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LOST IN TRANSIT:
PRODUCT REPLACEMENT BIAS AND PRICING TO MARKET

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ABSTRACT

The microdata underlying U.S. import and export price indexes exhibit frequent product turnover and highly rigid prices. As a consequence, 40% of products are replaced before a single price change is observed and 70% are replaced after two price changes or less. An aggregate price index that focuses on price changes for identical items over time may, therefore, miss an important component of price adjustment occuring at the time of product replacements. We provide a model of this "product replacement bias" and quantity its importance using U.S. microdata on improt and export prices. We show that, accounting for product replacement bias, long-run exchange rate "pass-through" into U.S. import and export price indexes is almost twice as high as conventional estimates suggest, and changes in the terms of trade are roughly 75% more volatile. Our adjustment makes pass-through statistics easier to account for with existing general equilibrium models.

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1 Introduction

Despite large swings in the U.S. dollar nominal exchange rate, U.S. import and export prices appear remarkably stable in U.S. dollar terms. Conventional measures of aggregate exchange rate "pass-through" imply that a 1% appreciation of the dollar leads to roughly a 0.2-0.4% long-run increase in non-oil import prices, and roughly a 0.1% long-run fall in export prices in U.S. dollar terms (Campa and Goldberg, 2005; Marazzi and Sheets, 2007; Gopinath et al., 2010). As a consequence, the ratio of export to import prices—the terms of trade—are much less volatile than the exchange rate. Low pass-through of exchange rates into aggregate price indexes persists at long horizons, despite highly persistent exchange rate movements, implying that it cannot be explained as a mechanical consequence of temporarily rigid prices alone.[1]

We argue, however, that conventional measures of exchange rate pass-through based on aggregate price indexes are seriously biased—both in the short run and in the long run—due to two pervasive features of the underlying micro-data: highly rigid prices and frequent product replacements. In constructing price indexes, price changes that occur at the time of product replacements tend to be dropped. This causes a "product replacement bias" that leads aggregate import and export price indexes to be too smooth. Adjusting for product replacement bias raises aggregate pass-through and makes it more consistent with earlier work on pass-through for narrowly defined product categories (Goldberg and Knetter, 1997)—the coarser product definitions used in these earlier studies imply less product turnover and are thus less susceptible to product replacement bias.

To understand how product replacement bias arises, it is useful to consider an extreme example. Consider an economy in which the price of each product remains fixed for the entire life of the product and all price adjustment occurs at the time of product replacements. Figure 1 depicts this type of setting. In the figure, the exchange rate is depreciating. Assume for simplicity that the product replacements involve no quality change. Agents living in this economy can observe the quality of each product. It is therefore obvious to them that prices are rising as the exchange rate depreciates.

Now consider the problem of a statistical agency in this setting. Such an agency would ideally like to measure the change in quality adjusted prices. In practice, however, most price indexes

[1] Exchange rate movements are likely endogenous to other macroeconomic shocks that affect prices directly. Our focus is on measuring the relationship between exchange rates and prices as opposed to providing evidence for a particular causal interpretation of this relationship.

(including the U.S. import and export price indexes) are close approximations of a "matched-model index," in which all price changes used to construct the index are for identical items and product replacements are "linked-into" the index; meaning that the price comparison between the first observation of the new product and the last observation of the old product is dropped when changes in the index are calculated.[2] A matched model index will remain constant throughout in our example since prices only change at the time of product replacements and price comparisons between old and new products are dropped when the price index is constructed. Estimates of exchange rate pass-through using this price index will yield zero pass-through irrespective of what the true degree of pass-through is.[3]

While this is obviously an extreme example, it captures important features of the actual data underlying the U.S. import and export price indexes. Price rigidity and frequent product turnover imply that about 40% of expenditure weighted price series in these data have no price changes and roughly 70% have two price changes or less.[4] Even products that do have price changes while they are in the index, typically exit the index after a prolonged spell of price rigidity. If the prices of new products entering the index have already adjusted to exchange rate movements over this interval (as in our simple example above), the response of these prices to movements in exchange rates over this interval will be "lost in transit" (i.e., neither picked up by an observed price change of the exiting nor entering products). In this case, the price index will never fully reflect the true comovement of prices and exchange rates, even in the long run.

We develop a model of this "product replacement bias" and show how it depends on observable features of price data. We estimate our model using BLS micro-data on import and export prices. Our "corrected" measure implies that pass-through of changes in the trade-weighted U.S. exchange rate into U.S. import prices for the period 1982-2007 was 0.64—almost twice as high as conventional measures of aggregate pass-through. For non-agricultural U.S. exports, our correction implies that long-run pass-through was 0.79 for this period (in foreign currency terms)—a significantly lower number than conventional estimates yield. We also calculate a corrected series for the U.S.

[2]An alternative would be to make hedonic adjustments for quality change. For most products, however, it is extremely costly and difficult to accurately measure quality change (Abraham et al., 1998). Feenstra (1994) and Broda and Weinstein (2006) develop and apply an alternative to hedonic methods. These papers apply a structural approach to back out quality adjusted prices from data on prices and quantities.

[3]If the price comparisons that are dropped in this way are a representative sample of all price comparisons, the matched model index will provide an unbiased estimate of the true index. However, if the dropped price comparisons are in some way special—as in this example—product replacement bias will arise.

[4]Similar figures are reported in Gopinath and Rigobon (2008) and Gopinath, Itskhoki, and Rigobon (2010), based on an unweighted average for high income OECD countries.

terms of trade. The volatility of changes in this series is 75% higher than that of the official series. Importantly, we show that our model with product replacements maps directly into standard general equilibrium models that abstract from product replacements.[5] Our adjusted pass-through estimates line up well with the implications of leading general equilibrium models such as Corsetti and Dedola (2005), Atkeson and Burstein (2008) and Drozd and Nosal (2011), which imply long-run pass-through between 0.7 and 0.9.[6] Our adjustment can also be applied to measures of pass-through based on the bilateral exchange rate. Gopinath and Itskhoki (2010b) show that these are only about half as large as pass-through of the trade-weighted exchange rate, underscoring the importance of spillovers among U.S. trading partners such as strategic complementarity in price setting and imported intermediate inputs.[7]

Our model of product replacement bias helps explain the wide range of pass-through estimates in the existing literature. Early work on pricing-to-market focused on industry studies of average prices for narrowly defined product categories where products were assumed to be relatively stable and homogenous (e.g., Knetter, 1989; Gagnon and Knetter, 1995). This literature typically found long-run pass-through of about 0.5 (Goldberg and Knetter, 1997). An important drawback of this literature was that even within narrow categories—say, compact cars—a manufacturer could potentially adjust quality in response to exchange rate changes—say, by incorporating more or less expensive accessories. Recent work by Gopinath, Itskhoki, and Rigobon (2010) (henceforth GIR) analyzes pass-through behavior using the "best practice" approach of national statistical agencies of tracking the prices of exactly identical items over time.[8] GIR present an estimate of aggregate pass-through for bilateral exchange rate changes that is extremely low—only 0.17% for dollar-priced imports. However, our analysis shows that the "best practice" approach of analyzing price responses for identical items also has a downside in that it is more likely to be sensitive to product replacement bias.[9]

[5]Standard models implicitly analyze quality-adjusted prices and quantities.

[6]These papers can match U.S. import price pass-through when oil imports are included but have a difficult time explaining why non-oil pass-through is so much lower. The model of Erceg et al. (2006) is designed to match this low rate of pass-through. Matching the behavior of non-oil prices seems important given that non-oil products account for the vast majority of U.S. imports. Drozd and Nosal (2010) provide a detailed discussion of pass-through in a number of leading general equilibrium models.

[7]More generally, there is a large amount of heterogeneity in pass-through across sectors and countries. Import price pass-through estimates are also highly sensitive to whether the oil is included or excluded from the price index. Marazzi et al. (2005) and Hellerstein et al. (2006) emphasize the sensitivity of pass-through to including commodity prices as a separate regressor. We have calculated our bias factor for a number of different potential samples (oil vs. non-oil, all countries vs. high income OECD) and found it to be quantitatively similar in all of these cases.

[8]Campa and Goldberg (2005) and Marazzi and Sheets (2007) also implicitly use this approach since they make use of the U.S. import and export price indexes.

[9]GIR caution that aggregate pass-through should be interpreted with caution given the large number of price

The bias we study can be seen as one application of a general measurement problem arising from the interaction between adjustment costs and product replacement. The ideal way of developing meaningful aggregates based on such data is to use hedonic methods to compare prices across products based on data on product characteristics and a full model of demand. In the absence of data on characteristics, an important problem arises. Adjustment costs—such as the barriers to price adjustment we consider—lead to a difference between the short-run and long-run response to a given shock. The more one disaggregates the data, the shorter the duration over which a "product" can be followed. This makes it increasingly likely that one's measure of the response to a shock reflects the short-run response and the difference between the short-run and long-run response will be "lost in transit." The growing richness of product-level data—which identify not only individual products at an extremely disaggregated level but also individual firms—increases the importance of dealing with this measurement problem.

Two key inputs into our adjustment for product replacement bias are the frequency of price change and the frequency of product replacement. Product replacement bias is larger when prices are more rigid and product replacement is more frequent, and disappears entirely if *either* prices are flexible or products last forever in the index. However, the magnitude of the bias also depends crucially on the degree of heterogeneity in the frequency of price change. Our empirical model allows for a highly flexible distribution of cross-sectional heterogeneity in price rigidity (at the level of individual products). This flexible specification is crucial in accounting for the large number of products with no observed price changes. Incorporating this heterogeneity amplifies product replacement bias substantially relative to a case with no variation in price rigidity across firms.

A third key input into our adjustment for product replacement bias is the degree of "overreaction" of the first observed price change of each product to past exchange rate changes. The simple example depicted in Figure 1 assumes that products enter the data set with prices that have already adjusted to past exchange rate changes. This is not necessarily the case in practice—i.e., products may enter the index with "stale" prices. In this case, when these products do adjust their prices, they will "overreact" to historical exchange rate movements, potentially making up for the price adjustment that would otherwise have been "lost in transit." We provide direct empirical evidence on the magnitude of "overreaction" of the first observed price change of each product by comparing the responsiveness of first versus second price changes to historical exchange rate movements.

Our estimates indicate that such overreaction is minimal. One potential reason for this finding

series with no price changes that are present in the data.

is that contracts are likely to be renegotiated when firms start buying or selling a product (Carlton, 1986), and this is often when products enter the BLS dataset. In addition, the nature of the BLS repricing procedure makes products more likely to enter the dataset with disproportionately "fresh" prices. While initial prices are collected using a detailed interview, subsequent prices are collected using a "repricing form" asking firms to confirm a previously reported price (and providing them with their previous price). BLS internal studies suggest that the repricing procedure sometimes yields spurious rigidity for continuing products, a problem that does not arise for products newly initiated to the dataset. Finally, firms may choose to adjust their price more when they introduce new products because they perceive this as being less likely to antagonize their customers (Rotemberg, 2005; Nakamura and Steinsson, 2008b).

GIR present an alternative micro-based "life-long" pass-through approach that yields pass-through of 0.49—almost twice as high as their aggregate estimate. We show that this finding corroborates our results regarding the quantitative importance of product replacement bias. Life-long pass-through is less sensitive to product replacement bias than standard aggregate measures of pass-through for reasonable parameter values. Indeed, our adjusted long-run pass-through measure reduces to GIR's life-long pass-through measure under certain conditions. A third approach proposed by GIR—in addition to aggregate pass-through and life-long pass-through—is to estimate pass-through "conditional on adjustment." This yields an estimate of 0.24. Low pass-through conditional on adjustment is entirely consistent with our much higher estimate of long-run pass-through. Pass-through conditional on adjustment provides an estimate of relatively short-run pass-through because a substantial fraction of pass-through is delayed beyond the first price change. The literature on pass-through has long recognized that there is a large difference between short-run and long-run pass-through (see, e.g., Gagnon and Knetter, 1995; Campa and Goldberg, 2005). Standard macroeconomic models generate such delays in pass-through (even beyond the duration of rigid prices) by incorporating staggered price adjustment and strategic complementarity in pricing.[10]

Product replacement bias causes a downward bias in pass-through for products that are priced in local currency (LCP) but an upward bias in pass-through for products that are priced in the producer's currency (PCP).[11] This helps explain several empirical findings. First, GIR document a large difference in long-run aggregate pass-through for dollar-prices (LCP) vs. non-dollar-priced

[10]These two features together imply that any given firm will not fully adjust to past shocks when it changes its price because other prices are rigid.

[11]To see why, notice that in the extreme example above, the price index is perfectly stable in units of domestic currency, but moves one-for-one in units of foreign currency.

(PCP) U.S. imports, but a much smaller such difference based on life-long pass-through—which is less sensitive to product replacement bias. This is consistent with product replacement bias explaining an important part of the measured difference in long-run aggregate pass-through between LCP and PCP products. Second, estimates of U.S. import pass-through are much lower than those of U.S. export pass-through (in foreign currency terms). Most U.S. imports are LCP (and thus downward biased), while most U.S. exports are PCP (and thus upward biased). Third, measured exchange rate pass-through for imports is lower in the U.S.—where most imports are LCP—than that in developing countries—where imports are more often PCP (see, e.g., Burstein, Eichenbaum and Rebelo, 2005).

While we have focused on the implications of product replacement bias for the effects of exchange rate movements, similar biases apply in other contexts. A particularly important application may be the issue of how shifts in sourcing from high-cost to low-cost countries—say from Europe to China—are reflected in U.S. price indexes. Diewert and Nakamura (2010) and Houseman et al. (2011) suggest that problems in measuring price changes at the time of sourcing changes between different countries (which often coincide with product replacements) may lead to an underestimate of the effects of offshoring on the U.S. economy. Also, the existence of product replacement bias limits the extent to which variation in the quality of new products will get reflected in aggregate price indexes. This may limit the extent to which the "extensive margin" forces emphasized by Auer and Chaney (2009), Rodriguez-Lopez (2008) and Ghironi and Melitz (2005) show up in the data, in practice.[12]

Product replacement bias may also lead measured *consumer* price inflation to respond less to aggregate shocks than actual consumer price inflation. Anecdotal evidence suggests that this may, in fact, have been an important phenomenon during the dramatic rise of inflation in the U.S. in the late 1970's. The BLS noticed that prices began rising rapidly in almost all sectors except apparel, which continued to show inflation rates near zero, suggesting that a large fraction of price increases in this sector was being "lost in transit" due to frequent product turnover. In response, the BLS changed their procedure for linking in products in apparel (Reinsdorf, Liegey, and Stewart, 1996). Another indication that product replacement bias may affect the CPI is that price changes are disproportionately large at the time when new products are linked into price indexes (Armknecht

[12]Mismeasurement of import and export price indexes also affects measured trade volumes and trade price elasticities. Holding fixed nominal quantities, if the increase in import prices in response to an exchange rate depreciation is underestimated, then the corresponding decline in import quantities will be underestimated as well. This will cause estimates of trade price elasticities to be biased away from one.

and Weyback, 1989; Liegey, 1993; Reinsdorf, Liegey and Stewart, 1996; Triplett, 1997; Greenlees and Mcclelland, 2010).

Our analysis of product replacement bias is related to the large measurement literature on the "new goods" or "quality change" bias.[13] An important distinction is that our adjustment for product replacement bias addresses a bias in the *responsiveness* of inflation to aggregate shocks—as opposed to the *level* of inflation. Our results do not rely on the idea that product replacements may be systematically associated with declines in the quality-adjusted price. Our results also build on recent papers studying the micro-level U.S. import and export price data. Rogers (2006) argues that there is a negative relationship across industries between the frequency of product substitutions and exchange rate pass-through. Berger et al. (2009) study the relationship across products between product substitutions and distribution wedges. Neiman (2010) and Clausing (2001) provide additional evidence on the nature and reasons for price rigidity in the trade price data.

