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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. We 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. We 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 using a structural oligopoly model that nests all three potential factors. The implied pricing model explains the main dynamic features of short and long-run pass-through. Local costs reduce long-run pass-through by a factor of 59% relative to a CES benchmark. Markup adjustment reduces pass-through by an additional factor of 33%, where the extent of markup adjustment depends on the estimated "super-elasticity" of demand. The estimated menu costs are small (0.23% of revenue) and have a negligible effect on long-run pass-through, but are quantitatively successful in explaining the delayed response of prices to costs. We 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 is unresponsive to exchange rate fluctuations. As a consequence, if local costs are large, even a substantial increase in the price of an imported factor of production could have little impact on marginal costs. Third, price rigidity and 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).

We 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]

The response of prices to changes in costs is intimately related to the response of prices to exchange rates. Indeed, the equations used to estimate the response of prices to exchange rates are derived from equations that relate prices to marginal costs. In standard exchange rate pass-through regressions, foreign inflation is used to proxy for marginal costs, and prices are regressed separately on costs and exchange rates. The coffee market is an ideal laboratory to study how costs pass-through into prices since a large fraction of marginal costs are observable for this industry. Coffee commodity costs are, moreover, buffeted by large, observable, non-monetary factors. This makes price responses easier to interpret than in the standard case of exchange rate pass-through, since exchange rate movements may be closely linked to monetary factors, at least in the long run, and such factors may have a direct effect on prices, independent of movements in the exchange rate (Corsetti, Dedola and Leduc, 2008; Bouakez and Rebei, 2008).[3]

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 (we refer to this as long-run pass-through). More than half of the price adjustment occurs with a delay of one quarter or more. By wholesale prices, we mean the prices charged by coffee roasters like Folgers and Maxwell House, which we also refer to as manufacturer prices.

[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". We focus instead on incomplete pass-through at the manufacturer and retail level, where imported inputs are an intermediate good.

Reduced form regressions indicate that delayed pass-through in this industry occurs almost entirely at the wholesale level. This evidence suggests that, to the extent that barriers to price adjustment contribute to delayed pass-through in this industry, it is wholesale price rigidity that matters. Recent research on price dynamics has focused on price rigidity at the retail level, partly because retail price data are more readily available to researchers. The finding that, at least in the coffee industry, the majority of incomplete pass-through arises at the level of wholesale prices indicates that studies that focus exclusively on retail prices may be incomplete in an important way.[4] We document substantial rigidity in coffee prices at both the wholesale and retail level: over the time period we consider, manufacturer prices of ground coffee adjust on average 1.3 times per year, while retail prices excluding sales adjust on average 1.5 times per year over the same time period. The frequency of wholesale price adjustment is highly correlated with commodity cost volatility: wholesale prices adjust substantially more frequently during periods of high commodity cost volatility. 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.

We build a structural model of the coffee industry and investigate its success in explaining the facts about pass-through. We begin by estimating a model of demand for coffee. 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. We 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, thereby resulting in a substantially more parsimonious model. We 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. We use these weather shocks as instruments to identify the price elasticity of demand.

We combine this demand model with a structural model of the supply side of the coffee industry. We fix the number of firms and the products produced by the firms to match the observed industry structure. We account for the observed degree of price rigidity by assuming that firms must pay a "menu cost" in order to adjust their prices. According to this model, firms face a fixed cost of price adjustment that leads them to adjust their prices infrequently: we do not take a stand on the sources of the barriers to price adjustment.[5] The barriers to price adjustment imply that the model is a dynamic game. We then analyze the equilibrium response of prices to costs in a Markov perfect equilibrium of this model. In our baseline estimation procedure, we use local costs estimated from

[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. Furthermore, though we do not analyze this channel, retailer-manufacturer interactions may play an important role in determining manufacturer pricing behavior, and may even be one motive for manufacturer-level price rigidity. The role of retail behavior in determining pricing behavior is analyzed in detail by Hellerstein (2005) and Villas-Boas (2007).

[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 we simply make use of the menu cost model as an empirical framework for the price rigidity observed in the data. 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 we discuss below, the data are broadly supportive of both predictions.

a static model in order to avoid the problem of searching over a large number of parameters in the dynamic estimation procedure. We also consider an alternative procedure in which we estimate a common component in marginal costs as part of the dynamic estimation procedure. Incorporating price rigidity in the model is crucial both because of its impact on short-run dynamics and because ignoring these factors could otherwise bias our estimates of the role of local costs and markup adjustment (Engel, 2002).

We find that the dynamic pricing model, estimated using panel data on prices and market shares, replicates the main dynamic features of pass-through in the short and long-run. We use the model to determine the role of local costs, markup adjustment and menu costs in long-run pass-through. We do this by comparing our baseline dynamic model to successively simpler models. We find that local costs reduce pass-through by a factor of 59% relative to a CES benchmark, while markup adjustment reduces pass-through by an additional factor of 33%. Menu costs have a negligible effect on long-run pass-through, though they play an important role in explaining short-run pricing dynamics as we discuss above.[6] Our conclusions underscore the need to allow for additional channels of incomplete pass-through in the large literature in international macroeconomics in which rigid prices are the main source of imperfect adjustment of prices to costs.[7]

In comparing the model to the data, we emphasize three main features of our results. First, in the long-run, markup adjustment in response to cost shocks is substantial: firms are estimated to compress their gross margins on average by a factor of 1/3 in response to a marginal cost increase. This 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, despite a much larger fraction of marginal costs being accounted for by green bean coffee. Klenow and Willis (2006) coin the term "super-elasticity" of demand for the percentage change in the price elasticity for a given percentage increase in prices and show that it is a key determinant of how prices respond to costs in macroeconomic models. While the Dixit-Stiglitz model implies a super-elasticity of demand of 0, we estimate a median super-elasticity of demand of 4.64, generating a substantial motive for markup adjustment.[8]

Second, the menu cost model parameterized to fit the overall frequency of price change is quantitatively successful in matching the short-run dynamics of pass-through. Most of the price adjustment occurs in the quarters *after* the initial change in costs. The menu costs imply a substantial amount of price rigidity: prices adjust only every 9 or 10 months. Yet, menu costs are found to play a negligible role in explaining long-run pass-through after 6 quarters.

Third, our analysis strongly favors the dynamic menu cost model over a pricing model in which firms set prices purely according to a fixed schedule as in the Taylor model (Taylor, 1980) or change prices with a fixed probability as in the Calvo model (Calvo, 1983). The central prediction of the menu cost model is that price adjustments occur more frequently in periods when marginal costs change substantially. While this is an important prediction of the menu cost model, it has been

[6]These results echo the findings of Goldberg and Verboven (2001) for the European car market, as well as the findings of Burstein, Eichenbaum, and Rebelo (2005) for the behavior of tradable goods prices following large devaluations in terms of the large role played by local costs. Our findings are also consistent with the results of Lubik and Schorfheide (2005). For other interesting attempts to distinguish between markup adjustment and price rigidity in explaining exchange rate pass-through see Giovannini (1988) and Marston (1990).

[7]See e.g. Engel (2002) for a discussion of this literature.

[8]See also Bulow and Pfleiderer (1983) for a useful discussion of how the shape of the demand curve affects the response of prices to costs.

difficult to study given the difficulty of observing marginal costs. This prediction of the model is borne out strongly by the data. There is a strong positive relationship between turbulence in the coffee commodity market and the frequency of price change in a given year.[9] Moreover, the observed price rigidity and delayed response of prices to costs can be explained by a plausibly small magnitude of adjustment costs (0.23% of revenue). Small menu costs are found to generate a large amount of price rigidity both because of relatively inelastic demand and because local costs account for a large fraction of marginal costs.

It is worth emphasizing 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 uses information on long-run average prices, demand, and frequency of price change, but does not make use of the empirical evidence on pass-through or the timing of price adjustments.

The predictions of this type of model depend on a number of factors that do not arise in a static context. Since firms consider not only current but future costs in making pricing decisions, pass-through 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 have 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. The unit root case is relevant for the coffee market since we cannot reject the hypothesis that coffee commodity costs have a unit root. Yet, we show that even in the unit root case, dynamic considerations matter for the magnitude of the menu costs required to explain a given amount of price rigidity. We also investigate quantitatively how sensitive our results on both pass-through and the magnitude of the menu cost are to the persistence of costs, the degree of consumer heterogeneity and the model of price adjustment behavior (i.e. menu cost vs. the Calvo (1983) model).

The basic approach we use to study pass-through in this industry builds on recent work by Goldberg and Verboven (2001) and Hellerstein (2005). These papers provide 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, we firm pricing policies in a dynamic framework. The menu cost pricing model in this paper builds on Slade (1998, 1999) and Aguirregabiria (1999) who incorporate menu costs into industrial organization models of price adjustment in order to estimate the barriers to price adjustment. Another closely related paper is Kano (2006) which also solves for the Markov Perfect Equilibrium of a dynamic menu cost model using numerical

[9]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.

methods. 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.[10] 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.

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. The major players in this industry—Proctor & Gamble, Kraft and Sara Lee—are some of the world's largest consumer packaged goods companies, suggesting that studying their pricing behavior in one market may give insights into their behavior in other markets as well. The extent of price rigidity observed in the coffee industry is also typical: the average duration of wholesale prices is approximately 9 months, which is similar to the median duration of prices in the U.S. producer price index (Nakamura and Steinsson, 2008). Our conclusions about the importance of price dynamics at the retail versus the wholesale level may also be useful in understanding price dynamics in other industries. Retailers play an important role in numerous sectors of the economy, particularly food, clothing and household furnishings, which account for more than 30% of US consumption. Understanding the relationship between retail and wholesale prices is therefore crucial in understanding price dynamics for a large part of the US economy. Relative to other industries, imported costs may be a particularly large fraction of marginal costs in the coffee industry—indeed, we selected the coffee industry in part because of the disproportionate share of marginal costs accounted for by imported intermediate goods (coffee beans).[11] Regarding our conclusions about the role of markup adjustment in explaining long-run pass-through, since coffee costs are highly correlated across firms, different coffee producers' incentives to adjust their prices tend to be coordinated. In markets where firms face disparate cost shocks, the incentive for a firm to compress its markup in response to a cost increase may be even greater. Finally, our conclusions regarding the limited role of menu costs in explaining long-run pass-through after 6 quarters depend importantly on the persistence and volatility of commodity costs, but are relevant to pass-through of other highly persistent costs such as exchange rates and wages. Our conclusions regarding the role of menu costs also depend on the nature of strategic interactions implied by our estimated model of demand, as we discuss in section 7.

