FREQUENCY OF PRICE ADJUSTMENT AND PASS-THROUGH*

GITA GOPINATH AND OLEG ITSKHOKI

We empirically document, using U.S. import prices, that on average goods with a high frequency of price adjustment have a long-run pass-through that is at least twice as high as that of low-frequency adjusters. We show theoretically that this relationship should follow because variable mark-ups that reduce long-run pass-through also reduce the curvature of the profit function when expressed as a function of cost shocks, making the firm less willing to adjust its price. We quantitatively evaluate a dynamic menu-cost model and show that the variable mark-up channel can generate significant variation in frequency, equivalent to 37% of the observed variation in the data. On the other hand, the standard workhorse model with constant elasticity of demand and Calvo or state-dependent pricing has difficulty matching the facts.

I. INTRODUCTION

There is a current surge in research that investigates the behavior of prices using micro data with the goal of comprehending key aggregate phenomena such as the gradual adjustment of prices to shocks. A common finding of these studies is that there is large heterogeneity in the frequency of price adjustment even within detailed categories of goods. However, there is little evidence that this heterogeneity is meaningfully correlated with other measurable statistics in the data.[1] This makes it difficult to discern what the frequency measure implies for the transmission of shocks and which models of price setting best fit the data, both of which are important for understanding the effects of monetary and exchange rate policy.

In this paper we exploit the open economy environment to shed light on these questions. The advantage of the international data over the closed-economy data is that they provide a

*We wish to thank the International Price Program of the Bureau of Labor Statistics (BLS) for access to unpublished micro data. We owe a huge debt of gratitude to our project coordinator, Rozi Ulics, for her invaluable help on this project. The views expressed here do not necessarily reflect the views of the BLS. We are grateful to Robert Barro, Elhanan Helpman, and three anonymous referees for detailed comments. We thank participants at several venues for comments and Loukas Karabarbounis for excellent research assistance. This research is supported by NSF Grant SES 0617256.

1. It is clearly the case that raw/homogeneous goods display a higher frequency of adjustment than differentiated goods, as documented in Bils and Klenow (2004) and Gopinath and Rigobon (2008). But outside of this finding, there is little that empirically correlates with frequency. Bils and Klenow (2004) and Kehoe and Midrigan (2007) are recent papers that make this point.

The Quarterly Journal of Economics, May 2010

well-identified and sizable cost shock, namely the exchange rate shock. We find that there is indeed a systematic relation between the frequency of price adjustment and long-run exchange rate pass-through. First, we document empirically that on average high-frequency adjusters have a long-run pass-through that is significantly higher than that of low-frequency adjusters. Next, we show theoretically that long-run pass-through is determined by primitives that shape the curvature of the profit function and hence also affect the frequency of price adjustment, and theory predicts a positive relation between the two in an environment with variable mark-ups. Last, we calibrate a dynamic menu-cost model and show that the variable mark-up channel can generate significant variation in frequency, equivalent to 37% of the observed variation in the data. The standard workhorse model with constant elasticity of demand and Calvo or state-dependent pricing generates long-run pass-through that is uncorrelated with frequency, contrary to the data.

We document the relation between frequency and long-run pass-through using micro data on U.S. import prices at the dock.[2] *Long-run* pass-through is a measure of pass-through that does not compound the effects of nominal rigidity. We divide goods imported into the United States into frequency bins and use two nonstructural approaches to estimate long-run exchange rate pass-through within each bin. First, we regress the cumulative change in the price of the good over its life in the sample, referred to as its lifelong price change, on the exchange rate movement over the same period. Second, we estimate an aggregate pass-through regression and compute the cumulative impulse response of the average monthly change in import prices within each bin to a change in the exchange rate over a 24-month period. Either procedure generates similar results: When goods are divided into two equal-sized frequency bins, goods with frequency higher than the median frequency of price adjustment display, on average, long-run pass-through that is at least twice as high as that for goods with frequency less than the median frequency.

For the sample of firms in the manufacturing sector, high-frequency adjusters have a pass-through of 44% compared to low-frequency adjusters with a pass-through of 21%. In the subsample

2. The advantage of using prices at the dock is that they do not compound the effect of local distribution costs, which play a crucial role in generating low pass-through into consumer prices.

of importers in the manufacturing sector from high-income OECD countries, high-frequency adjusters have a pass-through of 59% compared to 25% for the low-frequency adjusters. This result similarly holds for the subsample of differentiated goods based on the Rauch (1999) classification. When we divide goods into frequency deciles so that frequency ranges between 3% and 100% per month, long-run pass-through increases from around 18% to 75% for the subsample of imports from high-income OECD countries. Therefore, the data are characterized not only by a positive relationship between frequency and long-run pass-through, but also by a wide range of variation for both variables.

Both frequency and long-run pass-through depend on primitives that affect the curvature of the profit function. In Section III we show that it is indeed the case that higher long-run pass-through should be associated with a higher frequency of price adjustment. We analyze a static price-setting model where long-run pass-through is incomplete and firms pay a menu cost to adjust preset prices in response to cost shocks.[3] We allow for two standard channels of incomplete long-run exchange rate pass-through: (i) variable mark-ups and (ii) imported intermediate inputs.

A higher mark-up elasticity raises the curvature of the profit function with respect to prices; that is, it reduces the region of nonadjustment. However, it also reduces the firm's desired price adjustment, so that the firm's price is more likely to stay within the bounds of nonadjustment. We show that this second effect dominates, implying that a higher mark-up elasticity lowers both pass-through and frequency. Alternatively, it reduces the curvature of the profit function when expressed as a *function of the cost shocks*, generating lower frequency.

The positive relationship between frequency and long-run pass-through implies the existence of a selection effect, wherein firms that infrequently adjust prices are typically not as far from their desired prices due to their lower desired pass-through of cost shocks. On the other hand, firms that have high desired

3. Our price-setting model is closest in spirit to Ball and Mankiw (1994), whereas the analysis of the determinants of frequency relates closely to the exercise in Romer (1989), who constructs a model with complete pass-through (CES demand) and Calvo price setting with optimization over the Calvo probability of price adjustment. Other theoretical studies of frequency include Barro (1972), Sheshinski and Weiss (1977), Rotemberg and Saloner (1987), and Dotsey, King, and Wolman (1999). Finally, Devereux and Yetman (2008) study the relationship between frequency of price adjustment and short-run exchange rate pass-through in an environment with complete long-run pass-through.

pass-through drift farther away from their optimal price and, therefore, make more frequent adjustments. This potentially has important implications for the strength of nominal rigidities given the median duration of prices in the economy. It is important to stress that this selection effect is different from a classical selection effect of state-dependent models forcefully shown by Caplin and Spulber (1987), and it will also be present in time-dependent models with optimally chosen periods of nonadjustment as in Ball, Mankiw, and Romer (1988).

In Section IV we quantitatively solve for the industry equilibrium in a dynamic price-setting model. The standard model of sticky prices in the open economy assumes CES demand and Calvo price adjustment.[4] These models predict incomplete pass-through in the short run when prices are rigid and set in the local currency, but perfect pass-through in the long run. To fit the data, we depart from this standard setup. First, we allow endogenous frequency choice via a menu cost model of state-dependent pricing. Second, we allow variable mark-ups, *à la* Dornbusch (1987) and Krugman (1987), which generates incomplete long-run pass-through. This source of incomplete pass-through has received considerable support in the open economy empirical literature, as we discuss in Section IV. We examine how *variation* in the mark-up elasticity across firms affects the frequency of price adjustment.

We present four sets of results. First, variation in mark-up elasticity can indeed generate a strong positive relation between frequency and long-run pass-through (LRPT) and can generate significant variation in frequency, equivalent to 37% of the observed variation in the data. The model generates a standard deviation in frequency across goods of 11%, as compared to 30% in the data. Second, a menu cost model that allows for joint cross-sectional variation in mark-up elasticity and menu costs can quantitatively account for both the positive slope between LRPT and frequency and the close-to-zero slope between absolute *size* of price adjustment and frequency in the data. The model generates a slope of 0.55 between frequency and LRPT, whereas in

4. See the seminal contribution of Obstfeld and Rogoff (1995) and the subsequent literature surveyed in Lane (2001). Midrigan (2007) analyzes an environment with state-dependent pricing, but assumes constant mark-ups and complete pass-through; Bergin and Feenstra (2001) allow for variable mark-ups in an environment with price stickiness, but they assume exogenous periods of nonadjustment.

the data it is 0.56. Similarly, the slope coefficient for the relation between frequency and size is −0.05 in the model, close to the data estimate of −0.01. Further, it generates dispersion in frequency equivalent to 60% of the dispersion in the data. In both simulations the model matches the median absolute size of price adjustment of 7%. Third, we show that the nonstructural pass-through regressions estimated in the empirical section recover the true underlying LRPT. Fourth, we verify that the observed correlation between frequency and LRPT cannot be explained by standard sticky price models with only exogenous differences in the frequency of price adjustment and no variation in LRPT.

Section II presents the empirical evidence. Section III presents the static model of frequency and LRPT, and Section IV describes the calibration of a dynamic model and its ability to match the facts. Section V concludes. All proofs are relegated to the Appendix.

II. Empirical Evidence

In this section we empirically evaluate the relation between the frequency of price adjustment of a good and the *long-run* response of the price of the good to an exchange rate shock. The latter, referred to as long-run exchange rate pass-through (LRPT), is defined to capture pass-through beyond the period when nominal rigidities in price setting are in effect. In the presence of strategic complementarities in price setting or other forms of real rigidities, this can require multiple rounds of price adjustment.[5] We use two nonstructural approaches to estimate LRPT from the data. Our main finding is that goods whose prices adjust more frequently also have a higher exchange rate pass-through in the long run than low-frequency adjusters. In Section IV.C we estimate the same regressions on data simulated from conventional sticky price models and verify that both of these regressions indeed deliver estimates close to the true theoretical LRPT.

II.A. Data and Methodology

We use micro data on the prices of goods imported into the United States provided to us by the Bureau of Labor Statistics

5. Other sources of sluggish adjustment could include the presence of informational frictions or convex adjustment costs in price setting.

(BLS) for the period 1994–2005. The details regarding this data set are provided in Gopinath and Rigobon (2008).

We focus on a subset of the data that satisfies the following criteria. First, we restrict attention to market transactions and exclude intrafirm transactions, as we are interested in price setting driven mainly by market forces.[6]

Second, we require that a good have at least one price adjustment during its life. This is because the goal of the analysis is to relate the frequency of price adjustment to the flexible price pass-through of the good, and this requires observing at least one price change. In this database 30% of goods have a fixed price during their life. For the purpose of our study these goods are not useful and they are excluded from the analysis. We revisit this issue at the end of this section, when we comment on item substitution.

Third, we restrict attention to dollar-priced imports in the manufacturing sector.[7] The restriction to manufactured goods allows us to focus on price-setting behavior where firms have market power and goods are not homogeneous. We restrict attention to dollar-priced goods, in order to focus on the question of frequency choice, setting aside the question of currency choice. This restriction does not substantially reduce the sample size because 90% of goods imported are priced in dollars. For the analysis of the relation between currency choice and pass-through see Gopinath, Itskhoki, and Rigobon (2009). The relation between the two papers is discussed in Section II.D.

For each of the remaining goods we estimate the frequency of price adjustment following the procedure in Gopinath and Rigobon (2008). We then sort goods into high- and low-frequency bins, depending on whether the good's frequency is higher or lower than the median frequency, and estimate LRPT within each bin.

The first approach estimates exchange rate pass-through over the life of the good in the BLS sample. Specifically, for each good, we measure the cumulative change in the price of the good from its first observed new price to its last observed new price in the BLS data. We refer to this as the lifelong change in price. We then relate it to the cumulative change in the exchange rate over this

6. A significant fraction of trade takes place intrafirm and these transactions constitute about 40% of the BLS sample. For empirical evidence on the difference between intrafirm and arms-length transactions, using this data set, see Neiman (2007) and Gopinath and Rigobon (2008).

7. That is, goods that have a one-digit SIC code of 2 or 3. We exclude any petrol classification codes.

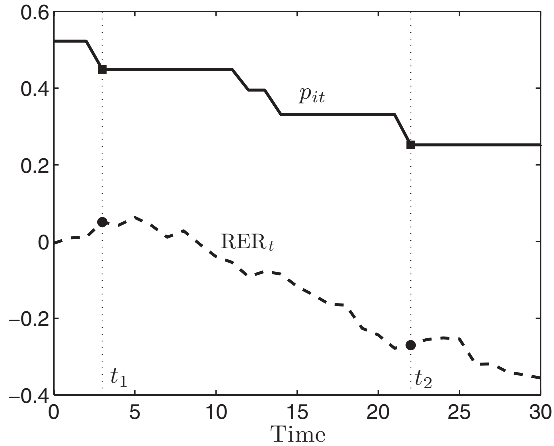

FIGURE I

Illustration for Lifelong Pass-Through Regression (1)

In this hypothetical example we observe the price of good i from $t = 0$ to $t = 30$ months. The figure plots the observed price and the corresponding bilateral real exchange rate for the same period, both in logs. The first observed new price is set at $t_1 = 3$ and the last observed new price is set at $t_2 = 22$. Therefore, for this good we have $\Delta p_L^{i,c} = p_{it_2} - p_{it_1}$ and $\Delta \mathrm{RER}_L^{i,c} = \mathrm{RER}_{t_2} - \mathrm{RER}_{t_1}$. In the baseline specification we additionally adjust $\Delta p_L^{i,c}$ by U.S. CPI inflation over the same period.

period. Specifically, *lifelong pass-through*, β_L, is estimated from the following micro-level regression:

$$\Delta p_L^{i,c} = \alpha_c + \beta_L \Delta \mathrm{RER}_L^{i,c} + \epsilon^{i,c}. \tag{1}$$

$\Delta p_L^{i,c}$ is equal to the lifelong change in the good's log price relative to U.S. inflation, where i indexes the good and c the country. $\Delta \mathrm{RER}_L^{i,c}$ refers to the cumulative change in the log of the bilateral real exchange rate for country c over this same period.[8] The construction of these variables is illustrated in Figure I. The real exchange rate is calculated using the nominal exchange rate and the consumer price indices in the two countries. An increase in the RER is a real depreciation of the dollar. Finally, α_c is a country fixed effect.

The second approach measures LRPT by estimating a standard aggregate pass-through regression. For each frequency bin,

8. The index i on the RER is to highlight that the particular real exchange rate change depends on the period when the good i is in the sample.

each country c, and each month t, we calculate the average price change relative to U.S. inflation, Δp_t^c, and the monthly bilateral real exchange rate movement *vis-à-vis* the dollar for that country, $\Delta \mathrm{RER}_t^c$. We then estimate a stacked regression where we regress the average monthly change in prices on monthly lags of the real exchange rate change,

$$(2) \qquad \Delta p_t^c = \alpha_c + \sum_{j=0}^{n} \beta_j \Delta \mathrm{RER}_{t-j}^c + \epsilon_t^c,$$

where α_c is a country fixed effect and n varies from 1 to 24 months. The *aggregate long-run pass-through* is then defined to be the cumulative sum of the coefficients, $\sum_{j=0}^{n} \beta_j$, at $n = 24$ months.

