Accounting for Incomplete Pass-Through

Emi Nakamura *
Harvard University

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Abstract

Recent theoretical work has suggested a number of potentially important factors in causing incomplete pass-through of exchange rates to prices, including markup adjustment, local costs and barriers to price adjustment. I empirically analyze the determinants of incomplete pass-through in the coffee industry. The observed pass-through in this industry replicates key features of pass-through documented in aggregate data: prices respond sluggishly and incompletely to changes in costs. I use microdata on sales and prices to uncover the role of markup adjustment, local costs, and barriers to price adjustment in determining incomplete pass-through. I carry out this decomposition in a structural oligopoly model with menu costs that nests all three potential factors. The implied pricing model explains the main dynamic features of pricing. I find that local costs and markup adjustment explain 78% and 20%, respectively, of incomplete pass-through, while menu costs explain only 2%. Menu costs nevertheless play an important role since they explain the delayed response of prices to costs. I find that delayed pass-through in the coffee industry occurs almost entirely at the wholesale rather than the retail level.

Keywords: exchange rate pass-through, menu costs, discrete choice model.

JEL Classifications: F10, L11, L16.

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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 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]

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] By wholesale prices, I mean the prices charged by coffee roasters like Folgers and Maxwell House, which I also refer to as manufacturer prices.

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

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

[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.

adjustment contribute to delayed pass-through in this industry, it is wholesale price rigidity that matters. 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. Goldberg and Hellerstein (2007) similarly document an important role for wholesale price rigidity in the beer market using data from a large US supermarket chain.[4] 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.

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). 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 (1995) 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. This is an empirical framework with fixed costs of adjusting prices: I do not take a stand

[4] Retailers nevertheless play an important role in determining the level of pass-through since they insert an additional wedge between imported costs and prices. The role of retail behavior in determining pricing behavior is analyzed in detail by Hellerstein (2005) and Villas-Boas (2007).

on the sources of the barriers to price adjustment.[5] 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.[6] 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 model to the data in terms of the level of prices and the overall average frequency of price change, but 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

[5] See, for example, Zbaracki et al. (2004) for an attempt to quantify different sources of barriers to price adjustment. While understanding the sources of barriers to price adjustment is an important topic for future research, in this paper I simply make use of the menu cost model as an empirical framework. This framework generates two main empirical predictions: prices adjust infrequently, and there are more price adjustments in periods when there is greater incentive to adjust. As I discuss below, the data are broadly supportive of both predictions.

[6] 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.

adjustment, and about 2% is explained by menu costs.[7] Menu costs nevertheless play an important role in explaining pricing dynamics. The barriers to price adjustment generate a delayed response of prices to costs.

The predictions of this type of model depend on a number of factors, only some of which 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 pass-through and may affect existing empirical results. Engel (2002) argues that Goldberg and Verboven (2001) overestimate the role of local costs because they do not allow for price rigidity. This paper extends the existing static 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

[7] 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 in terms of the large role played by local costs. For other interesting attempts to distinguish between markup adjustment and price rigidity in explaining exchange rate pass-through see Giovannini (1988) and Marston (1990).

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. More broadly, this paper is related to a large empirical literature on cost pass-through as well as a growling literature on state-dependent pricing models solved using numerical methods.[8] Bettendorf and Verboven (2000) study the relationship between Dutch coffee prices and commodity costs in a static oligopoly 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. The finding that the frequency of price change varies substantially over time with movements in commodity costs provides evidence for a central prediction of the menu cost model that has been difficult to study using aggregate data. 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, implying that local costs are likely to be even more important in other sectors. 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 provides an overview of the data used in the paper. Section 3 presents stylized facts about price adjustment in the coffee industry. Section 4 describes the demand model. Section 5 applies the demand model to estimate markups and local costs. Section 6 presents the menu cost oligopoly model and the computational algorithm used to solve for the equilibrium of this model. Section 7 establishes the predictions of the model for incomplete

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

pass-through, and documents the relative importance of markup adjustment, local costs and menu costs. Section 8 concludes.

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.[9] 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 cover 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 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

[9] AC Nielsen collects prices from cooperating supermarkets, with at least $2 million in sales. Sales by supercenters, 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.

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 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.[10] 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.

3 Cost Pass-Through Regressions

Let us begin by looking at the relative movements of coffee prices and costs over the past decade.[11] Figure 1 presents a graph of average retail, wholesale and commodity prices in US dollars per ounce.[12] To be clear about terminology, I shall refer to the price charged by supermarkets to

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

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

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

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).[13] 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 the rise and fall of the U.S. exchange rate.

Figure 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.[14] To quantify this relationship, I estimate the following standard pass-through regression,

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

where $l = r, w$, $\Delta \log p^{r}_{jmt}$ is the log retail price change of product j in market m, $\Delta \log p^{w}_{jmt}$ 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.[15] 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

[13]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.