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 and presents empirical estimates of the demand side of the model. Section 5 presents estimates of local costs derived using a static oligopoly model. We evaluate the robustness of these estimates to dynamic considerations in appendix B. Section 6 presents the full supply side of the model. This section presents the menu cost oligopoly model, as well as our menu cost estimates based on the dynamic model. Section 7 establishes the predictions of the model for incomplete pass-through in the short and long-run, and investigates the relative importance of markup adjustment, local costs and menu costs. Section 8 contains a number of counterfactual

[10] 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.

[11] Of course, some consumer goods are imported in finished form, and only contain local goods in the form of costs of distribution or transportation. However, most imported products are intermediate goods or investment goods rather than final consumer products.

simulations that investigate how our estimates of menu costs and results on incomplete pass-through depend on the persistence of costs, the curvature of demand and the model of price adjustment behavior. Section 9 concludes.

2 Data on Prices and Costs

We pull together data on prices and costs from a number of sources to develop our model of the coffee industry. We use data on prices and sales from two industry sources. Our 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. We use these data to construct series on retail prices and market shares.[12]

We use wholesale price data from PromoData. 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. The data start in January 1997 and end in December 2005. 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 than the retail data. Data are available for 31 of the 50 retail markets, though the time span covered varies by market, leading to an unbalanced panel of observations. Moreover, data are typically only available for the leading products in each market. The wholesale price data have certain advantages over the retail data. In particular, since the wholesale data are prices for individual products from particular manufacturers to a particular wholesaler in a particular week, we can 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 then resells 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. According to a former grocery wholesale executive, since advertising is often carried out collectively by grocery stores associated with a particular wholesaler, in many cases, the funds associated with the trade deal are used by a grocery collective for promotional purposes rather than being passed on to individual stores. The cost pass-through regressions we present are for prices including trade deals, though our results on pass-through are similar both including and excluding trade deals.

The commodity price data are based on commodity prices on the New York Physicals market collected by the International Coffee Organization (ICO). We focus on price responses to a "composite commodity index" that we construct in the following way. We take a weighted average of the

[12]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.

commodity prices for Colombian Mild Arabicas, Other Mild Arabicas, Brazilian and Other Natural Arabicas, and Robustas. We 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. We adjust the commodity price for the fact that roasted green coffee beans lose about 19% of their weight during the roasting process.

To construct the graphs of aggregate series in section 3, we make use of retail and wholesale price indexes from the Bureau of Labor Statistics. In particular, we 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 separately analyze the response of coffee retail and wholesale prices to movements in the prices of different types of green bean coffee.[13] 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 we 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.[14] Figure 1 presents a graph of average retail, wholesale and commodity prices in US dollars per ounce. To be clear about terminology, we shall refer to the price charged by supermarkets to consumers as the *retail* price, the price charged by coffee roasters such as Folgers and Maxwell House to grocery wholesalers as the *wholesale* price, and the price of green bean coffee on the New York market as the *commodity* cost.

The vast majority of coffee sold in the U.S. is imported in the form of green bean coffee (the largest coffee producing countries are Brazil, Colombia and Vietnam). Coffee manufacturers roast, grind, package and deliver the coffee to the American market.[15] Green bean coffee prices were highly volatile over the period we study, 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 value of the U.S. dollar.

We document three facts about prices and costs in the coffee market: 1)the pass-through of coffee commodity prices to retail and wholesale coffee prices, 2)the response of retail to wholesale coffee prices, and 3)the extent of price rigidity in wholesale prices in the coffee industry. First, we document the dynamics of the relationship between prices and costs. Figure 1 shows that retail and

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

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

[15] 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.

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.[16] To quantify this relationship, we 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 virtua.[17] The coefficients b_k may be interpreted as the percentage change in prices associated with a given percentage change in commodity costs k quarters ago. The empirical model follows the approach of Goldberg and Campa (2006). The model is motivated by the fact that, as in Goldberg and Campa (2006), the regressor is highly persistent: a Dickey-Fuller test for the hypothesis of a unit root in commodity prices cannot be rejected at a 5% significance level. Goldberg and Campa (2006) define the long-run rate of pass-through in this model as the sum of the coefficients $\sum_{k=1}^{6} b_k$. We 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. We estimate 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.[18]

Table 1 presents the results of the pass-through regression for retail and wholesale prices. We present estimates from two types of pass-through regressions. Columns 1 and 2 of table 1 present the results of the standard pass-through regression (1). The results reflect 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. We do not find evidence that prices systematically react asymmetrically to price increases or decreases.[19] This finding is consistent with the findings in Gomez and Koerner (2002) for the US, France and Germany. 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.[20] It is, of course, also possible to estimate standard exchange rate pass-through regressions instead of cost pass-through regressions.

[16] 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.

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

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

[19] We considered asymmetries in the response of prices to commodity costs at 1-4 lags. See Leibtag et al. (2005) for a more detailed discussion of this issue.

[20] Similar patterns of delayed and incomplete pass-through are found for the coffee market by the UK Competition Commission (1991).

Interestingly, these exchange-rate pass-through regressions yield substantially lower estimates of pass-through: 0.21 and 0.04 respectively, again with the majority of pass-through occurring after the initial quarter.

One might be concerned that long-term contracts for purchasing green bean coffee imply that the average purchasing price of coffee manufacturers may differ from the coffee commodity price. Yet, 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, so long as the firm is always on the margin of buying or selling at the observed commodity cost.

Columns 3 and 4 of table 1 present the results of the pass-through regression (1) in levels rather than logs. 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.[21] The difference between the regressions in levels and logs is explained by the substantial wedge between observed prices and marginal costs, which implies that a one cent change corresponds to a substantially smaller percentage change in prices than costs.[22] 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. Yet, a pass-through elasticity of 1 is an appealing benchmark both because it arises in the workhorse Dixit-Stiglitz model (absent local costs) and because it is only possible to calculate pass-through elasticities (rather than levels) using standard data sources on price indicies.[23]

Second, we document the responsiveness of retail prices to manufacturer prices. This analysis investigates 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, we consider the following

[21] An alternative approach would be to estimate a panel error correction model. We cannot reject the null of no cointegration of coffee prices and coffee bean costs in aggregate data over the time period we consider. Nevertheless, as a robustness check, we also estimated a number of specifications that allow for a cointegrating relationship between prices and green bean coffee costs. We estimated a vector error correction model (with a restricted constant) for aggregate data on ground coffee manufacturer prices and the commodity cost index (the data series underlying Figure 1) for the 1994-2005 period. This model implied similar results to specification 1: approximately cent-for-cent pass-through in the long-run with less than half of the pass-through occurring in the first quarter, though the parameter estimates were much less precise. Estimating panel vector error correction models for panel data remains econometrically challenging (Breitung and Pesaran, 2005) and a full analysis of these issues is beyond the scope of this paper. However, we also reestimated specification 1 in both levels and logs while including, as a vector error correction term, the price minus the commodity cost. These specifications yielded almost identical results to those reported in Table 1.

[22] 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. According to this metric, temporary sales contribute little to overall pass-through, though it is unclear how to interpret this fact given the complex dynamic response of demand to temporary sales.

[23] We also 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. We find similar results. The resulting estimates of long-run pass-through are 0.968 for retail prices and 0.960 for wholesale prices.

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, we estimate this equation by instrumental variables regression with commodity costs as instruments.[24] 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.

Third, we 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.[25] P&G commented to reporters in conjunction with its 2004 price increase that P&G "increases product prices when it is apparent that commodity price increases will be sustained". (Associated Press, Dec. 10 2004). Table 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 (2008). 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.[26]

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. These patterns reflect a large amount of synchronization in price-setting that coincides with times of high commodity cost volatility: in the quartile with the lowest

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

[25] These statistics are based on price change announcements reported in the Lexis Nexus news archive.

[26] 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. We 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. We estimated the regression, $\Delta \log p^r_{jmt} = \eta^0 + \sum_{k=0}^{1} \eta^C_k \Delta \log C_{t-k} + \sum_{k=0}^{1} \eta^r_k \Delta \log p^w_{jmt-k} + \sum_{k=1}^{4} \gamma^r_k q_k + \epsilon$, by instrumental variables regression with the same instruments used to estimate equation (2). The current wholesale price p^w_{jmt} had a coefficient of 1.001 while the remaining coefficients are statistically insignificant at standard confidence levels.

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.

4 Consumer Demand

The first building block of my structural model of the coffee industry is a model of consumer demand. We estimate a random coefficients discrete choice model for demand (Berry, Levinsohn and Pakes, 1995).[27] In this model, the consumer is assumed to select the product that yields the highest level of utility, where the indirect utility of individual i from purchasing product j takes the form,

$$U_{ijmt} = \alpha_i^0 + \alpha_i^p (y_i - p_{jmt}^r) + x_j \beta^x + \xi_{jmt} + \epsilon_{ijmt}, \tag{3}$$

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.[28] We 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, we 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, in ounces of coffee, 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, while still allowing for a substantial amount of flexibility in substitution patterns. To build intuition, we begin by estimating the logit model, a simplified version of the full 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,

$$\log s_{jmt} - \log s_0 = \alpha^0 - \alpha^p p_{jmt}^r + x_j \beta + \xi_{jmt}, \tag{4}$$

where α_0 is a constant. We 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.[29]

To give a feel for the market structure of the coffee industry, let us note that some of the largest coffee manufacturers in the U.S. are Folgers and Maxwell House, which are owned by Proctor & Gamble and Kraft Foods respectively. The market for ground coffee is highly concentrated. Across markets, the median Herfindahl index is 0.34 and the median fraction of coffee sales accounted

[27] 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.

