

Policy-Relevant Exchange Rate Pass-Through to U.S. Import Prices

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Abstract

We investigate three possible sources of downward bias that could affect standard estimates of exchange rate pass-through to import prices over policy-relevant horizons: improper lag selection, selection biases in the entry of items in the basket of prices, and selection biases in their exit. We first show that standard lag length selection criteria may, under certain model assumptions, lead one to underpredict pass-through over the medium run. We argue that the risks of overfitting the regression by adding extra lags are likely small relative to the potential benefits. Second, we investigate the bias induced by entry into a price index of items that are less responsive to recent exchange rate movements than items already in the index. We show that the size of this bias is sensitive to the speed at which pass-through occurs, and present a method for eliminating much of this bias over typical policy horizons. Finally, we examine the censoring of price changes through exits from the index. We argue that this source of downward bias is especially difficult to control for in standard pass-through regressions and its importance is sensitive to the underlying data-generating process.

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1 Introduction

In conducting monetary policy, central bankers are interested in how much exchange rate movements will affect the prices of imported goods ("exchange rate pass-through") as fluctuations in these prices can in turn affect domestic prices and output. The most common way to measure exchange rate pass-through is based on regressions of changes in published import price indexes on trade-weighted exchange rate indexes (along with other potentially important explanatory variables). Using these regressions, researchers have estimated low rates of exchange rate pass-through for the United States. Recent estimates suggest that, following a 10-percent depreciation of the dollar, U.S. import prices increase about 1 percent in the contemporaneous quarter and an additional 2 percentage points over the next year, with little if any subsequent increases.

The objective of this paper is to investigate three possible sources of downward bias that could affect standard estimates of exchange rate pass-through to import prices over policy-relevant horizons: improper lag selection, selection biases in the entry of items in the basket of prices, and selection biases in their exit. We first show that standard lag length selection criteria may, under certain model assumptions, lead one to underpredict pass-through over the medium run. We argue that the loss in efficiency resulting from overfitting the regression by adding extra lags are likely small relative to the potential benefits.

Our other two sources of biases pertain to changes in the composition of items in the price index. We distinguish between the entry and exit of items because the nature of these biases, their incidence, and the potential for correction are quite different. We investigate the bias induced by entry into a price index of items that are less responsive to recent exchange rate movements than items already in the index. We show that the size of this bias is sensitive to the speed at which pass-through occurs, and present a method for eliminating much of this bias over typical policy horizons. Finally, we examine the censoring of price changes through exits from the index. We argue that this source of downward bias is especially difficult to control for in standard pass-through regressions and its importance is sensitive to the underlying data-generating process.

Throughout the discussion, we focus on the dynamic response of import prices over the first few years following an exchange rate movement, which corresponds to the typical policy horizon of central bankers. As seen in Table 1, central banks typically seek to achieve their policy objectives over the "medium term," recognizing that monetary policy is forward-looking in nature. Some countries, such as Canada, Norway, or Sweden, have an inflation target to be achieved within 1 to 3 years. Other countries provide guidance about their relevant policy horizon through the release of economic projections. In the United States, the Federal Reserve staff forecast has a two-year horizon. In addition, the Federal Open Market Committee publishes a quarterly summary of their individual forecasts covering three years.

We will refer to the dynamic response of import prices over the first few years as being policy-relevant exchange rate pass-through. Other approaches in the literature consider the total effect on import prices of an exchange rate movement regardless of how long it take to materialize ("long-run pass-through") as well as the response between consecutive individual price adjustments ("medium-run pass-through," as defined by Gopinath, Itskhoki, and Rigobon, 2010).

In exploring the potential for biases, we observe that theoretical price-setting models often have

diverging implications for the magnitude and nature of biases that would be encountered by the econometrician. In a model with Calvo price setting, exchange-rate movements are passed-through to trade prices over extended periods when prices are updated infrequently. We show that one should be careful to incorporate a sufficiently large number of lags in the estimated specification. Although each additional lag contributes little to the regression, the inclusion of large number of extra lags may cumulate to a large contribution and thereby reduce the potential for biases. By contrast, in a model with menu costs, pass-through is very rapid and the role for extra lags is greatly diminished.

The challenge of estimating pass-through coefficients in infrequently-updated, time-dependent pricing environments may be compounded by alterations in the basket of items used to compute a price index. For example, Nakamura and Steinsson (2009) argue, under a certain set of assumptions, that estimated pass-through rates could be sharply downward biased, which they refer to as product replacement bias. We review their argument and show that the degree of bias induced by selection effects arising from the entry of items into a price basket is highly dependent on the price-setting assumptions. In particular, the product replacement bias is very small in a menu-cost model calibrated to match key features of individual price adjustments. Furthermore, we show that an essential condition for the existence of a large product replacement bias is that items added to the trade price index systematically differ from the population of items.

Given our exploration of biases described above, we have some recommendations for practitioners interested in estimating pass-through regressions. First, the sensitivity of the results to lag length over the policy-relevant horizon should be explored, especially when infrequent individual adjustments flags a potential for slow pass-through rates. Our Monte-Carlo simulations suggest that the risk of overfitting the regression by adding a few extra lag beyond the recommendation of standard lag-length selection criteria is minimal, while the gains are potentially large. Second, we show that one can mitigate the selection bias resulting from the entry of items in the basket by constructing an alternative price index. Our method revolves around delaying the entry of items into the trade price basket, a simple fix that is robust to the underlying data-generating process and that can produce substantial bias-reduction gains over the policy-relevant horizon. Finally, we note that selection effects in the exit of items from the basket remain perhaps the key source of biases in standard pass-through regressions using official price indexes. As such, there remains a strong need for conducting more research into the reasons triggering the exit of items from the import price basket.

The remainder of the paper is structured as follows. The next section presents key statistics about the composition of the import price basket used by the BLS. In Section 3, we introduce the baseline Calvo and menu-cost models that are used throughout our discussion to illustrate the nature of the various biases, gauge their importance, and illustrate the functioning of our fixes. In Section 4, we use these models to show that standard lag length selection criteria can provide poor guides for the choice of the optimal number of lags in the regression, especially when pass-through is very slow. In Sections 5 and 6, we discuss the possible biases associated with selection effects in the entry and exit of items in the basket, and show how some of them can be mitigated. In Section 7, we provide new estimates of exchange rate pass-through to U.S. import prices over the policy-relevant horizon using both the published BLS price indexes and our alternative bias-reducing price indexes. Section 8 concludes.

2 U.S. Import Prices and the International Price Program

With imports of goods and services accounting for nearly 20 percent of U.S. domestic demand, import prices are an important determinant of domestic consumer price inflation. As seen in Figure 1, import prices have been volatile over the past decade. For example, import prices reached a peak in July 2008, after rising 21 percent over the previous 12 months. These prices then reversed themselves, falling 23 percent over the next 6 months. What explains this volatility? To a large extent, the price of imported oil and other fuels explain a large share of the volatility in import prices. The trade share of fuel imports (about 16 percent) is much smaller than their contribution to the total variance of import prices. The second most important category is the prices of nonfuel material-intensive goods (including base metals and food). Likewise, the trade share of nonfuel material-intensive goods (about 18 percent) is well below that of its volatility share, reflecting these goods price volatility. The third category shown in the Figure 1 is the prices of finished goods. These goods have a large trade share (over 60 percent) but contribute little to the overall variance. However, although these goods have not contributed to the variance as much in certain episodes like early 2008, they rose sharply and contributed to overall inflation.

Table 2 enumerates statistics on price changes as well as item entries and exits from the price basket in the 3-digit Enduse categories used by the Bureau of Labor Statistics' International Price Program (IPP). The assumptions applied to compute these statistics largely mirror those of Gopinath and Rigobon (2008) and Nakamura and Steinsson (2009), though we additionally present details on the size of item price movements conditional on a change, unweighted aggregates, as well as the frequency of item exit. These summaries of item price change characteristics are concorded to the BEA Enduse 3-digit classifications to bring descriptions of the microdata closer to the groups of goods used in other tests of more aggregate pass-through (for instance: Bergin and Feenstra (2009) and Marazzi, Sheets, and Vigfusson et al. (2005)).

Given identical data and similar methodology to Gopinath and Rigobon (2008) and Nakamura and Steinsson (2009), we rely on their thorough descriptions to convey the details of IPP protocol and the parameters of the IPP sample. In brief, though, import prices are collected through a monthly survey of U.S. establishments and we observe the price microdata of approximately 20,000 sampled items per month over the period September 1993 – July 2007. The sample consists of rolling groups of unique items, each having a sampling duration of about 3 years, on average. IPP chooses its firms and items based on a proportional to size sampling frame with some degree of oversampling of smaller firms and items. We treat the data by dropping all IPP price imputations, firm estimates of prices in non-traded periods, and non-U.S. dollar transactions and then carrying forward prices to fill-in missing values. The frequency of price change within a given aggregate is then simply the average incidence of an observed price differing from its previously reported price in a given period. Weights, when used, are the import sales volume of a given disaggregate IPP category (similar to the U.S. Harmonized System 10-digit codes), and distributed evenly across items within those categories.

The overall weighted incidence of price changes is estimated to be 12.2 percent, declining from 13.0 percent in the first half of the sample to 11.8 in the latter half. These levels are consistent, though somewhat lower, than the weighted average of 14.1 percent in Nakamura and Steinsson (2009) and the median of 15 percent in Gopinath and Rigobon (2008). Part of this difference may reflect the inclusion

of intra-firm transfer prices in our computation, which were found to be slightly stickier in previous work. The statistics also seem to be sensitive to the manner of weighting, with the unweighted overall frequency declining to 9.5 percent. That larger products groups had higher frequency of price change is fairly ubiquitous across product types, with the exception of automotive products which moved slightly in the opposite direction.

The frequency of item entry and exit, due to both IPP sample rotation and endogenous item substitution, is approximately 4 percent with little difference between the weighted and unweighted aggregates. We note that at the aggregate level item entry and exit frequencies are about equal, indicating that the size of the IPP sample remained about the same size over the course of the sample. However, the steadiness of the overall sample size masks a degree of heterogeneity in entry and exit rates at the Enduse product level. For example, Enduse 100 (petroleum and products) had an exit rate that exceeded its entry rate (of 4 percent) by a full percentage point. Meanwhile, Enduse 212 (agricultural machinery and equipment) had an entry rate (of 3.5 percent) that exceeded its exit rate by two tenths of a percentage point. At very least, these differences suggest the importance of considering both the distribution of substitution rates across categories as well as the entry and exit rates within categories.

Lastly, the average absolute (nonzero) price change is 9.0 percent, in line with the mean overall estimate of 8.2 percent in Gopinath and Rigobon (2008). There is some dispersion across Enduse categories with items belonging to Enduse 101 (Fuels, n.e.s.-coal & gas) having an average price change of 14.4 percent, compared to 2.3 percent for Enduse 300 (Passenger cars, new and used).

3 Pass-Through and Micro Price Adjustments

This section introduces the baseline Calvo and menu-cost models that we will use to illustrate the nature of the various biases, how they interact with the frequency at which prices change, and our various strategies to mitigate their effects. As we will show, judgement on the quantitative importance of the biases is sensitive to the price-setting mechanism one sees as best representing the data-generating process. Although the Calvo and menu-cost models are only two of the many price setting mechanisms proposed in the literature, they are illustrative of the point that the severity of the biases often relates to the frequency of price changes and more generally to the speed at which exchange rate movements are passed-through to import prices.

3.1 Economic environment

We consider the following data-generating process for the change in the price (in logs) of an imported item i at period t ,

$$\Delta p_{it} = \begin{cases} 0 & \text{if } \mathcal{I}_{it}^f = 0 \\ u_{it} + \beta \Delta x_t + \varepsilon_{it} & \text{if } \mathcal{I}_{it}^f = 1 \end{cases} .$$

Given the opportunity (or decision) to change its price, a firm sets Δp_{it} equal to the sum of (a) the amount of price pressure inherited from previous periods, u_{it} , (b) the change in the exchange rate, Δx_t , and (c) the contribution of (mean-zero) idiosyncratic factors, ε_{it} . The occurrence of a price change is marked by the indicator variable \mathcal{I}_{it}^f . The price deviation carried to the beginning of the next period is

given by

$$u_{it+1} = \begin{cases} u_{it} + \beta \Delta x_t + \varepsilon_{it} & \text{if } \mathcal{I}_{it}^f = 0 \\ 0 & \text{if } \mathcal{I}_{it}^f = 1 \end{cases} .$$

If the firm does not change its price, then the aggregate and idiosyncratic shocks that have occurred in period t are simply added to the amount of price pressure that had already cumulated. If the firm adjusts its price, then the price is set to the optimum and no price pressure is carried into the next period. The set up so far is quite general and not specific to import prices. One could, for example, interpret Δx_t as the contribution of aggregate shocks, such as wage inflation, to a firm's reset price. In what follows, we will simply assume that Δx_t can be represented by an $AR(1)$ process,

$$\Delta x_t = \alpha + \rho \Delta x_{t-1} + \xi_t,$$

with Gaussian innovations, ξ_t .

We are ultimately interested in the impact of exchange rate movements on import prices in general. To this end, we define aggregate price inflation as the average change in item prices,

$$\Delta p_t = \int \Delta p_{it} di.$$

Suppose that the econometrician estimates a linear model containing L lags of the aggregate variable,

$$\Delta p_t = a + \sum_{l=0}^L b_l \Delta x_{t-l} + r_t. \tag{1}$$

where r_t is an error term. In what follows, we explore how various assumptions about the timing of nominal adjustments impacts the econometrician's estimates of the regression coefficients.

3.1.1 Calvo model

In the Calvo model, the decision to change the price is exogenous to the firm. The indicator variable \mathcal{I}_{it}^f is a random variable taking the value 1 with constant probability f , and 0 with probability $1 - f$. This assumption has strong implications for the dynamic responses of import prices to exchange rate movements. It is convenient to consider the case in which innovations to the exchange rate, Δx_t , are uncorrelated over time ($\rho = 0$), as it allows us to derive analytical expressions for the regression coefficients.

As shown in Appendix 1 (under a slightly more general environment), the (plim) linear estimate of b_l is

$$b_l = b_l = f (1 - f)^l \beta.$$

Intuitively, for a movement in the exchange l period earlier to impact an item's price today, the firm must be given the opportunity to adjust its price today (probability f) and no price change must have occurred in each of the previous l periods (probability $1 - f$ in each period). Otherwise, the current price would already reflect the effects of Δx_{t-l} . The Calvo model provides a textbook example of a geometric lag model in which the coefficient on the explanatory variable decays exponentially with the number of

lags. Summing up the (plim) coefficients in the regression, we get

$$\sum_{l=0}^L b_l = \left(1 - (1 - f)^{L+1}\right) \beta,$$

which converges to β as $L \rightarrow \infty$. Thus, although the effects of an exchange rate shock never are passed-through fully to import prices, we can nevertheless approximate β (the "long-run" pass-through) as the sum of the regression coefficients with an arbitrary degree of precision.