[14]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.

[15]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.

root in commodity prices cannot be rejected at a 5% significance level.[16] 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 in Section 2, for quarterly changes in prices and costs over the 2000-2005 period.[17]

The first panel of table 1 presents the results of the pass-through regression for retail and wholesale prices. Table 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.[18] Table 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 1 presents the results of the pass-through regression (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.[19] I

[16]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.

[17]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.

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

[19]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

find similar results for long-run pass-through when I estimate these regressions using the weather instruments discussed in section 4.[20]

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 are most relevant for parameterizing the model. In order to analyze this issue, I consider the following regression of retail prices on wholesale prices,

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

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.[21] Table 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 industry. Figure 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.[22] P&G commented to reporters in conjunction with its 2004 price

demand to retail sales.

[20]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 4. The resulting estimates of long-run pass-through are 0.968 for retail prices and 0.960 for wholesale prices.

[21]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.

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

increase that P&G "increases product prices when it is apparent that commodity price increases will be sustained". (Associated Press, Dec. 10 2004). Table 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 Nakamura and Steinsson (2006). 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 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 3 plots the relationship between the average 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 5 presents the results of the regression,

$$\Delta \log p_{jmt}^{r} = \eta^{0} + \sum_{k=0}^{1} \eta_{k}^{C} \Delta \log C_{t-k} + \sum_{k=0}^{1} \eta_{k}^{r} \Delta \log p_{jmt-k}^{w} + \sum_{k=1}^{4} \gamma_{k}^{r} q_{k} + \epsilon, \tag{3}$$

where η_k^r, η_k^C 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 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.[23]

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).[24] 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,

$$U_{ijmt} = \alpha_i^0 + \alpha_i^p (y_i - p^r_{jmt}) + x_j \beta^x + \xi_{jmt} + \epsilon_{ijmt}, \tag{4}$$

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_{jmt} is an unobserved demand shifter that varies across products and regions.[25] 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

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

[24]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.

[25]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).

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,

$$\log s_{jmt} - \log s_0 = \alpha^0 - \alpha^p p_{jmt}^r + x_j\beta + \xi_{jmt}, \tag{5}$$

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.[26]

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 6 presents estimates of equation (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.[27] 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 6 presents estimates for the logit model including brand-region fixed effects.[28] Including fixed effects dramatically increases the estimated price elasticity:

[26] 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%.

[27] 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.

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

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 approach 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 (1995) 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.[29] I estimate a simple version of the random coefficients model—equation (4)—in which an individual's price sensitivity as well as the mean utility of purchasing coffee is allowed to

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

vary with his or her household income.

$$\alpha_i = \alpha + \Pi \tilde{y}_i, \tag{6}$$

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 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).[30] 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.[31] 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 (1995) 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,

$$s_{jmt}(\delta_{jmt}, \Pi_y) - \hat{s}_{jmt} = 0, \tag{7}$$

for all j, m, t where $\hat{s}_{jmt}$ are the empirical market shares. Given a parameter Π_y, this equation may be solved for a vector of mean utilities δ_{jmt}. Berry, Levinsohn, and Pakes (1995) show how to solve for δ_{jmt} numerically using a contraction mapping property. The second set of moments requires

[30] 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.

[31] 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 $\mu_{ijmt} = -\Pi_y \tilde{y}_i p^r_{jmt}$.

that the instruments z_{jmt} be orthogonal to the aggregate demand shocks ξ_{jmt},

$$E(\xi_{jmt} z_{jmt}) = 0, \tag{8}$$

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,

$$E(s_{jkmt}(\delta_{jmt}, \Pi_y) - \hat{s}_{jkmt} | d_j) = 0, \tag{9}$$

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.[32]

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 (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 (7)-(9) yields the vector of moment conditions $G(\theta)$ where θ are the parameters to be estimated, $E[G(\theta^0)] = 0$ and θ^0 denotes the true value of these parameters. The GMM estimator is,

$$\hat{\theta} = \text{argmin}_\theta G(\theta)' W G(\theta), \tag{10}$$

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.[33] The market shares implied by the model in (7) and (9) are simulated using 250 draws of

[32] 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.

[33] 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

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.[34]

The estimated coefficients for the random coefficients model are presented in the last column of Table 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.[35] 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.[36] 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, 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

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.

[34]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).

[35]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.

[36]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.

confidence levels.

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.[37] 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. 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.[38]

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 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. 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 6 in which I estimate a common component local costs as part of the dynamic estimation procedure.

Let us begin by describing the static model. 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

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

[38]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).