[28] 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).

[29] This is fairly standard in the literature that estimates discrete choice demand models using supermarket data. See e.g. Nevo (2001). Many retailers do not stock multiple UPC's within a brand-size category, suggesting that this may be a more appropriate specification than one based on individual UPC's.

for by Folgers and Maxwell house alone is 0.80. On average, each brand produces two sizes of ground caffeinated coffee, and three distinct coffee UPC's. Among consumer packaged goods, "store brands" account for relatively small fraction of total sales (4.7%).

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.[30] To estimate the model, it is necessary to define the total potential market M. We 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.[31]

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 5 (OLS1) presents estimates of equation (4) 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. The advertising data are brand-level monthly national total advertising dollars per brand from the AdDollars database This specification yields an inelastic demand curve for the majority of products and time periods: the median price elasticity is 0.54.[32] An obvious potential explanation is the endogeneity problem described above.

The panel structure of the data implies that we 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 5 (OLS2) presents estimates for the logit model including brand-region fixed effects.[33] Including fixed effects dramatically increases the estimated price elasticity: the median price elasticity for the logit model including brand-region fixed effects is 1.96.

The inclusion of brand-region fixed effects does not, however, fully alleviate the endogeneity problem since demand shocks may be correlated with prices over time. We compare the implications of a number of alternative approaches for instrumenting for prices and advertising. In the third column (IV1), we 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). We refer to these instruments as Hausman instruments. The median price elasticity estimate given this instrumentation strategy is considerably higher than the OLS estimates: it is 3.02. The fourth column (IV2) presents the results of using commodity

[30] A simplifying feature of this market is that the leading ground coffee products have remained essentially unchanged over this time period. Product entry and exit has therefore not been a major factor in driving demand.

[31] 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%.

[32] In all of the regression estimates, we 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.

[33] We divide the U.S. into four regions: Northeast, Midwest, South and West using the suggested divisions in the CPS. As in Nevo (2001), the remaining cross-sectional price differences (across markets) help to identify the cross price-elasticities in some of our empirical specifications.

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 (IV3) presents results using the Brazilian and Colombian exchange rates as instruments. This yields a slightly lower price elasticity of 2.34.

The sixth column (IV4) presents the results from using weather instruments: lagged minimum and maximum temperatures for the Sao Paulo-Congonhas (Brazil) and the Cali-Alfonso Bonill (Colombia) weather stations as instruments. We 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 R^2 of 23% in explaining average monthly retail prices (27% for non-sale retail prices) and 13% in explaining average monthly advertising expenditures, once the series are adjusted for a year trend and a dummy for Christmas.[34] This approach yields a price elasticity of 3.2. Since the weather instruments have the advantage that they are least likely to be plagued by endogeneity concerns, we focus on this instrumentation strategy in the random coefficients estimates below.

A disadvantage of the logit model noted by many authors is that it implies unrealistic substitution patterns. For example, as 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. One way of generalizing the model is to allow for heterogeneity in individual preferences (Berry, Levinsohn and Pakes, 1995). In our baseline results, we estimate a simple version of the random coefficients model—equation (3)—in which an individual's price sensitivity as well as the mean utility of purchasing coffee is allowed to vary with his or her household income.

$$\alpha_i = \alpha + \Pi \tilde{y}_i, \tag{5}$$

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 we consider. We 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).[35] This model allows for both heterogeneity in income within individual markets and variation in the mean and variance of the income distribution across markets. A negative value for Π_{yp} indicates that higher income consumers are less responsive to prices. This parameter has important implications for the curvature of demand: if there is a substantial amount of heterogeneity in price sensitivity across consumers (Π_{yp} is large in absolute value), then as a firm raises its price, its consumer base is increasingly dominated by households with low price sensitivities, lowering the price elasticity faced by the firm.

Let us now describe our estimation procedure for our full demand model. It will be useful in describing the procedure 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

[34] This paper does not present a theory of how advertising expenditures are chosen. It is not clear why the weather instruments would be useful instruments. It turns out, however, that average monthly advertising expenditures are significantly positively correlated (over time) with average monthly prices, with a correlation coefficient of 0.48.

[35] We 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.

term that reflects individual deviations from this mean.[36] 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 basic estimation approach of Berry, Levinsohn, and Pakes (1995) relies on two sets of moments,

$$\begin{aligned} s_{jmt}(\delta_{jmt}, \Pi_y) - \hat{s}_{jmt} &= 0, \quad (6) \\ E(\xi_{jmt} z_{jmt}) &= 0, \quad (7) \end{aligned}$$

for all j, m, t, where $\hat{s}_{jmt}$ are the empirical market shares and the z_{jmt} are the instruments. We 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 parameters relating to consumer heterogeneity, so we have, Π_{yp} and Π_{y0},

$$E(s_{jkmt}(\delta_{jmt}, \Pi_y) - \hat{s}_{jkmt} | d_j) = 0, \quad (8)$$

where d_j is a dummy variable for brand j, and k is an income group. These moments match the model's predictions for market shares *within* particular income groups to the market shares observed in the data. 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.[37]

We estimate the model using a two-stage GMM estimation procedure. Stacking the moment conditions (6) -(8) yields the vector of moment conditions $G(\theta)$ where θ is a vector of parameters to be estimated, where the vector θ^0 denotes the true value of these parameters, and where $E[G(\theta^0)] = 0$. The GMM estimator is,

$$\hat{\theta} = \text{argmin}_\theta G(\theta)' W G(\theta), \quad (9)$$

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.[38] The market shares implied by the model in (6)-(8) are simulated using 250 draws of income y_i. The standard errors for the coefficients are based on standard GMM formulas (Hansen, 1982) where we 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.[39]

The estimated coefficients for the random coefficients model are presented in the last column of Table 5. 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.[40] This price elasticity estimate is very similar to the estimate of price

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

[37] 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.

[38] The asymptotic variance-covariance matrix of $G(\theta)$ is block-diagonal since the sources of error from the two moments are independent. The part of the variance-covariance matrix associated with the demographic moments is calculated using the procedure described in Appendix B.1 of Petrin (2002b). We 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.

[39] We 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).

[40] We 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.

elasticity for manufacturers reported by Foster, Haltiwanger, and Syverson (2005)—3.65—despite the fact that these two estimates are obtained using entirely different estimation strategies.[41] Our estimate implies a slightly more elastic demand curve than the the median price elasticities for individual varieties obtained by Broda and Weinstein (2006) for a broad range of products. Broda and Weinstein (2006) estimate a median price elasticity of 3.1 for individual product varieties of imported goods for the period 1990-2001. The main advantage of our estimation procedure compared to Broda and Weinstein (2006) is that, because we focus on a particular industry, we are able to account for the potential endogeneity of prices using instrumental variables. More generally, the price elasticity estimates we 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 since it affects the curvature of the demand curve. We 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 significantly different from zero at standard confidence levels.

A key determinant of the response of prices to changes in costs is the "super-elasticity" of demand–the percentage change in the price elasticity for a given percentage increase in prices (Klenow and Willis, 2006). The workhorse Dixit-Stiglitz demand model has a super-elasticity of zero, implying a constant markup under monopolistic competition. A positive super-elasticity of demand implies that as a firm raises its price, the price elasticity it faces increases. We estimate the super-elasticity of demand to be 4.64 in the random coefficients model. In other words, a 1% increase in prices leads to a 4.64% increase in the price elasticity of demand. This generates a substantial motive for the firm to adjust its markup.

Since the demand curve is an important input into our empirical exercise, we also carried out a number of robustness exercises. In addition to our baseline random coefficients demand model, we also estimated a specification that allows for an additional degree of heterogeneity in consumer preferences that is unrelated to income,

$$\alpha_i = \alpha + \Pi \tilde{y}_i + \Pi_\nu \nu_i, \tag{10}$$

where ν_i is distributed normally with mean zero and variance one. Since this specification is difficult to identify using only time series variation in prices, we estimated the model using both the weather instruments and the Hausman instruments described above. The Hausman instruments have the advantage that they vary across different products, as well as over time. This specification yields estimates of $\Pi_{yp} = -3.42$, $\Pi_{y0} = -0.91$ and $\Pi_\nu = -3.08$, with an implied median price elasticity

[41] Foster, Haltiwanger, and Syverson (2005) estimate price elasticities of demand for individual plants in the ground coffee market using a linear demand model and plant-level productivity as instruments.

of 3.96 and a super-elasticity of 5.04. As an additional robustness check, we also re-estimated our baseline specification of the random coefficients model using only the BLP moment conditions, equations (6) and (7), using the original weather instruments. While this approach yields must less precise estimates, it has the advantage that it relies less on the structure of the model, since in this case, the curvature of the demand curve is estimated purely based on time series variation in prices and costs. Again, this estimation approach yields similar point estimates of the key parameters to the baseline approach. This estimation approach yields a median price elasticity of 3.96 and a median price super-elasticity of 4.37.

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 total marginal costs by only a small fraction. Local costs are also important in determining the magnitude of adjustment costs, since they affect the incentives of a firm to adjust its price in response to a given change in commodity costs.

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.[42] 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 we know exactly how many ounces of green bean coffee are used to produce a given quantity of ground coffee, we can then obtain estimates of the local costs of production by subtracting commodity costs from the inferred marginal costs.[43]

We will ultimately be interested in a dynamic model of pricing that allows for price rigidity. We begin, however, by inferring markups for a static Nash-Bertrand equilibrium (Bresnahan, 1987; Berry, Levinsohn and Pakes, 1995). To avoid searching over a large parameter space as part of the dynamic estimation procedure, we use the estimates of local costs from the static model in the baseline parameterization of the dynamic model analyzed in section 6. This procedure is exactly correct if the introduction of menu costs only affects the dynamic response of prices to costs, but does not affect the level of prices. This holds exactly in some simple dynamic models with quadratic loss functions (e.g. Dixit, 1991). This property does not hold in the present model because of asymmetries in the profit function and strategic interactions that imply that certainty equivalence does not hold. To gauge how different this approach is from estimating local costs as

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

[43] 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).

part of the dynamic estimation procedure, we also consider an alternative approach in section 6 in which we estimate a common component of 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. We fix the number of firms and the products produced by the firms to match the observed industry structure. For example, Folgers and Maxwell House dominate the market for ground roasted coffee with a combined market share by volume of over 65% in many U.S. cities. Firm j's per-period profits π_{jmt} in a market m at time t may be written,

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

where mc_{kmt} is the marginal cost of producing the product, F_{km} is a fixed cost, Υ_j is the set of products produced by firm j, and M is the size of the market. We 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 empirical response of retail prices to wholesale price changes documented in section 3.[44]

We 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 as $-\partial s_{kmt}/\partial p^r_{jmt}$ for $k, j = 1, ..., J$, and the matrix $\hat{\Omega}$ is defined such that the element $\hat{\Omega}_{kj}$ equals 1 if the same firm owns both products k and j, 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 absolute 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.