The paper proceeds as follows. Section 2 describes the BLS micro data underlying the U.S. import and export price indexes that we use in our empirical analysis. Section 3 presents measures of pricing to market for U.S. imports and exports for the period 1982-2007 based on conventional methods using aggregate data. Section 4 derives expressions for product replacement bias as a function of the frequency of price change and the frequency of product replacement. Section 5 presents estimates of the frequency of price change, the frequency of product replacement, the degree of overreaction of first observed price changes and our quantitative estimates of product replacement bias. Section 6 analyzes how product replacement bias relates to alternative estimates of exchange rate pass-through in the empirical literature. Section 7 concludes.

2 Data Description

We use three main sources of data. First, we use the microdata underlying the U.S. import and export price indexes. These data are collected by the International Prices Program (IPP) of the Bureau of Labor Statistics (BLS). Second, we use aggregate U.S. import and export price indexes produced by the Bureau of Economic Analysis (BEA) as a part of the National Income

[13]Important papers include Court (1939), Griliches (1961), Nordhaus (1998), Bils and Klenow (2001), Hausman (2003), Pakes (2003), Boskin et al. (1996), Bils (2008), Moulton and Moses (1997) , Abraham et al. (1998), Triplett (1997) and Hobijn (2002). Erickson and Pakes (2011) develop an experimental hedonic price index for televisions that accounts, among other things, for price rigidity. Goldberg et al. (2008) show that new imported varieties contributed substantially to effective price declines for Indian firms after a trade liberalization. Reinsdorf (1993) studies the related idea of "outlet substitution bias."

and Product Accounts (NIPA). Third, we use exchange rate data from the Federal Reserve Board and the International Monetary Fund (IMF). We describe these data in turn.

The U.S. import and export price indexes were introduced in the early 1980's to provide a more accurate alternative to unit value indexes. The micro data we use cover the time period 1994-2004. We exclude intrafirm prices. The total number of product-months in our sample for which IPP attempts to record a price is roughly 1.6 million or about 150,000 per year. This dataset has previously been used by Clausing (2001), Gopinath and Rigobon (2008), Gopinath, Itskhoki, and Rigobon (2010), Gopinath and Itskhoki (2010a,b), Berger et al. (2009) and Neiman (2010). Below, we provide a brief description of how these data are collected. See the IPP Data Collection Manual for a much more detailed description (U.S. Department of Labor, 2005).

The IPP data are collected using voluntary surveys. To initiate a product into the dataset, IPP collects a detailed item description and a particular set of transaction terms. Transaction terms may include the number or type of units priced, the country of destination or origin, the port of exit or entry, the discount structure, and in some cases the duty applied to the product. The price provided during initialization is required to be a transaction price (rather than a list price), unless a discount structure can also be provided to adjust the list price. After initialization, subsequent prices are collected using a repricing form with pre-filled information about the last reported price and product characteristics. One concern about the repricing form is that it creates a differential reporting friction for reporting a new price. We return to this issue in section 5.[14]

Transaction prices are missing in about 40% of the product-months in the IPP dataset. This arises because of a combination of infrequent trade, "off-cycle" price collection carried out by the BLS to reduce reporting burden, and failure of reporters to return the repricing forms.[15] In the vast majority of cases, prices are missing for short periods (1-2 months). During these periods, IPP imputes prices using a variety of methods (see Feenstra and Diewert (2000) for a detailed discussion). In many cases, IPP simply "pulls forward" the last available price through missing periods. Another standard procedure is "cell mean imputation" whereby IPP imputes prices over the intervening months using the average inflation rate in the category. In all cases, when the price is again observed, the price series reverts back to the actual observed price. Therefore, the choice of imputation method has no effect on the trajectory of prices beyond the horizon over which

[14]To update the discount structure, the firm must cross out the existing discount information and pencil in new information. In practice, a discount structure is rarely reported and almost never changed.

[15]In the repricing process, the reporter is allowed to report an estimated or "list" price if there was no transaction or a transaction price is not available. We drop these prices from our analysis.

prices are imputed and thus no impact on long-run pass-through. We discuss this in more detail in appendix E.

The IPP accepts reported prices in any currency, but in practice about 92% of import prices and 97% of export prices are reported in U.S. dollars.[16] To avoid introducing spurious price changes associated with numerical issues in converting prices quoted in foreign currencies into dollars, we use the "reported price" rather than the "net price" in our baseline analysis.

We make use of detailed time-varying BLS product weights. Within product groups, the IPP sampling procedure is to sample product-firm pairs in proportion to their dollar sales from Census data. This implies that the effects of product-firm size are accounted for by the sampling procedure itself. We account for the fact that different product groups have different fractions of market and non-market based items. Since 1997, the BLS has also used additional weights to account for "sampling bias"—random deviations between the theoretical and actual sampling probabilities that arise in a finite sample and are uncorrelated with product-firm size. BLS studies confirm that these additional weights have little impact on the BLS index.[17]

The second set of data we use is from the U.S. NIPA. We use the import price deflator for imported goods excluding oil. We use the export price deflator for exported goods excluding agricultural products. Finally, we make use of trade-weighted and bilateral, monthly and daily exchange rates downloaded from the Federal Reserve Board's website.[18] as well as monthly bilateral exchange rates from the International Financial Statistics (IFS) database of the IMF.

3 Prices and Exchange Rates: Evidence

A common method for measuring the degree of long-run exchange rate pass-through for imports is to run the following regression:

$$\Delta(p_t^m - p_t) = \alpha + \sum_{k=0}^{6} \beta_k \Delta q_{t-k} + \epsilon_t, \tag{1}$$

where p_t^m denotes the log of the dollar price of U.S. imports, p_t denotes the log of the dollar price of U.S. production and q_t denotes the log of the trade-weighted U.S. real exchange rate. Long-run

[16]This is a substantially higher fraction of dollar priced goods than in GIR. The main reason for the difference is that GIR condition explicitly on countries with a substantial fraction of non-dollar goods.

[17]For estimates of the "lifelong" pass-through regression and the pass-through "conditional on adjustment" regression presented in section 6, we reweight the data in such a way as to avoid "overweighting" product categories with a high frequency of price change. Specifically, we reweight the observations such that the total weight within a given HS2 category in the new sample (including only price changes) is the same as in the original sample of all observations.

[18]http://www.federalreserve.gov/releases/h10/Hist/

pass-through is then defined as the sum of the coefficients, $B = \sum_{k=0}^{6} \beta_k$. If $B < 1$, long-run pass-through is said to be incomplete.[19] Recent papers that use this type of regression to estimate long-run pass-through include Campa and Goldberg (2005), Marazzi and Sheets (2007), and GIR. We follow GIR in referring to estimates of pass-through from this type of regression as "aggregate" pass-through estimates.

A concern with the aggregate pass-through specification is that it is misspecified if relative import prices and the real exchange rate are cointegrated. To allow for cointegration we also consider the following vector error correction model (VECM):

$$\Delta y_t = \Pi(Ay_{t-1} + \alpha + \gamma t) + \sum_{k=1}^{n-1} \Gamma_k \Delta y_{t-k} + \delta + \epsilon_t, \qquad (2)$$

where y_t is the vector $(p_t^m - p_t,\ q_t)$, and A is the vector of coefficients in the cointegrating relationship given by $[1\ \ -\beta]$. In this case, long-run pass-through is given by the parameter β. We find strong evidence of a cointegrating relationship between real import prices and the real exchange rate.[20]

To measure long-run pass-through for U.S. exports, we use an aggregate pass-through regression and VECM analogous to equations (1) and (2).[21] To get a pass-through measure for exports that is comparable to the measure we use for imports, we adopt the viewpoint of foreign importers of U.S. products. Our aggregate pass-through regression for exports thus regresses the foreign currency price of U.S. exports relative to the foreign currency price of foreign production on current and past values of the real exchange rate.

We use the NIPA price deflator for non-oil goods imports and non-agricultural goods exports. Our sample period is from 1982 through 2007. We begin our sample in 1982 because this is when the import and export price indexes were introduced in the United States. The exchange rate variable we use is the Federal Reserve's trade weighted real exchange rate index for major currencies.[22] We

[19] It is common to interpret incomplete pass-through as evidence of "pricing to market". However, there are a number of other potential reasons for empirical estimates of $\beta < 1$, as emphasized, for example, by Goldberg and Knetter (1997). Knetter (1989) and Marston (1990) pioneered empirical estimation of pricing to market using micro-data, which allows one to control for some other reasons for $\beta < 1$ in ways that are not possible using aggregate data. One potentially important reason why $\beta < 1$ is that imports into the U.S. contain components produced in the U.S. and exported. In addition, general equilibrium effects can drive a wedge between incomplete pass-through and pricing-to-market (see, e.g., Corsetti et al. 2008, and Bouakez and Rebei 2008).Bouakez and Rebei (2008)

[20] We reject the null hypothesis of no cointegrating equations using the Johansen trace statistic method (Johansen, 1995). The Schwarz Bayesian information criterion selects one lag in the vector error correction model, so we set $n = 2$.

[21] For exports, we again reject the null hypothesis of no cointegrating equations. The Schwarz Bayesian information criterion selects two lags in the vector error correction model, so we set $n = 3$. We allow for a structural break in the cointegrating relationship for exports in 2004 by adding a dummy variable that is equal to one in the first quarter of 2004 and thereafter into the vector y_t. This dummy variable accounts for an apparent level shift in the cointegrating relationship between export prices and the real exchange rate after 2004.

[22] The major currency exchange rate series seems more appropriate than the broader index for two reasons. First,

use consumer prices as our proxies for the prices of overall U.S. and foreign production.

Results for the four pass-through regressions discussed above are presented in Table 1. We find that the aggregate pass-through regression and the VECM yield similar estimates of long-run pass-through. For imports, the aggregate pass-through equation yields an estimate of 0.43, while the VECM yields an estimate of 0.41. These estimates are broadly in line with the existing literature on exchange rate pass-through. For example, Campa and Goldberg (2005) estimate long-run pass-through for U.S. imports to be 0.42 for the period 1975 to 2003. For export prices, the aggregate pass-through equation yields an estimate of long-run pass-through 0.85, while the VECM yields an estimate of 0.87.

Figures 2 and 3 display the stability of the relationship documented above. Figure 2 plots the relative dollar price of U.S. imports $p_t^m - p_t$ and the fitted values based on the cointegrating relationship, $\hat{\beta} q_t$. The two series are normalized to have the same means and detrended. Figure 3 plots analogous series for the case of exports. Over this time period, these relationships—both for imports and exports—have been quite stable aside from an apparent one-time upward level shift in the price of exports after 2003.

Several researchers have argued that exchange rate pass-through into U.S. imports has fallen in recent years (e.g., Olivei, 2002; Marazzi and Sheets, 2007). Table 2 reports pass-through estimates for U.S. imports from both the aggregate pass-through regression and the VECM for two subsamples: 1982-2008 and 1994-2008. Aggregate pass-through is indeed estimated to be quite a bit lower in the recent subsample—0.32 compared to 0.43 over the longer sample period. The results for the VECM, however, suggest that this apparent fall in pass-through might partly be due to model misspecification. For the VECM, the long-run pass-though estimate is slightly higher for the recent sample than it is for the longer sample—0.46 versus 0.41. Marazzi et al. (2005) and Hellerstein et al. (2006) show that pass-through estimates for this period are sensitive to whether commodity prices are included in the regression as a separate regressor.

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the weights in the import and export price index are often 3-5 years out of date. This implies that the growing role of countries outside the group of major currencies is captured only with a substantial lag and is therefore small for the majority of our sample period. Second, the major exchange rate index is potentially more similar to an index of non-oil import prices. However, we also estimated these regressions with the Federal Reserve's broad exchange rate indexes and we discuss the results for these alternative regressions in section 5. Which exchange rate measure we use here is not important for the main results of the paper since they involve the calculation of an adjustment factor that can be applied to pass-through estimates based on either exchange rate measure.

4 Prices and Exchange Rates: Theory

Consider an economy in which consumers purchase and consume a continuum of products, some of which are domestically produced and some imported. In each period, a fraction of both home and imported products are discontinued and an equal number of home and imported products are introduced. Some of the new products are new versions of the older products. Other new products are unrelated to the products that are discontinued that period. The amount of product churning may vary over time and depend on the state of the economy.

Products from region i enter the consumer's utility function through the following consumption aggregator

$$C_{it} = \left[\int_{J_i} (\gamma_{jit} C_{jit})^{\frac{\theta-1}{\theta}} dF(j) \right]^{\frac{\theta}{\theta-1}},$$

where C_{jit} denotes the number of units of product j produced in region i and consumed at time t, γ_{jit} denotes the quality of each of these units measured in terms of utility, $F(j)$ denotes the weight given by the consumer to product j and J_i denotes the set of products consumed from region i. Notice that we allow product quality for the product indexed j to change over time. Below we equate changes in quality with product turnover.

Let P_{jit} denote the price per unit of product j in region i at time t. The price index that gives the minimum cost of an additional unit of utility is then given by

$$P_{it} = \left[\int_{J_i} \left(\frac{P_{jit}}{\gamma_{jit}} \right)^{1-\theta} dF(j) \right]^{\frac{1}{1-\theta}}. \tag{3}$$

On the firm side of the economy, firm j in region i produces products according to the following production function

$$C_{jit} = \gamma_{jit}^{-1} F(K_{jit}, L_{jit}).$$

The function F is homogeneous of degree one in capital, K_{jit}, and labor, L_{jit}. Quality enters the production function multiplicatively. This implies that to raise the quality of its products by a factor ξ and produce the same number of units the firm must employ ξ times as much of each factor input. In other words, it costs the firm twice as much to produce products that are twice as good in utility terms.

Now let $\hat{C}_{jit} = \gamma_{jit} C_{jit}$ denote effective consumption of product j at time t and let $\hat{P}_{jit} = \gamma_{jit}^{-1} P_{jit}$ denote the corresponding effective price. Using these concepts, it is possible to rewrite both the consumer problem and the firm problem entirely without reference to γ_{jit}. In particular, the consumption aggregator and the price index become

$$C_{it} = \left[\int_{J_i} \hat{C}_{jit}^{\frac{\theta-1}{\theta}} dF(j)\right]^{\frac{\theta}{\theta-1}} \quad \text{and} \quad P_{it} = \left[\int_{J_i} \hat{P}_{jit}^{1-\theta} dF(j)\right]^{\frac{1}{1-\theta}}.$$

And the production function becomes

$$\hat{C}_{jit} = F(K_{jit}, L_{jit}).$$

This implies that the equilibrium allocations generated by models with this set of assumptions about product quality are the same as those of any number of standard models in the macroeconomics and international economics literature. The equilibrium allocations generated by standard models simply refer to effective consumption and effective prices in the corresponding model with changing product quality. Changing product quality, however, complicates the empirical evaluation of standard models if product quality is not observed. In this case, the models generate data on effective prices and quantities, while the real world data consists of raw prices and quantities.

Prices in the economy are sticky in local currency. Furthermore, the degree of price rigidity varies across firms. Let k index all firms that adjust their prices with probability $f_k(s)$ when the economy is in state s. It is not important for our purposes to describe what features of the economic environment govern the state-dependence of the frequency of price change. We therefore leave this unspecified.[23] Let P^*_{kt} denote the optimal price set by firms in product group k that adjust in period t. We assume that P^*_{kt} is independent of the time of the last price change of the product as well as the time the product was introduced into the economy. We make no assumption about the price firms set when they introduce products. Any difference between this price and P^*_{kt} is explicitly accounted for in our bias adjustment (by the α introduced below). We make no assumption about the dynamics of P^*_{kt} relative to the exchange rate. If strategic complementarity is important in price setting, movements in P^*_{kt} may lag movements in the exchange rate significantly.