Before we proceed to describe the results, we briefly comment on the two approaches. First, we use the real specification in both regressions to be consistent with the regressions run later on the model-generated data in Section IV.C. However, the empirical results from both the micro and aggregate regressions are insensitive to using a nominal specification, not surprisingly, given that the real and the nominal exchange rates move closely together at the horizons we consider.[9]

Second, a standard assumption in the empirical pass-through literature is that movements in the real or nominal exchange rate are orthogonal to other shocks that affect the firm's pricing decision and are not affected by firm pricing. This assumption is motivated by the empirical finding that exchange rate movements are disconnected from most macro variables at the frequencies studied in this paper. Although this assumption might be problematic for commodities such as oil or metals and for some commodity-exporting countries such as Canada, it is far less restrictive for most differentiated goods and most developed countries. Moreover, our main analysis is to rank pass-through across frequency bins as opposed to estimating the true pass-through number. For this reason, our analysis is less sensitive to concerns about the endogeneity of the real exchange rate.

Third, the lifelong approach has an advantage in measuring LRPT in that it ensures that all goods have indeed changed their price. In the case of the second approach it is possible that even after 24 months some goods have yet to change price and consequently pass-through estimates are low. A concern with the

9. In the nominal specification, we regress the lifelong change in the log of the nominal price of the good on the cumulative change in the log of the nominal exchange rate.

first approach, however, is that because it conditions on a price change, estimates can be biased, because although the exchange rate may be orthogonal to other shocks, when the decision to adjust is endogenous, conditioning on a price change induces a correlation across shocks. The lifelong regression addresses this selection issue by increasing the window of the pass-through regression to include a number of price adjustments that reduces the size of the selection bias. In Section IV.C we confirm this claim via simulations.

II.B. Lifelong Pass-Through

In Table I we report the results from estimating the lifelong equation (1). In Panel A the first price refers to the first *observed* price for the good, and in Panel B the first price refers to the first *new* price for the good. In both cases, the last price is the last new price. For the hypothetical item in Figure I, Panel A would use observations in $[0, t_2]$, whereas Panel B would use observations only in $[t_1, t_2]$. The main difference between the results in the two tables relates to the number of observations, because there are goods with only one price adjustment during their life. Otherwise, the results are the same.

The first column of Table I reports the subsample of the analysis. The next six columns report the median frequencies (Freq) within the low- and high-frequency bins, the point estimates for LRPT (β_L^{Lo} and β_L^{Hi}) and the robust standard errors ($s.e.(\beta_L^{\text{Lo}})$ and $s.e.(\beta_L^{\text{Hi}})$) for the estimates clustered at the level of country interacted with the BLS-defined Primary Strata Lower (PSL) of the good (mostly two- to four-digit harmonized codes). The next two columns report the difference in LRPT between high and low-frequency adjusters and the t-statistic associated with this difference. The number of observations, N_{obs}, and R^2 are reported in the last two columns.

The main finding is that high-frequency adjusters have a lifelong pass-through that is at least twice as high as for low-frequency adjusters. Consider first the specification in Panel A. In the low-frequency subsample, goods adjust prices on average every fourteen months and pass-through only 21% in the long run. At the same time, in the high-frequency subsample, goods adjust prices every three months and pass-through 44% in the long run. This is more strongly evident when we restrict attention to the high-income OECD sample: LRPT increases from 25% to 59% as we move from the low- to the high-frequency subsample.

TABLE I
FREQUENCY AND LIFELONG PASS-THROUGH

	Low frequency			High frequency			Difference			
	Freq	β_L^{Lo}	s.e.(β_L^{Lo})	Freq	β_L^{Hi}	s.e.(β_L^{Hi})	$\beta_L^{\mathrm{Hi}} - \beta_L^{\mathrm{Lo}}$	t-stat	N_{obs}	R^2
Panel A: Baseline specification										
All countries										
Manufacturing	0.07	0.21	0.03	0.38	0.44	0.05	0.23	4.18	14,227	.07
Differentiated	0.07	0.20	0.04	0.29	0.46	0.06	0.26	3.89	7,870	.08
High-income OECD										
Manufacturing	0.07	0.25	0.04	0.40	0.59	0.06	0.34	4.43	5,988	.08
Differentiated	0.07	0.25	0.07	0.33	0.59	0.08	0.34	3.50	2,982	.10
Panel B: Starting with a new price										
All countries										
Manufacturing	0.10	0.20	0.03	0.47	0.46	0.06	0.26	3.71	9,002	.09
Differentiated	0.09	0.16	0.05	0.33	0.48	0.08	0.32	3.68	4,708	.10
High-income OECD										
Manufacturing	0.10	0.19	0.05	0.50	0.67	0.06	0.49	6.00	4,079	.10
Differentiated	0.09	0.17	0.08	0.40	0.60	0.09	0.43	3.73	1,942	.11

Note. Robust standard errors clustered by country $\times$ PSL pair, where PSL is the BLS-defined Primary Strata Lower that corresponds to 2- to 4-digit sectoral harmonized codes. The baseline specification in Panel A computes the lifelong change in price starting with the first observed price of the good, whereas the specification in Panel B starts from the first new price of the good.

We also examine the subsample of manufactured goods that can be classified as being in the differentiated goods sector, following Rauch's classification.[10] For differentiated goods, moving from the low- to the high-frequency bin raises LRPT from 20% to 46% for goods from all source countries and from 25% to 59% in the high-income OECD sample. In all cases, the difference in pass-through across frequency bins is strongly statistically significant.

Similarly, the higher pass-through of high-frequency adjusters is evident in Panel B where the first price is a new price. Because the results are similar for the case where we start with the first price as opposed to the first new price, for the remainder of the analysis we report the results for the former case, as it preserves a larger number of goods in the sample.[11] All results in Table I also hold for the nominal specification, which is not reported for brevity.

As a sensitivity check, we also restrict the sample to goods that have at least three or more price adjustments during their life. Results for this specification are reported in Table II. As expected, the median frequency of price adjustment is now higher, but the result that long-run pass-through is at least twice as high for the high-frequency bin as for the low-frequency bin still holds strongly and significantly.

We also estimate median quantile regressions to limit the effect of outliers and find that the results hold just as strongly. In the case of the all-country sample, $\beta_L^{\text{Lo}} = 0.19$ and $\beta_L^{\text{Hi}} = 0.41$, with the difference having a t-statistic of 14.1. For the high-income OECD subsample, the difference is 0.30, with a t-statistic of 13.0.

We also verify that the results are not driven by variable pass-through rates across countries unrelated to frequency, by

10. Rauch (1999) classified goods on the basis of whether they were traded on an exchange (organized), had prices listed in trade publications (reference), or were brand name products (differentiated). Each good in our database is mapped to a 10-digit harmonized code. We use the concordance between the 10-digit harmonized code and the SITC2 (Rev 2) codes to classify the goods into the three categories. We were able to classify around 65% of the goods using this classification. Consequently, it must not be interpreted that the difference in the number of observations between all manufactured and the subgroup of differentiated represent nondifferentiated goods. In fact, using Rauch's classification, only 100 odd goods are classified as nondifferentiated.

11. Because there can be months during the life of the good when there is no price information, as a sensitivity test, we exclude goods for whom the last new price had a missing price observation in the previous month to allow for the case that the price could have changed in an earlier month but was not reported. This is in addition to keeping only prices that are new prices (as in Panel B). We find that the results hold just as strongly in this case. The median frequency for the high (low)-frequency goods is 0.35 (0.08) and the long-run pass-through is 0.61 (0.11) respectively. The t-stat of the difference in LRPT is 5.3.

TABLE II
FREQUENCY AND LIFELONG PASS-THROUGH: GOODS WITH THREE OR MORE PRICE CHANGES

	Low frequency			High frequency			Difference			
	Freq	β_L^{Lo}	s.e.(β_L^{Lo})	Freq	β_L^{Hi}	s.e.(β_L^{Hi})	$\beta_L^{\text{Hi}} - \beta_L^{\text{Lo}}$	t-stat	N_{obs}	R^2
All countries										
Manufacturing	0.13	0.25	0.04	0.57	0.48	0.07	0.23	3.06	6,111	.11
Differentiated	0.11	0.19	0.06	0.42	0.56	0.09	0.38	3.99	3,031	.16
High-income OECD										
Manufacturing	0.12	0.32	0.07	0.60	0.70	0.08	0.38	4.00	2,856	.11
Differentiated	0.11	0.28	0.11	0.50	0.71	0.09	0.43	3.20	1,312	.16

Note. Robust standard errors clustered by country × PSL pair (as in Table I). The subsample contains only goods with at least three price adjustments during their life in the sample.

controlling for differential levels of pass-through across countries. We estimate the difference in the coefficient between high- and low-frequency adjusters, within country, to be 27 percentage points with a t-statistic of 5.6. In Table III we additionally allow for variation across countries in the difference ($\beta_L^{\text{Hi}} - \beta_L^{\text{Lo}}$) and again find that the relation between LRPT and frequency holds for goods from the same country/region.

Alternative Specifications. We now verify that the documented positive relationship between frequency and pass-through is not an artifact of splitting the items into two bins by frequency. First, we address this nonstructurally by increasing the number of frequency bins. Specifically, we estimate the same regression across ten frequency bins (deciles). The point estimates and 10% robust standard error bands are reported in Figure II for all manufactured goods and all manufactured goods from high-income OECD countries, respectively. The positive relationship is evident in these graphs. For the high-income OECD subsample, long-run pass-through increases from around 18% to 75% as frequency increases from 0.03 to 1.[12] This wide range of pass-through estimates covers almost all of the relevant range of theoretical pass-through, which for most specifications lies between 0 and 1. Furthermore, the positive relation between long-run pass-through and frequency is most evident for the higher frequency range, specifically among the goods that adjust every eight months or more frequently and constitute half of our sample. This fact assuages concerns that the relation between frequency and pass-through is driven by an insufficient number of price adjustments for the very–low frequency goods.

As opposed to increasing the number of frequency bins, our second approach estimates the effect of frequency on long-run pass-through using a more structured specification. We estimate the regression[13]

$$\Delta p_L^{i,c} = \alpha_c + \beta_L \Delta \mathrm{RER}_L^{i,c} + \delta_L \tilde{f}_{i,c} + \gamma_L \big(\tilde{f}_{i,c} \cdot \Delta \mathrm{RER}_L^{i,c}\big) + \epsilon^{i,c}, \tag{3}$$

12. For the all-country sample the long-run pass-through ranges between 14% and 45%.

13. This specification results from the following two-stage econometric model:

$$\Delta p_L^{i,c} = \alpha_c + \beta_L^{i,c} \Delta \mathrm{RER}_L^{i,c} + \delta_L \tilde{f}_{i,c} + v^{i,c},$$
$$\beta_L^{i,c} = \beta_L + \gamma_L \tilde{f}_{i,c} + u^{i,c}.$$

Regression (3) consistently estimates γ_L provided that $u^{i,c}$ and $v^{i,c}$ are independent from $\Delta \mathrm{RER}_L^{i,c}$ and $\tilde{f}_{i,c}$.

TABLE III
FREQUENCY AND LIFELONG PASS-THROUGH: COUNTRIES AND REGIONS

	Low frequency			High frequency			Difference			
	Freq	β_L^{Lo}	s.e.(β_L^{Lo})	Freq	β_L^{Hi}	s.e.(β_L^{Hi})	$\beta_L^{\text{Hi}} - \beta_L^{\text{Lo}}$	t-stat	N_{obs}	R^2
Japan	0.07	0.31	0.07	0.27	0.62	0.15	0.31	1.81	1,418	.07
Euro area	0.07	0.24	0.09	0.31	0.49	0.10	0.25	2.03	1,802	.08
Canada	0.10	0.38	0.12	0.87	0.74	0.23	0.36	1.58	1,150	.07
Non-OECD	0.07	0.17	0.03	0.36	0.34	0.06	0.17	2.44	8,239	.06

Note. Robust standard errors clustered by country × PSL pair (as in Table I).

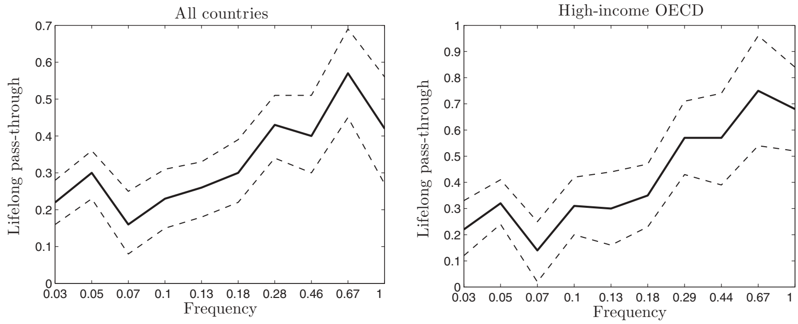

FIGURE II
Lifelong Pass-Through across Frequency Deciles

For each frequency decile we estimate LRPT from the lifelong regression (1). Dashed lines correspond to 10% confidence bands.

where $\tilde{f}_{i,c} \equiv f_{i,c} - \bar{f}_{i,c}$ is the demeaned frequency of the good relative to other goods in the sample. Therefore, coefficient β_L captures the average pass-through in the sample, whereas γ_L estimates the effect of frequency on long-run pass-through. The results from estimating this regression using both OLS and median quantile regression are reported in Table IV. In the case of the OLS estimates, robust standard errors clustered by country $\times$ PSL pair are reported. The lower panel presents the results for goods with at least three or more price changes. As is evident from the table, $\gamma_L > 0$ in all specifications. That is, goods that adjust prices more frequently also have higher LRPT. The reason the slope estimates vary across samples is partly driven by the fact that the relationship is nonlinear, as is evident in Figure II. These results are also robust to including controls for differential pass-through rates across countries.