We 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 6 presents summary statistics on the percentage markup of price over marginal cost implied by this procedure. Throughout this paper, we follow the convention in international economics and define the markup

[44]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 makes these issues challenging to analyze in our data.

as $(p - mc)/mc$. The median percentage markup of price over marginal cost is 58.3%. These estimates of the percentage markup are not unusual for consumer packaged goods industries. For example, Nevo (2001) estimates a median markup of about 67% for the ready-to-eat cereal industry. Villas-Boas (2007) estimates wholesale markups in the range of $25 - 100\%$ for yogurt.[45]

To obtain estimates of the local costs of production, we 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 6 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, we therefore extend the model to allow for adjustment costs in price-setting. The model builds on previous menu cost models estimated using dynamic methods by Slade (1998, 1999) and Aguirregabiria (1999). The model we use is, however, somewhat different from existing menu cost models due to the oligopoly framework. In particular, we 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.

The model is formally related to the dynamic oligopoly model studied by Pakes and McGuire (1994).[46] It is not possible to solve analytically for the Markov perfect equilibrium of the model. Therefore, we adopt methods from this literature (e.g. Benkard (2004)) to numerically solve for the equilibrium pricing policies of the firms. The equilibrium concept that we adopt is a Markov perfect Nash equilibrium, where the strategy space consists of firms' prices (Maskin and Tirole,

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

[46] As in the dynamic oligopoly literature, the assumptions that the adjustment cost is random and that it is private information are 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 dynamic oligopoly models. While the present model is related to the dynamic oligopoly models studied by Pakes and McGuire (1994) and Doraszelski and Pakes (2006), the dynamic pricing game we study is not formally equivalent to these models.

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.

We 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. We 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.[47]

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, and $1(\Delta p^w_{jmt} \neq 0)$ is an indicator function that equals one when the firm changes its price. Equation 15 assumes that, though each firm produces multiple products, its pricing decisions across products are coordinated. We discuss this assumption below. Each firm maximizes profits. We 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., $F(\gamma_{jmt}) = 1 - \exp(-\frac{1}{\sigma}\gamma_{jmt})$. The firm's draw of the menu cost γ_{jmt} is private information. In every period, the pricing game has the following structure:

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

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

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

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, the pricing rule $p^w_j(p^w_{mt-1}, C_t)$ for all firms $j = 1, ..., B$ gives the firm's price *if*

[47] We are 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. We 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.

it decides to change its price. Second, the probability function $\text{pr}_j(p^w_{mt-1}, C_t)$ 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 a firm chooses optimal policies (i.e. the Bellman equation (16) is satisfied), and the firm's expectations are consistent with the equilibrium behavior of the firm's competitors. As we note above, the firm's strategy is restricted to be Markov; i.e., to depend only on the payoff-relevant state.

To make the problem computationally tractable, we make the following simplifying assumptions. First, we 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). So we have,

$$p^w_{kmt} = p^w_{jmt} + \alpha_k, \tag{17}$$

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 owned by the same brand.[48]

Second, we assume that retail prices equal wholesale prices plus a known constant margin ξ_k,

$$p^r_{kmt} = \xi_k + p^w_{kmt}. \tag{18}$$

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

$$mc_{kmt} = \mu_k + C_t. \tag{19}$$

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, we also assume that the firm faces constant returns to scale in production.[49]

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 $N(0, \sigma^2_C)$ and σ^2_C, a_0 and ρ_C are known coefficients. Since a unit root in commodity costs cannot be rejected at standard confidence levels, we 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 we discuss in section 7. For computational reasons, we 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,

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

[48] Conditional on at least one product from a particular brand adjusting in a given month, the probability of adjustment across all products is 93.8% over the 1997-2005 period.

[49] This specification is consistent with the fact that the share of total variable costs accounted for by green bean coffee rises, as reported in the Annual Survey of manufacturers, rises 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).

where W_{ch} is the discounted expected value of the firm if it adjusts its price and W_{nch} is the discounted expected value of the firm if it maintains a fixed price, based on the firm's expectations regarding its competitors' prices. (Recall that the menu costs of a firm's competitors are assumed to be private information.) 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.

We solve the model numerically using the computational algorithm described in appendix A. The algorithm is conceptually straightforward but computationally intensive. We begin with some initial values of the firms' pricing policies. For a given firm, say Firm 1, we solve for the optimal dynamic pricing policy conditional on the initial pricing policies of its competitors by value function iteration. We use the solution to this problem to update the assumed pricing policy for Firm 1. Next, we solve for Firm 2's optimal dynamic pricing policy, conditioning on the updated pricing policy for Firm 1. We repeat this exercise until the maximum differences in the firms' pricing policies between successive iterations are sufficiently small. Once this point is reached, we run our algorithm for an additional 1500 iterations to check that the equilibrium does not change.

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. We focus on a representative market: the Syracuse market. The Syracuse market has a representative market structure dominated by P&G (Folgers), Kraft (Maxwell House) and Sara Lee (Hills Brothers). The average annual revenue in the Syracuse market is approximately 3 million dollars, which is close to the median across markets in my sample. Each brand produces two different products according to the definition discussed in section 4, so we have two products per firm and 6 products in total.

We parameterize the demand curve according to the random coefficients discrete choice model estimated in section 4. The demand curve estimation procedure is entirely independent of our assumptions about the supply side of the model. We do, however, need to rely on the implications of our model for average prices in determining the local cost parameters. In our baseline specification of the dynamic model, we make use of the estimates of average non-coffee costs, μ_{km}, implied by the static pricing model described in section 5. Specifically, we take μ_{km} 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 a quadratic loss function (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 that imply that certainty equivalence does not hold.[50] To gauge the robustness of the procedure used to estimate local costs, we also consider an alternative approach in which we 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. We 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.

We parameterize the retail margin ξ_k as the average difference between retail and wholesale prices for a particular market and brand. Moreover, we parameterize the average price difference α_k in equation (17) as the average observed difference in retail prices. We also condition on the observed value of wholesale prices in the period before the simulations begin (1999 Q4). We 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. We 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, we use the following procedure in selecting the menu cost parameter. For different values of the menu cost parameter σ, we simulate the model for the actual observed values of the commodity cost index over the 2000-2005 period. We 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 overall frequency of price change predicted by the model (across all time periods and brands), and $\hat{f}$ is the actual average frequency of price change excluding trade deals over the 2000-2005 period.[51] The average frequency of price change excluding trade deals over this period was 1.3 times per year or a monthly frequency of about 11%.[52] Figure 4 presents a diagram of L for different values of σ, where σ is reported 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 we consider.

[50] Empirically, asymmetries in the profit function imply that the losses to the firm from setting the price suboptimally low are greater than the losses from setting the price suboptimally high, where the deviations in the upward and downward direction are by the same amount. In our quantitative analysis of this issue below, we find that the average dynamic optimal price is typically slightly higher than the average static optimal price.

[51] 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.

[52] 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 we discuss in section 3, trade deals are relatively unimportant in explaining cost pass-through in this market.

Table 7 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. An advantage of the loss function (25) that we consider is that it is easy to minimize with numerical methods because it is a well-behaved function with a unique local minimum.[53]

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, we use a numerical estimate of the derivative of the loss function with respect to the parameter estimate. We estimate the variance of the sample moment using a parametric bootstrap.[54] 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%.

There are few existing estimates of the costs of price adjustment at the manufacturer level. Zbaracki et al. (2004), estimate that costs of price adjustment account for 1.22% of annual revenue in a large industrial firm based on direct measures of the costs of price adjustment. Goldberg and Hellerstein (2007) estimate lower and upper bounds for menu costs in the beer industry of between 0 and 0.443% of revenue.[55] Aguirregabiria (1999) and also Levy et al. (1997) estimate menu costs of 0.7% of revenue, though these estimates are less directly comparable to ours since they refer to retailer rather than manufacturer-level barriers to price adjustment. Slade (1998) estimates retail menu costs of $2.70 per price change for a particular retail store, but does not report the magnitude of the menu costs relative to annual revenues.

6.3 Equilibrium Pricing Policies

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 is $0.138 per ounce. At this price, the probability of adjustment is zero. The probability that the firm will adjust its price

[53] As a robustness check, we also considered two alternative estimators. We considered an estimator based on a loss function similar to (25), but defining f and $\hat{f}$ as vectors, with each element of the vectors defined as the average frequency of price change in a particular year. We also considered an analogous estimator, with each element of f and $\hat{f}$ defined as the average frequency of price change for a particular product. These alternative estimation approaches yielded similar results to our baseline approach, though the resulting loss functions were somewhat less smooth than in our baseline estimation approach.

[54] Specifically, we evaluate the sample moment for alternative draws of costs from the assumed Markov process for costs. We 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.

[55] Goldberg and Hellerstein (2007) estimate a static model of price adjustment while we estimate a dynamic model. We discuss this issue further in section 7.

increases monotonically with the distance from the dynamic optimal price.

The fact that firms only adjust their prices if they deviate sufficiently far away from the dynamic optimal price causes prices to respond in a delayed fashion to costs. The intuition is the following. In the first period after a shock, firms have a low probability of adjusting immediately in response to a change in costs. As shocks accumulate, however, the firm's probability of adjusting grows. Eventually, the firm adjusts to the new dynamic optimal price which reflects all of the cost shocks that have accumulated since its last price change. This pricing behavior leads to delayed pass-through of costs into prices.