Let $z(s)$ denote the fraction of products that are discontinued in state s. As noted above, we assume that an equal number of new products are introduced as are discontinued in each period. We therefore refer to $z(s)$ as the rate of product replacement. We model a product replacement as a change in γ_{jit}. For simplicity, we assume that each time a product is replaced, a new γ_{jit} is drawn from a distribution $\Gamma_t(s)$ and this level of quality remains constant for product j until it

[23] Also, our results are not sensitive to the strength of the "selection effect" (Golosov and Lucas, 2007). The selection effect affects the speed of price adjustment but does not affect the amount of long-run price adjustment. We have used the "CalvoPlus" model in Nakamura and Steinsson (2010) to verify this.

undergoes another replacement. In other words,

$$\gamma_{jit} \begin{cases} \sim & \Gamma(s) \quad \text{with probability } z(s) \\ = & \gamma_{jit-1} \quad \text{otherwise} \end{cases}$$

The distribution of product quality, $\Gamma(s)$, has no impact on our results since firm profits and consumer welfare depend only on quality adjusted prices and since inflation depends on price relatives $(\hat{P}_{jt}/\hat{P}_{j,t-1})$ for which quality drops out.[24]

4.1 Price Measurement

The government seeks to measure the changes in the price of imports over time. If the government could observe P_{ijt} and γ_{ijt} for all products as well as θ, it could calculate the ideal price index (3). In practice, the elasticity of substitution across products is not observed. We assume that the government is willing to make do with a first-order Taylor-series approximation to the logarithm of the ideal price index in order to avoid having to estimate θ. Written in terms of the change in the price index, this yields

$$\Delta p_{it} = \int_{J_i} \Delta \hat{p}_{jit} dF(j). \tag{4}$$

where lower case variables denote logarithms of upper case variables.[25] Notice, that here we are assuming that the government can measure the quality adjusted prices $\hat{p}_{jit}$. We will refer to this price index as measuring the "true" change in prices.

A major practical problem facing the government as it seeks to construct a price index is the fact that product quality γ_{ijt} is difficult to measure. The ideal solution would be to use hedonic methods to estimate product quality. However, such methods are rarely used in practice because they are extremely costly and difficult to apply in most cases. In practice, price comparisons that involve a change in quality—i.e., product replacements—are usually dropped from the index. Indexes constructed in this way are referred to as "matched model indexes". It is also prohibitively costly to measure the prices of all imports. The government therefore collects a sample of import prices each period to construct a price index. In our notation, a matched model index based on a sample of products is

$$\Delta p^{mm}_{it} = \int_{N_i} \Delta p_{jit} dF(j), \tag{5}$$

[24] If movements in the real exchange rate are systematically associated with movements in markups for new products—perhaps because of a combination of systematic movements in quality and non-CES demand—then the types of biases we consider associated with product replacement may be further exacerbated. See Auer and Chaney (2009) and Rodriguez-Lopez (2008).

[25] This price index is a special case of the Tornqvist index with fixed weights.

where N_i denotes the sample from J_i for which raw price changes can be constructed. The raw price change cannot be constructed in the period in which the product is introduced into the government's sample since the difference in the quality between the new product and the old product exiting the sample is unknown.

4.2 Product Replacement Bias: A Factor Calculation

Consider the following regression of the change in the true import price index on a vector of current, lagged (and possibly future) changes in the exchange rate denoted by Λ_t,

$$\Delta p_{it} = \alpha + B\Lambda_t + \epsilon_t, \tag{6}$$

where B is a vector of coefficients. The vector Λ_t is meant to include all exchange rate changes that are correlated with Δp_{it}. In practice, this includes the current and a number of lagged exchange rate changes. Our primary interest is long run pass-through or $\sum_n B_n$, where B_n denotes the nth element of B. Given equation (4), it is straight-forward to show (see appendix A.1 for details) that the vector of regression coefficients for this regression, B, may be "decomposed" as

$$B = \int_S \int_{J_i} B_k(s) dF_s(k) ds, \tag{7}$$

where $F_s(k)$ denotes the distribution of the frequency of price change in state s and $B_k(s)$ is calculated as follows. Consider constructing a sub-price index, $\Delta p_{ikt}(s)$, that consists of all price change observations for products in product group k and state s and regressing this sub-price index on Λ_t. $B_k(s)$ denotes the resulting vector of coefficients. Equation (7) allows us to analyze each product group k and each state of the world s separately and then take an average over products and states.[26] An analogous decomposition is possible if the dependent variable in regression (6) is the change in the price index collected by the government, Δp_{it}^{mm}. Denote the regression coefficients from such regressions analogously by B^{mm} and $B_k^{mm}(s)$.

In the absence of product replacements, changes in the optimal price—the price $p_{ikt}^*(s)$ that firms adjust to when they change their prices—over a particular span of time are always eventually incorporated into the government's price index and estimates of the pass-through regression (6) through the subsequent price change. Thus, in this case, all movements in the optimal price

[26] Here we must assume that for each state of the world we have data from enough time periods that $B_k(s)$ is identified. This implies that the state space for the frequency of price change and the frequency of substitutions must be somewhat "coarser" than the state space for the aggregate variable Λ_t.

are eventually "accounted for." The presence of product replacements complicates matters by potentially leaving some time periods "unaccounted for" even in the long run.

To build intuition, consider a simple case in which the government's dataset consists of a sample of "product lines." Product replacement arises in this case because one model of a product is replaced by a new model. Suppose for simplicity that the new model is introduced with a new price equal to the optimal price $p^*_{ikt}(s)$. In this case, changes in the optimal price that occur following the last observed price change of the old model are "accounted for" by the price change at the time when the new model enters the dataset. In the case of a matched model index, however, this price change is dropped (due to the difficulty of measuring quality changes). This implies that changes in the optimal price that occurred after the old model's last measured price change but before the product exits the dataset are never "accounted for" and thus never incorporated into the government's price index or the pass-through regression (6). The fact that product replacements leave a fraction of time periods in the governments' dataset "unaccounted for" in this way is what gives rise to product replacement bias.

In this product line example, it is simple to calculate the fraction of time "accounted for" in the matched model index. All time periods belonging to price spells that end with a price change that does not coincide with a product replacement are accounted for. All time periods that belong to price spells that end with a product replacement are not. The fraction of time accounted for in the matched model index is thus equal to the fraction of price spells that do not end with a product replacement. This fraction is

$$\frac{f_k(s)}{f_k(s) + z(s) - f_k(s)z(s)}. \tag{8}$$

Since this is the fraction of time periods accounted for in the government's matched model price index, this is also the fraction of exchange rate movements that are captured in the pass-through regression (6) when the government's matched model price index is used as the dependent variable. True pass-through in product group k and state s is then understated because of product replacement bias by the factor in equation (8). Notice that the assumption that gives rise to product replacement bias in this simple case is the assumption that periods of product replacement are "special" in that all new models are introduced with a "fresh" price—i.e., product replacements represent a "free" opportunity to change prices. This implies that a disproportionate amount of price adjustment occurs at these points (because the frequency of price change is one as oppose to $f_k(s)$) and, thus, a disproportionate amount of adjustment is "lost in transit" by a matched model index.

Integrating over k and s and assuming for simplicity that long-run pass-through is the same for all products yields an overall bias factor of

$$\int\int \frac{f_k(s)}{f_k(s)+z(s)-f_k(s)z(s)} dF_s(k)ds. \tag{9}$$

Since the function $f_k(s)/(f_k(s)+z(s)-f_k(s)z(s))$ is concave in $f_k(s)$, product replacement bias is greater the greater is the amount of heterogeneity in the frequency of measured price changes across products.

In practice, not all product replacements in the dataset are product upgrades for a well defined "product line." Rather some products are discontinued without being replaced and other unrelated products are introduced into the dataset. This gives rise to the complication that the timing of product introductions into the dataset may not always coincide with the timing of price adjustments. In other words, products may enter the dataset with "stale" prices. This implies that it is unclear what periods the first observed price change for any given product accounts for, since we don't actually observe when the previous price change for that product occurred.

To derive the extent of product replacement bias for this more general case, we must introduce some additional notation. Let $B_k^{ch}(s)$ denote the coefficients from regression (6) with the dependent variable constructed as the average price change for products that are changing their price but excluding those that are changing the price for the first time since they entered the dataset. Let $(1+\alpha_{nk}(s))B_{nk}^{ch}(s)$ denote the nth element of the vector of regression coefficients when regression (6) is run with the dependent variable constructed as the average size of the price changes of those products in the dataset that are changing their price for the first time since they entered the dataset. This notation implies that $\alpha_{nk}(s)$ is a factor governing the extent of "overreaction" of the first versus subsequent observed price changes to Λ_{nt}. In section 5, we will present an empirical estimate of $\alpha_{nk}(s)$.

Given this notation, we can state the main result of this section as follows.

Proposition 1. *The relationship between measured long-run pass-through, $\sum_n B_{nk}^{mm}(s)$, and true long-run pass-through, $\sum_n B_{nk}(s)$, in equation (6) is*

$$\sum_n B_{nk}^{mm}(s) = \frac{f_k(s)}{f_k(s)+z(s)-f_k(s)z(s)} \left[\Phi_k(s)\sum_n(1+\alpha_n)B_{nk}(s) + (1-\Phi_k(s))\sum_n B_{nk}(s)\right] \tag{10}$$

where $\Phi_k(s)$ denotes the fraction of all price changes that are the first observed price change for a product

Notice that the term in front of the square brackets on the right hand side of equation (10) is the same factor as in the simple product line case. However, the bias expression also incorporates an adjustment for overreaction of the first observed price change for each product. Intuitively, we allow for the fact that the first observed price change may react more strongly to past exchange rate changes because products may enter the dataset with stale prices. Notice, that if $\alpha_n = 0$ we are back to the simple case of the product-line model.

Proof of Proposition 1: The derivation of equation (10) proceeds in several steps. First, it is useful to consider the set of price spells in product group k and state s that are uncensored, i.e., that are neither the first nor the last observed price spell for the product in question. Let $\Delta p^u_{ikt}(s)$ denote the change in a price index constructed from a large sample of such price spells (including the price change at the end of each spell but not the price change at the beginning of the spell). Let $B^u_{nk}(s)$ denote the regression coefficients for regression (6) with $\Delta p^u_{ikt}(s)$ as the dependent variable. The first step of the proof is to show that true long-run pass-through is equal to long-run pass-through for the sample of uncensored spells:

$$\sum_n B_{nk}(s) = \sum_n B^u_{nk}(s). \tag{11}$$

We establish this in appendix A.2. The intuition for this result is that the price changes in the sample used to construct $\Delta p^u_{ikt}(s)$ account for movements in the optimal price over exactly the time period for which the product is included in $\Delta p^u_{ikt}(s)$.

Second, notice that the frequency of price change for uncensored price spells used to construct $\Delta p^u_{ikt}(s)$ is equal to the hazard that such price spells end each period, which is $f_k(s)+z(s)-f_k(s)z(s)$ (see appendix A.3 for a derivation). Intuitively, the frequency of price change in this sample is higher than the frequency of price change in the full government sample because long price spells are more likely to be censored than short spells. Given this, the properties of the OLS estimator imply that the pass-through coefficients for the sample of uncensored spells is

$$B^u_{nk}(s) = (f_k(s) + z(s) - f_k(s)z(s))B^{ch}_{nk}(s). \tag{12}$$

Intuitively, $B^u_{nk}(s)$ is a scaled down version of $B^{ch}_{nk}(s)$ since the observations with no price change contribute nothing to $B^u_{nk}(s)$. The scaling factor is the fraction of observations that have a price change in the sample that is used to construct $B^u_{nk}(s)$.

Third, combining equations (11)-(12), implies that true long-run pass-through is

$$\sum_n B_{nk}(s) = (f_k(s) + z(s) - f_k(s)z(s)) \sum_n B^{ch}_{nk}(s). \tag{13}$$

Fourth, we derive a relationship between pass-through for price change observations—$B^{ch}_{nk}(s)$—and measured pass-through for a matched model index—$B^{mm}_{nk}(s)$. To do this we must take account of the potential overreaction of the first observed price change represented by α_n. In the full sample, the frequency of observed price changes is $f_k(s)$. Using this fact and the same logic as we used to derive equation (12), we find that measured long-run pass-through is

$$\sum_n B^{mm}_{nk}(s) = f_k(s)\left[\Phi_k(s)\sum_n(1+\alpha_n)B^{ch}_{nk}(s) + (1-\Phi_k(s))\sum_n B^{ch}_{nk}(s)\right], \tag{14}$$

where $\Phi_k(s)$ the fraction of price changes that are a first observed price change for a product (see appendix A.4 for a derivation).

Finally, combining equations (13) and (14) yields equation (10) ■

To arrive at a factor that applies to pass-through for the entire price index, we must integrate over sectors k and states of the world s. This yields

$$\begin{aligned}\sum_n B^{mm}_n = \int\int \frac{f_k(s)}{f_k(s)+z(s)-f_k(s)z(s)} & \left[\Phi_k(s)\sum_n(1+\alpha_n)B_{nk}(s)\right.\\ & \left. +(1-\Phi_k(s))\sum_n B_{nk}(s)\right] dF_s(k)ds. \end{aligned} \tag{15}$$

Since we allow both the frequency of price change and pass-through to vary across sectors, our model can accommodate the type of heterogeneity emphasized by Gopinath and Itskhoki (2010a).

The factor calculation above focuses on regressions in which the dependent variable is Δp^m_t rather than $\Delta(p^m_t - p_t)$. In practice, there is a slight positive correlation between prices and the real exchange rate, which implies that equation (15) yields a slight underestimate of product replacement bias. For the case of $\alpha_n = 0$, our derivations for product replacement bias also extends easily to the VECM specification.[27] In section 5, we show that $\alpha_n = 0$ is the empirically relevant case.[28]

The discussion above considers the case of local currency priced (LCP) products and shows that for these products, product replacement bias causes a *downward* bias in measured pass-through. However, product replacement bias causes an *upward* bias in measured pass-through for producer

[27] With $\alpha_n = 0$, the measured index is simply missing a random fraction of price changes within each product group k and state s. The regression coefficients in the cointegrating relationship for each product group k and state s will therefore be biased downward by this fraction.

[28] In practice, some of the measurement concerns we discuss above also apply to unit value indexes. Price comparisons in unit value indexes are often dropped because of lack of availability of data for the previous period—for example, because the product was not traded in the previous period—potentially leading to product replacement bias. Also, large price changes are often excluded as outliers or trimmed. Alterman (1991) estimates that the U.S. unit value indexes, produced in 1985, were calculated from only 56 percent of the value of imports and 46 percent of the value of exports.

currency priced (PCP) products. To see this, consider a U.S. export into the Euro area that is priced in U.S. dollars (i.e. PCP) and the price of which is only adjusted at the time of product replacements. A matched model Euro area price index based on a collection of such products would display one-for-one comovement with the exchange rate regardless of the true relationship between prices and exchange rates.

Notice that the lifelong regression considered by GIR coincides with our adjusted estimate of aggregate pass-through in the special case when firms' optimal prices are a function only of the current exchange rate, and there is no overreaction of the first observed price change, i.e., $\alpha_n(s) = 0$. (See appendix A.5 for details.) However, if adjustment to exchange rate changes is delayed—e.g., due to strategic complementarities in price setting—lifelong pass-through will be downward biased, while our estimator will yield an unbiased estimate of long-run pass-through. To see this it is helpful to consider an extreme example. Suppose firms desired prices are related to the exchange rate from 2 years prior but that products last only for 2 years in the dataset. In this case, the lifelong regression will yield pass-through of zero regardless of true long-run pass-through since observed price changes are responses to exchange rate movements before a product was introduced, which are not included in the lifelong regression. In practice, this bias is likely to be modest relative to the bias in aggregate pass-through. We explore this issue further in section 6.