3.1.2 Menu-cost model

In the menu-cost model, the decision to change the price is the result of a cost-benefit analysis performed by the firm. As shown by Sheshinski and Weiss (1977), it is optimal for the firm to keep its price unchanged if the deviation from the reset price, $u_{it} + \beta\Delta x_t + \varepsilon_{it}$, falls within a certain range. One can show that, to a first-order approximation, this range of inaction is symmetric around the price that sets the price pressure to zero (see Gopinath and Itskhoki, 2010, for a formal derivation). We thus approximate the decision to change the price as

$$\mathcal{I}_{it}^f = \begin{cases} 0 & \text{if } |u_{it} + \beta\Delta x_t + \varepsilon_{it}| \leq K \\ 1 & \text{if } |u_{it} + \beta\Delta x_t + \varepsilon_{it}| \geq K \end{cases}.$$

Unfortunately, analytical results are challenging to derive for the menu-cost model unless one is willing to make stringent assumptions (see Danziger (1999) and Gertler and Leahy (2008) for examples). However, the assumptions required for tractability in these papers seem less suitable here. Therefore, we will proceed by simulations to illustrate our main points. Moreover, note that the decision to change the price now depends on the value of β : The larger the pass-through coefficient, to more a shock to the exchange rate is likely to trigger a price adjustment. More generally, the more shocks are large and persistent (and thus associated with relatively large benefit of adjusting the price), the more likely is a firms to change the price immediately. The estimated coefficients in equation 1 are thus sensitive to the particular realization of the shocks the menu-cost model.

3.2 Calibration of the models

We first set the mean, standard deviation, and autoregressive coefficient of exchange rate innovations to match the corresponding moment of the broad dollar index computed by the Federal Reserve from January 1995 to March 2010. The standard deviation of monthly (end-of-period) exchange rate movements was 1.5 percent over that period, with no drift. Exchange rate movements were slightly autocorrelated over time ($\rho = 0.19$). We report results for $\beta = 0.3$, which is in-line with recent estimates in the literature (e.g., Marazzi et al (2005), Gopinath, Itskhoki, Rigobon (2010)), but somewhat lower than the consensus value for pass-through in the 1980s (see Goldberg and Knetter, 1997).

The remaining parameters are calibrated to match salient features of individual import price adjustments. As shown by Gopinath and Itskhoki (2009), the median size of individual price changes rather insensitive to the frequency of price change changes, hovering between 6 and 7 percent. In the case of

the Calvo model, we set the probability of a price change equal to a given frequency and calibrate the variance of individual innovations (which is assumed to be Gaussian) to match a median size of price changes of 6.5 percent. In the case of the menu-cost model, we choose the menu cost K and the standard deviation of ε_{it} to match both the median size and the average frequency of price changes. We make the additional assumption that ε_{it} is normally distributed with mean zero. The larger is K , the less frequent and the larger are the individual price changes. Likewise, the larger is the standard deviation of ε_{it} , the more frequent and large are individual price changes.

3.3 Impulse response to an exchange rate movement

The response of import price inflation to an exchange rate movement in the Calvo and menu-cost models are shown in the upper, middle, and bottom panels of Figure 4 for (steady state) frequencies of price changes of 5 percent, 20 percent, and 35 percent, respectively. In the case of the Calvo model, the frequency of price changes has a direct impact on the speed at which exchange rate disturbances are transmitted to the import price index. For a relatively low frequency of price changes (upper panel), the exchange rate movement has not yet fully diffused by then end of the forecast horizon, although the impact on import price inflation is rather small. For a frequency of price changes close to the median in the basket of imports (middle panel), the chose is almost entirely passed-through by the end of the forecast period, with negligible amount of trade price inflation left. Higher frequencies of price changes lead to even faster pass-through. The cumulative response of the import price index can be seen in figures 9 as the sum of the dark and light bars. For example, when the frequency of price changes is 5 percent, just over 70 percent of the long-run response of the import price index has taken place after two years, leaving almost 30 percent of the price response beyond the forecast horizon. By contrast, the transmission of the exchange rate shock is virtually complete after two years at frequencies of 20 percent or higher.

The speed of pass-through is markedly higher in the menu-cost model at all frequencies. Under our low-frequency calibration (upper panel), figure 4 shows negligible amount of import price inflation as a result of the shock after a year, even for frequencies as low as 5 percent. well over 90 percent of the long-term response of the price level has already taken place after a year. The speed of transmission is even higher for higher-frequency calibrations, with the bulk of the price level response taking place over just a handful of months. The cumulative response of the price index in the menu-cost model as a share of the long-run response is presented figure 11 (sum of light- and dark-shaded areas).

Our exercise illustrate the point that the choice of a particular data-generating model can have important consequences for the dynamic response of the import price index. The Calvo and menu-cost models were similar in that they shared the same frequency of price change (in steady-state) and the same long-run pass-through coefficient. However, the dynamic transmission of the exchange rate shock was markedly different, with faster rates of pass-through at short horizons in the menu-cost model than in the Calvo model.¹

¹In practice, the frequency of price changes and the degree of exchange rate pass-through interrelated. Gopinath and Itskhoki (2010) present evidence that items with relatively low frequencies of price changes tend to be associated with relatively low rates of pass-through.

4 Lag Length Selection

When estimating distributed lags models, such as the one shown in equation 1, the econometrician must take a stand on the number of lags of exchange rate movements to include in the regression. The common practice is to guide this choice using one or several of the lag length selection criteria proposed in the literature. These criteria aim to balance the greater functional flexibility of adding an extra lag to the regression against the risk of overfitting the data. In this section, we argue that standard lag length selection criteria must be used with caution when pass-through is slow and the econometrician is interested ultimately in the effects of exchange rate movements over medium-term horizons. Intuitively, lag length selection criteria generally are designed to limit forecast errors of the immediate reaction of prices to an exchange rate movement. By contrast, the econometrician may be interested in measuring pass-through at the end of the forecast horizon or in analyzing the shape of the entire impulse response function. While the inclusion of a small number of lags may provide reasonably accurate forecasts of the immediate reaction, it may be preferable to incorporate additional lags to capture the effects over longer horizons. The risk of including too few lags to assess the medium-term response of prices may be especially large when the effects of exchange rate movements diffuse slowly. In such cases, the coefficient on each additional lag is small, meaning that the corresponding marginal contribution to the fit of the regression is small.²

4.1 Monte-Carlo simulations

We conduct Monte-Carlo simulations in order to formalize our argument. For simplicity, we focus our attention on two popular lag length selection criteria, namely the Akaike information criterion (AIC),

$$AIC = 2L - 2 \ln(\sigma_r^2),$$

and the Schwartz criterion (SC),

$$SC = \ln(\sigma_r^2) + \frac{L}{T} \ln(T).$$

The term σ_r^2 is the variance of the error term in the distributed lag model displayed in equation 1, L is the number of lags, and T is the number of usable observations. The AIC and SC criteria are derived from different optimality principles and consequently may offer different lag length recommendations. When the true model has an infinite number of lags, the AIC chooses the finite lag model that minimizes the sum of squared errors of the immediate reaction (see Shibata, 1981). When the true number of lags is finite, the SC provides a consistent estimator of the true lag length, while the AIC asymptotically places some positive probability on overstating the true number of lags. See Judge et al. (1985) for a discussion and additional references.

The various versions of our Calvo and menu-cost models are calibrated as described in section 3.2 for targeted frequencies of price changes of 5 percent, 20 percent, and 35 percent. For each calibration, we

²A related question is whether a distributed lag model provides the most appropriate approximation of the underlying data-generating process. Alternatively, one could consider econometric models incorporating lagged dependent variables or specify the coefficients on the exchange rate as a function of a small number of parameters (e.g., a geometric decay model). We leave for future research the study of the implications of slow pass-through on the lag length choice in these environments.

perform 10,000 simulations, each of which tracking the price of 2,000 items over 180 periods, and record the optimal lag length recommended by the AIC and the SC as well as the corresponding amount of pass-through by the end of the forecast horizon. Figure 5 shows the distribution of lag lengths selected by the criteria in the Calvo and menu-cost versions of the model. As seen in the upper-left panel, under a Calvo model with a very slow diffusion of exchange rate movements to import prices, the median lag length selected by the AIC and SC are 16 months and 9 months, respectively. These values imply that the impulse response of import price inflation to a shock dies well before the end of the typical medium-term forecast horizon in a distributed lag model, even though the true impulse response to a shock (shown in the upper panel of figure 4), decays very slowly over time. As a consequence, the median estimate of the amount of pass-through by the end of the 2-year forecast horizon is well below the true value. As seen in the upper-left panel of figure 6, the median 2-year pass-through estimate is about 40 percent below the truth under the AIC, and almost 60 percent under the SC. We also note that there is considerable uncertainty surrounding the choice of an optimal lag length under this slow pass-through case. The 5-95 percent range of the distribution of optimal lag length stretches from 8 to 25 lags in the case of the AIC, and from 2 to 21 lags in the case of the SC (see the upper-left panel of figure 6). This uncertainty translates into a similarly wide range of estimates for the cumulative pass-through at the end of the medium-term forecast horizon (upper-left panel of figure 6). The bias towards finding estimates that are too small is nevertheless very clear, with only 5 percent of 2-year pass-through estimates in the AIC simulations exceeding the true measure, and about 2 percent in the SC simulations. Such underestimation of the two-year response is not optimal in a root mean-square error (RMSE) sense. As illustrated in the upper-left panel of figure 7, we find that the RMSE of the predicted 2-year response systematically declines as we increase the number of lags in the regression until we reach 24 lags, after which the RMSE flattens. Increasing the number of lags in the regression from 9 (the median value recommended by SC) to 24 reduces the RMSE by a factor of three, while the RMSE nearly halves when we increase it from 16 (the median value recommended by SC) to 24.

As we consider higher frequencies of price changes in the Calvo model, and thus faster rates of pass-through, the lag length recommended by the AIC and SC criteria falls, consistent with the diminished importance of coefficients on long lags. The share of true 2-year pass-through estimated increases, although it remains clearly biased downward at a 20-percent frequency of price changes (middle-left panel of figure 6), and the dispersion of the estimates falls noticeably. For a frequency of 35 percent, the estimates are tightly clustered near the true 2-year pass-through.

The lag length selection issue is not as acute when the true model is menu cost. Even at a (steady-state) frequency as low as 5 percent (upper-right panel of figure 6), the median recommendation of the AIC and SC is sufficient to capture most although not all of the pass-through occurring over a period of 24 months. Importantly, the estimates are tightly clustered, indicating that the root mean square error of the predicted cumulative pass-through over the forecast horizon is markedly smaller than under the Calvo model. The lag length selection criteria are typically good at recommending the inclusion of lags whose coefficient is large. The menu-cost model with a (steady-state) frequency of price changes of 35 percent provides a good illustration of this phenomenon. The coefficients on the first and second lags about 80 percent and 15 percent of the long-run response of prices, respectively. The AIC and SC were ambivalent regarding the importance of including the second lag in the regression. As a result, the

distribution of 2-year pass-through estimates is bimodal (lower-right panel of figure 6). This case of fast pass-through would suggest the use of only three relatively few lags to maximize the RMSE. We note, however, that the RMSE is small relative to the other models even if we were to include as many more lags.

4.2 Relevance for empirical work

Our Monte-Carlo simulations suggest that it is good practice to verify the robustness of the estimates to including additional lags, even if standard lag length selection criteria recommend specifications with relatively small number of lags. The costs of overfitting the regression appear quite small in comparison to the potential biases that could be introduced by using too few lags. Figure 8 presents the impulse response of finished goods prices to an exchange rate movements for various selection of the lag length. As is apparent in the picture, the index rises almost a full percentage point in the initial and next periods in response to a 10-percent exchange rate movement. It then rises another percentage point over the next twelve months and just over half a percentage point from month 13 to month 25. Interestingly, the inclusion of an increasingly large number of lags has little impact on the point estimates at short duration. Selecting a lag length that is relatively short, say 12 months, would result pass-through that is only three quarters of the price index's response over the first two years relative to our baseline case with 24 lags. Based on the above analysis, the regressions presented in the remainder of this paper include as many lags as there are periods (24) in our forecast horizon.

5 Implications of Item Entries

As noted in the opening sentences of the final report of the Boskin Commission, "*[the] American economy is flexible and dynamic. New products are being introduced all the time and existing ones improved, while others leave the market. [...] This makes constructing an accurate cost of living index more difficult than in a static economy.*" Indeed, there is vast literature on quality-adjustment and the addition, disappearance, and substitution of items in the basket concerned with the possibility that measured inflation systematically underestimates or overestimates the true change in the cost of living of individuals.³ By contrast, little attention has been devoted to the implications of changes in the composition of the basket for the dynamic response of the index.

In this section, we analyze the possibility that selection effects in the entry of items in the basket lead to biased estimates of exchange rate pass-through. (We perform a similar exercise with exits in the next section.) We first provide some intuition for why the entry of items could bias pass-through estimates. We then enlarge the model developed in the previous section to illustrate how the magnitude of the related bias depends on the frequency of price changes and the underlying data-generating model. Finally, we show how the computation of an alternative price index can eliminate much of the bias coming from selective entries over the policy-relevant horizon.

³The conference summaries of the Ottawa Group, which operates under the auspices of the United Nations Statistical Commission, provide good overviews of the research conducted at statistical agencies worldwide on these issues. See the Bureau of Labor Statistics' "Measurement Issues in the Consumer Price Index" for a more succinct introduction. Several survey papers also have appeared in the economic literature, including Gordon (2006), Moulton (1996), and Nordhaus (1998).

5.1 Intuition

Recently, Nakamura and Steinsson (2009) argued that, under certain assumptions, standard estimates of long-run exchange rate pass-through to import prices likely are only about half the true size due to an improper treatment of product replacements. The intuition behind what they call "product replacement bias" revolves around the treatment of additions to the basket, such as the one illustrated in Figure 2. In that figure, we consider the entry of an item in the index in replacement of another item that had experienced no price change since period $t - 4$. We suppose that the exit was completely exogenous (the implications of endogenous exit will be analyzed later) and that the price of the added item is changed at the beginning of period t , before its introduction in the basket. As was the case earlier, we posit that firms fully incorporate past and current exchange rate movements whenever they adjust prices. Consequently, had the exiting item remained in the basket longer, its next price change would have reflected developments in the exchange rate that occurred from period $t - 3$ to t (and possibly later depending on the timing of the next price change). By contrast, the price of the item entering the basket already incorporates past movements in the exchange rate because it was changed at period t , so that its next adjustment will be unresponsive to exchange rate movements up to period t . The nature of the product replacement bias discussed by Nakamura and Steinsson (2009) is that items entering the basket *systematically* are less sensitive to past movements in the exchange rate than items in general, like the substitute in our example. Their inclusion in pass-through regressions thus lowers the effective estimates.