Between- and Within-Sector Evidence. Does the relation between frequency and LRPT arise across aggregate sectors or is this a within-sector phenomenon? To answer this we first perform a standard *variance decomposition* (see Theorem 3.3 in Greene [2000, p. 81]) for frequency:

$$S_f^T = S_f^B + S_f^W.$$

S_f^T is the total variance of frequency across all goods in the sample. S_f^B is the *between-sector* component of the variance, measured as the variance of frequency across the average goods

TABLE IV
SLOPE COEFFICIENT FOR FREQUENCY–PASS-THROUGH RELATION

	OLS					Median quantile regression					
	β_L	s.e.(β_L)	γ_L	s.e.(γ_L)	t-stat	β_L	s.e.(β_L)	γ_L	s.e.(γ_L)	t-stat	N_{obs}
Panel A: All goods											
All countries											
Manufacturing	0.33	0.03	0.40	0.14	2.79	0.31	0.01	0.43	0.03	14.09	14,227
Differentiated	0.33	0.04	0.70	0.18	3.96	0.32	0.01	0.72	0.05	12.57	7,870
High-income OECD											
Manufacturing	0.42	0.04	0.63	0.15	4.35	0.35	0.02	0.57	0.04	13.27	5,988
Differentiated	0.43	0.05	0.95	0.15	6.17	0.39	0.02	0.84	0.08	10.83	2,982
Panel B: Goods with three or more price changes											
All countries											
Manufacturing	0.37	0.04	0.36	0.17	2.12	0.37	0.02	0.37	0.06	6.43	6,111
Differentiated	0.38	0.06	0.88	0.20	4.35	0.40	0.02	0.92	0.08	10.94	3,031
High-income OECD											
Manufacturing	0.51	0.06	0.60	0.18	3.42	0.45	0.02	0.47	0.08	6.30	2,856
Differentiated	0.52	0.07	0.94	0.19	4.86	0.51	0.04	0.90	0.13	6.83	1,312

Note. The table reports OLS and median quantile regression estimates of coefficients in specification (3): β_L estimates average LRPT for the subsample and γ_L estimates the slope coefficient for the frequency–LRPT relation. Robust standard errors clustered by country × PSL pair are reported for the OLS regressions (as in Table I). t-statistics are reported for the hypothesis $\gamma_L = 0$.

TABLE V
FREQUENCY–LRPT RELATION: WITHIN- VERSUS BETWEEN-SECTOR EVIDENCE

	Freq within	OLS γ_L^W	OLS γ_L^B	OLS Within	Median quantile regression γ_L^W	Median quantile regression γ_L^B	Median quantile regression Within
Two-digit	85%	0.49	0.17	98%	0.40	0.51	78%
		(0.09)	(0.12)		(0.03)	(0.05)	
Four-digit	70%	0.48	0.30	86%	0.40	0.48	68%
		(0.07)	(0.08)		(0.04)	(0.04)	

Note. The second column reports the contribution of the within-sector component to total variation in frequency according to the standard variance decomposition. The estimates γ_L^W and γ_L^B are from the unrestricted version of regression (3), where we allow separate coefficients on average sectoral frequency (γ_L^B) and on the deviation of the good's frequency from the sectoral average (γ_L^W), as described in footnote 14. Robust standard errors in parentheses. Columns (5) and (8) report the contribution of the within-sector component to the relation between frequency and pass-through according to the formula in the text.

from each sector. Finally, S_f^W is the *within-sector* component of variance, measured as the average variance of frequency across goods within sectors.

We perform the analysis at both the two-digit and four-digit sector levels. At the two-digit sector level (88 sectors), the fraction of total variance in frequency (equal to 0.073) explained by variation across two-digit sectors is 15%, whereas the remaining 85% is explained by variation across goods within two-digit sectors. At the four-digit level (693 sectors), the between-sector component accounts for 30% of variation in frequency, whereas the within-sector variation accounts for the remaining 70%. This evidence suggests that variation in frequency is driven largely by variation at highly disaggregated levels.

The second exercise we perform is to estimate the counterpart to equation (3) allowing for separate within- and between-sector effects of frequency on pass-through.[14] The results are reported in Table V. The within-sector estimates (γ_L^W) are positive and statistically significant in all specifications. The between-sector estimates (γ_L^B) are positive, but the level of significance varies across specifications.

14. Specifically, instead of $\gamma_L(\tilde{f}_{i,c} \cdot \Delta\text{RER}_L^{i,c})$, we include two terms, $\gamma_L^B(\bar{f}_{j(i),c} \cdot \Delta\text{RER}_L^{i,c})$ and $\gamma_L^W(f_{i,c} - \bar{f}_{j(i),c}) \cdot \Delta\text{RER}_L^{i,c}$, where j indicates the sector that contains good i and $\bar{f}_{j(i),c}$ is the average frequency in sector j. Note that our earlier specification (3) is the restricted version of this regression under the assumption that $\gamma_L^W = \gamma_L^B$. Furthermore, the unconstrained specification allows a formal decomposition of the effect of frequency on pass-through into within- and between-sector contribution as discussed in the text.

We can now quantify the contribution of the within-sector component to the relation between LRPT and frequency using the formula

$$\frac{(\gamma_L^W)^2 S_f^W}{(\gamma_L^W)^2 S_f^W + (\gamma_L^B)^2 S_f^B},$$

where the denominator is the total variance in LRPT explained by variation in frequency. Using the OLS (quantile regression) estimates, the within-sector contribution is 98% (78%) at the two-digit level and 86% (62%) at the four-digit level.

Therefore the relation between frequency and LRPT is largely a within-sector phenomenon, consistent with the evidence that most variation in frequency arises within sectors and not across aggregated sectors.[15]

II.C. Aggregate Regressions

The next set of results relates to the estimates from the aggregate pass-through regressions defined in (2). We again divide goods into two bins based on the frequency of price adjustment and estimate the aggregate pass-through regressions separately for each of the bins. We again report the results only for the real specification, because the nominal specification delivers very similar results. The results are plotted in Figure III. The solid line plots the cumulative pass-through coefficient, $\sum_j^n \beta_j$, as the number of monthly lags increases from 1 to 24. The dashed lines represent the 10% robust standard-error bands. The left-column figures are for the all-country sample and the right-column figures are for the high-income OECD subsample; the top figures correspond to all manufactured goods, whereas the bottom figures correspond to the differentiated good subsample.

Although pass-through at 24 months is lower than lifelong estimates, it is still the case that high-frequency adjusters have a pass-through that is at least twice as high as for low-frequency adjusters, and this difference is typically significant. The results from this approach are therefore very much in line with the results

15. This is not to say that there is no variation in frequency and pass-through across sectors. More homogeneous sectors, such as "Animal and Vegetable Products," "Wood and Articles of Wood," and "Base Metals and Articles of Base Metals," on average have higher frequency and higher long-run pass-through. More differentiated sectors have lower average frequency (with little variation across sectors) and lower long-run pass-through. However, the amount of variation across sectors is insufficient to establish a strong empirical relationship.

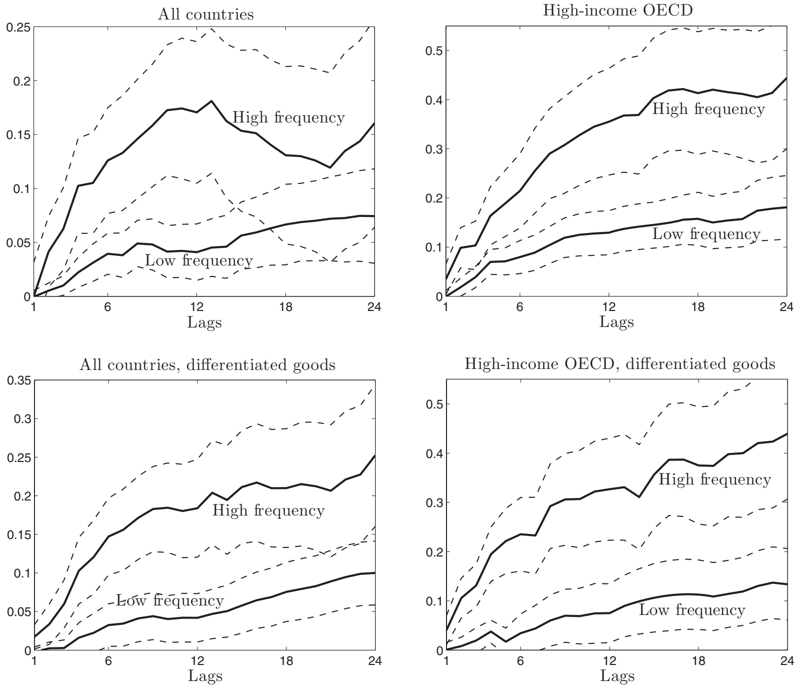

FIGURE III
Aggregate Pass-Through

Solid lines plot the cumulative pass-through coefficients for the two frequency bins estimated from aggregate regression (2) with different number of lags. The dashed lines correspond to 10% confidence bands.

from the lifelong specification. Similar aggregate pass-through results hold for the subsample of goods with at least three price adjustments and for specific countries and regions (as in Table III); however, estimates in these smaller subsamples become a lot noisier, especially for the non-OECD countries. We do not report these results here, for brevity, but the reader can refer to the working paper version (Gopinath and Itskhoki 2008).

II.D. Additional Facts

In closing the empirical section, we discuss a number of additional relevant findings in the data.

Product Replacement. For the previous analysis we estimate LRPT for a good using price changes during the life of the good. Because goods get replaced frequently, one concern could be that

TABLE VI
SUBSTITUTIONS

Decile	Freq	Life 1	Life 2	Eff freq 1	Eff freq 2
1	0.03	59	42	0.05	0.05
2	0.05	50	34	0.07	0.08
3	0.07	52	32	0.09	0.10
4	0.10	55	36	0.12	0.13
5	0.13	52	33	0.15	0.16
6	0.18	49	32	0.20	0.21
7	0.29	50	26	0.30	0.31
8	0.44	51	34	0.46	0.46
9	0.67	52	33	0.67	0.68
10	1.00	43	30	1.00	1.00

Note. Effective frequency (Eff freq) corrects the measure of frequency during the life of the good (Freq) for the probability of the good's discontinuation/replacement according to [Freq+(1-Freq)/Life] for the two measures of the life of the good in the sample (Life).

goods that adjust infrequently have shorter lives and get replaced often, and because we do not observe price adjustments associated with substitutions, we might underestimate the true pass-through for these goods.[16] To address this concern, we report in Table VI the median life of goods within each frequency bin for the high-income OECD sample. Very similar results are obtained for other subsamples.

For each of the ten frequency bins we estimate two measures of the *life* of the good. For the first measure we calculate for each good the difference between the discontinuation date and initiation date to capture the life of the good in the sample. "Life 1" then reports the median of this measure for each bin. Goods get discontinued for several reasons. Most goods get replaced during routine sampling and some get discontinued due to lack of reporting. As a second measure, we examine only those goods that were replaced either because the firm reported that the particular good was not being traded any more and had/had not been replaced with another good in the same category, or because the firm reported that it was going out of business.[17] This captures most closely the kind of churning one might be interested in and does not suffer from

16. Note that substitutions pose a bigger concern only if there is reason to believe that pass-through associated with substitutions is different from that associated with regular price changes. Otherwise, our measures that condition on multiple rounds of price adjustment capture LRPT.

17. Specifically this refers to the following discontinuation reasons reported in the BLS data: "Out of Business," "Out of Scope, Not Replaced," and "Out of Scope, Replaced."

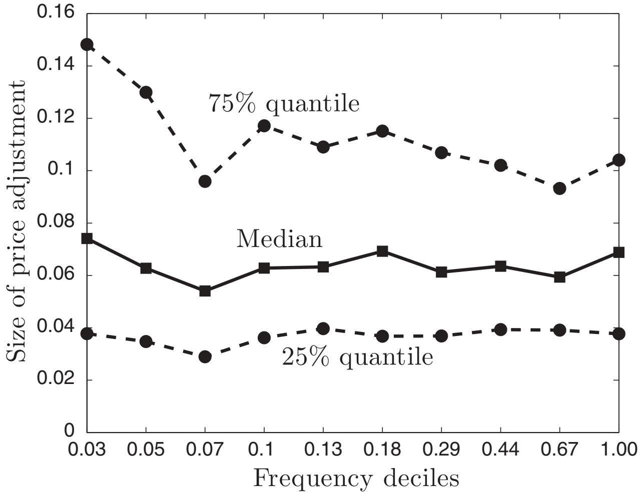

FIGURE IV
Frequency and Absolute Size of Price Adjustment

right censoring in measuring the life of the good. "Life 2" is then the median of this measure within each bin. As can be seen, if anything, there is a negative relation between frequency and life: that is, goods that adjust infrequently have longer lives in the sample.

In the last two columns we report [Freq + (1 − Freq)/Life] for the two measures of life. This corrects the frequency of price adjustment to include the probability of discontinuation. As is evident, the frequency ranking does not change when we include the probability of being discontinued using either measure. As mentioned earlier, there are several goods that do not change price during their life and get discontinued. We cannot estimate pass-through for these goods. The median life of these goods is twenty months (using the second measure), which implies a frequency of 0.05. What this section highlights is that even allowing for the probability of substitution, the benchmark frequency ranking is preserved.

Size of Price Adjustment. Figure IV plots the median absolute size of price adjustment across the ten frequency bins for the high-income OECD subsample. Median size is effectively the same across frequency bins, ranging between 6% and 7%.[18] This feature is not surprising given that size, unlike pass-through, is not scale-independent and, for example, depends on the average size of the shocks. This illustrates the difficulty of using measures such as size in the analysis of frequency. We discuss this issue later in the paper.

Long-Run versus Medium-Run Pass-Through. In this paper we estimate the long-run pass-through for a good. A separate measure of pass-through is pass-through conditional on only the first price adjustment to an exchange rate shock. In Gopinath, Itskhoki, and Rigobon (2009), we refer to this as medium-run pass-through (MRPT). As is well known, estimating pass-through conditional on only the first price adjustment may not be sufficient to capture LRPT due to staggered price adjustment by competitors, among other reasons. These effects can be especially pronounced for goods that adjust prices more frequently than their average competitors.

In Gopinath and Rigobon (2008), we sort goods into different frequency bins and estimate MRPT within each bin, which is distinct from estimating LRPT. Second, we use both dollar (90% of the sample) and non–dollar (10% of the sample) priced goods. We document that goods that adjust less frequently have higher MRPT than goods that adjust more frequently. This result, relating to MRPT, was driven by the fact that goods that adjust less frequently were goods that were priced in a nondollar currency. If the nondollar goods are excluded from the sample, there is no well-defined pattern in the relation between MRPT and frequency. This is further demonstrated in Figure V, where we plot both LRPT and MRPT against frequency. Unlike LRPT, there is no relation between MRPT and frequency for dollar-priced goods. We also estimate equation (3) for the case where the left hand–side variable conditions on first price adjustment instead of lifelong price change. The coefficient that estimates the effect of frequency on MRPT is -0.04 with a t-statistic of -0.9, confirming the result in Figure V that MRPT is unrelated to frequency in the dollar sample.

18. We also plot in this figure the 25% and 75% quantiles of the size of price adjustment distribution. Just as for median size, we find no pattern for the twenty-fifth quantile, which is roughly stable at 4% across the ten frequency bins. On the opposite, the seventy-fifth quantile decreases from 15% to 10% as we move from low-frequency to high-frequency bins.