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 most (but not all) cases, 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's dynamic optimal price lies above its price in the previous period. Since Firm 3's price and its competitors' prices are strategic complements, 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. Non-monotonic relationships of this nature arise frequently in this pricing game for the following reason. Firm 3 cares about the past prices of its competitors only through their potential effect on current prices. As a competitor's time $t-1$ price rises, it becomes increasingly likely that the competitor will readjust its price downward in period t—and this, in turn, lessens Firm 3's incentive to raise its price.

7 Dynamic Pricing Implications

In this section, we analyze the implications of our model for short and long-run price dynamics. We begin by investigating whether the model can generate quantitatively realistic predictions for the timing of price adjustments, a key determinant of short-run price dynamics. To do this, we simulate the model for the actual sequence of costs over the 2000-2004 period based on the equilibrium policy rules. For each simulation, we draw new values of the firms' menu costs. We then calculate the average frequency of price change by year across the simulations. We 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. In the model, as in the data, the frequency of wholesale price change is strongly positively related to the volatility of commodity costs: the minimum average frequency of price adjustment in both the model and the data occurs in 2003, while the maximum occurs in 2000. The model is also able to explain a substantial component of the short-run dynamics in the timing of price adjustments. The observed pattern of price adjustments strongly favors menu cost models over pricing models in which firms set prices in a purely "time-dependent" fashion. A central prediction of the menu cost model is that price adjustments occur more frequently in periods when marginal costs change substantially. This prediction has typically been challenging to test given the difficulty of observing marginal costs. In contrast, time dependent models of price-setting in which firms set prices according to a fixed schedule (Taylor, 1980) or adjust prices with a fixed probability (Calvo, 1983) predict that the timing of price adjustments is unrelated to changes in costs. The finding that the timing of price changes responds to movements in costs also contrasts with the predictions of "rational inattention" models of price adjustment in which firms are assumed to have a limited capacity to process information (e.g. Mackowiak and Wiederholt, 2008). A shortcoming of the model revealed by figure 7 is that the frequency of price change covaries even more with commodity cost volatility in the data than the model. For example, the frequency of price change falls even more between 2000 and 2003 in the data than in our dynamic pricing model.[56]

To provide more insight into the timing of price adjustments, figure 8 depicts the frequency of price change at a quarterly frequency for the model vs. the data. The local peaks in the probability of price change in the model and the data coincide closely in 4 of 5 cases (in the fifth case, there is a peak in the simulated data in 2004Q1, but no corresponding peak in the data). The figure also plots the absolute value of the commodity cost change over the course of the corresponding quarter (measured on the right-hand axis). While there is a clear positive correlation between the magnitude of commodity cost movements and price adjustments at low frequencies, the relationship is more complex at a quarterly frequency. For example, the absolute movement in coffee commodity costs is particularly high in early 2002 relative to the previous or subsequent months, but the probability of price change is particularly low in both the model and the data. In the model, the low correlation between commodity cost movements and price adjustments at high frequencies is explained by the fact that commodity cost movements must build up for several quarters before a firm has an incentive to adjust. It is therefore the cumulative movement in commodity costs over several quarters that matters, rather than the movement in any particular quarter. This low correlation between the timing of price adjustments and commodity cost movements at high frequencies is also present in the data.[57]

Next, we analyze the dynamics of the short-run response of prices to costs. We estimate a cost pass-through regression of the form of equation (1) for the simulated data. Figure 9 depicts the impulse response function of wholesale prices in response to a given percentage change in commodity costs. The impulse response is constructed from the estimated pass-through regression for wholesale prices using the simulated data. The model generates quantitatively realistic predictions for the short-run dynamics of prices. We find that in the model as in the data, less than half of the long-run response of prices to costs occurs in the quarter of the shock. The impulse response for model fits the data particularly well for the first two quarters after the shock to costs. There is a slightly greater responsiveness of prices in the third quarter after the shock in the model than in the data.

The short-run dynamics of prices are driven by two factors: the frequency of price adjustment and strategic interactions among firms. It goes without saying that there can be no price response to an exchange rate change so long as the price remains unchanged. But even once the price adjusts, if prices are strategic complements, then the failure of one firm to adjust to a movement in exchange rates leads another firm to delay adjustment as well (Bulow et al., 1985). In this way, strategic

[56]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. However, the exponential distribution leads to important simplifications in terms of both simulation and estimation. We therefore leave this generalization to future research.

[57]The statistics for the model are averages over a very large number of price simulations, so it is not surprising that the empirical series exhibits somewhat more "spikiness" than the corresponding theoretical series.

complementarities among prices can substantially amplify the delays in price adjustment associated with price rigidity. We find, however, that these effects are quantitatively small for our estimated model. Almost all of pass-through takes place within three quarters, which is slightly longer than the average duration of prices in the model. One reason why strategic complementarity has a limited ability to amplify delays in pass-through due to price rigidity is that there is a substantial amount of coordination in the timing of price adjustments around times of large movements in commodity costs.

The model also yields quantitatively realistic predictions for long-run pass-through. The fourth column of table 8 presents the results of a pass-through regression using the simulated data. Long-run pass-through for the simulated data into retail prices is 0.272 vs. 0.252 in the data. Thus, the model successfully explains almost all of the incomplete pass-through observed in the data.

It is worth emphasizing 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 menu costs are estimated based on the frequency of price change over the entire sample period. The demand curve estimation procedure is based purely on the response of consumer demand to fluctuations in prices—the estimation procedure does not make use of information regarding firm's pricing behavior. The estimates of local costs make use of the average difference between prices and green bean coffee costs over the entire sample period for each product, as well as the demand system estimates, but again do not make use of any information on how prices respond to movements in costs. The model's implications for pass-through depend on properties of the demand curve, the estimated menu costs, as well as the specification of the supply side of the model. We discuss how these factors affect pass-through in greater detail in section 8.

We next use the dynamic model to investigate the sources of long-run incomplete pass-through. In evaluating this question, the Dixit-Stiglitz pricing model serves as a useful benchmark both because it is the workhorse model of demand in international economics and because, as is well-known, this specification implies a constant markup pricing rule. This allows us to quantify the effect of introducing the estimated random coefficients demand curve on the extent of markup adjustment by firms.[58]

Table 8 presents the results of pass-through regressions for simulated data from each of the four alternative pricing models. The first specification is the standard monopolistic-competition Dixit-Stiglitz model. The second specification introduces local costs. In this specification, we again assume the Dixit-Stiglitz demand model, but we allow for local costs parameterized according to equation (24) and a retail margin parameterized by equation (18).[59] This specification implies a long-run pass-through of 0.407.

The third specification incorporates markup adjustment as well as local costs. We replace the constant elasticity of substitution demand model with the static random coefficients discrete choice model examined in section 5.[60] This specification yields a long-run pass-through of 0.273. Long-

[58]The constant markup result also holds for the case of a finite number of firms, though in that case the markup depends on the number of firms in the market. (Anderson, Palma and Thisse, 1992).

[59]We 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 $\theta = 2.92$.

[60]Since the solution method for this model is standard, we 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.

run pass-through therefore falls substantially in the discrete choice model relative to the constant elasticity of substitution model. The fourth column adds pricing dynamics in the form of the menu cost model presented in section 6, implying that long-run pass-through falls to 0.272.

Comparing this set of statistics, we find that local costs reduce long-run pass-through by a factor of 59% relative to a CES benchmark, while markup adjustment reduces pass-through by an additional factor of 33%. We find that menu costs have a negligible effect on pass-through after 6 quarters. The result that local costs play a key role in explaining low observed pass-through echoes the conclusions of other industry studies by Goldberg and Verboven (2001), Hellerstein (2005) and Goldberg and Hellerstein (2007), as well as the analysis by Burstein et al. (2003) of local costs based on input-output tables. Our conclusions differ significantly from those of Burstein et al. (2003) who attribute the entire difference between prices and marginal costs—and therefore all of the observed incomplete pass-through—to local costs. In contrast, our estimated demand curve and structural pricing model imply that markups are substantial, leaving considerable room for markup adjustment.

Our estimates imply that the markup adjustment in response to cost shocks is substantial in the long-run: firms are estimated to compress their gross margins on average by a factor of 1/3 in response to a marginal cost increase. The magnitude of the markup adjustment depends crucially on the curvature of the demand curve. If the elasticity of demand increases as the firm raises its price, the firm is less inclined to raise its price in response to a rise in costs.

One way of summarizing this curvature is in terms of the estimated "super-elasticity" of demand–the percentage change in the price elasticity for a given percentage increase in prices (Klenow and Willis, 2006). This super-elasticity is zero by assumption in the Dixit-Stiglitz model. In contrast, an advantage of the random coefficients demand system we consider is that it permits a great deal of flexibility in the specification of the curvature of demand. Our estimated demand curve, which implies a super-elasticity of demand of 4.64, generates a substantial motive for markup adjustment. Depending on the parameters used, however, the random coefficients demand system can generate a wide variety of possible curvatures of demand—and therefore, a wide variety of potential implications for pass-through. We investigate how our results vary for alternative parameterizations of the demand curve in section 8.

Finally, our estimates imply that menu costs have almost no impact on long-run pass-through. In this regard, our results contrast with a large literature in international macroeconomics in which sticky prices play a central role in lowering the responsiveness of prices to exchange rates (see e.g. Engel (2002)). This conclusion depends importantly on the dynamics of marginal costs. If marginal costs are highly transitory, then firms only adjust partially to a given cost shock in order to avoid having to readjust their prices in the near future. We analyze this effect quantitatively in the next section.[61]

8 Counterfactual Experiments

We next carry out a quantitative investigation of a number of the factors discussed above—the volatility and persistence of costs, the timing of price adjustments, and the curvature of demand—

[61]The role of menu costs in slowing the response of prices to costs also depends on the nature of strategic interactions, as we discuss above.

in explaining the short-run and long-run dynamics of pass-through. We do this by repeating the types of quantitative experiments we carried out above for various alternative parameter values.