A few observations are worth making. First, the product replacement bias is of a different nature than the well-known "new item bias" (difficulty in assessing the value of new items to consumers) or the "quality-change bias" (difficulty in reflecting changes in quality). These traditional sources of bias imply that the change in the price level is systematically overstated, leading to increasingly large biases as they cumulate over time. By contrast, the product replacement bias implies that the *dynamic* adjustment of the price level in the wake of shocks is impeded, but the level of the index needs not be biased in a specific direction. The product replacement bias also differs from the "dynamic aggregation bias" uncovered by Imbs et al. (2005) by which the estimated speed at which price indexes respond to exchange rate movements is driven by sectors that are slowest to react. In the presence of such a bias, the long-run pass-through estimate remain nevertheless consistent. Second, contrary to our example, we do not know in practice if the price of the substitute was changed upon its entry in the basket since its price history typically is not observed. Finally, the expression "product replacement bias" is slightly misleading since the issue is not specific to the replacement of items. Even with no items exiting the basket, and hence no replacement, any entry of items could result in a product replacement bias if the prices of these added items systematically are less responsive than other prices to past movements in the exchange rate.

5.2 A model of selective item entry

We consider a more general version of the economic environment presented in the previous section in which there is a selection effect associated with the entry of items to the basket. For convenience, we keep the size of the basket constant over time by postulating that entering items simply replace those exiting exogenously. Each item faces a constant probability s of being substituted every period. A

fraction n of items entering the basket *systematically* are sampled from price trajectories with $u_{it} = 0$, so that their price already reflects current and past movements in the exchange rate. The remaining entries have their u_{it} distributed similarly as the rest of the population, with some fraction f of them having their price reset during the period. Finally, we assume that prices are collected at the end of the period after price adjustments and substitutions have been made. Past prices of items entering the basket are unknown to the econometrician so that new observations cannot be used to compute inflation in the period of their introduction. This model nests as a special case the environment considered by Nakamura and Steinsson (2009) under the assumption that all new items are priced optimally ($n = 1$).

5.3 Calvo model

To derive some intuition, we first consider a Calvo model in which exchange rate movements are uncorrelated over time. As shown in Appendix 1, under this extra assumption, one can recover a simple expression for the (plim) coefficient on the l -th lag of the exchange rate in the distributed lag regression,

$$b_l = f(1-f)^l(1-sn)^l\beta.$$

This expression has a very intuitive interpretation. For a movement in the exchange rate l periods ago to contribute to inflation in the current period, one must observe a price change in the current period (probability f) and no price reset in the previous l periods. Price resets can occur either through the visit of a Calvo price fairy (probability f each period, whether a substitution takes place or not) or the replacement of an exiting item by one whose price is systematically new (probability sn each period). In the special case of $l = 0$, we have $b_0 = f\beta$; the estimated initial impact of an exchange rate movement on the trade price index is unbiased. Coefficients on subsequent lags are downwardly biased whenever price collectors have a tendency to *systematically* replace exiting items by substitutes whose prices were reset during the period ($sn > 0$). If price collectors simply were replacing exiting items by observations randomly selected from the population ($n = 0$), then no bias would be present. We also note that the accuracy of estimated coefficients decays exponentially with the number of lags considered, so that the importance of the bias is smaller when one is interested in the short-term response of import prices rather than the long-term response.

The left panels of Figure 9 illustrate the product replacement bias over the policy-relevant horizon in our calibration of the Calvo model by plotting the cumulative contribution of the coefficients. In addition to the assumptions made in Section 3.2, we posit that items face a 5 percent probability of being replaced every period and then consider the worst-case scenario of $n = 1$ (which corresponds to the assumption in Nakamura and Steinsson (2009)). As seen in the figure, the bias increases in severity with the degree of price stickiness. Only two-third of the actual cumulative pass-through is correctly estimated at the two-year horizon when the frequency of price changes is 5 percent, and almost one fifth is still missing when the frequency is 20 percent. For a frequency of 35 percent, the econometrician captures more than 95 percent of the response over the forecast horizon.

The estimates presented in Figure 9 should be interpreted as an upper bound given the worst-case assumption that $n = 1$. As a rule of thumb, the reduction in the bias by the end of the forecast horizon is roughly proportional to $1 - n$; setting $n = 0.5$ would roughly halve the area represented by the light

bars. The implications are similar in the case of long-run pass-through estimates, which is the focus of Nakamura and Steinsson's (2009) study. In the special case of uncorrelated shocks, the (plim) long-run response is

$$\lim_{L \rightarrow \infty} \sum_{l=0}^L b_l = \frac{f}{f + (1-f)ns} \beta.$$

As shown in Figure 3, the reduction in the product replacement bias associated with the long-run pass-through estimate is roughly linear in n for the frequencies considered.

Finally, in theory, one could recover the long-run pass-through coefficient, β , from the coefficient on the contemporaneous lag, $b_0 = f\beta$, since the frequency of price changes, f , is directly observed by the econometrician. In practice, the coefficients need not decay geometrically with the number of lags, so that computing the cumulative sum is the standard approach to estimating pass-through over any horizon.

5.4 Menu-cost model

The left panels of Figure 11 show the cumulative contribution of the regression coefficients on the various lags of exchange rate movements over the policy-relevant horizon under the worse-case scenario of $n = 1$ (the dark-shaded bars), along with the product replacement bias left out by the econometrician (the light-shaded bars). As was the case with lag length, the product replacement bias is much less severe in the menu-cost model. Even for frequencies of price changes as low as 5 percent (upper-left panel), the econometrician captures almost 90 percent of the price index response at the two-year horizon.

The size of the bias appears to be related to the *speed* at which the price index responds to an exchange rate shock. As noted above, in a Calvo model with uncorrelated exchange rate shocks, only $(1 - sn)^l$ of the contribution of lag l to pass-through is correctly estimated. In general, this term is decreasing exponentially at a slow rate since sn typically is small, meaning that the product replacement bias kicks in most strongly when much of the exchange rate response occurs at long lags. Under low frequencies of price changes, the coefficients associated with long lags in the Calvo model account for a substantial share of the price level response, so that the product replacement bias can have an important effect over long horizons. In the menu-cost model, most of the pass-through occurs in the first few periods following a shock – even at low frequencies – so that the product replacement bias does not have time to cumulate to something large even under a worse-case scenario ($n = 1$).

5.5 An alternative price index

We propose a simple trick to purge the estimates of a substantial share of the product replacement bias over the policy-relevant horizon. Our approach revolves around the observations that the longer an item has been in the basket, the more its deviation from the optimal price is likely to be distributed like the rest of the population (i.e., the distribution is "mixing"). By simply delaying the entry of substitutes in the basket, one can thus mitigate the product replacement bias. In Appendix 2, we formally derive expressions for the (plim) coefficients of the pass-through regression under a Calvo model with uncorrelated exchange rate shocks and an M -period delay in item entry,

$$b_l = \begin{cases} \beta(1-f)^l f & \text{if } l \leq M \\ \beta(1-f)^l (1-sn)^{l-M} f & \text{if } l > M \end{cases} .$$

As the above expressions indicate, there is no bias associated with the coefficients on the current and first M lags of the exchange rate. Moreover, the size of the bias on the subsequent coefficients is reduced by a factor of $(1 - sn)^{-M}$.

The right panels of Figure 9 show the bias in the Calvo model at various frequencies of price changes when entries in the basket are delayed by 6 months. The estimate of pass-through is markedly less biased over the policy-relevant horizon, becoming negligible when prices are adjusted 20 percent of the time or more. Even at frequencies as low as 5 percent, the prediction over the first year of the forecast suffers little product replacement bias. The bias reduction is even larger in the menu-cost model, as seen in the right panels of Figure 11. Delaying the introduction of new items by 6 months virtually eliminates the bias at all frequencies considered. These large gains arise because delaying entries removes most of the bias on the short lags, which is when most of the price level response occurs.

[Note: We are in the process of implementing this approach using micro data from the IPP. The results will be added to the paper as soon as they become available. They will allow us to take a stand on the empirical relevance of the product substitution bias. If the 2-year response under our alternative price index is similar to that computed using the official import price index, then the product replacement bias is likely small in practice. On the other hand, if the 2-year response is much larger under the alternative price index, then standard pass-through estimates likely are downwardly biased.]

5.6 Other approaches

Gopinath, Itskhoki, and Rigobon (2010) have proposed to estimate "medium-run" pass-through by regressing the size of individual price changes over the cumulative change in the exchange rate since the last nominal adjustment. As discussed in Appendix 4, their approach is immune to the product replacement bias. Their medium-run pass-through estimates are largely in-line with standard estimates of 2-year pass-through derived from distributed lag models.⁴ There is a similitude between their approach and the use of our alternative aggregate price indexes as both methods involve censoring some of the initial observations. The ensuing econometrics is quite different, however. In particular, the medium-run pass-through approach is silent about how exchange-rate movements are transmitted dynamically to import prices, which is of central interest in a policy context. On the other hand, medium-run pass-through estimates may be immune to certain issues related to the endogenous exits of items, which is the subject of our next section.

⁴An interesting point highlighted by Gopinath, Itskhoki, and Rigobon (2010) is that pass-through to U.S. import prices, either measured using the standard approach or over individual price spells, is significantly larger for items invoiced in foreign currency than for items priced in U.S. dollar.

6 Implications of Item Exits

Another potential source of bias in our pass-through regressions is the presence of endogenous item exits. If the probability that an item leaves the basket increases with the size of the deviation from its reset price, then the pass-through regression will underestimate the amount of price pressure created by exchange rate movements. In this section, we first extend our baseline model to include a selection effect in the exit of item and derive its implications for pass-through over the policy-relevant horizon. We then argue selective exit likely is more consequential for standard pass-through estimate than selective entry, and significantly more difficult to purge from the estimates.

6.1 A model of selective item exits

We consider a simple extension of the economic environment in Section 3 that captures the selection effect by which items with large deviations from their optimal price are more likely to exit the basket than others. We posit that firms can adjust their real price either by changing the posted price or by altering the item's characteristics. Conditional on the decision to change an item's real price, a firm faces an exogenous probability e of changing the item's characteristics. Moreover, we assume that the price of the old and new models are not linked through a hedonic adjustment, in which case the price change would be properly recorded. Instead, the price collector seeks a substitute. With probability n , this substitute is the new item (or model) itself, and thus has $u_{it} = 0$. With probability $1 - n$, the substitute is drawn randomly from the universe of items and may or may not have $u_{it} = 0$. Our model is not properly one in which exit from the basket is "endogenous" since the decision to exit is not a choice variable of the firm. Nevertheless, it captures the crucial aspect that the adjustment of individual prices following an exchange rate movement is partly censored.

As was the case earlier, we can derive explicit expressions for the (plim) regression coefficients in the Calvo model under the extra assumption that exchange rate innovations are uncorrelated (see Appendix 3 for the derivation). In that specific case, the contemporaneous response of the price index is

$$b_0 = \frac{(1 - e)}{1 - ef} f\beta.$$

Contrary to the model of selective entry discussed earlier, the initial response of the import price index is always biased downward relative to the unbiased case ($b_0 = f\beta$) whenever prices change infrequently ($f < 1$) and selective exits take place ($e > 0$). Importantly, this bias can be large even when the rate of exit in the entire basket (i.e., ef) is low since what matters crucially is rather the proportion of exits conditional on an adjustment of the real price.

The direction of the bias on the coefficients of subsequent lags depends on the strongest of two opposite forces. On the one hand, selective exits censor only price adjustments, thus dampening the response of the price index to past exchange rate movements. On the other hand, exits also create opportunities to replace items whose price is being adjusted by items that have not experienced a price change for some time. This possibility can subsequently make the price level more responsive to past

exchange rate movements. As shown in Appendix 3,

$$b_l = \left(\frac{1-e}{1-fe} \right) (1+l(1-n)fe)(1-f)^l f\beta, \quad (2)$$

with the terms $(1-e)/(1-fe)$ and $(1+l(1-n)fe)$ representing the first and second forces, respectively.

One interesting special case is $n = 1$, which allies both selective exits and selective entries. This particular case would occur if, for example, firms engineered price adjustments through the introduction of new models while price collectors, rather than linking the price of new and old models through quality adjustments, treated them as unrelated exits and entries. All coefficients in the regression would then be biased by the same factor relative to the case without bias

$$b_l = \left(\frac{1-e}{1-fe} \right) (1-f)^l f\beta.$$

This particular case is perhaps the poster child of what can go wrong with the treatment of substitutions as it combines a selection effect in both the exit and entry of items in the basket.

6.2 Impact of exits in Calvo and menu-cost models

The left and right panels of Figure 13 show the cumulative response of the price index to an exchange rate movement in the Calvo and menu-cost models, respectively, as a share of long-run pass-through. We tentatively assumed that a quarter of all price changes are accompanied by an exit, and left the calibration of the other parameters of the model unchanged relative to our base case described in Section 3.2. We also consider both the special cases $n = 1$ and $n = 0$ to show the implications of assuming that items are replaced at random. Note first that censoring price changes reduces the frequency of price changes observed by the econometrician. For underlying frequencies of 5, 20 and 35 percent, the econometrician would report frequencies in the order of 4, 16, and 29 percent, respectively.

The size of the bias created by selective exit is somewhat large over the forecast horizon at all frequencies considered when the price of entering items has been optimized ($n = 1$). In the case of the Calvo model, assuming that exiting items are replaced by sampling at random from the population ($n = 0$) reduces the size of the bias significantly over the forecast horizon. For frequencies near the median, the estimated two-year cumulative response is nearly the same as the true one. The gains of resampling at random are much more modest in the menu-cost model because pass-through is very rapid. As hinted by equation 2, the counterbalancing effect of random substitutions grows with the number of lags, l , but since coefficients on long lags are tiny, this ultimate impact on pass-through is small.

6.3 Correcting for endogenous exits

Mitigating the effects of selective exits is markedly more challenging than doing so for selective entries. One could conjecture that hastening exits by M periods would remove some of the bias in a way similar to our strategy of delaying additions to the basket in the case of selective entries. Unfortunately, this approach does not address the fundamental problem that observations with price changes are more likely

to be censored than observations without no nominal price adjustment. The medium-run pass-through approach of Gopinath and Itskhoki (2009) is immune to the selection bias described above (see Appendix 4). As noted earlier, however, it is not suited for the estimation of the dynamic response to an exchange rate shock.

Perhaps the most promising way forward is to gain a better understanding of what triggers exits from the basket and of how substitutes are chosen. The IPP database currently provides generic descriptions of the reasons why items leave the basket, but many of them are uninformative given our objective of separating endogenous from exogenous exits. There are reasons to be optimistic, however. Central bankers and other individual interested by the dynamic response of import prices to exchange rate movements are likely to benefit from ongoing research conducted by the BLS and statistical agencies worldwide on the presence of systematic biases in price indexes. In particular, as hedonic pricing is extended to an increasing proportion of items in the basket, and as better ways of linking disappearing products with new ones are devised, the selection effects stemming from changes to the composition of the basket are likely to diminish.