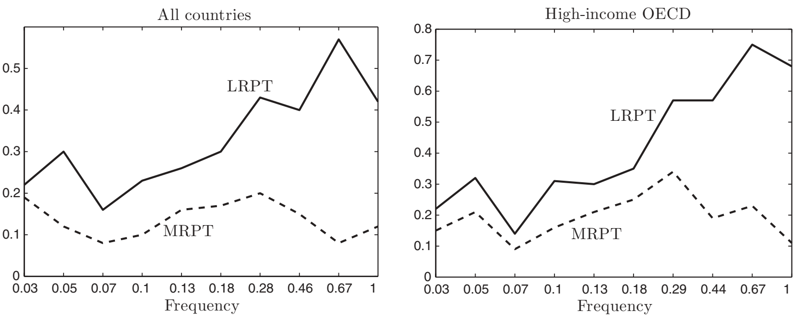

FIGURE V
Long-Run versus Medium-Run Pass-Through

LRPT is as in Figure II. MRPT is estimated for each frequency decile from a counterpart to regression (1), which conditions on the first price change instead of the lifelong price change.

In Gopinath, Itskhoki, and Rigobon (2009) we present further systematic evidence on the relation between the currency in which goods are priced and MRPT. We argue theoretically that one should expect to find that goods priced in nondollars indeed have a higher MRPT. In addition, they will have longer price durations, conditioning on the same LRPT.

To clarify again, the measure of pass-through we estimate in this paper is a different concept from the main pass-through measures reported in Gopinath and Rigobon (2008) and Gopinath, Itskhoki, and Rigobon (2009). The evidence we find about the relation between frequency and pass-through relates to the long-run pass-through for dollar-priced goods. As we argue below theoretically, the relevant concept relating frequency to the structural features of the profit function is indeed long-run pass-through, and that is why it is the focus of the current paper.

III. A STATIC MODEL OF FREQUENCY AND PASS-THROUGH

In this section we investigate theoretically the relation between LRPT and frequency. Before constructing in the next section a full-fledged dynamic model of staggered price adjustment, we use a simple static model to illustrate the theoretical relationship between frequency of price adjustment and flexible price pass-through of cost shocks. The latter is the equivalent of LRPT in a dynamic environment and we will refer to it simply as pass-through. We show that, all else equal, higher pass-through is associated with higher frequency of price adjustment. This follows because the primitives that reduce pass-through also reduce the curvature of the profit function in the space of the *cost shock*, making the firm less willing to adjust its price.

We consider the problem of a single monopolistic firm that sets its price before observing the cost shock.[19] Upon observing the cost shock, the firm has an option to pay a menu cost to reset its price. The frequency of adjustment is then the probability with which the firm decides to reset its price upon observing the cost shock. We introduce two standard sources of incomplete pass-through into the model: variable mark-ups and imported inputs.

III.A. Demand and Costs

Consider a single price-setting firm that faces a residual demand schedule $Q = \varphi(P|\sigma, \varepsilon)$, where P is its price and $\sigma > 1$ and $\varepsilon \geq 0$ are two demand parameters.[20] We denote the price elasticity of demand by

$$\tilde{\sigma} \equiv \tilde{\sigma}(P|\sigma, \varepsilon) = -\frac{\partial \ln \varphi(P|\sigma, \varepsilon)}{\partial \ln P}$$

and the *superelasticity* of demand (in the terminology of Klenow and Willis [2006]), or the elasticity of elasticity, as

$$\tilde{\varepsilon} \equiv \tilde{\varepsilon}(P|\sigma, \varepsilon) = \frac{\partial \ln \tilde{\sigma}(P|\sigma, \varepsilon)}{\partial \ln P}.$$

Here $\tilde{\sigma}$ is the *effective* elasticity of demand for the firm, which takes into account both direct and indirect effects from price adjustment.[21] Note that we introduce variable mark-ups into the model by means of variable elasticity of demand. This should be viewed as a reduced-form specification for variable mark-ups that would arise in a richer model due to strategic interactions between firms.[22]

19. Our modeling approach in this section is closest to that of Ball and Mankiw (1994), whereas the motivation of the exercise is closest to that in Romer (1989). References to other related papers can be found in the Introduction.

20. Because this is a partial equilibrium model of the firm, we do not explicitly list the prices of competitors or the sectoral price index in the demand functions. An alternative interpretation is that P stands for the relative price of the firm.

21. For example, in a model with large firms, price adjustment by the firm will also affect the sectoral price index, which may in turn indirectly affect the elasticity of demand.

22. The Atkeson and Burstein (2008) model is an example: in this model the effective elasticity of residual demand for each monopolistic competitor depends

We impose the following normalization on the demand parameters: When the price of the firm is unity ($P = 1$), elasticity and superelasticity of demand are given by σ and ε, respectively (that is, $\tilde{\sigma}(1|\sigma, \varepsilon) = \sigma$ and $\tilde{\varepsilon}(1|\sigma, \varepsilon) = \varepsilon$). Moreover, $\tilde{\sigma}(\cdot)$ is increasing in σ and $\tilde{\varepsilon}(\cdot)$ is increasing in ε for any P. Additionally, we normalize the level of demand $\varphi(1|\sigma, \varepsilon)$ to equal 1 independent of the demand parameters σ and ε (see Section IV for an example of such a demand schedule). These normalizations prove to be useful later when we approximate the solution around $P = 1$.

The firm operates a production technology characterized by a constant marginal cost,

$$MC \equiv MC(a, e; \phi) = (1 - a)(1 + \phi e)c,$$

where a is an idiosyncratic productivity shock and e is a real exchange rate shock. We will refer to the pair (a, e) as the cost shock to the firm. We further assume that a and e are independently distributed with $\mathbb{E}a = \mathbb{E}e = 0$ and standard deviations denoted by σ_a and σ_e respectively. Parameter $\phi \in [0, 1]$ determines the sensitivity of the marginal cost to the exchange rate shock and can be less than 1 due to the presence of imported intermediate inputs in the cost function of the firm (see Section IV).

We normalize the marginal cost so that $MC = c = (\sigma - 1)/\sigma$ when there is no cost shock ($a = e = 0$). Under this normalization, the optimal flexible price of the firm when $a = e = 0$ is equal to 1, because the marginal cost is equal to the inverse of the markup. This normalization is therefore consistent with a symmetric general equilibrium in which all firms' relative prices are set to 1 (for a discussion see Rotemberg and Woodford [1999]).

Finally, the profit function of the firm is given by

$$\Pi(P|a, e) = \varphi(P)\big(P - MC(a, e)\big), \tag{4}$$

where we suppress the explicit dependence on parameters σ, ε, and ϕ. We denote the *desired price* of the firm by $P(a, e) \equiv \arg\max_P \Pi(P|a, e)$ and the maximal profit by $\Pi(a, e) \equiv \Pi(P(a, e)|a, e)$.

on the primitive constant elasticity of demand, the market share of the firm, and the details of competition between firms.

III.B. Price Setting

For a given cost shock (a, e), the desired flexible price maximizes profits (4), so that[23]

$$P_1 \equiv P(a,e) = \frac{\tilde{\sigma}(P_1)}{\tilde{\sigma}(P_1) - 1}(1-a)(1+\phi e)c, \tag{5}$$

and the corresponding maximized profit is $\Pi(a, e)$. Denote by $\bar{P}_0$ the price that the firm sets prior to observing the cost shocks (a, e). If the firm chooses not to adjust its price, it will earn $\Pi(\bar{P}_0|a, e)$. The firm will decide to reset the price if the profit loss from not adjusting exceeds the menu cost, κ:

$$L(a,e) \equiv \Pi(a,e) - \Pi(\bar{P}_0|a,e) > \kappa.$$

Define a set of shocks upon observing which the firm decides not to adjust its price by

$$\Delta \equiv \big\{(a,e) : L(a,e) \leq \kappa\big\}.$$

Note that the profit-loss function $L(a, e)$ and, hence, Δ depend on the preset price $\bar{P}_0$.

The firm sets its initial price, $\bar{P}_0$, to maximize expected profits where the expectation is taken conditional on the realization of the cost shocks (a, e) upon observing which the firm does not reset its price,[24]

$$\bar{P}_0 = \arg\max_P \int_{(a,e)\in\Delta} \Pi(P|a,e)\, dF(a,e),$$

where $F(\cdot)$ denotes the joint cumulative distribution function of the cost shock (a, e). Using the linearity of the profit function in costs, we can rewrite the *ex ante* problem of the firm as

$$\bar{P}_0 = \arg\max_P \{\varphi(P)(P - \mathbb{E}_\Delta\{(1-a)(1+\phi e)\}\cdot c)\}, \tag{6}$$

where $\mathbb{E}_\Delta\{\cdot\}$ denotes the expectation conditional on $(a, e) \in \Delta$. We prove the following:

LEMMA 1. $\bar{P}_0 \approx P(0, 0) = 1$, up to second-order terms.

23. The sufficient condition for maximization is $\tilde{\sigma}(P_1) > 1$ provided that $\tilde{\varepsilon}(P_1) \geq 0$. We assume that these inequalities are satisfied for all P.
24. We implicitly assume, as is standard in a partial equilibrium approach, that the stochastic discount factor is constant for the firm.

Proof. See the working paper version, Gopinath and Itskhoki (2008). ■

Intuitively, a firm sets its *ex ante* price as if it anticipates the cost shock to be zero ($a = e = 0$), that is, equal to its unconditional expected value. This will be an approximately correct expectation of the shocks (a, e) over the region Δ, if this region is nearly symmetric around zero and the cost shocks have a symmetric distribution, as we assume. The optimality condition (5) implies that, given our normalization of the marginal cost and elasticity of demand, $P(0, 0) = 1$.

III.C. Pass-Through

Using Lemma 1 we can prove (see the Appendix)

PROPOSITION 1. i. The following first-order approximation holds:

$$\text{(7)} \qquad \frac{P(a,e) - \bar{P}_0}{\bar{P}_0} \approx \Psi \cdot (-a + \phi e), \quad \text{where} \quad \Psi \equiv \frac{1}{1 + \frac{\varepsilon}{\sigma - 1}}.$$

ii. Exchange rate pass-through equals

$$\text{(8)} \qquad \Psi_e = \phi\Psi = \frac{\phi}{1 + \frac{\varepsilon}{\sigma - 1}}.$$

Lemma 1 allows us to replace $\bar{P}_0$ with $P(0, 0) = 1$. Thus, a and ϕe constitute proportional shocks to the marginal cost, and the desired price of the firm responds to them with elasticity Ψ. This pass-through elasticity can be smaller than one because mark-ups adjust to limit the response of the price to the shock. The *mark-up elasticity* is given by

$$\frac{\partial \tilde{\mu}(P)}{\partial \ln P}\Big|_{P=1} = -\frac{\tilde{\varepsilon}(P)}{\tilde{\sigma}(P) - 1}\Big|_{P=1} = -\frac{\varepsilon}{\sigma - 1},$$

where $\tilde{\mu}(P) \equiv \ln[\tilde{\sigma}(P)/(\tilde{\sigma}(P) - 1)]$ is the log mark-up. A higher price increases the elasticity of demand, which, in turn, leads to a lower optimal mark-up.

Mark-up elasticity depends on both the superelasticity and elasticity of demand: it is increasing in the superelasticity of demand ε and decreasing in the elasticity of demand σ provided that $\varepsilon > 0$. Exchange rate pass-through, Ψ_e, is the elasticity of the desired price of the firm with respect to the exchange rate shock.

It is increasing in cost sensitivity to the exchange rate, ϕ, and decreasing in the mark-up elasticity, $\varepsilon/(\sigma-1)$.[25]

III.D. Frequency

In this static framework, we interpret the probability of resetting price in response to a cost shock (a, e) as the frequency of price adjustment. Formally, frequency is defined as

$$\Phi \equiv 1 - \Pr\{(a, e) \in \Delta\} = \Pr\{L(a, e) > \kappa\}, \tag{9}$$

where the probability is taken over the distribution of the cost shock (a, e).

To characterize the region of nonadjustment, Δ, we take a second-order approximation to the profit-loss function. In the Appendix we prove

LEMMA 2. The following second-order approximation holds:

$$L(a, e) \equiv \Pi(a, e) - \Pi(\bar{P}_0|a, e) \approx \frac{1}{2}\frac{\sigma-1}{\Psi}\left(\frac{P(a, e)-\bar{P}_0}{\bar{P}_0}\right)^2,$$

where Ψ is again as defined in (7).

Note that Lemma 2 implies that the curvature of the profit function with respect to prices is proportional to

$$\frac{\sigma-1}{\Psi} = (\sigma-1)\left[1+\frac{\varepsilon}{\sigma-1}\right],$$

and increases in both σ and ε. That is, higher elasticity of demand and higher mark-up elasticity increase the curvature of the profit function. Holding pass-through (i.e., the response of desired price to shocks) constant, this should lead to more frequent price adjustment. However, greater mark-up elasticity also limits desired pass-through, which, as we show below, more than offsets the first effect.

This is seen when we combine the results of Proposition 1 and Lemma 2 and arrive at the final approximation to the profit-loss

25. In the working paper version (Gopinath and Itskhoki 2008) we also allowed for variable marginal costs as an additional channel of incomplete pass-through. In this case, the effect of σ on Ψ can be nonmonotonic. Although greater elasticity of demand limits the variable mark-up channel, it amplifies the variable marginal cost channel.

function:

$$L(a,e) \approx \frac{1}{2}(\sigma - 1)\Psi(-a + \phi e)^2, \tag{10}$$

which again holds up to third-order terms. This expression makes it clear that forces that reduce pass-through (i.e., decrease Ψ and ϕ) also reduce the profit loss from not adjusting prices and, as a result, lead to lower frequency of price adjustment. Note that in the space of the cost shock, the curvature of the profit-loss function decreases as pass-through elasticity Ψ decreases.

Alternatively, primitives that lower Ψ reduce the region of nonadjustment in the price space (Lemma 2). However, a lower Ψ implies that the desired price adjusts by less and therefore is more likely to remain within the bounds of nonadjustment, thus reducing the frequency of price adjustment. This second effect always dominates (equation (10)).

Combining (9) and (10), we have

$$\Phi \approx \Pr\left\{|X| > \sqrt{\frac{2\kappa}{(\sigma - 1)\Psi\Sigma}}\right\}, \tag{11}$$

where $X \equiv \Sigma^{-1/2} \cdot (-a + \phi e)$ is a standardized random variable with zero mean and unit variance and $\Sigma \equiv \sigma_a^2 + \phi^2\sigma_e^2$ is the variance of the cost shock $(-a + \phi e)$. This leads us to

PROPOSITION 2. The frequency of price adjustment decreases with mark-up elasticity and increases with the sensitivity of costs to exchange rate shocks. It also decreases with the menu cost and increases with the elasticity of demand and the size of shocks.