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,

$$\pi_{jmt} = \sum_{k \in \Upsilon_j} (p^w_{kmt} - mc_{kmt}) M s_{kmt} - F_{km}, \tag{11}$$

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 3.[39]

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,

$$s_{kmt} + \sum_{k \in \Upsilon_j} (p^w_{kmt} - mc_{kmt}) \frac{\partial s_{kmt}}{\partial p^r_{kmt}} = 0. \tag{12}$$

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,

$$s_{mt} - \Omega(p^w_{mt} - mc_{mt}) = 0, \tag{13}$$

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,

$$p^w_{mt} - mc_{mt} = \Omega^{-1} s_{mt}. \tag{14}$$

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 (14) while a more concentrated market structure implies a higher markup.

I use equation (14) to derive markups based on the observed wholesale prices and the random coefficients discrete choice demand system estimated in section 4. Table 7 presents summary statistics on the percentage markup of price over marginal cost implied by this procedure. The median

[39] 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.

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.[40]

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 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.

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 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). The model I use is, however, somewhat different from existing menu cost models due to the oligopoly framework. In particular, 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, 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.

[40]As a check on whether the estimates are reasonable, I also investigated the fraction of implied marginal costs that are negative: I find that negative implied marginal costs occur extremely infrequently—less than 0.2% of the time.

The model is formally related to the dynamic oligopoly model studied by Pakes and McGuire (1994).[41] 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 4. As in the case of the Pakes-McGuire algorithm, there is no guarantee that this algorithm converges.[42]

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,

$$E_0 \sum_{t=0}^{\infty} \beta^t \left[\pi_{jmt}(p^w_{mt}, C_t) - \gamma_{jmt} 1(\Delta p^w_{jmt} \neq 0) \right], \tag{15}$$

where p^w_{mt} is the vector of wholesale prices (per ounce) 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 (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}.

[41] 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.

[42] 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.

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,

$$V_j(p^w_{mt-1}, C_t, \gamma_{jmt}) = \max_{p^w_{jmt}} E_t \left[\pi_{jmt}(p^w_{mt}, C_t) - \gamma_{jmt} 1(\Delta p^w_{jmt} \neq 0) + \beta V_j(p^w_{mt}, C_{t+1}, \gamma_{jmt+1}) \right], \quad (16)$$

where E_t is the expectation conditional on all information known by firm j at time t *including* its own menu cost γ_{jmt}. The expectation is taken over two sources of uncertainty: uncertainty about the future commodity cost C_{t+1} and uncertainty about competitors' prices arising because the menu costs are private information. Notice that a given firm's profits and value function depend on all firms' prices through the demand curve. From the perspective of a firm's competitors, its strategy has 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 for a particular value of the publicly observable variables (p^w_{mt-1}, C_t).

An equilibrium is defined as a situation where the firm chooses optimal policies (i.e. the Bellman equation (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).

$$p^w_{kmt} = p^w_{jmt} + \alpha_k, \quad (17)$$

for all $k \in \Upsilon_j$, 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,

$$p^r_{kmt} = \xi_k + p^w_{kmt}. \quad (18)$$

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

$$mc_{kmt} = \mu_k + C_t. \quad (19)$$

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.[43]

Uncertainty about future costs takes the form,

$$C_t = a_0 + \rho_C C_{t-1} + \epsilon_C, \tag{20}$$

where ϵ_C is distributed $N(0, \sigma_C^2)$ and σ_C^2, 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 $\rho_C = 1$. Firms' perceptions about the stochastic process of costs play a key role in determining pass-through as I discuss in section 7. 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.

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,

$$\Delta W = W_{ch} - W_{nch}, \tag{21}$$

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,

$$p_{jmt} = \begin{cases} p^w_{jmt-1} & \text{if } \Delta W < \gamma_{jmt} \\ p^{w*}_{jmt} & \text{otherwise} \end{cases} \tag{22}$$

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

$$p^{w*}_{jmt} = \arg\max_{p^w_{jmt}} E_t \left[\pi_{jmt}(p^w_{mt}, C_t) + \beta V_j(p^w_{mt}, C_{t+1}, \gamma_{jmt+1}) \right]. \tag{23}$$

In an equilibrium, all firms set their prices according to the decision rule implied by equations (22) and (23). Solving for the firms' optimal policy functions is complicated 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

[43] 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).

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 in the firms' pricing policies between successive iterations are sufficiently small.

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 3.07 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 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 4. I also estimate the constant non-coffee cost μ_k from the marginal costs implied by the static pricing model described in section 5. Specifically, I take μ_k to be the average non-coffee costs,

$$\mu_{km} = \frac{1}{T}\sum_{t=1}^{T}\left[\hat{p}^{w}_{kmt} - \Omega^{-1}\hat{s}_{kmt} - C_t\right]. \tag{24}$$

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. To evaluate the sensitivity of the results to using the static estimates of local costs, I also consider an alternative procedure where I estimate a common component in marginal costs as part of the dynamic estimation procedure (see below). 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 parameter σ, 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 σ. The menu cost estimate is chosen to minimize the loss function,

$$L = (f - \hat{f})^2, \tag{25}$$

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.[44] 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%.[45] Figure 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 2000-2005 period. Figure 4 shows that the frequency of price changes is monotonically decreasing in the menu cost. Thus, the loss function has a clear minimum in the range of parameters I consider. Table 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 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.[46] 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

[44] 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.