7 Concluding Remarks

This paper has explored three sources of downward bias in standard exchange rate pass-through regressions to import prices. First, we have shown that popular lag length selection criteria can underpredict the number of lags required to minimize the root mean square error of the import price response to an exchange rate movement over the typical policy horizon. This unprediction likely extends beyond the distributed lag model considered here because the focus of most lag length selection criteria is on finding a parsimonious specification that fits the immediate response to a shock rather than the medium-term response. The problem is especially severe when pass-through is slow. In such a case, each extra lag raises total pass-through by a small amount but the addition of several of them can nevertheless cumulate into a large increase. Our Monte-Carlo simulations indicate that the efficiency loss from adding a few extra lags beyond the statistical criteria's recommendation is small relative to the potential gains in reducing bias. This finding is robust to the economic models considered here as well as to the speed at which pass-through occurred. Our advice to estimate a model with many lags may seem at odds with the conventional wisdom that values parsimony in developing out-of-sample forecasting model. We intend to explore further the trade-off between within-sample estimation of pass-through coefficients and out-of-sample forecasting accuracy.

Second, we have investigated the bias induced by entry into a price index of items that are less responsive to recent exchange rate movements than the rest of the population. In doing so, we have clarified the nature of the product replacement bias discussed by Nakamura and Steinsson (2009). We have shown that the size of this bias is sensitive to the speed at which shocks are transmitted to prices and generally small when one is interested by the short-run response of import prices. We have proposed a simple method to purge much of the product replacement bias from aggregate pass-through estimates over the policy-relevant horizon. **[The next draft will report the results.]**

Third, we have explored the censoring of price changes caused by endogenous exit of items from the basket, which can result in underestimating pass-through. Relative to the bias induced by selective

entry, the endogenous exit is more challenging as there are few tricks to mitigate its effects, which can be large even for the short-run response. In a Calvo model setting, the endogenous-exit bias can be mitigated by randomly selecting substitutes for the exiting items.

Finally, we believe that future research should aim at better identifying the causes of item exits as well as the characteristics of added items. Currently, the information contained in the IPP database provides only limited guidance on these aspects.

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Appendix 1: Effect of Selective Entry on the Regression Coefficients in the Calvo Model

In this appendix, we derive analytical expressions for the coefficients in the exchange rate pass-through regression (equation 1) under the special assumptions that (a) firms face of constant probability of changing their price and (b) exchange rate innovations are uncorrelated. We also assume that items in the basket are subject to an exogenous probability s of being replaced by an item not previously sampled. When such a substitution occurs, the econometrician cannot use the new observation immediately to compute its contribution to inflation since its price in the previous period is unknown. Finally, we suppose that a fraction n of substitutes *systematically* are sampled from price trajectories with $u_{it} = 0$ (referred to as "new" goods). The remaining substitutes have their u_{it} distributed similarly as the rest of the population, so that a fraction f of them have their price reset in the period. For convenience, we define the indicator variables \mathcal{I}_{it}^f , \mathcal{I}_{it}^s , and \mathcal{I}_{it}^n to capture the occurrence of a price change, a substitution, and the replacement by a "new" item, respectively. Price collection takes place at the end of the period, after the price adjustment and substitution decisions have been made. Our model incorporates as a special case the environment considered by Nakamura and Steinsson when $n = 1$.

We first derive an expression for the impact of contemporaneous movements in the exchange rate on the price index using the covariance approach,

$$\begin{aligned}
 b_0 &= \frac{\text{cov}(\Delta p_t, \Delta x_t | \mathcal{I}_{it}^s = 0)}{\text{var}(\Delta x_t)} = \frac{\text{cov}(\int \Delta p_{it} di, \Delta x_t | \mathcal{I}_{it}^s = 0)}{\text{var}(\Delta x_t)} = \frac{\int \text{cov}(\Delta p_{it}, \Delta x_t | \mathcal{I}_{it}^s = 0) di}{\text{var}(\Delta x_t)} & (3) \\
 &= f \frac{\text{cov}(u_{it} + \beta \Delta x_t + \varepsilon_{it}, \Delta x_t | \mathcal{I}_{it}^s = 0, \mathcal{I}_{it}^f = 0)}{\text{var}(\Delta x_t)} + (1-f) \frac{\text{cov}(0, \Delta x_t | \mathcal{I}_{it}^s = 0, \mathcal{I}_{it}^f = 0)}{\text{var}(\Delta x_t)} \\
 &= f\beta. & (4)
 \end{aligned}$$

Intuitively, for a movement in the exchange rate in the current period to have an impact on trade prices, it must be the case the firms are given the opportunity to adjust their prices, which happens with probability f . The conditioning of the covariance term on $\mathcal{I}_{it}^s = 0$ reflects the fact that items new to the basket cannot be used in the period of their introduction to compute a price change. Notice that our estimate of the initial impact of an exchange rate movement does not depend on the presence of item substitutions or their potentially systematic replacement by "new" prices.

Proceeding similarly for b_1 ,

$$\begin{aligned}
 b_1 &= \frac{\int \text{cov}(\Delta p_{it}, \Delta x_{t-1} | \mathcal{I}_{it}^s = 0) di}{\text{cov}(\Delta x_{t-1})} \\
 &= f \frac{\text{cov}(u_{it} + \beta \Delta x_t + \varepsilon_{it}, \Delta x_{t-1} | \mathcal{I}_{it}^s = 0, \mathcal{I}_{it}^f = 0)}{\text{cov}(\Delta x_t)}.
 \end{aligned}$$

Since Δx_t and ε_{it} are assumed to be independent from Δx_{t-1} , the covariance term is impacted solely through the possible interactions between the cumulated price pressure u_{it} and Δx_{t-1} . Conditioning on

past realizations of the indicator variables, there are five distinct cases:

$$u_{it} = \begin{cases} u_{it-1} + \beta\Delta x_{t-1} + \varepsilon_{it-1} & \text{if } \{\mathcal{I}_{it-1}^s = 0, \mathcal{I}_{it-1}^f = 0\} \\ 0 & \text{if } \{\mathcal{I}_{it-1}^s = 0, \mathcal{I}_{it-1}^f = 1\} \\ u_{it-1} + \beta\Delta x_{t-1} + \varepsilon_{it-1} & \text{if } \{\mathcal{I}_{it-1}^s = 1, \mathcal{I}_{it-1}^n = 0, \mathcal{I}_{it-1}^f = 0\} \\ 0 & \text{if } \{\mathcal{I}_{it-1}^s = 1, \mathcal{I}_{it-1}^n = 0, \mathcal{I}_{it-1}^f = 1\} \\ 0 & \text{if } \{\mathcal{I}_{it-1}^s = 1, \mathcal{I}_{it-1}^n = 1\} \end{cases}. \quad (5)$$

Consequently,

$$\begin{aligned} b_1 &= f \frac{\int \text{cov}(\beta\Delta x_{t-1}, \Delta x_t | \mathcal{I}_{it}^s = 0, \mathcal{I}_{it}^f = 0) di}{\text{cov}(\Delta x_t)} \left(\Pr[\mathcal{I}_{it-1}^s = 0, \mathcal{I}_{it-1}^f = 0] + \Pr[\mathcal{I}_{it-1}^s = 1, \mathcal{I}_{it-1}^n = 0, \mathcal{I}_{it-1}^f = 0] \right) \\ &= f\beta((1-f)(1-s) + (1-f)s(1-n)) \\ &= f(1-f)(1-sn)\beta. \end{aligned}$$

Intuitively, for the current price change to be impacted by Δx_{t-1} , it must be the case that the price changed in the current period (probability f), and that there was neither a price change nor a substitution by a new item in the previous period (with probabilities $1-f$ and $1-sn$, respectively). More generally, one can show that

$$b_l = f(1-f)^l(1-sn)^l\beta.$$

Appendix 2: An Alternative Price Index with Delayed Entry

We now consider the environment described in Appendix 1 with the additional assumption that the econometrician discards the first $M \geq 1$ price observations at the beginning of every price trajectory prior to computing the import price index. As it turns out, by effectively delaying the introduction of items in the basket, one can purge the estimates of a substantial portion of the product replacement bias.

Using the covariance approach, the first estimated coefficient is given by

$$\begin{aligned} b_0 &= \frac{\text{cov}(\int \Delta p_{it} di, \Delta x_t | \mathcal{I}_{it}^s = \dots \mathcal{I}_{it-M}^s = 0)}{\text{cov}(\Delta x_t)} \\ &= f \frac{\int \text{cov}(u_{it} + \beta\Delta x_t + \varepsilon_{it}, \Delta x_t | \mathcal{I}_{it}^s = \dots \mathcal{I}_{it-M}^s = 0, \mathcal{I}_{it}^f = 0) di}{\text{cov}(\Delta x_t)} \\ &= f\beta. \end{aligned}$$

This expression is identical to what we had previously, with no bias in the estimate of the contemporaneous response of price to a movement in the exchange rate. Consider now the coefficient on the first lag of the exchange rate. Since $M \geq 1$, items introduced in the basket at period $t-1$ are not used in the estimation, even though a price change at period t can in principle be computed (absent another substitution at t). To reflect the movement in the exchange rate at $t-1$ on prices today, it must also

be the case that a price change is observed at t but not at $t - 1$, otherwise Δx_t would not impact the change in the price even if it were different from 0. Consequently,

$$\begin{aligned} b_1 &= \frac{\int \text{cov}(\Delta p_{it}, \Delta x_{t-1} | \mathcal{I}_{it}^s = \mathcal{I}_{it-1}^s = 0) di}{\text{cov}(\Delta x_{t-1})} \\ &= f \frac{\text{cov}(u_{it} + \beta \Delta x_t + \varepsilon_{it}, \Delta x_{t-1} | \mathcal{I}_{it}^s = \mathcal{I}_{it-1}^s = 0, \mathcal{I}_{it}^f = 0)}{\text{cov}(\Delta x_t)} \\ &= f \frac{\text{cov}(u_{it} + \beta \Delta x_t + \varepsilon_{it}, \Delta x_{t-1} | \mathcal{I}_{it}^s = \mathcal{I}_{it-1}^s = 0, \mathcal{I}_{it}^f = 0)}{\text{cov}(\Delta x_t)}. \end{aligned}$$

Again, since Δx_t and ε_{it} are independent from Δx_{t-1} , only u_{it} is potentially correlated with Δx_{t-1} . Absent a substitution in period $t - 1$, there are only two possible cases

$$u_{it} = \begin{cases} u_{it-1} + \beta \Delta x_{t-1} + \varepsilon_{it-1} & \text{if } \left\{ \mathcal{I}_{it-1}^f = 0 \right\} \\ 0 & \text{if } \left\{ \mathcal{I}_{it-1}^f = 1 \right\} \end{cases},$$

so that

$$b_1 = f(1 - f)\beta.$$

In short, we have eliminated entirely any product replacement bias from the estimation of b_1 . Using a similar approach, it is straightforward to show that there is no bias in the estimation of the coefficients on lags smaller or equal to the censoring horizon,

$$b_l = \beta(1 - f)^l f \quad \text{if } l \leq M.$$

Our method can also purge some of the bias associate with lags beyond the censoring horizon. As an illustration, consider the estimation of b_2 when $M = 1$,

$$\begin{aligned} b_2 &= \frac{\int \text{cov}(\Delta p_{it}, \Delta x_{t-2} | \mathcal{I}_{it}^s = \mathcal{I}_{it-1}^s = 0) di}{\text{cov}(\Delta x_t)} \\ &= f(1 - f) \frac{\int \text{cov}(u_{it-1}, \Delta x_{t-2} | \mathcal{I}_{it}^s = \mathcal{I}_{it-1}^s = 0, \mathcal{I}_{it}^f = 1, \mathcal{I}_{it-1}^f = 0) di}{\text{cov}(\Delta x_t)}. \end{aligned}$$

The cumulated inflation pressure contained in u_{it-1} can be decomposed in a similar way as in equation 5, so that $b_2 = f(1 - f)^2(1 - sn)$. More generally, we can show that

$$b_l = \beta(1 - f)^l (1 - sn)^{l-M} f \quad \text{if } l > M.$$

Intuitively, for the movement in the exchange rate at period $l > M$ to be reflected in prices today, we must observe a price change in the current period, no price change in any of the previous l periods, as well as no substitution by "new" items prior to the truncation horizon. Note that the reduction in the bias beyond the self-imposed censoring horizon is greatest for the coefficients on lags close to M . For example, suppose the econometrician drops the first 6 price observations of every price trajectory. The estimate of

the seventh lag of exchange rate movements increases from $f(1-f)^7(1-zn)^7$ to $f(1-f)^7(1-zn)^1$, which is much closer to the unbiased value $f(1-f)$. Under an average substitution rate $n = 0.05$ and the worse-case hypothesis that $n = 1$, we would effectively have eliminated 83% of the product replacement bias contributed by b_7 . The gains in bias reduction fall as we consider periods increasingly beyond the truncation horizon. However, the unbiased coefficients are also decreasing exponentially with duration, so that the precision gains from correcting the early lags can nevertheless be substantial, especially if one is mainly interested in the policy-relevant horizon.

Finally, we derive an expression for the estimate of the long-run pass-through coefficient under our censoring method. If the censoring horizon is greater than the number of lags in the regression ($M \geq L$), then

$$\sum_{l=0}^L b_l = \left(1 - (1-f)^{L+1}\right) \beta,$$

the same expression we have in an environment with no product replacement bias. If the censoring horizon is shorter than the number of lags ($L > M$), then

$$\sum_{l=0}^{L>M} b_l = \sum_{l=0}^M f(1-f)^l \beta + \sum_{l=M+1}^L f(1-f)^l (1-sn)^{l-M} \beta.$$

Asymptotically,

$$\lim_{L \rightarrow \infty} \sum_{l=0}^{L>M} b_l = \frac{f + (1-f)sn \left(1 - (1-f)^M\right)}{f + (1-f)sn} \beta.$$

One can easily check that this expression converges to β as $M \rightarrow \infty$. Moreover, it equals the product replacement bias argued by Nakamura and Steinsson under their implicit assumptions that $n = 1$ and $M = 0$.

Appendix 3: Impact of selective exit on regression coefficients

This appendix derives analytical expressions for the (plim) regression coefficients in the environment considered in Section 6.1 under the special assumption of Calvo pricing and uncorrelated exchange rate innovations. We denote the event of an item exit by the indicator variable \mathcal{I}_{it}^e . We also assume that the price collector replaces the exiting item by one sampled from the universe of items. Finally, we suppose that exchange rate innovations are uncorrelated over time. For simplicity, we assume that there are no other substitutions in the basket so that the probability of exiting the basket when the firm would have kept the posted price unchanged is zero. Under these assumptions, we can derive explicit expressions for the coefficients in the regression when the data are generated by the Calvo model.