A potential alternative approach to solving the problem of product replacement bias in our model economy is to calculate the price index simply as the weighted average of all prices including both new and continuing products. In practice, an import price index calculated from average prices in this way is extremely noisy. The simple average of prices for imports and exports routinely fluctuates by 10-20% per month. This reflects the fact that such an index is comparing the prices of entirely different products—say, last year's wool jacket versus this year's down coat—and products are highly heterogeneous as well as being measured in highly variable units. The massive amount of sampling error in this type of index generates sufficiently large standard errors in the estimated relationship between an average price index and the exchange rate that almost nothing can be concluded about the nature of exchange rate pass-through. A second problem with analyzing average prices is that an appreciation of the exchange rate may lead consumers to systematically switch toward higher quality products. This could bias upward the estimated relationship between prices (per unit quality) and the exchange rate.[29]

Many products in the IPP data are intermediate products. An important question in interpret-

[29]See e.g., Ghironi and Melitz (2005) for a more detailed discussion of this issue.

ing the evidence on price rigidity for imported products is thus whether the observed rigid prices are "allocative" (Barro, 1977). We do not address this issue, since our focus is on documenting rather than interpreting the observed relationship between prices and exchange rates. However, it is worth noting that this phenomenon is less likely to influence the long run relationship between prices and exchange rates than it is to affect the short term dynamics of this relationship.

4.3 Sample Rotation and Reporting Errors

The discussion above implicitly makes two assumptions that we can relax easily. First, we can allow the frequency of product replacement in the government's dataset to differ from that in the economy as a whole. This may arise if the government rotates products out of the dataset once they have been in the dataset for a certain amount of time and more generally periodically replaces products to ensure that the products in the dataset reflect well actual imports and exports.

As we discuss in detail in section 5.2, an additional potential measurement problem is "satisficing" behavior by firms that are contacted about their prices, i.e., the tendency of firms to report no change in price even if a price change or product substitution has occurred because reporting no change requires less effort by the reporter. We can allow for this type of reporting error by assuming that firms make accurate price reports with probability $g(s)$ and report no-change irrespective of the accuracy of that report with probability $1 - g(s)$.[30]

Sample rotation and satisficing behavior by firms implies that the measured frequency of price change and product replacements in the government's dataset will be different from their true value. Let $\tilde{f}_k(s)$ denote the measured frequency of price change in the government's data for product group k in state s and $\tilde{z}(s)$ the measured frequency of product replacement in the government's data set. Expressions for these rates in terms of $f_k(s)$, $z(s)$, and $g(s)$ are derived in appendix A.6.

In our model extended to include sample rotation and reporting errors, we can follow exactly the same steps as above to derive a product replacement bias factor. The only difference is that the frequency of price change and the frequency of substitutions that enter the factor become the measured frequency of price change, $\tilde{f}_k(s)$, and the measured frequency of product replacement $\tilde{z}(s)$.[31]

[30]We would like to thank Virgiliu Midrigan for suggesting that we incorporate this feature into our model.

[31]For tractability, here we assume that both the true price index—equation (4)—and the matched model price index—equation (5)—are subject to reporting error. In other word, we define the "true" price index as an index of the quality-adjusted prices firms would report if they were all in the government's dataset and had the same tendency to erroneously report no-change as the firms that are actually in the government's dataset. The difference between the two indexes is then entirely due to product replacement bias. However, our results are not sensitive to this

5 Prices and Exchange Rates: Measurement

Before the introduction of the IPP, import and export price indexes were based on unit value data for highly disaggregated categories. This practice was criticized by, among others, the Stigler Commission (Stigler et al., 1961) because it did not control for changes in quality and composition within these categories. It has since become an important part of the BLS mandate to track the prices of exactly identical items over time to avoid mistaking quality changes for price changes. The IPP therefore takes great care in the way it defines a product. The definition of a product in the IPP data includes not only a unique product identifier such as a bar code, but also other "price determining characteristics" identified by the BLS such as the terms of the transaction, size of the shipment and in some cases even the identity of the seller. We adopt the product definitions in the IPP. A product, as we use the term, is therefore often a contract between a particular buyer and seller. A new product is not necessarily totally new to the world but rather new to a particular buyer-seller interaction. Carlton (1986) shows that defining products in this way is crucial in analyzing price rigidity for producer prices—which often differ across purchasers and may be infrequently renegotiated over the course of a given buyer-seller relationship even if average prices for a product change more frequently.[32]

5.1 The Frequencies of Price Change and Product Replacement

We show in section 4 that product replacement bias is most severe when the frequency of product replacements is large relative to the frequency of price change. Table 3 reports our estimates of the weighted fraction of products that have less than or equal to 0, 1, 2, 3 and so on price changes. For LCP imports, 44% of products have no price changes, while 69% have two or fewer price changes. For PCP exports, 39% of products have no price changes, while, 68% have two or fewer price changes. These statistics motivate the idea that product replacement bias may be a quantitatively important phenomenon in import and export price data.[33]

assumption.

[32]In our data, the frequency of product substitutions is slightly higher for exports than for imports. This is interesting because the export price data is gathered from sellers while the import price data is gathered from buyers. If sellers have list prices which apply to a large number of customers for each product, one might expect substitutions to be more frequent in data gathered from buyers than in data gathered from sellers. Each time the buyer switched products, a product substitution would occur in import price data. But in the export price data the BLS would continue to sample the product as long as there was another buyer buying at the same price. We do not find support for this in the data. This supports the view that there is a great deal of price dispersion across different buyers for identical products (Carlton, 1986).

[33]Our estimate of the fraction of price spells with no price change is somewhat higher than the estimate of Gopinath, Itskhoki, and Rigobon (2010). Most of the difference arises because our estimate is for the entire dataset, while theirs

The small number of price changes per product reflects substantial price rigidity and frequent product replacement in the microdata on import and export prices collected by the BLS. Table 4 reports statistics on the frequency of price change and product replacement. We report these statistics separately for imports and exports as well as for LCP and PCP products.[34] Most U.S. imports are local currency priced (92%), while most U.S. exports are producer currency priced (97%). Our discussion therefore focuses on these two categories.

Product replacements occur for a number of reasons in the IPP data. Consequently, we report three different measures for the frequency of substitution. About half of all product replacements occur either because the firm no longer sells the product in question or because the firm itself has gone out of business. We refer to these product replacements as forced substitutions. The frequency of forced substitution of 2.5% for LCP imports and 2.0% for PCP exports. In the case of roughly one quarter of product replacements, the firm refuses to provide a new price quote without giving a reason. Some of these cases may also involve the product being discontinued.[35] The frequency of forced substitutions including refusals is 3.7% for LCP imports and 3.2% for PCP exports. The remaining 25% of product substitutions in the IPP dataset are due to product phaseout by the BLS. The overall frequency of substitutions is 4.9% for LCP imports and 4.6% for PCP exports. For our baseline results on product replacement bias, we use the more conservative measure of forced substitutions.[36]

is for a subset of high income OECD countries. Another difference is that our estimates incorporate product-level weights.

[34]We calculate the frequency of price change by constructing an indicator variable for whether a price change occurred and taking the mean of this variable. We calculate the frequency of product substitutions as the total number of product substitutions observed in the data, divided by the total number of periods that the price series are observed. The series we use for this are constructed by "filling in" the previously observed price through the large number of missing spells in the import price data as we discuss in section 2. This is the procedure used by the BLS in many but not all cases when prices are missing. See section 2 for a discussion of BLS imputation procedures. The key object when it comes to the size of product replacement bias is the amount of time over which exchange rate movements may be "unaccounted for" by subsequent price changes because they occur at the end of a price series. This is unaffected by price changes that are subsequently reversed, such as those associated with the BLS cell mean imputation procedure. We discuss this issue in greater detail in Appendix E. All of the statistics we report are calculated as weighted averages using the item-level weights described in section 2.

[35]It is difficult to estimate the fraction of substitutions that involve a version change or upgrade. There are at least two reasons why this variable in the dataset is unreliable. First, for most of the time period we study, to qualify as a version change or upgrade, the replacement product must fall into the same HS10 category. Since these categories are extremely disaggregated, it often happens that the replacement product falls in a different HS10 code. For example, male cows and female cows have different HS10 codes as do VHS players and DVD players. Second, BLS economists have indicated to us that many product discontinuations are followed by reinitiations of similar products by a BLS field agent. This may happen because firms find it easier to simply discontinue a product than to report the details of a replacement product to the BLS.

[36]In some cases, the IPP deems a change in a product to be sufficiently small that the concurrent change in price is used in the index with no adjustment for a change in quality. In these cases, the IPP does not record a product substitution. Also, if a product tends to differ from one shipment to the next, it is often considered "out-of-scope" by IPP since the IPP seeks to select product that can be repriced consistently. The IPP index is, therefore, likely to

Table 4 also shows that both imports and exports exhibit substantial price rigidity. For LCP imports, the mean monthly frequency of price change is 15.1% and the median is 6.6%. For PCP exports, the mean monthly frequency of price change is 13.0% while the median is 6.0%. These statistics parallel those reported in Gopinath and Rigobon (2008), though our analysis differs somewhat from theirs in that we study a longer time period, and make use of product-level weights.

Heterogeneity in the frequency of price change is an important determinant of the quantitative impact of product replacement bias as we discuss in section 4.2. The frequency of price change varies widely across different sectors for imported products—from over 40% for Animal Products and Vegetables to less than 10% for such categories as Footware, Textiles and Machinery. There is also much heterogeneity within each sector. Since the adjustment factor for product replacement bias is highly concave in the frequency of price change, ignoring intra-sector heterogeneity would seriously bias our estimate of product replacement bias. We therefore estimate a flexible distribution for the overall heterogeneity in the frequency of price change across products. Suppose that a product j has a constant hazard of adjusting its price, f_j, in each month. Suppose also that $f_j \sim \mathrm{Beta}(a, b)$. We denote the product's lifetime by n_j. The total number of price changes x_j for a product are then distributed according to a binomial distribution, i.e., $x_j \sim \mathrm{Bin}(n_j, f_j)$.

In appendix C, we derive a simple expression for the log-likelihood function in this setting. We estimate this model by maximum likelihood for four groups of products: LCP imports, PCP imports, LCP exports and PCP exports. Table 4 reports our estimates for the parameters of the beta distribution. For LCP imports, the estimated parameters are $a = 0.44$ and $b = 3.50$. These parameters imply a very large amount of heterogeneity in the frequency of price change across products. Figure 4 plots the cumulative distribution function of the distribution $\mathrm{Beta}(0.44, 3.50)$. For PCP exports, the estimated parameters are $a = 0.50$ and $b = 4.59$.

The average frequency of product replacement varies less across industry groups than the frequency of price change. The frequency of all product replacements in most industry groups is between 3% and 6%.[37] In our baseline results, we assume a homogeneous frequency of product replacement across goods. We have also considered the robustness of our results to using a sectoral model in which the frequency of substitutions is allowed to vary across sectors and the distribution of the frequency of price change across products within a sector is a different beta distribution for

have somewhat less product turnover than the universe of products.

[37] Product replacement bias is especially important for a number of durable goods categories such as autos, furniture and computers. For autos, the frequency of price change in the IPP is 6.8%, while the frequency of substitution is 5.1%. For furniture, these frequencies are 8.2% and 4.4%, respectively, and for computers they are 13.7% and 5.8%, respectively.

each sector.[38] This model yields very similar results.

5.2 Do First Price Changes React More Strongly to Past Exchange Rates?

In section 4, we show that an important determinant of product replacement bias is the extent to which the first observed price change "overreacts" to historical exchange rate movements relative to subsequent price changes. Simple manipulation of equation (10) (see appendix D for details) implies that a conservative measure of product replacement bias is

$$\sum_n B_n^{mm} = \int \frac{f_k}{f_k + z - f_k z} dF(k) \sum_n B_n + \Psi, \tag{16}$$

where

$$\Psi = z \frac{\bar{d}}{\bar{d}_2} \left[\sum_n (1 + \alpha_n) B_{2n}^{ch} - \sum_n B_{2n}^{ch} \right], \tag{17}$$

$\bar{d}$ denotes the average duration of all price spells, $\bar{d}_2$ denotes the average duration of all price spells of products with two or more price changes, and $\sum_n (1 + \alpha_n) B_{2n}^{ch}$ and $\sum_n B_{2n}^{ch}$ denote the sum of the pass-through coefficients from regression (6) with the first observed price change and second observed price change, respectively, as the dependent variables and restricted to products with two or more price changes.

Equations (16) and (17) clearly indicate that if the degree of overreaction of the first observed price change is sufficiently strong, this can completely eliminate any product replacement bias. However, there are several reasons why such overreaction may not occur. First, a large fraction of product substitutions occur because one product is discontinued, to be replaced by a new product. Firms tend to negotiate new prices when they sign new contracts with their customers and this is also the time when many products are initiated into the dataset (Carlton, 1986).

Second, "satisficing" behavior by firms may result in spurious rigidity for continuing products, while newly introduced products are more likely to be recorded correctly. For continuing products, the BLS collects prices using a "repricing form" that first asks whether the price has changed relative to the previous month and then asks the respondent to report a new price if the price did change. The easiest response is to simply check the box indicating "no change" in price.[39] In contrast, the prices of products that are newly initiated into the BLS dataset are collected using a detailed personal interview and are therefore less likely to be spuriously stale.

[38]This version of the model is discussed in greater detail in appendix B.

[39]Liu et al. (2009) document the severity of this kind of bias in a different context.

The BLS has had a longstanding concern about this issue. In 1988, the BLS carried out a study to investigate it, known as the "Quality Through Correspondence" initiative. In this study, the BLS contacted a sample of firms who had reported "no change" in prices for 24 months or more and asked them to either confirm that their prices were unchanged or provide updated information. They found that the vast majority of firms either reported an updated price or reported that the product had been discontinued. Given the success of this initiative, the BLS implemented a second Quality Through Correspondence initiative on a broader scale in 1999, again targeted at firms who had reported "no change" for 24 months or more. During the initiative, the frequency of price change and discontinuation for the targeted firms rose by 50-100% relative to surrounding periods. Most recently, the BLS carried out a study to analyze how firms' reporting behavior changes over time. They found that when reporters are first initiated into the dataset, they tend to report many price changes, but that fewer price changes are reported over time, suggesting that seasoned reporters tend to become fatigued with the reporting process.

Because of these concerns, the BLS has at some points tried to systematically contact reporters who have reported no change in prices for more than 12 months on the repricing form, as noted by Gopinath and Rigobon (2008). Unfortunately, funding limitations have meant that this policy has not been consistently implemented.[40] Other researchers have considered alternative ways of investigating how important underreporting of price changes might be. In particular, Gopinath and Rigobon (2008) argue that these biases are likely to be small since the frequency of price change was essentially unchanged when the BLS was forced to switch to phone surveys during the 2001 anthrax attacks. However, since reporters were provided with their previous prices over the phone, the phone surveys may have exhibited a similar bias toward "no change" as the regular repricing forms.[41] Our model of product replacement bias in section 4.3 explicitly allows for satisficing behavior by firms.

We measure the extent to which the first observed price change for each product reacts more strongly to past exchange rates than subsequent price changes—i.e., we estimate Ψ—using the BLS micro-data. Our results on this are reported in Table 5. Panel A of Table 5, reports results for the following regression:

$$\Delta p^r_{jk} = \alpha + \beta_S \Delta q_{jk,S} + \beta_{1Q} \Delta q_{jk,1Q} + ... + \beta_{6Q} \Delta e_{jk,6Q} + \epsilon_{jk}, \tag{18}$$

where Δp^r_{jk} denotes the log size of the kth price change for product j relative to the change in the

[40] We thank Rozi Ulichs and Will Adonizio for detailed correspondence on this issue.

[41] See the IPP Data Collection Manual for a discussion of the survey procedure during this episode.

price of domestic production over the kth price spell for product j, Δq_{jkS} denotes the log change in the real exchange rate over the course of the kth price spell for product j and $\Delta q_{jk\#Q}$ denotes the log change in the real exchange rate over the course of the #th quarter prior to the kth price spell for product j. We run this regression for the first and second observed price changes ($k = 1$ and 2) of all products that have two or more price changes. We run these regressions separately for import and exports.

