MICRO-PRICE DYNAMICS IN SMALL OPEN ECONOMIES: LESSONS FROM ECUADOR

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To my family

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Chapter 1

Introduction

Prices have always been understood to have an important impact on the creation of goods and services, but the extent of that impact has swayed back and forth as the tides of economics have turned. At first glance, the nominal price should be nothing more than a number that can be changed arbitrarily without distortion in the production of goods and services. Adding a zero to the denomination of all ten dollar bills should leave the consumer in the exact same situation as he had been previously. However, since Keynes, these merely nominal changes in the price have been understood to have much longer and more meaningful impacts. As the birth of Keynes and macroeconomics was more than one hundred years ago, it would seem like there would be little left to be said about such a critical phenomenon. Nevertheless, the information age has exposed new questions as more precise data in the form of micro-prices has become available. The introduction of micro-price data has led to new analyses that contribute to understanding the connection between the nominal and the real. This study contributes to that tradition through a careful analysis of the movement of retail prices in three separate but equally important dimensions through the lens of one small but dynamic country with a fascinating monetary history. Those dimensions are the frequency of price change, the relationship of prices to each other, and the reaction of prices to external shocks, in this case, a shock to the exchange rate.

While seemingly narrow in its subject, the use of a single, small, export-dependent country such as Ecuador serves as a case study for investigating much broader topics throughout both monetary economics and international finance. For example, the stickiness of retail prices has large and lasting impacts on the neutrality of money, a subject covered in great detail with respect to the United States. By looking at the subject through the lens of Ecuador, we can observe the magnitudes of and changes in variables that are not present in a US context. At no point in recent history has the developed world had inflation reach the levels as we see in in Ecuador nor has it stabilized so abruptly. By looking at the changes we can observe their impact more readily on the variables of interest to broaden our understanding of the factors in play. All three chapters are important not just because of the implications for Ecuador and developing nations but for the world as a whole. Ecuador is merely the magnifying glass we can use to shed light on prices throughout the world.

Chapter 2 investigates the movement of prices. The parameter of interest here is the frequency of price change and how this number relates to various conditions or states within the country of Ecuador. In this chapter, my co-authors and I demonstrate that prices in Ecuador have a structural pattern in the frequency of adjustment. As is true in all menu cost models, firms reprice more frequently in higher inflationary regimes, but we also see that goods that are more likely to reprice in a period of hyperinflation are also more likely to reprice in a period of stability brought about by dollarization. These patterns are robust across three vastly different macroeconomic regimes in Ecuador.

To explain this phenomenon, we create a menu cost model of price adjustment where firms import goods from competitive markets overseas and use labor to distribute final goods throughout the country. Using this model, we show that cost structure plays a critical role in explaining the frequency of price adjustment. Movements in the price of underlying components shift the costs of the firm and thus lead to more frequent repricing. As the traded component is much more volatile than the wage, our model predicts that goods that are more reliant on traded inputs will change their price more frequently than goods dependent on non-traded inputs such as labor. However, the model also predicts that goods more reliant on one component will also reprice more frequently than goods that use an equal combination of traded and non-traded inputs. Firms that use a diverse set of inputs can adjust to cost shocks more easily by substituting production towards the cheaper input; they also benefit from the benefit of diversification to the extent inputs prices are imperfectly correlated with each other.

Chapter 3 looks at prices and their relation to each other within Ecuador. Leaning on the prior literature relating to the purchasing power parity paradox and the law of one price, I present evidence strengthening the law of one price within the country of Ecuador. Using an Augmented Dickey-Fuller test and an Im et al. (2003) test for stationarity, I find a strong likelihood to reject the null hypothesis of a unit root. Furthermore, I estimate persistence of deviations in the law of price to be extremely low, with half-lives on the order months. This suggests prices within Ecuador converge more quickly compared to other studies, especially those in developed nations.

In addition, Chapter 3 argues that because prices are a combination of both traded inputs and non-traded inputs, this leads to a phenomenon known in the literature as compositional bias where retail prices take on unit root properties of their non-traded input, even if the final good is considered tradable. Under the assumption of a Cobb-Douglas production function, I scrutinize the process of combining the components into one retail price. Assuming both inputs follow an AR(1) process and estimating parameters for each, I construct a mapping function that shows how the time series properties of the two inputs combine to form the final price. My results indicate that the good's autoregressive coefficients is not merely the cost-share weighted sum of the underlying coefficients. Instead, the non-stationary, non-traded input may dominate the effect of the traded input, and the overall price of the good may appear to lack stationarity even if its underlying traded component is stationary. This paper strengthens Crucini and Landry (2017), which suggests that the classical dichotomy still holds when applied to the input prices rather than the prices of final goods. This classical dichotomy is weakened when looking at goods prices because of the compositional bias involved in combining those inputs into final goods' prices.

Lastly, Chapter 4 examines the reaction of prices in Ecuador to a shock in the exchange-rate. This chapter shows that exchange-rate pass-through plays a differing impact in different cities and goods throughout Ecuador. I further investigate pass-through under the assumption that firms import goods from the coast and distribute these goods to the interior of the country. I find that producer currency pricing is more prevalent in cities closer to the coast while local currency pricing is the more applicable theory on the interior of the country. In other words, when the exchange rate adjusts, prices in coastal cities like Guayaquil will adjust their prices to a greater degree than interior cities like Quito.

Chapter 2

On What States Do Prices Depend: Answers from Ecuador

with Mario J. Crucini and Anthony Landry

2.1 Introduction

A growing literature documents large cross-sectional variation in the frequency and size of price adjustments. To date, this literature has mostly focused on idiosyncratic shocks specific to individual firms to explain these patterns. For example, Dotsey et al. (1999) emphasize heterogeneous menu costs of price adjustment among firms, while Golosov and Lucas (2007) and Midrigan (2011) emphasize idiosyncratic productivity shocks. Both of these mechanisms generate cross-sectional variation in the frequency and size of price changes but fail to address the Boivin et al. (2009) finding that sector-specific shocks are important in explaining the frequency and size of price adjustments. In particular, they find that disaggregated prices appear sticky in response to macroeconomic and monetary disturbances but flexible in response to sector-specific shocks.

As Gopinath and Itskhoki (2010) point out, there is little evidence that the cross-sectional variation in the frequency and size of price adjustments is meaningfully correlated with measurable statistics in the data. In this paper, we unpack some of the cross-sectional variation in the frequency and size of price adjustments and show that the firms cost structure is an important dimension explaining this heterogeneity. Specifically, we argue that differences in the cost structure across sectors play a central role in the price adjustment process.[1] For instance, a hair salon will have a cost function that is relatively sensitive to local wage conditions whereas a gas station will have a cost structure that is relatively sensitive to the wholesale price of gasoline, which in turn is sensitive to the world price of oil.

To study how different sectors react to a given cost shock, we develop a two-factor menu cost model of a retail firm operating in a particular sector and selling goods or services. Retail firms purchase traded intermediate inputs and hire local labor to make goods and services available for final sale to consumers. To capture real frictions associated with intermediating trade between manufacturers and final consumers, we incorporate heterogeneous distribution margins to create distinct pricing decision responses to an identical shock. As in most menu cost models of price adjustment, firms hold their prices constant until the difference between their optimal price and their current price is sufficient to justify paying the menu cost to adjust the price. However, in our model, the inducement to adjust prices depends on both the size of the shock to the price of traded-intermediate inputs and their share in the total cost of making a particular good or service available to final consumers at their location of consumption.

We use a novel Ecuadorian micro-price panel to test and calibrate the model because Ecuador has two attractive properties. First, Ecuador's macroeconomic history provides three regimes where the inflation rate, import price and wages have distinct stochastic properties. Comparing across these three regimes allows us to relate changes in macroeconomic states to changes in the average frequency of price changes. Second, developing countries such as Ecuador face larger external shocks to input prices which help identify the inducements to changes in the optimal pricing behavior of firms in a menu cost framework.

[1] Other papers have considered the effect of sector-specific shocks on aggregate and disaggregate prices, but none that we know of rely on the cost structure to explain the cross-sectional variations in the frequency and size of price adjustments. Carlos (2006) generalizes the Calvo model to allow for heterogeneity in price stickiness across sectors, while in the models of Gertler and Leahy (2008) and Mackowiak and Wiederholt (2009), firms pay more attention to firm-specific conditions. Nakamura and Steinsson (2010) rely on a multi-sector menu cost model with heterogeneous menu costs to look at impact of monetary shocks in the presence of heterogeneity in the frequency of price adjustment.

We first look at trends in the frequency of price adjustment to show that all firms reprice more frequently in a higher inflation environment. While this is common in the theoretical state-dependent pricing literature, a number of empirical studies, such as Klenow and Kryvtsov (2008), have shown that inflation and price adjustment frequencies are not highly correlated. Our empirical results are closer to those of Gagnon (2009), who used Mexican data to show that, when annual inflation is greater than 10-15 percent annually, the correlation between inflation and price adjustment frequency intensifies. Put differently, when inflation changes by a substantial amount—as is certainly true in Ecuador and Mexico—it is easier to detect the positive relationship between aggregate inflation and average price adjustment frequencies. In mild inflationary environments, idiosyncratic factors specific to particular goods or markets obscure the impact of aggregate inflation.

Our second and more novel finding relates to differences in the frequency of price adjustment across sectors within a given inflationary regime. Sectors in the context of retail prices are categories of consumer products (food, clothing, housing and so forth). An emerging literature establishes that individual consumer goods differ significantly in the cost-share of distribution, the difference between what consumers pay and producers receive. In our micro-data the distribution share ranges from 0.2 for gasoline to a high of 0.85 for a haircut. As Crucini and Landry (2017) note, this effectively means the non-traded factor content (distribution costs) of haircuts is 4.25 times that of gasoline. Because wages are less volatile than traded inputs, our state-dependent pricing model will predict that haircuts reprice less frequently than does gasoline. A more subtle prediction of this two input model of retail goods is that haircuts need not be the good with the stickiest price. This is due to the fact that a more diversified cost profile (e.g., goods that do not rely mostly on a single factor input) has a lower unconditional variance than the cost function of haircuts. These properties influence the shape of a firm's optimal pricing function and are borne out in our micro-data from Ecuador.

This paper elucidates the states upon which a firm's price depends. Our results show that the widespread perception that state-dependent pricing models fail to account for cross-sectional heterogeneity in the frequency of price changes is an artifact of assuming symmetry of the cost function for consumer goods in terms of their traded factor content. Moreover, while it is understandably tempting to adapt models by adding idiosyncratic productivity shocks at the firm level, such an approach may serve to obscure the key states upon which costs and firm pricing decisions depend. In contrast, our parsimonious treatment of distribution costs with a two-shock model allows a direct point of contact with the focus of policymakers attempting to divine the differences between core and overall inflation. While the relevance of our model is demonstrated in the case of Ecuador, our findings are likely to carry over to more stable, low-inflation environments. For example, our model provides a natural explanation for the relatively frequent and volatile movements in food and energy, sectors that epitomize our definition of retail goods high in traded input content on a cost basis.

This paper is organized as follows. Section 2 provides the context for using Ecuador as a natural experiment and presents key stylized facts from the data. Section 3 lays out the theoretical framework we use to generate a set of predictions for how prices should respond, given the state of macroeconomic conditions in Ecuador. In Section 4, we calibrate and simulate the model to assess its ability to capture salient features of the observed frequencies of price changes across goods for three distinct inflationary environments experienced in Ecuador. Section 5 concludes.

2.2 A Brief Monetary History of Ecuador

In this section, we review Ecuadorian monetary history from 1997 to 2003 to give context to the model and to introduce key stylized facts that help motivate our analysis. We show that the cross-sectional (i.e., good-specific) distribution of the frequency of price changes exhibits remarkable stability even as Ecuador moves from a hyperinflationary regime to a modest inflation regime (dollarization). This pattern will serve as a key motivation for the model presented in Section 3.

2.2.1 The Data

Our main source of data is a monthly database of retail prices from the National Institute of Statistics and Census (INEC), the official national statistical agency of Ecuador and a subdivision of its central bank. These data comprise monthly retail prices from 1997 to 2003 in 12 different Ecuadorian cities spanning both the Western Coastal region and the Central Sierra region, including both the country's capital, Quito, and largest city, Guayaquil. These prices cover a wide variety of goods and services. The data are described in detail in Penaloza-Pesantes (2005).[2]

Our second source of data is from the Bureau of Economic Analysis Personal Consumption Expenditure Bridge Tables (1992). These tables show the value of consumer expenditures by expenditure category in producers' and purchasers' prices. The macroeconomic literature refers to this as the distribution share: the difference between what consumers pay and what producers receive divided by what consumers pay. For example, if final consumption expenditure on bread is \$1.00 and bread producers receive \$0.64, the distribution share is 0.36. This share includes wholesale and retail services, marketing and advertisement, local transportation services and markups.

For services, however, this is problematic as a measure of the traded inputs in final consumption. The reason is simple: according to these tables, what consumers pay and what producers receive for a service is the same. Conceptually, this is inconsistent with the approach used for goods. For example, when a consumer (or that consumer's health insurance provider) receives a medical bill, the charges may include wage compensation for the physician and the cost of goods and non-physician services included in the overall treatment, whether or not it is itemized on the invoice. Since the doctors' services are

[2]The Ecuadorian micro-price panel was obtained from INEC by Penaloza-Pesantes (2005) who studied Ecuadorian real exchange rates with respect to the United States in his Ph.D. dissertation.

local inputs while the goods used in production of medical services are traded inputs, it is necessary to separate the two. For this reason we use the 1990 U.S. input-output data to measure the non-traded and traded factor content of services.

In this paper, the distribution share is the cost-share percentage of non-traded inputs in production. After assigning each retail item in the Ecuadorian micro-price survey to an expenditure category found in the U.S. PCE data we have a distribution cost-share for that item. The goods and services covered in this retail price database are representative of the full span of household expenditure patterns. Consequently, distribution shares vary widely, from an automobile with a non-traded input share of only 0.167 to postage for a letter, which has a non-traded input share of 1. The median across the 223 goods and services in the Ecuadorian micro-panel is 0.52. The distribution share for each good and service is listed in Appendix A.

Overall, our distribution shares are similar to those used in Burstein et al. (2003a) and Goldberg and Campa (2010). Instead of estimating the size of the distribution sector using aggregate data, Berger et al. (2012) measured the distribution shares using U.S. retail and import prices of specific items from the U.S. CPI and producer price index (PPI) data. They find that the distribution shares in these data are larger (on average) than the estimates reported for U.S. consumption goods using aggregate data. Their median U.S. distribution shares across all items in their cross-section is 0.57 for imports priced on a c.i.f. (cost, insurance, and freight) basis and 0.68 for imports priced on an f.o.b. (freight-on-board) basis. While their dataset allows for a more disaggregated calculation of the distribution shares, it does not include services, which constitutes a large fraction of consumption expenditure. Importantly for our results, Burstein et al. (2003a) and Berger et al. (2012) found that the distribution shares are stable over time.

2.2.2 Three Inflation Regimes

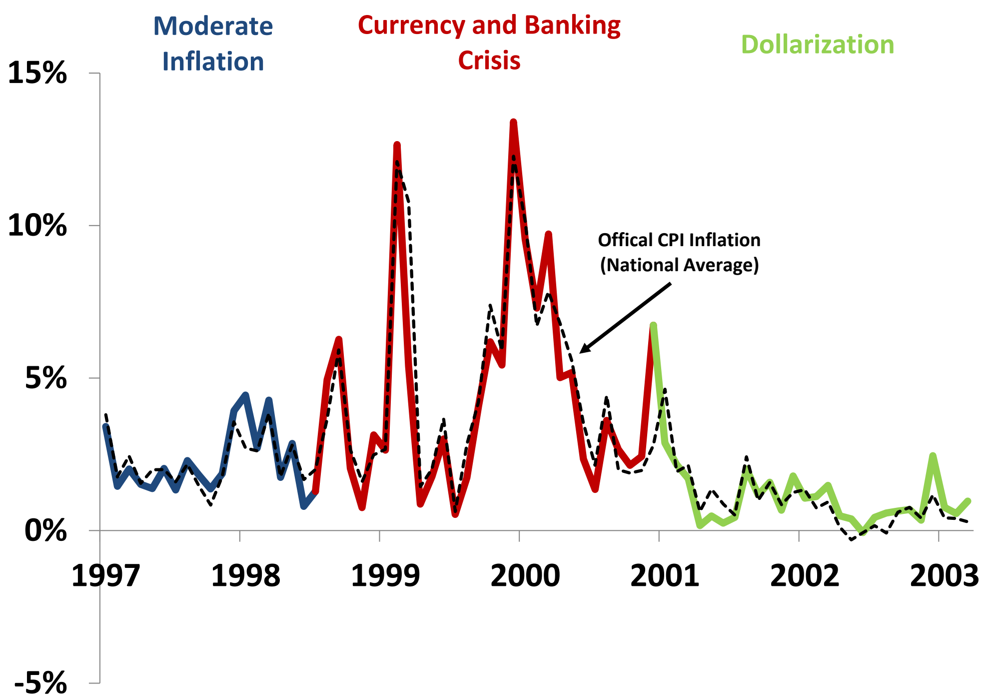
Our panel data of retail prices span the period from January 1997 to April 2003. These years represent a tumultuous period in Ecuadorian history spanning three distinct inflation regimes. The first regime is referred to as the Moderate regime and represents a period of moderate and stable inflation. At this time, Ecuador was on a crawling peg to the US dollar, and although Ecuador's monthly inflation rate of 2.2 percent seems high compared with a developed country like the United States, it was typical for a Latin American country over this time period.

In mid-1998, Ecuador was hit with a series of exogenous, negative shocks. El Niño had negative effects on agriculture and the warming trend reduced the price of oil, an important Ecuadorian export. Only a year prior, the Asian financial crisis appeared to leave developing and emerging markets susceptible to capital flight. Ecuadorian GDP per capita fell by more than 7 percent from 1998 to 1999. During this second regime, which we call the Crisis regime, Ecuador experienced hyperinflation with inflation averaging approximately 4.7 percent per month, contributing to further paralysis of the economy.

Unable to rein in inflation using standard monetary policy actions, in January 2001, the Ecuadorian government announced that it would replace the Sucre with the US dollar for all retail transactions. The results of dollarization were impressive, with inflation falling from 4.7 percent to a mere 1.1 percent per month between 2001 and 2003, the end point of our sample.

Figure 2.1 plots our monthly inflation measure together with INEC's official Consumer Price Index. Our measure is an equally weighted average of inflation across all goods and cities. Comparing the two lines, it is obvious that our simple construct tracks the official CPI almost exactly. The inflation rate time series is shown in three colors to distinguish each inflation regime: blue for Regime 1 (Moderate regime), red for Regime 2 (the period of financial and exchange rate crisis known as the Crisis regime), and green for Regime 3 (the Dollarization regime).

Figure 2.1: Monthly CPI Inflation in Ecuador by Regime



Note: Monthly inflation rate over the sample period of January 1998 to April 2003, calculated as an equally weighted average of inflation across all goods and cities from our dataset. The black line represents the official CPI from INEC, Ecuador's national statistical agency.

Table 2.1 presents our summary statistics across the three inflation regimes. The first row conveys the narrative history of inflation in Ecuador. In the first regime, inflation is very high compared with industrial countries, averaging 2.2 percent per month. In the second regime, during the financial and exchange rate crisis, inflation reaches hyperinflationary levels. The average is a bit deceptive in the sense that some inflationary spikes extended to more than 10 percent per month. The inflationary situation moderated in the third regime, with inflation stabilizing to 1.1 percent per month, presumably as a consequence of the dollarization together with a commitment to open trade and integration with international capital markets.

Table 2.1: Summary of Monthly Price Facts

	Full sample	**Regime 1**	**Regime 2**	**Regime 3**
		Moderate regime	Crisis regime	Dollarization regime
	1997:01-2003:04	1997:01-1998:07	1998:08-2000:12	2001:01-2003:04
Mean inflation	2.8%	2.2%	4.7%	1.1%
Price adjustment frequency	57.6%	53.9%	67.3%	50.0%
Price increases	43.2%	42.7%	54.3%	32.1%
Price declines	14.4%	11.3%	13.0%	17.9%
Size of price changes	9.1%	7.8%	11.1%	7.4%

Note: Mean inflation and price adjustment frequency are statistics across goods, cities, and time periods.The size of price changes are average absolute values across goods, cities, and time periods.