Consider first the coefficient on the contemporaneous response of the import price index to an exchange rate movement,

$$b_0 = \frac{\text{cov}\left(\int \Delta p_{it} di, \Delta x_t | \mathcal{I}_{it}^e = 0\right)}{\text{cov}(\Delta x_t)}.$$

We condition on $\mathcal{I}_{it}^e = 0$ since exiting items are not used by the econometrician to compute inflation.

The share of usable observation in the basket is thus $1 - ef$. For an item to remain in the basket, it must either be the case that no price change took place ($\mathcal{I}_{it}^f = 0$) or that the price change took place through a change in the posted price ($\mathcal{I}_{it}^f = 1$ and $\mathcal{I}_{it}^e = 0$). Since the item does not contribute to inflation in the former case, we have

$$\begin{aligned} b_0 &= \frac{\text{cov}\left(\Delta p_{it}, \Delta x_t | \mathcal{I}_{it}^f = 1, \mathcal{I}_{it}^e = 0\right)}{\text{cov}(\Delta x_t)} \Pr\left[\mathcal{I}_{it}^f = 1 | \mathcal{I}_{it}^e = 0\right] \\ &= \frac{\text{cov}\left(u_{it} + \beta \Delta x_t + \varepsilon_{it}, \Delta x_t | \mathcal{I}_{it}^f = 1, \mathcal{I}_{it}^e = 0\right)}{\text{cov}(\Delta x_t)} \frac{(1 - e) f}{1 - ef} \\ &= \frac{(1 - e)}{1 - ef} f \beta. \end{aligned}$$

Contrary to the product replacement bias, the coefficient capturing the contemporaneous response to the exchange rate is biased in the presence of selective exits. In the extreme case in which all decisions to change the price lead to an exit, the initial response of the import price index is exactly zero.

Consider now the coefficient on the second lag of the exchange rate,

$$b_1 = \frac{\text{cov}\left(\int \Delta p_{it} di, \Delta x_{t-1} | \mathcal{I}_{it}^e = 0\right)}{\text{cov}(\Delta x_t)}.$$

For a movement in the exchange rate in the previous period to have an impact on the import price index today, it must be the case that there is a price change today but no exit (probability $f(1 - e)$), and that there was either no price change in the previous period (probability $1 - f$) or, if a price change occurred, that it resulted in an exit accompanied by the introduction of an item whose price was unchanged at $t - 1$ (probability fe of exiting and probability $1 - f$ that the substitute had no price change). Consequently,

$$b_1 = ((1 - f) + fe(1 - f)) \frac{(1 - e) f}{1 - ef} \beta.$$

More generally, for the price of an item at period t to reflect an exchange rate movement at $t - l$, we must have that a price change with no exit occurs at period t (probability $f(1 - e)$) and that either (a) the item has been in the basket with no price changes for the past l periods (probability $(1 - f)^l$) or (b) that a substitution took place over any of the past l periods (probability fe per period) resulting in the introduction of an item with no price change from period $t - l$ to period $t - 1$ and a price change with no exit at t (probability $(1 - f)^l f(1 - e)$ of drawing such price trajectory). Summing up,

$$b_l = \left(\frac{1 - e}{1 - fe}\right) (1 + (1 - n) l fe) (1 - f)^l f \beta.$$

Appendix 4: Medium-Run Pass-Through and Selection Biases in the Entry and Exit of Items

Gopinath, Itskhoki, and Rigobon (2010) regress (nonzero) changes in individual prices on a constant and the cumulative change in the exchange rate since the last nominal price adjustment τ periods earlier, $\Delta RER_t^\tau = \sum_{s=0}^{\tau-1} \Delta x_t$. The total number of observations in the regression thus corresponds to the number of uncensored price spells. The regression takes the form of

$$\Delta p_{i,t} = \alpha + \beta \Delta RER_t^\tau + \epsilon_{it}.$$

Under our data-generating assumption,

$$\Delta p_{i,t} = \beta \Delta RER_t^\tau + \sum_{s=0}^{\tau-1} \epsilon_{it}$$

so that

$$\hat{\beta} = \frac{\text{cov}\left(\beta \Delta RER_t^\tau + \sum_{s=0}^{\tau-1} \epsilon_{it}, \Delta RER_t^\tau\right)}{\text{cov}\left(\Delta RER_t^\tau\right)} = \beta.$$

In short, their approach suffers no bias associated with the selective entry and exit of items in the basket considered in this paper.

Table 1: Inflation objectives and policy horizons

| Economy | Target rate (%) | Target horizon | Forecast horizon |
|----------------------------|------------------------|-----------------------------|------------------------------|
| Australia | 2-3 | average over business cycle | 2 years |
| Canada | 1-3 | 6 to 8 quarters | 2 to 3 years |
| Euro area | just below 2 | medium term | current year and next |
| Japan | 0-2 ^a | medium to long term | current fiscal year and next |
| New Zealand | 1-3 | medium term | 3 years |
| Norway | 2.5 | 1 to 3 years ahead | 3 to 4 years |
| Sweden | 1-3 | 2-year ahead | 3 to 4 years |
| Switzerland | less than 2 | medium term | 3 years |
| United Kingdom | 2 | informal 2-year | 3 years |
| United States ^b | no target | n.a. | 2 to 3 years |

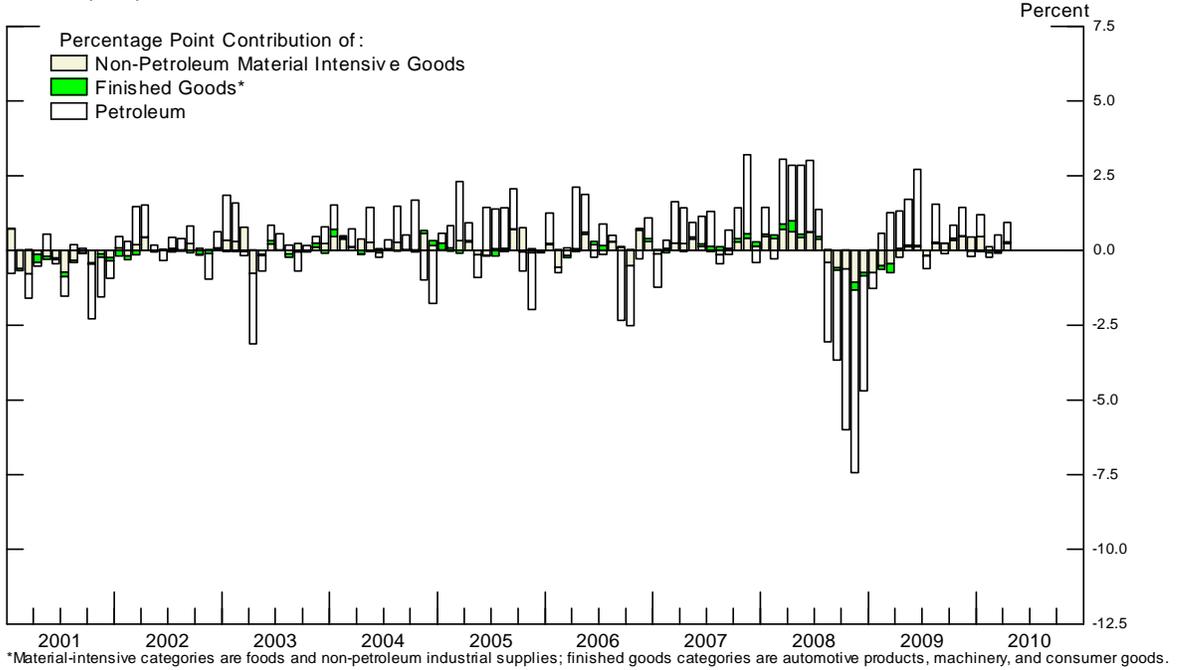
Notes: (a) 0-2% is consistent with the distribution of Board members' understanding of medium to long-term price stability. (b) Based on the forecasts released periodically by FOMC members. The staff's forecasts ("Greenbook") most recently made publicly available have horizons ranging from about 1 and half to 2 and half years.

Table 2: The frequency and size of import price changes and IPP item entry and exit rates

| | Enduse | Weight (2006) | Weighted by classification group size | | | | | | Unweighted | | | | | |
|--------------------------------------|--|------------------|---------------------------------------|-------|------|-------|------|--------------|--------------------|-------|------|-------|------|--------------|
| | | | Freq. Price Change | | | Entry | Exit | Abs. Size | Freq. Price Change | | | Entry | Exit | Abs. Size |
| | | | All | Early | Late | | | | All | Early | Late | | | |
| Foods, Feeds & Beverage | 000 Green coffee, cocoa beans, cane sugar | 0.3 | 53.4 | 58.8 | 48.2 | 3.1 | 3.5 | 10.0 | 50.5 | 55.5 | 45.9 | 3.4 | 3.4 | 9.7 |
| | 001 Other agricultural foods | 2.7 | 16.2 | 24.6 | 11.8 | 3.3 | 3.7 | 8.4 | 20.2 | 24.9 | 16.1 | 3.6 | 3.6 | 10.2 |
| | 010 Nonagricultural products | 1.0 | 32.6 | 37.8 | 29.1 | 3.1 | 3.4 | 6.3 | 21.9 | 24.1 | 19.6 | 3.2 | 3.2 | 7.1 |
| Industrial Supplies & Materials | 100 Petroleum & products, excluding gas | 15.6 | 48.5 | 48.7 | 47.8 | 4.0 | 5.1 | 10.0 | 44.1 | 46.6 | 35.2 | 4.0 | 3.9 | 9.2 |
| | 101 Fuels, n.e.s.-coal & gas | 1.7 | 64.9 | 69.2 | 64.1 | 5.1 | 5.9 | 14.4 | 55.0 | 55.1 | 54.7 | 4.8 | 4.8 | 13.7 |
| | 110 Paper base stocks | 0.2 | 36.7 | 36.9 | 36.6 | 3.3 | 3.6 | 7.1 | 35.2 | 36.1 | 33.8 | 4.1 | 4.1 | 7.6 |
| | 111 Newsprint & other paper products | 0.6 | 30.9 | 25.5 | 41.0 | 3.6 | 3.7 | 5.3 | 20.9 | 19.7 | 22.8 | 3.7 | 3.8 | 5.7 |
| | 120 Agricultural industrial supplies | 0.4 | 36.3 | 47.9 | 25.9 | 2.9 | 3.2 | 7.2 | 31.0 | 37.4 | 24.0 | 3.1 | 3.1 | 7.3 |
| | 121 Textile supplies & related materials | 0.7 | 9.8 | 11.2 | 8.1 | 3.3 | 3.1 | 6.4 | 7.9 | 9.9 | 5.8 | 3.4 | 3.3 | 7.3 |
| | 125 Chemicals, excl. medcs., food additives | 3.2 | 15.3 | 18.8 | 13.2 | 3.1 | 3.4 | 9.1 | 11.0 | 11.7 | 10.4 | 3.2 | 3.2 | 8.6 |
| | 130 Lumber & unfinished building materials | 1.0 | 55.8 | 60.8 | 52.6 | 3.2 | 3.4 | 8.2 | 31.0 | 31.5 | 30.6 | 3.6 | 3.6 | 8.0 |
| | 131 Building materials, finished | 0.9 | 14.1 | 12.2 | 14.7 | 3.9 | 4.9 | 10.1 | 9.8 | 10.5 | 9.3 | 3.7 | 3.7 | 7.0 |
| | 140 Steelmaking materials-unmanufactured | 0.4 | 31.8 | 20.8 | 41.0 | 2.8 | 3.3 | 8.2 | 21.8 | 20.9 | 22.9 | 2.9 | 2.9 | 8.2 |
| | 141 Iron & steel mill products-semifinished | 1.2 | 19.2 | 14.4 | 21.4 | 4.1 | 4.9 | 11.6 | 15.1 | 13.0 | 16.6 | 4.4 | 4.3 | 8.4 |
| | 142 Major non-Fe metals-crude & semifin. | 2.5 | 51.2 | 50.9 | 51.5 | 3.5 | 4.4 | 6.7 | 43.6 | 42.7 | 44.8 | 3.8 | 3.8 | 6.5 |
| | 150 Iron & steel products, ex. advanced mfg. | 0.5 | 9.6 | 7.7 | 11.6 | 3.4 | 3.4 | 7.5 | 10.0 | 9.9 | 10.2 | 3.4 | 3.3 | 7.8 |
| | 151 Iron & steel mfg.-advanced | 0.4 | 13.3 | 16.1 | 9.8 | 3.0 | 3.2 | 6.8 | 14.0 | 16.2 | 10.8 | 3.2 | 3.0 | 6.7 |
| | 152 Fin. metal shapes & adv. mfg., ex. steel | 0.9 | 14.1 | 17.2 | 13.0 | 3.0 | 4.0 | 7.4 | 15.5 | 19.0 | 11.8 | 3.4 | 3.5 | 5.9 |
| | 161 Finished nonmetals | 1.4 | 6.8 | 8.5 | 6.1 | 3.6 | 4.2 | 8.8 | 7.0 | 7.7 | 6.4 | 3.6 | 3.7 | 8.0 |
| Capital Goods | 210 Oil drilling, mining & const. machinery | 1.0 | 9.1 | 6.7 | 10.7 | 3.3 | 3.8 | 5.8 | 7.8 | 7.5 | 8.0 | 3.4 | 3.3 | 5.9 |
| | 211 Industrial & service machinery, n.e.c. | 5.8 | 5.4 | 5.4 | 5.3 | 3.1 | 3.4 | 6.4 | 5.4 | 5.6 | 5.1 | 3.2 | 3.2 | 6.8 |
| | 212 Agricultural machinery & equip. | 0.4 | 7.3 | 6.6 | 8.2 | 3.5 | 3.3 | 4.4 | 8.5 | 8.2 | 8.8 | 3.5 | 3.4 | 4.9 |
| | 213 Computers, periph. & semiconductors | 7.0 | 11.1 | 12.4 | 10.1 | 5.2 | 4.9 | 8.9 | 8.7 | 9.7 | 8.3 | 4.8 | 4.8 | 8.7 |
| | 214 Telecommunications equip. | 2.2 | 5.4 | 6.5 | 4.3 | 5.1 | 4.8 | 8.7 | 5.5 | 6.5 | 4.7 | 4.4 | 4.3 | 7.8 |
| | 215 Business mach. & equip., ex. Computers | 0.5 | 6.9 | 8.1 | 3.7 | 4.1 | 3.7 | 5.1 | 5.3 | 6.4 | 3.5 | 3.8 | 3.7 | 5.7 |
| | 216 Scientific, hospital & medical machinery | 1.4 | 4.8 | 5.1 | 4.6 | 4.1 | 4.5 | 9.1 | 5.0 | 5.5 | 4.6 | 3.8 | 3.9 | 7.4 |
| Auto- motive | 300 Passenger cars, new & used | 7.5 | 4.9 | 3.5 | 5.1 | 3.4 | 4.2 | 2.3 | 5.3 | 4.9 | 5.5 | 3.7 | 3.7 | 2.2 |
| | 301 Trucks, buses, & special-purp. vehicles | 1.3 | 5.2 | 5.6 | 4.6 | 5.1 | 4.9 | 2.8 | 5.9 | 6.1 | 5.6 | 4.0 | 3.8 | 3.1 |
| | 302 Parts, engines, bodies, & chassis | 5.1 | 7.0 | 7.3 | 6.8 | 3.7 | 3.7 | 6.3 | 7.3 | 7.6 | 7.0 | 3.7 | 3.6 | 6.0 |
| Consumer Goods (Ex. Food & Auto.) | 400 Apparel, footwear, & household goods | 6.2 | 3.7 | 4.0 | 3.6 | 4.9 | 4.6 | 6.4 | 3.8 | 4.2 | 3.4 | 4.5 | 4.4 | 6.6 |
| | 401 Other consumer nondurables | 4.7 | 5.1 | 6.3 | 4.8 | 3.7 | 4.6 | 10.5 | 5.2 | 6.0 | 4.6 | 3.4 | 3.4 | 8.5 |
| | 410 Household goods | 5.7 | 4.8 | 4.0 | 5.0 | 4.3 | 5.1 | 8.5 | 4.3 | 4.5 | 4.2 | 3.8 | 3.8 | 6.8 |
| | 411 Recreational equip. & materials | 2.1 | 3.7 | 4.7 | 3.0 | 4.3 | 4.7 | 6.6 | 4.8 | 5.4 | 4.2 | 4.1 | 4.0 | 6.5 |
| | 412 Home entertainment equip. | 2.9 | 6.0 | 6.6 | 5.6 | 5.7 | 5.6 | 6.7 | 5.6 | 6.1 | 5.2 | 4.8 | 4.8 | 6.0 |
| | 413 Coins, gems, jewelry, & collectibles | 1.2 | 8.8 | 5.1 | 10.8 | 4.0 | 4.5 | 7.3 | 7.4 | 6.9 | 7.9 | 3.8 | 3.8 | 6.3 |
| | 500 Imports, N.E.S. | 3.3 | 4.7 | 7.0 | 1.5 | 1.8 | 2.2 | 10.8 | 5.0 | 6.5 | 0.7 | 2.6 | 2.6 | 14.0 |
| Total | 93.7 | 12.2 | 13.0 | 11.8 | 4.1 | 4.4 | 9.0 | 9.5 | 10.6 | 8.5 | 3.8 | 3.7 | 7.9 | |

