

International Trade Price Stickiness and Exchange Rate Pass-through in Micro Data: A Case Study on US-China Trade*

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Abstract

Price-setting behavior of exporters and exchange rate pass-through (ERPT) are crucial issues in international macroeconomics. This paper studies these topics, using a novel dataset of goods-level US-China trade prices collected by the US Bureau of Labor Statistics. We document that the duration of US-China trade prices has declined almost 30% since China began appreciating its currency in 2005. A benchmark menu cost model that is calibrated to the data can replicate the documented decrease in price stickiness. We also estimate ERPT of RMB appreciation into US import prices between 2005 and 2008. The lifelong ERPT is close to one for prices that have at least one change, while the pass-through is less than half when all goods are included. A reason for the difference in pass-through rates is that about one-third of the goods never experience a price change.

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1 Introduction

In this paper, we are interested in two issues. First, has the pricing behavior of Chinese and US exporters changed since 2005? In June 2005, China abandoned its hard currency peg to the US dollar and began appreciating its currency. It provides an excellent opportunity to study the impact of exchange rate policy on the price setting behavior of firms in international trade. Second, how much of RMB appreciation between 2005 and 2008 is passed on to US import prices (exchange rate pass-through, or ERPT)? Given China's large current account surplus with the US and the view that this surplus has played a large role in global economic imbalances, several prominent policymakers and economic researchers have pressed China to revalue its currency in order to rebalance the global economy.¹ A fundamental assumption in this argument though is high ERPT of RMB appreciation into US import prices, which is found not true with aggregate price data. Using goods-level micro data of US-China trade prices collected by the US Bureau of Labor Statistics (BLS), we study the above two issues.

Theoretical studies have found that different price-setting models can have strikingly different macroeconomic implications.² To discriminate among these theoretical models and provide empirical guidance on future theoretical studies, there has been a significant increase in empirical work that uses goods-level price data to study price-setting behavior, especially after statistical agencies in the US, Europe, and other countries began allowing researchers to access their unpublished goods-level micro price data.³ For instance, Nakamura and Steinsson (2008) document that the frequency of price increases is positively correlated with US CPI inflation, while the frequency of price decreases is not. Gagnon (2009) finds in Mexican store-level prices that the relation between aggregate inflation and price stickiness is different in high and low inflation regimes.⁴

These studies show that firm's pricing behavior change with the macro environment such as inflation. Such empirical findings are not consistent with time-dependent sticky-price models that take price stickiness as exogenous and constant, but can be replicated in a state-dependent model (e.g., a menu cost model). Our paper is complementary to the existing literature, by documenting that exporting firm's pricing behavior is

¹For instance, see Timothy Geithner's remarks made at the public confirmation hearing by the US Senate Finance Committee on January 21, 2009.

²For instance, Golosov and Lucas (2007) show that monetary shocks are almost neutral in a menu cost model, but they have significant real effects in a time-dependent pricing model. Betts and Devereux (2000) and Devereux and Engel (2003) emphasize that the choice of invoicing currency in international trade transactions critically determines the short-run ERPT and the optimal exchange rate policy in sticky-price open macroeconomic models.

³Important references for studies using the BLS micro price data include Bils and Klenow (2004), Klenow and Kryvtsov (2008), Nakamura and Steinsson (2008), and Bhattarai and Schoenle (2012). See Alvarez et al. (2006) and Dias et al. (2007) for examples of studying European data and Gagnon (2009) for Mexican data.

⁴Gagnon (2009) documents that when the inflation rate is low, the frequency of price changes is barely correlated with inflation. In contrast, when inflation rises above 10-15%, the frequency and magnitude of price changes are strongly correlated with the inflation rate.

also associated with the change in another macro environment: the exchange rate regime. We also show that a simple open-economy menu cost model that is calibrated to the data can replicate this empirical finding.

Using goods-level US-China trade prices collected by the BLS, we examine the relationship between the choice of exchange rate regime and the pricing behavior of exporters.⁵ Because both the exchange rate and a firm's pricing behavior are endogenously determined when the exchange rate is fully flexible, it is difficult to pin down a causal relationship between aggregate macro variables and pricing behavior of firms. For instance, the choice of pricing currency determines the short-run ERPT. At the same time, Gopinath, Itskhoki, and Rigobon (2010) find evidence that desired ERPT determines the choice of invoicing currency. Firms that prefer low ERPT will choose local currency pricing, while firms that prefer high ERPT will set prices in their own currency. China's regime switching is largely an exogenous event for exporting firms and provides a great case to study this issue.

We first examine the following features of the data: price stickiness, the size of price changes, the fraction of price increases in all price adjustments, and invoicing currency. In particular, our interest lies in investigating if these features change with China's exchange rate regime change. We find that indeed they do, and that this finding can be replicated in a benchmark menu cost model.

More specifically, we document significant price stickiness in US-China trade prices. As in Nakamura and Steinsson (2012), a large fraction of goods in our dataset never change their prices: about a quarter of US export prices to China and one third of import prices from China never changed. As argued in Nakamura and Steinsson (2012), price changes for same goods may take the form of product replacement instead of regular price changes. Since including these goods will over-estimate price stickiness, we then restrict our dataset to only those goods that have at least one price change.⁶ Even conditional on goods that have at least one price change, the median frequency of price change is 11.1% for US exports to China, which implies a price duration of 8.5 months, while the median duration of US import prices from China is 10.1 months.

Not only is there significant price stickiness, but this price stickiness also changes over time in our sample. Using the structural break tests of Bai and Perron (2003), we detect a structural break around June 2005. Price duration declined after June 2005: the median duration of US export prices to China decreases from 9.1 months in the pre-June 2005 subsample to 6.5 months in the post-June 2005 subsample. The median duration of US import prices from China decreases from 11.5 months to 8.6 months. Price stickiness also

⁵Several recent studies examine exporting firms' pricing behavior and ERPT using data from the same BLS micro trade price dataset. Some examples include Gopinath and Rigobon (2008), Gopinath, Itskhoki, and Rigobon (2010), Gopinath and Itskhoki (2010), Nakamura and Steinsson (2012), and Neiman (2010), among others. Schoenle (2010) examines how firm's pricing behavior differs across domestic and export market. These empirical studies, like ours, provide valuable micro foundations for modeling price-setting behavior of exporters and importers.

⁶Goods with no price change have a frequency of zero, which implies a duration of infinity.

declined at sectoral levels, indicating that the decrease is not mainly caused by the composition effect. In addition, the fraction of price changes that are price increases rises after June 2005 for both import and export prices. The size of price changes also increases for US export prices to China in the post-June-2005 subsample.

We consider a benchmark menu cost model to examine whether the model can replicate the decrease of price stickiness after June 2005. We consider the case of US export prices to China since the structural break is more pronounced in this case than for US import prices from China. The model is similar to the one in Nakamura and Steinsson (2008), but modified with a shock related to exchange rate movements. Each firm is subject to three shocks: an aggregate inflation shock, an aggregate demand shock related to exchange rate movements, and a firm-specific productivity shock. Given these shocks, demand for its product, and marginal cost, a firm chooses a price in dollars, as documented in the data, to maximize expected lifetime profit. The firm has to pay a real cost if it decides to change its price.

We first calibrate the model to match the extent of price stickiness, the fraction of price increases, and the size of price changes in the pre-June 2005 subsample. Then we replace the parameters of the exogenous processes with their estimates from the post-June 2005 data, while keeping other parameters constant. We find that the model can successfully replicate the decrease of price stickiness after June 2005. The model can also partially explain the increase in the fraction of price increases and the size of price changes in the data.

In our model, exchange rate movement contributes significantly (about 60%) to the decline of price stickiness in the data. When the dollar depreciates, aggregate demand for US exports increases, which induces US firms to change their prices. The interaction between the exchange rate and price stickiness and its implications on important macroeconomic issues have been discussed in previous theoretical papers. In a menu cost model, Floden and Wilander (2006) study ERPT and volatility of import prices when firms are subject menu costs and adjust prices in response to exogenous exchange rate fluctuations. They show that firms update prices more frequently when the exchange rate is more volatile. Landry (2009) compares state-dependent and time-dependent pricing in a two-country dynamic model. He finds that state-dependent pricing model matches aggregate data better than time-dependent pricing because the nominal exchange rate and export demand influence price adjustment probabilities in state-dependent pricing, but not in time-dependent pricing. These studies highlight the importance of the interaction between firms' pricing behavior and exchange rate fluctuations in international macroeconomic models. The results in our paper provide empirical support for these studies.⁷

⁷Other examples of recent studies on open-economy models with menu costs include Midrigan (2007) and Landry (2010).

A second issue of interest is ERPT, measured as the percentage change in prices following a one percent change in the exchange rate. The extent to which Chinese yuan appreciation is passed on to US import prices is important for many policy-related issues, such as the international transmission of inflation shocks. ERPT is especially important with regard to China for another reason – China’s huge current account surplus with the US. The magnitude of ERPT is crucial in determining the effect of exchange rate movements on the trade balance. However, most empirical studies using aggregate price data find that ERPT into US import prices is usually low.⁸ Empirical studies focusing on the appreciation of the Chinese Yuan usually also find that ERPT is small. For instance, Cui, Shu, and Chang (2009) find that ERPT to China’s aggregate export price index is less than 50%. Using sectoral level data, Auer (2012) finds that ERPT of the Chinese yuan’s appreciation from 2005 to 2008 into the US import price index is about 20%.⁹

Our paper differs from the above studies in a very important way: we use goods-level price data rather than aggregate price index data. Nakamura and Steinsson (2012) document that a large fraction of US imported goods never change prices during their lifetimes. They argue that these goods change prices through produce replacement instead of ordinary price adjustments. As a result, ERPT estimated from the aggregate price indexes, which do not take into account these product replacements, can be seriously downward biased. Indeed, Nakamura and Steinsson (2012) estimate that the product replacement bias can underestimate ERPT in the aggregate price index by nearly a factor of two.¹⁰

Therefore we consider two cases when estimating ERPT with goods-level price data. We first include all goods, and then we only include goods that have at least one price change. In this way, we can show to what extent the products with no price change potentially underestimates ERPT. Following Gopinath, Itskhoki, and Rigobon (2010), we estimate lifelong ERPT, where lifelong price changes of imported goods are regressed on exchange rate changes during the same period, for the period from June 2005 to July 2008.¹¹ The point estimate of lifelong ERPT for all US imported goods from China is 0.39. This finding is similar to previous estimates of long-run ERPT using aggregate price indexes (e.g., US import price index or China’s export price index). However, lifelong ERPT increases substantially to 0.88 when only goods with at least one price change are included. These findings suggest that ERPT estimated from trade price indexes has substantially understated the effect of RMB appreciation on US-China trade prices.

⁸For instance, Campa and Goldberg (2005) document that ERPT into the US import price index is less than 40% and has declined since the 1990s. Marazzi and Sheets (2007) find that ERPT to US import prices declined to only 20% after 2000. They argue that competition from China contributes to the decline of ERPT.

⁹Since imports from China account for only 22% in US total imports, Auer (2012) argues that actual ERPT of US imports from China could be very large.