[45] 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 3, trade deals relatively unimportant in explaining cost pass-through in this market.

[46] 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.

revenue in a large industrial firm.

To gauge the robustness of the procedure used to estimate local costs, I also consider an alternative approach in which I estimate a common component of marginal costs as part of the dynamic estimation procedure. The alternative estimation procedure is presented in appendix B. 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 5. I find, however, that these effects are numerically small. This procedure yields almost identical estimates of local costs to the estimates based on the static model described above. This is not particularly surprising since the marginal costs from the static model come close to rationalizing the observed level of prices: the static model implies average wholesale prices of 14.3 cents per ounce versus 14.4 cents in the data.

6.3 Equilibrium Pricing Policies

The equilibrium consists of pricing policies for all firms. From the perspective of a firm's competitors, a firm's pricing policy gives 1) what price the firm adjusts to conditional on adjusting and 2) the probability of adjustment conditional on the publicly observable variables i.e. p^w_{mt-1} and C_t. 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 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 4 implies that prices may be either strategic complements or substitutes. For the estimated parameter values, prices are in general strategic complements. Figure 6 plots an example of 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 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.

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 (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 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 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.[47]

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 (1) for the simulated data. The last column of Table 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 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

[47]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.

(i.e. equation (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 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 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 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 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 10 also 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 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.

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 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 fixed prices to profits when prices are set at the static optimum in every period (e.g. Leslie, 2004; Goldberg and Hellerstein, 2007).[48] 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. The last column of Table 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

[48] Goldberg and Hellerstein (2007) note that in this approach, the menu cost estimate may be interpreted exactly as a combination of both the fixed costs of price adjustment and the option value of not adjusting.

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. 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 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 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 (19) and a retail margin parameterized by equation (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 by replacing the constant elasticity of substitution demand model with the static random coefficients discrete choice model examined in section 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 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. The role of menu costs in the model depends crucially on the persistence of marginal costs, as I discuss above. Menu costs nevertheless play an important role in price dynamics since they provide an explanation for the delayed response of prices to costs.

[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 $\theta = 2.92$.

[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.

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 imported inputs 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 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 estimated to match the frequency of wholesale price adjustment. I find that the model provides a quantitatively realistic explanation for both 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 adjustments. 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 relative importance 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%. Quantitatively, the persistence of commodity costs implies that barriers to price adjustment play a small role in explaining pass-through for horizons of over a year. Nevertheless, menu costs play an important role in pricing dynamics since they explain the delayed response of prices to costs.

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 firm j's expected value EV_j at time $t-1$,

$$EV_j(p^w_{1t-1}, p^w_{2t-1}, C_{t-1}) = E_{t-1}V_j(p^w_{1t-1}, p^w_{2t-1}, C_t, \gamma_{jt}), \tag{26}$$

where V_j is the value function described in section 6 and E_{t-1} is the expectation conditional on all information known by firm j at time $t-1$.

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,

$$W'(p^w_{1t}, p^w_{2t}, c_t) = \pi_{jt}(p^w_{1t}, p^w_{2t}, C_t) + \beta EV_j(p^w_{1t}, p^w_{2t}, C_t). \tag{27}$$

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^{w*}_{jt}. A given firm's pricing strategy depends on the entire vector of past prices (p^w_{1t-1}, p^w_{2t-1}). Denoting the expectation over competitors' prices as W'' we have,

$$W''(C_t, p^w_{1t}; p^w_{1t-1}, p^w_{2t-1}) = (1 - \mathrm{pr}_2)W'(p^w_{1t}, p^w_{2t-1}, C_t) + \mathrm{pr}_2 W'(p^w_{1t}, p^{w*}_2, C_t). \tag{28}$$

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

$$W_{nch}(p^w_{1t-1}, p^w_{2t-1}, C_t) = W''(C_t, p^w_{1t-1}; p^w_{1t-1}, p^w_{2t-1}), \tag{29}$$

while the expectation if it does adjust its price is

$$W_{ch}(p^w_{1t-1}, p^w_{2t-1}, C_t) = \max_{p^w_{1t}} W''(C_t, p^w_{1t}; p^w_{1t-1}, p^w_{2t-1}). \tag{30}$$

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,

$$\Delta W = W_{ch}(p^w_{1t-1}, p^w_{2t-1}, C_t) - W_{nch}(p^w_{1t-1}, p^w_{2t-1}, C_t). \tag{31}$$

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,

$$E(\gamma_{jt}|\gamma_{jt} < \Delta W) = \sigma - \frac{\Delta W \exp \frac{-1}{\sigma}\Delta W}{\exp \frac{-1}{\sigma}\Delta W}. \tag{32}$$