Figure 5 provides a graphical illustration of these "first" and "second" price change regressions—i.e. equation (18) for $k = 1$ and 2. While we do not observe how much prices change when a new good is introduced into the dataset, we can observe how responsive subsequent price adjustments are to exchange rate movements that occurred before the good was introduced. If the first observed price change for each product is more strongly related to exchange rate movements that occur before that product's introduction into the data set than the second observed price change is to exchange rate changes that occurred before the first observed price change, this would suggest that the initial prices of products in our data were not newly reset. In fact, we find no evidence of this.

For imports, the pattern of coefficients is very similar for the first and second price change. In both cases β_S is larger than 0.2. The coefficients then fall rapidly over the first two quarters before the price spell in question and are insignificant in most cases after that. There is no evidence that the first observed price change responds more to exchange rate changes before first price spell than the second observed price change responds to exchange rate changes before the second price spell. Importantly, the average number of months between the time the products in these regressions are introduced and the first observed price is almost exactly the same as the average time between the first and second observed price changes (8.5 and 8.7 months, respectively). The pattern is similar for exports.[42]

Given the pattern of coefficients reported in panel A, we have also run the following more parsimonious specification:

$$\Delta p^r_{jk} = \alpha + \beta_{S+1}\Delta q_{jk,S+1} + \beta_{2-4Q}\Delta q_{jk,2-4Q} + \epsilon_{jk}, \tag{19}$$

where $\Delta q_{jk,S+1}$ denotes the log change in the real exchange rate over the course of the kth price spell and one quarter before this price spell for product j and $\Delta q_{jk,2-4Q}$ denotes the log change in the real exchange rate over the course of the 2nd, 3rd and 4th quarter prior to the kth price spell

[42]For exports, we report the pass-through from the domestic exporters' perspective since these are more easily compared to the results for imports. Pass-through from the foreign importers' perspective is one minus the pass-through reported in the Table 5.

for product j. This regression again yields very similar results for the first and second observed price changes for both imports and exports. There is no evidence that the first observed price change responds more to past exchange rate movements than the second observed price change. If anything, the opposite is true.

We use these results to estimate Ψ (see equation 17). Since the second price change is estimated to be slightly more responsive to past exchange rates, we estimate $\Psi < 0$. Recall that if the first price change overreacts to past exchange rates, Ψ will be positive. Our results thus suggest that factors such as firms' preferences for raising their price when a product is introduced rather than at other times—which can make $\Psi < 0$—may be more important than factors that would lead to $\Psi > 0$. In what follows we set $\Psi = 0$, to be conservative. In this case, product replacement bias simplifies to

$$\sum_n B_n^{mm} = \int \frac{f_k}{f_k + z - f_k z} dF(k) \sum_n B_n. \tag{20}$$

To gauge the robustness of our estimates of product replacement bias to sampling variation, we consider an "upper bound" estimate for Ψ. Specifically, we add two standard errors to the point estimates for the first price change regression and subtract two standard errors from the point estimates for the second price change regression—using our estimates for imports from Panel B in Table 5. We recalculate Ψ based on these alternative values. Using this estimate of Ψ, we report this "lower bound" estimate for true pass-through in Panel C of Table 6. Even for this very conservative measure, our analysis implies a large adjustment to measured pass-through.[43]

5.3 Adjusting Pass-Through for Product Replacement Bias

Given the estimates in Table 4, we can use equation (20) to produce estimates of the factor by which exchange rate pass-through is mismeasured because of product replacement bias. These estimates are reported in Table 6. We assume for empirical tractability that the frequency of price change and the frequency of substitutions are constant over time for each product.[44] We present

[43] We thank an anonymous referee for encouraging us to do this exercise. We have also run a Monte Carlo in which we compare data from a model in which products enter with fresh prices with data from a model in which new additions to the dataset are drawn randomly from the population of products in the economy (and thus enter with stale prices on average). We find substantial differences between the regression on the second and first observed price changes in the latter dataset but not the former.

[44] Empirical evidence suggests that these are reasonable assumptions for the particular application we study. We have regressed the frequency of product replacements for dollar-priced imports and exports on the absolute magnitude of log movements in the trade-weighted exchange rate for the years 1995-2006. The resulting coefficient is -0.023 (0.131) for imports and -0.078 (0.308) for exports, where we report standard errors in parentheses. For periods and countries for which exchange rate variation was more dramatic, there may be a stronger relationship between the frequency of product replacement and the real exchange rate. Burstein, Eichenbaum, and Rebelo (2005) document

estimates of the product replacement bias factor for the three different measures of the frequency of product replacement reported in Table 4 and two sets of assumptions regarding heterogeneity in true pass-through across products with different frequencies of price change.

Our benchmark results are presented in the first data column of panel A of Table 6. In this case, we use the most conservative measure of product replacement.[45] We also allow for variation in true pass-through across products with different frequencies of price change. Gopinath and Itskhoki (2010a) argue that this pattern exists in the data. Their estimates suggest that true pass-through for LCP imports with a frequency of price change below about 25% per month is only about 65% of true pass-through for LCP imports with a higher frequency of price change.[46] Under these assumptions, the factor by which traditional estimates of pass-through are biased because of product replacement bias is 1.63 for LCP imports and 1.57 for PCP exports. The next two columns report factors for our other two measures of the frequency of product replacement.

Using these factors, we can adjust measured exchange rate pass-through for product replacement bias. The results of these calculations for the aggregate pass-through regression are reported in the lower panel of Table 1 (and also in Table 6). Gopinath, Itskhoki, and Rigobon (2010) argue that there is a large difference in pass-through between LCP and PCP imports. We allow for this difference in our calculations. We adopt their estimate of 0.94 for measured pass-through of PCP imports and use this in our calculation of aggregate pass-through adjusted for product replacement bias.[47] For exports, virtually all products are PCP. So, any reasonable heterogeneity across LCP and PCP products makes virtually no difference.

For our benchmark measure of the frequency of product replacement, adjusting for product replacement bias raises exchange rate pass-through for U.S. imports from 0.43 to 0.64 and lowers exchange rate pass-through for U.S. exports from 0.85 to 0.79. For our other measures of the frequency of substitutions, the adjustment is even larger. The adjustment based on the overall frequency of substitutions yields exchange rate pass-through for both U.S. imports and exports of

clear evidence of a rise in the number of products that ceased to be imported into Argentina at the time of Argentina's 2000-2002 financial crisis and devaluation. In this case, it would be important to account for time variation in the frequency of price change and frequency of substitutions when calculating the adjustment factor.

[45] The analysis in section 4.3, indicates that we should use the overall frequency of product substitutions when estimating product replacement bias—as opposed to only the frequency of product substitutions that coincide with products entering the economy. However, to be conservative, we adopt a more restrictive measure of the frequency of product substitutions for our benchmark results.

[46] This difference in measured true pass-through could alternatively arise due to spurious price changes in the micro data. See section 2 for a discussion of reasons why spurious price changes may exist in the micro data on imports and exports.

[47] Reasonable variations on this assumption have negligible effects on our results.

0.74.

In Table 6, we presents results for several additional cases. We report results for cases in which true long-run pass-through does not vary with the frequency of price change. This raises the product replacement bias factor by about 0.1. We also present results using the Fed's "Broad" real exchange rate series. Measured pass-through is somewhat higher for imports and slightly lower for exports using the Broad real exchange rate. Using this exchange rate series and our benchmark assumptions about the frequency of product replacement and heterogeneity in true pass-through yields a pass-though estimate of 0.80 for imports and 0.77 for exports.

5.4 Adjusting the Terms of Trade for Product Replacement Bias

Our results indicate that the U.S. import and export price indexes are too smooth. One consequence of this is that the U.S. terms of trade is also too smooth. Above, we focus on results for long-run pass-through. In section 6, we estimate a simple model of the dynamics of pass-through. Using this estimated model, we can construct time series for the U.S. import and export price indexes that are adjusted for product replacement bias.[48]

Adjusting for product replacement bias raises the standard deviation of the quarterly change in the log price index for non-oil imported goods from 1.1% to 1.6%, while it raises this measure of volatility for non-agricultural exported goods from 1.1% to 1.9%. Figure 6 plots the U.S. terms of trade adjusted for product replacement bias along with the same series without such an adjustment.[49] The standard deviation of the quarterly change in the terms of trade rises by 75% from 0.97% to 1.70%.

This adjustment for product replacement bias brings the data closer in line with standard models. Simple two country RBC models imply that the terms of trade should be more volatile than the real exchange rate. The official non-oil terms of trade is however only about 30% as volatile as the real exchange rate. Adjusting for product replacement bias raises the volatility of the terms of trade to about half the volatility of the real exchange rate. New Keynesian models designed to match the volatility of the real exchange rate generate a more volatile terms of trade series than

[48] We first simulate data from the estimated model in section 6. We then construct a matched model index and the true price index from this data (we can construct the true index since we know the relative quality of different products in our simulation). We then run a regression of the true index on the current value and eight lags of the matched model index. Finally, we apply the resulting filter to the U.S. import and export price indexes from 1982 to 2010.

[49] For comparability to the rest of our analysis, the measure of the terms of trade we present here is the ratio of the price index for non-oil imported goods and non-agricultural exported goods.

the official series (Corsetti et al., 2008). Adjusting the terms of trade for product replacement bias raises its volatility in the data to roughly match its volatility in these models.

6 Alternative Measures of Pass-Through

In addition to analyzing "aggregate" pass-through—based on a regression similar to equation (1)—GIR propose two alternative pass-through measures: pass-through "conditional on adjustment" and "life-long" pass-through.[50] In this section, we study the implications of product replacement bias for these alternative statistics. We make two main points. First, low pass-through "conditional on adjustment" is entirely consistent with a large bias in aggregate pass-through and much higher pass-through in the long-run. Second, GIR's finding that life-long pass-through is much higher than aggregate pass-through are corroborating evidence for our findings of large biases in aggregate pass-through associated with product replacement bias. We also use the analysis in this section to construct the adjusted measure of the U.S. terms of trade presented in section 5.4.

GIR define pass-through "conditional on adjustment" as β_Δ in the regression,

$$\Delta(p_{jit} - p_t) = \alpha + \beta_\Delta \Delta^* q_t + \epsilon_{jit}, \tag{21}$$

where Δ^* is a difference operator representing the difference between the current real exchange rate and the real exchange rate at the time of the previous price change of product j (or in the case of the first price change of product j, the introduction of product j). They define "life-long" pass-through as $\beta_{\tilde{\Delta}}$ in the regression,

$$\tilde{\Delta}(p_{jit} - p_t) = \alpha + \beta_{\tilde{\Delta}} \tilde{\Delta} q_t + \epsilon_{jit}, \tag{22}$$

where $\tilde{\Delta}$ is a difference operator representing the difference between the time the product is introduced into the dataset and the time of the last new price.

Table 7 reports the results of these regressions for our main specification and sample, which extends the sample used in GIR to more countries and a slightly longer time period. The results are very similar to their original findings.[51] Pass-through conditional on adjustment is 0.24, while

[50] Life-long pass-through is motivated in part by concerns regarding the effects of product substitutions on aggregate indexes similar to those we emphasize here.

[51] Our sample and specification differ from GIRs in the following ways. First, they focus on a sample of high-income OECD countries that have a non-negligible number of non-dollar priced goods, while we include all countries. In addition, our analysis covers a slightly longer time period, and uses the trade-weighted as opposed to the bilateral real exchange rate. While the choice of high-income OECD countries yields higher pass-through than when all countries are included, the use of bilateral exchange rates yields lower pass-through than the trade-weighted exchange rate. The two effects roughly cancel out, implying that the results in Table 7 is very similar to the results reported in GIR.

life-long pass-through is 0.51, roughly twice as high. Life-long pass-through is lower for the sample of products with a low frequency of price change, consistent with the results reported in Gopinath and Itskhoki (2010b) and used to calibrate our model in section 5. The aggregate measure of long-run pass-through based on the dynamic adjustment equation is 0.33, much lower than the estimate of long-run pass-through based on the "life-long" approach.[52]

To be able to capture the large differences between the alternative pass-through measures documented in Table 7, we extend the model presented in section 4 by specifying a process for the evolution of firms' desired prices. This yields a full quantitative model of pass-through that is nested within the framework presented in section 4 and shares many features with the models analyzed in GIR and Gopinath and Itskhoki (2010a), but incorporates additional features that generate product replacement bias. We allow for delayed adjustment to exchange rate movements due to strategic complementarities. We parameterize these in a reduced-form way by assuming that desired prices p^*_{jit} are affected by a distributed lag of past real exchange rates

$$p^*_{jit} - p_t = \phi \Upsilon \sum_{s=0}^{23} \psi^s q_{it-s} + \eta_{jit}, \tag{23}$$

where $\Upsilon = (1-\psi)/(1-\psi^{24})$. The parameter ϕ governs the overall level of long-run pass-through, while ψ determines the degree to which pass-through is delayed.[53] As in our previous analysis, we allow for heterogeneity in ϕ across products that is correlated with the frequency of price change. The variable η_{jit} captures all influences on p^*_{jit} that are orthogonal to the real exchange rate. It follows the stochastic process,

$$\eta_{jit} = \mu + \rho \eta_{jit-1} + \epsilon_{jit}, \tag{24}$$

where $\epsilon_{jit} \sim \mathrm{N}(0, \sigma^2_\epsilon)$.

We also allow for measurement error in the timing of price observations. This is motivated by features of the data gathering procedure used by the IPP. The prices requested by the IPP are the prices of products *received* by the firm as close as possible to the reference date. Production lags and delivery lags may therefore imply that these prices will refer to products ordered at a substantially earlier point in time. Furthermore, while the IPP requests that reporters provide a

[52] This estimate is very similar to the estimate of long-run pass-through reported in Gopinath and Itskhoki (2010b) for the same sample and specification. It is considerably higher than the estimate reported in GIR. This difference arises from a combination of a different sample (GIR focus on a sample of high income OECD countries selected as those with a substantial fraction of non-dollar priced goods), a different exchange rate measure (GIR focus on bilateral exchange rates) and the fact that GIR do not use product-level weights in constructing their price index.

[53] Woodford (2003, ch. 3) discusses several sources of strategic complementarity that generate gradual delayed adjustment.

price for the transaction that occurs as close as possible to the first day of the month, in practice, importers and exporters often go for long periods of time without importing or exporting. As a consequence, reporters often provide prices for other days in the month. In some cases, average monthly prices are provided. The large amount of price imputation done in the IPP and discussed in section 2 is an additional source of timing error.

To allow for such timing error in reported prices, we assume that the price that the IPP records for a firm at time t is the price that firm charged at a different time $t + u_t$, where u_t reflects random timing error. We assume that the timing error u_t has two components, $u_t = u_{1,t} + u_{2,t}$. The first component $u_{1,t}$ is distributed $u_{1,t} \sim \text{Unif}[-1, 0]$. This term reflects the fact that the reported price changes for a particular month occur randomly over the course of the preceding month, but are observed at discrete intervals. The second term $u_{2,t}$ is distributed, $u_{2,t} = -x d_{jit}$, where d_{jit} is the time in months since the last price change, and $x \sim \text{Unif}[0, X]$. This term is motivated by the various forms of timing error discussed above—which lead recorded prices to be somewhat "stale".

We calibrate the distribution of the frequency of price change as well as the frequency of substitutions based on the results reported in table 4. For the frequency of substitutions, we use the frequency of forced substitutions of 2.5% per month. When simulating the model, we use actual daily observations on the U.S.-German exchange rate over the time period 1995-2007. We use the fractional values generated by the timing error model described above to infer on which day of the month a price change occurs.[54] For simplicity, we assume that the difference between home and foreign inflation is constant. We set $\rho = 0.5$ based on previous estimates in Nakamura and Steinsson (2008), and we set σ_ϵ^2 to match the average size of price changes in the data (in practice, these assumptions have little impact).

The remaining parameters are the two delayed adjustment parameters—ϕ and ψ—and the timing error parameter X. We use a simulated method of moments procedure to estimate these parameters. The moments we use in this procedure are the coefficients of the regression equations reported in Table 7. We select the values of (ϕ, ψ, X) that minimize the sum of the squared deviations between these moments in the simulated and actual data. Since we are able to come very close to exactly matching the actual moments in the data, the choice of a weighting matrix makes little difference to our results.