¹⁰Gagnon, Mandel, and Vigfusson (2012) argue that the downside bias on ERPT due to selective entry and exit in the BLS’s sampling method is modest over the first two years. However, the selective entry bias may not fully capture all product replacement bias discussed in Nakamura and Steinsson (2012).

¹¹We choose the above sample period because China started to appreciate its currency in June 2005, but re-pegged to the dollar in July 2008 when the global financial crisis broke out.

High ERPT of US import prices from China suggests that RMB appreciation has a much bigger impact on US-China trade prices than what is estimated from the aggregate data. If US-China trade imbalances are caused by RMB undervaluation, our results suggest that RMB appreciation can be much more effective in balancing US-China trade than we previously thought. However, several recent studies attribute China's trade surpluses to structural factors rather than nominal currency undervaluation. For instance, see Song et al (2011), Wen (2011), and Ju, Shi, and Wei (2012), among others. In this case, RMB appreciation may substantially disrupt US-China trade through high ERPT, without improving US-China trade imbalances.

The remainder of the paper is arranged as follows. Section 2 describes the import and export prices data used in this paper and reports some summary statistics. Section 3 presents our empirical results of price rigidity, and Section 4 reports the results of ERPT. Section 5 concludes and discusses directions for future research.

2 Data Description

To our best knowledge, our paper is the first to focus on the subset of data collected by the International Price Program (IPP) of the BLS pertaining to US-China trade prices. Our sample includes monthly import and export prices from the IPP Research Database (Blackburn, Kim, and Ulics, 2012) for the period from September 1993 to March 2011. The IPP surveys a sample of US companies based on how much they import and/or export in a given year. These firms are asked to provide transaction prices for a given item on a monthly basis, which are used to produce a modified Laspeyres index of import and export prices. Sampling occurs at the elementary level item (ELI) level, which in most cases corresponds to a 10-digit Harmonized System (HS) classification code.

The BLS currently selects establishments, ELIs, and individual goods using probability sampling techniques. Before the sampling process begins, the BLS obtains data from the Census Bureau or Customs Service on the value and frequency of imports or exports by US companies involved in trade. Such data are consolidated by company and by ELI within each company to decide from which company/ELI combination to sample. Next, the number of goods to request for each firm/ELI combination is determined based on a probability proportionate to size. Firms that import/export more from an ELI have a higher probability of being sampled for the prices of goods under that ELI. The last stage is to select goods within a given firm/ELI combination. The chance of an individual good being selected is proportionate to its share of trade within the firm/ELI combination. A more detailed description of the data and the collection process

is provided by Gopinath and Rigobon (2008).¹²

The IPP dataset includes two types of prices: reported prices and net prices. Reported prices are those reported by importers/exporters on BLS survey forms. Reported prices can be either list prices, transaction prices, or estimated prices. Whenever possible, the BLS requests actual transaction prices. When transaction prices are not available or if a transaction does not take place in a particular period, firms are allowed to provide list prices (i.e., sticker prices that sellers ask for) or estimated prices.

Reported prices are adjusted for discounts, duties, freight charges, or exchange rates, when applicable, to obtain net prices. Such adjustments are done by the BLS to reflect actual transaction prices as much as possible. Net prices are then used by the BLS to calculate import and export price indexes. Although net prices may better reflect the market prices, it can also potentially introduce spurious price changes by firms. For instance, the adjustment of the prices for exchange rate changes by the BLS will show price changes even if firms do not change their prices. To avoid this problem, we construct a series of net prices where prices imputed by the BLS are excluded (labeled as net prices exclusive thereafter). We use both reported prices and net prices exclusive in our study.

In addition, we exclude intra-firm prices from our data following Gopinath, Itskhoki, and Rigobon (2010) and Nakamura and Steinsson (2010). Neiman (2010) finds that intra-firm prices are characterized by less stickiness, less synchronization, and greater exchange rate pass-through. These characteristics may just reflect the transfer pricing strategy used to minimize tax payment of multinational firms. Figure 1 shows the share of intra-firm prices for US imports from China. The share remains below 20% for most of our sample period, though it increases steadily over time. In contrast, currently about 48% of the prices for US total imports are intra-firm. This difference could result from China's restrictions on FDI. Or it may also be that firms are endogenously choosing arm's length trade based on the types of goods that China exports. We think it may be an interesting topic for future research.

Another potential data issue that must be addressed is missing values, which is common in studies using micro price data. We pull forward the last observation to close the gap between observations in our sample, following the standard treatment in the literature.¹³

Lastly, we exclude services and petroleum from our dataset. Various services indexes have been introduced and discontinued at different points during our sample period. Currently, the BLS produces only air freight and air passenger services indexes. Indexes for petroleum and ocean tanker freight are two examples that

¹²Examples of other studies using the dataset include Clausing (2001), Gopinath and Rigobon (2008), Gopinath, Itskhoki, and Rigobon (2010), Gopinath and Itskhoki (2010), Berger et al. (2009), Nakamura and Steinsson (2012), and Neiman (2010).

¹³For instance, see Nakamura and Steinsson (2012) and Gagnon, Mandel, and Vifugsson (2012). About 25% of our sample are missing values, and are filled by pulling the last observation forward.

use weighted average prices (BLS, 1997). Moreover, due to the lagged nature of the weights, the volatility in the trade of petroleum can have a large (and possibly misleading) effect on the movement of price indexes.

2.1 Share of Prices from China

Figure 2 shows the share of import prices from China in total US imports at sectoral levels. The share increased substantially from less than 10% to more than 35%. Under the BLS's probability sampling methods, the higher the value or frequency of trade for a good, the more likely that good is included in the sample. Thus, the increasing share of import prices from China in total US imports reflects the sharp rise in US-China trade. The increase in the number of goods in our sample also suggests that China began exporting goods that it had not exported or had exported only minimally before.

The number of varieties of traded goods is commonly referred to as the extensive margin in the international trade literature. Recent research has focused on the role of the extensive margin in driving trade patterns. For instance, Yi (2003) uses the extensive margin to explain the growth in global trade following trade liberation. Ruhl (2008) argues that the extensive margin is important to understand high trade elasticities following a permanent shock. Naknoi (2008) shows that the extensive margin may also help explain real exchange rate volatility in macroeconomic models.

Kehoe and Ruhl (2009) investigate the extensive margin using disaggregated (four-digit SITC code) trade data. They find significant evidence of growth in the extensive margin following a decrease of trade barriers. In particular, they document that China's WTO membership in 2001 had a large effect on the extensive margin for US-China trade. Our findings are consistent with Kehoe and Ruhl (2009), but we show that the effect on the extensive margin is strong even at more disaggregated levels; in Figure 2, the share of imports from China exhibits a sharp increase after 2001 in most sectors. Similar results exist at more disaggregated levels, such as the HS 10-digit level.

Figure 3 displays the share of price quotes in countries that have a declining share of prices in the BLS survey. These countries mainly include East Asian countries and Germany. The decline in the share of imported goods from East Asian countries reflects increasing vertical specialization in international trade among these countries and China. In the last two decades, China has become the hub of assembling final products for international trade due to its low labor costs.

In contrast, exports to China only account for a very small fraction of total US export prices in the IPP survey, though the share has increased over time in our sample. At its peak, the share of export prices to China in total US export prices is less than 4%. This contrasts sharply with the import price data, where

US import prices from China account for more than 35% of total import prices.

2.2 Product Duration and Price Changes

Table 1 reports summary statistics of our data. For reported prices of US imports from China, 311,696 price quotes are reported for 14,543 goods. On average, a good lasts for 22.2 months before it is discontinued or replaced by a new product. This is much shorter than the mean life of a good in US total imports, which is 37.5 months as reported in Gopinath and Rigobon (2008). There is substantial heterogeneity in duration across goods: some goods exist for only one month, while the longest duration is as long as 125 months, or 10 years and 5 months. There is also substantial heterogeneity in the number of price changes across goods. The average number of price changes for each good is 1.9. A large share of goods (about 35%) never change prices during their lifetime, while some goods have more than 50 price changes. Net prices that exclude imputed prices by the BLS behave similarly to reported prices in the above statistics.

The same summary statistics are also reported for US exports to China in Table 1. Much fewer goods and prices are recorded for US exports to China. In total, 23,043 reported prices are included for 1,048 goods. 23.4% of prices never changed, which is smaller than that for US imports from China. On average, each good lasts for 23.2 months, similar to US import prices from China. US export prices on average have 5.4 price changes, which is more than double that for import prices from China. Since the average duration of goods is about the same for US imports from and exports to China, more price changes indicate that US exporters change their prices more frequently than their counterparts in China. Statistics for net prices exclusive of imputed prices are similar.

2.3 Invoicing Currency

The choice of invoicing currency plays an important role in international macroeconomic issues. For instance, when prices are sticky and set in the producer's currency (producer currency pricing or PCP), all short-run exchange rate changes will be passed on to the importing country's prices (100% ERPT). In contrast, when prices are set in the importer's currency (local currency pricing, or LCP), the short-run ERPT is zero. Devereux and Engel (2003) find that the optimal exchange rate policy is different under PCP and LCP. Engel (2011) emphasizes the importance for the monetary policy to target currency misalignments under LCP.

In our sample, more than 97% of US import prices from China and almost 100% of US export prices to China are in the US dollar. This is consistent with Gopinath and Rigobon's (2008) finding that more

than 90% of US imported goods are priced in dollars. Figure 4 shows the percent of non-dollar prices in US imports from China. Non-US-dollar currencies that are used to price Chinese imports include the Japanese yen, Taiwanese dollar, Hong Kong dollar, Chinese yuan, Deutsche mark, and euro.¹⁴ Before 2004, most non-dollar transactions of US imports from China are in Hong Kong dollars. Since then, the share of the Hong Kong dollar has declined substantially. While the Chinese yuan is used as an invoicing currency after 2006, it only accounts for less than 0.2% of all prices.

For US exports to China, the US dollar was the only invoicing currency until 2009. After 2009, the euro started to be used as an invoicing currency for US exports to China. However, the usage of the euro remains low: only about 1% of US export prices to China are priced in the euro. Although China switched from the fixed exchange rate regime in June 2005 to a managed floating one, it seems that the regime switching has not affected the choice of invoicing currency by exporters. Overall the US dollar still dominates as an invoicing currency in the trade between the US and China.

3 Price Stickiness

In this section, we report our results on the stickiness of US-China trade prices. The BLS adjusts reported prices for exchange rate fluctuations, discounts, and other changes. As argued by Gopinanth and Rigobon (2008) and Nakamura and Steinsson (2008), such adjustments may introduce spurious price changes. Thus, we focus on reported prices when presenting our results for price stickiness.

Following the literature, we use the frequency of price changes and frequency-implied durations to measure price stickiness. For each good, the frequency is defined as the number of price changes divided by the total number of price quotes. Then we calculate the mean and median frequencies of price changes across all goods. The frequency-implied duration is calculated as in Nakamura and Steinsson (2008):

$$d = -\frac{1}{\ln(1-f)},$$

where d is the duration and f is the frequency of price changes.