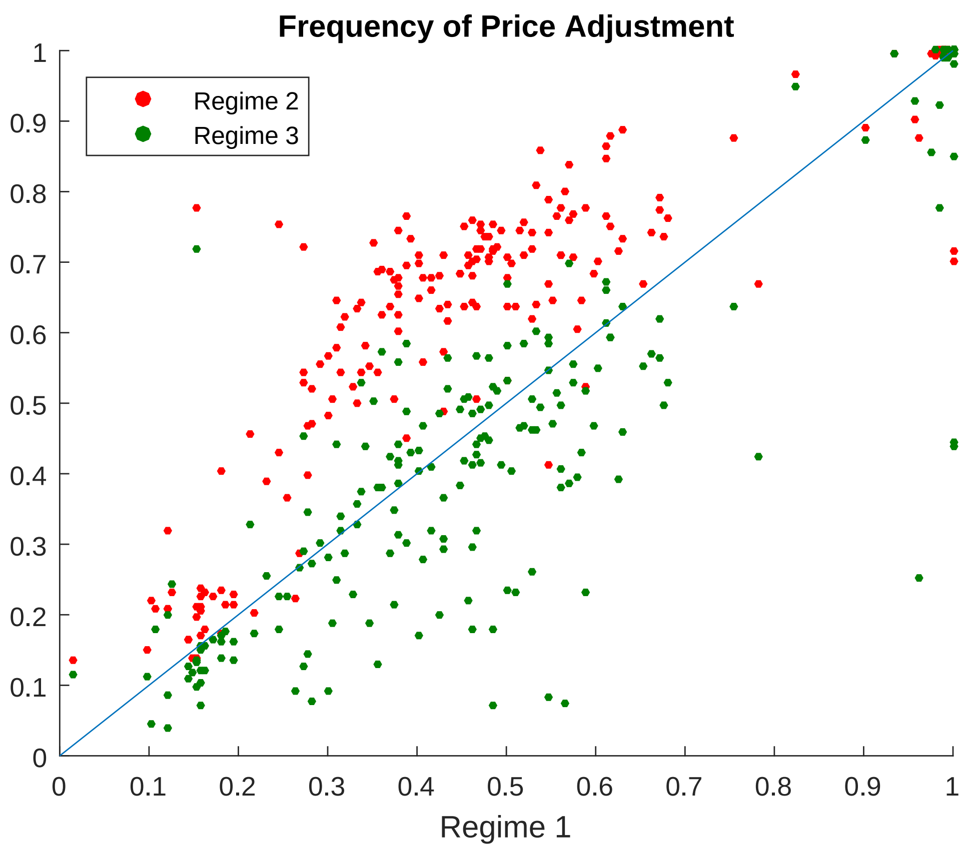
2.2.3 Price Changes in Ecuador

We now turn to individual prices and present new stylized facts observed in our novel data set. To help answer our question about the states upon which price adjustment depend, we begin with an analysis of the frequencies of price changes in Ecuador. Looking at Table 2.1, we see higher inflation periods are also periods with more frequent price changes consistent with a state-dependent or menu cost theory of price adjustment. We see this pattern consistently across the three regimes of our sample with the average frequency of price changes increasing from 50 percent (Regime 3) to 53.9 percent (Regime 1) and then to 67.3 percent (Regime 2) as we move from the lowest- to highest-inflation regime. These frequencies are about twice as high as those reported in Nakamura and Steinsson (2008) for the United States. In addition, this strong correlation between frequency of price change and inflation runs counter to much of the empirical literature (e.g., Klenow and Kryvtsov (2008)). Both of these differences are accounted for by the fact that inflation is much higher in Ecuador than in the United States, even during the most stable period of Dollarization. A more appropriate comparison of inflation rates is Gagnon (2009), who studies the frequency of price changes in Mexico from 1994 to 2002 and shows that inflation is strongly positively correlated with price change frequency when inflation is over 10 percent (per annum). Even during the stable Dollarization regime, Ecuadorian annual inflation is about 14 percent annually. Table 2.1 also shows that higher inflation periods are associated with larger price changes as pointed out by Ahlin and Shintani (2007).

As other authors have pointed out, the frequency of price adjustment differs much more substantially across items in the consumption basket than across inflation regimes. This heterogeneity of frequencies across goods is a universal feature of micro-price data. An important question to ask is whether the cross-sectional variance in the frequency of price changes reflects an economic structure that macroeconomists should be building into their models or just uninteresting noise. We suspect that economic structure underlies these patterns.

Answering a simple question has direct bearing on this issue: Does the frequency of price adjustment maintain its cross-sectional distribution as macroeconomic conditions move from one regime to another? Figure 2.2 plots the frequency of price adjustment by goods in our microsample as individual data points. The x-coordinates of this figure are the frequencies of price adjustment in Regime 1, the sample with the inflation rate closest to the historical mean. The y-coordinates for the red and green dots are the frequencies of price adjustment in Regime 2 (the Crisis regime) and Regime 3 (the Dollarization regime), respectively. The higher (lower) average price adjustment frequencies in Regime 2 (Regime 3) are evident with the red (green) scatter lying systematically above (below) the 45-degree line. Here we see a striking pattern in the data: items with above (or below) average frequencies of price adjustment in one regime are also items with above (or below) average frequencies of price adjustment in the next regime. What changes across regimes is the average frequency of price change, but this is trivial relative to the dispersion in frequencies of price change across goods. This pattern is inconsistent with menu cost models in which the heterogeneity in price adjustments comes from firms drawing randomly from a common distribution of menu costs (e.g., Dotsey et al. (1999) and the open-economy versions of Landry (2009) and Landry (2010)) or from a common distribution of productivity shocks (e.g., Golosov and Lucas (2007)). In these cases, we would expect a cloud of points tightly clustered around the mean frequency in each regime with little or no pattern in relation to the 45-degree line.

Figure 2.2: Monthly Frequency of Price Adjustment in the Data



Note: Comparison of price adjustment frequencies across regimes. Each dot represents one good's frequency of price adjustment across two regimes. The x-coordinates represent the price adjustment frequencies in Regime 1, while the y-coordinates represent the price adjustment frequencies in the Regime 2 (the Crisis regime) and Regime 3 (the Dollarization regime).

Evidence of a structural relationship comes from the fact that the cross-sectional distribution of price adjustment frequencies is preserved across regimes. That is, the frequencies of price changes across goods is strongly positively correlated across regimes (i.e., the green and red scatter diagrams show strong positive correlation with each other). What this suggests is that there is some factor specific to an individual good that induces more- or less-frequent price adjustments whereas the inflation regime shifts the mean frequency of price change across goods. Next, we turn to our explanation for this stable cross-sectional distribution of price adjustment frequencies.

2.3 The Model

In this section, we develop a menu cost model of pricing in which retail firms intermediate trade between producers and consumers. The model we develop is a multi-sector generalization of the model presented by Golosov and Lucas (2007) akin to Nakamura and Steinsson (2010)'s multisector model, but where the intermediate inputs are tradable inputs. In contrast to Nakamura and Steinsson (2010), however, we let heterogeneity in the firms' cost structure dictate the frequency of price adjustment—instead of relying on heterogeneous menu costs.

Like traditional menu cost models, firms must pay a common fixed menu cost in order to adjust their price. However, unlike these models, each firm's cost function may have a different weight on local and imported factors of production and, therefore leave the firm differentially exposed to the two cost shocks. Naturally, then, firms with a higher cost share of more volatile input price will adjust their prices more frequently. In most macroeconomic settings, the more volatile input prices in retail goods is the traded input component. Food and energy provide good examples due to their ties to volatile commodity prices via traded inputs. We turn now to the structural details of the model.

2.3.1 A Menu Cost Model of Price Adjustment

We develop a partial equilibrium model in which a continuum of firms indexed by i belongs to a sector that combines labor (i.e., retail services) and a wholesale good purchased in global markets to produce a differentiated final consumption good. The production function for firm i at time t is

$$y_{it} = l_{it}^{\alpha_i} m_{it}^{1-\alpha_i}, \tag{2.1}$$

where y_{it} is the final good the consumer purchases, l_{it} denotes retail services involved in making the good available to the final consumer and m_{it} is the intermediate-imported good.

Consumers have CES preferences over goods and thus the demand for the good i at time t is

$$y_{it} = y\left(\frac{P_{it}}{P_t}\right)^{-\theta}, \tag{2.2}$$

where P_{it} is the nominal price of good i and the price index, P_t, is consistent with the CES preference function; it will be proxied with the CPI price index in the data. Real aggregate demand (and income) is y, and θ is the elasticity of demand.

Firm i maximizes the value of its expected discounted profits

$$E_t \sum_{s=t}^{\infty} \beta_{t,s} \pi_{is}, \tag{2.3}$$

where $\beta_{t,s}$ is the discount factor between period t and future period s. Real profits in period t are given by

$$\pi_{it} = \frac{P_{it}}{P_t} y_{it} - \frac{W_t}{P_t} l_{it} - \frac{P_{it}^m}{P_t} m_{it} - \chi I_{it}, \tag{2.4}$$

where W_t is the nominal wage, P_{it}^m is the nominal price of the intermediate imported good, I_{it} is an indicator variable equal to one if the firm changes its price in period t and zero otherwise, and χ is the common menu cost of price adjustment in units of aggregate consumption.

The price adjustment decision of a firm in our model has two dimensions: First, the price adjustment decision is a function of three relative prices: the firm's price relative to the aggregate price level, the real wage and the real price of the intermediate-imported good. Second, the size of the inaction region and the magnitude of the price jumps are different for each component of marginal cost, and depend on the cost share of labor and traded inputs into production. To see this more clearly, consider a log-linearized version of the nominal cost function implied by the model,

$$c_{it} = \alpha_i w_t + (1 - \alpha_i) p_{it}^m. \tag{2.5}$$

The two state variables are the wage rate in Ecuador, w_t, and the import price, p_{it}^m. In our setting, the variance of the marginal cost function depends on the variance of wages, the variance of import prices, and their covariance. It also depends on the cost share of the two inputs, α_i. In Golosov and Lucas (2007), the frequency of price changes is increasing in the variance of idioynscratic firm-level productivity shocks because this translates directly into higher variance in marginal cost. In our setting, however, the frequency of price adjustment depends on the cost share of the two inputs and on the variance of the wage relative to the import price. The variance of cost, assuming a zero covariance between the traded input and the wage, is

$$\sigma_{c,i}^2 = \alpha_i^2 \sigma_w^2 + (1 - \alpha_i)^2 \sigma_{im}^2. \tag{2.6}$$

Under the plausible restriction that the variance of traded input prices exceed that of wages, retail items with more traded content should reprice more frequently. However, the good or service with the lowest repricing frequency is not generally a pure labor service since a mix of inputs provides diversification against idiosyncratic factor price risk. Put differently, the U-shaped relationship between the distribution share and the total cost variance will also generally produce a U-shaped frequency of price change when plotted against the distribution share.

2.3.2 Model's Solution and Calibration

Due to the lack of monthly wage and import price data available for Ecuador, we make two simplifying assumptions. First, we assume that the price of haircuts can be used as a proxy for the wage.[3] After setting the nominal wage, W_t, equal to the price of haircuts, we rely on the model, our observed retail price, P_{it}, and measures of the distribution cost share from the U.S. Personal Consumption Expenditure Bridge Table to back out the import price, P_{it}^m. Assuming constant markups and using our log-linear nominal cost function,

$$p_{it} = \alpha_i w_t + (1-\alpha_i) p_{it}^m, \tag{2.7}$$

rearranging the equation gives the (log) price of the traded intermediate good i

$$p_{it}^m = \frac{p_{it} - \alpha_i w_t}{(1-\alpha_i)}. \tag{2.8}$$

The variables p_t, w_t, and p_{it}^m, form the basis of our three-variable stochastic state space:

$$p_t = \mu + p_{t-1} + \varepsilon_{p,t}, \tag{2.9}$$

$$w_t - p_t = \rho_w (w_t - p_t) + \varepsilon_{w,t}, \tag{2.10}$$

$$p_{it}^m - p_t = \rho_{im} (p_{it-1}^m - p_{t-1}) + \varepsilon_{im,t}. \tag{2.11}$$

In these equation, the error terms are assumed to be normally distributed with mean zero and variances σ_ε^2, $\sigma_{\varepsilon_w}^2$, and $\sigma_{\varepsilon_{im}}^2$. Table 2.2 gives the results of this estimation exercise.

In our benchmark calibration, we assume that all firms face the same import-price shocks (using the median volatility across regimes and goods) as this allows us to isolate the role of heterogeneous distribution margins in accounting for the cross-sectional

[3]We ran an AR(1) on all non-traded goods prices for which $\alpha > 0.85$ (e.g., haircuts, automobile tune-up, dry cleaning service, taxi, rent of a house). Haircut prices happens to be the AR(1) process with the median volatility among retail items with high distribution shares. Using the least volatile AR(1) process across regimes as a proxy for the wage does not change the qualitative results.

heterogeneity in price-change frequencies.[4] Later in the text, we relax this assumption and look at the model's predictions of our model when import-price shocks are heterogeneous across regimes and goods.

Table 2.2: Stochastic Properties of Shocks

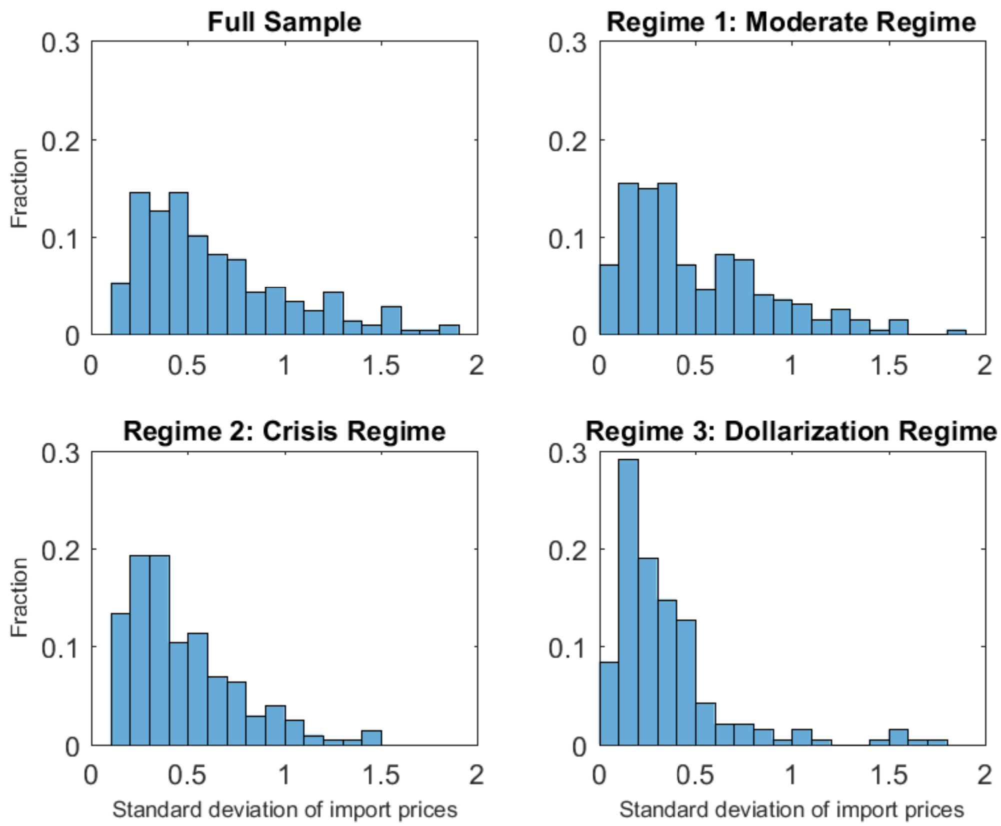
	Full sample	**Regime 1**	**Regime 2**	**Regime 3**
		Moderate regime	Crisis regime	Dolarization regime
	1997:01-2003:04	1997:01-1998:07	1998:08-2000:12	2001:01-2003:04
Inflation				
μ	0.028	0.022	0.047	0.011
σ_{ε_p}	0.026	0.008	0.031	0.010
Real wage				
(real price of haircuts)				
ρ_w	0.986	0.647	0.887	0.977
σ_{ε_w}	0.021	0.015	0.026	0.015
Real import price				
(median across α_i)				
ρ_m	0.941	0.950	0.923	0.899
$\sigma_{\varepsilon_{im}}$	0.185	0.108	0.164	0.102

Anticipating this, Figure 2.3 is a histogram showing the variance of the import price series for each of the regimes and the full sample. As expected, the import price shocks are more widely distributed in Regime 2 and in the full sample. The heterogeneity in the veracity of import price shocks across retail items adds an additional source of heterogeneity in price change frequency and (as we shall see) further advances the model's ability to account for the diversity of pricing behavior exhibited in the Ecuadorian micro-data.

Firm i's optimization problem may be written recursively in the form of the Bellman equation

[4]The volatility of our AR(1) processes is defined as $\sigma^2_{\varepsilon_{im}}/(1-\rho^2_{im})$.

Figure 2.3: Distribution of Import Price Volatility



Note: Distribution of import prices standard deviation across regimes bins width of 0.1.

$$V\left(\frac{P_{it-1}}{P_t}, \frac{W_t}{P_t}, \frac{P_t^m}{P_t}\right) = \frac{max}{\{P_{it}\}}\left[\pi_{it} + \beta E_t V\left(\frac{P_{it}}{P_{t+1}}, \frac{W_{t+1}}{P_{t+1}}, \frac{P_{t+1}^m}{P_{t+1}}\right)\right], \tag{2.12}$$

where $V(\cdot)$ is firm i's value function. We solve the model numerically for each firm i's (defined by a non-traded share, α_i) by iterating the Bellman operator that yields the value (2.12), and policy function on a discrete grid.

To match Ecuador's historical data, we allow for the stochastic process of the relative prices, the real wage, and the real import price to vary across regimes according to Table 2.2. The non-traded shares α_i and the menu cost χ do not change over time. We choose the menu cost so as to match the average frequency of price adjustments across firms in the full sample (i.e., 57.7 percent). This approach results in a menu cost parameter, χ, of 0.0004, which implies that the cost of price adjustment equals about 0.60 percent of the average firm's revenues in the full sample. Appendix B provides a full explanation of the solution method.

2.4 Results

Having estimated the stochastic processes for the two components of the firm's cost function, we are in a position to compare our benchmark model's predictions for the frequencies of price change across sectors and regimes with the micro-data. To isolate the impact of heterogeneous distribution margins, we first present results where the variance of import price shocks are the same for all firms. Then, we look into the prediction of a more realistic model in which each firm faces import price shocks with a different veracity.

2.4.1 Benchmark model

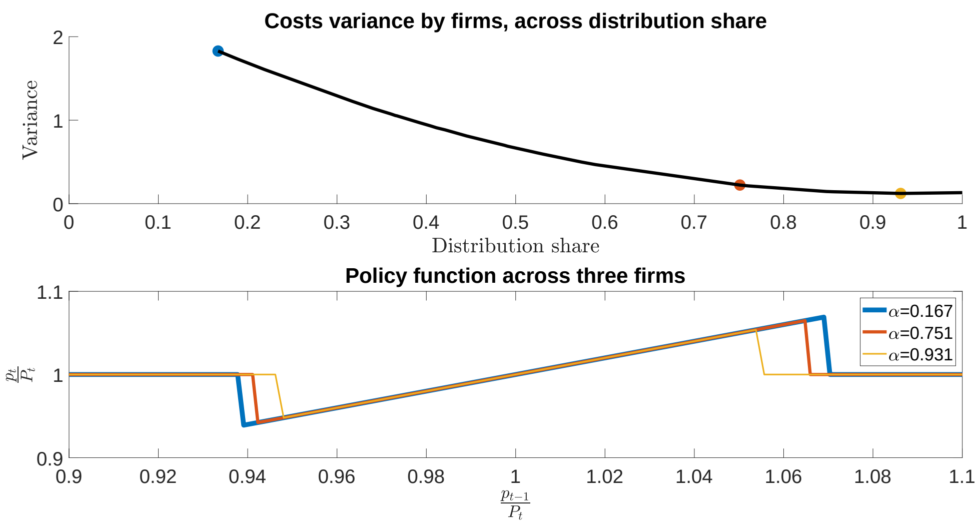
Before turning to the simulation results, it is instructive to compare the policy functions of three representative firms with different distribution shares to gain some intuition for the relationship between menu costs and price adjustment. Figure 2.4 shows the firms' policy functions using the full sample calibration. In this figure, we hold constant the aggregate price level, the import price, and the wage.[5] This is a common figure within the menu cost literature, which shows the price adjustment cutoffs as the firm's real price fluctuates around its optimal price. In Figure 2.4, each firms has a different policy function because each firm has a different cost structure.

The sensitivity of the cost structure to cost shocks also leads firms to have slightly different bands of inaction (or price adjustment cutoffs) relative to their optimal price. Consistent with our theory, we observe that firms that rely more heavily on one cost (i.e. wage

[5] Note that these policy functions have normalized around the firms' optimal price, as the cost structure shifts firms' marginal cost and optimal price.

or import prices) have wider inaction bands.[6] For example, a firm that heavily rely on imports (e.g., $\alpha = 0.167$) requires a larger deviation in its relative price to induce an optimal price change than does a firm that relies mostly on labor (e.g., $\alpha = 0.931$). In practice, the volatility of inputs prices is so much larger than wages that the direct effect of higher cost volatility dominates the indirect effect of the option value of waiting (widening of the bands of inaction) and prices change more frequently for retail items with more traded factor content.