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

$$W = (1 - Pr_{ch})W_{nch} + Pr_{ch}[W_{ch} - E(\gamma_{jt}|\gamma_{jt} < \Delta W)]. \tag{33}$$

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 (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,

$$EV_j = \Lambda W. \tag{34}$$

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, $Pr_{ch} = 1 - \exp(-\frac{1}{\sigma}\Delta W)$ 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 6, I use the static model to infer local costs in equation (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,

$$mc_{kmt} = \kappa + \mu_k + C_t, . \tag{35}$$

where κ is the common shift parameter in costs. I use an analogous indirect estimation procedure to the procedure described in section 6 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,

$$L = (f - \hat{f})^2 + (\bar{p^w} - \bar{\hat{p^w}})^2, \tag{36}$$

where $\bar{p^w}$ is the average wholesale price implied by the model and $\bar{\hat{p^w}}$ 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 5 I show that equilibrium prices must satisfy the first-order conditions,

$$s_{mt} - \Omega(p^w_{mt} - mc_{mt}) = 0, \tag{37}$$

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,

$$p^r_{kt} = \xi_k + p^w_{kt}. \tag{38}$$

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

$$mc_{kt} = \mu_k + C_t, \tag{39}$$

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 (24). I solve for the static equilibrium prices by solving numerically for the vector of prices that solves equation (37) and checking that the second order conditions are satisfied.

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TABLE 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.

TABLE 2

IV Regression of Retail 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.

TABLE 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 Nakamura and Steinsson (2006) based on monthly data from the CPI research database collected by the Bureau of Labor Statistics.

TABLE 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.

TABLE 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.

TABLE 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.

TABLE 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.

TABLE 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.

TABLE 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.

TABLE 10
Pass-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

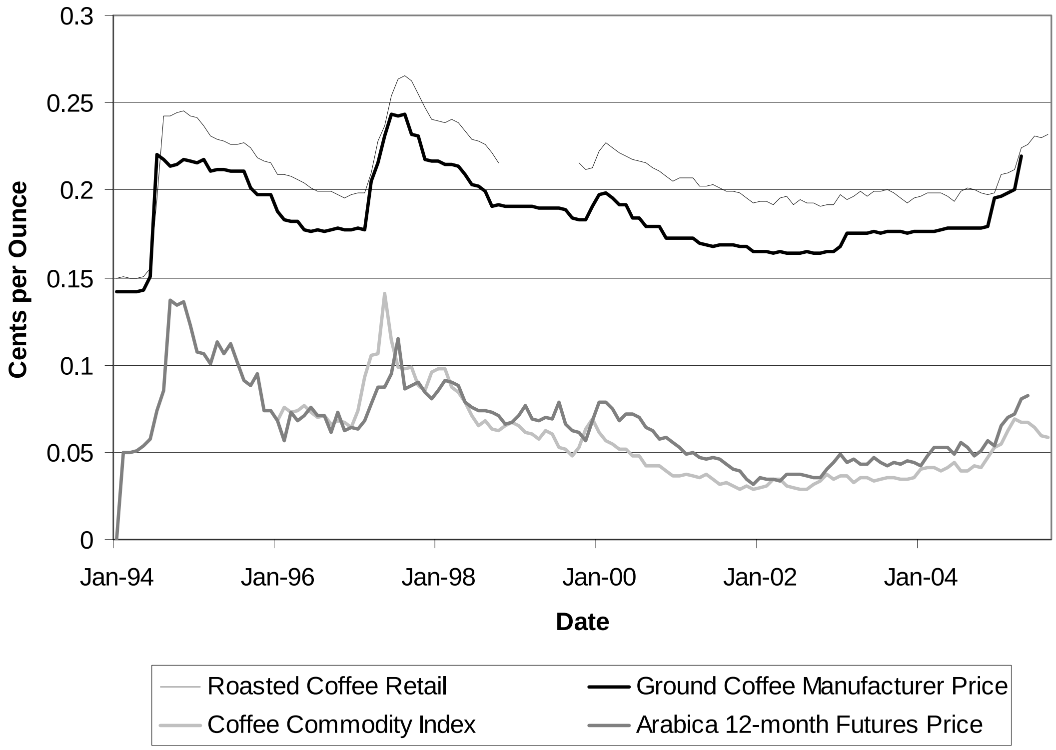
The dependent variable in all of the specifications is the simulated retail price per ounce. The price and cost variables are in logs. The second column repeats the results for the baseline model. Columns 3-4 present pass-through regressions for the cases where ρ_C=0.5 and 0.9 respectively. Columns 5-6 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.