Table 2 reports our results. The median frequency of price changes for US exports to China is 6.6%, which implies a duration of 14.6 months in our monthly data. Goods with zero price changes, of which there are many in our dataset, also have a frequency of zero, implying a duration of infinity using the above equation. Since the inclusion of these goods overstates the price duration, we also calculate the frequency

¹⁴The currency index is the major non-dollar currency that is used as invoicing currency. In this case, the good is priced based on a basket of currencies which are not disclosed to the BLS.

and duration conditional on a price change (i.e., for goods that have at least one price change). Even in this case, significant price rigidity remains: the median frequency is 11.1%, implying a duration of 8.5 months.

There is significant heterogeneity of price stickiness across goods. Some products change prices much more often than others. As a result, the mean frequency is higher than the median frequency. The mean frequency of price changes for US exports to China is 14.1%, implying a duration of 6.6 months.

The median fraction of price changes that are price increases is 61.8%. This finding is similar to Nakamura and Steinsson's (2008) finding that about two thirds of changes in US consumer prices are price increases. The mean fraction of price increases is slightly smaller at 59.2%.

Figure 5 presents the distribution of nonzero price changes for US exports to China. The distribution of price changes is very dispersed. The data have both very small and very large price changes. A similar pattern is also reported in Midrigan (2011) for scanner price data in retail stores.¹⁵ When looking at the average absolute size of price changes for each good, we find that the median size of price changes is 8.4% and the mean is 15% (see Table 2). These statistics also point to substantial heterogeneity across goods.

The distribution of price changes for US imports from China has a similar pattern, but the size of price changes is smaller for US import prices than export prices. The median size of price changes is 7.5% and the mean is 11.6%. With regard to price stickiness, US imports from China exhibit higher price stickiness than US exports to China. The median frequency-implied duration is 19.5 months for all goods and 10.1 months for goods with at least one price change. The mean duration is much smaller than the median: 11.7 months for all goods and 7.4 months conditional on a price change. The mean and median fraction of price changes that are price increases are about the same at 55%.

Next, we split our sample into two subsamples: pre- and post-June-2005 to determine if price stickiness differs after China began to appreciate its currency. As shown in Table 2, conditional on a price change, the median price duration of US exports to China is 9.1 months in the pre-June-2005 subsample and decreases to 6.5 months in the post-June-2005 subsample for goods with at least one price change. For all goods, a similar pattern exists for median and mean price durations. The median fraction of price increases is 50% in the pre-June-2005 subsample, but rises to 66.7% in the post-June-2005 subsample. The median size of price changes also increases from 7.3% to 8.5% in these two subsamples.

Similar results hold for US import prices from China. The price duration declines and the fraction of price increases rises after June 2005. However, the size of price changes is almost identical in the two subsamples,

¹⁵Midrigan (2011) extends the standard menu cost model to match the distribution of price changes and the existence of sales in price changes. He finds that after taking into account this additional set of micro price facts, the model generates a much larger real effect of monetary shocks than that in Golosov and Lucas (2007). Other important contributions to the second generation of state-dependent sticky-price models include Burstein and Hellwig (2007), Gertler and Leahy (2008), Costain and Nakov (2011), and Dotsey, King, and Wolman (2011), among others.

which is different from the findings for US export prices to China.

Note that we have only 68 observations in the post-June-2005 subsample, which is much smaller than that in the pre-June-2005 subsample. As a result, for the above frequency calculations, truncation bias may be a more serious issue in the post-June-2005 subsample than in the pre-June-2005 subsample. To address this problem, we follow Gagnon, Mandel, and Vigfusson (2012) and calculate the fraction of price changes in each month as a measure of frequency:

$$fraction_change(t) = \frac{change(t)}{change(t) + no_change(t)},$$

where $change(t)$ is the number of prices at time t that are different from their levels at time $t - 1$ and $no_change(t)$ is the number of prices that do not change from $t - 1$ to t . The above equation calculates the share of price changes in the total number of prices in each month.

Figure 6 presents the fraction of price changes for US trade with China for each month. An increase in the fraction of prices changes indicates an increase in price flexibility, or a decrease in price rigidity. Figure 6(a) shows that the fraction of price changes for US exports to China increases substantially after 2005, suggesting a decline in price stickiness. A similar decline in price stickiness occurs around 2005 for US imports from China as shown in Figure 6(b).

3.1 Structural Break Tests

Next, we perform formal structural break tests based on Bai and Perron (2003) to identify the date and number of breaks for the stickiness of US-China trade prices. Two specifications are considered in our tests. In the first specification,

$$y_t = a_j + \varepsilon_t \tag{1}$$

for $t = T_{j-1} + 1, \dots, T_j$ and $j = 1, 2, \dots, m + 1$, where y_t is the fraction of price changes in Figure 6, m is the number of breaks, and T_j is the date of the j^{th} structural break. Both the number of breaks and the date of breaks are unknown and so are estimated from the data. In each regime, y_t has a different mean a_j . So we call this the mean model. In the second specification, y_t is allowed to have a different mean and a different deterministic time trend:

$$y_t = a_j + b_j \times \frac{t}{T} + \varepsilon_t, \tag{2}$$

for $t = T_{j-1} + 1, \dots, T_j$ and $j = 1, 2, \dots, m + 1$.¹⁶ We call this specification the trend model.

Four tests are used to determine the number of breaks in each model:

1. Test $H_0 : m = 0$ against $H_A : m > 0$;
2. Test $H_0 : m = 0$ against $H_A : m = k$ for pre-specified k ;
3. Test $H_0 : m = k$ against $H_A : m = k + 1$ sequentially for $k = 0, 1, \dots$;
4. BIC.

The first test is used to test the null hypothesis of no break against the alternative that there is at least one break. In the second test, we test the null of no break against the alternative of k breaks for $k = 1, \dots, 5$. We use the third test to find the number of breaks k by testing the null of k breaks against the alternative of $k + 1$ breaks. The test is conducted sequentially for $k = 0, 1, \dots$ until we fail to reject the null hypothesis. The BIC is also used to select the number of breaks.

3.1.1 Results for US Exports to China

In the mean model,

1. The null of no breaks ($H_0 : m = 0$) is strongly rejected;
2. The null of no breaks ($H_0 : m = 0$) is rejected in favor of the alternative of 1, 2, 3, 4, or 5 breaks;
3. The null of $H_0 : m = k$ is rejected in favor of the alternative of $H_A : m = k + 1$ for $k = 0$, but we fail to reject the null for $k = 1$.
4. BIC suggests that there is one break and the model with two breaks is the second best model.

All tests strongly reject the null of no breaks. Tests 3 and 4 suggest that there is one structural break (two regimes) in the data. Given one structural break, the mean model indicates the break date is January 2006. Table 3 presents the results of the structural break tests. The coefficient a_j increases from 0.181 in the first regime to 0.235 in the second regime. On average, 18.1% of prices change in each month for the first regime and the share increases to 23.5% in the second regime.

Similar results are found in the trend model. As in the mean model, our tests indicate one structural break in the sample with a break date of May 2005, which coincides with the date that China started to appreciate the RMB. The share of price changes has a downward slope (-0.052) in the first regime, indicating

¹⁶ T is the number of periods. Time t in equation (2) is expressed as a fraction $\frac{t}{T}$ purely due to technical reasons documented in Bai and Perron (2003).

an increase in price stickiness in the 1990s. However, the price rigidity decreased substantially in the second regime with a slope of 0.147.

Figure 7 displays the share of price changes in each month for US exports to China and the fitted values from the mean and trend models. The evidence of regime switching is very strong in these charts. US export prices to China become less sticky after 2005. The most obvious explanation is the change in China's exchange rate policy: when firms face more exchange rate fluctuations that drive their prices out of the optimal price, they change their prices more frequently to align their prices with the optimal one. A competing explanation to the above finding could be that there is a composition effect: the US exports more products after 2005 in sectors with less sticky prices.

To discern which explanation holds in our data, we check the extent of price stickiness at disaggregated levels. Table 4 reports the sectoral level median price duration of US exports to China. The sectors are aggregations at the two-digit level HS codes. First, significant heterogeneity exists across sectors. The price duration varies from about two months in the sector of Animals and Vegetable Products to more than 12 months in several sectors such as Machinery/Electrical. In addition, the post-June-2005 sample has shorter durations than the pre-June-2005 sample in most sectors (8 out of 12), indicating a decline in price stickiness after June 2005 at disaggregated levels. Figure 8 shows the share of price changes for a select number of representative sectors at the two-digit HS level. A decline in price stickiness around 2005 is also evident in these charts. These findings in the disaggregated data suggest that the decline in price stickiness of US exports to China after 2005 is unlikely to be mainly driven by the composition effect.

3.1.2 Results for US Imports from China

In the mean model,

1. The null of no breaks ($H_0 : m = 0$) is strongly rejected;
2. The null of no breaks ($H_0 : m = 0$) is rejected in favor of the alternative of 1, 2, 3, 4, or 5 breaks;
3. The null of $H_0 : m = k$ is rejected in favor of the alternative of $H_A : m = k + 1$ for $k = 0, 1, 2$, but we fail to reject the null for $k = 3$.
4. BIC suggests that there are two breaks and the model with three breaks is the second best model.

Tests 1 and 2 strongly reject the null of no breaks. Test 3 suggests that there are three breaks (four regimes) in the data. The BIC test indicates that the model with two breaks is the best, but the model with three

breaks also performs well. Based on the results of tests 3 and 4, we choose three breaks as our benchmark model. Similar results are also found in the trend model.

The results of the structural break tests for US import prices from China are reported in the lower panel of Table 3. In the mean model, three break dates are identified: July 1999, May 2005, and December 2007. These break dates are closely linked to China's entry into the WTO, China's change in its exchange rate policy, and the global financial crisis. From 1993 to 2005, the coefficient a_j decreases from 0.07 to 0.051, indicating an increase in price stickiness. This is consistent with Gopinath and Rigobon's (2008) finding that price stickiness of US imports has increased from 1994 to 2005.¹⁷ However, price stickiness of US imports from China has decreased substantially since 2005. The coefficient a_j increased back to 0.07 from 0.051 in the period from 2005 to 2007 and rose further to 0.102 in the period from 2007 to 2011.

We find that the decrease in price stickiness after 2005 for US imports from China is not mainly due to a composition effect.¹⁸ Figure 9 shows the monthly share of price changes in different sectors. For all sectors in the figure, the fraction of price changes displays a decline in the 1990s, but an increase around 2005. These findings at the sectoral level suggest that the decline in price stickiness of US import prices from China after June 2005 are more likely due to changes in the macroeconomic environment after June 2005 (such as the change of the exchange rate regime or the expectation on future inflation). Although Gopinath and Rigobon (2008) find that price rigidity does not change following big exchange rate movements, it is likely that exchange rate regime switching may have a much bigger impact than exchange rate fluctuations on the pricing behavior of firms.