Figure 2.4: Costs Variance and Policy Functions



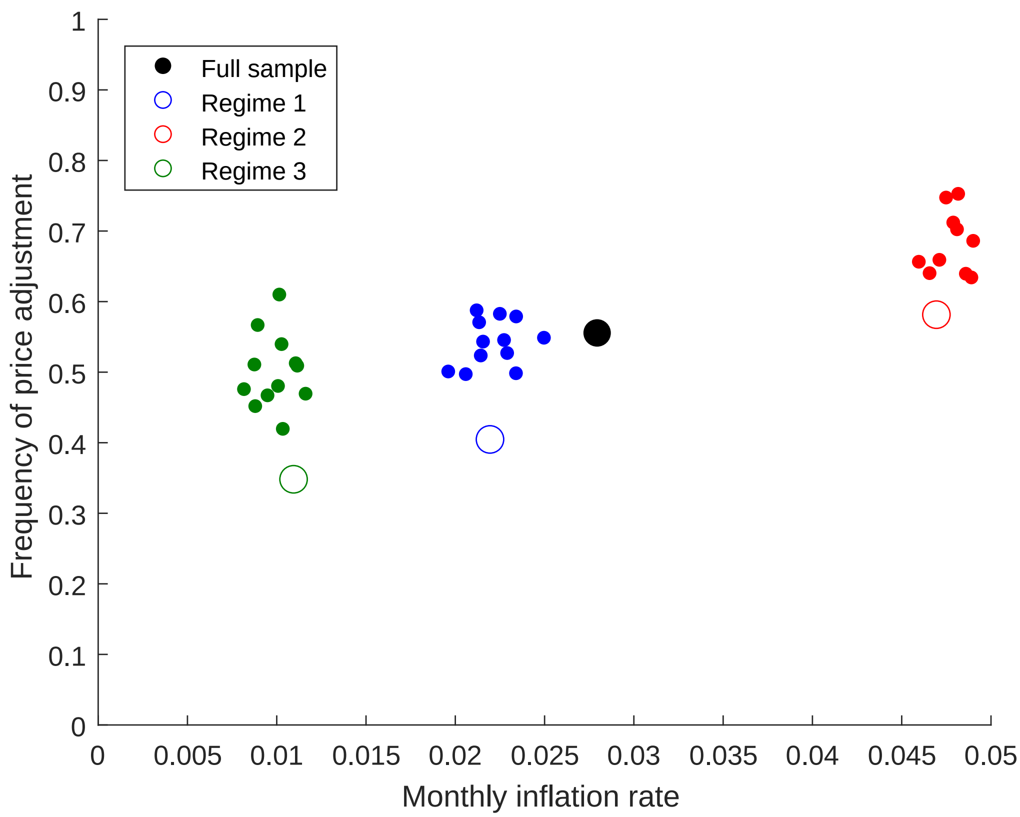
Note: The top panel shows the firms' costs variance, by distribution share. The bottom panel shows the policy function of three firms with different distribution share, normalized around their optimal price in the full sample calibration, holding constant the aggregate price level, the import price, and the wage. This figure shows that firms that experience higher costs variance have larger inaction bands.

In our first exercise, we test the ability of our model to match the median frequency of prices changes across all three regimes. Figure 2.5 presents the median frequencies of price adjustments by regime for each city in the Ecuadorian micro-panel as well as the predictions of the baseline calibration of the model. The large circles are the predictions

[6]As pointed out by the referees, Barro (1972), and more recently Vavra (2014), increase in the volatility of input prices have two effects: First, there is a direct effect where greater volatility pushes more firms to adjust for a given region of inaction. Second, greater volatility also increases the option value of waiting, which widens the size of the inaction region and decreases the frequency of price adjustment. The first effect typically dominates with an increase in volatility, leading more frequent price adjustments despite wider inaction bands.

from the model while the small dots are the median frequency of price adjustment across cities. For example, the cluster of green dots represents the median frequencies of price adjustments across goods, city-by-city, for the Dollarization regime (Regime 3). Figure 2.5 confirms that our benchmark calibration model captures well the frequency of price adjustment across regimes.

Figure 2.5: Average Frequency of Price Adjustment by Regime, Data versus Model



Note: Comparison of the frequency of price adjustment by regime, in the data and in the model.

Our next exercise is to see how the model fares in accounting for the heterogeneity of price adjustment frequencies across goods. Panel A of Figure 2.7 displays the frequency of price adjustment for each distribution share in the benchmark model. In this panel, each dot represents a distribution share across the regimes in the same fashion as the data were presented in Figure 2.2: Regime 1's simulations are on the x-axis and Regime 2's and 3's are the y-coordinates. It should be kept in mind that we have fewer distribution shares than goods, which limits to some extent the cross-sectional variance that results. That being said, the variation is smaller than what we saw in Figure 2.2 earlier. We suspect that this is partly due to our adherence to a common variance of import-price shocks across goods. In the next subsection, we relax this assumption and extend the model to include heterogeneity in import prices.

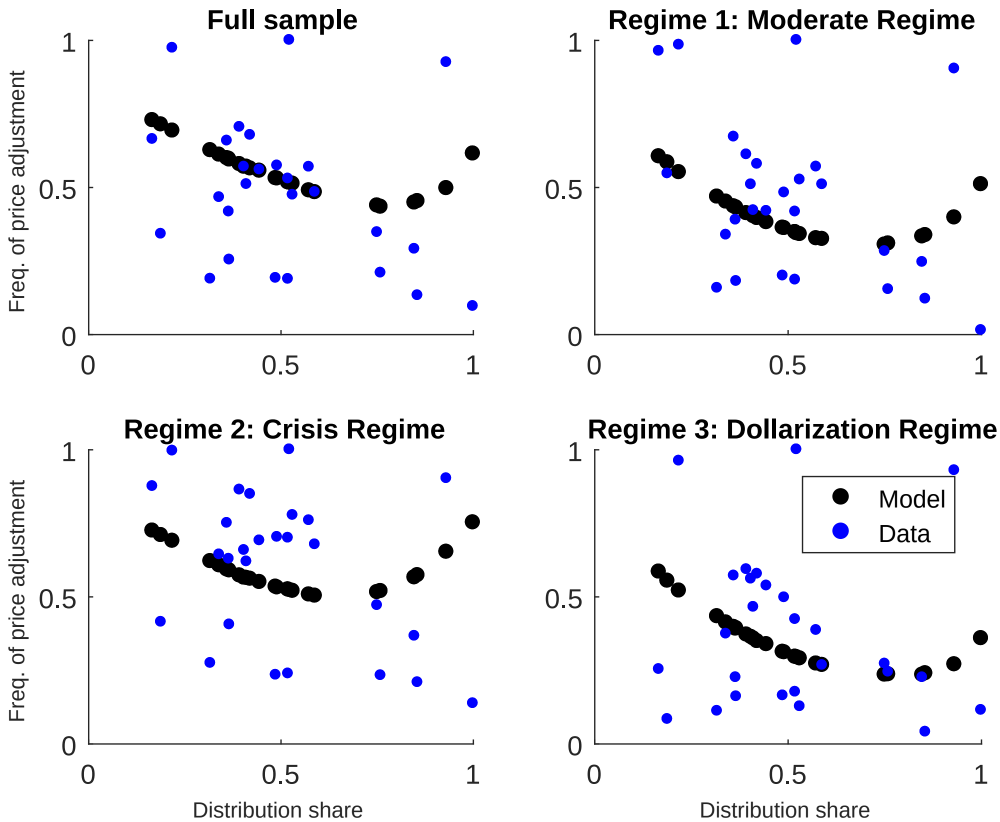
Finally, Figure 2.6 displays the relationship between the distribution share (on the x-axis) and the frequency of price adjustment (on the y-axis) in the model and in the data. The blue dots show the median frequency of price adjustment for each distribution share in the data. These dots show that firms that rely more heavily of both inputs (i.e., a distribution share close to 0.5) usually reprice less frequently than firms that rely more heavily on one input. In the model, this corresponds to the U-shape relationship discussed above and readily apparent by the black dots. Our model not only accounts for the fact that goods maintain a certain frequency of price adjustment pattern across regimes, but it also distinguishes which goods are more likely to reprice based on their cost structure.

Together, these results indicate that our menu cost model can account for many of the stylized facts we found in Section 2 and Section 3 regarding the price adjustment process of firms that are heterogeneous in their cost structure. In addition to matching the positive correlation between frequencies of price changes and aggregate inflation, our structural model provides a novel explanation for the different frequencies of price changes observed across the distribution of goods in the CPI.

2.4.1.1 Model with idiosyncratic import prices

In the baseline calibration, we use the stochastic property of the import price with the median volatility as a proxy for import prices. In this section, we extend the model to take into account differences in the volatility of import prices across retail goods. That is, we will use the stochastic property of the import price (as found in equation (2.11)) for each α_i firm. We use the median volatility import-price series for each sector that has more than

Figure 2.6: Frequencies of price adjustment by regime and distribution share



Note: The blue dots represent the median frequency of price adjustment across distribution shares in the data. The black dots represent the monthly frequency of price adjustment across firms in the model. The x-coordinate is the distribution share of the firms and the y-coordinate is the monthly frequency of price adjustment.

one retail good.[7]

Figure 2.7, Panel B, displays the frequency of price adjustment for each distribution share in our model with idiosyncratic import prices. As for Panel A, each dot represents a distribution share across the regimes in the same fashion as the data were presented in Figure 2.2: Regime 1's simulations are on the x-axis and Regime 2's and 3's are the y-coordinates. As opposed to Panel A, however, the variation in the frequency of price adjustment is much closer to that in Figure 2.2. In particular, the scatter plot for Regime 2 is

[7]In addition, Gopinath and Itskhoki (2010) and Berger and Vavra (2017) show that variation in markup elasticity across firms can generate significant variation in the frequency of price adjustment. As an alternative to our benchmark model, Appendix C looks into the pricing dynamics of firms facing variable markups.

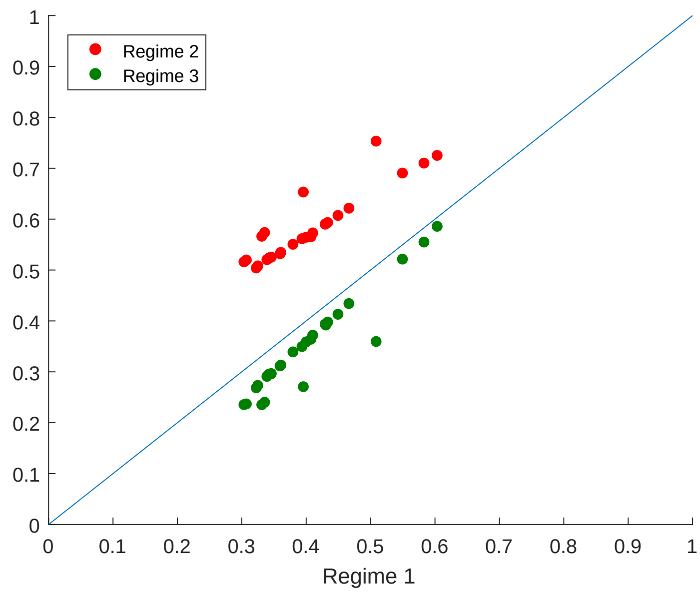
concentrated above the 45 degree line, while that of Regime 3 are mostly below the scatter of Regime 2.

In particular, this panel speaks to Boivin et al. (2009) evidence that disaggregated prices appear sticky in response to macroeconomic and monetary disturbances but flexible in response to sector-specific shocks: Panel B shows that sector-specific shocks (i.e., idiosyncratic import prices) increase the frequency of price adjustment compared to the benchmark model's where firms face common shocks (Panel A). In other words, the model with idiosyncratic import prices generates responses to sector-level and aggregate shocks that are closer to what we observe in the data.

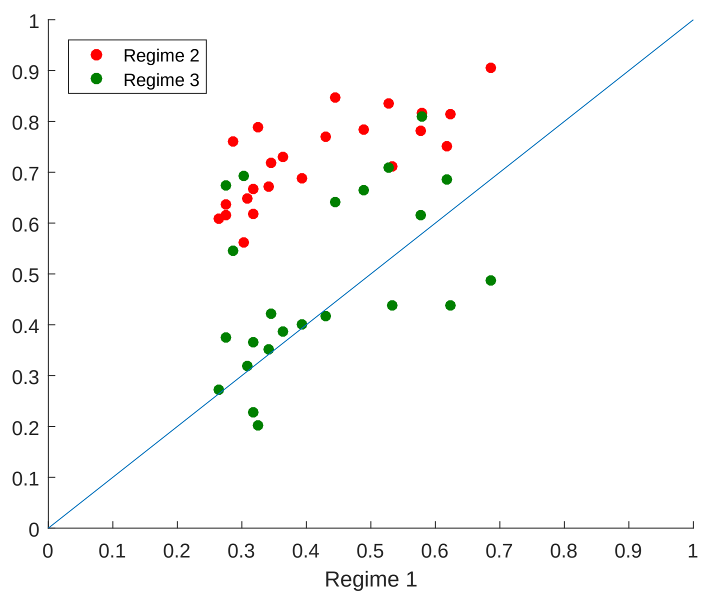
2.5 Conclusion

In making decisions about changes in the federal funds rate, it is essential that monetary policymakers distinguish generalized inflationary impulses from changes in relative prices that may affect some, but not all, market prices. The structure of our model helps to elucidate these differences. Changes in the prices of imported goods are often large and induce frequent changes in the retail prices of these goods. Essentially, this is why food and energy are typically excluded in measures of core inflation. The typical explanation for the volatility of these prices is that the markets for them are subject to particularly large sector-specific shocks. Our approach generalizes this conventional wisdom by recognizing that final goods have distinct production functions in the sense of requiring different intensities of retail labor in making them available to final consumers. This allows us to parse the inflationary impulse of, say, an indexed wage (typically the cost-push dimension of monetary policy) from shocks that are idiosyncratic to the good or sector (such as imported goods). Ecuador provides an ideal setting to explore this mechanism by virtue of high-frequency micro-price data by good and city spanning a varied inflationary experience.

Figure 2.7: Monthly Frequency of Price Adjustment in the Model



A. Benchmark model



B. Model with idiosyncratic import prices

Note: Comparison of price adjustment frequencies across regimes in the model. Each dot represents one firm's frequency of price adjustment across two regimes. The x-coordinates represent the price adjustment frequencies in Regime 1, while the y-coordinates represent the price adjustment frequencies in the Regime 2 (the Crisis regime) and Regime 3 (the Dollarization regime).

Our hope is that our work will motivate similar studies in other countries to validate the menu cost model developed here using a broader cross-section of nations and inflationary environments closer to that of the United States.

Appendix A

Distribution Shares

The distribution share for each good and service available in the Ecuadorian monthly database of retail prices is listed in the table below.

Table A.1 List of Goods and Services

	Distribution	Frequency of Price Adjustment			
Item	Share	Full Sample	Reg. 1	Reg. 2	Reg. 3
Automobile or pick-up truck	0.167	0.663	0.963	0.875	0.253
Gasoline	0.189	0.341	0.546	0.414	0.083
Newspaper	0.318	0.184	0.120	0.319	0.086
Magazine	0.318	0.192	0.194	0.229	0.136
Toilet Paper	0.341	0.466	0.338	0.643	0.374
Milk, fresh	0.361	0.429	0.468	0.506	0.318
Cheese	0.361	1.000	1.000	1.000	1.000
Eggs	0.361	1.000	1.000	1.000	1.000
Oil, vegetable	0.361	0.658	0.681	0.762	0.528
Margarine	0.361	0.636	0.676	0.735	0.497
Fruit cocktail, can	0.361	0.656	0.616	0.750	0.593
Raisins	0.361	1.000	1.000	1.000	1.000
Peas, dry	0.361	0.999	1.000	1.000	0.997
Beans, dry	0.361	0.999	1.000	1.000	0.997
Lentils	0.361	0.999	1.000	1.000	0.997
Peanuts	0.361	0.999	1.000	0.997	1.000
Sugar	0.361	0.994	0.995	0.997	0.991

Chocolate, candy	0.361	0.612	0.500	0.637	0.670
Candy	0.361	0.630	0.546	0.741	0.583
Gelatine	0.361	0.563	0.551	0.646	0.472
Marmalade	0.361	0.670	0.532	0.810	0.602
Honey	0.361	0.482	0.338	0.545	0.528
Panela	0.361	0.996	0.991	1.000	0.994
Salt	0.361	0.622	0.653	0.670	0.553
Ketchup	0.361	0.606	0.630	0.732	0.460
Broad beans, flour	0.361	0.993	1.000	1.000	0.982
Soup, dry	0.361	0.642	0.546	0.789	0.546
Coffee, ground	0.361	0.687	1.000	0.714	0.444
Coffee, instant	0.361	0.590	0.491	0.720	0.519
Cocoa	0.361	0.689	0.611	0.765	0.661
Mineral water	0.361	0.410	0.333	0.500	0.358
Soft drink, store	0.361	0.364	0.375	0.506	0.213
Orange juice	0.361	0.508	0.454	0.637	0.420
Soft drink in powder	0.361	0.381	0.389	0.449	0.303
Beer, at store	0.361	0.340	0.306	0.506	0.188
Rum	0.361	0.590	0.482	0.708	0.565
Wine	0.361	0.582	0.380	0.744	0.559
Milk of magnesia	0.361	0.453	0.509	0.637	0.232
Chicken, rotisserie	0.361	1.000	1.000	1.000	1.000
Glass	0.366	0.490	0.357	0.688	0.380
Medicines in general	0.366	0.941	0.977	0.997	0.855
Aspirin (medicine)	0.366	0.344	0.357	0.545	0.130
Linconcin (medicine)	0.366	0.472	0.458	0.696	0.219
Flagil (medicine)	0.366	0.364	0.347	0.554	0.188

Garamicina (medicine)	0.366	0.417	0.500	0.533	0.235
Neurobion (medicine)	0.366	0.414	0.245	0.753	0.179
Voltaren (medicine)	0.366	0.429	0.588	0.524	0.232
Megacilina (medicine)	0.366	0.410	0.403	0.649	0.170
Apronax (medicine)	0.366	0.428	0.463	0.643	0.179
Redoxon (medicine)	0.366	0.400	0.273	0.720	0.127
Hepabionta (medicine)	0.366	0.330	0.301	0.569	0.093
Baycuten, cream (medicine)	0.366	0.442	0.431	0.571	0.293
Comtrex (medicine)	0.366	0.422	0.426	0.634	0.201
Mucosolvan (medicine)	0.366	0.478	0.375	0.676	0.349
Cataflam (medicine)	0.366	0.460	0.528	0.619	0.262
Fungirex (medicine)	0.366	0.417	0.310	0.646	0.250
Imodium (medicine)	0.366	0.298	0.282	0.521	0.077
Acrosin-B (medicine)	0.366	0.417	0.319	0.622	0.287
Glasses	0.366	0.416	0.407	0.560	0.278
Cigarrettes	0.367	0.253	0.181	0.405	0.161
Stove, gas	0.393	0.753	0.755	0.875	0.636
Blender	0.393	0.707	0.616	0.878	0.593
Refrigerator	0.393	0.704	0.611	0.863	0.614
Pot, cooking	0.393	0.534	0.505	0.699	0.404
Cup with dish	0.393	0.472	0.417	0.661	0.318
Bleach, for laundry	0.405	0.572	0.458	0.711	0.509
Detergent	0.405	0.550	0.583	0.646	0.429
Soap for dishwashing	0.405	0.620	0.574	0.708	0.556
Soap for laundry	0.405	0.523	0.579	0.604	0.395
Cologne	0.405	0.466	0.343	0.580	0.438
Cream, moisturizer	0.405	0.598	0.500	0.679	0.580

Deodorant	0.405	0.552	0.435	0.616	0.565
Soap, deodorant	0.405	0.567	0.468	0.637	0.568
Toothpaste	0.405	0.620	0.602	0.702	0.549
Shampoo	0.405	0.537	0.361	0.625	0.574
Talc powder	0.405	0.610	0.546	0.670	0.593
Sanitary pads	0.405	0.612	0.519	0.711	0.583
TV set, color	0.411	0.721	0.611	0.848	0.673
Rent of VHS movie	0.411	0.299	0.232	0.390	0.256
Sewing machine	0.421	0.632	0.588	0.777	0.519
Iron, electric	0.421	0.640	0.537	0.857	0.494
Sound system, stereo	0.421	0.723	0.630	0.887	0.636
VCR	0.421	0.714	0.569	0.839	0.698
Shoe polish	0.445	0.571	0.389	0.696	0.583
Disinfectant, domestic	0.445	0.548	0.449	0.685	0.491
Cupboard, wooden	0.487	0.614	0.556	0.765	0.515
Bed, wooden	0.487	0.579	0.472	0.744	0.491
Chest of drawers, wooden	0.487	0.546	0.426	0.682	0.485
Matches	0.487	0.307	0.278	0.467	0.145
Book, primary school (typical)	0.487	0.141	0.144	0.164	0.127
Notebook for primary school	0.487	0.179	0.157	0.226	0.157
Notebook for secundary school	0.487	0.192	0.181	0.235	0.170
Paper, bond	0.487	0.182	0.162	0.232	0.157
Algebra book	0.487	0.190	0.218	0.202	0.173
Dictionary for school	0.487	0.130	0.148	0.140	0.117
Razor, standard manual	0.491	0.573	0.482	0.702	0.497
Cassimere, fabric	0.519	0.557	0.495	0.744	0.414
Chalis, fabric	0.519	0.566	0.389	0.765	0.488