This estimation procedure yields $\phi = 0.86$, $\psi = 0.85$ and $X = 0.66$. The estimated value of

[54]For robustness, we have carried out analogous experiments using the Canadian, Japanese, and U.K. exchange rates. These experiments yield almost identical results.

X implies that, on average, delivery lags and other sources of timing error account for a delay in price reporting of about 33% of the average duration since the last price change or product replacement. This corresponds to an average reporting lag of about 3 months, which is consistent with existing estimates of delivery lags (e.g., Abel and Blanchard, 1988). The estimated value of ψ implies that there is a substantial amount of delayed adjustment due to strategic complementarity. Prices respond to a distributed lag of past levels of the exchange rate with about 30% of the weight on values of the exchange rate from more than 6 months earlier. The estimated value of ϕ implies that the high frequency of price change products in our model have a desired pass-through of 0.86, while the low frequency of price change products have a desired pass-through of 0.57. This implies that aggregate pass-through is 0.60.

6.1 Discussion

The second column of Table 7 reports the fit of the model to the data using the parameters described above. The model is able to match the data for all the pass-through measures we consider. Incorporating product replacement bias allows us to explain the large observed difference between the life-long and aggregate measures of long-run pass-through. Consistent with our analysis in section 4, aggregate pass-through is substantially downward-biased due to product replacement bias, but life-long pass-through is much less biased.[55] Our estimates also imply that a substantial amount of delayed adjustment in firms' desired prices is required to explain the large difference between "pass-through conditional on adjustment" and longer-run measures of pass-through. Substantial amounts of timing error in the IPP data due to the delivery lags described above also contribute to this difference between short and long-run measures.

It is useful to note that delayed pass-through alone—due, for example, to strategic complementarities in pricing—cannot explain why life-long pass-through is so much higher than long-run aggregate pass-through. For example, GIR present a model with strategic complementarities in pricing but no product replacement. Their model yields virtually the same estimates for long-run aggregate pass-through and life-long pass-through. Gopinath and Itskhoki (2010a) present a model with heterogeneity in the frequency of price change and true pass-through as well as strategic complementarity and product replacement. This model also yields nearly identical estimates for

[55] The downward bias in the life-long pass-through measure grows with the extent of delays in price adjustment. The downward bias is substantially larger in a Calvo model than in a menu cost model since the latter implies more rapid adjustment of prices to exchange rates. See the working paper version of GIR for a more detailed discussion of this issue (Gopinath, Itskhoki and Rigobon, 2007).

long-run aggregate pass-through and lifelong pass-through.

The absence of product replacement bias in the model of Gopinath and Itskhoki (2010a) arises largely from two features of their model that our analysis in section 4 shows are crucial in determining product replacement bias. First, they assume that products fall into one of seven frequency of price change "bins," ranging from about 10% to 35% per month and do not allow for heterogeneity in the frequency of price change within these bins. To accurately assess the quantitative force of product replacement bias, however, it is important to allow for the large number of products in the dataset with no observed price changes—about 40% of products in the data have no price changes.[56] Second, Gopinath and Itskhoki (2010a) assume that products enter the dataset randomly, implying a substantially higher value of the "overreaction" parameter, α_n, than we estimate in the data. In other words, their model assumes that price changes at the time of product replacements are "accounted for" by subsequent observed price changes—something we do not find evidence for in our empirical analysis.

7 Conclusion

This paper argues that the simultaneous presence of price rigidity and frequent product replacements lead aggregate price indexes to appear smoother than they actually are—biasing import price pass-through measures and the volatility of the terms of trade toward zero. We propose a model of this "product replacement bias." Our model yields an adjustment to aggregate indexes based on empirical measures of the frequency of price change and product replacements. The adjustment depends importantly on the nature of cross-sectional heterogeneity in the frequency of price change and true "pass-through." More generally, our results suggest an important interaction between adjustment costs (such as price rigidity) and product turnover that leads aggregate indexes to appear more stable than they actually are in response to macroeconomic shocks.

[56] Since the lowest frequency bin in Gopinath and Itskhoki (2010a) has a frequency of price change of roughly 10% (excluding substitutions) there is less than a 3% probability of observing zero price changes over the course of a product's 35 month lifetime—substantially less than in the data. Gopinath and Itskhoki (2010a) exclude products with no price changes from their empirical analysis.

A Steps in the Derivation of the Product Replacement Bias Factor

A.1 Decomposing the Regression Coefficients

The OLS estimator of B in equation (6) is

$$B = (\Lambda'\Lambda)^{-1}\Lambda'\Delta p_i,$$

where Λ is a $T \times (\kappa + 1)$ matrix with the Λ_t's as rows and Δp_i is a $T \times 1$ vector with Δp_{it} as its elements.[57] Equation (4) then implies

$$\begin{aligned} B &= (\Lambda'\Lambda)^{-1}\Lambda' \int \Delta p_{ik}(s)dkds \\ &= \int (\Lambda'\Lambda)^{-1}\Lambda'\Delta p_{ik}(s)dkds \\ &= \int B_k(s)dkds \end{aligned}$$

A.2 Deriving Equation (11)

It is convenient to consider the regression in equation (6) with an index of the firms' unobserved optimal price in product group k and state s—$\Delta p^*_{ik}(s)$—as the dependent variable. Denote the vector of regression coefficients from this regression by $B^*_k(s)$. Notice that for each change in the effective price in this sample we have $\Delta\hat{p}_{ijkt}(s) = \sum_{\tau=\ell_j(t)+1}^{t} \Delta p^*_{ijk\tau}(s)$, where $\ell_j(t)$ denotes the time of the previous change in the effective price for product j before the one at time t.

The OLS estimator of $B^*_k(s)$ is

$$B^*_k(s) = (\Lambda'\Lambda)^{-1}\Lambda'\Delta p^*_{ik}(s),$$

where Λ is defined as in appendix A.1 and $\Delta p^*_{ik}(s)$ is a $T \times 1$ vector with $\Delta p^*_{ikt}(s)$ as its elements. Define $X = (\Lambda'\Lambda)^{-1}\Lambda'$ and let $X(n,t)$ denote the (n,t) element of X. Notice that

$$\sum_n B^*_{nk}(s) = \sum_n \sum_t X(n,t)\Delta p^*_{ikt}(s). \tag{25}$$

It is convenient to also consider the regression in equation (6) with an index of all price changes for products in product group k and state s that undergo changes in their effective prices in period t—$p^{allch}_{ikt}(s)$—as the dependent variable. Denote the vector of regression coefficients from this regression by $B^{allch}_k(s)$.[58] The OLS estimator of $B^{allch}_k(s)$ is

$$B^{allch}_k(s) = (\Lambda'\Lambda)^{-1}\Lambda'\Delta p^{allch}_{ik}(s).$$

[57] For notational convenience, the derivations below assume that all variables have been demeaned and omit having a constant in all regressions. It is well known that a regression on demeaned data yields the same result as the same regression with a constant term on non-demeaned data.

[58] $p^{allch}_{ikt}(s)$ and $B^{allch}_k(s)$ differ from $p^{ch}_{ikt}(s)$ and $B^{ch}_k(s)$, discussed in the text, in that they include all price changes, while $p^{ch}_{ikt}(s)$ and $B^{ch}_k(s)$ exclude the first price change for each product.

Notice that

$$\begin{aligned}\sum_n B_{nk}^{allch}(s) &= \sum_n \sum_t X(n,t)\Delta p_{ikt}^{allch}(s) \\ &= \sum_n \sum_t X(n,t)\frac{1}{J}\sum_j \sum_{\tau=\ell_j(t)+1}^{t} \Delta p_{ijk\tau}^{*}(s)\end{aligned}$$

where j indexes particular products that undergo a price change. The innermost sum in equation (26) has different numbers of elements depending on the length of the spell in question.

For each good that undergoes a price change at time t, the innermost sum has at least one element with $\tau = t$. This element has the same form as the right hand side of equation (25). It thus follows that this term is equal to $\sum_n B_k^*(s)$.

For price spells of length larger than one period, the innermost sum in equation (26) has additional terms. The canonical earlier term takes the form $\sum_n \sum_t X(n,t)\Delta p_{ik,t-j}^*(s)$. Notice that this is the expression for the regression coefficient of $\Delta p_{ik,t-j}^*(s)$ regressed on Λ_t. We assume that Λ_t contains enough leads and lags that $\sum_n B_{nk}^*(s)$ is unchanged even when the last $\ell_j(t)$ regressors are dropped and the same number of additional leads included.[59] This implies that

$$\sum_n \sum_t X(n,t)\Delta p_{ik,t-j}^*(s) = \sum_n B_{nk}^*(s).$$

The preceding results and that fact that the average length of price spells in the economy is $1/(f_k(s) + z(s) - f_k(s)z(s))$ implies that

$$\sum_n B_{nk}^*(s) = (f_k(s) + z(s) - f_k(s)z(s)) \sum_n B_{nk}^{allch}(s), \tag{26}$$

The properties of the OLS estimator and the observations with no effective price change contribute nothing to $B_k(s)$ implies that

$$\sum_n B_{nk}(s) = (f_k(s) + z(s) - f_k(s)z(s)) \sum_n B_{nk}^{allch}(s). \tag{27}$$

Together, equations (26)-(27) imply that $\sum_n B_{nk}(s) = \sum_n B_{nk}^*(s)$.

The same logic that yielded equation (26) also implies

$$\sum_n B_{nk}^*(s) = (f_k(s) + z(s) - f_k(s)z(s)) \sum_n B_{nk}^{ch}(s), \tag{28}$$

where $f_k(s) + z(s) - f_k(s)z(s)$ is the frequency of price change in the government's data set from sector k and state s.

[59] In practice, this involves including enough lags so that the last lag is relatively unimportant.

The properties of the OLS estimator and the observations with no effective price change contribute nothing to $B^u_k(s)$ implies that

$$\sum_n B^u_{nk}(s) = (f_k(s) + z(s) - f_k(s)z(s)) \sum_n B^{ch}_{nk}(s). \tag{29}$$

Together, equations (28)-(29) imply that $\sum_n B^u_k(s) = \sum_n B^*_{nk}(s)$, which implies that $\sum_n B^u_{nk}(s) = \sum_n B_{nk}(s)$ as we set out to show.

A.3 Derivation of the Frequency of Price Change in Sample of Uncensored Spells

The probability that a given spell is a one period uncensored spell is $f_k(s)(1-z(s))$. The probability that a given spell is a two period uncensored spell is $f_k(s)(1-f_k(s))(1-z(s))^2$, and so on. The overall probability of an uncensored spell is then

$$\sum_{j=0}^{\infty} f_k(s)(1-f_k(s))^j(1-z(s))^{j+1} = \frac{f_k(s)(1-z(s))}{1-(1-f_k(s))(1-z(s))}.$$

Using this we can calculate the average duration of uncensored spells as

$$\frac{1-(1-f_k(s))(1-z(s))}{f_k(s)(1-z(s))} \sum_{j=0}^{\infty} (j+1) f_k(s)(1-f_k(s))^j(1-z(s))^{j+1} = \frac{1}{f_k(s)+z(s)-f_k(s)z(s)}.$$

which implies that the frequency of price change in a sample of uncensored spells is

$$f_k(s) + z(s) - f_k(s)z(s)$$

A.4 Deriving the Fraction of Price Changes that Are the First Price Change for a Product

Since the first observed price change for a product is different from subsequent price changes, we need to know what fraction of price changes are the first observed price change for a product. For a randomly selected price change, the observed "event" preceding this price change is either the product's introduction or another price change. Since these events occur with frequency $\tilde{z}^d(s)$ and $(1-z(s))f_k(s)$, the fraction of measured price changes that are first price changes for a product is $\Phi_k(s) = z(s)/(f_k(s) + z(s) - f_k(s)z(s))$.

A.5 Lifelong Pass-Through as a Special Case

Consider the special case in which firms' optimal prices p^*_{jkt} are a function only of the current exchange rate, and there is no "overreaction" of the first price change, i.e., $\alpha_n(s) = 0$. In this case, $\Delta p^*_{jkt} = B \sum_{\tau=l_j(t)+1}^{t} \Delta e_\tau$, where $l_j(t)$ denotes the time of the previous change in the price of product j before the one at time t and B denotes true pass-through.

The lifelong regression estimates the equation, $\sum_{life} \Delta p^*_{jkt} = B \sum_{life} \Delta e_\tau$, yielding an unbiased estimator of B. Under these assumptions, our bias adjustment equation—equation (10)—simplifies to

$$\begin{aligned}
\textstyle\sum_n B_{nk}(s) &= \tfrac{f_k(s)+z(s)-f_k(s)z(s)}{f_k(s)} \textstyle\sum_n B^{mm}_{nk}(s) \\
&= (f_k(s)+z(s)-f_k(s)z(s)) \textstyle\sum_n B^{ch}_{nk}(s) \\
&= (f_k(s)+z(s)-f_k(s)z(s)) B \textstyle\sum_n nProb(l_j = n) \\
&= B,
\end{aligned}$$

where the first step follows from the properties of an OLS regression, the second step follows from the structural assumption on pricing behavior and the last step follows because the expected duration of price spells in this setting is $1/(f_k(s)+z(s)-f_k(s)z(s))$.

A.6 Deriving the Relationship between True and Measured Frequencies of Price Change and Product Replacement

Here we derive expressions for $\tilde{z}(s)$ and $\tilde{f}_k(s)$ in terms of $f_k(s)$, $z(s)$, and $g(s)$. This allows for the possibility that the observed frequency of price change is lower than the true frequency of price change due to "satisficing behavior by firms responding to the government's pricing survey as discussed in section 5.2. A product replacement into the economy is measured by the government at time t if the product accurately observed and a product replacement into the world occurs at time t. A product replacement into the economy is also measured at time t if the product is accurately observed at time t but was not accurately observed a time $t-1$ and a product replacement into the economy occurred at time $t-1$. And so on for earlier periods. This implies that the measured frequency of product replacement is

$$\tilde{z}(s) = g(s)z(s) \sum_{r=0}^{\infty} (1-z(s))^r (1-g(s))^r = \frac{g(s)z(s)}{z(s)+g(s)-z(s)g(s)}$$

If the frequency of product replacement in the government's dataset differs from the frequency of product replacement in the world—e.g., because of sample rotation—the expression for $\tilde{z}(s)$ except that $z(s)$ is replaced by the frequency of product replacement in the government's dataset.

To calculate $\tilde{f}_k(s)$, we first calculate the probability that a product is observed in period t and neither a price change nor product replacement has occurred. This is the case if the product was observed at time $t-1$ and no price change or product replacement occurred in period t—an event that has probability $g(s)^2(1-z(s))(1-f_k(s))$. It is also the case if the product was last observed in period $t-2$ and has not had a price change or product replacement since—an event that has probability $g(s)^2(1-g(s))(1-z(s))^2(1-f_k(s))^2$; and so on. The total probability of this occurring is thus

$$\frac{g(s)^2(1-z(s))(1-f_k(s))}{1-(1-g(s))(1-z(s))(1-f_k(s))}.$$

Notice that the probability that the product is observed and either a price change or product substitution is observed is then given by

$$g(s)-\frac{g(s)^2(1-z(s))(1-f_k(s))}{1-(1-g(s))(1-z(s))(1-f_k(s))}=g(s)\frac{1-(1-z(s))(1-f_k(s))}{1-(1-g(s))(1-z(s))(1-f_k(s))}.$$

Finally, the probability that the product is observed and a price change is observed is the probability that the product is observed and either a price change or product substitution is observed minus the probability that a product substitution is observed

$$g(s)\frac{1-(1-z(s))(1-f_k(s))}{1-(1-g(s))(1-z(s))(1-f_k(s))}-\tilde{z}(s)=\frac{((g(s)-\tilde{z}(s))f_k(s)}{1-(1-g(s))(1-z(s))(1-f_k(s))}.$$

One must divide this by $1-\tilde{z}(s)$ to get the observed frequency of price change since the denominator in our estimate of the frequency of price change does not include the periods in which a product substitution occurred.