3.2 Menu Cost Model

The documented changes in trade price stickiness are not consistent with time-dependent stickiness price models (e.g., Calvo model), in which price stickiness is assumed to be constant and exogenous. Several recent studies find that a menu cost model can successfully replicate the correlation between price stickiness and aggregate inflation, providing support to state-dependent sticky-price models. We extend the simple menu cost model in Nakamura and Steinsson (2008) to a case of international trade and examine whether it can replicate the decrease in price stickiness for US exports to China after 2005. Our findings provide further support for the menu cost model, but through the channel of exchange rate movements. We do not consider US import prices from China because the structural break tests suggest that price stickiness in this case may be driven by other factors such as China's accession to the WTO membership. Our simple menu cost model

¹⁷Gopinath and Rigobon's (2008) data ended in April 2005.

¹⁸Gopinath and Rigobon (2008) document that the increase in US import price rigidity from 1994 to 2005 is mainly due to the increase of price stickiness at disaggregated levels rather than the composition or country effects of US imports.

does not take into account such factors.

The menu cost model is first calibrated to match some micro price features of US exports to China (e.g., price stickiness) in the pre-June-2005 subsample. Then we replace the calibration of exogenous shocks with estimates from the post-June-2005 subsample, while keeping all other parameters constant. We find that the model can replicate the decline in price stickiness both qualitatively and quantitatively.

Let China be the home country. Suppose that China's demand for total imported goods is a CES function of imports from the US and the rest of the world (ROW):

$$C_{M,t} = \frac{C_{ROW,t}^\alpha C_{US,t}^{1-\alpha}}{\alpha^\alpha (1-\alpha)^{1-\alpha}}, \quad (3)$$

where $C_{M,t}$ is China's total import demand and $C_{US,t}$ and $C_{ROW,t}$ are demands for imports from the US and the rest of the world (ROW), respectively.

It is easy to derive the demand for imports from the US:

$$C_{US,t} = (1-\alpha) \left(\frac{S_t P_{US,t}}{P_{ROW,t}} \right)^{-\alpha} C_{M,t}, \quad (4)$$

where S_t is the nominal exchange rate (yuan per dollar), $P_{US,t}$ is the US-dollar price index of US exports to China, and $P_{ROW,t}$ is the price index of China's imports from the ROW (in Chinese yuan). Note that we use the US dollar for US export prices to China (producer currency pricing or PCP), which is consistent with the data.

Assume that the US-goods composite is a CES aggregate of differentiated US goods with the elasticity of substitution θ . As a result, the demand for good z is:

$$C_{US,t}(z) = \left(\frac{P_{US,t}(z)}{P_{US,t}} \right)^{-\theta} C_{US,t} = \left(\frac{P_{US,t}(z)}{P_{US,t}} \right)^{-\theta} (1-\alpha) \left(\frac{S_t P_{US,t}}{P_{ROW,t}} \right)^{-\alpha} C_{M,t}, \quad (5)$$

where exporting firms take the nominal exchange rate S_t , aggregate prices $P_{US,t}$ and $P_{ROW,t}$ as exogenous processes.

The production function for US exporting firm z is linear in labor:

$$y_{US,t}(z) = A_{US,t}(z) L_{US,t}(z), \quad (6)$$

where $A_{US,t}(z)$ is firm-specific productivity and $L_{US,t}(z)$ is labor input of firm z . Let $W_{US,t}$ be the nominal wage in the US. It is straightforward to find that the marginal cost for firm z is $\frac{W_{US,t}}{A_{US,t}(z)}$.

In each period, the firm can choose to pay a fixed cost of k units of labor to change its price. Otherwise, it charges the same price as in the last period. Nominal profits of the firm are:

$$\pi_{US,t}(z) = \begin{cases} \left(P_{US,t-1}(z) - \frac{W_{US,t}}{A_{US,t}(z)} \right) C_{US,t}(z) & \text{if no price change} \\ \left(P_{US,t}(z) - \frac{W_{US,t}}{A_{US,t}(z)} \right) C_{US,t}(z) - W_{US,t}k & \text{if change price} \end{cases}. \quad (7)$$

The real profit of firm z is:

$$\hat{\pi}_{US,t}(z) = \frac{\pi_{US,t}(z)}{P_{US,t}} = \begin{cases} \left(\frac{\hat{P}_{US,t-1}(z)}{P_{US,t}/P_{US,t-1}} - \frac{\hat{W}_{US,t}}{A_{US,t}(z)} \right) \hat{P}_{US,t}^{-\theta}(z) (1-\alpha) \tau_t^{-\alpha} C_{M,t} & \text{if no price change} \\ \left(\hat{P}_{US,t}(z) - \frac{\hat{W}_{US,t}}{A_{US,t}(z)} \right) \hat{P}_{US,t}^{-\theta}(z) (1-\alpha) \tau_t^{-\alpha} C_{M,t} - \hat{W}_{US,t}k & \text{if change price} \end{cases}, \quad (8)$$

where $\tau_t = \frac{S_t P_{US,t}}{P_{ROW,t}}$ and prices with a hat are the corresponding nominal prices divided by $P_{US,t}$.

Following Nakamura and Steinsson (2008), we assume that the aggregate demand and real marginal cost are constant:

$$C_{M,t} = C, \\ \hat{W}_{US,t} = \frac{W_{US,t}}{P_{US,t}} = \frac{\theta - 1}{\theta}.$$

The logarithms of productivity, the price level, and τ_t are assumed to follow:

$$\log(A_{US,t}(z)) = \rho \log(A_{US,t-1}(z)) + \varepsilon_t(z), \quad (9)$$

$$\log(P_{US,t}) = \mu + \log(P_{US,t-1}) + \eta_t, \quad (10)$$

$$\log(\tau_t) = \nu + \phi \log(\tau_{t-1}) + \varepsilon_{\tau,t}, \quad (11)$$

where $\varepsilon_t(z)$, η_t , and $\varepsilon_{\tau,t}$ are iid with zero mean and standard deviations of σ_ε , σ_η , and σ_τ , respectively.

Given the above exogenous processes, each firm chooses whether or not to change the price and determines the optimal price to maximize real profits in equation (8) if it chooses to change its price. This model is very similar to Nakamura and Steinsson's (2008), but has an additional exogenous process, τ_t , compared to their model. Nakamura and Steinsson (2008) consider a closed economy; therefore their model does not have τ_t , which is related to the exchange rate. If parameter α is set to zero, τ_t in equation (8) drops out and the model reduces to the one in Nakamura and Steinsson (2008).

To calibrate the data, we set $\alpha = 0.93$, which matches the average share of the ROW in China's total

imports from 1993 to 2011. Following Nakamura and Steinsson (2008), the discount factor is set equal to $\beta = 0.96^{1/12}$ and θ is set to 4. We calculate the US export price index to China from our dataset and estimate $\mu = 1$ and $\sigma_\eta = 0.009$ in the pre-June-2005 subsample.

We need a measure of τ to calibrate ν , ϕ and σ_τ . Unfortunately, China's import price index from the ROW ($P_{ROW,t}$) is unavailable. A potential replacement option is China's aggregate import price index from all trading partners including the US. Since imports from the US only account for 7% of China's total imports, including US imports in the import price index may not change the index significantly. However, China's aggregate import price index is only available after 2005. As a result, we use China's producer price index (PPI) for all industries (available after 1996m1) as a proxy for China's import price index. During overlapping periods of availability, the PPI for all industries traces well the general trends in the import price index. The import price index just shows more volatility than the PPI. We take this as evidence that the PPI is a good proxy for China's import price index. We estimate $\nu = 0.79$, $\phi = 0.885$, and $\sigma_\tau = 0.01$ in the pre-June-2005 subsample.

Similar to Nakamura and Steinsson (2008), we calibrate $\frac{K}{(1-\alpha)\tau^{-\alpha}C_M}$, ρ , and σ_ε to match the share of price changes in each month, the fraction of price increases in price changes, and the average size of price changes. In the pre-June-2005 subsample (from 1996m1 to 2005m6), the median share of price changes in each month is 10.6%, the fraction of price increases in price changes is 50%, and the median absolute size of price changes is 7.2%. We choose $\frac{K}{(1-\alpha)\tau^{-\alpha}C_M}$, ρ , and σ_ε to minimize the sum of percent deviations of our model from the targeted statistics. The share of price changes in our model is 10.6%, and the fraction of price increases is 50%, which are very close to the data. The average absolute size of price changes is 7.6% in our model, which is higher than 7.2% in the data.

Next, we keep everything else constant, but re-estimate the processes of $\log(P_{US,t})$ and $\log(\tau_t)$ with the post-June-2005 subsample. Then we feed the new estimates of these two processes into our model and examine how that changes the share of price changes and other statistics. We estimate that $\mu = 1.002$ and $\sigma_\eta = 0.019$. μ is higher in the second subperiod, indicating that US export prices to China ($P_{US,t}$) increase faster after June 2005. The standard deviation of the inflation (σ_η) also increases from 0.009 to 0.019. For the process of $\log(\tau_t)$, we estimate that $\nu = 0.19$, $\phi = 0.971$, and $\sigma_\tau = 0.014$.

Table 5 presents the results of the menu cost model. We consider three models for the post-June-2005 subsample with the first one as the benchmark model. In the benchmark model, we keep everything else constant while replacing the processes of $\log(P_{US,t})$ and $\log(\tau_t)$ with estimates from the post-June-2005 data. The share of price changes increases from 10.6% to 15.9% in the model. Given that the share of price changes is actually 14.3% in the post-June-2005 data, the menu cost model seems to match well the decrease in price

rigidity both qualitatively and quantitatively. The fraction of price increases and the size of price changes also increase in the model after June 2005, but to a lesser extent than in the data.

Inflation of $P_{US,t}$, μ , is higher in the post-June-2005 subsample than in the pre-June-2005 subsample. Since Gagnon (2009) shows that high inflation in the menu cost model can reduce price stickiness, in the second model “Only $P_{US,t}$ ”, we examine the effect of the change in μ in driving our benchmark results. In this model, we only replace μ and σ_η in the process of $\log(P_{US,t})$ with their estimates from the post-June-2005 subsample while keeping all other parameters the same as in the pre-June-2005 subsample. We find that this inflation effect contributes to 54.7% of the increase in the share of price changes. This model also generates bigger increases in the fraction of price increases and the size of price changes compared to the benchmark model.

In the third model, “Only τ_t ”, we investigate the effect of $\log(\tau_t)$. We only replace ν and σ_τ in the process of $\log(\tau_t)$ with their estimates from the post-June-2005 subsample while keeping all other parameters the same as in the pre-June-2005 subsample. The share of price changes increases from 10.6% to 12.9%, which accounts for 43.4% of the increase in the share of price changes in the benchmark model. The fraction of price increases rises remains the same at 50%. On the other hand, the size of price changes declines from 7.6% to 7.4%.

Note that the share of price changes increases more than the sum of increases in models “Only $P_{US,t}$ ” and “Only τ_t ”. This result indicates that the interaction between $\log(P_{US,t})$ and $\log(\tau_t)$ also contributes to the decrease of price stickiness in the benchmark model.