Silk, fabric	0.519	0.433	0.315	0.607	0.340
Dress for woman, making	0.519	0.434	0.273	0.530	0.454
Pants for man, making	0.519	0.483	0.380	0.655	0.386
Suit for man, making	0.519	0.582	0.486	0.717	0.525
Socks, mens	0.519	0.507	0.431	0.711	0.367
Underwear, mens	0.519	0.561	0.477	0.735	0.454
Shirt, mens	0.519	0.550	0.560	0.711	0.380
T-shirt, mens	0.519	0.546	0.472	0.717	0.417
Pants, mens	0.519	0.623	0.574	0.768	0.528
Shorts, for sports, mens	0.519	0.512	0.380	0.679	0.441
Suit for men	0.519	0.541	0.468	0.705	0.426
T-shirt, childrens	0.519	0.590	0.500	0.708	0.531
Pants, boys	0.519	0.537	0.394	0.732	0.429
Blouse, womens, typical	0.519	0.512	0.370	0.688	0.423
Underwear, womens	0.519	0.513	0.417	0.679	0.411
T-shirt, womens	0.519	0.513	0.449	0.685	0.383
Skirt, womens	0.519	0.461	0.310	0.577	0.441
Pantyhose, nylon	0.519	0.407	0.431	0.488	0.309
Pants, womens	0.519	0.618	0.560	0.777	0.497
Dress, womens	0.519	0.501	0.380	0.667	0.420
Pants, girls	0.519	0.518	0.403	0.699	0.404
Underwear, girls	0.519	0.580	0.528	0.741	0.463
Dress, girls	0.519	0.547	0.352	0.726	0.503
Shirt, babies	0.519	0.472	0.380	0.601	0.414
Suit for baby	0.519	0.492	0.361	0.691	0.380
Shoes, leather, mens	0.519	0.558	0.463	0.759	0.414
Shoes, sneakers, mens	0.519	0.441	0.370	0.637	0.287

Shoes, boys	0.519	0.549	0.468	0.717	0.441
Shoes, leather, womens	0.519	0.568	0.472	0.753	0.451
Shoes, sneakers, womens	0.519	0.561	0.482	0.735	0.448
Shoes, girls	0.519	0.586	0.454	0.750	0.506
Shoe polishing	0.519	0.184	0.157	0.238	0.151
Dining set	0.519	0.588	0.519	0.756	0.469
Living room set	0.519	0.586	0.528	0.717	0.506
Blanket, thick, very warm	0.519	0.480	0.463	0.682	0.296
Blanket, thick, warm	0.519	0.443	0.333	0.634	0.327
Mattress	0.519	0.529	0.403	0.711	0.432
Blanket, thin	0.519	0.579	0.514	0.744	0.466
Towel	0.519	0.557	0.463	0.702	0.485
Broom	0.519	0.529	0.407	0.679	0.469
Uniform for school	0.519	0.158	0.181	0.173	0.139
School supplies in general	0.519	0.267	0.269	0.286	0.265
Compass, drawing, primary school	0.519	0.184	0.171	0.226	0.164
Ruler, primary school	0.519	0.188	0.185	0.214	0.176
Pen for primary school	0.519	0.163	0.153	0.211	0.133
Folder	0.519	0.159	0.153	0.196	0.136
Geometry set for school	0.519	0.179	0.120	0.208	0.201
Ruler, secondary school	0.519	0.184	0.194	0.214	0.161
Pen for secundary school	0.519	0.160	0.157	0.211	0.120
Diapers, disposable for children	0.519	0.542	0.435	0.640	0.522
Vegetable fat	0.523	0.591	0.597	0.685	0.469
Avocado	0.523	0.981	0.935	0.997	0.997
Bananas	0.523	0.993	0.991	0.997	0.991
Lemons	0.523	0.946	1.000	1.000	0.849

Apples	0.523	1.000	1.000	1.000	1.000
Raspberries	0.523	1.000	1.000	1.000	1.000
Oranges	0.523	0.903	0.986	1.000	0.778
Naranjilla	0.523	1.000	1.000	1.000	1.000
Papaya	0.523	1.000	1.000	1.000	1.000
Pineapple	0.523	0.998	0.991	1.000	1.000
Plantain	0.523	0.999	1.000	0.997	1.000
Watermelon	0.523	0.987	1.000	1.000	1.000
Tomatillo	0.523	1.000	1.000	1.000	1.000
Grapes	0.523	0.999	0.995	1.000	1.000
Peas, fresh	0.523	1.000	1.000	1.000	1.000
Onion, white	0.523	1.000	1.000	1.000	1.000
Onion, red	0.523	1.000	1.000	1.000	1.000
Cabbage	0.523	1.000	1.000	1.000	1.000
Cauliflower	0.523	1.000	1.000	1.000	1.000
Corn, fresh	0.523	1.000	1.000	1.000	1.000
Broad beans, fresh	0.523	1.000	1.000	1.000	1.000
Beans, fresh	0.523	1.000	1.000	1.000	1.000
Lettuce	0.523	1.000	1.000	1.000	1.000
Bell pepper	0.523	1.000	1.000	1.000	1.000
Tomatoes	0.523	1.000	1.000	1.000	1.000
Potatoes	0.523	1.000	1.000	1.000	1.000
Yucca	0.523	1.000	1.000	1.000	1.000
Carrots	0.523	1.000	1.000	1.000	1.000
Garlic	0.523	1.000	1.000	1.000	1.000
Bicycle, typical	0.531	0.473	0.565	0.801	0.074
Typewriter	0.531	0.474	0.486	0.753	0.179

Light bulb, typical	0.574	0.569	0.569	0.759	0.386
Tire, with tube if needed	0.589	0.547	0.532	0.640	0.463
Soccer ball	0.589	0.420	0.486	0.714	0.071
Inter-province trip	0.751	0.157	0.157	0.205	0.071
Transportation, public in bus	0.751	0.137	0.102	0.220	0.046
Entertainment, dancing	0.751	0.342	0.213	0.455	0.327
Lunch, typical	0.751	0.448	0.380	0.625	0.315
Soft drink, at bar	0.751	0.347	0.282	0.470	0.272
Beer, at bar	0.751	0.371	0.329	0.524	0.228
Lodging, typical	0.751	0.400	0.315	0.545	0.318
Water (utility)	0.760	0.209	0.125	0.232	0.244
Electricity	0.760	0.599	0.153	0.777	0.719
Gas, natural, domestic	0.760	0.194	0.264	0.223	0.093
Shoe repair	0.848	0.382	0.273	0.545	0.290
Laundry service	0.848	0.290	0.255	0.366	0.225
Dry cleaning	0.848	0.392	0.292	0.557	0.303
Doctors visit	0.848	0.349	0.278	0.399	0.346
Lab test, typical medical	0.848	0.359	0.301	0.482	0.281
Automobile tune-up	0.848	0.567	0.625	0.714	0.392
Soccer game	0.848	0.170	0.107	0.208	0.179
Tuition, kindergarden	0.848	0.134	0.144	0.164	0.108
Tuition, primary school	0.848	0.149	0.162	0.179	0.120
Registration, secondary school	0.848	0.124	0.153	0.140	0.099
Tuition, secondary school	0.848	0.139	0.157	0.170	0.105
Registration, university	0.848	0.119	0.097	0.149	0.111
Haircut	0.848	0.309	0.245	0.429	0.225
Taxi, urban	0.856	0.132	0.120	0.208	0.040

Rent of house, typical	0.931	0.924	0.824	0.967	0.948
Rent of apartment, typical	0.931	0.886	0.903	0.890	0.874
Rent of room, efficiency	0.931	0.924	0.958	0.902	0.929
Postage for letter, typical	1.000	0.096	0.014	0.137	0.114

Appendix B

Equations, and Solution Method

B.0.1 Profit function

Firm i maximizes the value of its expected discounted profits,

$$E_t \sum_{s=t}^{\infty} \beta_{t,s} \pi_{i,s}, \tag{B.1}$$

where real profit is,

$$\pi_{it} = \frac{P_{it}}{P_t} y_{it} - \frac{W_t}{P_t} l_{it} - \frac{P_{it}^m}{P_t} m_{it} - \chi I_{it}. \tag{B.2}$$

With a Cobb-Douglas production function, the cost index is

$$P_{it}^c = \left(\frac{W_t}{\alpha_i}\right)^{\alpha_i} \left(\frac{P_{it}^m}{1-\alpha_i}\right)^{1-\alpha_i}. \tag{B.3}$$

Hence, we compute real profit as

$$\pi_{it} = \left(\frac{P_{it}}{P_t} - \frac{P_{it}^c}{P_t}\right) y_{it} - \chi I_{it}. \tag{B.4}$$

B.0.2 Solution Method

Here are the steps we use to solve and simulate the model.

1. Define the grids and transition probability matrix for $\frac{P_{it}}{P_t}$, $\frac{W_t}{P_t}$, and $\frac{P_{it}^m}{P_t}$, using the Rouwenhorst method (as in Kopecky and Suen (2010)). We use a grid with increments of one percent for the firms real price, and with increments of two percent for the real wage and the real import price.

2. Create the profits grid in the space $\frac{P_{it}}{P_t}$, $\frac{W_t}{P_t}$, and $\frac{P^m_{it}}{P_t}$.

3. Iterate the Bellman equation (2.12) to convergence.

4. Compute the price adjustment policy function.

5. Repeat step 1. to 4. for each α_i firm.

6. Simulate the model for each α_i firm over an horizon of 10,000 periods (months).

Appendix C

Model with variable markups

Gopinath and Itskhoki (2010) and Berger and Vavra (2017) show that variation in markup elasticity across firms can generate significant variation in the frequency of price adjustment. In these studies, however, variation in the markup elasticity were meant to generate time-variation in price adjustment dispersion—as oppose to steady-state outcomes across regimes.

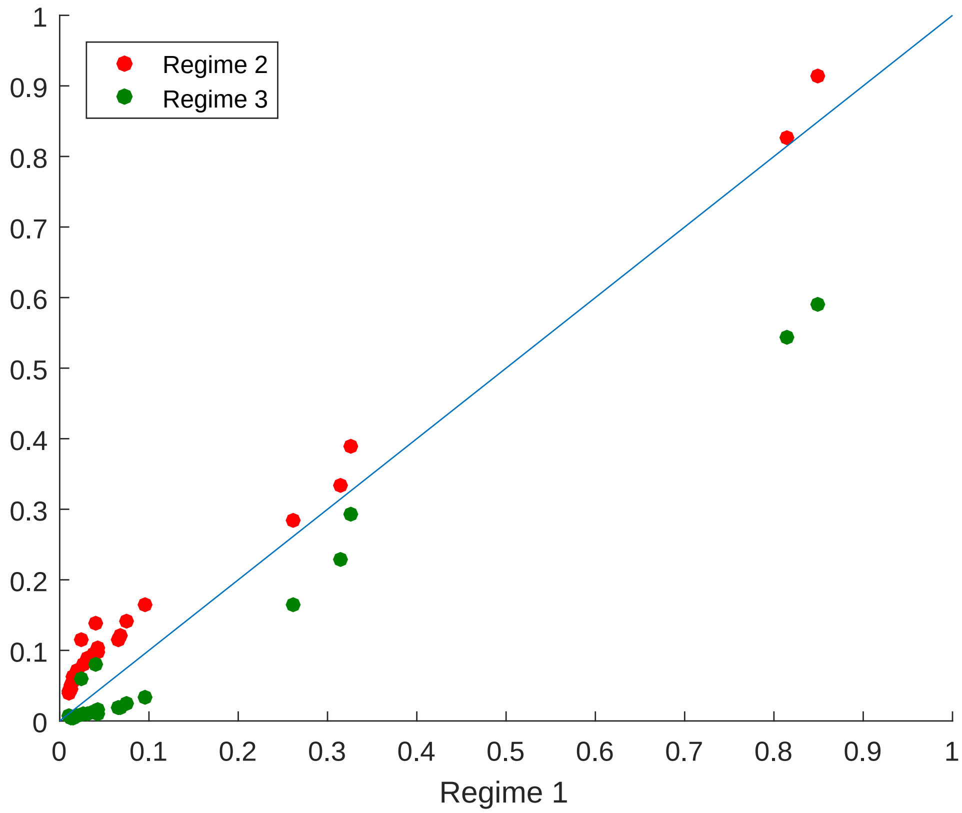
As in Gopinath et al. (2010a), we allow for variable markups through the non-constant demand elasticity schedule proposed by Klenow and Willis (2016). This specification is a useful abstraction for modeling variable markups arising from strategic interactions between monopolistic competitors because the super-elasticity of demand provide a strong incentive for a firm to keep its price close to the aggregate price level. Specifically, consumers' preferences are represented by an aggregator over the consumption of a continuum of products $i \in [0,1]$ such that the demand for the i^{th} product take the form

$$y_{it} = \left(1 - \gamma \ln\left(\frac{P_{it}}{P_t}\right)\right)^{\theta/\gamma} y_{i,t}, \tag{C.1}$$

where $\theta > 0$ governs the elasticity of demand and $\varepsilon > 1$ the super-elasticity of demand. In this exercise, we keep the values from the benchmark model calibration and set ε to 3 as in Gopinath et al. (2010a).

Figure C.1 displays the frequency of price adjustments for each distribution share in the model with variable markups. In this figure, each dot represents a distribution share across the regimes in the same fashion as the data were presented in Figure 2.2: Regime 1's simulations are on the x-axis and Regime 2's and 3's are the y-coordinates. The figure shows that variation in markup elasticity across firms changes the frequency of price adjustment across firms. The central message of this exercise, however, is that the cross-sectional distribution of price adjustment frequencies is preserved across regimes—as in Figure 2.2.

Figure C.1: Monthly Frequency of Price Adjustment in the Model with Variable Markups



Note: Comparison of price adjustment frequencies across regimes in the model with variable markups. Each dot represents one firm's frequency of price adjustment across two regimes. The x-coordinates represent the price adjustment frequencies in Regime 1, while the y-coordinates represent the price adjustment frequencies in the Regime 2 (the Crisis regime) and Regime 3 (the Dollarization regime).

Chapter 3

The Law of One Price in Ecuador

3.1 Introduction

While the law of one price (LOP) and the related theory of purchasing power parity (PPP) are taught in almost every undergraduate international finance class, its regular occurrence has always been perceived as more of a theoretical desire than an empirical reality. The former theory is straightforward. If goods in location A were to cost more than goods in location B, then a profit-seeking agent could simply buy the goods in location B and transport them to location A, selling them at the higher price. Assuming low transportation costs, the process could be repeated indefinitely making a nice profit for the arbitrageur who would continue to have the incentive to transport goods as long as the price discrepancy remained. This would increase demand in location B and supply in location A until their prices eventually converged, eliminating the incentive for arbitrage and settling at an equilibrium where the price of similar goods were the same across locations. PPP is the related theory that if all retail prices were to converge to the same level for all goods, then national price aggregates of those goods should converge as well. It is commonly divided into two variants: absolute PPP and the less restrictive relative PPP. Absolute PPP states that after accounting for exchange rate differences, the national price level should converge to the same level. Relative PPP states that while the price levels may not converge to the same point, the growth rates of two countries equal each other after accounting for the growth rate of the exchange rate.

However, as many authors including Rogoff (1996) have pointed out, the empirical evidence does not match well with the theory. What has become known in the literature as the "PPP Paradox" is one of the most researched areas of international finance over the last three decades. Despite the logic of the theory, the results of studies relating to the PPP paradox have been clear and consistent in their opposition to PPP. Studies have demonstrated this in a number of ways, but the most relevant to this study is to calculate the convergence properties of the real exchange rate (RER) using unit root tests. The "consensus view" is that a shock to the RER may in fact never die out or at the very least, take a while to do so. Most papers in the field have estimated a half-life to these shocks in the range of approximately three to five years on the lower end. Frankel and Rose (1996) estimate the half-life to be about 4 years. Murray and Papell (2002) estimate half-lives at about 4.6 years. These large and long-lasting deviations of the real exchange rate have been documented extensively. Even when focusing purely on intranational price convergence, Cecchetti et al. (2002) looks at a panel of 19 US cities over a 77 year period and estimates half-life of RER deviations to be approximately 9 years.

A number of explanations were put forward but again quickly rejected by the data. One argument, was that both LOP and PPP rely on low transaction costs associated with the goods' prices. If a good were non-traded, then an arbitrage process could not occur and the prices would not converge. However, Engel (1999) has demonstrated that even with this caveat, the theory may be lacking. In a seminal paper, he creates price indices of traded and non-traded goods. He finds that traded goods are, contrary to the theory, more likely to be responsible for movements in the real exchange rate and deviations from purchasing power parity. Non-traded goods' prices are negligible in the movement of the real exchange rate. Cecchetti et al. (2002) finds support to an extent but argues that it depends on econometric methods used. Using an Im, Pesaran, and Shin unit root test, they find faster convergence for traded goods but a Levin and Lin unit root test shows results that mirror those of Engel.

Despite these initial drawbacks through, much of the recent literature has seemed to come from what Taylor (2001) dubs the "whittling down half-life team," a phenomenon described by Taylor that suggests the LOP may be a more reasonable approach than believed two decades ago. The lack of corroboration of PPP lies not in the theory but in the data. Specifically, the past two decades has seen the introduction of micro-data or prices at much more disaggregated levels. More refined prices at the good and sector level and data being collected at much higher frequencies has led to LOP studies rather than just the aggregate counterpart of PPP. This field of research has led to lower and lower half-lives when evaluated at the goods level as we understand more about their aggregation into price indices. Taylor, for example, suggests the frequency and the nonlinearity of the data plays significant role in biasing these half-lives upwards and moreover, he shows that these nonlinearities and low frequency data work in conjunction with each other to magnify each other's bias effects. As earlier analyses were typically reliant on annual data with linear specification, half-life estimates can be over one and a half as large as the same data being estimated with a nonlinear specification and monthly data. Fan and Wei (2006) put this challenge to the test using a dataset of monthly prices for 92 goods in 36 cities in China. Using both a Maddala and Wu (1999) test for linear convergence and an ESTAR model for nonlinear mean reversion, they found that prices overwhelmingly converged to the LOP and half-lives were on the order of months, rather than the years found by the prior PPP studies. O'Connell and Wei (2002) look at goods prices and use a model of non-linear mean reversion for 24 US cities. They find that stationary price dynamics for all cities.

In addition, Imbs et al. (2005) further reduced half-lives by showing a phenomenon known in the literature as aggregation bias. According to Imbs et al. (2005), current time-series and econometric methods fail to take into account heterogeneous dynamics in the goods that comprise the aggregate series. To account for this heterogeneity, they estimate persistence for a panel of sectoral real exchange rates and then average the half-lives using the weighted averages of the AR coefficients. By controlling for this bias, they show that the RER half-life may fall as low as 11 months. Chen and Engel (2005) challenge this view in a follow-up by first estimating the average half-life across sectors and then averaging the estimates. By doing so, they show average persistence of sectoral RERs within the range of the prior literature strengthening the PPP paradox.

Crucini and Shintani (2008) further investigate two phenomena known in the literature as categorization and compositional bias. Categorization bias refers to the fact that while goods may be classified as traded or non-traded for the purposes of creating a price index, not for calculating LOP deviations. Therefore, there may be positive bias in estimating variation in the real exchange rate because non-traded goods enter the traded good index and vice versa. Additionally, Crucini and Shintani point out that many goods use both traded and non-traded and non-traded components in their production. A beer served in a bar for example, would be dependent not only on the price of the beer, which could be arbitraged easily across locations, but also on the labor of the bartender as well, which could not be transferred with the same ease. Therefore looking at goods level prices, which are aggregates of the inputs used in them, creates upward bias on convergence rates. Using retail price data from the EIU, they show both strong convergence of prices and lower half-lives than the consensus estimate. Additionally, they show that the persistence of LOP deviations in traded goods are positive correlated with distribution margin. Although the median half-life for traded goods only 6 months greater than the non-traded goods' half-life, this disparity grows when looking at the inputs rather than the outputs. Thus, they show that the classical view that traded goods should converge faster than non-traded goods applies when looking input prices rather than goods prices. Crucini and Landry (2017) further investigate the role distribution margins play but instead calculate the volatility of traded and non-traded goods. Using EIU micro-data they challenge the view put forth by Engel (1999) and add further support to the role played by aggregation bias and compositional bias in RER volatility.

This paper adds to the whittling down half-life team by using the micro-price dataset described in Chapter 2. Combining approaches in Crucini and Landry (2017) and Crucini and Shintani (2008) I find that convergence rates are on the order of months. To test for aggregation bias, I begin by constructing a price index for each of the 66 bilateral city-pairs in Ecuador. Using an Augmented Dickey-Fuller (ADF) test I show that convergence at the aggregate price level resembles that of other PPP studies relying on price indexes. These unit root rejection rates are similar to the average rejection rates calculated for individual goods, indicating minimal aggregation bias. Furthermore, comparing the traded and non-traded indexes with individual traded and non-traded goods, I show that the classical dichotomy is more appropriate when applied to the index. These results vanish when using a Im et al. (2003) test at the goods level. In the Ecuadorian data, I can reject the unit root, in almost every good and all three aggregate indexes. Turning to the question of persistence, I calculate the half-life of LOP deviations and show that by persistence is extraordinarily low compared to the consensus estimates. In my data, at the goods level, half-lives are on the order of months, rather than years, replicating the findings of both Imbs et al. (2005) and Fan and Wei (2006).

Lastly, I turn to the question of compositional bias. To show the effects, I estimate parameters for the underlying processes and use those parameters to calculate a mapping function which relates the underlying coefficients to the index coefficients. This mapping function shows even the highly stationary goods level prices may be less stationary and have longer half-lives than the weighted sum of the underlying components. Additionally, if we treat goods prices as the sum of traded and non-traded inputs, then the process magnifies itself potentially leading to a unit-root process when aggregated up to a full price index.