Figure 1: Decomposition of Monthly Trade Price Inflation (BLS basis)

total import price inflation



core (non-fuel and non-computer) import price inflation

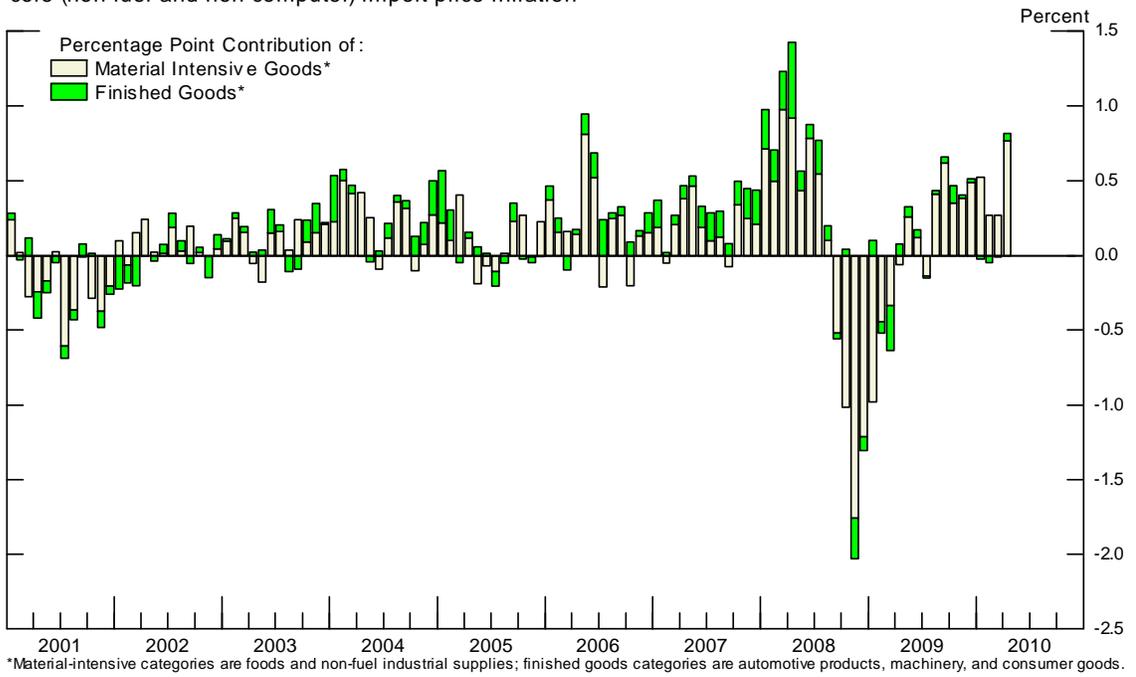
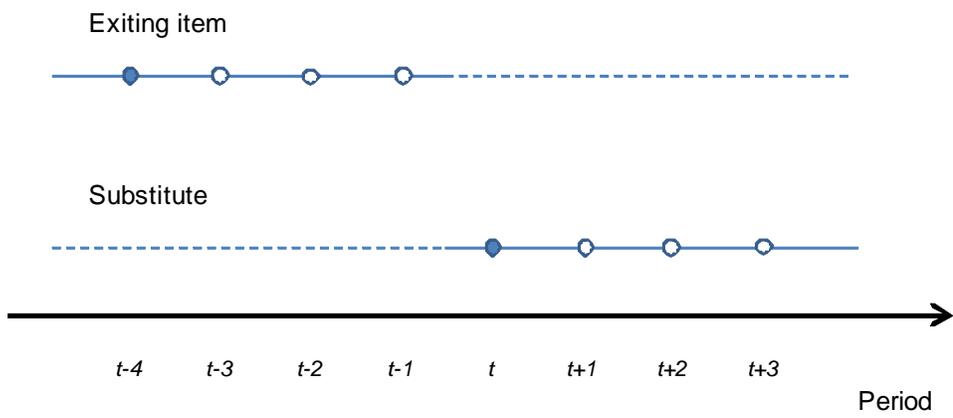


Figure 2: Illustration of an item replacement



Notes: Price changes are indicated by full circles and constant prices by empty ones.

Figure 3: Share of long-run pass-through estimated with an infinite number of lags ($100 \times \frac{f}{f+(1-f)sn}$)

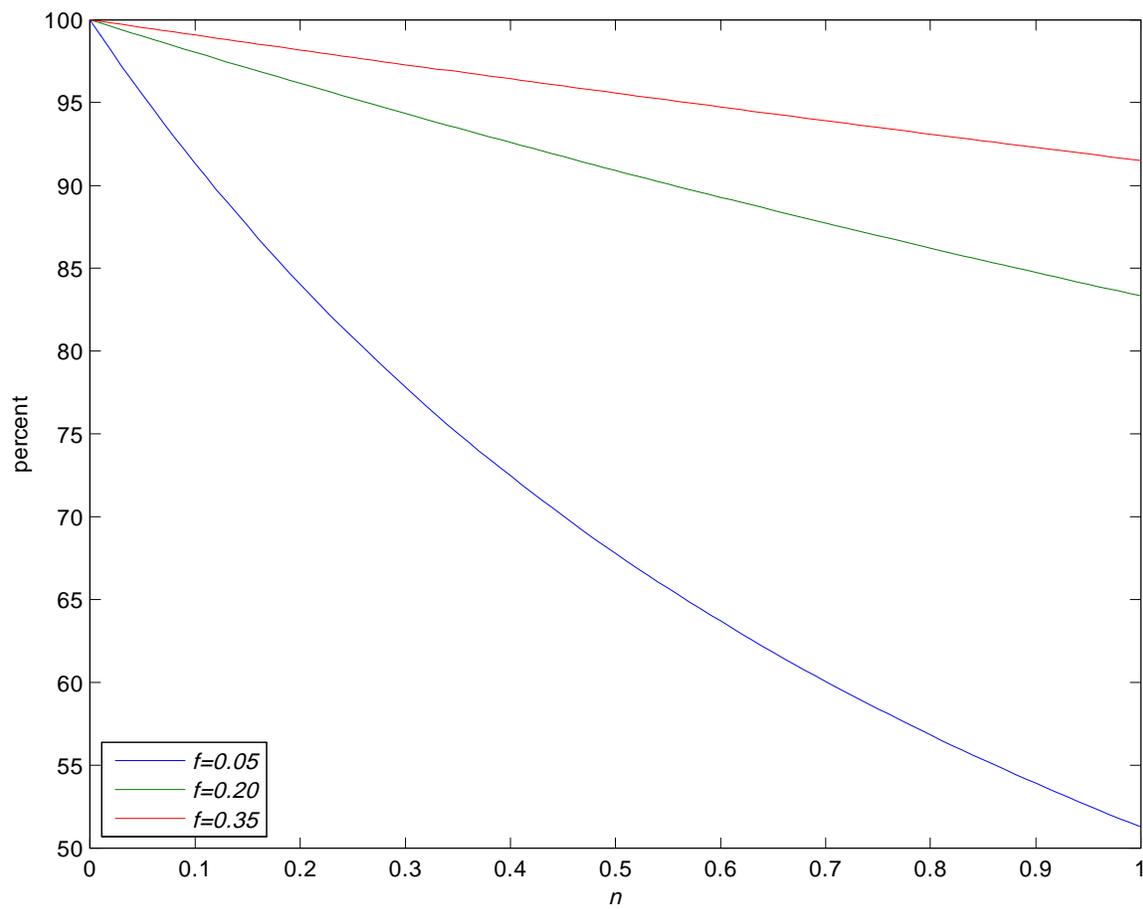


Figure 4: Coefficients on lags of the exchange rate in pass-through regressions conditional on frequency of micro price adjustment