Taken together, the results on pass-through and frequency in Propositions 1 and 2 imply that

PROPOSITION 3. (i) Higher mark-up elasticity as well as lower sensitivity of cost to exchange rate shocks reduces both frequency of price adjustment and pass-through; (ii) higher menu costs and smaller cost shocks decrease frequency, but have no effect on pass-through.

Proposition 3 is the central result of this section. It implies that as long as mark-up elasticity varies across goods, we should observe a positive cross-sectional correlation between frequency and pass-through. Similarly, variation across goods in cost sensitivity to exchange rate, ϕ, can also account for the positive relationship between frequency and pass-through.[26] Furthermore, other sources of variation in frequency do not affect pass-through and hence cannot account for the observed empirical relationship between the two variables.

As for the absolute size of price adjustment, conditional on adjusting price, the effect of mark-up elasticity and the volatility of cost shocks works through two channels. The direct effect of lower mark-up elasticity or more volatile shocks is to increase the change in the desired price, whereas their indirect effect is to increase the frequency of price adjustment. The first effect increases the average size of price adjustment whereas the second reduces it. In Gopinath and Itskhoki (2008) we discuss conditions under which the direct effect dominates, such that lower mark-up elasticity ($\varepsilon/(\sigma-1)$) or larger cost shocks (Σ) are associated with a larger absolute size of price adjustment. On the other hand, size of price adjustment increases with the size of the menu cost (κ) as frequency of price adjustment decreases. Consequently, as long as there is variation across goods in both κ and ε or Σ, one should not expect to see a robust correlation between frequency and size (see further discussion in Section IV.C).

IV. Dynamic Model

We now consider a fully dynamic specification with state-dependent pricing and variable mark-ups and quantitatively solve for the industry equilibrium in the U.S. market. First, we show that cross-sectional *variation in mark-up elasticity* can generate a positive relation between frequency and LRPT in a dynamic setting and can generate significant variation in frequency, equivalent to 37% of the observed variation in the data. Further, a menu cost model that allows for joint cross-sectional variation in mark-up elasticity and menu costs can quantitatively account for both the positive slope between LRPT and frequency and the close-to-zero slope between size and frequency in the data. Second, we show that the pass-through regressions estimated in Section II recover the true underlying LRPT. Third, we verify that

26. Quantitatively, however, the effect of ϕ on frequency is limited by the ratio of the variances of the exchange rate and idiosyncratic shocks, σ_e^2/σ_a^2, because ϕ affects frequency through $\Sigma = \sigma_a^2(1+\phi^2\sigma_e^2/\sigma_a^2)$. We calibrate this ratio in Section IV and show that the effect of ϕ on frequency is negligible.

the observed correlation between frequency and LRPT cannot be explained by standard sticky price models with only exogenous differences in frequency of price adjustment and no variation in LRPT.

The importance of the variable mark-up channel of incomplete pass-through, as argued for theoretically by Dornbusch (1987) and Krugman (1987), has been documented in the empirical evidence of Knetter (1989), Goldberg and Knetter (1997), Fitzgerald and Haller (2008), and Burstein and Jaimovich (2009) among others.[27]

We model the variable mark-up channel of incomplete pass-through using Kimball (1995) kinked demand. Our setup is most comparable to that in Klenow and Willis (2006), with two distinctions. First, we have exchange rate shocks that are more idiosyncratic than the aggregate monetary shocks typically considered in the closed economy literature. Second, we examine how *variation* in mark-up elasticity across goods affects the frequency of price adjustment.[28]

IV.A. Setup of the Model

In this section we lay out the ingredients of the dynamic model. Specifically, we describe demand, the problem of the firm, and the sectoral equilibrium.

Industry Demand Aggregator. The industry is characterized by a continuum of varieties indexed by j. There is a unit measure of U.S. varieties and a measure $\omega < 1$ of foreign varieties available for domestic consumption. The smaller fraction of foreign varieties

27. Unlike the evidence for import prices, Bils, Klenow, and Malin (2009) find that variable mark-ups play a limited role in consumer/retail price data. These two sets of findings can be potentially reconciled by the evidence in Goldberg and Hellerstein (2007), Burstein and Jaimovich (2009), and Gopinath et al. (2009), who find that variable mark-ups play an important role at the wholesale cost level and a limited role at the level of retail prices. Atkeson and Burstein (2008) also argue for the importance of variable mark-ups in matching empirical features of wholesale traded goods prices.

28. Klenow and Willis (2006) argue that the levels of mark-up elasticity required to generate sufficient aggregate monetary nonneutrality generate price and quantity behavior that is inconsistent with the micro data on retail prices. We differ from this analysis in the following respects. First, we match facts on import prices, which have different characteristics such as the median frequency of price adjustment. Second, we calibrate the mark-up elasticity to match the evidence on the micro-level relationship between frequency and pass-through for wholesale prices, and as discussed in footnote 34, this implies a lower mark-up elasticity for the median good, and the model-generated data are consistent with the micro facts.

captures the fact that not all varieties of the differentiated good are internationally traded in equilibrium.

The technology of transforming the intermediate varieties into the final good is characterized by the Kimball (1995) aggregator,

$$\frac{1}{|\Omega|}\int_{\Omega}\Upsilon\left(\frac{|\Omega|C_j}{C}\right)dj = 1 \tag{12}$$

with $\Upsilon(1) = 1$, $\Upsilon'(\cdot) > 0$, and $\Upsilon''(\cdot) < 0$. C_j is the quantity demanded of the differentiated variety $j \in \Omega$, where Ω is the set of available varieties in the home country with measure $|\Omega| = 1 + \omega$. Individual varieties are aggregated into sectoral final good demand, C, which is implicitly defined by (12).

The associated demand schedules with aggregator (12) are given by

$$C_j = \psi\left(D\frac{P_j}{P}\right)\cdot\frac{C}{|\Omega|}, \quad \text{where} \quad \psi(\cdot) \equiv \Upsilon'^{-1}(\cdot), \tag{13}$$

P_j is the price of variety j, P is the sectoral price index, and $D \equiv \int_{\Omega}\Upsilon'(|\Omega|C_j/C)\frac{C_j}{C}dj$. The sectoral price index satisfies

$$PC = \int_{\Omega} P_j C_j dj \tag{14}$$

because the aggregator in (12) is homothetic.

Firm's Problem. Consider a home firm producing variety j. Everything holds symmetrically for foreign firms and we superscript foreign variables with an asterisk. The firm faces a constant marginal cost:

$$MC_{jt} = \frac{W_t^{1-\phi}(W_t^*)^{\phi}}{A_{jt}}. \tag{15}$$

A_j denotes the idiosyncratic productivity shock that follows an autoregressive process in logs:[29]

$$a_{jt} = \rho_a a_{j,t-1} + \sigma_a u_{jt}, \qquad u_{jt} \sim \text{iid}\,\mathcal{N}(0, 1).$$

29. In what follows, corresponding small letters denote the logs of the respective variables.

W_t and W_t^* denote the prices of domestic and foreign inputs, respectively, and we will interpret them as wage rates. Parameter ϕ measures the share of foreign inputs in the cost of production.[30]

The profit function of a firm from sales of variety j in the domestic market in period t is

$$\Pi_{jt}(P_{jt}) = \left[P_{jt} - \frac{W_t^{1-\phi}(W_t^*)^{\phi}}{A_{jt}} \right] C_{jt},$$

where demand C_{jt} satisfies (13). Firms are price setters and must satisfy demand at the posted price. To change the price, both domestic and foreign firms must pay a menu cost κ_j in local currency (dollars).

Define the state vector of firm j by $\mathbb{S}_{jt} = (P_{j,t-1}, A_{jt}; P_t, W_t, W_t^*)$. It contains the past price of the firm, the current idiosyncratic productivity shock and the aggregate state variables, namely, sectoral price level and domestic and foreign wages. The system of Bellman equations for the firm is given by[31]

$$(16) \qquad \begin{cases} V^N(\mathbb{S}_{jt}) = \Pi_{jt}(P_{j,t-1}) + \mathbb{E}\big\{Q(\mathbb{S}_{j,t+1})V(\mathbb{S}_{j,t+1})\big|\mathbb{S}_{jt}\big\}, \\ V^A(\mathbb{S}_{jt}) \ = \max\limits_{P_{jt}}\{\Pi_{jt}(P_{jt}) + \mathbb{E}\{Q(\mathbb{S}_{j,t+1})V(\mathbb{S}_{j,t+1})|\mathbb{S}_{jt}\}\}, \\ V(\mathbb{S}_{jt}) \quad = \max\{V^N(\mathbb{S}_{jt}), V^A(\mathbb{S}_{jt}) - \kappa_j\}, \end{cases}$$

where V^N is the value function if the firm does not adjust its price in the current period, V^A is the value of the firm after it adjusts its price, and V is the value of the firm making the optimal price adjustment decision in the current period. Q represents the stochastic discount factor.

Conditional on price adjustment, the optimal resetting price is given by

$$\bar{P}(\mathbb{S}_{jt}) = \arg\max_{P_{jt}}\{\Pi_{jt}(P_{jt}) + \mathbb{E}\{Q(\mathbb{S}_{j,t+1})V(\mathbb{S}_{j,t+1})|\mathbb{S}_{jt}\}\}.$$

Therefore, the policy function of the firm is

$$(17) \qquad P(\mathbb{S}_{jt}) = \begin{cases} P_{j,t-1}, & \text{if } V^N(\mathbb{S}_{jt}) > V^A(\mathbb{S}_{jt}) - \kappa_j, \\ \bar{P}(\mathbb{S}_{jt}), & \text{otherwise.} \end{cases}$$

30. The marginal cost in (15) can be derived from a constant returns to scale production function that combines domestic and foreign inputs.

31. In general, one should condition expectations in the Bellman equation on the whole history $(\mathbb{S}_{jt}, \mathbb{S}_{j,t-1}, \ldots)$, but in our simulation procedure we assume that $\mathbb{S}_{jt}$ is a sufficient statistic, following Krusell and Smith (1998).

In the first case the firm leaves its price unchanged and pays no menu cost, whereas in the second case it adjusts its price optimally and pays the menu cost.

Sectoral Equilibrium. Sectoral equilibrium is characterized by a path of the sectoral price level, $\{P_t\}$, consistent with the optimal pricing policies of firms given the exogenous paths of their idiosyncratic productivity shocks and wage rates in the two countries $\{W_t, W_t^*\}$. We define $E_t \equiv W_t^*/W_t$ to be the wage-based (real) exchange rate.

We assume that all prices are set in the domestic unit of account, consistent with the evidence of dollar (local currency) pricing documented in the data. We further assume that the value of the domestic unit of account is stable relative to movements in the exchange rate and the domestic real wage is also stable. These assumptions that domestic price and real wage inflation are negligible relative to real exchange rate fluctuations are a good approximation for the United States. From the modeling perspective this amounts to setting $W_t \equiv 1$ and assuming that all shocks to the (real) exchange rate arise from movements in W_t^*.

The simulation procedure of the model is discussed in detail in the Appendix, whereas below we discuss the calibration of the model and simulation results.

IV.B. Calibration

We adopt the Klenow and Willis (2006) specification of the Kimball aggregator (12) that results in

$$\psi(x_j) = \left[1 - \varepsilon \ln\left(\frac{\sigma x_j}{\sigma - 1}\right)\right]^{\sigma/\varepsilon}, \quad \text{where} \quad x_j \equiv D\frac{P_j}{P}. \tag{18}$$

This demand specification is conveniently governed by two parameters, $\sigma > 1$ and $\varepsilon > 0$, and the elasticity and superelasticity are given by

$$\tilde{\sigma}(x_j) = \frac{\sigma}{1 - \varepsilon \ln\left(\frac{\sigma x_j}{\sigma - 1}\right)} \quad \text{and} \quad \tilde{\varepsilon}(x_j) = \frac{\varepsilon}{1 - \varepsilon \ln\left(\frac{\sigma x_j}{\sigma - 1}\right)}.$$

Note that this demand function satisfies all normalizations assumed in Section III. When ε goes to 0 it results in CES demand with elasticity σ.

The calibrated values for the parameters $\{\beta, \kappa, \sigma_a, \rho_a, \sigma_e, \rho_e, \omega, \phi, \varepsilon, \sigma\}$ are reported in Table VII. The period of the model

TABLE VII
PARAMETER VALUES

Parameter	Symbol	Value	Source
Discount factor	β	$0.96^{1/12}$	Annualized interest rate of 4%
Fraction of imports	$\omega/(1+\omega)$	16.7%	BEA input–output tables and U.S. import data
Cost sensitivity to ER shock			OECD input–output tables
Foreign firms	ϕ^*	0.75	
U.S. firms	ϕ	0	
Menu cost	κ	2.5%	Price duration of 5 months when $\varepsilon = 4$
Demand elasticity	σ	5	Broda and Weinstein (2006)
Exchange rate process, e_t			
Std. dev. of ER shock	σ_e	2.5%	U.S.–Euro bilateral RER
Persistence of ER	ρ_e	0.985	Rogoff (1996)
Idiosyncratic productivity process, a_t			
St. dev. of shock to a_t	σ_a	8.5%	Absolute size of price adjustment of 7%
Persistence of a_t	ρ_a	0.95	Autocorrelation of new prices of 0.77

corresponds to one month and, as is standard in the literature, we set the discount rate to equal 4% on an annualized basis ($\beta = 0.96^{1/12}$).

To calibrate the share of imports, $\omega/(1+\omega)$, we use measures of U.S. domestic output in manufacturing from the Bureau of Economic Analysis input output tables and subtract U.S. exports in manufacturing. We calculate U.S. imports in manufacturing using U.S. trade data available from the Center for International Data at UC Davis web site. The four-year average import share for the period 1998–2001 is close to 17%, implying an $\omega = 0.2$.

Calibrating the cost sensitivity to the exchange rate shock, ϕ and ϕ^*, requires detailed information on the fraction of imports used as inputs in production by destination of output and the currency in which these costs are denominated. Such information is typically unavailable. For our purposes we use the OECD input–output tables to calculate the ratio of imports to industrial output and find that the share for manufacturing varies between 8% and 27% across high-income OECD countries. For our benchmark calibration we use a value of $1 - \phi^* = 0.25$ for foreign firms and $\phi = 0$ for domestic firms, because almost all imports into the

United States are priced in dollars. This implies that for an average firm in the industry the sensitivity of the marginal cost to the exchange rate is $\bar{\phi} = \phi^* \cdot \omega/(1+\omega) = 12.5\%$.

The (log of) the real exchange rate, $e_t \equiv \ln(W_t^*/W_t)$, is set to follow a very persistent process with an autocorrelation of around 0.985, and the monthly innovation to the real exchange rate is calibrated to equal 2.5%. These parameter values are consistent with the empirical evidence for developed countries. For instance, for countries in the euro zone, the standard deviation of the change in the bilateral monthly real exchange rate ranges between 2.6% and 2.8%. The persistence parameter is in the midrange of estimates reported in Rogoff (1996).