The paper is organized as follows: Section 2 calculates the convergence properties of the aggregate price indices, traded and non-traded indices, and compares the results with the convergence properties of the goods prices. Section 3 discusses the presence of the three biases in the data and estimates the effect these biases may have on results from the preceding section. Section 4 examines compositional and aggregation bias. Section 5 concludes.

3.2 Unit Root Tests for LOP Convergence

According to the law of one price, two identical goods being sold in different locations should converge to the same price over time. Econometrically, this means a time series of the log difference of prices for a given bilateral city pair should be stationary and deviations should converge to zero. However, to fully investigate the impact of aggregation and categorization bias, I start with a baseline approach that more accurately mirrors what was done in the earlier literature before the prevalence of micro-data studies. I begin by testing for convergence at the most aggregated levels, that is I am looking at the RER rather than deviations in the LOP. To accomplish this task, I first construct a price index for each city. Although, expenditure weights are not available for the Ecuadorian data, I use equally weighted good for composite city-level index.[1] It should be noted that because we are only concerned with the intranational real exchange rate, I focus on the CPI for each of the twelve cities, not the official national CPI released by INEC.

Following the literature, I test for convergence by estimating the following equation.

$$\Delta q^H_{jkt} = \eta_{jk} + \rho_1 q^H_{jkt-1} + \sum_{n=1}^{N} \rho_n \Delta q^H_{jkt-n} + \nu_{jkt} \tag{3.1}$$

where q^H_{jkt} represents the difference in logs of the price index between cities j and k at time t. η_{jkt} represents the time-invariant component of the real exchange rate. $H = T, N, A$ where A is the aggregate price level for the city, T is the traded goods index, and N is the non-traded goods index.

Following Crucini and Shintani (2008), the good is considered to follow absolute price convergence if $\eta_{ijk} = 0$ for all j and k and follow conditional price convergence for cases in which the real exchange rate exhibits some permanent component, η_{jk}, but initial shocks die out over time. It is assumed that the error term, ν_{jkt}, has a mean of 0 and variance, σ^2_ν conditional upon η and the lagged real exchange rate terms. N lags were included to account for serial correlation where N was chosen to minimize the Bayesian Information Criterion (BIC). Consideration was also given to the Aikaike Information Criterion, but in almost all cases, the two criteria chose the same lag structure and results were not

[1] Chapter 2 shows that a constructed price index of equally-weighted goods closely resembles Ecuador's official inflation rate. Although I lack accurate data to show this holds true for city aggregates and traded/non-traded aggregates, I assume expenditure weights across cities are similar to the national average.

significantly affected.

The first column of Table 3.1 reports the results of the ADF test for the three panels of price indexes. The column reports the percentage of city pairs that reject the null hypothesis of a unit root. Accordingly, the unit root can only be rejected about half of of the time for the full index at the 5% level, which demonstrates a lack of stationarity. However, compared to other studies of the subject, there exists a large discrepancy between stationarity for traded goods and non-traded goods with the traded goods seemingly driving the overall RER.

After looking at aggregate price indexes, I then compare the results for stationarity for price of individual goods. Formally, I estimate the following equation to test for convergence.

$$\Delta q_{ijkt} = \eta_{ijk} + \rho_{i1} q_{ijkt-1} + \sum_{n=1}^{N} \rho_{in} \Delta q_{ijkt-n} + \nu_{ijkt} \tag{3.2}$$

where q_{ijkt} represents the difference in logs of the price for good i between cities j and k at time t. η_{ijkt} represents the time-invariant component of the real exchange rate. Again, it is assumed that the error term, ν_{ijk} has has a mean of 0 and variance, σ_ν^2 conditional upon η and the lagged real exchange rate terms. N lags were included to account for serial correlation where N was chosen to minimize the Bayesian Information Criterion (BIC). The bottom rows of Table 3.1 shows the proportion of goods that reject the unit root demonstrating absolute and relative price convergence. I use INEC's categorization of traded and non-traded goods and compare the average rejection frequency across the classical dichotomy.

While much of the literature goes on to use a standard augmented Dickey-Fuller tests to estimate the equation above, Levin et al. (2002) have shown that the ADF tests tend to overly reject the null hypothesis and declare nonstationarity where stationarity is present. Many studies have used Maddala and Wu (1999) to help correct for this problem. Because our data forms a balanced panel across all 66 bilateral city pairs, I am able to use the methods described in Im et al. (2003) which Monte Carlo simulations suggest has even

Table 3.1: ADF Unit Root Rejection Frequencies

	City Price Index		Traded Index		Non-traded Index	
	Conditional	Absolute	Conditional	Absolute	Conditional	Absolute
10%	69.7%	66.7%	74.2%	63.6%	37.9%	22.7%
5%	63.6%	53.0%	63.6%	53.0%	25.8%	15.2%
1%	53.0%	30.3%	59.1%	37.9%	9.1%	7.6%

	Goods Prices		Traded Goods		Non-traded Goods	
	Conditional	Absolute	Conditional	Absolute	Conditional	Absolute
10%	61.3%	62.1%	64.4%	66.3%	44.4%	39.4%
5%	51.6%	51.9%	55.1%	56.2%	33.0%	29.1%
1%	35.3%	36.3%	38.6%	40.2%	17.6%	15.5%

greater power and the lower size distortions than Maddalla and Wu's test. Table 3.2 presents these results. The lowest for conditional price rejection rate is 98.2 percent convergence at the 1 percent significance level. These rejection frequencies indicate LOP deviations are conditionally stationary across all city pairs and goods. Although these results compare favorably with the LDC results in Crucini and Shintani (2008) they are much higher than comparable papers in the literature[2]. The high convergence rates can be explained by a number of factors. As discussed earlier, Taylor (2001) shows that persistence estimates are biased upwards with lower frequency data. As the Ecuadorian data uses monthly data compared to previous studies that frequently relied on quarterly or annual data, convergence should be stronger. Cheung and Lai (2000) shows faster adjustment of PPP in LDCs due to higher inflation rates and larger variability in nominal exchange rates. These two features figure prominently into Ecuador's history of the observed time period. Lastly, many LOP and PPP studies focus on international price convergence[3]. The lack of a border likely increases the stationarity of our sample.

3.2.1 Persistence in LOP Deviations

Once the stationarity of the panel has been established convincingly, I move on to estimate the persistence of the time series equation. In order to do so, I employ a two-step GMM estimator of ρ_i based upon the first difference transformation. In order to fully capture the serial correlation associated with deviation in the real exchange rate, I use 6 lags. My results were not sensitive to my choice of lag structure. Due to the number of lags, I choose two separate statistics to measure the persistence of price deviations. The first measure of persistence is the coefficient on the first autoregressive term, ρ_{i1} By using only the first autoregressive coefficient, it allows for a simple, intuitive approach and allows more readily available comparisons across the literature. One problem with this measure is that

[2] Fan and Wei (2006), for example, have a rejection rate of between 22 percent for services and 71 percent for perishable consumer goods

[3] Engel and Rogers (1996), Parsley and Wei (1996), Gopinath et al. (2011)

Table 3.2: IPS Unit Root Rejection Frequencies

	Goods Prices		Traded Goods		Non-traded Goods	
	Conditional	Absolute	Conditional	Absolute	Conditional	Absolute
10%	99.1%	65.0%	98.9%	72.3%	100.0%	25.7%
5%	99.1%	63.2%	98.9%	70.7%	100.0%	22.9%
1%	98.2%	61.0%	98.4%	68.1%	97.1%	22.9%

much of the deviation may dissipate after the first month but remain for the following periods. To account for this, I use a second measure of persistence known as the cumulative impulse response (CIR). The statistic is calculated by

$$CIR_5 = \sum_{h=1}^{5} IR_h \tag{3.3}$$

where IR_h represents the impulse response in period h to a unit shock. The CIR shows the cumulative impact of a shock over the next five periods. This measure takes into account that a shock my have long-lasting effects on the price deviations and will capture goods in which deviations fall considerably after the first period but then persist for long periods of time afterwards.

Engel (1999) divided goods into two different indexes, a tradable RER and a non-tradable one and showed that there was little difference in the magnitude of RER fluctions whichever group was used. Table 3.3 shows the estimated half-life and persistence estimates between traded goods and non-traded goods using the classical discrete distinction between the two. A couple of observations are readily apparent. Firstly, half-lives in our estimations are on an order months rather than the years suggested by earlier studies. A number of factors have already been discussed such as high inflation rates and lack of a border variable. The second observation is that discussed in Crucini and Shintani (2008). While there is an observable difference between traded goods and non-traded goods, the half-lives differ only by two months. This is hardly the strong relationship suggested by the law of one price. Furthermore, Figure 3.1 shows the kernel density estimates for law of one price deviations. In this data, traded goods have more dispersion than the non-traded goods. This first possible explanation is through the concept of categorization bias, which refers to the misplacement of goods into traded and non-traded baskets due to their classification. The standard example described in Crucini and Shintani (2008) is restaurant food versus groceries. Both would be listed in Food and Beverage, a traded good, but their tradability differs vastly. The second type of bias is that we examine in the next section. Goods may use both traded and non-traded inputs which consequently have substantive effects on the persistence of deviations from the law of one price. They call this the compositional bias of the good.

Table 3.3: Median Persistence Estimates

	Half-Life	CIR
All Goods	4	3.18
Traded Goods	4	2.98
Non-Traded Goods	6	3.71

Figure 3.1: Kernel Density for the Law of One Price Deviations

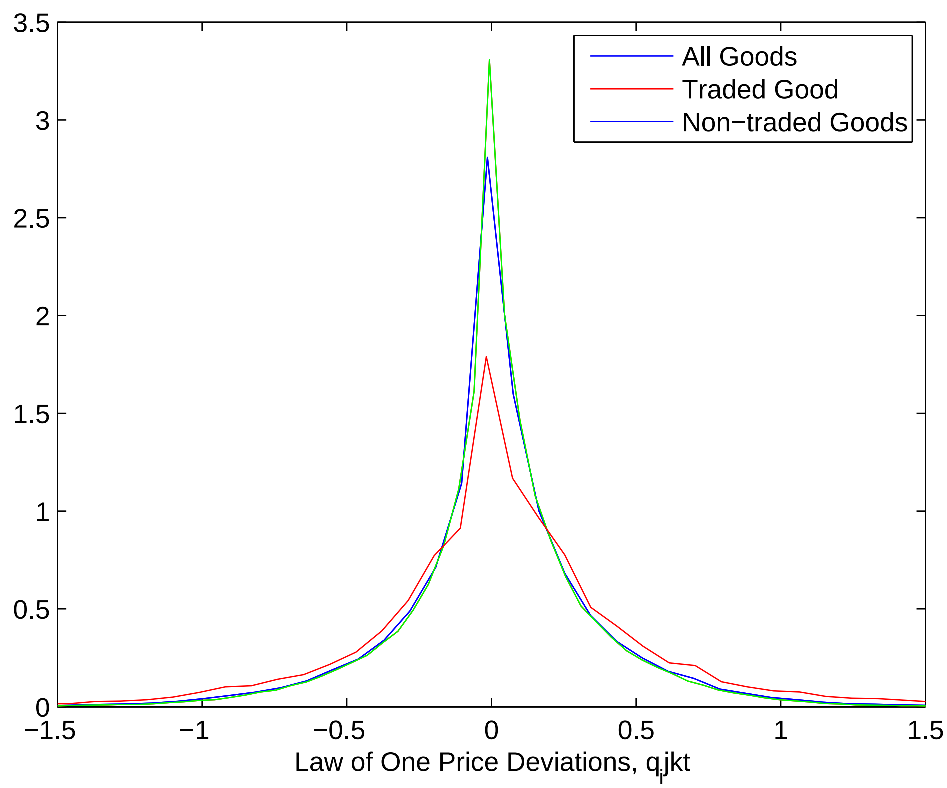


Figure 3.2: Kernel Density of Persistence Estimates

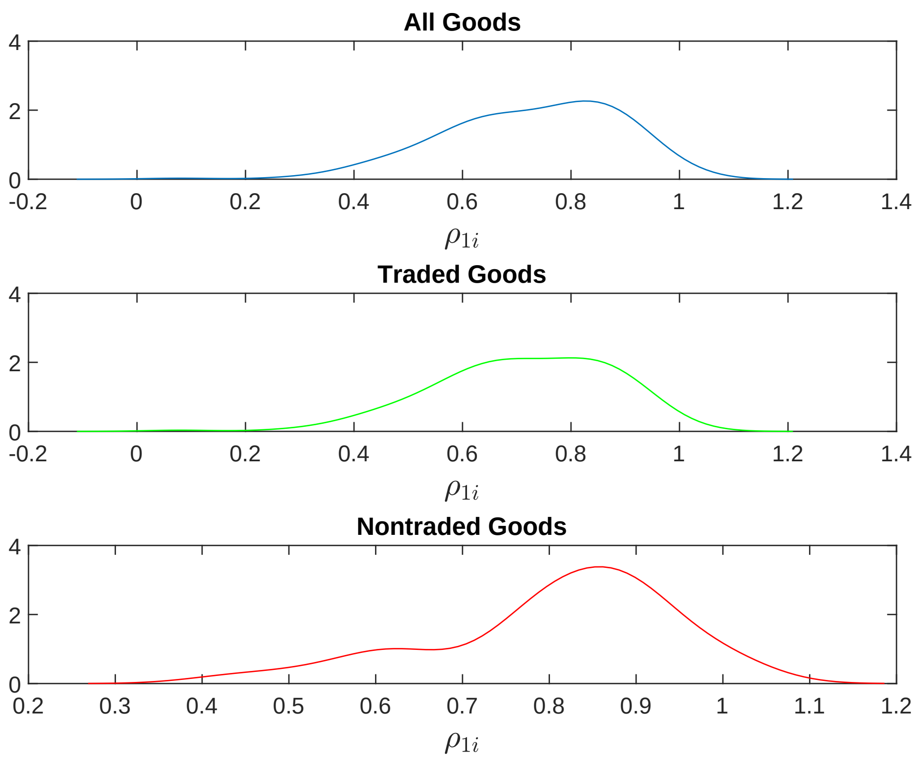
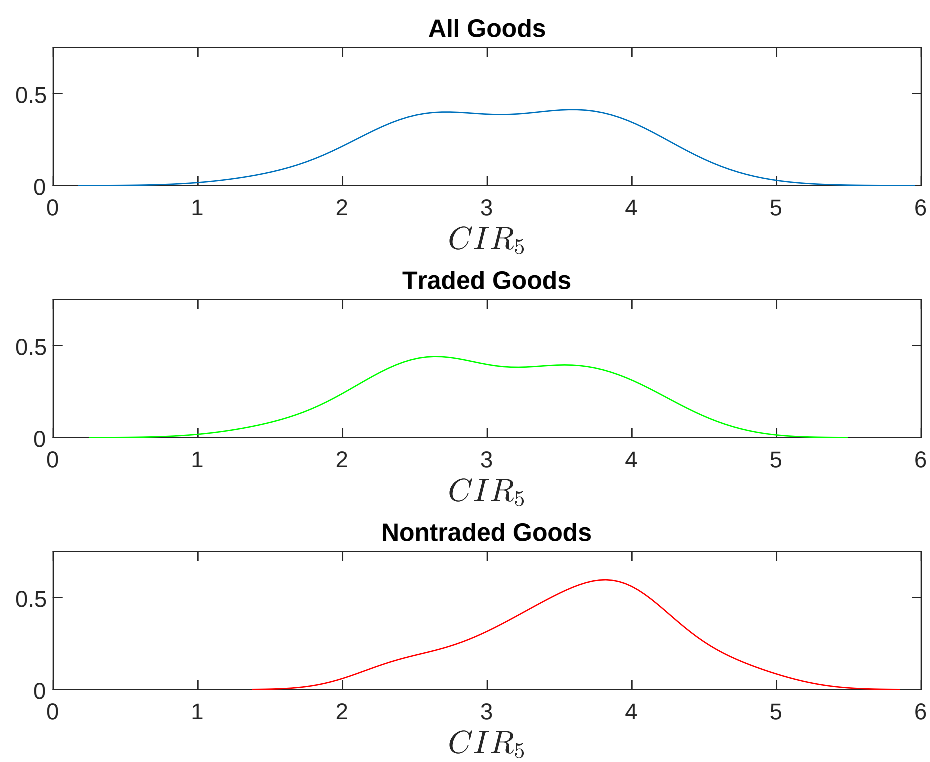


Figure 3.2 further demonstrates this point with the kernel estimates of the distributions for ρ_{i1}. All persistence estimates are calculated at the goods level. The bottom two panels show the kernel estimates when looking at traded goods and non-traded goods, respectively. The magnitude of ρ is much larger than other studies although this is misleading based on the choice of lag structure, and the frequency of the data. The more interesting magnitudes can be found in 3.3 the kernel estimates for the distribution of CIR. Again these estimates are done for persistence at the good level and the bottom panels show densities when goods are divided for traded and non-traded goods. Looking at the two figures, there are three readily available observations. First, regardless of the measure, LOP deviations in traded goods seem to be less persistent. In using ρ_{i1}, the median is about 0.15 lower than in the non-traded goods. In the CIR estimates, the median is 0.73 lower indicating that an LOP

shock in traded good will have a larger initial dissipation and then continue dissipate faster after the next four months as well. Second, there is much more variability in the traded goods persistence estimates than the CIR persistence estimates. Both persistence measures for traded goods indicate a slight bimodal distribution, while the non-traded goods more resemble a normal distribution. Lastly, all goods together more closely resemble the traded goods distribution, but that might be due to the large number of traded goods in the sample relative to non-traded goods. Despite these differences in the median, the two density functions are much more similar than they appear at first glance. Although the medians differ from each other, there is considerable overlap between both traded and non-traded goods, suggesting that the persistence of traded goods and non-traded goods are not as different as one might expect from the LOP.

Figure 3.3: Kernel Density Cumulative Impulse Response Estimates



3.3 Compositional Bias

In the preceding section, I established the difficulty in applying the classical dichotomy to goods' prices. In this section, I draw on the work of Crucini and Landry (2017) to reexamine the classical dichotomy at the input level, rather than at the level of retail goods.

To investigate the degree of compositional bias in our data, I first regress the persistence estimates on the distribution share. Figures 3.4 and 3.5 present these findings for both measures of persistence. Regardless of the measure used, there is a clear positive relationship between the distribution share and persistence showing that persistence in LOP deviations is much greater in goods that use more non-traded inputs. Looking at the two graphs, while both measures of persistence of a positive relationship, the relationship is much stronger when the CIR_5 is used. This suggests that a shock to the LOP might dissipate at a similar rate at first, but over the following months, the residual deviation is more likely to remain in the good with a higher distribution share. Taken together, these graphs both reiterate the point in Crucini and Shintani (2008) that the classical dichotomy should be applied at the inputs level rather than the retail level. One other point of interest are the two extremes of the sectoral distribution shares.