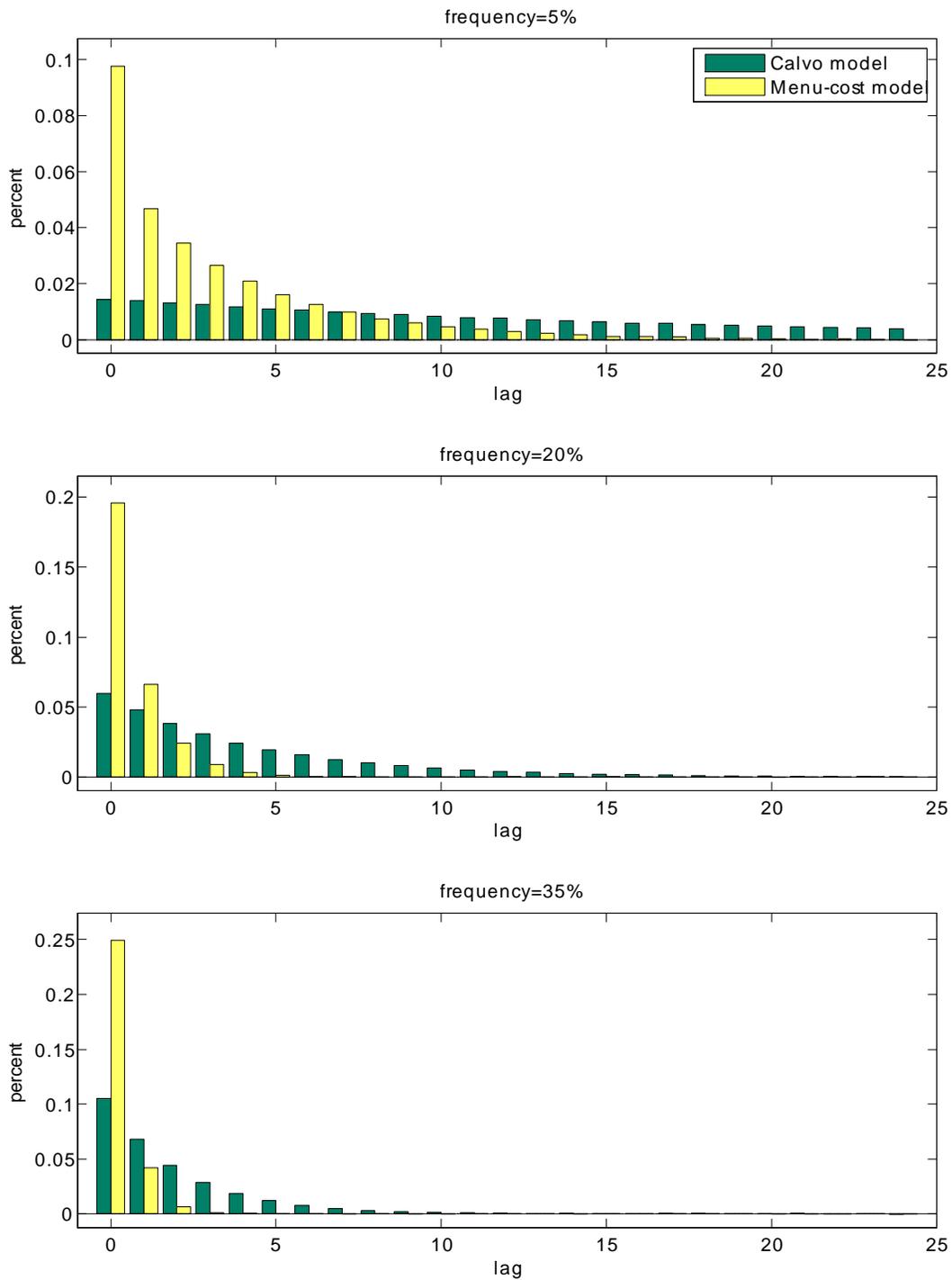


Figure 5: Distribution of optimal lag length in Monte-Carlo simulations

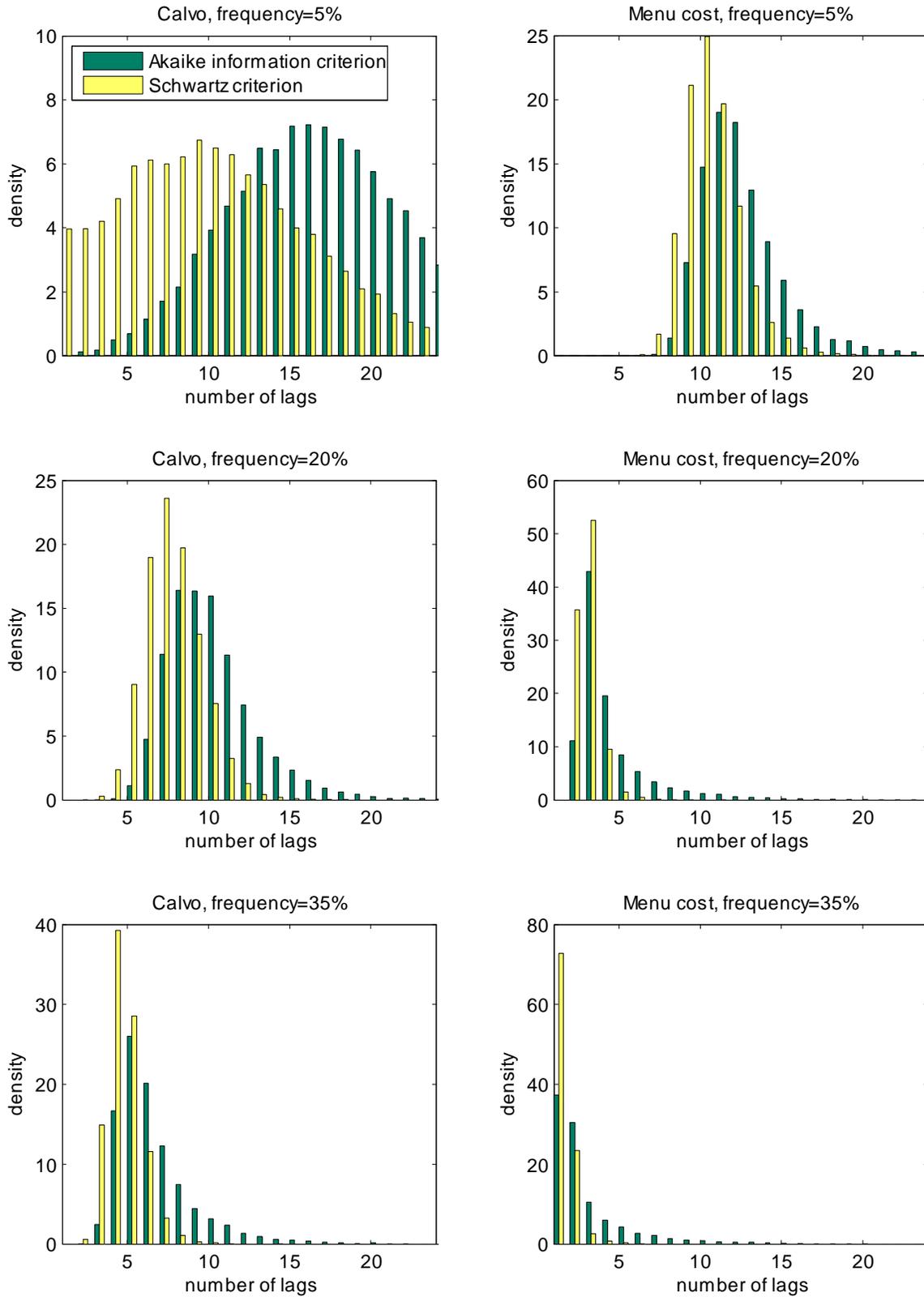


Figure 6: Distribution of cumulative pass-through after 24 months in Monte-Carlo simulations (as a share of true pass-through)

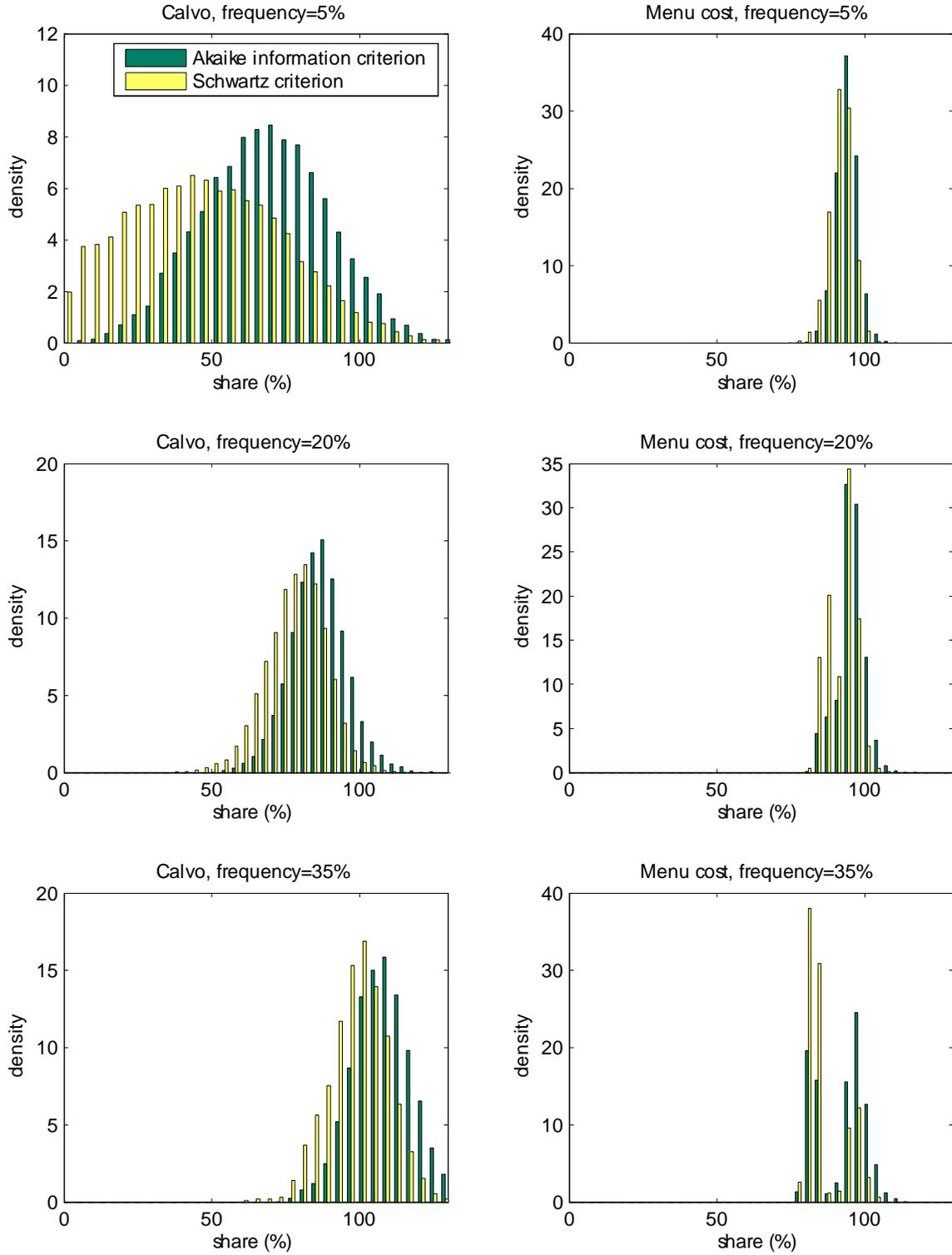


Figure 7: Root Mean Square Error (RSME) of predicted Pass-Through after 24 Months in Monte-Carlo simulations

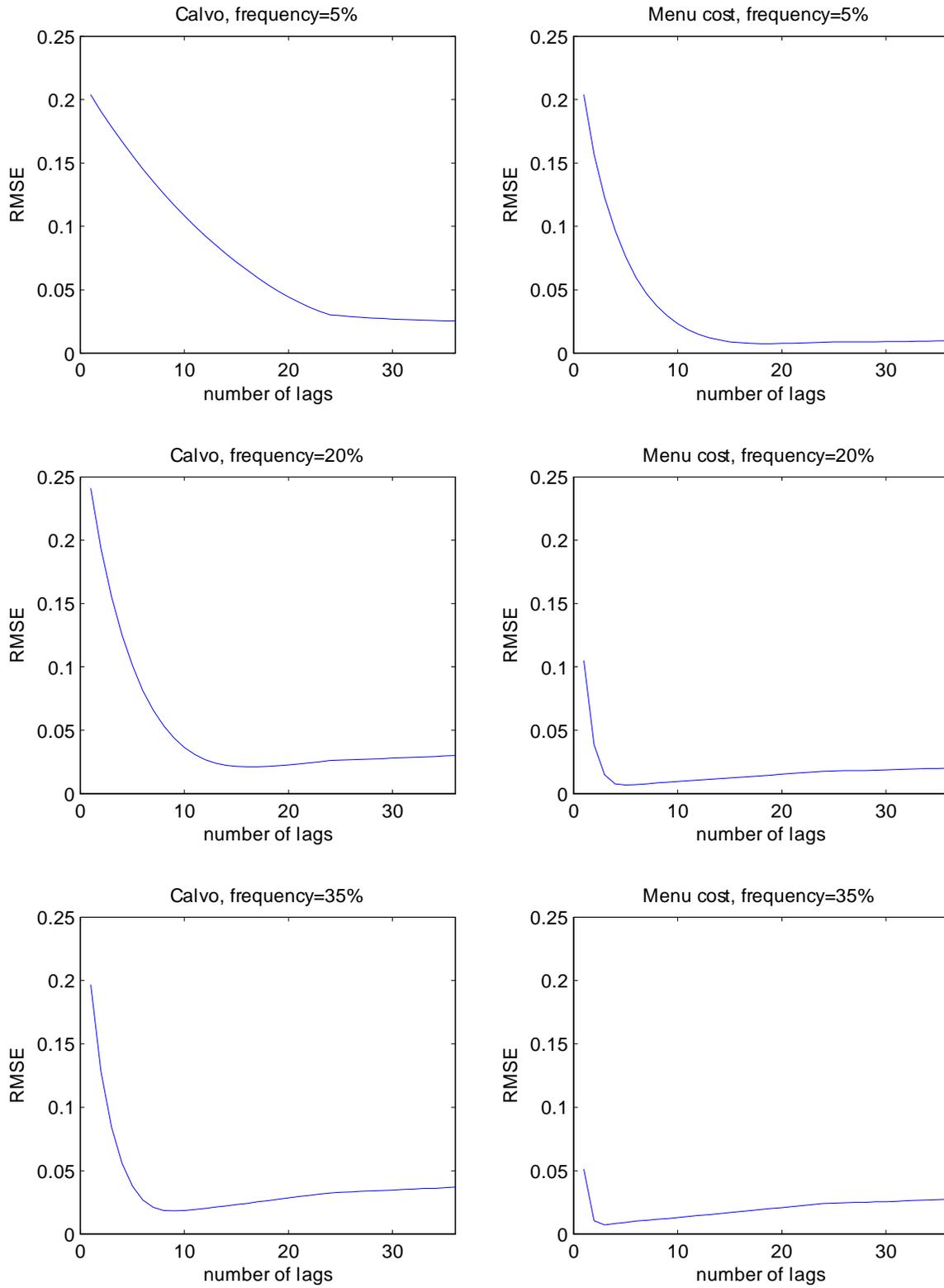


Figure 8: Impact of lag length selection on estimated response of imported finished goods prices to an exchange rate movement

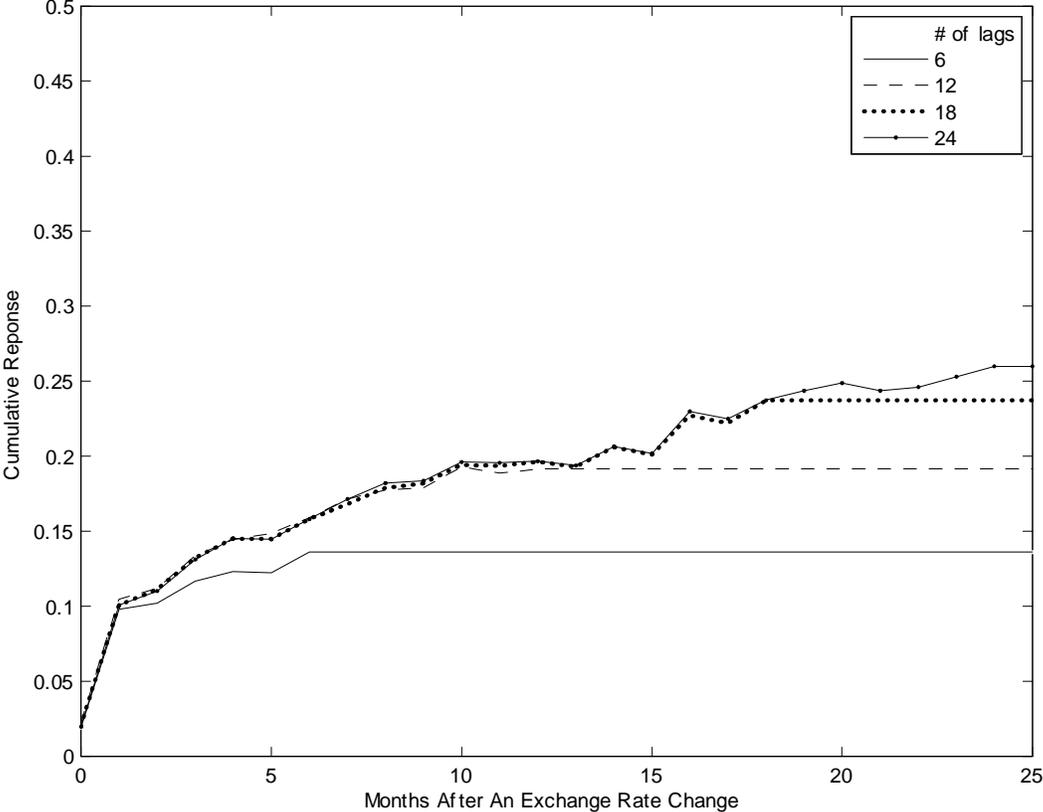


Figure 9: Cumulative contribution of coefficients on lagged exchange rate variables in Calvo model under severe product replacement bias ($n = 1, z = 0.05$)