We set the steady state elasticity of demand $\sigma = 5$, which implies a mark-up of 25%. This value is in the middle of the range for mean elasticity estimated by Broda and Weinstein (2006) using U.S. import data for the period 1990–2001. They estimate the mean elasticity for SITC-5 to be 6.6 and for SITC-3 to be 4.0.

We simulate the model for different values of the superelasticity of demand, ε. The range of values is chosen to match the range of LRPT for the high-income OECD sample of 10% to 75%. Note that $\phi = 0.75$ bounds the long-run pass-through from above. The specific values used are $\varepsilon \in \{0, 2, 4, 6, 10, 20, 40\}$. Our baseline good that matches the middle of the LRPT range has $\varepsilon = 4$.[32] Given the value $\sigma = 5$, this implies that the range of mark-up elasticity is between 0 and 10, with a baseline value of 1.

The parameters κ, σ_a, ρ_a are jointly calibrated to match moments of the data on the median duration of price adjustment, the median size of price adjustment, and the autocorrelation of new prices in the data. This is done holding other parameters constant and with $\varepsilon = 4$, as for the baseline good that has a price duration of five months in the data. The implied menu cost, κ, in the baseline calibration is equal to 2.5% of the revenues conditional on adjustment. We set the standard deviation of the innovation in productivity to 8.5% and the persistence of the idiosyncratic shock to 0.95. These parameter values allow us to match the median absolute size of price change of 7% conditional on adjustment and the autocorrelation of new prices in the data. More precisely, we estimate a pooled regression in the data where we regress the

32. See Dossche, Heylen, and Van den Poel (2006) for a discussion of calibrations of ε in the literature and for empirical evidence on the importance of nonzero ε.

new price of each good on its lagged new price, allowing for a fixed effect for each good. The autocorrelation coefficient is estimated to be 0.77.[33] For the model to match this, we need a high persistence rate for the idiosyncratic shock of at least 0.95.[34] Note that the data moments imply that the ratio of variance of the innovation to the exchange rate shock relative to the idiosyncratic shock is low, $\sigma_e^2/\sigma_a^2 = (2.5\%/8.5\%)^2 < 0.1$.

IV.C. Quantitative Results

The first set of simulation results is about the relation between frequency and LRPT in the model-simulated data. We simulate the dynamic stationary equilibrium of the model for each value of the superelasticity of demand and compute the frequency of price adjustment and LRPT for all firms in the industry and then separately for domestic and foreign firms. Figure VI plots the resulting relationship between frequency and LRPT for these three groups of firms. The LRPT estimates are computed using the lifelong regression (1). An exchange rate shock has two effects: a direct effect that follows from the firm's costs changing and an indirect effect that follows from the change in the sectoral price index, as other firms respond to the cost shock. The magnitude of the second effect depends on the fraction of firms that are affected by the exchange rate shock and consequently, the extent of pass-through depends also on how widespread the shock is. In our calibration this is determined by $\bar{\phi}$.

In Figure VI the line marked "Foreign" captures the strong positive relation between LRPT and frequency in the model-simulated import prices into the United States. The variation in ε that matched the empirical range in LRPT generates a frequency range of approximately 0.10 to 0.35, equivalent to durations of three to ten months. On the other hand, the relation between frequency and pass-through is effectively absent for domestic firms, as well as for the sample of all firms in the industry: as frequency varies between 0.1 and 0.35, the LRPT estimate for domestic firms

33. We also estimate the regression with a fixed effect for every two-digit sector $\times$ date pair to control for sectoral trends, in addition to the fixed effect for each good. The autocorrelation coefficient in this case is 0.71.

34. Note that in our calibration we need to assume neither very large menu costs, nor very volatile idiosyncratic shocks, as opposed to Klenow and Willis (2006). There are a few differences between our calibration and that of Klenow and Willis (2006). First, we assume a smaller mark-up elasticity: Our baseline good has a superelasticity of 4, as opposed to 10 in their calibration. Second, they assume a much less persistent idiosyncratic shock process and match the standard deviation of relative prices rather than the average size of price adjustment.

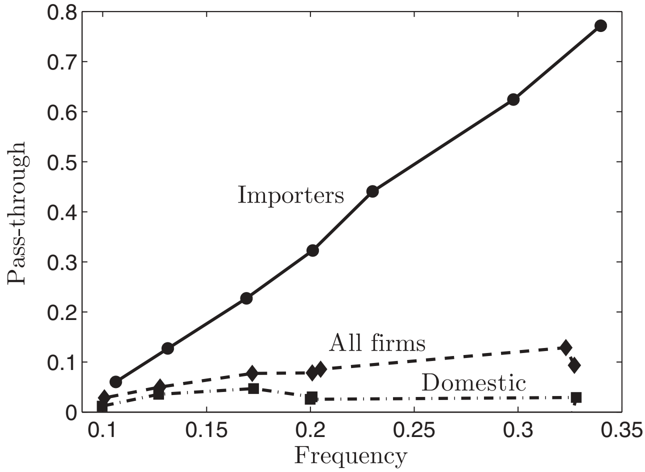

FIGURE VI
Frequency and LRPT in the Model (Variation in ε)

fluctuates between 0% and 5%, whereas for the full sample of firms it lies between 5% and 12%. For domestic firms the nonzero LRPT is because of the indirect effect working through the sectoral price index. The overall low LRPT estimates for the industry are consistent with empirical estimates of low pass-through into consumer prices. Goldberg and Campa (2009) estimate exchange rate pass-through into import prices and consumer prices for a large sample of developed countries and document that pass-through into consumer prices is far lower than pass-through into import prices across all countries. For the case of the United States, for the period 1975–2003, they estimate LRPT into import price to be 42% and into consumer prices to be 1%. This supports our emphasis on at-the-dock prices and international data as a meaningful environment for our study.

A second set of results relates to the performance of the two LRPT estimators employed in the empirical section—the lifelong regression (1) and the aggregate regression (2)—when applied to the simulated panel of firm prices. Figure VII plots the relationship between frequency and three different measures of long-run pass-through for the exercise described above. The first measure of long-run pass-through ("Aggregate") is the 24-month cumulative pass-through coefficient from the aggregate pass-through regression. The second measure ("Lifelong 1") corresponds to the

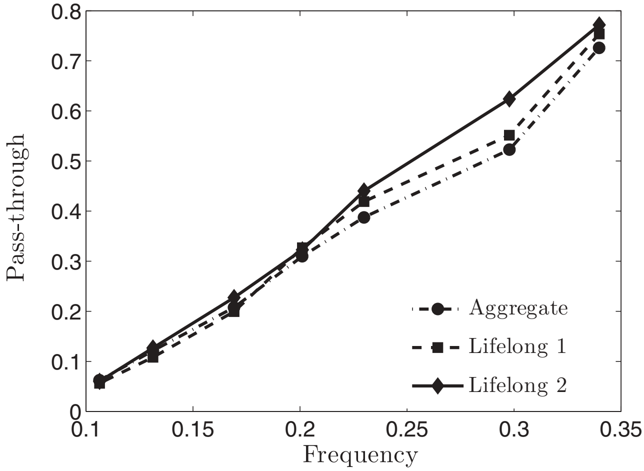

FIGURE VII
Measures of LRPT

lifelong micro-level regression in which we control for firm idiosyncratic productivity. This ensures that the long-run pass-through estimates do not compound the selection effect present in menu cost models. This type of regression is, however, infeasible to run empirically because firm-level marginal costs are not observed. The third measure ("Lifelong 2") corresponds to the same lifelong micro-level regression, but without controlling for firm idiosyncratic productivity. This estimate is the counterpart to the empirical lifelong estimates we presented in Section II. We observe from the figure that all three measures of LRPT produce the same qualitative patterns and very similar quantitative results. In addition, all the estimates are close to the theoretical long-run (flexible-price) pass-through.[35] We conclude that within our calibration both estimators produce accurate measures of long-run pass-through. Specifically, 24 months is enough for the aggregate regression to capture the long-run response of prices, and lifelong regressions do not suffer from significant selection bias.

In a third set of simulation results, we argue that variation in ϕ or κ alone cannot quantitatively explain the findings in the

35. One can show that the theoretical flexible price pass-through is approximated by $\bar{\phi} + \Psi(\phi - \bar{\phi})$, where $\bar{\phi}$ is the average sectoral sensitivity of the firms marginal cost to exchange rate and Ψ is the pass-through elasticity as defined in Section III. Note the close relation between this expression and the one in equation (8).

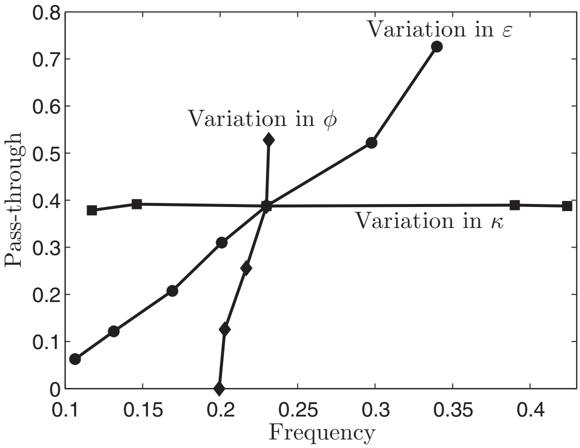

FIGURE VIII
Frequency and LRPT: Variation in ϕ and κ

data. This far we have only considered variations in ε. For this exercise we instead set a fixed $\varepsilon = 4$ and first vary ϕ between 0 and 1 for the baseline value of $\kappa = 2.5\%$ and then vary κ between 0.5% and 7.5% for the baseline value of $\phi = 0.75$. Figure VIII plots the results. First, observe that variation in ϕ indeed generates a positive relationship between frequency and LRPT; however, the range of variation in frequency is negligible, as predicted in Section III (see footnote 26). As ϕ increases from 0 to 1, LRPT increases from 0 to 55%, whereas frequency increases from 0.20 to 0.23 only. An important implication of this is that frequency of price adjustment should not be very different across domestically produced and imported goods, despite their ϕ being very different. This is indeed the case in the data. Gopinath and Rigobon (2008) document that for categories of goods in the import price index that could be matched with the producer price index and using the duration measures from Nakamura and Steinsson (2008) for producer prices, the mean duration for the import price index is 10.3 months, and it is 10.6 months for the producer price index.

Next observe that the assumed range of variation in the menu cost, κ, easily delivers a large range of variation in frequency, as expected. However, it produces almost no variation in LRPT, which is stable around 39%. Not surprisingly, in a menu cost model, exogenous variation in the frequency of price adjustment cannot

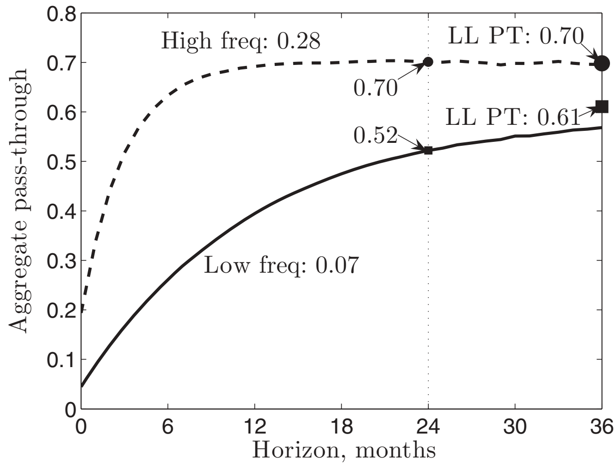

FIGURE IX
Frequency and LRPT in a Calvo Model

LL PT refers to LRPT estimated from the lifelong micro regression (1) (circle for high-frequency goods and square for low-frequency goods).

generate a robust positive relationship between frequency and measured long-run pass-through.[36]

The fourth set of results, reported in Figure IX, presents a robustness check by examining whether a Calvo model with large exogenous differences in the flexibility of prices can induce a positive correlation between frequency and measured LRPT even though the true LRPT is the same. We simulate two panels of firm prices—one for a sector with low probability of price adjustment (0.07) and another for a sector with high probability of price adjustment (0.28), the same as in Table I. We set $\varepsilon = 0$ (CES demand) and keep all parameters of the model as in the baseline calibration. The figure plots both pass-through estimates from aggregate regressions at different horizons, as well as lifelong pass-through estimates (depicted as the circle and the square over the 36-month horizon mark). Aggregate pass-through at 24 months is 0.52 for low-frequency adjusters, whereas it is 0.70 for high-frequency adjusters. At the same time, the lifelong pass-through estimates are 0.61 and 0.70, respectively. As is well known, the Calvo model

36. A similar pattern emerges for variation in the elasticity of demand σ when the superelasticity ε is set to zero (i.e., CES demand): variation in σ leads to variation in frequency with long-run pass-through stable at ϕ.

TABLE VIII
QUANTITATIVE RESULTS: MODEL AGAINST THE DATA

	Data	Variation in: Superelasticity, ε	Menu cost, κ	ε and κ
Slope(freq,LRPT)	0.56	1.86	0.03	0.55
Min(LRPT)	0.06	0.13	0.44	0.22
Max(LRPT)	0.72	0.76	0.46	0.57
Slope(freq,size)	−0.01	0.23	−0.15	−0.05
Min(size)	5.4%	3.8%	4.8%	5.8%
Max(size)	7.4%	11.8%	12.2%	8.2%
Std. dev. (freq)	0.30	0.11	0.17	0.18
Min(freq)	0.03	0.07	0.06	0.05
Max(freq)	1.00	0.44	0.59	0.61

generates much slower dynamics of price adjustment as compared to the menu cost model. This generates a significant difference in aggregate pass-through even at the 24-month horizon; however, this difference is far smaller than the one documented in Section II. The difference in pass-through is yet much smaller for the Calvo model if we consider the lifelong estimates of long-run pass-through. Further, as Figure II suggests, the steep relation between frequency and pass-through arises once frequency exceeds 0.13. A Calvo model calibrated to match a frequency of at least 0.13 converges sufficiently rapidly and there is no bias in the estimates. Therefore, we conclude that standard sticky price models with exogenous differences in the frequency of adjustment would have difficulty matching the empirical relationship between frequency and pass-through.

In the last set of simulation results, we evaluate the quantitative performance of the model in matching the following three moments of the data: the standard deviation of frequency, the slope coefficients in the regressions of LRPT on frequency, and size on frequency. The last two represent the slopes in Figures II (for the high-income OECD subsample) and IV, respectively. We estimate these moments in the model simulated series, just as we do in the data, by sorting goods into ten bins based on their frequency of adjustment and then estimate LRPT within each bin. Table VIII describes the results. The second column provides the moments in the data.