Figure 3.4: Sectoral-mean first order autocorrelation estimates against sectoral distribution shares

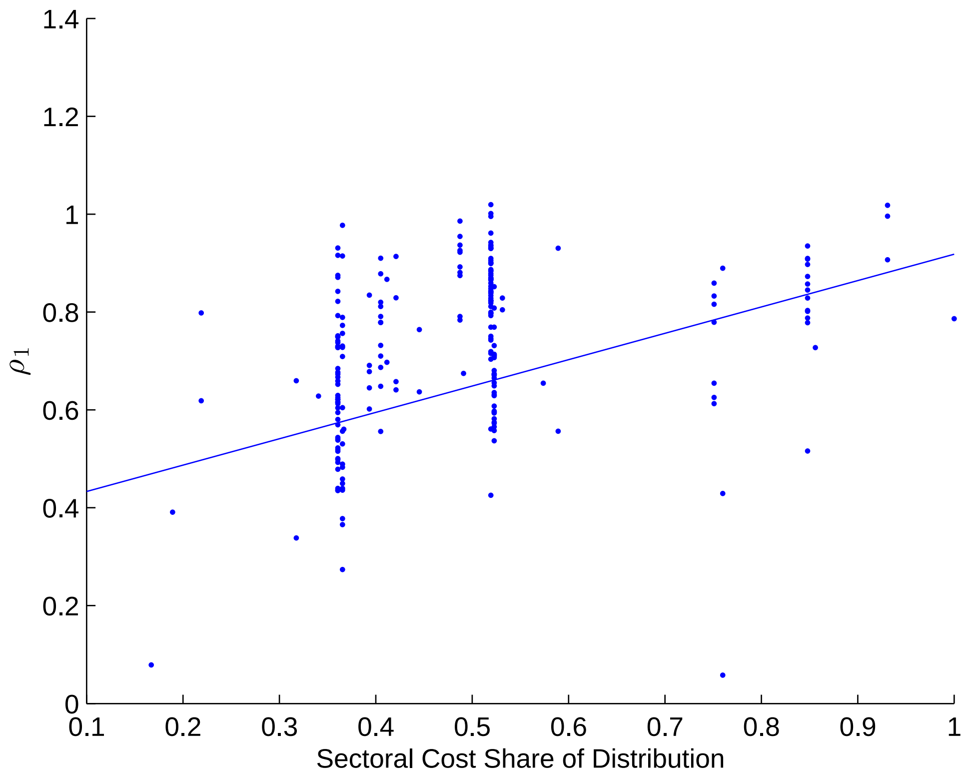
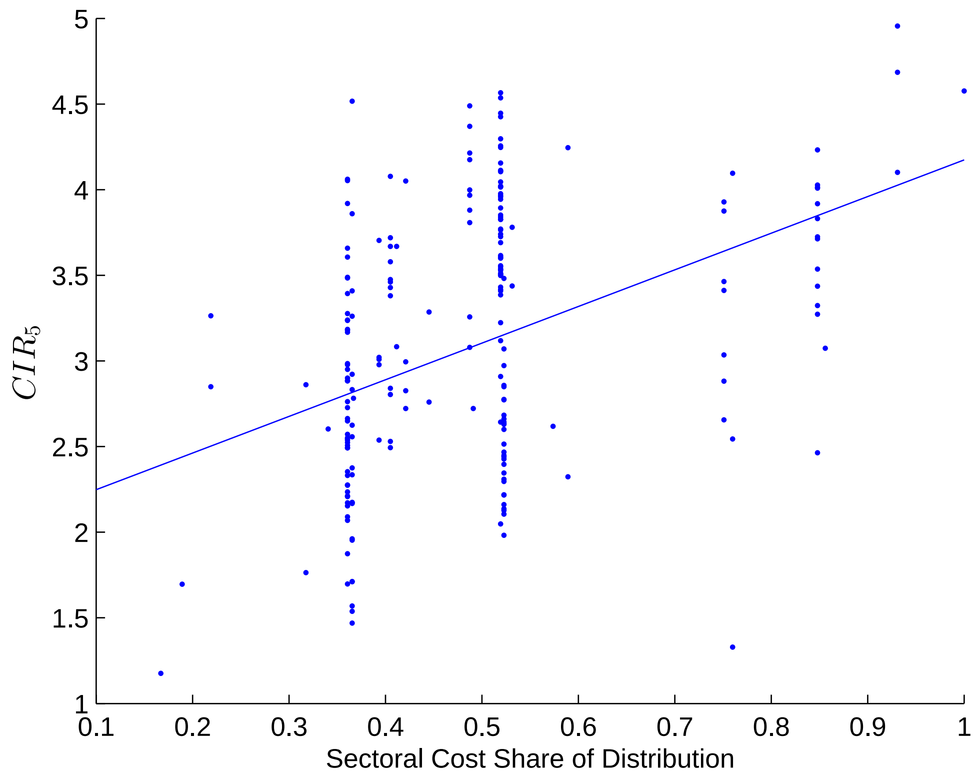


Figure 3.5: Sectoral-mean CIR estimates against sectoral distribution shares



In order to examine this relationship further, I begin by assuming goods are Cobb-Douglas in traded and non-traded inputs following the literature as precedent[4]. Formally, I define the price of good i in city j at time t as

$$P_{ijt} = W_{jt}^{\alpha_i} T_{ijt}^{1-\alpha_i} \tag{3.4}$$

where T_{ijt} represents the traded component for of the price of good i in city j at time t. W_{jt} represents the non-traded component in city j at time t. This component captures distribution costs, rents, and other non-traded inputs involved in the production of good i. Taking logs and subtracting the price across cities, I arrive at the LOP deviation for an

[4]Crucini et al. (2005) and Engel and Rogers (1996) among others

individual good i as

$$q_{ijkt} = \alpha_i w_{jkt} + (1-\alpha_i)\tau_{ijkt} \tag{3.5}$$

where w_{jkt} and t_{ijkt} are the relative cost of non-traded and trade inputs, respectively, faced by retailers in locations j and k for each good i.

To dig further into the mechanics behind how compositional bias can occur, I simplify analysis into the traded component and the non-traded component and assume each follows an autoregressive process with one lag and abstracts from differences across location pairs.

$$w_t = \rho_N w_{t-1} + \varepsilon_{N,t} \tag{3.6}$$

$$\tau_{it} = \rho_T \tau_{it-1} + \varepsilon_{T,t} \tag{3.7}$$

where w_t represents the non-traded component of the relative price and τ_{it} represents the traded component. Using equation 3.5 above, the covariance between the relative price and its first lagged term are

$$cov(q_{it}, q_{it-1}) = cov(\alpha_i w_t + (1-\alpha)\tau_{it}, \alpha w_{t-1} + (1-\alpha_i)\tau_{it-1}) \tag{3.8}$$

Assuming the shocks are identically and independently distributed, we can further assume $cov(w_t, \tau_{t-1}) = cov(w_{t-1}, \tau_t) = 0$. Therefore equation 3.8 simplifies to

$$cov(q_{it}, q_{it-1}) = \alpha_i^2 cov(w_t, w_{t-1}) + (1-\alpha_i)^2 cov(\tau_{it}, \tau_{it-1}) \tag{3.9}$$

We can then use equation 3.9 to calculate the autorrelation coefficient.

$$\rho_i = \frac{cov(q_{it}, q_{it-1})}{var(q_{it})} = \alpha_i^2 \frac{cov(w_t, w_{t-1})}{var(q_{it})} + (1-\alpha_i)^2 \frac{cov(\tau_{it}, \tau_{it-1})}{var(q_{it})} \tag{3.10}$$

Multiplying the first term on the left-hand side by $var(w_t)$ and the second term $var(\tau_{it})$, I arrive at the autoregressive coefficient where

$$
\begin{aligned}
\rho_i &= \alpha_i^2 \frac{var(w_t)}{var(q_{it})} \frac{cov(w_t, w_{t-1})}{var(w_t)} + (1-\alpha)^2 \frac{var(\tau_{it})}{var(q_{it})} \frac{cov(\tau_{it}, \tau_{it-1})}{var(\tau_{it})} \\
&= \psi_i \rho_N + (1-\psi_i)\rho_T
\end{aligned} \tag{3.11}
$$

where

$$
\begin{aligned}
\psi_i &= \frac{\alpha_i^2 var(w_t)}{\alpha^2 var(w_t) + (1-\alpha)^2 var(\tau_{it})} \\
1-\psi_i &= \frac{(1-\alpha_i)^2 var(\tau_{it})}{\alpha^2 var(w_t + (1-\alpha)^2 var(\tau_{it}^T)}
\end{aligned} \tag{3.12}
$$

Finally, using the fact that the variance of the non-traded and traded relative prices are

$$
\begin{aligned}
var(q_t^N) &= \frac{\sigma_N^2}{1-\rho_N^2} \\
var(q_{it}^T) &= \frac{\sigma_{iT}^2}{1-\rho_T^2}
\end{aligned} \tag{3.13}
$$

We can substitute them into equation 3.12 and we have

$$
\begin{aligned}
\psi_i &= \frac{\alpha_i^2 \frac{\sigma_N^2}{1-\rho_N^2}}{\alpha_i^2 \frac{\sigma_N^2}{1-\rho_N^2} + (1-\alpha_i)^2 \frac{\sigma_T^2}{1-\rho_T^2}} \\
1-\psi_i &= \frac{(1-\alpha_i)^2 \frac{\sigma_T^2}{1-\rho_T^2}}{\alpha_i^2 \frac{\sigma_N^2}{1-\rho_N^2} + (1-\alpha_i)^2 \frac{\sigma_T^2}{1-\rho_T^2}}
\end{aligned} \tag{3.14}
$$

This demonstrates the highly-nonlinear relationship of the bias toward the high persistence component due to its appearance in the weight, ψ_i. The key insight here is that the whole is not the weighted sum of the parts.

3.3.1 Estimation

To demonstrate this nonlinear relationship and the impact of aggregating the traded and non-traded components into one price, I calculate the function mapping the relationship between α_i and ψ_i using reasonable parameters estimated from the Ecuadorian data. In the model of the previous section, we can observe the persistence parameters of the relative price, but the traded persistence parameter ρ_T, non-traded persistence parameter, ρ_N, the variance of the traded process σ_T, and the variance of the non-traded process, σ_N remain unobserverable. To recover these unobservables, I first consider the following AR(1)

$$q_{ijkt} = \rho_i q_{ijkt-1} + \varepsilon_{it} \tag{3.15}$$

I perform the regression separately for each city pair and take the median for each good to form ρ_i. I also take the variance for each process and take median across those values. In order to back out the unobservable ρ_T and ρ_N, I order the ρ_i from the least persistent to most persistent and take the top and bottom deciles[5]. On the ends of the traded non-traded distribution is where I am most likely to find ρ_T isolated from the effects of ρ_N and vice versa. In addition, I take the variance of those processes estimate σ_T and σ_N. Table 3.4 shows the estimated persistence and variance parameters.

The estimated ρ_T and ρ_N parameters is striking. ρ_N is extremely persistent with a half-life is 53.5 [6] or the equivalent of 4.5 years. Its traded counterpart is a mere 2.3 months. These parameters indicate a very strong role being played in the LOP, but the effects are muted when combined with each other. Also, the variance of the non-traded process is about 3.2 times the variance of the traded process. The greater volatility of this non-traded process is what drives the mapping of ψ_i.

[5]Not surprisingly, the least persistent ρ's came from the goods with the lowest distribution margins and vice versa.

[6]In the AR(1) model with an autoregressive coefficient of ρ, the half-life is simply $\frac{1}{1-\rho}$.

Table 3.4: Estimated parameters of the AR(1) model

ρ_T	0.5688
$var(q_{it}^T)$	0.0023
ρ_N	0.9813
$var(q_t^N)$	0.0074

3.3.2 Results

The blue line in figure 3.6 shows the estimate of each ψ_i for each value of α_i. The black 45 degreee line is added as a reference. If the two processes were weighted in proportion to their share, the ψ_i function would be identical to the 45 degree line where $\alpha_i = \psi_i$. However, one can see the nonlinear relationship between ψ_i and α_i. The function has three notable features. Trivially, at values of 0 and 1, the impact of a purely traded good or non-traded good, $\psi_i = \alpha_i$ so both components of the weighted process have the same impact as their weight would suggest because there is only one subprocess contributing to the overall process.

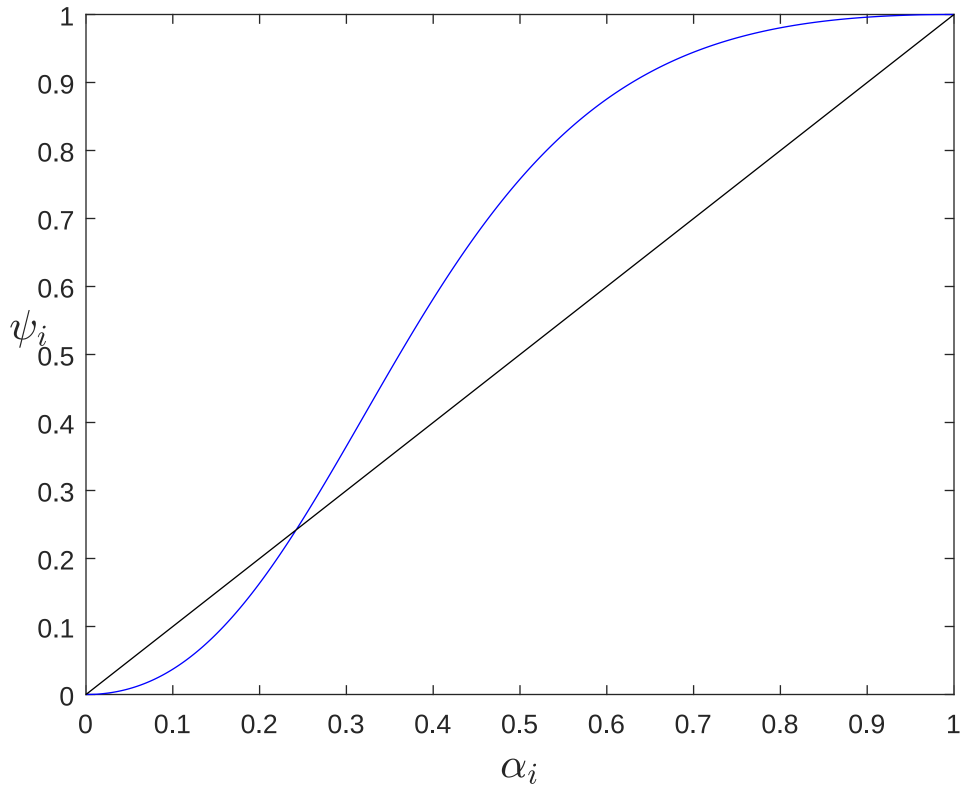


Figure 3.6: ψ_i Function

A more notable feature is observed at the tail ends of the function. This means that for low values of alpha, $\alpha_i > \psi_i$ and $\alpha_i < \psi_i$ at the higher distribution margins. Take for instance $\alpha_i = 0.10$. In this good, 10 percent of the cost structure comes from the non-traded component, but the non-traded AR process only has a weight of 0.037. In such a case, a good that is heavily dependent on traded inputs may take exhibit stationrity and persistence properties even more closely aligned with the traded component than the input shares would suggest. Looking at figure 3.5 above, we see this to some extent. As α_i approaches 0, for example, the dots demonstrate stronger persistence than the regression would indicate. The reverse is true as alpha approaches 0. A good like gasoline, where the distribution margin is 0.167, will take on a larger proportion of the traded AR process and magnify the effects.

The interior point at $\alpha_i = \psi_i = 0.24$ suggests that this effect might be rare to observe in practice. Most goods have an alpha of greater than 0.24 and therefore were more likely to take on properties of the non-traded process. In our sample only four goods had a distribution margin less than 0.24[7]. In the other 219 goods, the ψ_i function would work to make goods more similar to each other. We see this play out in the data, in figure 3.3, we see the kernel density distribution of for both traded and non-traded goods. For traded goods, there are two humps. One with considerably lower persistence estimates than the rest of the data. The second hump resembles the kernel density estimate for the non-traded goods. Comparing this to the present analysis, there are two types of traded goods. Goods with distribution margins of less than 0.24 (or at least very close to that distribution margin) will take be heavily weighted towards the traded process. However, for a large proportion of the traded goods, they will look exactly the non-traded goods, not only because they use a larger share of non-traded inputs, but also because the non-traded input process has a disproportionate influence on overall process.

The third and most notable feature of the ψ_i function is that based on the estimated parameters, the center of the psi function is to the northwest corner of the graph. At $\alpha_i = 0.5$, ψ_i is much greater coming in at 0.7579. This indicates that there is a general bias towards the highly persistent non-traded process. A good that uses equal parts traded and non-traded goods will still take on much more of the non-traded process than the traded process leading to lower rates of convergence or longer persistence. This explains how a number of studies of the law of one price have shown significant overlap in the persistence estimates of traded and non-traded goods.

Taken together, these facts stregthen the case for the classical dichotomy but with the caveat that it be applied at the most fundamental level. In the Ecuadorian dataset, traded goods have a general tendeny to exhibit lower levels of persistence compared to non-traded goods, but even this is misleading. By estimating the individual ρ_T and ρ_N the traded input has a half-life on the order of months, while the non-traded half-life is on the order of

[7]Gasoline, automobiles, shrimp, and fish

years. Therefore, it is not sufficient to say that traded and non-traded goods have similar persistence estimates because they are a combination of traded and non-traded inputs. They are also upward biased because the non-traded input has a disproportionate influence on the overall process.

3.4 Conclusion

Using panel unit root tests, my results show that retail prices in Ecuador overwhelmingly converge to purchasing power parity in both a relative sense and traded goods are substantially stationary in an absolute sense. Dividing goods up into a traded index and a non-traded index only present a more complicated picture. Non-traded goods especially have difficulty converging to purchasing power parity. However, the unit root is rejected and the half-life of LOP deviations is on the order of months, not years. This shows the PPP paradox may partly be explained by the lack of micro-data and the use of aggregate indexes to show the connection between prices in different locations. While the PPP paradox is alive and well, its implications may be weaker than previously assumed.

This bias continues even for the highly converging goods prices. Results show that estimating an AR(1) process, as much as the literature has done, can lead to results that fail to account for the stationarity of the underlying processes. Goods prices that are a combination of traded and non-traded inputs are not equally affected by their parts.

Finally, this study provides the first rigorous empirical study on the law of one price in Ecuador. Morever this study helps confirm the existence of compositional bias and how it works to nullify the important effects a good's tradeability has on deviations from similar priced goods in other markets.

Chapter 4

Exchange Rate Pass-through in Ecuadorian Cities

4.1 Introduction

Exchange rate pass-through is an area of interest that has spanned both time and fields. In short, pass-through describes how an increase in the cost of inputs can lead to an increase in the price the consumer pays. While earlier examinations focused on domestically centered costs, more recent applications have migrated to international finance and the costs associated with imports and exports. In this specific context, the question is how a change in the exchange rate impacts prices at the retail level. While the LOP and exchange rate pass-through are related, the previous chapter focused on prices and their relationship to each other within the country of Ecuador. The primary endeavor of this chapter is to see the movement of prices in response to an external shock, specifically the exchange rate.

Although exchange rate pass-through is typically a point along a continuum, the literature has narrowed the discussion by describing opposing theories, labeling them local-currency pricing (LCP) and producer-currency-pricing (PCP). Local-currency pricing refers to the idea that prices are denoted in the local currency. Therefore a change in the exchange rate would have little to no effect on the prices in the destination country. As such, changes in the nominal exchange rate would have real effects. As the nominal price remains constant, the real import price is affected. Producer-currency pricing refers to a situation of full pass-through where prices are continuously updated with information on the exchange rate. Therefore, as the exchange rate changes, import prices would change along with them and goods would fully reflect the exchange rate shock. PCP, on the other hand, is indicative of a situation with complete pass-through. As the exchange rate changes, these variations are fully reflected in the price and therefore adjust at the exact same magnitude as the change in the exchange rate. A shift of producers' imported costs would be passed down to consumers.

Despite these two diametrically opposed views, empirical evidence to date indicates some mix of PCP and LCP, but that both consumer and producer prices tend more to the LCP side of the argument. Prices of a good are largely unaffected by the exchange rate. Goldberg and Campa (2010) provides some the earliest work on the subject comparing pass-through in 23 OECD countries. They show average short-run pass-through of 0.46 and long-run pass-through of 0.64. At the same time, they show pass-through is highly dependent on the country studied with Ireland's pass-through being 0.16 and 0.79. Many other papers have replicated these results. Gopinath et al. (2010b) constructs a measure called life-long pass-through (LLPT) and show that it is just 28 percent in the US, matching CG with a LRPT of 23 percent.

Despite a general consensus towards LCP for most retail prices, border prices typically do reflect these shocks to the exchange rates. Burstein et al. (2003b) show that the degree of measured pass-through is dependent on whether the prices used are in the import price index or the consumer price index with the former tending to PCP. Another important finding in the empirical literature is that real exchange rates of tradable goods typically comove with the nominal exchange rate even when the goods are produced in the same location. Nakamura (2008) uses suggests that price variance occurs more dramatically at the retail level and the variance is the result of dynamic pricing strategies by retailers. Therefore, as the nominal exchange rate changes, the retail price of the good stays the same indicating a strong role of LCP even when taking differing production prices into account. Such a finding indicates some role demand plays in the pass-through.

Distance is not a new area of study for price dynamics, but typically these studies involving distance focus on international borders. In a seminal paper, Engel and Rogers (1996) shows that that two cities located further away do have a greater discrepancy in their price, but that the border adds the equivalent volatility of 75,000 miles. Parsley and Wei (1996) replicates this experiment with US and Japanese cities and again finds that estimates

43,000 trillion miles. According to Parsley and Wei (1996) distance, unit-shipping costs, and exchange rate variability all explain international market segmentation.

Typically, the exchange rate pass-through literature is intimately connected with the LOP and PPP literature presented in previous section. A change in the exchange rate ultimately impacts the deviations between two prices. If pass-through were strong, then the LOP would hold more fundamentally. As we have seen though, PCP is not the dominant theory to apply. In the present study, while the previous paper focused on the relative price discrepancies of cities to each other, this paper's lies clearly in the realm of how prices react to an external shock in the form of the exchange rate. I abstract from the direct relationship between two cities' prices and focus more on the distance of each city from the coast.

This paper looks to add details to the literature on pass-through. In this paper, I examine the degree of pass-through across two separate dimensions: goods and cities. By using an empirical model similar to Goldberg and Campa (2010), I predict implications for how we expect pass-through to vary by city and by good. I then run estimates across cities and goods report the findings.

4.2 The Geography of Ecuador

In addition to the reasons discussed in prior chapters, Ecuador's geography provides a strong motivation for examining pass-through within the country. Figure 4.1 shows a map of Ecuador and many of Ecuador's largest cities. The twelve red dots represent the twelve cities in the sample. Ecuador is divided geographically and culturally into three regions. The first region is called La Costa and reprents the western coastal region on Ecuador's border with the Pacific Ocean. This region contains Guayaquil, the country's largest city as well as Esmereldas, Portoviejo, Machala, and Manta. The second region is known as La Sierra or the central mountainous region containing the Andes Mountains and a number of volcanos. Quito, the capital of Ecuador is located in the Northern part of the region. In addition, it contains the other The final Eastern region is known as El Oriente, which is largely characterized by the Amazonian rainforest. This is area is very sparsely populated and due to its lack of major cities, does not appear in ther dataset.

Figure 4.1: Map of Ecuador

Red dots on the map indicate the twelve cities used in the INEC price database.