TABLE 11
Menu Cost Estimates (Counterfactual Parameters)

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

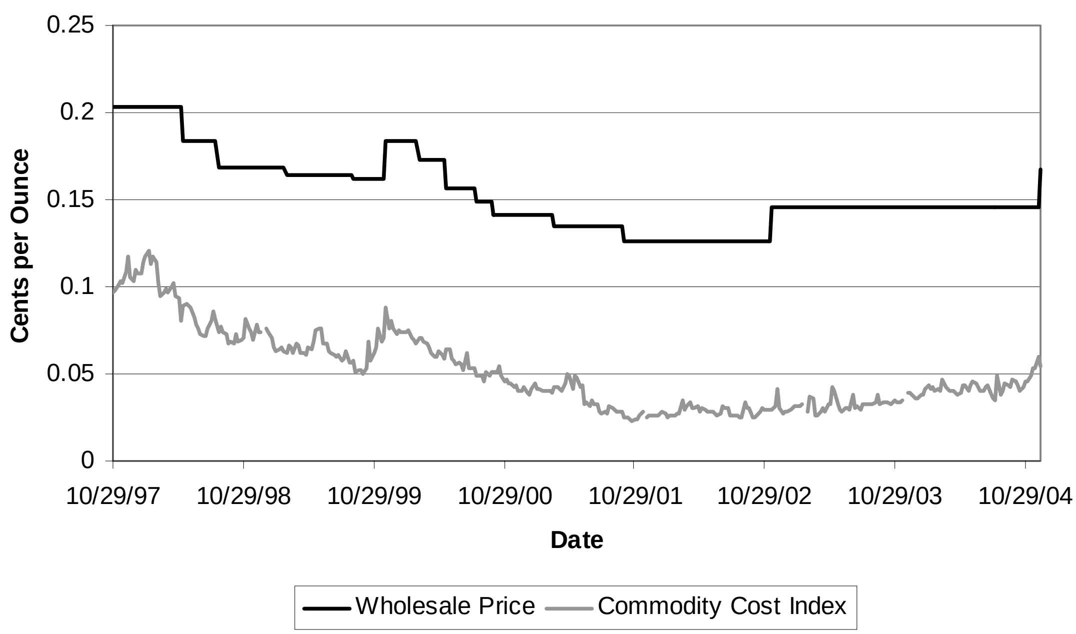
The table presents menu cost estimates as a fraction of average annual firm revenue in the Syracuse market. The first column repeats the baseline results. Columns 3-7 present results for counterfactual parameter values. Columns 3-4 present results for the cases where ρ_C=0.5 and 0.9 respectively. Columns 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.

Figure 1: Retail, Wholesale and Commodity Prices



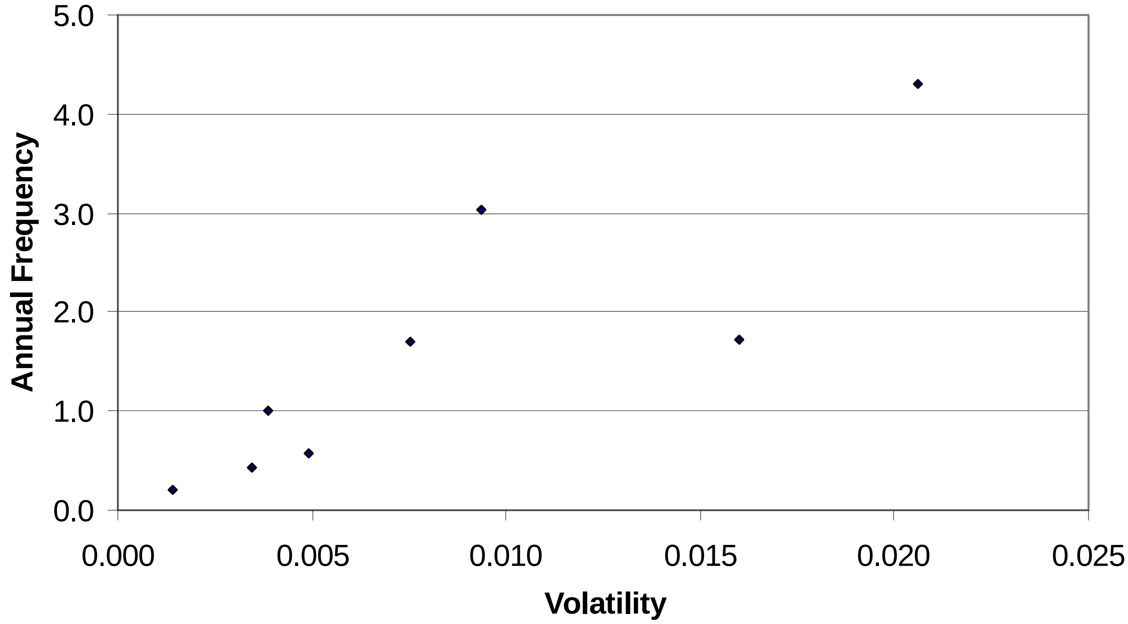
*The roasted coffee retail and ground coffee manufacturer prices are average prices from the Bureau of Labor Statistics database on consumer and producer prices. The Arabica 12 month futures price is from the New York Board of Trade. The coffee commodity index is a weighted average of the prices of different types of green bean coffee. The gap in the retail price series from Nov. 1998 to Sept. 1999 arises from missing data.