We first investigate how pass-through depends on the persistence of marginal costs. To do this, we consider counterfactual experiments where we hold fixed the *actual* sequence of costs faced by the firms, but make different assumptions about what firms believe regarding the stochastic process generating marginal costs (i.e., equation (20)). The menu cost is adjusted to hold the frequency of price change in each simulation equal to the observed frequency of price change.

Table 9 (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 in which costs have a unit root to the case with $\rho_C = 0.5$, the long-run pass-through drops from 0.272 (the baseline case) to 0.161. Even for the case with $\rho_C = 0.9$ the pass-through is 0.210, which is 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 have 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, we consider how the timing of price changes implied by the menu cost model affects pass-through. We compare pass-through in the menu cost model to pass-through in the Calvo (1983) model in which the timing of price changes is random. The Calvo model is a workhorse of the macroeconomics and international economics literatures. In the Calvo specification, we 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}. We 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 9 (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 9 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 0.272 in the baseline specification to 0.162 in the specification with lower persistence.

Third, we investigate how the predictions of our model depend on the curvature of demand. In our structural model of demand, the key parameters that determine the curvature of demand are those that relate to the degree of consumer heterogeneity. 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. Yet, a high degree of consumer heterogeneity also has important implications for pass-through. The more heterogeneous are consumers in their degree of price sensitivity, the more a firm has an incentive to raise its markup as costs rise, since the firm's consumer base is increasingly dominated by less price sensitive consumers.

To illustrate this effect, the last column of table 9 presents the results of a pass-through regression for a case where heterogeneity is 350% larger than in the baseline case; i.e., where we raise the standard deviation of heterogeneity in price sensitivity Π_{yp} by 350%. This change in the parameter values significantly affects the curvature of the demand curve. The median super-elasticity of demand is about 20% lower in this case than the baseline case (3.72 vs. 4.64). This specification also leads to substantially greater long-run pass-through: long-run pass-through is about 1/3 greater than in the baseline case.

Finally, we study how the dynamics of marginal costs affect our estimates of price rigidity. Table 10 (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 match 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.

Similarly, 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 match 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).[62] 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 10 shows that this procedure yields a menu cost estimate that is only 30% of what it is in the dynamic model with forward-looking behavior. The static procedure underestimates the magnitude of menu costs because it overlooks the fact that in deciding whether to adjust, the firm not only considers benefits today but also benefits in the future. These benefits are substantial when costs are persistent. Thus, menu cost estimates based on static procedures are likely to be substantially lower than estimates from dynamic models when costs are persistent.[63]

It is important to note that the presence of local costs, as well as the low estimated demand elasticity, also contribute to the ability of small menu costs to sustain a large amount of price

[62] 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.

[63] 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.

rigidity. Though we do not report these comparative statics here, if the price elasticity were higher, the costs to the firm of not adjusting its prices would be much greater. Larger menu costs would therefore be required to sustain the observed price rigidity. Similarly, if local costs were a smaller fraction of overall marginal costs, the firm's incentive to adjust its price in response to a given movement in the commodity cost would be greater, all else constant, implying that a higher menu cost would be required to sustain the observed degree of price rigidity.

9 Conclusion

A large literature in international economics studies the response of domestic prices to fluctuations in imported costs. We 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 downstream prices. For both retail and wholesale prices, we 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. We document substantial rigidity in manufacturer coffee prices: over the time period we 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. We find a strong positive relationship between the frequency of wholesale price changes and the magnitude of movements in commodity costs.

We 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. The model explains the strong tendency of prices to adjust more frequently in periods when commodity costs experience large adjustments. We also find that the model provides a quantitatively realistic explanation for both long-run and short-run pass-through. The long-run implications of the model depend crucially on the estimated curvature of demand.

We use the model to analyze the relative importance of markup adjustment, local costs, and barriers to price adjustment in determining incomplete pass-through. We successively introduce these features into a benchmark Dixit-Stiglitz pricing model to determine their role in explaining long-run incomplete pass-through. The decomposition implies that local costs reduce long-run pass-through by a factor of 59% relative to a CES benchmark, while markup adjustment reduces pass-through by an additional factor of 33%. Menu costs have a negligible effect on long-run pass-through. Nevertheless, menu costs are quantitatively successful in explaining the observed delayed response of prices to costs.

Finally, we carry out a number of counterfactual simulations to investigate how pass-through in the model depends on the persistence of costs, the degree of consumer heterogeneity and the model of price adjustment behavior (i.e., menu cost vs. Calvo). We show that all of these factors play an important role in determining pass-through. We also show that menu cost estimates based on static procedures are likely to differ substantially from estimates based on dynamic models. We find that the direction of the bias of static estimates of menu costs depends importantly on the persistence of marginal costs.

The dynamic pricing model we analyze provides considerable insight into the timing of wholesale price changes, which is driven largely by volatility in the underlying coffee commodity costs, as we discuss above. In contrast, many retail price adjustments are associated with temporary sales. The timing of temporary sales appears largely unrelated to both wholesale price movements and commodity costs. Nakamura (2008) notes that the timing of price adjustments is also largely uncorrelated across different retail chains. These facts suggest that complex dynamic pricing strategies are likely to be important in understanding the timing of retail price adjustments in relation to movements in underlying manufacturer marginal costs. This is an important topic for future research.

A Computational Algorithm

We solve for equilibrium prices in the dynamic pricing model using the following iterative procedure. For expositional simplicity, we 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. We 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. We next describe the procedure we 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 we 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 we 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, we use the the stochastic process for costs to take an expectation over future commodity costs at time $t-1$. We 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,

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

We 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, we first solve for firm 1's optimal policy, conditional on an initial value for the pricing policy of firm 2; and use the results to update firm 1's policy rule. We then solve for firm 2's optimal policy, conditional on the updated pricing policy of firm 1. We use the results of this exercise to update firm 2's policy rule. We repeat this exercise until the maximum differences in firm pricing policies between successive iterations are sufficiently small. Once this point is reached, we run our algorithm for an additional 1500 iterations to check that the equilibrium does not change.

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 firm 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, we 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, we also consider the following procedure in which we estimate a common component in marginal costs as part of the dynamic estimation procedure. We 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. We use an analogous indirect estimation procedure to the procedure described in section 6 to estimate the parameters of the model. We 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 we 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, we 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). We 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 Retail	Log Specification Wholesale	Levels Specification Retail	Levels Specification 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 (2008) 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
Demand Estimates

	Logit						Random Coefficients
	OLS1	OLS2	IV1	IV2	IV3	IV4	IV
Price	2.92	10.59	16.36	14.60	12.67	17.29	17.76
	(0.37)	(1.05)	(1.54)	(1.17)	(3.59)	(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	0.14	-0.21	-0.28
	(0.13)	(0.10)	(0.11)	(0.10)	(0.19)	(0.10)	(0.08)
Total advertising (1000's, quarterly)	0.45	0.05	0.19	0.13	0.26	0.20	0.20
	(0.02)	(0.004)	(0.20)	(0.02)	(0.03)	(0.01)	(0.02)
Year dummies	YES	YES	YES	YES	YES	YES	YES
Christmas dummy	YES	YES	YES	YES	YES	YES	YES
Brand x Region dummies	NO	YES	YES	YES	YES	YES	YES
Instrument			Hausman	Commodity Cost	Exchange Rates	Weather	Weather
Median Price Elasticity	0.54	1.96	3.02	2.69	2.34	3.20	3.46* [2.59 4.48]
Number of Observations	22411	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. Exchange rate instruments: Brazil/US exchange rate and Colombia NEER (Source: IFS). 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 6
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 7
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 8
Pass-through Regressions for Simulated Data

	Log Specification			
Variable	Dixit-Stiglitz (no local costs)	Dixit-Stiglitz (local costs)	Static Discrete Choice	Dynamic Discrete Choice
Δ Commodity Cost (t)	1	0.407	0.213	0.105
Δ Commodity Cost (t-1)	0	0.028	0.063	0.117
Δ Commodity Cost (t-2)	0	-0.005	0.025	0.033
Δ Commodity Cost (t-3)	0	-0.015	0.004	-0.007
Δ Commodity Cost (t-4)	0	-0.011	-0.024	-0.011
Δ Commodity Cost (t-5)	0	0.006	-0.021	0.020
Δ Commodity Cost (t-6)	0	-0.003	0.014	0.016
Constant	0	0.011	0.009	-0.0008
Long-run Pass-through	1	0.407	0.273	0.272

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. Columns 2-5 estimate pass-through using the log specification. 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 9
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	Baseline (Unit Root)
Δ Commodity Cost (t)	0.105	0.118	0.089	0.066	0.072	0.104
Δ Commodity Cost (t-1)	0.117	0.085	0.097	0.098	0.103	0.117
Δ Commodity Cost (t-2)	0.033	0.001	0.021	0.042	0.015	0.079
Δ Commodity Cost (t-3)	-0.007	-0.044	-0.013	0.009	-0.015	0.017
Δ Commodity Cost (t-4)	-0.011	-0.016	-0.013	0.000	-0.020	-0.013
Δ Commodity Cost (t-5)	0.020	0.017	0.013	0.017	0.010	0.014
Δ Commodity Cost (t-6)	0.016	0.000	0.014	0.016	-0.003	0.036
Constant	-0.0008	-0.009	0.001	-0.004	-0.010	0.013
Long-run Pass-through	0.272	0.161	0.210	0.249	0.162	0.353