Geography plays a large role here because the motivation for examining cities is based upon the idea that imported goods, are purchased at the border and shipped to the interior of the country. As a result, provides a direct comparison with the model where goods will essentially be imported into La Costa and then combined with non-traded labor in order to distribute the goods to La Sierra. Table 4.1 lists the 12 cities, their population 2001, and their distance from the coast.

Table 4.1: Ecuadorian Cities

City	Population	Distance from Coast	Region
Esmeraldas	95,124	0	Coastal
Guayaquil	1,985,379	0	Coastal
Machala	204,578	0	Coastal
Manta	183,105	0	Coastal
Portoviejo	171,847	13	Coastal
Ambato	154,095	135	Sierra
Cuenca	277,374	59	Sierra
Latacunga	51,689	131	Sierra
Loja	118,532	74	Sierra
Quito	1,399,378	110	Sierra
Riobamba	124,807	103	Sierra
Quevedo	120,379	74	Sierra

4.2.1 Empirical Strategy

This paper's empirical strategy resembles that of Campa and Goldberg (2005) and others in the literature. Campa and Goldberg (2005) suggest that pass-through can vary significantly from country to country based on the types of prices. Pass-through is usually much more visible in border prices while less so in retail prices.

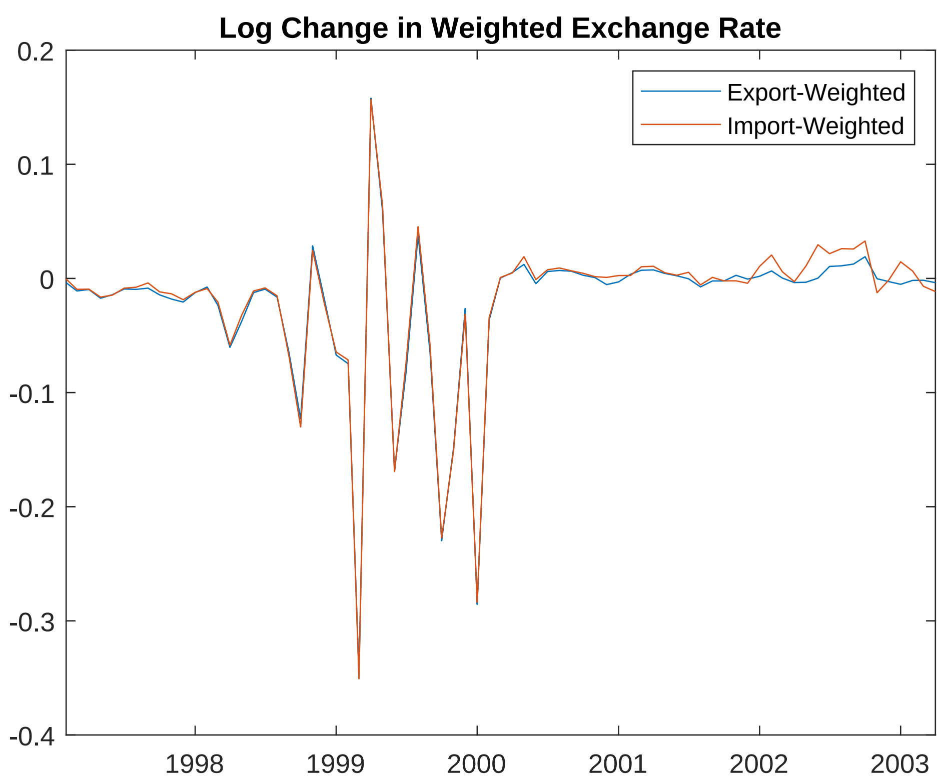
To set the baseline, I first estimate pass-through for Ecuador. The first specification considered looks at pass-through for a variety of goods.

$$\Delta p_t = \alpha + \sum_{k=0}^{4} \beta_k \Delta e_{t-k} + \sum_{k=0}^{4} \gamma_t \Delta w_{t-k} + \varepsilon_t \tag{4.1}$$

where p_t represents a consumer price index comprising retail prices of goods and services from Ecuador's national statistical agency INEC. w_{t-k} is the wage which I use as a control for retailer costs. e_{t-k} represents the official exchange rate from the International Financial

Statistics database. In order to get a complete measure, I use a trade weighted exchange rate based on the value of imports of Ecuador's top 30 trading partners. Figure 4.2 shows the log changes in the exchange rate weighted by the both imports and exports. The choice of weighting by imports or by exports seems to be largely irrelevant. To construct my measure of the exchange rate I use the export-weighted exchange rate.

Figure 4.2: Weighted Exchange Rate



One key obstacle with running this regression at such a detailed the city and good level, is that wage data is not available at a monthly frequency. In order to proxy for this wage, one could simply use haircuts to represent wage, but such a measure might be biased by haircut seasonality or demand shocks. To help alleviate these concerns, I take an average of prices with the highest nontraded input shares based on the data from Chapter 2 and create an index of the prices with each good receiving an equal weight.

In the baseline specification, I use a composite of all 223 goods in the database an estimate pass-through which represents a Consumer Price Index. The results of my estimation can be found in Table 4.2.

Table 4.2: Pass-through into CPI

Coefficient	β	SE	tStat	pValue
α	0.00716	0.00502	1.43	0.1591
Δe_t	-0.14056	0.03031	-4.64	0.0000
Δe_{t-1}	-0.19847	0.02964	-6.70	0.0000
Δe_{t-2}	-0.11568	0.02847	-4.06	0.0001
Δe_{t-3}	-0.10386	0.03007	-3.45	0.0010
Δe_{t-4}	-0.05218	0.03037	-1.72	0.0910
Δw_t	0.15170	0.07438	2.04	0.0458
Δw_{t-1}	0.02511	0.06328	0.40	0.6929
Δw_{t-2}	0.02264	0.06395	0.35	0.7246
Δw_{t-3}	-0.01532	0.06208	-0.25	0.8060
Δw_{t-4}	0.05317	0.06070	0.88	0.3846
Long-run pass-through =			-0.61075	

There are two numbers of interest. The first is simply the coefficient attached to the contemporaneous exchange rate. This value represents the short-run elasticity and measures the immediate impact of the exchange rate on price. In 4.2, you can see that Ecuador as a whole has a short-run elasticity of -0.141 and that this coefficient is significantly different from both zero and one. The coefficient itself is negative because exchange rates are denominated with the Ecuador's currency in the denominator. Therefore a decrease in the exchange rate represents a depreciation of the currency and vice versa. In this case, a negative value signifies what is typically true in exchange rate pass-through - an appreciation of the foreign currency leads to an increase in the prices in local currency units.

The second number of interest comes from CG and is referred to as the long run elasticity. It is calculated by summing the coefficients on the four lagged exchange rate terms with the short run elasticity. In our baseline specification, long-run pass-through is -0.61 which indicates that a 1 percent appreciation in the exchange rate leads to a 0.61 percent increase in the price.

Two important benchmarks in comparing these pass-through numbers relate to 0 and -1. Pass-through of zero indicates that a change in the exchange rate has no impact on prices, a phenomenon referred to Local Currency Pricing or LCP. On the other hand, pass-through of 1 indicates that movements in the exchange rate are fully passed on to consumers. In all of the regresssions to follow, discussion is made as to whether the estimate differ significantly from 0 and -1.

Compared to CG, both of the numbers compare favorably. Goldberg and Campa (2010) find an average short-run pass-through of 0.46 and long-run pass-through of 0.64. Ecuador has a low degree of short-run pass-through, but its long-run pass-through is extremely close to CG's average. Ecuador's low rate of pass-through is mildly puzzling as countries with higher exchange rate volatility typically experience more pass-through, but it should be noted that while some periods of the sample have large movements in the exchange rate, the final third of the sample includes a fully fixed exchange rate in the form of dollarization with Ecuador's largest trading partner, the United States. Furthermore, the literature has shown that macroeconomic volatility has little impact on pass-through, so while the exchange rate did experience rapid movement over the sample's years, the crisis was primarily a monetary one, with little impact on the degree of pass-through within Ecuador.

4.2.2 Pass-through by Good

We now turn to looking at pass-through for each individual good in the sample. We use a similar regression to the baseline specification, but rather than a composite price index, we estimate pass-through using each individual good. Cities are aggregated into a national average provided by INEC. I use the specification below to estimate the pass-through.

$$\Delta p_{it} = \alpha_i + \sum_{k=0}^{4} \beta_{ik} \Delta e_{t-k} + \sum_{k=0}^{4} \gamma_t \Delta w_{t-k} + \varepsilon_{it} \tag{4.2}$$

Again, the short-run pass-through is defined as the contemporaneous coefficient to the exchange rate, β_{i0} and long-run pass-through is defined as the sum of all the coefficients on the exchange rates, $\sum_{k=0}^{4}\beta_k$.

Complete results are presented in Table D.1 in the Appendix. Overall, the results paint a mixed picture. The degree of pass-through varies dramatically depending on the good in question and unlike the aggregate picture which followed neither LCP or PCP, many goods do not reject either one. One particular dimension that might relate to the degree of pass-through is the degree to which the good or service uses non-traded inputs in production. Although the evidence is mixed, the non-traded goods seem to have less pass-through when compared to their traded counterparts. Figure 4.4 and Figure 4.4 plot the nontraded share against SR and LR pass-through, respectively. We can see that in this connection be non-traded goods and pass-through is much more pronounced. Such a result is not surprising. If a good requires more use of local inputs in order to produce the good, exchange rate pass-through will be muted by the non-traded component.

Figure 4.3: Nontraded Input Share versus Short-Run Pass-through

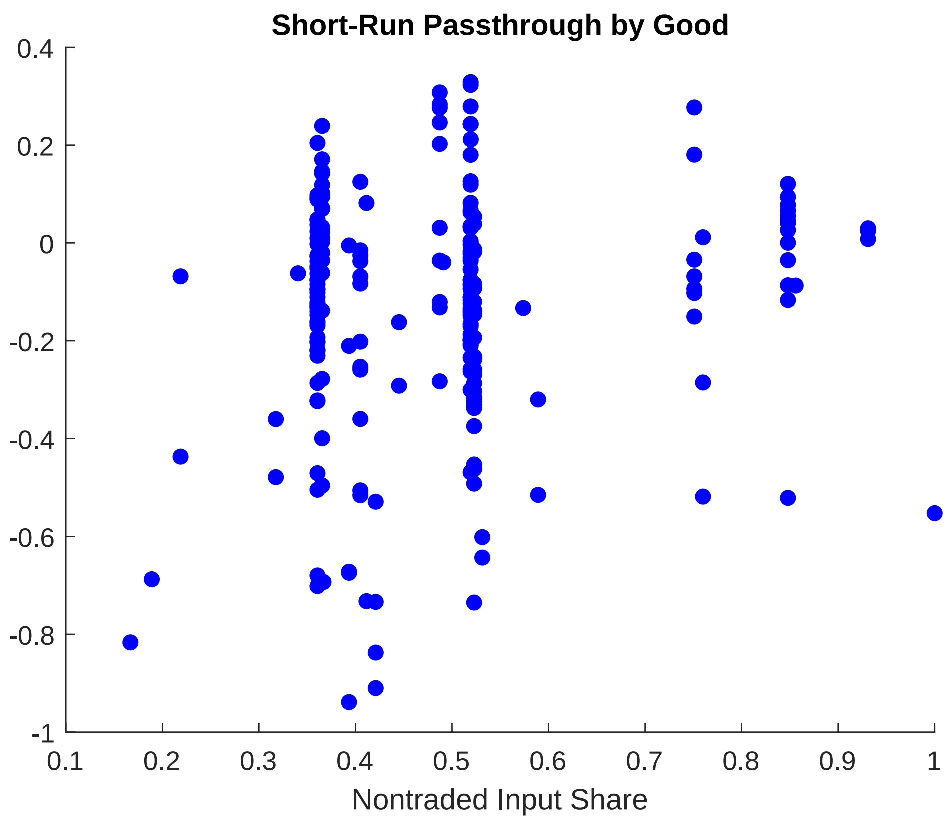
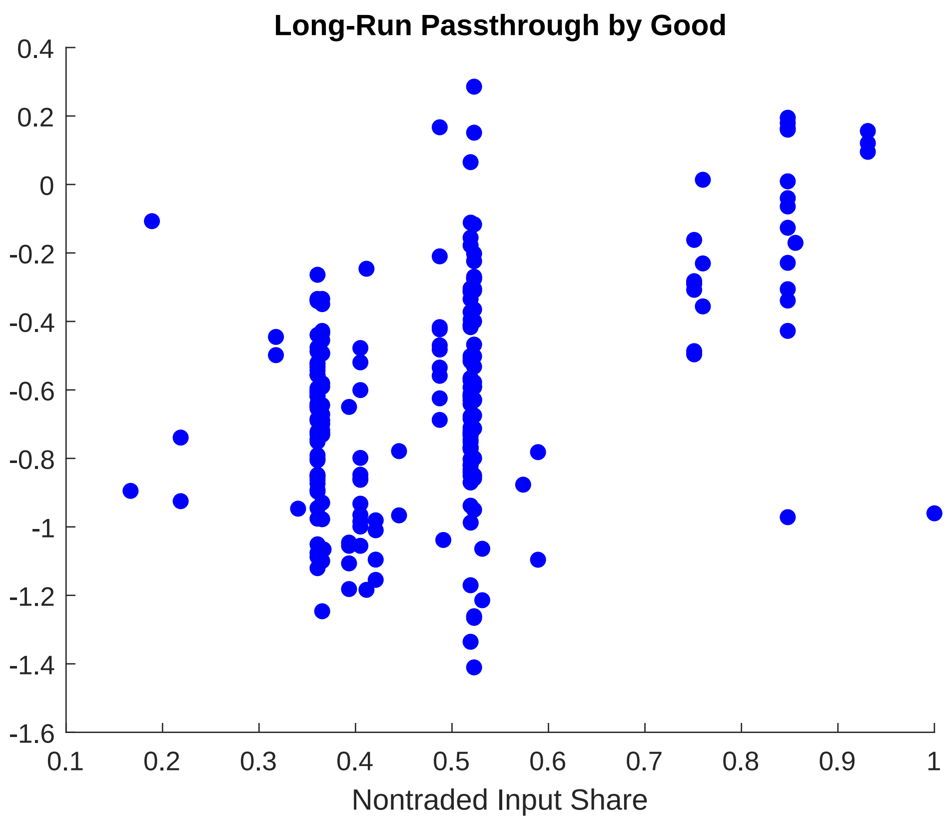


Figure 4.4: Nontraded Input Share versus Long-Run Pass-through



4.2.3 Pass-through by Cities

While many papers have investigated the empirics behind the first two specifications, this paper adds to the literature by examing the pass-through to individual cities in the same country. In particular, we look at how pass-through affects cities based on their distance from the coastline. The motivating factor here is the goods receive traded imports from the docks and then use non-traded inputs to distribute that throughout the country. If this reasoning is correct, we should expect to see more pass-through in cities located in La Costa and less pass-through in cities located in La Sierra. In order to investigate this more fully, we use a similar regression to baseline regression, but rather than aggregating cities into a national average, we take a consumer price index for each of the twelve cities. The specification for this regression is

$$\Delta p_{jt} = \alpha_j + \sum_{k=0}^{4} \beta_{jk} \Delta e_{t-k} + \sum_{k=0}^{4} \gamma_t \Delta w_{j,t-k} + \varepsilon_{jt} \tag{4.3}$$

Results are summarized in Table 4.3. The first noticable difference from the good-specific regressions is that pass-through is much more similar across cities than it is across goods. In fact, when comparing pass-through among the cities, all cities can reject both PCP and LCP. In the table, the first five cities represent coastal cities. Pass-through does seem to exhibit slightly more PCP characteristics in the coastal cities, but the difference is minimal as no city deviates more than 0.017 from the average.

Table 4.3: Pass-through by city

Cities	SR Pass-through	LR Pass-through
Esmeraldas	-0.136	-0.592
Guayaquil	-0.139	-0.606
Machala	-0.135	-0.589
Manta	-0.148	-0.580
Portoviejo	-0.145	-0.585
Ambato	-0.122	-0.607
Cuenca	-0.123	-0.606
Latacunga	-0.127	-0.606
Loja	-0.122	-0.604
Quito	-0.124	-0.600
Riobamba	-0.122	-0.600
Quevedo	-0.131	-0.596
Average	-0.131	-0.598

4.2.4 Pass-through and Distance from the Coast

To investigate this relationship between coastal differences and more fully, I rerun the regression with an interaction term to determine

$$\Delta p_{ijt} = \alpha_{ij} + \sum_{k=0}^{4} \beta_k dist_j \Delta e_{t-k} + \sum_{k=0}^{4} \gamma_t \Delta w_{j,t-k} + \varepsilon_{it} \tag{4.4}$$

In addition to the usual variables, $dist_j$ represents the distance of the city from the coast. Here the meaning of β_k changes. Table D.2 shows the results for each good. However, the coefficients no longer represent elasticity of exchange rate pass-through. It now shows the both pass-through and the impact of coastal distance on pass-through. Although at first glance, the results seem small, there are two important conclusions to draw from this regression. The first point of notice is that both for the SR and the LR, the coefficients have generally flipped from negative to positive. As we have seen, the pass-through component of the coefficient is negative, so a positive coefficient points towards a negative distance effect. This implies that interior cities do in fact have less pass-through than their coastal counterparts. Furthermore, while the magnitude is small, it is significant for all goods. These results are consistent with a model where firms import traded goods and distribute them throughout the country.

4.3 Conclusion

While narrow in scope, this paper uses a novel data set to show the dynamics of price pass-through within Ecuador. Using the Ecuadorian price data of the previous two chapters, this paper confirms that while Ecuador experiences similar pass-through phenomena as other countries, cities respond differently to exchange rates based on distance from the coast. Furthermore, this paper provides further empirical evidence relating pass-through on the non-tradability of goods and services.

Appendix D

Pass-through Regression Results

Table D.1: Pass-through by Goods

Goods	SR Pass-through		LR Pass-through	
Rice	-0.16885		-1.05094	+
Oat meal	-0.13998	*	-0.89705	+
Cereal	-0.00229	*	-0.68506	+
Spaghetti	0.088999	*	-0.61859	*+
Bread	-0.32191		-0.59478	+
Beef, with bone	-0.12604	*	-0.94489	+
Beef, without bone	-0.1106	*	-0.86289	+
Chicken	-0.13283	*	-0.84809	+
Shrimp	-0.4368		-0.92485	+
Fish, fresh	-0.0683	*	-0.73922	*+
Tuna, can	-0.20132		-0.80516	+
Sardines in can	-0.21911		-0.87319	+
Milk, powder	-0.10174	*	-0.34051	*
Milk, fresh, homogenized/pasteurized	-0.08463	*	-0.64768	+
Cheese	-0.02782	*	-0.52084	*+
Eggs	-0.70149		-0.85432	*+
Oil, vegetable	-0.47074		-0.79988	*+
Vegetable fat	-0.09263	*	-0.63042	+
Margarine	-0.32335		-0.85044	+
Avocado	-0.33085	*	-0.57746	*+

Bananas	-0.01482	*	-0.26952	*+
Lemons	-0.32306	*+	0.285648	*+
Apples	-0.2587	*	-0.95011	*+
Raspberries	-0.01328	*	-0.50166	*+
Oranges	-0.73515	+	-0.11665	*+
Naranjilla	-0.46219		-0.58879	*+
Papaya	0.053782	*	-0.2019	*+
Pineapple	-0.14633	*	-0.36494	*+
Plantain	-0.37447		-0.59206	*+
Watermelon	-0.0834	*	-0.71268	*+
Tomatillo	-0.28663		-0.53196	*+
Grapes	-0.19351	*	-0.39946	*+
Fruit cocktail, can	-0.07512	*	-0.79064	+
Raisins	-0.07604	*	-0.97604	+
Peas, fresh	-0.33741	*	-1.41037	*+
Onion, white	-0.30296	*	-0.27304	*+
Onion, red	-0.45289		-1.26098	*+
Cabbage	0.038886	*	-0.67466	*+
Cauliflower	-0.01812	*	-0.84972	*+
Corn, fresh	-0.49203		-0.30508	*+
Broad beans, fresh	-0.31568		-0.79927	*+
Beans, fresh	-0.31628		-0.85851	*+
Lettuce	-0.23229	*	-0.62847	*+
Bell pepper	-0.2383	*	0.151274	*+
Tomatoes	-0.23448	*	-0.30962	*+
Peas, dry	-0.12947		-0.68949	+
Beans, dry	-0.1219	*	-0.43941	*+

Lentils	-0.50455		-0.89183	+
Peanuts	-0.28611		-0.33423	*+
Potatoes	-0.13851	*	-1.26579	*+
Yucca	-0.26941	*	-0.22373	*+
Carrots	-0.13754	*	-0.46767	*+
Sugar	-0.67976		-1.07589	*+
Chocolate, candy	0.036956	*	-0.53338	+
Candy	0.048292	*	-0.64005	*+
Gelatine	-0.16394		-0.5254	*+
Marmalade	-0.14746		-0.60556	+
Honey	0.046626	*	-0.4876	*+
Panela	-0.03765	*	-1.12049	+
Garlic	-0.12017	*	-0.27536	*+
Salt	-0.21968		-0.64735	*+
Ketchup	-0.16011		-0.6181	+
Broad beans, flour	-0.09514	*	-0.47592	*+
Soup, dry	-0.20321		-0.72971	+
Coffee, ground	0.092544	*	-0.60992	*+
Coffee, instant	0.097597	*	-0.72206	+
Cocoa	-0.19314		-0.2637	*
Mineral water	0.023499	*	-0.33708	*
Soft drink, store	-0.0943	*	-0.65386	*+
Orange juice	-0.2305		-0.74351	+
Soft drink in powder	0.009864	*	-0.5565	*+
Beer, at store	-0.04729	*	-0.60158	*+
Rum	-0.05193	*	-0.54296	+
Wine	-0.02552	*	-0.55596	*+