Figure 2: A Typical Wholesale Price Series



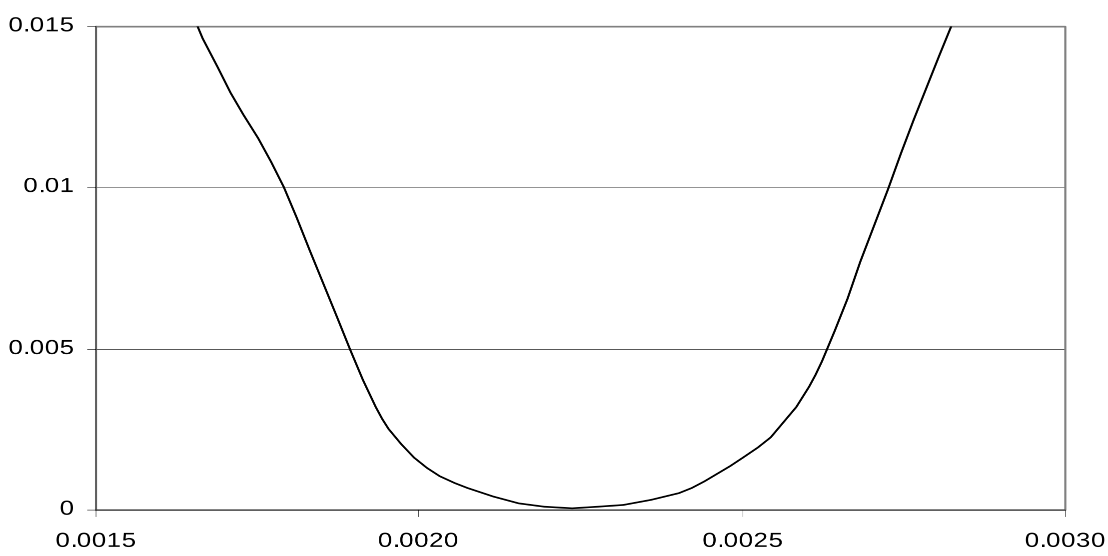
*The gross wholesale price of a leading coffee brand. The coffee commodity price is a weighted average of the prices of different types of coffee on the New York Board of Trade.

Figure 3: Price Change Frequency vs. Commodity Cost Volatility



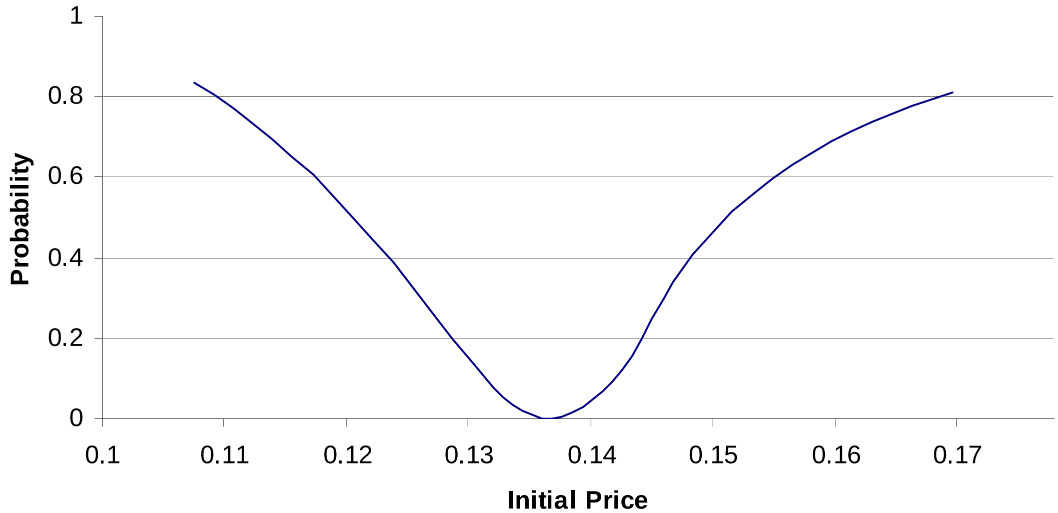
*This figure plots the average annual frequency of price change for the wholesale price (not including trade deals) vs. the volatility of the commodity cost index for each of the years 1997-2004. These statistics are based on weekly wholesale price data for the period 1997-2004. The observations are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

Figure 4: Squared Deviation between Observed and Predicted Price Change Frequency