The third column of Table VIII presents the results for the case when there is only variation in ε. Variation in ε alone can generate 37% of the empirical dispersion in frequency. The LRPT–frequency slope coefficient, although large and positive (1.86), is much steeper than in the data (0.56). The range in pass-through is, however, comparable by design. The model with only variation in ε generates a positive relation between size and frequency, as discussed in Section III, with a wide range of sizes that varies from 3.8% to 11.8% as ε decreases. In the data, however, this slope is close to 0 and the size range is small, between 5.4% and 7.4%. This is not surprising given that in the data we sort goods based on frequency and consequently a high-frequency bin combines goods that adjust frequently either because they have a low superelasticity of demand, ε, or because they have a low menu cost, κ. A calibration that allows for such additional sources of variation across goods should improve the fit of the model.

We show that this is indeed the case by introducing variation in κ alongside variation in ε. Specifically, for each ε, we have firms facing a range of menu cost parameters from 0.1% to 20% of steady state revenues conditional on adjustment.[37] The cross-sectional distribution of menu costs is independent of the distribution of ε. This additional variation in κ makes it possible to match the two slope statistics almost perfectly, as reported in column (5) of Table VIII. The model generates a slope of 0.55 between frequency and LRPT, whereas in the data it is 0.56 and also matches the close-to-zero slope between size and frequency in the data, −0.05 versus −0.01. The fraction of the standard deviation in frequency explained by the model increases to 60%. Last, for the fourth column, we shut down variation in ε, so all of the variation is in κ. The model with only κ performs poorly for reasons described earlier, as it predicts no slope between frequency and pass-through (as emphasized in Figure VIII) and a sizable negative slope for the size–frequency relationship (as seen in Figure XI).

In Figures X and XI we plot the relationships between frequency and LRPT and between frequency and size for the case with variation in ε alone and for the case with joint variation in ε and κ against the data series from Figures II and IV respectively. As follows from the results in Table VIII, a menu cost

37. Note that a firm with a 20% menu cost adjusts at most once a year, implying an annual cost of adjustment of less that 2% of revenues.

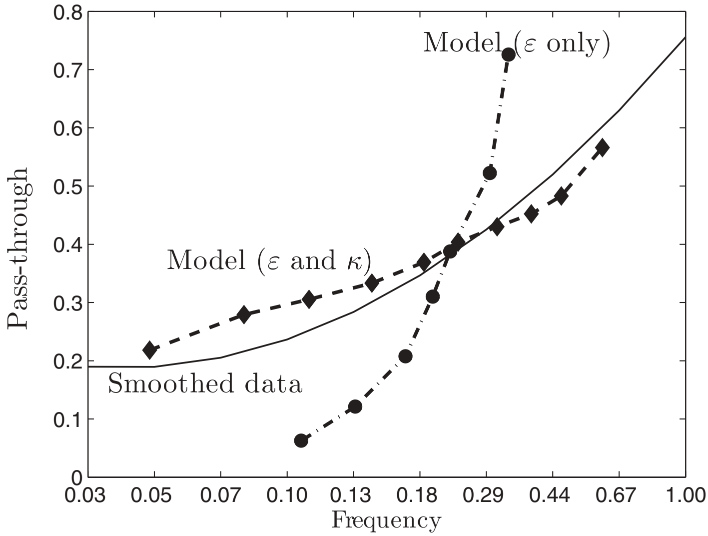

FIGURE X
Frequency and LRPT: Model against the Data

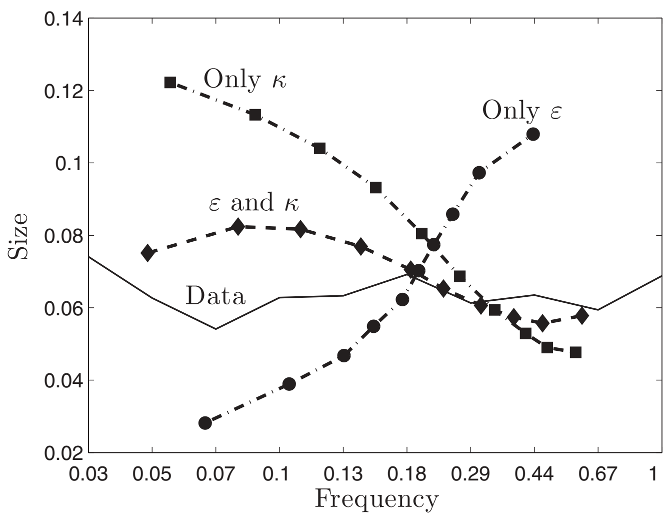

FIGURE XI
Frequency and Size: Model against the Data

model that allows for joint cross-sectional variation in mark-up elasticity, and menu costs can quantitatively account for both the LRPT–frequency and size–frequency relationships and generate a large dispersion in frequency across goods. Further, the variable mark-up channel is essential to matching the relation between LRPT and frequency and can generate a significant fraction of the variation in frequency observed in the data.

V. Conclusion

We exploit the open economy environment with an observable and sizable cost shock, namely the exchange rate shock, to shed light on the mechanism behind the sluggish response of aggregate prices to cost shocks. We find that firms that adjust prices infrequently also pass through a lower amount even after several periods and multiple rounds of price adjustment, as compared to high-frequency adjusters. In other words, firms that infrequently adjust prices are typically not as far from their desired prices due to their lower desired pass-through of cost shocks. On the other hand, firms that have high pass-through drift farther away from their optimal price and, therefore, make more frequent adjustments.

We also show evidence that there is interesting variation within sectors in the frequency of price adjustment that is linked to LRPT. This within-sector variation is not surprising in models with variable mark-ups. In a model where the strategic interactions between firms is explicitly modeled, as in Feenstra, Gagnon, and Knetter (1996) and Atkeson and Burstein (2008), mark-up elasticity will, among other things, depend on the market share of the firm, and this relationship is in general nonmonotonic. Hence firms in a sector with the same elasticity of substitution across goods will differ in their mark-up elasticity depending on their market share. Consequently, one should expect to see differences in mark-up elasticity, pass-through, and frequency of price adjustment even within the same disaggregated sector.

We have evaluated the empirical evidence through the lens of standard dynamic pricing models and find that a menu cost model with variation in the mark-up elasticity can match the facts in the data, whereas models with exogenous frequency of price adjustment and no variation across goods in LRPT have a difficult time matching the facts.

APPENDIX

A. Proofs for Section III

Proof of Proposition 1. The desired flexible price of the firm (5) can be rewritten in logs as

$$\ln P(a,e) = \tilde{\mu}(P(a,e)) + \ln(1-a) + \ln(1+\phi e),$$

where $\tilde{\mu} \equiv \tilde{\mu}(P) = \ln[\tilde{\sigma}(P)/(\tilde{\sigma}(P)-1)]$ is the log mark-up. Taking a first-order Taylor approximation around the point $a = e = 0$ gives

$$\left(1 - \frac{\partial \tilde{\mu}(P(0,0))}{\partial \ln P}\right) \cdot [\ln P(a,e) - \ln P(0,0)] \\ + O(P(a,e) - P(0,0))^2 = (-a + \phi e) + O(\|a,e\|)^2,$$

where $O(x)$ denotes the same order of magnitude as x and $\|\cdot\|$ is some norm in $\mathbb{R}^2$.

Using the definitions of $\tilde{\mu}$, $\tilde{\sigma}$, and $\tilde{\varepsilon}$, we obtain $\partial\tilde{\mu}(P)/\partial \ln P = -\tilde{\varepsilon}(P)/(\tilde{\sigma}(P)-1)$. Given our demand and cost normalization, we have $P(0,0) = 1$ and hence $\tilde{\sigma}(P(0,0)) = \sigma$ and $\tilde{\varepsilon}(P(0,0)) = \varepsilon$. This allows us to rewrite the Taylor expansion as

$$\ln P(a,e) - \ln P(0,0) + O(P(a,e) - P(0,0))^2 \\ = \Psi(-a + \phi e) + O(\|a,e\|)^2,$$

where $\Psi \equiv \left[1 + \frac{\varepsilon}{\sigma-1}\right]^{-1}$. This immediately implies that $O(P(a,e) - P(0,0)) = O(\|a,e\|)$, so that we can rewrite

$$\ln P(a,e) - \ln P(0,0) = \Psi(-a + \phi e) + O(\|a,e\|)^2.$$

The final step makes use of Lemma 1, which states that $\bar{P}_0 = P(0,0) + O(\|a,e\|)^2$ and allows us to substitute $\bar{P}_0$ for $P(0,0)$ in the Taylor expansion above without affecting the order of approximation:

$$\ln P(a,e) - \ln \bar{P}_0 = \Psi(-a + \phi e) + O(\|a,e\|)^2.$$

Last, for small shocks, the difference in logs is approximately equal to the percentage change, which results in expression (7) in the text of the proposition. Exchange rate pass-through is defined as $\Psi_e \equiv \partial \ln P/\partial e = \phi\Psi$, which follows from the above approximation. ■

Proof of Lemma 2. Taking a second-order Taylor approximation to the profit-loss function around the desired price $P(a, e)$ results in

$$\begin{aligned} L(a,e) &\equiv \Pi(a,e) - \Pi(\bar{P}_0|a,e) \\ &= -\frac{1}{2}\frac{\partial^2\Pi(a,e)}{\partial P^2}(P(a,e)-\bar{P}_0)^2 + O(\|a,e\|)^3, \end{aligned}$$

where the first-order term is zero due to the first-order condition (FOC) of profit maximization and $O(P(a,e)-\bar{P}_0) = O(\|a,e\|)$ from Lemma 1 and the proof of Proposition 1. The second derivative of the profit function with respect to price is

$$\begin{aligned} \frac{\partial^2\Pi(P|a,e)}{\partial P^2} &= \varphi'(P)\frac{\partial\Pi(P|a,e)}{\partial P} \\ &\quad -\frac{\tilde{\sigma}(P)\varphi(P)}{P}\left\{\tilde{\varepsilon}(P) + \frac{MC}{P}\left[1-\tilde{\varepsilon}(P)\right]\right\}. \end{aligned}$$

Evaluating this expression at $P_1 = P(a,e)$, we have

$$\frac{\partial^2\Pi(a,e)}{\partial P^2} = -\frac{(\tilde{\sigma}(P_1)-1)\cdot\varphi(P_1)}{P_1}\left[1+\frac{\tilde{\varepsilon}(P_1)}{\tilde{\sigma}(P_1)-1}\right],$$

where we used the FOC, which implies that $MC/P_1 = (\tilde{\sigma}(P_1)-1)/\tilde{\sigma}(P_1)$. Note that $\tilde{\sigma}(P_1) > 1$ and $\tilde{\varepsilon}(P_1) \geq 0$ are indeed sufficient conditions for profit maximization at P_1.

Assuming that $\tilde{\varepsilon}(\cdot)$ is a smooth function, we can use the approximation

$$\frac{\partial^2\Pi(a,e)}{\partial P^2} = \frac{\partial^2\Pi(0,0)}{\partial P^2} + O(\|a,e\|) = -\frac{\sigma-1}{\Psi} + O(\|a,e\|),$$

where the second equality evaluates the second derivative of the profit function at $a = e = 0$, taking into account that $P(0,0) = 1$ and $\varphi(1) = 1$, $\tilde{\sigma}(1) = \sigma$, and $\tilde{\varepsilon}(1) = \varepsilon$ due to our normalizations.

Combining the above results and the implication of Lemma 1 that $\bar{P}_0 = P(0,0) + O(\|a,e\|)^2 = 1 + O(\|a,e\|)^2$, we can rewrite the approximation to the profit loss function as

$$\begin{aligned} L(a,e) &\equiv \Pi(a,e) - \Pi(\bar{P}_0|a,e) \\ &= \frac{1}{2}\frac{\sigma-1}{\Psi}\left(\frac{P(a,e)-\bar{P}_0}{\bar{P}_0}\right)^2 + O(\|a,e\|)^3. \qquad \blacksquare \end{aligned}$$

B. Simulation Procedure

To simulate the dynamic model of Section IV, we first need to make a few approximations. As described in the text, the demand for a variety j is a function of the normalized relative price, $x_{jt} = D_t P_{jt}/P_t$, where the general expression for the normalization parameter D_t was provided in the text. In the case of the Klenow and Willis (2006) demand specification, this expression becomes

$$D_t = \frac{\sigma - 1}{\sigma} \int_\Omega \frac{C_{jt}}{C_t} \exp\left\{ \frac{1}{\varepsilon} \left[1 - \left(\frac{|\Omega| C_{jt}}{C_t} \right)^{\varepsilon/\sigma} \right] \right\} dj, \tag{19}$$

where

$$\exp\left\{ \frac{1}{\varepsilon} \left[1 - \left(\frac{|\Omega| C_{jt}}{C_t} \right)^{\varepsilon/\sigma} \right] \right\} = \Psi' \left(\frac{|\Omega| C_{jt}}{C_t} \right) = \psi^{-1} \left(\frac{|\Omega| C_{jt}}{C_t} \right).$$

In a symmetric steady state $P_j = P = \bar{P}$, $C_j = \bar{C}/|\Omega|$ for all j, so that $x_j \equiv \bar{D} = (\sigma - 1)/\sigma$, and the elasticity and superelasticity of demand equal σ and ε, respectively. Equations (14) and (13) in the text, together with our demand specification, imply the following (implicit) expression for the sectoral price level:

$$P_t = \frac{1}{|\Omega|} \int_\Omega P_{jt} \left[1 - \varepsilon \ln \left(\frac{\sigma D_t}{\sigma - 1} \frac{P_{jt}}{P_t} \right) \right]^{\sigma/\varepsilon} dj. \tag{20}$$

We can now prove

LEMMA A.1. (i) The first-order deviation of D_t from $\bar{D} = (\sigma - 1)/\sigma$ is nil. (ii) The geometric average provides an accurate first-order approximation to the sectoral price level:

$$\ln P_t \approx \frac{1}{|\Omega|} \int_\Omega \ln P_{jt} dj.$$

In both cases the order of magnitude is $O(\|\{\hat{P}_{jt}\}_{j\in\Omega}\|)$, where $\|\cdot\|$ is some vector norm in L^∞ and the circum flex denotes log-deviation from steady state value, $\hat{P}_{jt} \equiv \ln P_{jt} - \ln \bar{P}$.