B Multi-Sector Model

For robustness, we have also analyzed product replacement bias in a multi-sector version of our model. In this model, divide product into 15 sectoral groupings of 2 digit HS codes. Within each sector, we assume that the frequency of price change is distributed according to a beta distribution $\mathrm{Beta}(a,b)$. To obtain estimates of these parameters, we maximize the log likelihood function presented in section C separately for each sector. One interesting fact revealed by this analysis is that there is a large amount of heterogeneity in the frequency of price change both *within* the 15 major groups as well as across these groups. We also allow the frequency of product replacement to differ across sectors. Otherwise, the model is identical to the model presented in section 4. We find that this model yields quantitatively similar results to our baseline model. Product replacement bias is slightly larger in the multi-sector model than our baseline model.

C Log-Likelihood in the Presence of Unobserved Heterogeneity in the Frequency of Price Change

We assume that product i has a constant hazard of adjusting, f_i, in each month, where $f_i \sim \text{Beta}(a,b)$. Let us denote the product's lifetime by n_i. These assumptions imply that the total number of price changes in a product's lifetime is distributed according to the binomial distribution, $x_i \sim \text{Bin}(n_i, f_i)$. We assume, furthermore, that f_i is distributed according to the beta distribution, $f_i \sim \text{Beta}(a,b)$.

Given this model, we can write the likelihood of observing a product with length n_i and the total number of price changes x_i as,

$$
\begin{aligned}
L &= \prod_{i=1}^{I} \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} f_i^{a-1}(1-f_i)^{b-1} \binom{n_i}{x_i} f_i^{x_i}(1-f_i)^{n_i-x_i} && (30)\\
&= \prod_{i=1}^{I} \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} f_i^{x_i+a-1}(1-f_i)^{n_i-x_i+b-1} \binom{n_i}{x_i} && (31)
\end{aligned}
$$

We can integrate out the $f_i's$ to get,

$$
L = \prod_{i=1}^{I} \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} \binom{n_i}{x_i} \frac{\Gamma(a+x_i)\Gamma(b+n_i-x_i)}{\Gamma(a+b+n_i)}. \qquad (32)
$$

The log-likelihood function is, therefore,

$$
\begin{aligned}
\log L &= n\log\Gamma(a+b) - n\log\Gamma(a) - n\log\Gamma(b)^n + \sum_{i=1}[\log n_i! - \log x_i! && (33)\\
&\quad - \log(n_i-x_i)! + \log\Gamma(a+x_i) + \log\Gamma(b+n_i-x_i) - \log\Gamma(a+b+n_i)]. && (34)
\end{aligned}
$$

D Derivation of Equations (16) and (17)

Under the simplifying assumptions that the frequency of price change and product substitution are constant over time for each product group and that long-run pass-through is the same for all products, equation (15) simplifies to

$$
\sum_n B_n^{mm} = \int \frac{f_k}{f_k + z - f_k z}\left[\Phi_k \sum_n (1+\alpha_n)B_{nk} + (1-\Phi_k)\sum_n B_{nk}\right] dF(k).
$$

Manipulation of this equation and equation (13) yields

$$
\begin{aligned}
\sum_n B_n^{mm} = &\int \frac{f_k}{f_k + z - f_k z} dF(k) \sum_n B_n \\
&+ z\int \frac{f_k}{f_k + z - f_k z}\left[\sum_n (1+\alpha_n)B_{nk}^{ch} - \sum_n B_{nk}^{ch}\right] dF(k).
\end{aligned}
$$

Since $f_k/(f_k + z - f_k z) < 1$, this equation implies that

$$\sum_n B_n^{mm} < \int \frac{f_k}{f_k + z - f_k z} dF(k) \sum_n B_n + z \left[\int \sum_n (1+\alpha_n) B_{nk}^{ch} dF(k) - \int \sum_n B_{nk}^{ch} dF(k) \right].$$

A conservative measure of product replacement bias is thus given by

$$\sum_n B_n^{mm} = \int \frac{f_k}{f_k + z - f_k z} dF(k) \sum_n B_n + z \left[\int \sum_n (1+\alpha_n) B_{nk}^{ch} dF(k) - \int \sum_n B_{nk}^{ch} dF(k) \right].$$

The last term in this expression reflects the correction for "overreaction" of the first price change discussed in the body of the paper. Empirically, we estimate the size of this term by comparing the sum of the coefficients for a regression of the first observed price change for all products with two or more price changes on lagged exchange rate changes with the sum of the coefficients for a regression of the second observed price change for all products with two or more price changes on lagged exchange rate changes. Since this comparison is based on the sample of products with two or more price changes (recall that B_{nk}^{ch} is the regression coefficient for all price changes after the first price change), we need to adjust for the fact that the frequency of price change is higher for this subsample of products than the population as a whole. Specifically, $\int \sum_n (1+\alpha_n) B_{nk}^{ch} dF(k)$ is smaller in this subsample by a factor equal to the ratio of the average duration in the subsample of products with two or more price changes relative to the average duration in the population as a whole. (This follows from equation 29.) Applying this adjustment, yields

$$\sum_n B_n^{mm} = \int \frac{f_k}{f_k + z - f_k z} dF(k) \sum_n B_n + z \frac{\bar{d}}{\bar{d}_2} \left[\sum_n (1+\alpha_n) B_{2n}^{ch} - \sum_n B_{2n}^{ch} \right], \tag{35}$$

where $\bar{d}$ denotes the average duration of all price spells, $\bar{d}_2$ denotes the average duration of all price spells of products with two or more price changes, and the subscript "2" in B_{2n} indicates that we are calculating the sum of the coefficients for products that have two or more price changes. If pass-through is higher for products with a higher frequency of price change this adjustment will be smaller, since the ratio of $\int \sum_n (1+\alpha_n) B_{nk}^{ch} dF(k)$ will be less than the ratio of average lengths. Equation (35) therefore presents a very conservative (i.e., lower bound) estimate of the magnitude of product replacement bias.

E Product Replacement Bias and BLS Price Imputation

As we discuss in section 2, transaction prices are missing in about 40% of the product-months in the IPP dataset. During these periods, IPP uses various imputation procedures to "connect the dots" between reported prices. The primary method used by the BLS to impute prices between periods when it gets a new price quote is to "carry forward" the last observed price (the method we use in our empirical analysis). In some cases, however, the BLS uses other imputation procedures including linear interpolation and cell mean imputation methods (see Feenstra and Diewert, 2000 for more details). Below, we discuss the robustness of the method we use in our empirical analysis to alternative imputation procedures.

All the BLS imputation procedures merely "fill in the dots" between the observed prices for short periods when prices are not observed. Any price change that is introduced as a part of the imputation procedure is reversed as soon as a new transaction price is observed. As a consequence, any adjustment to exchange rates that such imputed price changes may contain are reversed and do not affect long-run pass-through.

The "fill in the dots" nature of BLS imputation implies that whatever such imputation method the BLS uses, one can produce an alternative index using a "carry forward" imputation method and this alternative index will yield the same measured long run pass-through as the actual BLS series. To verify this we have constructed an alternative index based solely on the "carry forward" imputation method and find that it yields identical estimates of long-run pass-through to the official aggregate BLS index, and in addition tracks the official index closely (except at very high frequencies).

Since both the actual index and the alternative index based solely on "carry forward" imputation yield the same measured log-run pass-through, one can formulate an adjustment for product replacement bias based on either one. The theoretical adjustment we present in section 4 is formulated for the alternative "carry forward" index in that prices are assumed to remain unchanged whenever firms fail to report prices accurately (see section 4.3). This implies that the frequency of price change concept that appears in our adjustment for product replacement bias is the frequency of price change for the carry forward index. This is why, in section 5, we use a "carry forward" procedure when calculating the frequency of price change that we input into our estimate of the product replacement bias factor.

Intuitively, product replacement bias arises because some movements in exchange rates are "unaccounted for" by subsequent price changes when the price series is prematurely truncated by a substitution. Imputation procedures such as cell-mean imputation may lead to additional price changes between existing observed prices—and slight differences in high frequency dynamics of the resulting price index—but they will never add any additional long-run "responsiveness" to exchange rates to the series or affect long-run pass-through, since price changes associated with imputations are always subsequently reversed when the products price is again observed. Thus, any exchange rate movements that are "unaccounted for" in a "carry-forward" index will still be unaccounted for in an index based on cell-mean imputation or other methods of imputation. The crucial statistic for adjusting for product replacement bias is the fraction of time that is unaccounted for because it belongs to the last observed price change of a product. One way to calculate this is based on the frequency of price change estimated from carry forward index.

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TABLE I
Exchange Rate Pass-Through

	Imports	Exports
Measured:		
Aggregate	0.43	0.85
	(0.05)	(0.05)
VECM	0.41	0.87
	(0.05)	(0.06)
Adjusting for Product Replacement Bias:		
Benchmark	0.64	0.79
Forced Substitutions Including Refusals	0.69	0.76
All Substitutions	0.74	0.74

The top panel presents alternative measures of the long-run relationship between the trade-weighted real exchange rate and aggregate import or export price indexes (standard errors in parentheses). "Aggregate" reports the sum of the coefficients on lagged exchange rate changes in a linear model for exchange rate changes with 6 quarterly lags (equation (1)). "VECM" reports the estimated coefficient on exchange rates in the cointegrating relationship between prices and exchange rates (equation (2)). The bottom panel presents the estimated relationship based on the aggregate pass-through regression adjusted for "product replacement bias" according to the methods discussed in the paper, under alternative assumptions about heterogeneity in pricing behavior across products and the frequency of product replacement.

TABLE II
Exchange Rate Pass-Through over Subsamples

Period	Aggregate	VECM
1982-2008	0.43	0.41
	(0.05)	(0.05)
1994-2008	0.32	0.46
	(0.08)	(0.08)

The table presents alternative measures of the long-run relationship between trade-weighted exchange rate series and aggregate import or export price indexes for the time periods 1982-2008 and 1994-2008 (standard errors in parentheses). "Aggregate" reports the sum of the coefficients on lagged exchange rate changes in a linear model for exchange rate changes with 6 quarterly lags (equation (1)). "VECM" reports the estimated coefficient on exchange rates in the estimated cointegrating relationship between prices and exchange rates (equation (2)).

TABLE III

Number of Price Changes Per Product

Number of Price Changes	Imports LCP	Imports PCP	Exports LCP	Exports PCP
0	44.3	43.8	16.3	39.2
1 or less	59.3	65.2	27.0	57.6
2 or less	68.7	77.7	30.0	68.2
3 or less	74.8	84.4	32.3	75.6
4 or less	79.2	90.7	34.7	80.8
5 or less	82.1	93.7	35.3	83.8
10 or less	88.4	98.1	77.0	90.1
15 or less	91.6	99.2	84.3	93.0

The table presents the fraction of products in the BLS microdata on import and export price data with less than or equal to a given number of price changes over the entire timespan for which they are in the data set. These statistics are for market based products for 1994-2004 and are reported for both local currency priced (LCP) and producer currency priced (PCP) products. The statistics are weighted percentiles, using as weights the cumulative product-level weights over each product's lifetime.

TABLE IV

The Distribution of Price Changes and Substitutions

	Imports LCP	Imports PCP	Exports LCP	Exports PCP
Fraction of Imports/Exports	0.922	0.078	0.032	0.968
Mean Frequency of Price Change	0.151	0.061	0.572	0.130
Median Frequency of Price Change	0.066	0.033	0.573	0.060
Mean Frequency of Substitutions				
Forced	0.025	0.016	0.062	0.020
Forced Including Refusals	0.037	0.026	0.064	0.032
All	0.049	0.046	0.067	0.046
Distribution of the Frequency of Price Change				
a	0.44	0.82	0.36	0.50
	(0.01)	(0.06)	(0.06)	(0.01)
b	3.50	20.72	3.52	4.59
	(0.05)	(1.74)	(0.87)	(0.10)

The top panel reports summary statistics for the mean and median frequency of price change and product substitution calculated using IPP microdata on import and export prices. The sample period is 1994-2004. Statistics are reported for both local currency priced (LCP) and producer currency priced (PCP) products. The weighted means are and medians are calculated using the item-level weights described in the paper. The lower panel reports our estimates of "a" and "b" which are the parameters in the estimated distribution of the frequency of price change, assumed to be Beta(a,b). This distribution is estimated using the BLS microdata on imports and exports.

TABLE V

Price Change for First and Second Spell on Exchange Rate

	Imports		Exports	
	First Price Change	Second Price Change	First Price Change	Second Price Change
<u>Panel A:</u>				
Exchange rate change:				
During price spell that is ending	0.23	0.26	0.13	0.11
	(0.03)	(0.03)	(0.03)	(0.03)
1st quarter before price spell that is ending	0.19	0.18	0.03	0.14
	(0.05)	(0.04)	(0.07)	(0.06)
2nd quarter before price spell that is ending	0.13	0.11	-0.06	-0.02
	(0.04)	(0.04)	(0.06)	(0.06)
3rd quarter before price spell that is ending	-0.01	0.05	0.14	0.15
	(0.05)	(0.04)	(0.06)	(0.05)
4th quarter before price spell that is ending	0.07	0.09	-0.09	0.09
	(0.04)	(0.04)	(0.05)	(0.05)
5th quarter before price spell that is ending	0.05	0.04	0.19	0.08
	(0.04)	(0.04)	(0.06)	(0.06)
6th quarter before price spell that is ending	0.14	0.06	0.06	-0.01
	(0.05)	(0.04)	(0.07)	(0.06)
P-value for the null that coefficients for price spell and 2nd qrt before price spell are equal	0.052	0.002	0.008	0.059
<u>Panel B:</u>				
Exchange rate change:				
During the price spell that is ending and 1 quarter before this spell	0.21	0.24	0.09	0.12
	(0.02)	(0.02)	(0.03)	(0.03)
2nd to 4th quarter before the price spell that is ending	0.06	0.09	-0.02	0.08
	(0.02)	(0.02)	(0.03)	(0.03)
P-value for the null that the two coefficients are equal	0.000	0.000	0.021	0.340
Average duration of spells in months	8.7	8.5	9.5	9.5
Number of observations	3356	3339	2212	2230

Panel A presents coefficients from OLS regressions of price changes on current and lagged exchange rate changes, including the exchange rate change during the price spell that is ending, and exchange rate changes over the 1st to 6th quarters before this price spell (standard errors in parentheses). These regressions are run for market based transactions for OECD countries. The table also reports the p-value testing the null that the coefficients on the current price spell and the 2nd quarter before the price spell are equal. Panel B reports the results of similar regressions where the regressors are 1) the exchange rate change during the current price spell and the quarter before the spell and 2) the exchange rate change over the 2nd-4th quarters before the spell started. The p-value for the null that these coefficients are equal is also reported.