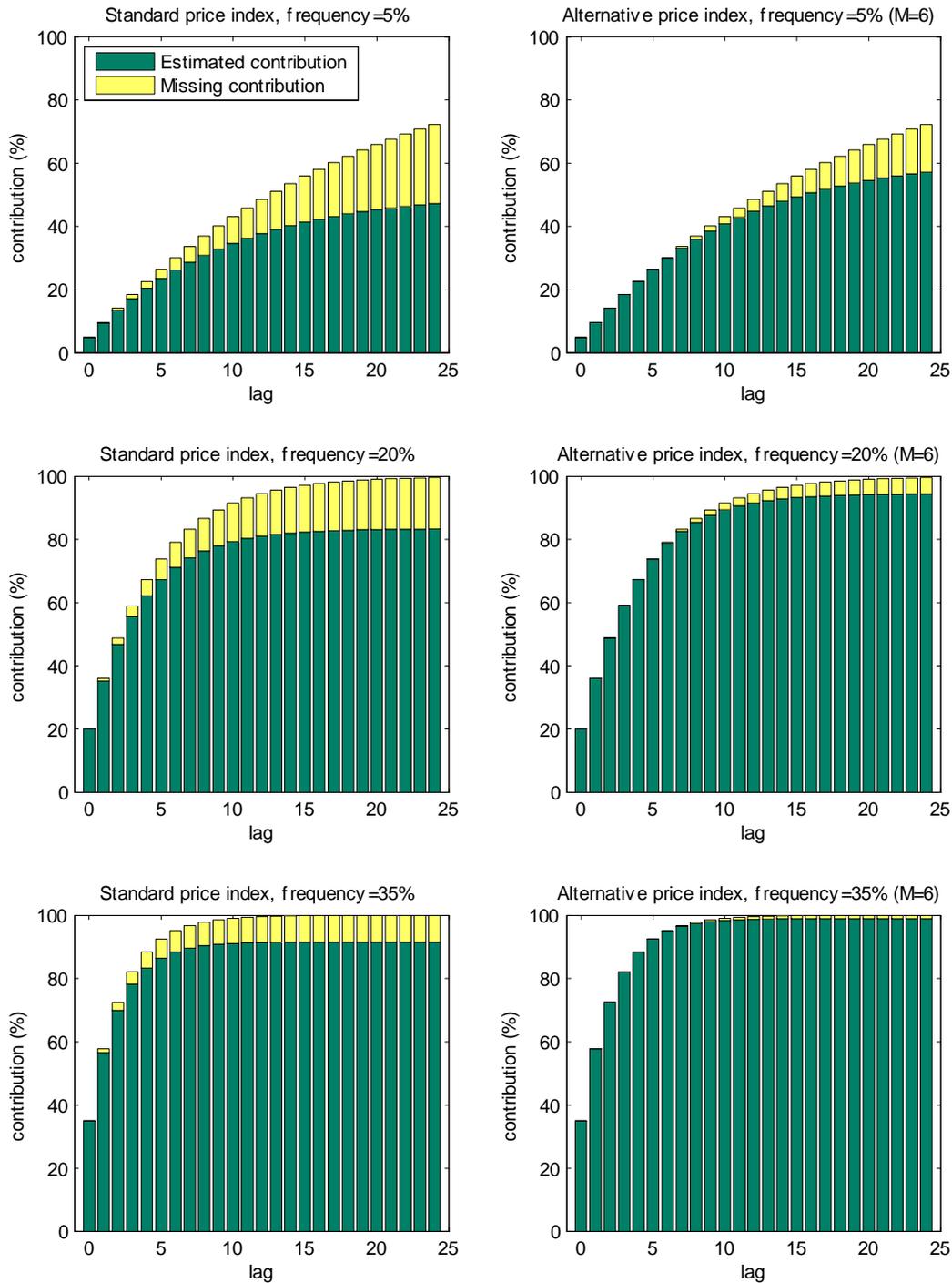


Figure 10: Marginal contribution of coefficients on lagged exchange rate variables in Calvo model under severe product replacement bias ($n = 1, z = 0.05$)

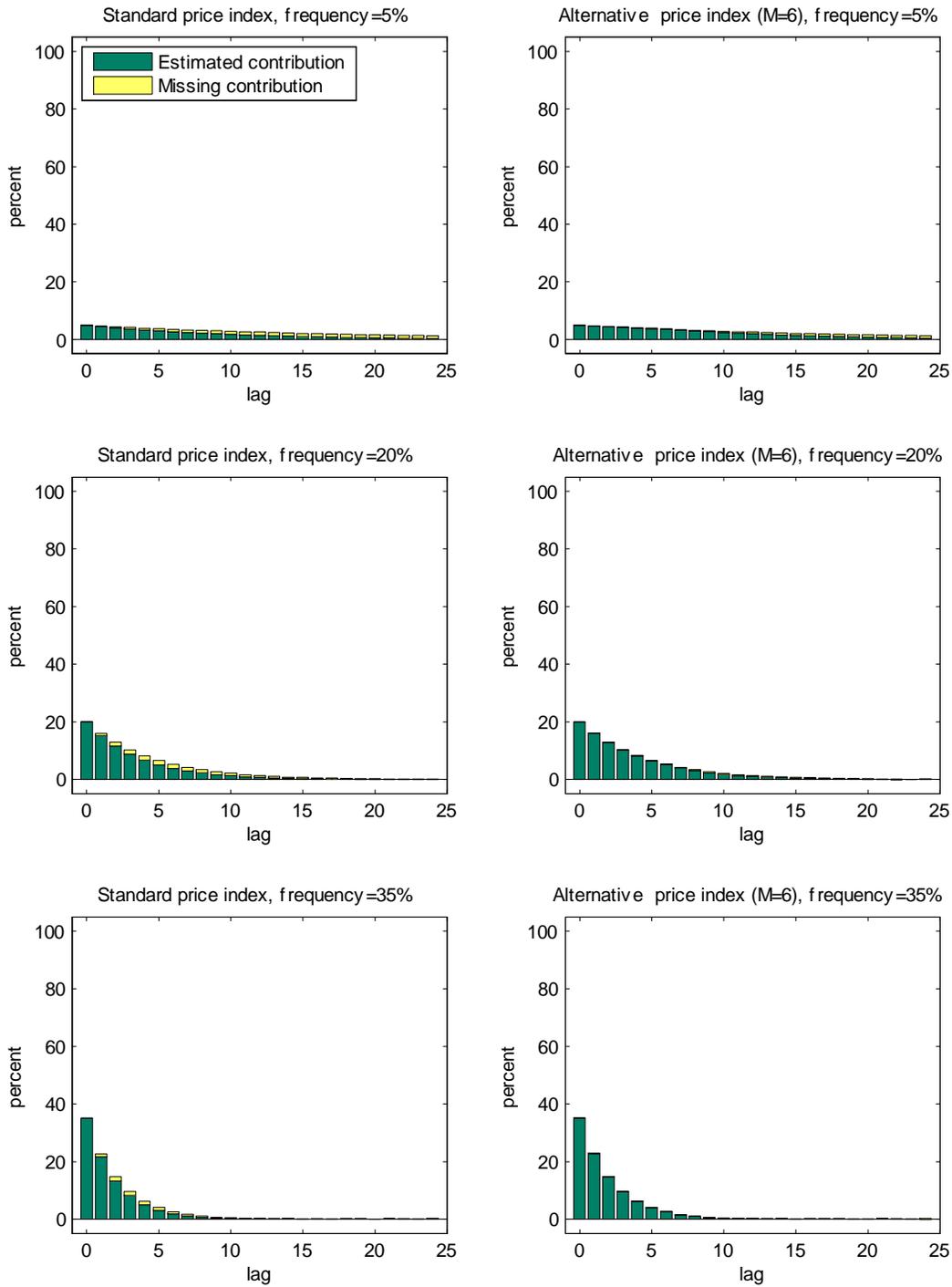


Figure 11: Cumulative contribution of coefficients on lagged exchange rate variables in menu-cost model under severe product replacement bias ($n = 1, z = 0.05$)

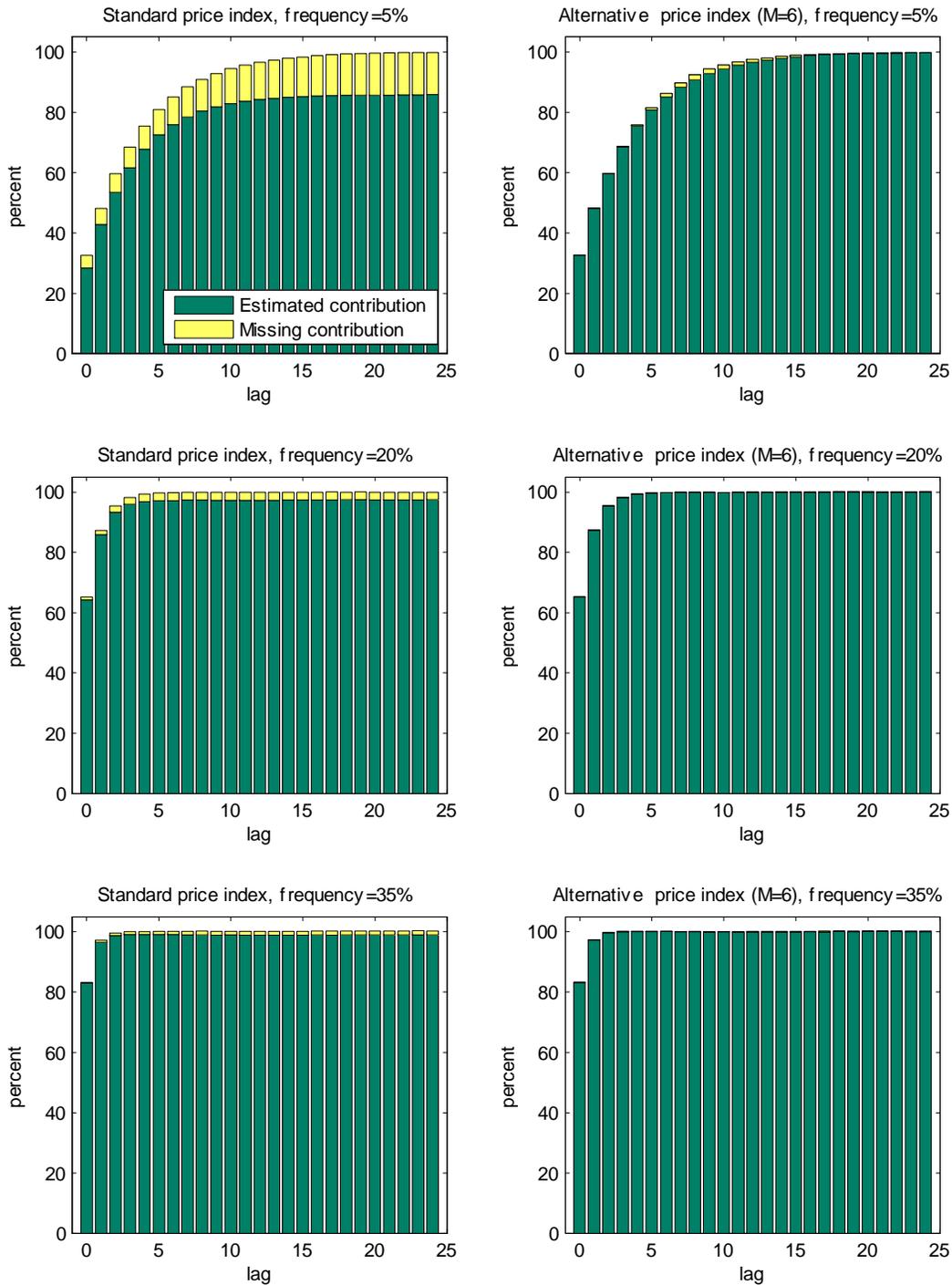


Figure 12: Marginal contribution of coefficients on lagged exchange rate variables in menu-cost model under severe product replacement bias ($n = 1, z = 0.05$)

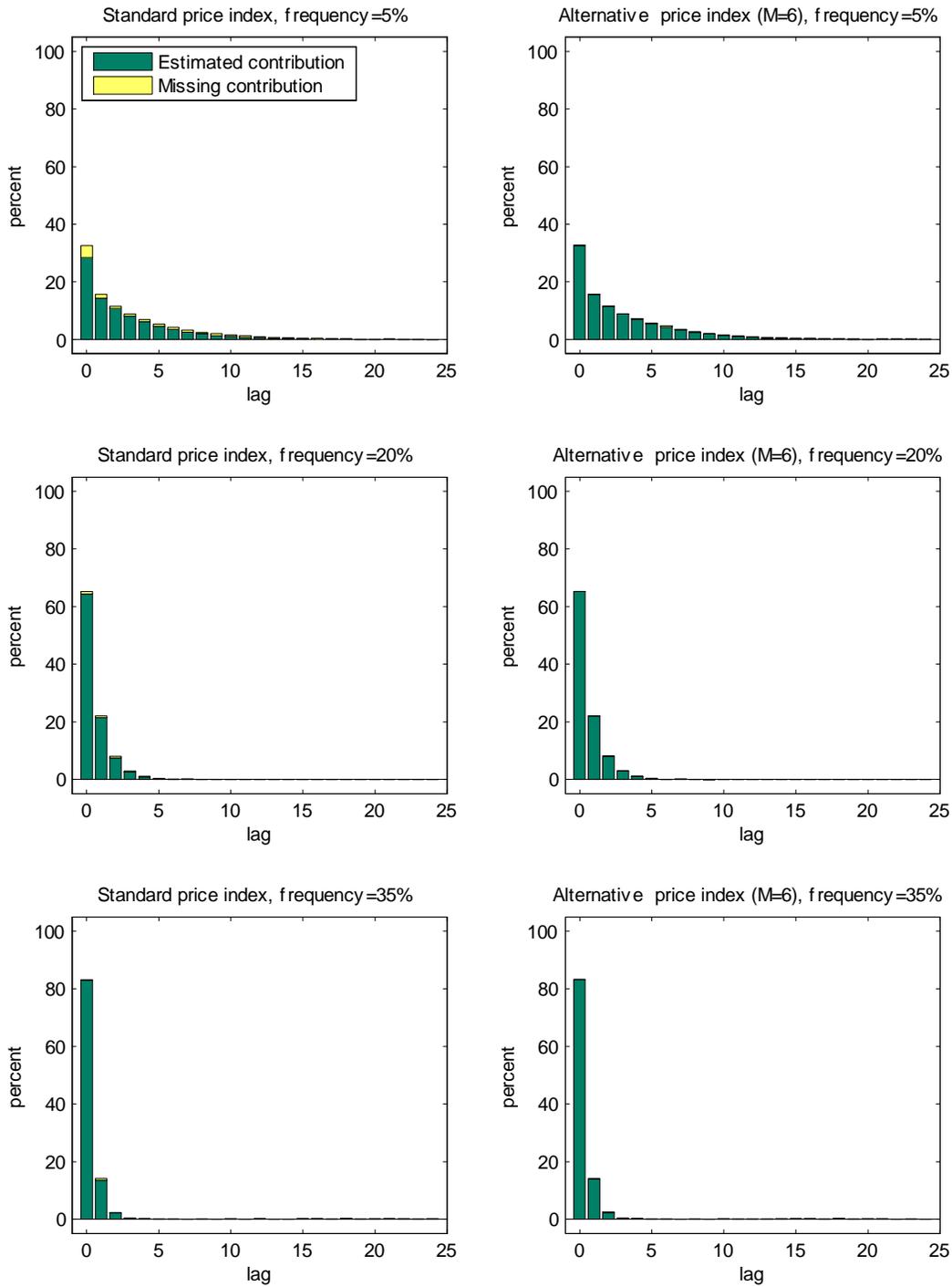


Figure 13: Cumulative contribution of coefficients on lagged exchange rate variables under selective exit ($e = 0.25$)