Proof. Writing (19) and (20) in log-deviations from the symmetric steady state, we obtain two equivalent first-order accurate representations for $\hat{D}_t$,

$$\frac{\sigma}{\sigma - 1} \hat{D}_t = \frac{1}{|\Omega|} \int_\Omega (\hat{C}_{jt} - \hat{C}_t) dj = -\frac{1}{|\Omega|} \int_\Omega (\hat{P}_{jt} - \hat{P}_t) dj.$$

Now using the definition of the Kimball aggregator (12) and the fact that $\Psi(\cdot)$ is a smooth function, we have

$$\frac{1}{|\Omega|}\int_{\Omega}(\hat{C}_{jt}-\hat{C}_t)dj=0$$

up to second-order terms; specifically, the approximation error has order $O(\|\{\hat{C}_{jt}\}_{j\in\Omega}\|^2)$. Combining the two results immediately implies that $\hat{D}_t=0$ and $\hat{P}_t=|\Omega|^{-1}\int_{\Omega}\hat{P}_{jt}dj$ up to the second-order terms, $O(\|\{\hat{C}_{jt}\}_{j\in\Omega}\|^2)$. Taking the log-differential of the demand equation (18), we have

$$\hat{C}_{jt}-\hat{C}_t=-\sigma(\hat{D}_t+\hat{P}_{jt}-\hat{P}_t),$$

which allows us to conclude that $O(\|\{\hat{C}_{jt}\}_{j\in\Omega}\|)=O(\|\{\hat{P}_{jt}\}_{j\in\Omega}\|)$. Finally, note that the expression for $\hat{P}_t$ is equivalent to

$$\ln P_t=\frac{1}{|\Omega|}\int_{\Omega}\ln P_{jt}dj$$

because in a symmetric steady state $P_j=P=\bar{P}$. ∎

This result motivates us to make the following assumptions: In our simulation procedure we set $D_t\equiv\bar{D}=(\sigma-1)/\sigma$ and compute the sectoral price index as the geometric average of individual prices. Lemma A.1 ensures that these are accurate first-order approximations to the true expressions and using them speeds up the simulation procedure considerably as we avoid solving for another layer of fixed point problems.[38] We verify, however, that computing the sectoral price index according to the exact expression (20) does not change the results.

Additionally, we introduce two more approximations. First, we set the stochastic discount factor to be constant and equal to the discount factor $\beta<1$. Second, we set the sectoral consumption index to $C_t\equiv 1$. Both of these assumptions are in line with our partial equilibrium approach, and they introduce only second-order distortions to the price-setting problem of the firm.

The assumptions in Section IV.A allow us to reduce the state space for each firm to $\mathbb{S}_{jt}=(P_{j,t-1},A_{jt};P_t,e_t)$, where $e_t=\ln(W_t^*/W_t)=\ln W_t^*$. We iterate the Bellman operator (16) on a logarithmic grid for each dimension of $\mathbb{S}_{jt}$. Specifically, the grid for individual price P_{jt} is chosen so that an increment is no greater

38. This is also an assumption adopted by Klenow and Willis (2006).

than a 0.5% change in price (typically, around 200 grid points). The grid for idiosyncratic shock A_{jt} contains eleven grid points and covers ± 2.5 unconditional standard deviations for the stochastic process. The grid for the sectoral price level P_t is such that an increment is no greater than a 0.2% change in the price level (typically, around thirty grid points). Finally, the grid for the real exchange rate e_t has fifteen grid points with increments equal to σ_e and covering $\pm 7\sigma_e$.[39]

To iterate the Bellman operator (16), a firm needs to form expectations about the future path of the exogenous state variables, (A_{jt}, e_t, P_t). Because A_{jt} and e_t follow exogenous stochastic processes specified above, the conditional expectations for these variables are immediate.[40] The path of the sectoral price index, P_t, however, is an endogenous equilibrium outcome, and to set prices the firm needs to form expectations about this path. This constitutes a fixed point problem: the optimal decision of a firm depends on the path of the price level and this optimal decision feeds into the determination of the equilibrium path of the price level.[41] Following Krusell and Smith (1998), we assume that firms base their forecast on the restricted set of state variables; specifically,

$$\mathbb{E}_t \ln P_{t+1} = \gamma_0 + \gamma_1 \ln P_t + \gamma_2 e_t.$$

In principle, the lags of $(\ln P_t, e_t)$ can also be useful for forecasting $\ln P_{t+1}$; however, in practice, $(\ln P_t, e_{t+1})$ alone explains over 95% of the variation in $\ln P_{t+1}$, and e_t is a sufficient statistic to forecast e_{t+1}. The firms use the forecasting vector $(\gamma_0, \gamma_1, \gamma_2)$ consistent with the dynamics of the model. This reflects the fact that they form rational expectations given the restricted set of state variables which they condition on. To implement this, we

39. We let the (log of) the real exchange rate, e_t, follow a binomial random walk process within wide boundaries. Specifically, its value each period either increases or decreases by σ_e with equal probabilities and reflects from the boundaries of a grid. We use this procedure to numerically generate a highly persistent process for the exchange rate, which is harder to obtain using the Tauchen routine.

40. Recall that A_{jt} follows a first-order autoregressive process; we discretize it using the Tauchen routine.

41. In fact, there are two distinct fixed point problems, one static and one dynamic. The price that the firm sets today, P_{jt}, depends both on the price level today, P_t, and on the expectation of the price level in the future, $\mathbb{E}_t P_{t+1}$. The static problem is easy to solve: holding the expectations constant, we find P_t consistent with

$$\ln P_t = \frac{1}{|\Omega|} \int_{\Omega} \ln P_{jt}(P_t) dj,$$

where $P_{jt}(P_t)$ underlines the dependence of the individual prices on the sectoral price level.

i. start with an initial forecasting vector $(\gamma_0^{(0)}, \gamma_1^{(0)}, \gamma_2^{(0)})$;
ii. given the forecasting vector, iterate the Bellman equation till convergence to obtain policy functions for price setting;
iii. using the policy functions, simulate M dynamic paths of the sectoral price level $\{P_t\}_{t=0}^{T}$, where in every period we make sure that P_t is consistent with the price setting of firms;
iv. for each simulation m estimate $\hat{\gamma}^{(0,m)} \equiv (\hat{\gamma}_0^{(0,m)}, \hat{\gamma}_1^{(0,m)}, \hat{\gamma}_2^{(0,m)})$ from regressing $\ln P_{t+1}$ on a constant, $\ln P_t$ and e_t, and obtain $(\gamma_0^{(1)}, \gamma_1^{(1)}, \gamma_2^{(1)})$ by taking the median of $\hat{\gamma}^{(0,m)}$;
v. iterate this procedure till joint convergence of the forecasting equation coefficients.

This constitutes a reasonable convergence procedure in a stochastic environment.

Once the forecasting vector is established, we iterate the Bellman operator to find policy functions for domestic and foreign firms in every state. This then allows us to simulate a panel of individual prices similar to the one we use in the empirical section. Specifically, we simulate a stationary equilibrium with 12,000 domestic and 2,400 foreign firms operating in the local market. We simulate the economy for 240 periods and then take the last 120 periods. During this time interval each firm appears in the sample for, on average, 35 consecutive months (on average, four price adjustments for each firm), which generates an unbalanced panel of firm price changes, as we observe in the data.[42] On these simulated data, we estimate the same regressions (1) and (2) as we do on the BLS data set. We repeat the simulation B times and take the median of all statistics across these B simulations to exclude noise in the estimates.

In the final simulation exercise we allow firms to be heterogeneous in both their menu cost κ and superelasticity of demand ε. Specifically, for every value of ε, we have firms with different values of κ distributed uniformly on $\{0.1\%, 0.5\%, 1.25\%, 2.5\%, 5\%, 10\%, 20\%\}$. We simulate price data for a panel of firms using the procedure described above. We then estimate frequency for every firm and sort firms into frequency deciles. For each frequency decile we estimate lifelong pass-through and median size of price

42. Specifically, for each firm we choose a random time interval during which its price is observed by the econometrician, although the good exists in all time periods. This captures the feature that in the data the BLS only observes price changes when the good is in the sample and only a few price changes are observed.

adjustment. This parallels the procedure that we used in our empirical analysis of Section II.

Department of Economics, Harvard University, and National Bureau of Economic Research
Department of Economics, Princeton University

References

Atkeson, Andrew, and Ariel Burstein, "Pricing-to-Market, Trade Costs, and International Relative Prices," *American Economic Review*, 98 (2008), 1998–2031.
Ball, Laurence, and N. Gregory Mankiw, "Asymmetric Price Adjustment and Economic Fluctuations," *Economic Journal*, 104 (1994), 247–261.
Ball, Laurence, N. Gregory Mankiw, and David Romer, "The New Keynesian Economics and the Output–Inflation Trade-Off," *Brookings Papers on Economic Activity*, 19 (1988), 1–65.
Barro, Robert J., "A Theory of Monopolistic Price Adjustment," *Review of Economic Studies*, 39 (1972), 17–26.
Bergin, Paul R., and Robert C. Feenstra, "Pricing to Market, Staggered Contracts, and Real Exchange Rate Perisistence," *Journal of International Economics*, 54 (2001), 333–359.
Bils, Mark J., and Peter J. Klenow, "Some Evidence on the Importance of Sticky Prices," *Journal of Political Economy*, 112 (2004), 947–85.
Bils, Mark J., Peter J. Klenow, and Benjamin Malin, "Reset Price Inflation and the Impact of Monetary Policy Shocks," NBER Working Paper No. 14787, 2009.
Broda, Christian, and David E. Weinstein, "Globalization and the Gains from Variety," *Quarterly Journal of Economics*, 121 (2006), 541–585.
Burstein, Ariel, and Nir Jaimovich, "Understanding Movements in Aggregate and Product-Level Real Exchange Rates," Stanford University Working Paper, 2009.
Caplin, Andrew S., and Daniel F. Spulber, "Menu Costs and the Neutrality of Money," *Quarterly Journal of Econmics*, 102 (1987), 703–726.
Devereux, Michael B., and James Yetman, "Price Adjustment and Exchange Rate Pass-Through," University of Hong Kong Working Paper, 2008.
Dornbusch, Rudiger, "Exchange Rate and Prices," *American Economic Review*, 77 (1987), 93–106.
Dossche, Maarten, Freddy Heylen, and Dirk Van den Poel, "The Kinked Demand Curve and Price Rigidity: Evidence from Scanner Data," National Bank of Belgium Research Paper No. 200610-11, 2006.
Dotsey, Michael, Robert G. King, and Alexander L. Wolman, "State-Dependent Pricing and the General Equilibrium Dynamics of Money and Output," *Quarterly Journal of Economics*, 114 (1999), 655–690.
Feenstra, Robert C., Joseph E. Gagnon, and Michael M. Knetter, "Market Share and Exchange Rate Pass-Through in World Automobile Trade," *Journal of International Economics*, 40 (1996), 187–207.
Fitzgerald, Doireann, and Stefanie Haller, "Exchange Rates and Producer Prices: Evidence from Micro Data," Stanford University Working Paper, 2008.
Goldberg, Linda S., and José Manuel Campa, "The Sensitivity of the CPI to Exchange Rates: Distribution Margins, Imported Inputs, and Trade Exposure," *Review of Economics and Statistics*, forthcoming, 2009.
Goldberg, Pinelopi K., and Rebecca Hellerstein, "A Framework for Identifying the Sources of Local-Currency Price Stability with an Empirical Application," NBER Working Paper No. 13183, 2007.
Goldberg, Pinelopi K., and Michael M. Knetter, "Goods Prices and Exchange Rates: What Have We Learned?" *Journal of Economic Literature*, 35 (1997), 1243–1272.
Gopinath, Gita, Pierre-Olivier Gourinchas, Chang-Tai Hsieh, and Nicholas Li, "Estimating the Border Effect: Some New Evidence," NBER Working Paper No. 14938, 2009.

Gopinath, Gita, and Oleg Itskhoki, “Frequency of Price Adjustment and Pass-Through,” NBER Working Paper No. 14200, 2008.
Gopinath, Gita, Oleg Itskhoki, and Roberto Rigobon, “Currency Choice and Exchange Rate Pass-through,” *American Economic Review*, forthcoming, 2009.
Gopinath, Gita, and Roberto Rigobon, “Sticky Borders,” *Quarterly Journal of Economics*, 123 (2008), 531–575.
Greene, William H., *Econometric Analysis*, 4th ed. (Upper Saddle River, NJ: Prentice-Hall, 2000).
Kehoe, Patrick J., and Virgiliu Midrigan, “Sticky Prices and Real Exchange Rates in the Cross-Section,” New York University Working Paper, 2007.
Kimball, Miles, “The Quantitative Analytics of the Basic Neomonetarist Model,” *Journal of Money, Credit and Banking*, 27 (1995), 1241–1277.
Klenow, Peter J., and Jonathan L. Willis, “Real Rigidities and Nominal Price Changes,” Federal Reserve Bank of Kansas City Research Working Paper 06-03, 2006.
Knetter, Michael M., “Price Discrimination by U.S. and German Exporters,” *American Economic Review*, 79 (1989), 198–210.
Krugman, Paul R., “Pricing to Market When the Exchange Rate Changes,” in *Real Financial Linkages among Open Economies*, Swen W. Arndt and J. David Richardson, eds. (Cambridge, MA: MIT Press, 1987).
Krusell, Per, and Anthony A. Smith, Jr., “Income and Wealth Heterogeneity in the Macroeconomy,” *Journal of Political Economy*, 106 (1998), 867–896.
Lane, Philip R., “The New Open Economy Macroeconomics: A Survey,” *Journal of International Economics*, 54 (2001), 235–266.
Midrigan, Virgiliu, “International Price Dispersion in State-Dependent Pricing Models,” *Journal of Monetary Economics*, 54 (2007), 2231–2250.
Nakamura, Emi, and Jón Steinsson, “Five Facts about Prices: A Reevaluation of Menu Cost Models,” *Quarterly Journal of Economics*, 123 (2008), 1415–1464.
Neiman, Brent, “Multinationals, Intrafirm Trades, and International Macroeconomic Dynamics,” University of Chicago Working Paper, 2007.
Obstfeld, Maurice, and Kenneth S. Rogoff, “Exchange Rate Dynamics Redux,” *Journal of Political Economy*, 103 (1995), 624–660.
Rauch, James E., “Networks versus Markets in International Trade,” *Journal of International Economics*, 48 (1999), 7–35.
Rogoff, Kenneth S., “The Purchasing Power Parity Puzzle,” *Journal of Economic Literature*, 34 (1996), 647–668.
Romer, David, “Staggered Price Setting with Endogenous Frequency of Adjustment,” NBER Working Paper No. 3134, 1989.
Rotemberg, Julio J., and Garth Saloner, “The Relative Rigidity of Prices,” *American Economic Review*, 77 (1987), 917–926.
Rotemberg, Julio J., and Michael Woodford, “The Cyclical Behavior of Prices and Costs,” in *Handbook of Macroeconomics*, John B. Taylor and Michael Woodford, eds. (Amsterdam, Netherlands: Elsevier North Holland, 1999).
Sheshinski, Eytan, and Yoram Weiss, “Inflation and Costs of Price Adjustment,” *Review of Economic Studies*, 44 (1977), 287–303.