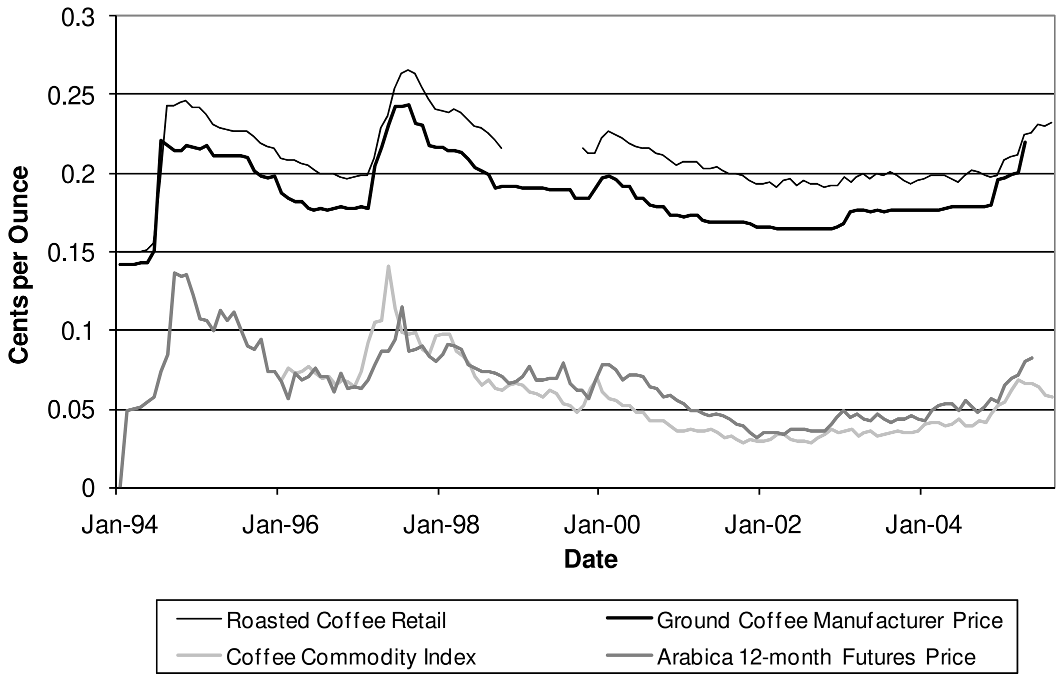
The dependent variable in all of the specifications is the simulated retail price per ounce. The price and cost variables are in logs. The second column repeats the results for the baseline model. Columns 3-4 present pass-through regressions for the cases where ρ_C=0.5 and 0.9 respectively. Columns 5-6 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 10
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%

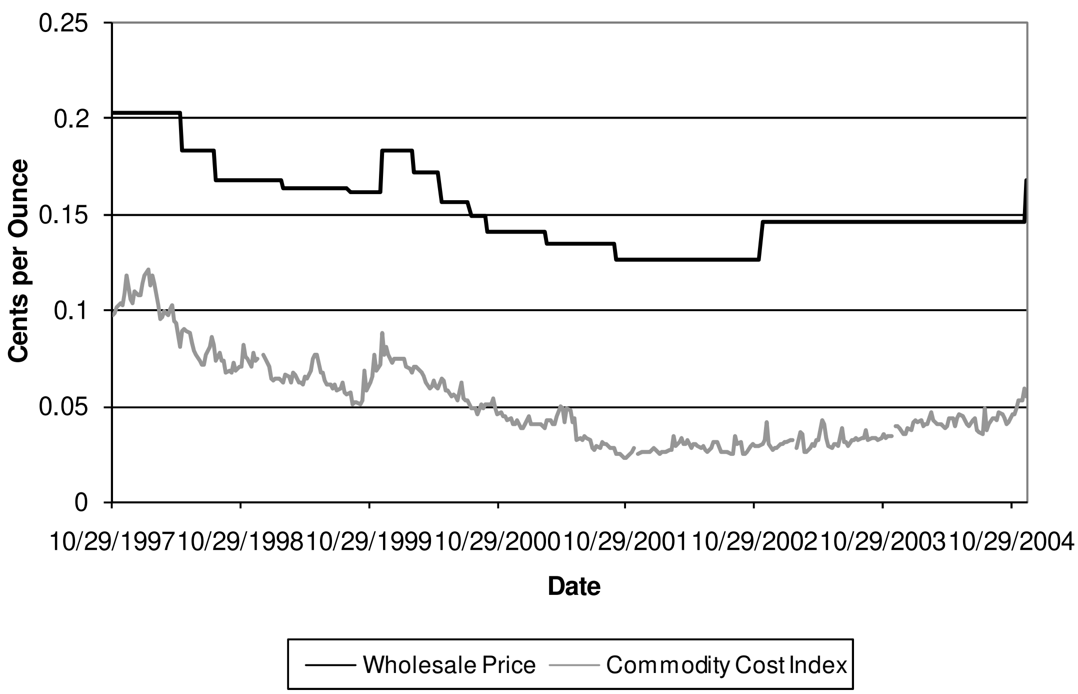
The table presents menu cost estimates as a fraction of average annual firm revenue in the Syracuse market. The first column repeats the baseline results. Columns 3-7 present results for counterfactual parameter values. Columns 3-4 present results for the cases where ρ_C=0.5 and 0.9 respectively. Columns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



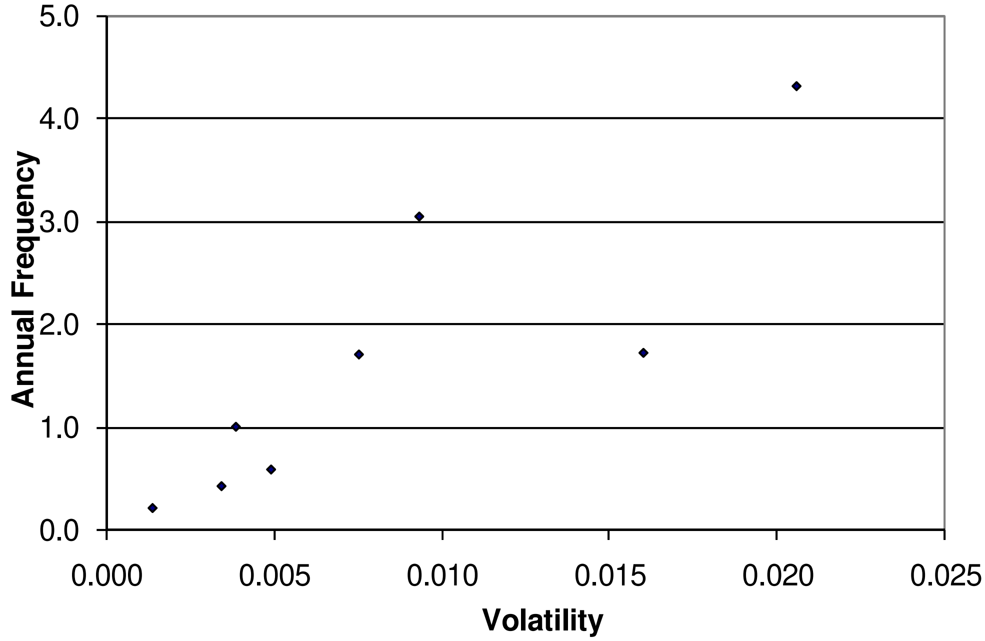
*The roasted coffee retail and ground coffee manufacturer prices are average prices from the Bureau of Labor Statistics database on consumer and producer prices. The Arabica 12 month futures price is from the New York Board of Trade. The coffee commodity index is a weighted average of the prices of different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



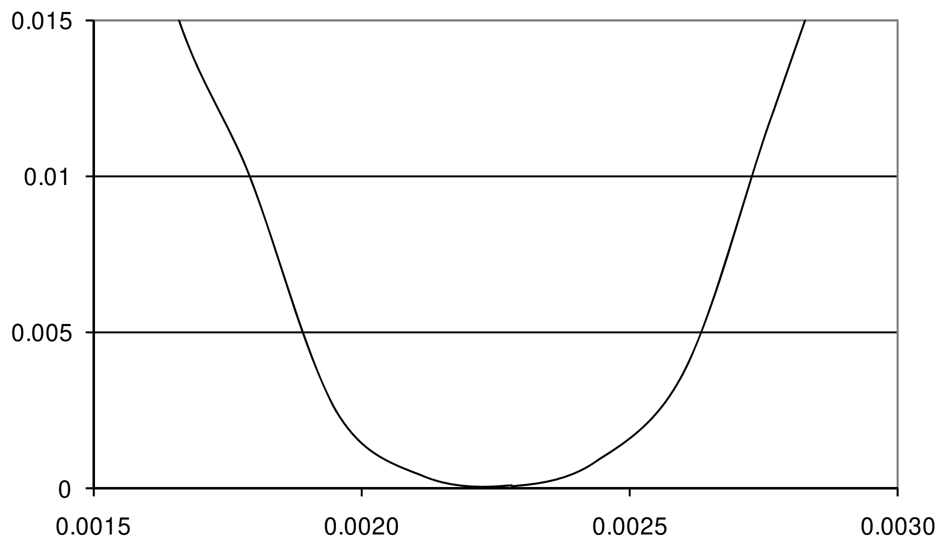
*The gross wholesale price of a leading coffee brand. The coffee commodity price is a weighted average of the prices of different types of coffee on the New York Board of Trade.