Cigarrettes	-0.69308		-1.06581	+
Cassimere, fabric	-0.08404	*	-0.87036	+
Chalis, fabric	-0.26259		-0.93817	+
Silk, fabric	-0.14926		-0.76832	+
Dress for woman, making	0.06261	*	-0.15537	*
Pants for man, making	0.034099	*	-0.31125	*
Suit for man, making	0.00387	*	-0.17787	*
Socks, mens	-0.18709		-0.82021	+
Underwear, mens	-0.11042	*	-0.67709	+
Shirt, mens	-0.17019		-0.71016	+
T-shirt, mens	-0.20641		-0.63003	+
Pants, mens	-0.11724		-0.62013	+
Shorts, for sports, mens	-0.05413	*	-0.76882	*+
Suit for men	-0.12452	*	-0.61106	*+
T-shirt, childrens	-0.13363	*	-0.83983	*+
Pants, boys	-0.30025		-0.8023	+
Blouse, womens, typical	-0.19848		-0.7254	*+
Underwear, womens	0.06721	*	-0.73013	+
T-shirt, womens	-0.20954		-0.85063	+
Skirt, womens	-0.13764	*	-0.59236	*+
Pantyhose, nylon	-0.07531	*	-1.33556	+
Pants, womens	-0.03655	*	-0.68408	+
Dress, womens	-0.0172	*	-0.30352	*+
Pants, girls	-0.14525		-0.76712	+
Underwear, girls	-0.19606		-0.61492	+
Dress, girls	-0.2577		-0.57269	*+
Shirt, babies	-0.07645	*	-0.62145	*+

Suit for baby	-0.00342	*	-0.75207	*+
Shoes, leather, mens	-0.02186	*	-0.71941	+
Shoes, sneakers, mens	-0.09487	*	-0.98757	+
Shoes, boys	0.033529	*	-0.41667	*+
Shoes, leather, womens	-0.03067	*	-0.61568	+
Shoes, sneakers, womens	-0.1655		-0.74533	*+
Shoes, girls	-0.23454		-0.73353	*+
Shoe polish	-0.16201	*	-0.96632	+
Shoe polishing	-0.00148	*	-0.11149	*
Shoe repair	-0.08655	*	-0.42763	*+
Rent of house, typical	0.029897	*	0.1209	*
Rent of apartment, typical	0.008048	*	0.156207	*
Rent of room, efficiency	0.024913	*	0.095346	*
Water (utility)	0.011603	*	-0.2306	*+
Electricity	-0.28524	*	-0.35611	*+
Gas, natural, domestic	-0.51852	*+	0.013759	*+
Cupboard, wooden	-0.03593	*	-0.53473	*+
Bed, wooden	-0.28284		-0.6246	*+
Chest of drawers, wooden	-0.1318	*	-0.48205	*+
Dining set	-0.14121		-0.56527	*+
Living room set	-0.19926		-0.5666	*+
Blanket, thick, very warm	-0.19893		-0.81868	+
Blanket, thick, warm	-0.11115		-0.77301	+
Mattress	-0.0867	*	-0.83234	+
Blanket, thin	0.030783	*	-0.64127	+
Towel	-0.09324	*	-0.72529	+
Stove, gas	-0.67428		-1.1066	+

Blender	-0.67208		-1.18155	+
Sewing machine	-0.52896		-1.00985	+
Iron, electric	-0.73383		-1.15478	+
Refrigerator	-0.93868	+	-1.05517	+
Light bulb, typical	-0.13308		-0.87671	+
Pot, cooking	-0.21042		-1.04593	+
Cup with dish	-0.00516	*	-0.64972	*+
Glass	-0.39931		-1.09949	+
Bleach, for laundry	-0.25308		-0.79855	+
Disinfectant, domestic	-0.29177		-0.77875	+
Detergent	-0.51577		-1.05531	+
Broom	0.126134	*	-0.50116	*+
Matches	-0.1207		-0.68757	+
Soap for dishwashing	-0.50585		-0.47767	*+
Soap for laundry	-0.25898		-0.51953	*+
Toilet Paper	-0.06208	*	-0.94684	+
Laundry service	0.094109	*	-0.30584	*
Dry cleaning	0.055204	*	-0.33904	*
Medicines in general	0.022631	*	-0.69931	+
Aspirin (medicine)	0.002462	*	-0.92938	+
Linconcin (medicine)	0.239251		-0.49222	*+
Flagil (medicine)	-0.01988	*	-0.45481	*+
Garamicina (medicine)	0.069526	*	-0.43418	*
Neurobion (medicine)	0.010319	*	-0.73081	+
Voltaren (medicine)	-0.06148	*	-0.49371	*+
Megacilina (medicine)	0.102055	*	-0.59091	+
Apronax (medicine)	0.170957		-0.72749	+

Redoxon (medicine)	0.094518	*	-0.71787	*+
Hepabionta (medicine)	0.032122	*	-0.58064	*+
Milk of magnesia	0.204476	*	-1.08769	+
Baycuten, cream (medicine)	-0.27797		-0.9776	*+
Comtrex (medicine)	-0.13848	*	-1.24643	+
Mucosolvan (medicine)	-0.03549	*	-0.68866	+
Cataflam (medicine)	0.071179	*	-0.34937	*
Fungirex (medicine)	0.146383	*	-0.42768	*+
Imodium (medicine)	0.142348	*	-0.64447	*+
Acrosin-B (medicine)	0.118511	*	-0.33427	*+
Glasses	-0.49584		-0.67127	+
Doctors visit	0.06611	*	-0.06422	*
Lab test, typical medical	-0.11664	*	-0.22888	*
Automobile or pick-up truck	-0.81658		-0.89489	+
Bicycle, typical	-0.6014		-1.06394	+
Tire, with tube if needed	-0.51506		-0.78169	*+
Automobile tune-up	-0.52119		-0.97162	+
Gasoline	-0.68749	+	-0.10711	*+
Inter-province trip	0.180541	*	-0.29072	*+
Transportation, public in bus	0.276995	*	-0.28761	*+
Taxi, urban	-0.08713	*	-0.17047	*+
Sound system, stereo	-0.90995	+	-1.09562	+
TV set, color	-0.73234		-1.18387	+
VCR	-0.83738		-0.98081	+
Soccer ball	-0.31995		-1.09594	+
Entertainment, dancing	-0.03423	*	-0.4961	*+
Soccer game	-0.03526	*	0.164122	*+

Rent of VHS movie	0.081671	*	-0.24612	*
Newspaper	-0.47877		-0.49839	*+
Magazine	-0.36006		-0.44521	*+
Uniform for school	0.081965	*	0.065257	*+
Tuition, kindergarden	0.044754	*	0.194971	*
Tuition, primary school	0.120723	*	-0.04002	*
Registration, secondary school	0.000463	*	0.179596	*
Tuition, secondary school	0.040867	*	0.160091	*
Registration, university	0.026467	*	0.009228	*
Typewriter	-0.64322		-1.2142	+
School supplies in general	0.242934		-0.33479	*+
Book, primary school (typical)	0.202518		-0.20987	*+
Notebook for primary school	0.307758		-0.46982	*+
Compass, drawing, primary school	0.243352	*	-0.40985	*+
Ruler, primary school	0.211621	*	-0.39445	*+
Pen for primary school	0.32883		-0.50861	*+
Notebook for secundary school	0.246322		-0.42304	*+
Folder	0.279094		-0.41122	*+
Paper, bond	0.283489		-0.55887	*+
Geometry set for school	0.119225	*	-0.31337	*+
Ruler, secondary school	0.180225	*	-0.37224	*+
Pen for secundary school	0.323097		-0.51638	*+
Algebra book	0.276424		-0.41665	*+
Dictionary for school	0.031027	*	0.167051	*+
Lunch, typical	-0.06832	*	-0.28239	*
Chicken, rotisserie	-0.06261	*	-0.7511	*+
Soft drink, at bar	-0.1024	*	-0.30759	*

Beer, at bar	-0.09365	*	-0.48671	*+
Lodging, typical	-0.15044	*	-0.16189	*+
Haircut	0.07776	*	-0.12648	*
Cologne	-0.06853	*	-0.6005	*+
Cream, moisturizer	-0.20178		-0.86254	+
Deodorant	-0.02531	*	-0.93229	+
Soap, deodorant	-0.01514	*	-0.98439	+
Razor, standard manual	-0.03963	*	-1.03826	+
Diapers, disposable for children	-0.46895		-1.17043	+
Toothpaste	-0.35977		-0.96528	+
Shampoo	0.125001	*	-0.85935	+
Talc powder	-0.03724	*	-0.84769	+
Sanitary pads	-0.08309	*	-0.99894	+
Postage for letter, typical	-0.55249		-0.9604	*+

Table D.2: Coastal Difference Regression

Goods	SR Pass-through		LR Pass-through	
Rice	0.0003	*	0.0005	*
Oat meal	0.0008	*	-0.0003	*
Cereal	0.0005	*	0.0008	*
Spaghetti	0.0001	*	-0.0003	*
Bread	0.0005	*	0.0007	*
Beef, with bone	0.0008	*	0.0001	*
Beef, without bone	0.0007	*	-0.0004	*
Chicken	0.0007	*	0.0010	*
Shrimp	0.0010	*	-0.0003	*
Fish, fresh	-0.0002	*	-0.0013	*

Tuna, can	0.0005	*	0.0001	*
Sardines in can	0.0005	*	0.0004	*
Milk, powder	0.0000	*	-0.0009	*
Milk, fresh, homogenized/pasteurized	0.0003	*	0.0002	*
Cheese	0.0004	*	0.0011	*
Eggs	0.0008	*	0.0018	*
Oil, vegetable	0.0002	*	0.0001	*
Vegetable fat	0.0008	*	0.0003	*
Margarine	-0.0001	*	-0.0003	*
Avocado	0.0008	*	0.0004	*
Bananas	0.0004	*	-0.0010	*
Lemons	0.0018	*	0.0004	*
Apples	0.0005	*	0.0017	*
Raspberries	0.0005	*	0.0053	*
Oranges	0.0029	*	0.0002	*
Naranjilla	0.0006	*	-0.0011	*
Papaya	0.0015	*	0.0004	*
Pineapple	0.0000	*	-0.0013	*
Plantain	0.0000	*	-0.0025	*
Watermelon	0.0012	*	-0.0033	*
Tomatillo	0.0013	*	0.0011	*
Grapes	0.0003	*	0.0016	*
Fruit cocktail, can	0.0007	*	0.0004	*
Raisins	0.0001	*	-0.0006	*
Peas, fresh	-0.0012	*	-0.0026	*
Onion, white	-0.0021	*	-0.0016	*
Onion, red	0.0006	*	-0.0022	*

Cabbage	0.0003	*	-0.0010	*
Cauliflower	-0.0010	*	-0.0034	*
Corn, fresh	-0.0027		-0.0038	*
Broad beans, fresh	0.0018		-0.0014	*
Beans, fresh	-0.0002	*	0.0001	*
Lettuce	-0.0002	*	-0.0061	*
Bell pepper	0.0012	*	-0.0061	*
Tomatoes	0.0001	*	-0.0035	*
Peas, dry	0.0000	*	0.0004	*
Beans, dry	0.0012		-0.0002	*
Lentils	0.0001	*	0.0008	*
Peanuts	0.0012	*	0.0006	*
Potatoes	0.0002	*	0.0013	*
Yucca	-0.0005	*	-0.0009	*
Carrots	0.0019	*	-0.0022	*
Sugar	0.0000	*	-0.0012	*
Chocolate, candy	0.0002	*	0.0001	*
Candy	0.0004	*	0.0004	*
Gelatine	0.0001	*	0.0007	*
Marmalade	0.0003	*	0.0007	*
Honey	0.0005	*	0.0007	*
Panela	-0.0002	*	-0.0004	*
Garlic	-0.0010	*	-0.0007	*
Salt	0.0000	*	-0.0004	*
Ketchup	0.0007	*	-0.0003	*
Broad beans, flour	-0.0001	*	0.0000	*
Soup, dry	0.0000	*	0.0010	*

Coffee, ground	0.0003	*	0.0001	*
Coffee, instant	0.0006	*	0.0012	*
Cocoa	0.0003	*	0.0005	*
Mineral water	-0.0002	*	0.0010	*
Soft drink, store	0.0005	*	0.0014	*
Orange juice	0.0000	*	0.0008	*
Soft drink in powder	0.0003	*	0.0006	*
Beer, at store	0.0007	*	-0.0013	*
Rum	0.0001	*	0.0013	*
Wine	0.0006	*	0.0007	*
Cigarrettes	0.0004	*	0.0004	*
Cassimere, fabric	-0.0001	*	0.0001	*
Chalis, fabric	0.0006	*	0.0009	*
Silk, fabric	0.0007	*	-0.0001	*
Dress for woman, making	-0.0003	*	0.0005	*
Pants for man, making	0.0004	*	0.0006	*
Suit for man, making	-0.0002	*	0.0000	*
Socks, mens	0.0006	*	0.0008	*
Underwear, mens	0.0010		0.0008	*
Shirt, mens	0.0006	*	0.0009	*
T-shirt, mens	0.0002	*	0.0002	*
Pants, mens	0.0009		0.0005	*
Shorts, for sports, mens	0.0002	*	0.0022	*
Suit for men	0.0002	*	0.0007	*
T-shirt, childrens	0.0007	*	0.0004	*
Pants, boys	0.0001	*	0.0001	*
Blouse, womens, typical	0.0004	*	0.0001	*

Underwear, womens	0.0001	*	0.0005	*
T-shirt, womens	0.0006	*	0.0001	*
Skirt, womens	0.0007	*	0.0016	*
Pantyhose, nylon	0.0012	*	0.0010	*
Pants, womens	0.0008		0.0005	*
Dress, womens	0.0004	*	0.0004	*
Pants, girls	0.0001	*	0.0004	*
Underwear, girls	0.0003	*	-0.0002	*
Dress, girls	0.0000	*	0.0001	*
Shirt, babies	0.0006	*	0.0010	*
Suit for baby	0.0000	*	0.0010	*
Shoes, leather, mens	0.0004	*	0.0002	*
Shoes, sneakers, mens	0.0002	*	-0.0002	*
Shoes, boys	0.0001	*	-0.0003	*
Shoes, leather, womens	0.0006	*	0.0006	*
Shoes, sneakers, womens	-0.0001	*	-0.0011	*
Shoes, girls	0.0003	*	0.0004	*
Shoe polish	0.0005	*	0.0020	*
Shoe polishing	0.0003	*	0.0006	*
Shoe repair	-0.0004	*	0.0001	*
Rent of house, typical	0.0000	*	-0.0012	*
Rent of apartment, typical	-0.0004	*	-0.0001	*
Rent of room, efficiency	-0.0001	*	-0.0002	*
Water (utility)	-0.0008	*	-0.0001	*
Electricity	0.0003	*	0.0006	*
Gas, natural, domestic	0.0006	*	0.0046	*
Cupboard, wooden	0.0005	*	0.0003	*

Bed, wooden	0.0007	*	0.0016	*
Chest of drawers, wooden	0.0004	*	0.0006	*
Dining set	0.0004	*	0.0005	*
Living room set	0.0003	*	0.0007	*
Blanket, thick, very warm	0.0007	*	0.0006	*
Blanket, thick, warm	0.0004	*	0.0001	*
Mattress	0.0005	*	0.0011	*
Blanket, thin	0.0004	*	0.0004	*
Towel	0.0005	*	0.0010	*
Stove, gas	0.0002	*	-0.0008	*
Blender	0.0001	*	-0.0004	*
Sewing machine	0.0009	*	-0.0003	*
Iron, electric	0.0002	*	-0.0007	*
Refrigerator	0.0005	*	-0.0004	*
Light bulb, typical	0.0004	*	0.0001	*
Pot, cooking	0.0001	*	0.0000	*
Cup with dish	0.0000	*	0.0000	*
Glass	0.0002	*	-0.0002	*
Bleach, for laundry	0.0006	*	0.0008	*
Disinfectant, domestic	0.0003	*	0.0004	*
Detergent	0.0005	*	-0.0002	*
Broom	0.0003	*	0.0005	*
Matches	0.0008	*	0.0003	*
Soap for dishwashing	-0.0013		-0.0002	*
Soap for laundry	0.0002	*	-0.0005	*
Toilet Paper	0.0006	*	0.0002	*
Laundry service	-0.0002	*	0.0003	*

Dry cleaning	0.0003	*	0.0014	*
Medicines in general	0.0005		0.0006	*
Aspirin (medicine)	0.0011	*	0.0016	*
Linconcin (medicine)	0.0008	*	0.0019	*
Flagil (medicine)	0.0004	*	0.0008	*
Garamicina (medicine)	0.0002	*	0.0005	*
Neurobion (medicine)	0.0004	*	-0.0001	*
Voltaren (medicine)	0.0004	*	-0.0002	*
Megacilina (medicine)	0.0003	*	0.0010	*
Apronax (medicine)	0.0000	*	0.0000	*
Redoxon (medicine)	0.0004	*	0.0005	*
Hepabionta (medicine)	0.0000	*	-0.0011	*
Milk of magnesia	0.0010	*	-0.0005	*
Baycuten, cream (medicine)	0.0010	*	-0.0004	*
Comtrex (medicine)	0.0008	*	0.0020	*
Mucosolvan (medicine)	0.0004	*	0.0007	*
Cataflam (medicine)	0.0005	*	-0.0008	*
Fungirex (medicine)	0.0004	*	0.0005	*
Imodium (medicine)	0.0008	*	-0.0008	*
Acrosin-B (medicine)	0.0008	*	0.0012	*
Glasses	0.0000	*	0.0006	*
Doctors visit	-0.0001	*	0.0000	*
Lab test, typical medical	0.0001	*	0.0011	*
Automobile or pick-up truck	0.0002	*	-0.0001	*
Bicycle, typical	-0.0002	*	-0.0008	*
Tire, with tube if needed	0.0000	*	0.0004	*
Automobile tune-up	0.0007	*	0.0008	*

Gasoline	-0.0009	*	-0.0022	*
Inter-province trip	-0.0006	*	-0.0011	*
Transportation, public in bus	-0.0004	*	-0.0013	*
Taxi, urban	-0.0004	*	-0.0009	*
Sound system, stereo	0.0006	*	-0.0007	*
TV set, color	0.0002	*	-0.0003	*
VCR	-0.0001	*	-0.0010	*
Soccer ball	0.0000	*	0.0014	*
Entertainment, dancing	-0.0005	*	0.0007	*
Soccer game	0.0013	*	0.0009	*
Rent of VHS movie	0.0004	*	0.0010	*
Newspaper	-0.0006	*	0.0004	*
Magazine	0.0002	*	0.0008	*
Uniform for school	0.0005	*	0.0009	*
Tuition, kindergarden	0.0003	*	0.0011	*
Tuition, primary school	0.0000	*	0.0012	*
Registration, secondary school	0.0001	*	0.0012	*
Tuition, secondary school	0.0001	*	0.0013	*
Registration, university	0.0000	*	0.0003	*
Typewriter	0.0002	*	0.0002	*
School supplies in general	0.0002	*	0.0015	*
Book, primary school (typical)	0.0001	*	0.0016	*
Notebook for primary school	0.0002	*	0.0014	*
Compass, drawing, primary school	0.0002	*	0.0014	*
Ruler, primary school	0.0000	*	0.0015	*
Pen for primary school	0.0002	*	0.0018	*
Notebook for secundary school	0.0001	*	0.0013	*

Folder	0.0002	*	0.0014	*
Paper, bond	0.0002	*	0.0013	*
Geometry set for school	0.0006	*	0.0011	*
Ruler, secondary school	0.0001	*	0.0014	*
Pen for secundary school	0.0003	*	0.0016	*
Algebra book	0.0002	*	0.0015	*
Dictionary for school	0.0001	*	0.0014	*
Lunch, typical	0.0006	*	0.0014	*
Chicken, rotisserie	0.0005	*	0.0017	*
Soft drink, at bar	0.0003	*	0.0008	*
Beer, at bar	0.0002	*	-0.0001	*
Lodging, typical	0.0000	*	0.0012	*
Haircut	0.0001	*	0.0006	*
Cologne	0.0006	*	0.0003	*
Cream, moisturizer	0.0005	*	-0.0004	*
Deodorant	0.0005	*	0.0005	*
Soap, deodorant	0.0005	*	0.0008	*
Razor, standard manual	0.0007	*	0.0010	*
Diapers, disposable for children	0.0005	*	0.0011	*
Toothpaste	0.0011	*	0.0013	*
Shampoo	-0.0006	*	-0.0002	*
Talc powder	0.0002	*	-0.0002	*
Sanitary pads	0.0007	*	0.0020	*
Postage for letter, typical	0.0000	*	0.0004	*

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