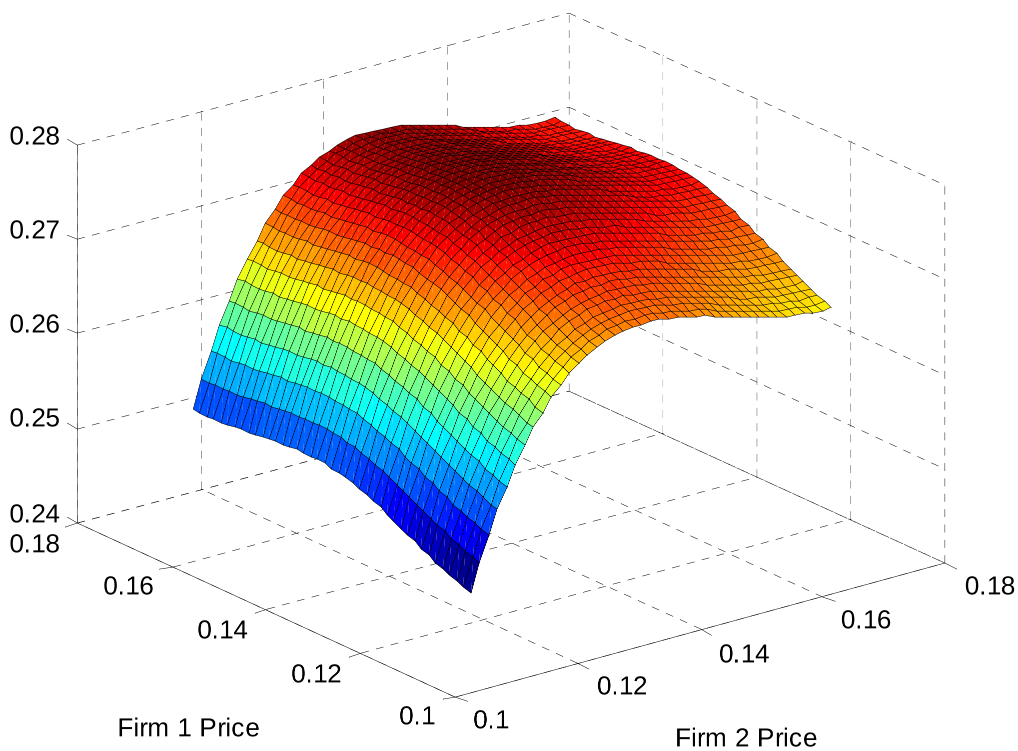
*This figure plots the squared deviation between the average observed frequency of price change over the 2000-2005 period and the frequency of price change predicted by the menu cost oligopoly model as a function of the menu cost. The menu cost is reported as a fraction of average annual retail revenue per firm over the 2000-2005 period.

Figure 5: Probability of Adjustment vs. Initial Price



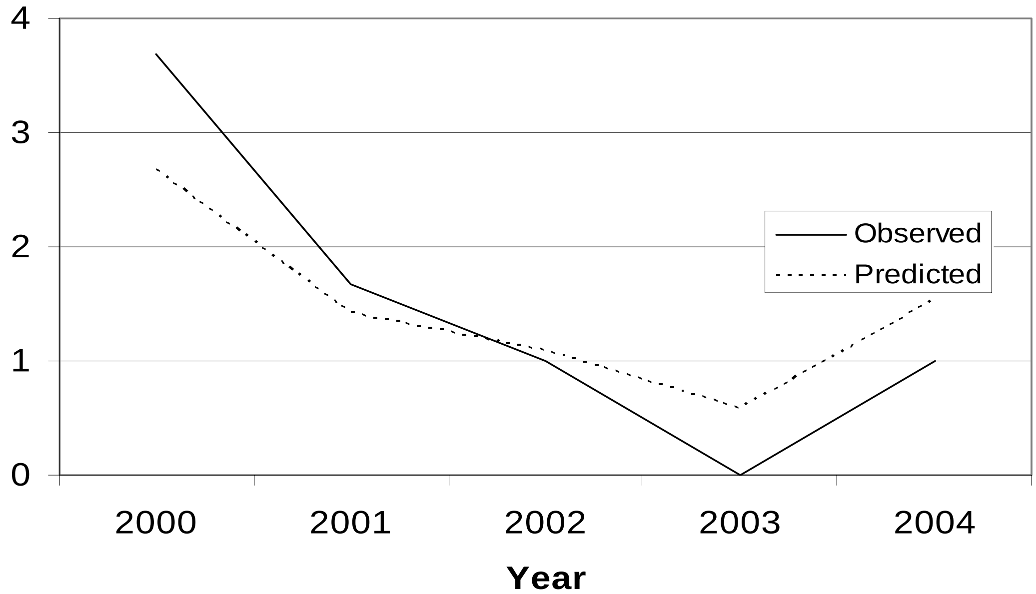
*This figure plots an example of the relationship between the probability of adjustment and the initial price in the menu cost model.

Figure 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.

Figure 7: Predicted vs. 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.