4 Exchange Rate Pass-through

The extent of pass-through of the exchange rate into local currency import prices is critical for policy issues such as the international transmission of the inflation and the optimal exchange rate policy. The exchange rate pass-through of Chinese products has attracted great interest for both policymakers and academic researchers due to China’s large current account with the US and its exchange rate policy. The standard pass-through regression takes the form:

$$\Delta p_t = \alpha + \gamma \Delta s_t + \delta \Delta c_t^* + \beta \Delta d_t + \varepsilon_t, \quad (12)$$

where p_t is the log import price denominated in the importing country's currency, s_t is the log exchange rate, c_t^* is the log production cost of exporters, and d_t is the log import demand.¹⁹ The coefficient γ measures the percentage change in the import price given a 1% change in the exchange rate. Pass-through is usually found incomplete ($\gamma < 1$) and has declined in the last two to three decades for US import prices.

Given the limitations of data, previous studies on the exchange rate pass-through of US imports from China have used aggregate price indexes. However, Nakamura and Steinsson (2012) point out an important caveat when estimating the exchange rate pass-through using aggregate price indexes. They argue that some US imports experience no price changes during their lifetime because price adjustments can take the form of product replacement. The product replacement usually cannot be adequately measured in the price index because it is difficult to link a product with its replacement in practice. In this case, including goods that are replaced in aggregate price indexes smooths the price indexes and results in a downward biased estimate of exchange rate pass-through.

As shown in the previous section, more than a third of US imported goods from China never change their prices. Our paper contributes to the literature by estimating ERPT of US imports from China using goods-level prices. We can therefore exclude prices that never change in our estimation of ERPT and investigate how much such prices may affect the estimate of ERPT.

We estimate lifelong ERPT as in Gopinath, Itskhoki, and Rigobon (2010), in which the following regression is estimated:

$$\Delta p_i = \gamma \Delta s_i + \beta' z_i + \varepsilon_i, \quad (13)$$

where Δp_i is the change of the price of good i during its life, Δs_i is the change in the exchange rate over the same period, and z_i includes corresponding changes in other control variables. Following Gopinath, Itskhoki, and Rigobon (2010), we include the US CPI inflation rate, China's CPI inflation rate, and US GDP growth in vector z_i . Our sample begins in June 2005 when the RMB started to appreciate against the US dollar and ends in July 2008 to avoid the effect of the global financial crisis. China had also temporarily halted RMB appreciation between July 2008 and May 2010, rendering that period unsuitable for the estimate of ERPT.

Table 6 presents the results of aggregate lifelong ERPT. In our estimation, each good is weighted by annual trade weight at the HS4 level. When all prices are included, ERPT is much smaller than one: ranging from 0.39 to 0.48. This is in the range of ERPT estimated from aggregate price indexes. However, when we condition our estimate on goods that have at least one price change, the estimated ERPT is much

¹⁹Lags of Δp_t or Δs_t usually are also used in the regression.

higher: ranging from 0.88 to 1.02. This is about twice as large as the estimate with all prices. Besides the product replacement bias as discussed in Nakamura and Steinsson (2012), the above difference in ERPT can be from a composition effect. Gopinath and Itskhoki (2010) document that goods with a high frequency of price adjustment also have high ERPT. In Table 6, we also estimate ERPT for goods with one or two price changes and goods with more than two price changes. As in Gopinath and Itskhoki (2010), US imports from China that change prices more frequently are found to have higher ERPT. When we remove prices with zero price change, it is likely that goods with low ERPT and low frequency of price adjustment are deleted disproportionately from our sample. However, the share of items with no price change is similar across most sectors at the two-digit HS level in our sample. This suggest that the bias caused by the composition effect may be small.

The variation of exporter’s profit margin is usually believed an important contributor to incomplete long-run ERPT into import prices. However, most of China’s exports are labor-intensive products with low profit margins. It is unlikely that Chinese exporters can absorb more than half of exchange rate appreciation by squeezing their profit margins. Our finding of high ERPT is more consistent with this observation compared to that estimated from aggregate price indexes. Li, Ma, Xu, and Xiong (2010) use firm-level data of 2000-2006 to study Chinese firms’ export behavior. They find that ERPT to China’s export prices (in importing country’s currency) is very high: between 0.83 to 1. Like ours, their results also suggest that Chinese exporting firms absorb only a small portion of exchange rate changes.²⁰

High ERPT for Chinese exports to the US suggest that RMB appreciation has a big impact on US-China trade prices, which is in sharp contrast to the results based on aggregate price indexes. This is good news if the US-China trade imbalance is caused by currency undervaluation and should be corrected. However, if the trade imbalance is caused by factors unrelated to nominal exchange rate, our findings suggest that RMB appreciation is very disruptive. It will cause unnecessary price adjustment without solving the structural issue that induces the trade imbalance. Therefore, the factors that contribute to the US-China trade imbalance deserves careful evaluation in the future by researchers and policymakers.

The finding that ERPT is high for US imports from China, which are almost always priced in the dollar, differs from the results found in Gopinath, Itskhoki, and Rigobon (2010) for a group of advanced economies.²¹ They find that even conditional on a price change, ERPT of imports that are priced in the dollar remains much lower than those priced in exporting countries’ currencies. Their findings suggest that firms will choose

²⁰Our price data have several advantages compared to those in Li, Ma, Xu, and Xiong (2010). Our goods-level actual price data are more accurate than their unit-value prices (export value divided by trade volume) that are at the eight-digit HS level. Their data are not suitable for estimating ERPT between the US and China either because the annual data ended in 2006, with only one observation after the RMB started to appreciate against the dollar.

²¹More than 97% of US imports from China are priced in the dollar.

the importing country’s currency if they prefer low ERPT, while exporters that prefer high ERPT will set prices in their own currency. Our result leads one to question why Chinese firms use the dollar as invoicing currency even if their preferred ERPT is high. This could be because the Chinese yuan is not yet freely convertible due to China’s capital control measures. It will be interesting to see if more Chinese imports are priced in the Chinese yuan when China relaxes its capital controls.

5 Conclusion

Competing theoretical models based on different assumptions about the pricing behavior of firms give sharply different answers to important policy issues such as the impact of monetary shocks and the optimal monetary and exchange rate policies. Several recent studies investigate the pricing behavior of firms and their implications on theoretical models using the micro price data collected by the BLS. In this paper, we focus on the trade prices between the US and China in the BLS dataset. China’s exchange rate regime switching in 2005 provides a great opportunity to study how a change in the macroeconomic environment can affect price setting.

We document several interesting findings. First, significant price rigidity exists for US-China trade prices even after we exclude prices that never change. The median duration is 8.5 months for US exports to China and 9.4 months for US imports from China. Second, price rigidity substantially decreases after the summer of 2005. The frequency-implied duration declined more than 30% for US exports to China and 20% for US imports from China. A benchmark menu cost model that is calibrated to the data can replicate the decline of price rigidity both qualitatively and quantitatively. Third, lifetime ERPT into US import prices from China is close to complete conditional on goods having at least one price change, while it is much smaller when all goods are included. This result is due to the fact that a large fraction of goods never change their prices. Our results support findings in Nakamura and Steinsson (2012) that product replacement may substantially underestimate ERPT in aggregate price data.

Our findings also raise several interesting issues for future research. First, Gopinath and Rigobon (2008) find that the price stickiness for US imports increased in the 1990s. They argue that the increase in price stickiness contributed to the decline of ERPT into US import prices. It would be interesting to see if price rigidity for goods from other countries has also increased in the last decade and its impact on ERPT.

Second, we find that ERPT for goods with at least one price change is quite large for US imports from China. However, these imports are still priced in the dollar. This result contradicts what Gopinath, Itskhoki, and Rigobon (2010) find for a group of advanced economies. They find that firms usually choose

home currency to price their products if high ERPT is preferred. It is of interest to see if more Chinese exports are priced in RMB in the future and to investigate why if they are not.

Third, as in Midrigan (2011) we document that the distribution of price changes differs from that in the standard menu cost model. Midrigan (2011) shows that incorporating this empirical feature into the menu cost model can substantially increase the real effect of the monetary shock. For future research, we want to study the impact of incorporating the distribution of price changes into a trade model.

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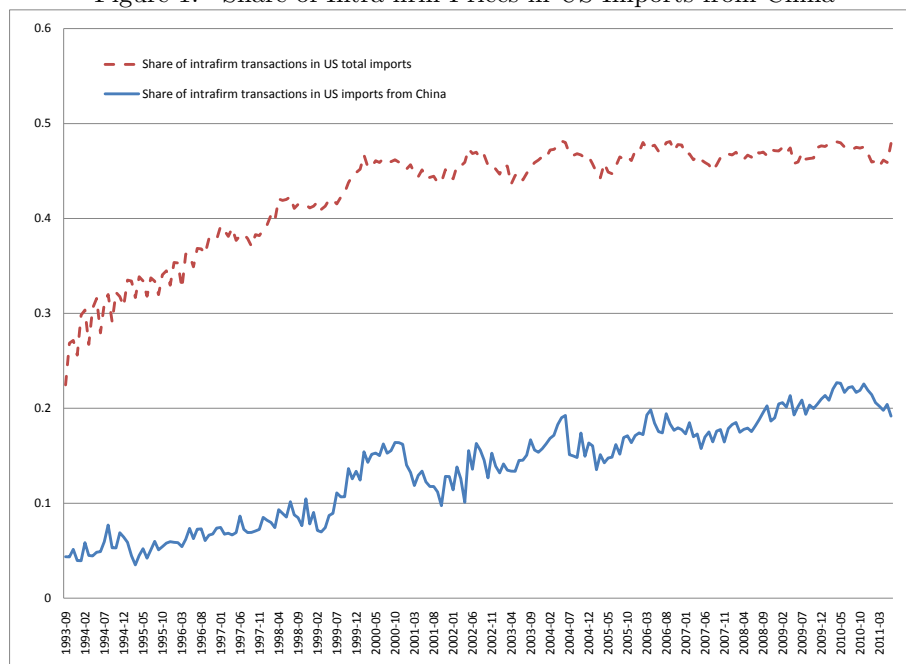
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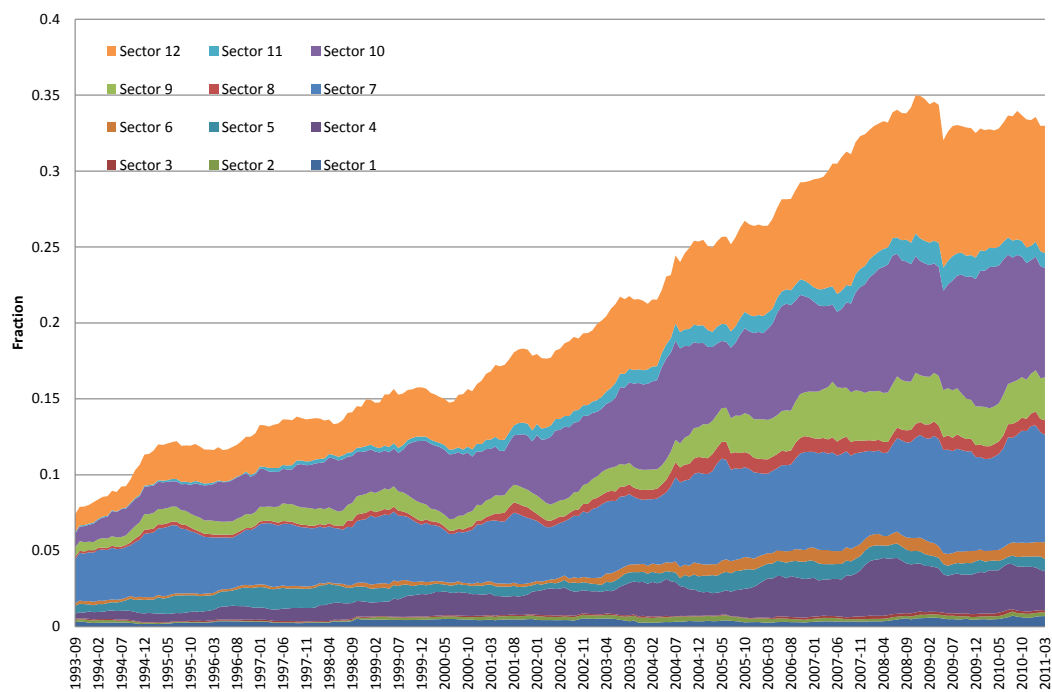
Figure 1: Share of Intra-firm Prices in US Imports from China



Note:

-Shares are calculated from the raw data in the IPP database.