TABLE VI

Exchange Rate Pass-Through and Product Replacement Bias

	Major Country RER Frequency of Subsitutions			Broad RER Frequency of Subsitutions		
	Forced (benchm)	Forced (incl. ref)	All	Forced (benchm)	Forced (incl. ref)	All
Measured Pass-Through						
Imports		0.43			0.52	
		(0.05)			(0.06)	
Exports		0.85			0.84	
		(0.05)			(0.06)	
A. With Heterogeneity in Pass-Through						
Factors						
LCP Imports	1.63	1.78	1.91	1.63	1.78	1.91
PCP Imports	1.80	2.12	2.72	1.80	2.12	2.72
LCP Exports	2.30	2.32	2.36	2.30	2.32	2.36
PCP Exports	1.57	1.74	1.91	1.57	1.74	1.91
Adjusted Pass-Through						
Imports	0.64	0.69	0.74	0.80	0.86	0.92
Exports	0.79	0.76	0.74	0.77	0.75	0.73
B. No Heterogeneity in Pass-Through						
Factors						
LCP Imports	1.71	1.88	2.03	1.71	1.88	2.03
PCP Imports	1.80	2.12	2.72	1.80	2.12	2.72
LCP Exports	2.47	2.50	2.54	2.47	2.50	2.54
PCP Exports	1.62	1.81	2.01	1.62	1.81	2.01
Adjusted Pass-Through						
Imports	0.67	0.73	0.78	0.83	0.90	0.97
Exports	0.77	0.76	0.73	0.77	0.74	0.71
C. "Lower Bound" Based on Sampling Variation in Ψ						
Adjusted Pass-Through						
Imports	0.56	0.56	0.55	0.71	0.73	0.73

The table presents the estimated adjustment factor for product replacement bias under various alternative assumptions. We present results for three frequencies of substitutions: "Forced (benchm) is our benchmark measure of forced substitutions, "Forced (incl. ref)" is forced substitutions including refusals, "All" is the frequency of product substitutions using all observed substitutions. Panel A and B present results for different assumptions regarding heterogeneity in pricing behavior across products. The results are presented for local currency priced (LCP) and producer currency priced (PCP) imports and exports. The first two columns present results for the "Major Country" real exchange rate (RER) while the measure in the last two columns present results for the "Broad" real exchange rate measure. Panel C presents "lower bound" estimates of true pass-through based on the sampling variation in our estimate of Ψ.

TABLE VII

Reconciling Differing Measures of Pass-Through

	Real Data	Simulated Data
Pass-Through Conditional on Price Adjustment	0.24	0.24
	(0.07)	
Lifelong Pass-Through	0.51	0.52
	(0.12)	
Lifelong for freq. less than 0.25	0.41	0.41
	(0.12)	
Aggregate Pass-Through	0.33	0.32
	(0.08)	
True Pass-Through		0.60

The table reports regression coefficients from analogous regressions run using actual and simulated data. The "Real Data" statistics are based on calculations using BLS microdata on the prices of local currency priced imports. The "Simulated Data" statistics are based on output from our simulation model using our benchmark measure of forced substitutions. A detailed discussion of the regressions is presented in section 6. The last row presents the average long-run pass-through assumed in the model that gives rise to the simulated data. For the "Real Data" results, standard errors are reported in parentheses . The standard errors for the first three regressions have been clustered by year. Clustering these standard errors by country yields somewhat smaller standard errors. For the aggregate pass-through regression, robust standard errors are reported.

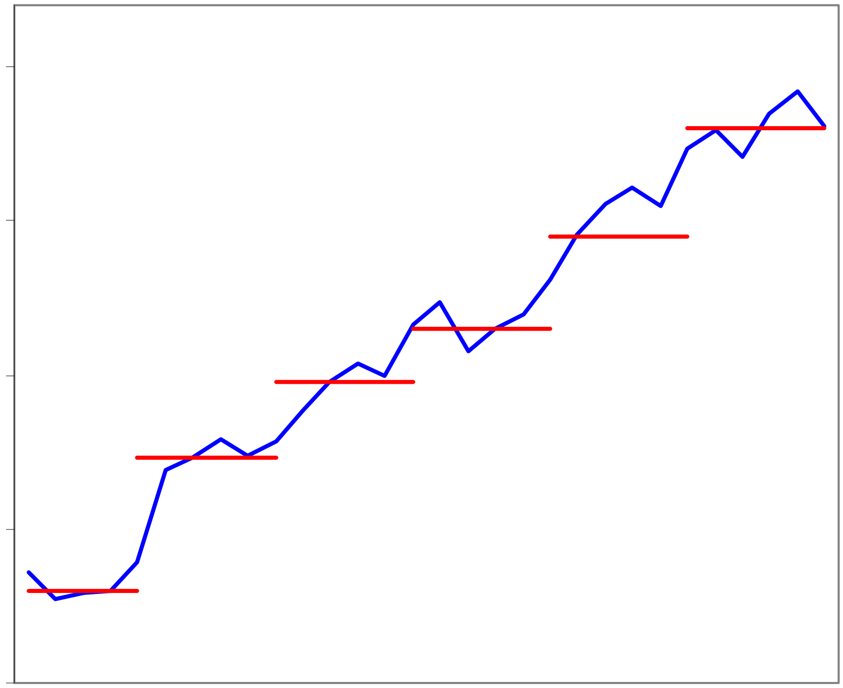

Figure I
Product Replacement and the Comovement of Prices and Exchange Rates

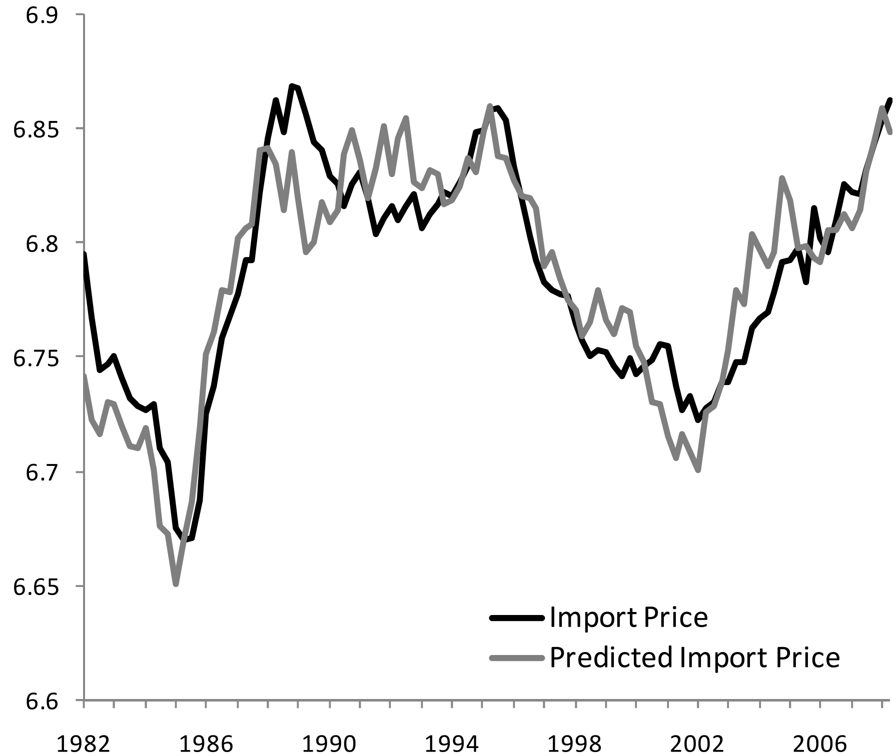

Figure II
U.S. Import Prices and the Real Exchange Rate

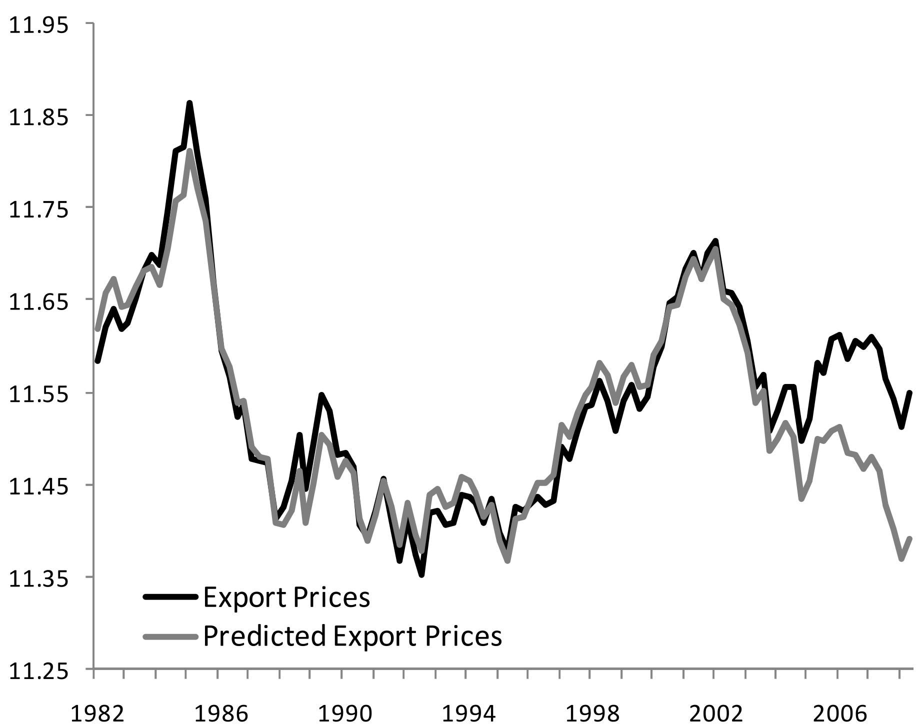

Figure III
U.S. Export Prices and the Real Exchange Rate

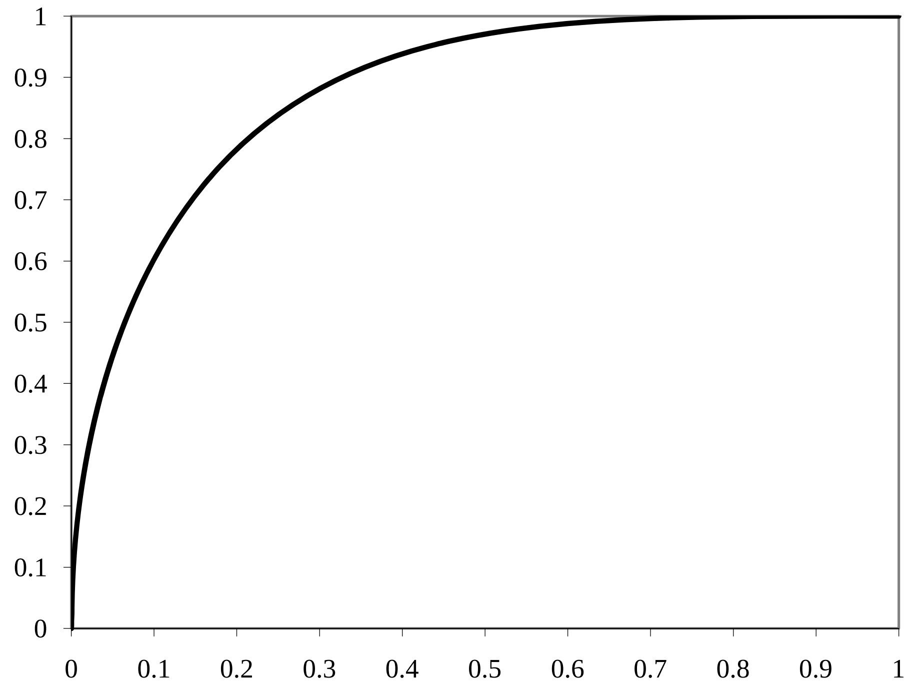

Figure IV
Cumulative Probability Distribution of Beta(0.50,3.65)

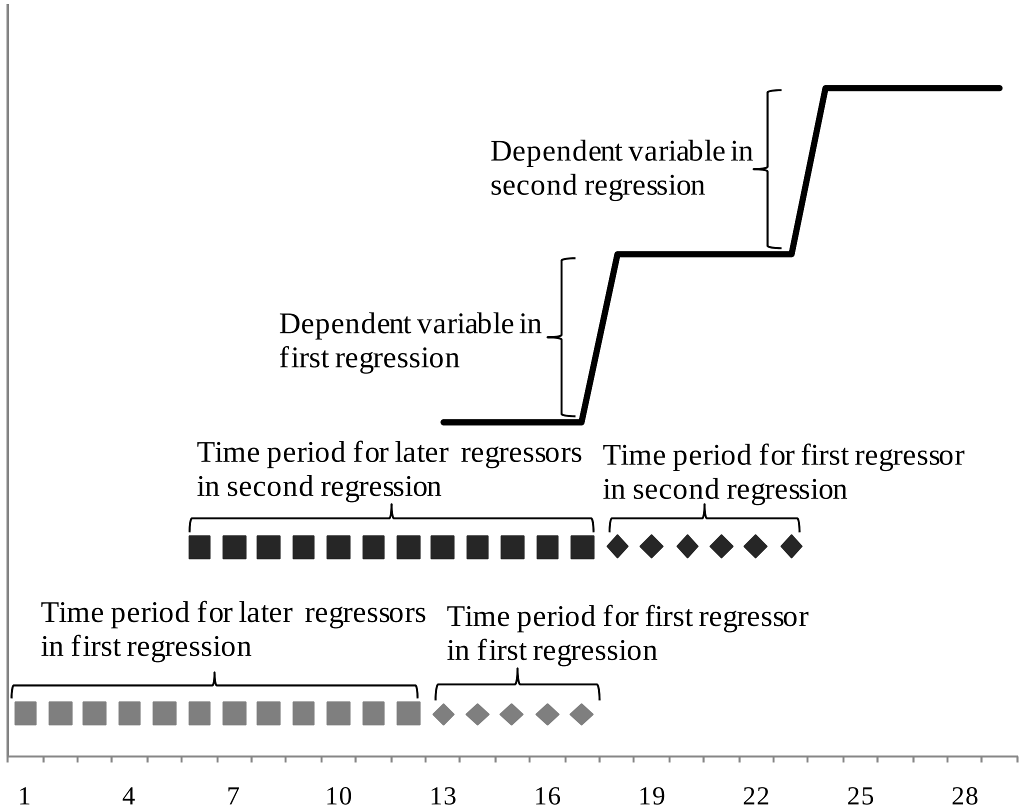

Figure V
Graphical Depiction of Regressions in Table V

This figure provides a graphical depiction of the regression equation presented in equation (17). The solid line denotes the price of a product that has two price changes. The first regression has as its dependent variable the first price change and as explanatory variables exchange rate movements over the first price spell as well as the six quarters preceding the product's introduction. The second regression has as its dependent variable the second price change, and as explanatory variables exchange rate movements over the course of the second price spell as well as exchange rate movements in the preceding six quarters. If the first price is "stale" then the first price change should respond more to exchange rate movements preceding the first price spell, than the second price change does to exchange rate movements preceding the second price spell.

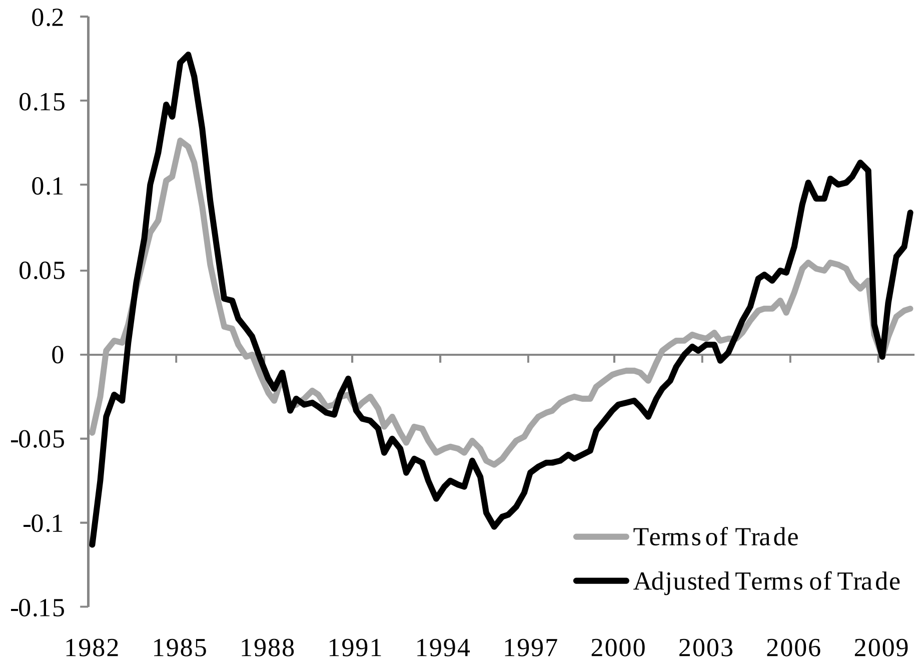

Figure VI
U.S. Terms of Trade Adjusted for Product Replacement Bias