{1}{\sigma}x)$.

Fourth, in order to update the firm's value, we must calculate the expected menu cost if the firm changes its price. The expected menu cost differs from the mean of the menu cost distribution since the firm is more likely to adjust its price when it faces a low menu cost. The optimal pricing policy implies that the firm adjusts only when $\Delta W > \gamma_{jt}$. Since I assume that the menu cost is distributed exponentially, the firm's expected menu cost takes the form,

$$E(\gamma_{jt}|\gamma_{jt} < \Delta W) = \sigma - \frac{\Delta W \exp \frac{-1}{\sigma}\Delta W}{\exp \frac{-1}{\sigma}\Delta W}. \tag{A.7}$$

The expected value is a weighted average of its value conditional on adjusting and not adjusting,

$$W = (1 - Pr_{ch})W_{nch} + Pr_{ch}[W_{ch} - E(\gamma_{jt}|\gamma_{jt} < \Delta W)]. \tag{A.8}$$

Finally, I use the the stochastic process for costs to take an expectation over future commodity costs at time $t-1$. I discretize the process for costs given by (2.20) using the method of Tauchen (1986). This implies a discrete Markov process with the transition matrix Λ. Applying this Markov transition matrix to W we have,

$$EV_j = \Lambda W. \tag{A.9}$$

I solve for the firm's optimal policy by repeatedly applying this procedure to update EV_j until a fixed point is found.

This value function iteration procedure is nested within an "outer loop" that searches for a fixed point in the firms' dynamic pricing policies. In this outer loop, I first solve for firm 1's optimal policy, conditional on an initial the pricing policy of firm 2; and use the results to update firm 1's policy rule. I then solve for firm 2's optimal policy, conditional on the updated pricing policy of firm 1. I use the results of this exercise to update firm 2's policy rule. I repeat this exercise until the maximum differences the firms' pricing policies between successive iterations are sufficiently small.

One interesting feature of the dynamic model is that only the size of the menu cost relative to the market size, γ_{jt}/M, matters in determining firms' behavior. This can be seen by the following argument. Let us assume that the value function V scales with M. By the definitions above, ΔW and W'' also scale with M in this case, implying that the firm's optimal price conditional on adjusting is invariant to M. Moreover, since ΔW scales with M, the probability of adjustment, $Pr_{ch} = 1 - \exp\left(-\frac{1}{\sigma}\Delta W\right)$ depends only on γ_{jt}/M. Thus, given our assumptions, the firm's pricing policy depends only on γ_{jt}/M. Since the value function is the discounted expected sum of future profits (which scale with M conditional on prices), this allows us to verify our original claim that the value function scales with M.

B. ROBUSTNESS OF THE DYNAMIC ESTIMATION PROCEDURE

In section 2.6, I use the static model to infer local costs in equation (2.24) to parameterize the dynamic menu cost model. This is an approximation since the static first order conditions do not hold in the dynamic model. In order to investigate the robustness of the dynamic estimation procedure, I also consider the following procedure in which I estimate an additional parameter in marginal costs as part of the dynamic estimation procedure. I assume that the firms' costs are given by,

$$mc_{kmt} = \kappa + \mu_k + C_t, . \tag{B.1}$$

where κ is the common shift parameter in costs. I use an analogous indirect estimation procedure to the procedure described in section to estimate the parameters of the model. I select the common shift parameter κ and the mean of the menu cost distribution σ to minimize the loss function,

$$L = (f - \hat{f})^2 + (p^{\bar{w}} - \hat{\bar{p}})^2, \tag{B.2}$$

where $p^{\bar{w}}$ is the average wholesale price implied by the model and $\hat{\bar{p}}$ is the average wholesale price in the data.

The resulting estimated shift parameter is 0.3 cents, implying that the average wholesale price from the dynamic model is 14.4 cents rather than 14.3 cents for the original estimation procedure. The menu cost estimate using this procedure is 0.26% (rather than 0.3%) of annual revenue. The implications of the model for pass-through are almost identical to the implications of the model parameterized according to the original estimation procedure.

C. CALCULATING THE STATIC EQUILIBRIUM PRICES

In section 2.5 I show that equilibrium prices must satisfy the first-order conditions,

$$s_{mt} - \Omega(p^w_{mt} - mc_{mt}) = 0, \tag{C.1}$$

where s_{mt}, p^w_{mt} , mc_{mt} and ξ_{mt} are vectors consisting of s_{kmt}, p^w_{kmt}, mc_{kmt}, and ξ_{kmt} for $k = 1, ..., K$ respectively. As in the dynamic model, I assume that retail prices equal wholesale prices plus a known constant margin ξ_k,

$$p^r_{kt} = \xi_k + p^w_{kt}. \tag{C.2}$$

Marginal cost is modeled as the sum of a product-specific constant and the commodity cost,

$$mc_{kt} = \mu_k + C_t, \tag{C.3}$$

where μ_k is a constant component of marginal costs that differs across products, estimated in the same way as in the dynamic pricing model (using equation (2.24). I solve for the static equilibrium prices by solving numerically for the vector of prices that solves equation (C.1) and checking that the second order conditions are satisfied.