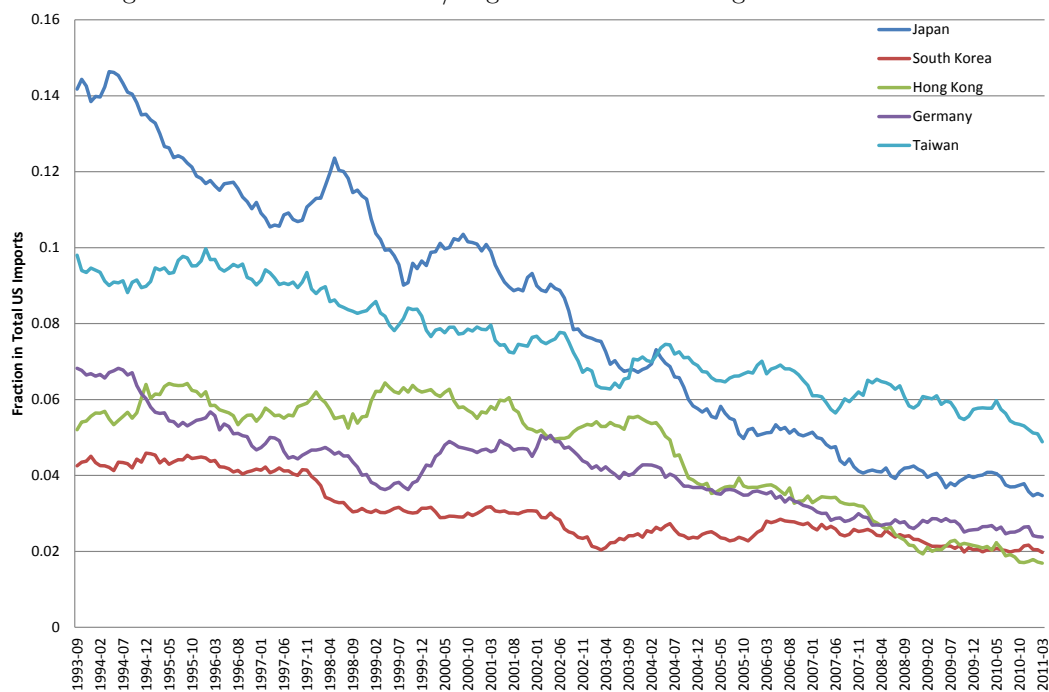
Figure 2: Share of Price Quotes from China in US Total Imports (Excluding Intra-firm Prices)



Note:

-Shares are calculated from our constructed dataset based on reported prices.

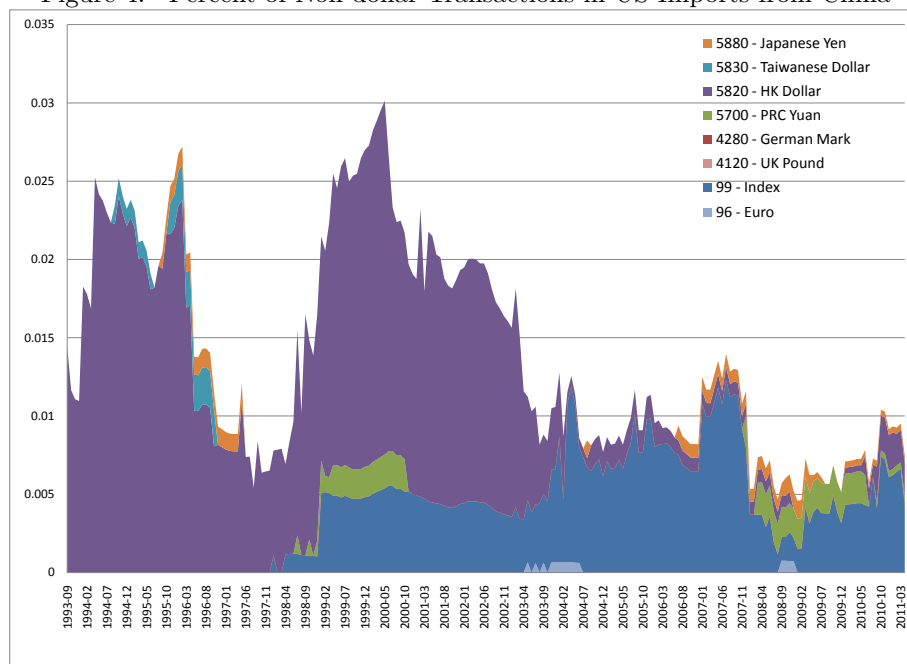
Figure 3: Share of Countries/Regions with a Declining Number of Prices



Note:

-Shares are calculated from our constructed dataset based on reported prices.

Figure 4: Percent of Non-dollar Transactions in US Imports from China



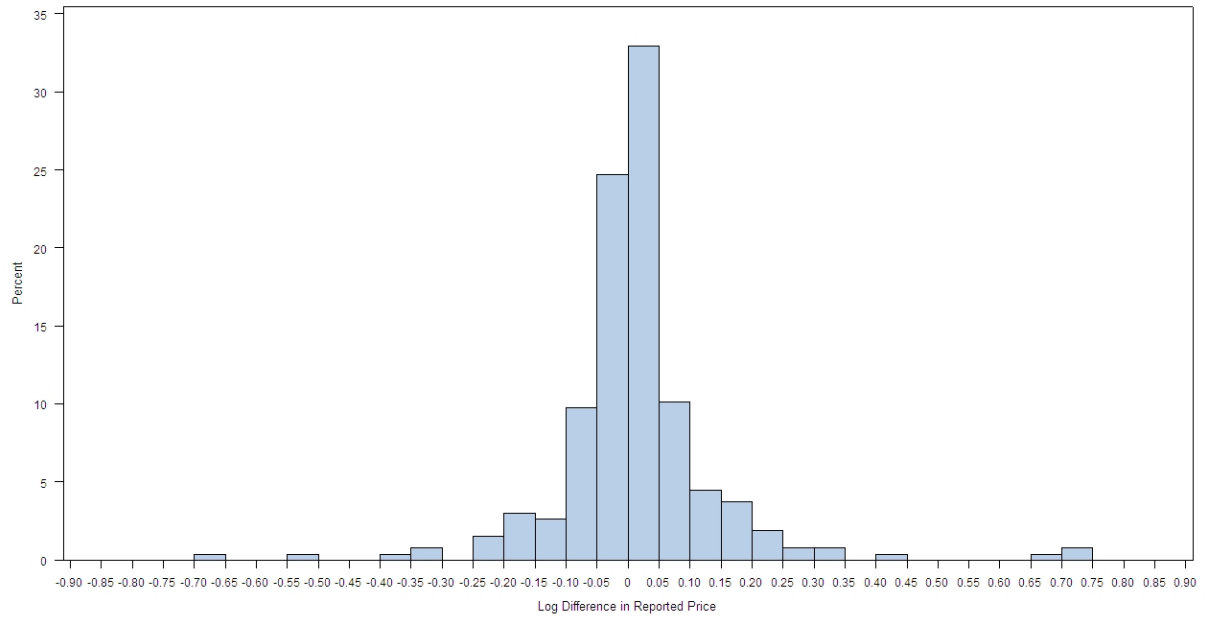
Note:

-97% of imports are priced in the US dollar.

-Shares are calculated from our constructed dataset based on reported prices.

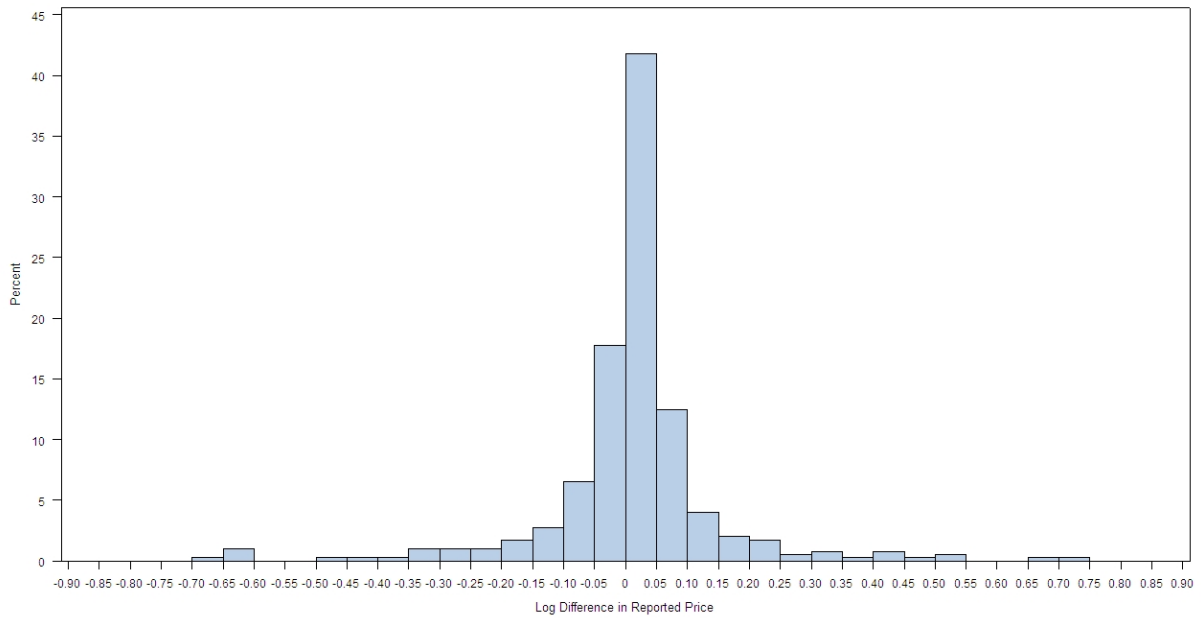
Figure 5: Distribution of Non-zero Price Changes (US Exports to China)

Histogram of Non-Zero Mean Price Changes of Items - Exports (Pre June 2005)