Figure 3: Price Change Frequency vs. Commodity Cost Volatility



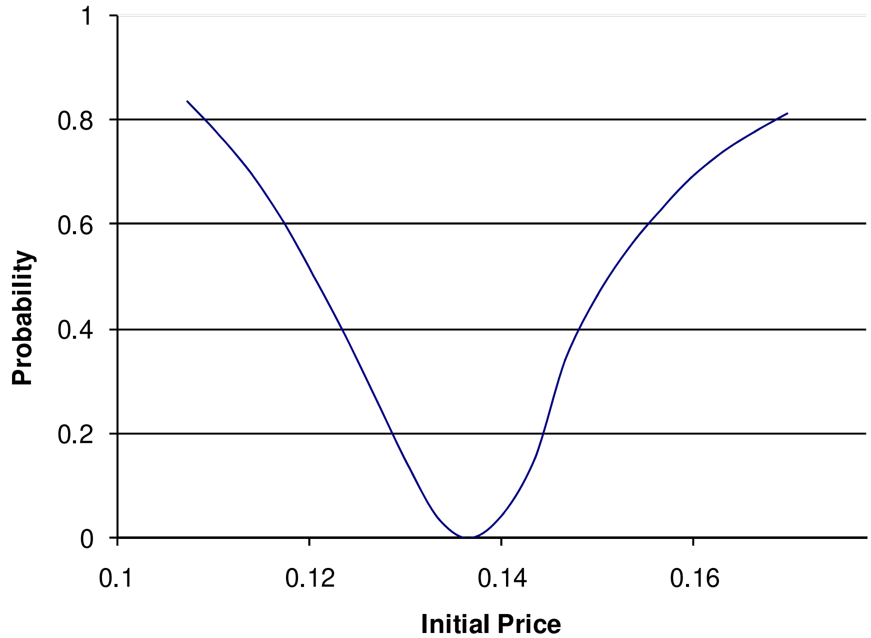
*This figure plots the average annual frequency of price change for the wholesale price (not including trade deals) vs. the volatility of the commodity cost index for each of the years 1997-2004. These statistics are based on weekly wholesale price data for the period 1997-2004. The observations are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



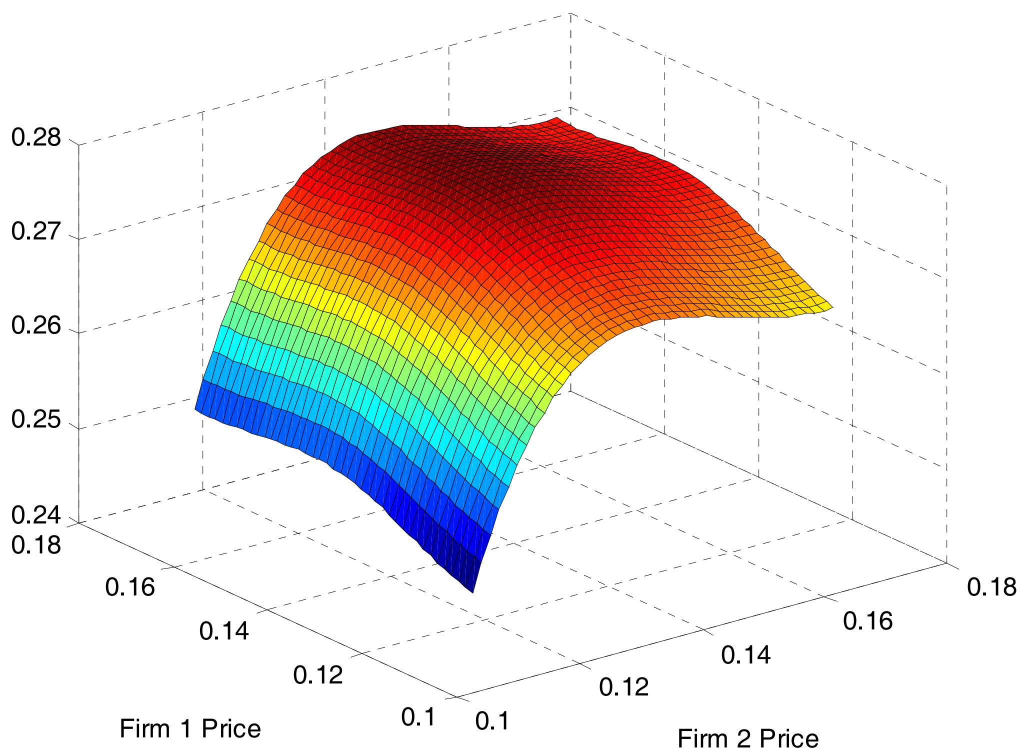
*This figure plots the squared deviation between the average observed frequency of price change over the 2000-2005 period and the frequency of price change predicted by the menu cost oligopoly model as a function of the menu cost. The menu cost is reported as a fraction of average annual retail revenue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

Figure 5: Probability of Adjustment vs. Initial Price



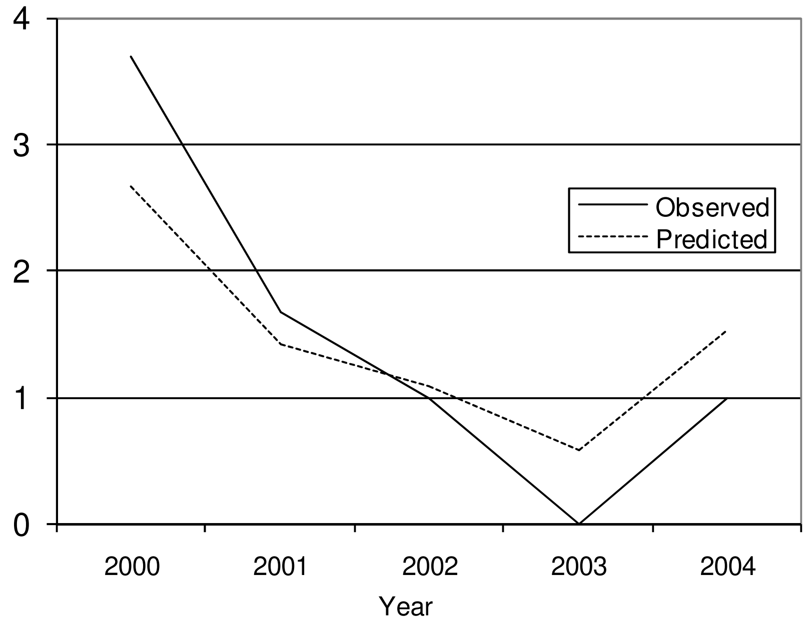
*This figure plots an example of the relationship between the probability of adjustment and the initial price in the menu cost model.

Figure 6: Probability of Adjustment as a Function of Competitors' Prices



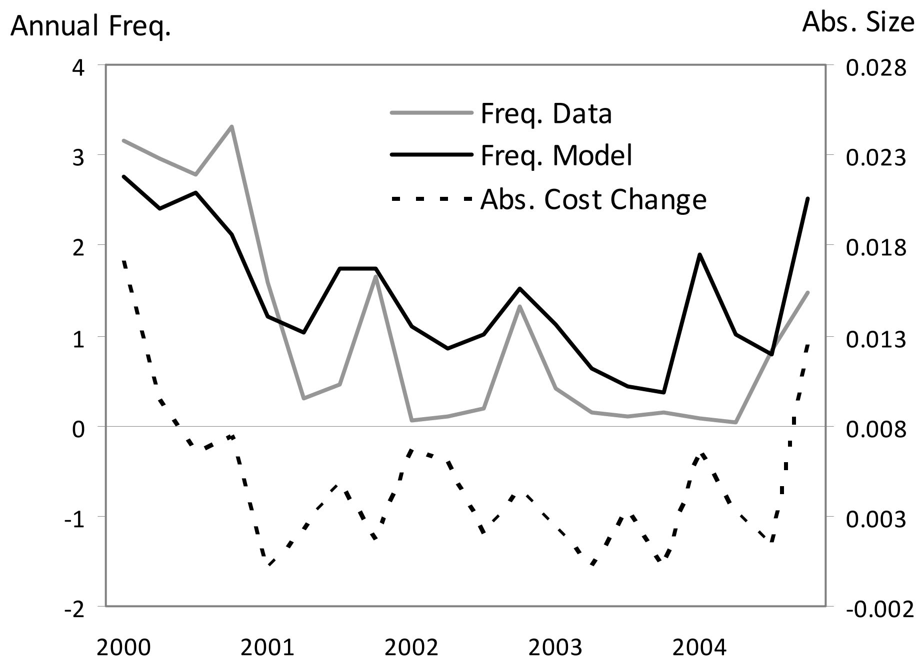
*This figure plots an example of the probability of adjustment as a function of competitors' prices in the menu cost model.

Figure 7: Annual Predicted vs. Observed Frequency of Price Change



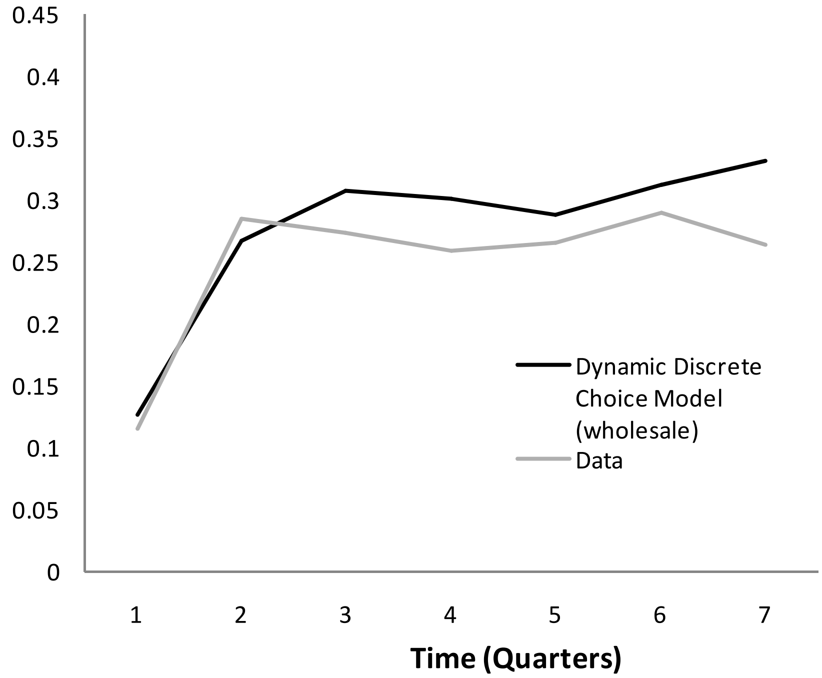
*This figure plots the predicted annual frequency of price change for the dynamic model over the years 2000-2005 as well as the observed frequency of price change for wholesale prices over this period. The statistics for the model are based on 10000 simulated price series.

Figure 8: Predicted and Observed Frequency of Price Change vs. Abs. Cost Change



*This figure plots predicted quarterly frequency of price change for the dynamic model over the years 2000-2005 as well as the observed average frequency of wholesale price change. The figure also plots the average absolute size of commodity cost change by quarter. The statistics for the model are based on 10000 simulated price series.

Figure 9: Impulse response to a Cost Shock



*This figure plots the impulse response of wholesale prices to a permanent 1 percent cost shock implied by the model and the data. The statistics for the model are based on 10000 simulated price series.