D. PROFIT FUNCTION

Cost minimization by firm z implies that labor demand and demand for the composite intermediate input be governed by

$$\frac{W_t}{P_t} = (1 - s_m) A_t L_t(z)^{-s_m} M_t(z)^{s_m} \Omega_t(z),$$

$$1 = s_m A_t L_t(z)^{1-s_m} M_t(z)^{s_m - 1} \Omega_t(z),$$

where $\Omega_t(z)$ denotes the marginal costs of firm z at time t. Combining these two equations yields

$$\frac{W_t}{P_t} = \frac{1 - s_m}{s_m} \frac{M_t(z)}{L_t(z)}. \tag{D.1}$$

Using this equation we can rewrite the profits of firm z in period t as

$$\begin{aligned} \Pi_t^R(z) &= \left(\frac{p_t(z)}{P_t}\right) y_t(z) - \left(\frac{W_t}{P_t}\right) L_t(z) - M_t(z) - K \left(\frac{W_t}{P_t}\right) I_t(z) \\ &= \left(\frac{p_t(z)}{P_t}\right) y_t(z) - \frac{1}{1 - s_m} \left(\frac{W_t}{P_t}\right) L_t(z) - K \left(\frac{W_t}{P_t}\right) I_t(z). \end{aligned}$$

Combining the production function—equation (3.8)—and equation (D.1) yields

$$L_t(z) = \left(\frac{y_t(z)}{A_t(z)}\right) \left(\frac{s_m}{1 - s_m}\right)^{-s_m} \left(\frac{W_t}{P_t}\right)^{-s_m}.$$

Using this equation, we can rewrite profits as

$$\Pi_t^R(z) = \left(\frac{p_t(z)}{P_t}\right) y_t(z) - (1 - s_m)^{s_m - 1} s_m^{-s_m} \left(\frac{W_t}{P_t}\right)^{1 - s_m} \left(\frac{y_t(z)}{A_t(z)}\right) - K \left(\frac{W_t}{P_t}\right) I_t(z). \tag{D.2}$$

Using the firm's demand curve—equation (3.12)—and the labor supply curve—equation (3.7)—we can rewrite profits as

$$\Pi_t^R(z) = Y_t \left(\frac{p_t(z)}{P_t}\right)^{1-\theta} - (1-s_m)^{s_m-1} s_m^{-s_m} \omega^{1-s_m} L_t^{\psi(1-s_m)} C_t^{\gamma(1-s_m)} \left(\frac{1}{A_t(z)}\right) Y_t \left(\frac{p_t(z)}{P_t}\right)^{-\theta} - K\omega L_t^{\psi} C_t^{\gamma} I_t(z).$$

Finally, log-linear approximations of $Y_t = C_t + \int_0^1 M_t(z)dz$, the production function and labor supply around the steady state with flexible prices yield $\hat{Y}_t = a_1\hat{C}_t$ and $\hat{L}_t = a_2\hat{C}_t$. Here $\hat{Y}_t = \log(Y_t/Y)$ and Y denotes the steady state of Y_t with flexible prices. $\hat{C}_t$ and $\hat{L}_t$ are defined analogously. Using these log-linear approximations and the fact that $C_t = S_t/P_t$, we can rewrite profits as a function of $(A_t(z), p_{t-1}(z)/P_t, S_t/P_t)$ and $p_t(z)$.

E. STATIONARY DISTRIBUTION

We solve for the stationary distribution over the state space of the firm's problem using the following algorithm:

0. Start with an initial distribution $Q(A(z), p_{-1}(z)/P, S/P)$. We use a uniform distribution as our initial distribution.
1. Map $Q(A(z), p_{-1}(z)/P, S/P)$ into $Q(A(z), p(z)/P, S/P)$ using the policy function F.
2. Map $Q(A(z), p(z)/P, S/P)$ into $Q(A_{+1}(z), p(z)/P, S/P)$ using the transition probability matrix for the technology process.
3. Map $Q(A_{+1}(z), p(z)/P, S/P)$ into $Q(A_{+1}(z), p(z)/P, S_{+1}/P)$ using the probability transition matrix for the nominal aggregate demand process.
4. Map $Q(A_{+1}(z), p(z)/P, S_{+1}/P)$ into $Q(A_{+1}(z), p(z)/P_{+1}, S_{+1}/P_{+1})$ using the function Γ.
5. Check whether $|Q(A_{+1}(z), p(z)/P_{+1}, S_{+1}/P_{+1}) - Q(A(z), p_{-1}(z)/P, S/P)| < \xi$ where $|\cdot|$ denotes a sup-norm. If so, stop. If not, go back to step one.

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