(a) Pre-June-2005 Subsample

Histogram of Non-Zero Mean Price Changes of Items - Exports (Post June 2005)

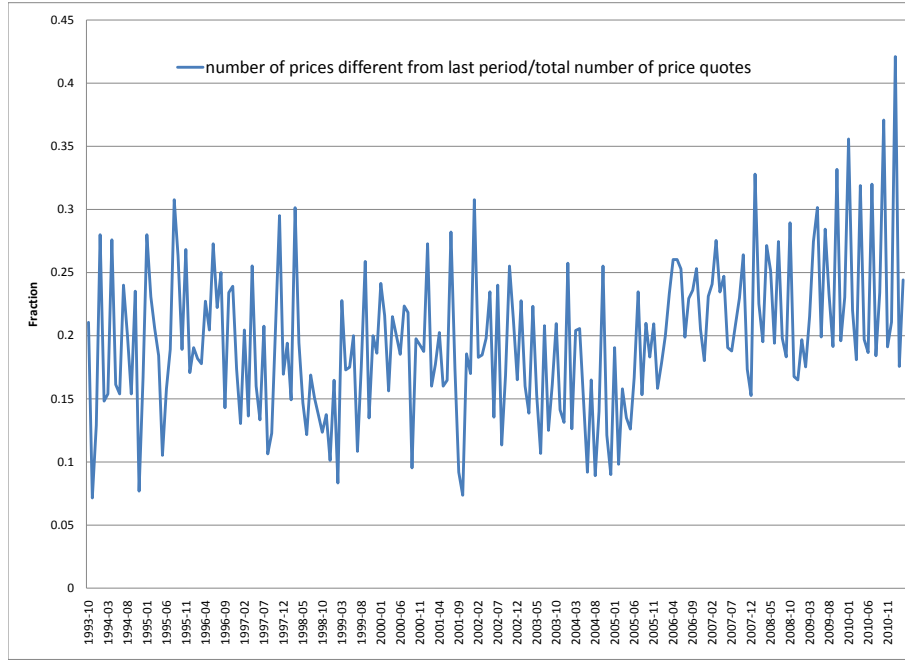


(b) Post-June-2005 Subsample

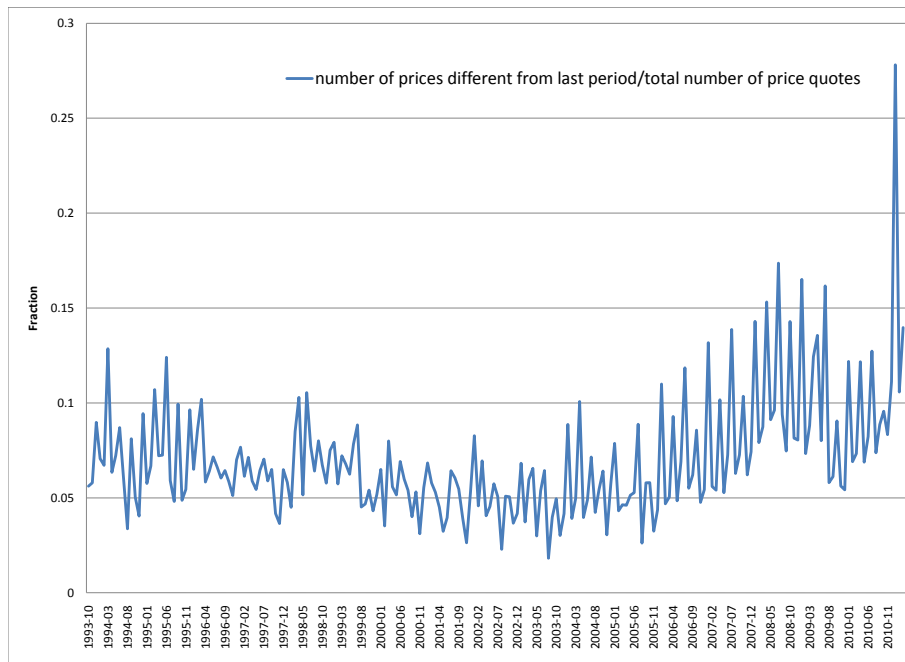
Note:

-Shares are calculated from our constructed dataset based on reported prices.

Figure 6: Fraction of Price Changes in Each Month



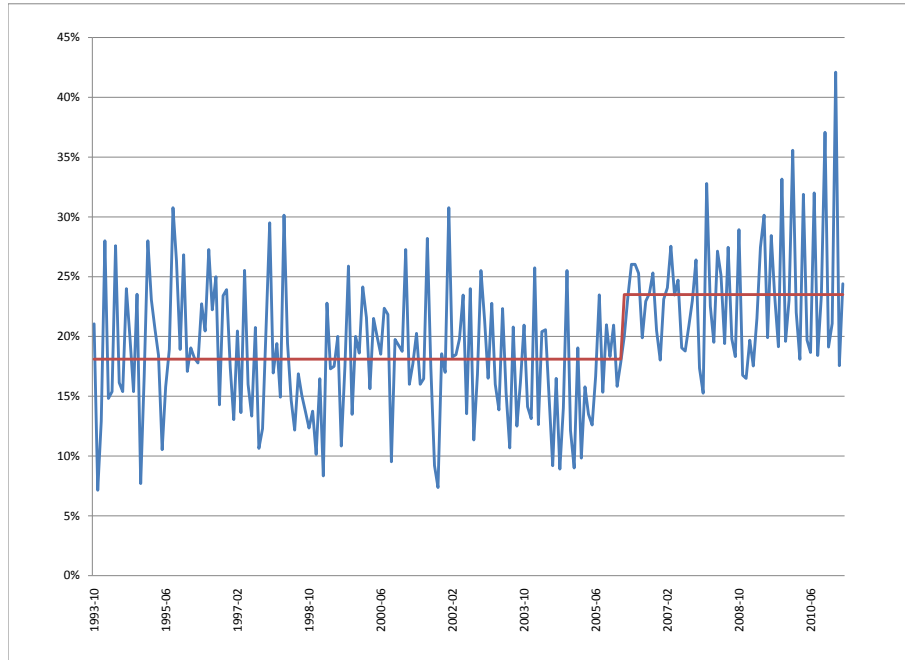
(a) US Exports to China



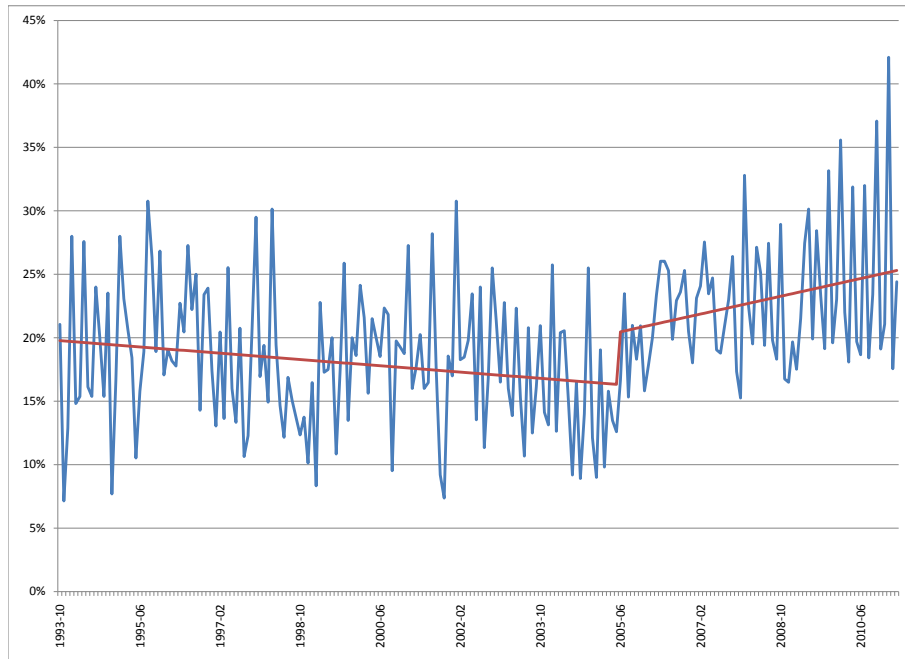
(b) US Imports from China

Note:
-Shares are calculated from our constructed dataset based on reported prices.

Figure 7: Fraction of Price Changes in Each Month (US Exports to China)



(a) Mean Model

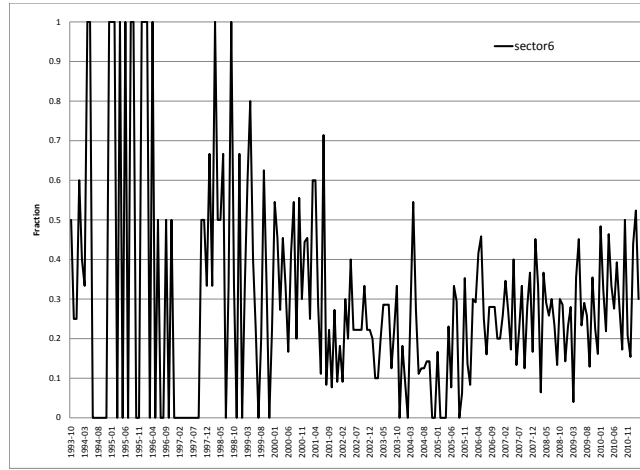


(b) Trend Model

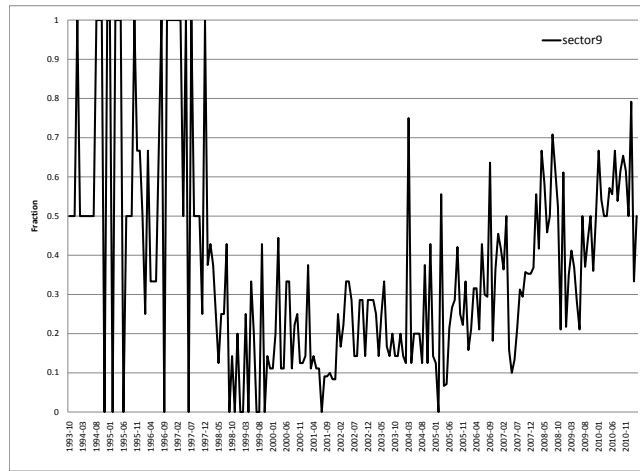
Note:

-Shares are calculated from our constructed dataset based on reported prices.

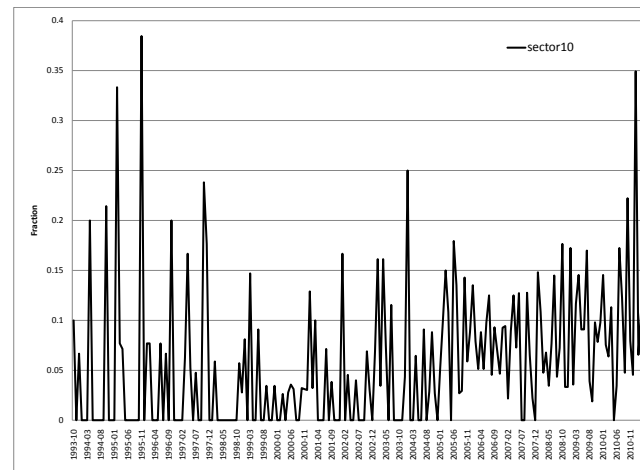
Figure 8: Fraction of Price Changes by Sectors (US Exports to China)



(a) Sector 6: Wood and Wood Products



(b) Sector 9: Metals

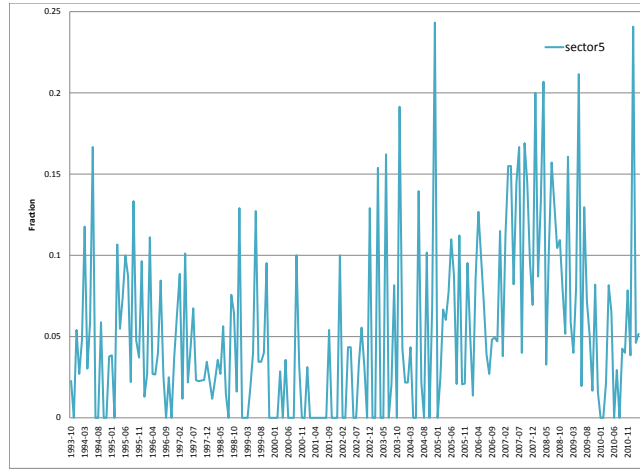


(c) Sector 10: Machinery/Electrical

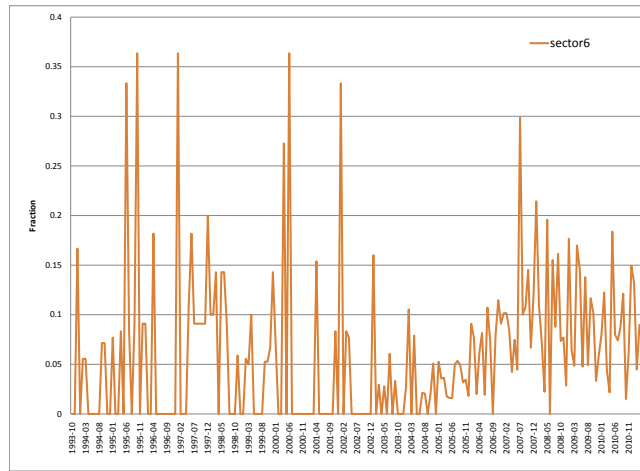
Note:

-Shares are calculated from our constructed dataset based on reported prices.

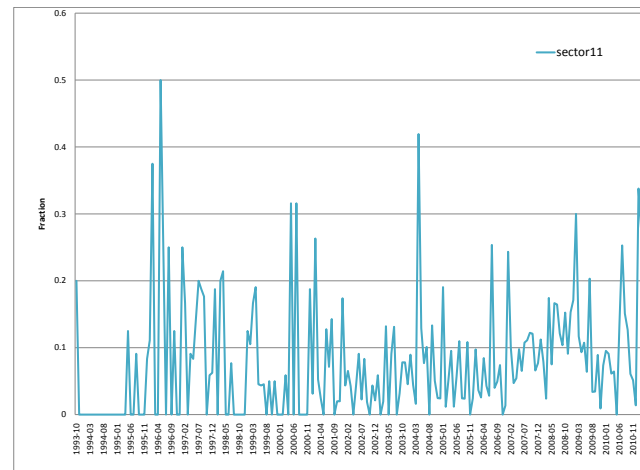
Figure 9: Fraction of Prices that Change in Each Month by Sectors (US Imports from China)



(a) Sector 5: Chemical and Allied Industries, Plastics, and Rubber



(b) Sector 6: Rawhide, Skins, Leather, and Furs



(c) Sector 11: Machinery/Electrical

Note:

-Shares are calculated from our constructed dataset based on reported prices.

Table 1: Summary Statistics

	Number of goods	Number of prices	Goods duration (months)			Price changes for each good			Goods with no price change
			min	max	mean	min	max	mean	
US Imports from China									
Reported	14,543	311,696	1	125	22.22	0	58	1.85	34.90%
Net exclusive	14,534	323,805	1	125	24.63	0	75	1.93	37.10%
US Exports to China									
Reported	1,048	23,043	1	139	23.23	0	79	5.39	23.47%
Net exclusive	1,047	23,638	1	139	23.33	0	80	5.33	24.55%

Note:

- This table reports summary statistics for prices of US imports from and exports to China.
- Reported is the reported prices and net exclusive is net prices excluding estimated and imputed prices by the BLS. See the section of data description for more information on these prices.
- Our data are monthly observations from September 1993 to March 2011.

Table 2: Price Rigidity of US-China Trade Goods

US Exports to China						
	Whole Sample		Pre-June-2005		Post-June-2005	
	All goods	At least 1 change	All goods	At least 1 change	All goods	At least 1 change
Frequency (%)						
Mean	14.13	20.20	11.10	18.13	16.55	24.02
Median	6.60	11.11	4.82	10.36	7.98	14.29
Duration (months)						
Mean	6.6	4.4	8.5	5.0	5.5	3.6
Median	14.6	8.5	20.2	9.1	12.0	6.5
Fraction up (%)						
Mean	59.24		53.97		63.82	
Median	61.80		50.00		66.67	
Size of Changes (%)						
Mean	15.00		10.34		17.34	
Median	8.36		7.32		8.52	
US Imports from China						
	Whole Sample		Pre-June-2005		Post-June-2005	
	All goods	At least 1 change	All goods	At least 1 change	All goods	At least 1 change
Frequency (%)						
Mean	8.20	12.68	6.20	11.46	9.41	14.56
Median	5.00	9.40	3.13	8.33	5.97	10.95
Duration (months)						
Mean	11.68	7.37	15.63	8.22	10.12	6.36
Median	19.50	10.13	31.50	11.49	16.25	8.62
Fraction up (%)						
Mean	55.34		47.55		62.20	
Median	55.00		50.00		66.67	
Size of Changes (%)						
Mean	11.58		11.84		11.63	
Median	7.53		7.52		7.51	

Note:

- The data are monthly observations from September 1993 to March 2011 and the statistics are calculated from reported prices.
- To calculate the mean and median frequencies, we first find the frequency of each entry level item (ELI). Then the unweighted mean and median of frequencies across ELIs are calculated.
- Duration is calculated from $d = -1/\ln(1 - f)$, where f is frequency and d is frequency-implied duration.
- Fraction up is the fraction of price increases in total price changes.
- Size of changes is measured by the absolute value of percentage price changes.
- Columns “All goods” include all goods in our sample. Columns “At least 1 change” only include goods that have at least one price change in their lifetime.

Table 3: Results of Structural Break Tests

US Exports to China				
	Regime	Regime Date	a_j	b_j
Mean Model	1	October 1993 to January 2006	0.181***	NA
	2	February 2006 to March 2011	0.235***	NA
Trend Model	1	October 1993 to May 2005	0.198***	-0.052**
	2	June 2005 to March 2011	0.106*	0.147**
US Imports from China				
	Regime	Regime Date	a_j	b_j
Mean Model	1	October 1993 to June 1999	0.070***	NA
	2	July 1999 to April 2005	0.051***	NA
	3	May 2005 to November 2007	0.070***	NA
	4	December 2007 to March 2011	0.102***	NA
Trend Model	1	October 1993 to January 1998	0.078***	-0.075*
	2	February 1998 to December 2003	0.099***	-0.103***
	3	January 2004 to November 2007	-0.028	0.132*
	4	December 2007 to March 2011	0.147**	-0.050

Note:

- This table reports the results of structural break tests for price stickiness of US trade with China.
- Superscripts *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Table 4: Median Price Durations (months) at Sectoral Level

Sector		Whole Sample	Pre-June-2005	Post-June-2005
1	Animals, Animals and Vegetable Products	2.33	1.80	2.70
2	Prepared Foodstuff	8.20	11.46	4.84
3	Mineral Products	9.99	9.99	4.42
4	Chemical and Allied Industries, Plastics, and Rubber	6.49	11.46	4.73
5	Rawhide, Skins, Leather, and Furs	1.63	2.44	1.63
6	Wood and Wood Products	3.98	2.47	3.36
7	Textile and Footwear/Headgear	7.82	3.65	8.14
8	Stone/Glass	13.90	55.49	11.99
9	Metals	3.11	4.60	1.76
10	Machinery/Electrical	12.99	15.99	9.49
11	Transportation	11.15	21.00	4.48
12	Miscellaneous	12.49	9.06	12.32

Note:

- This table reports sectoral-level median durations of US exports to China. Durations are calculated from $d = -1/\ln(1 - f)$, where f is frequency and d is frequency-implied duration. The sectors are aggregations at the 2-digit level HS codes.
- The statistics are calculated from reported prices of goods that have at least one price change.
- The data are monthly observations from September 1993 to March 2011.

Table 5: Menu Cost Model

	Pre-June-2005		Post-June-2005			
	Data	Model	Data	Benchmark	Only $P_{US,t}$	Only τ_t
Share of price changes (%)	10.6	10.6	14.3	15.9	13.5	12.9
Fraction of price increases (%)	50	50	67	57	58	50
Size of price changes (%)	7.2	7.6	8.5	8.2	8.6	7.4
μ		1.000		1.002	1.002	1.000
σ_η		0.009		0.019	0.019	0.009
ν		0.79		0.19	0.79	0.19
ϕ		0.885		0.971	0.885	0.971
σ_τ		0.010		0.014	0.010	0.014
α		0.93		0.93	0.93	0.93
β		$0.96^{1/12}$		$0.96^{1/12}$	$0.96^{1/12}$	$0.96^{1/12}$
θ		4		4	4	4
ρ		0.76		0.76	0.76	0.76
σ_ε		0.0335		0.0335	0.0335	0.0335
$\frac{K}{(1-\alpha)\tau^{-\alpha}C_M}$		0.00022		0.00022	0.00022	0.00022

Note:

- The pre-June-2005 subsample is from January 1996 to June 2005 and the post-June-2005 subsample is from July 2005 to March 2011.
- The share of price changes (%) in the data is the median share of price changes in each month during each subsample. The fraction of price increases (%) is the median fraction of price increases in all prices changes during each subsample. The size of price changes (%) is the median absolute size of price changes.
- Parameters μ and σ_η are estimated from the data of the US export price index to China, which is assumed to follow a process of $\log(P_{US,t}) = \mu + \log(P_{US,t-1}) + \eta_t$. σ_η is the standard deviation of η_t .
- Parameters ν , ϕ , and σ_τ are estimated from the data of τ_t , which is assumed to follow an AR(1) process: $\log(\tau_t) = \nu + \phi \log(\tau_{t-1}) + \varepsilon_{\tau,t}$. σ_τ is the standard deviation of $\varepsilon_{\tau,t}$.
- All other parameters are calibrated and see section 3 for the details of calibration.

Table 6: Lifelong Exchange Rate Pass-through (ERPT)

	All Prices			1 or More Price Changes		
	ERPT	s.e.	N	ERPT	s.e.	N
Reported Prices	0.39	0.41	5177	0.88	0.86	2435
Net Prices Exclusive	0.48	0.41	5180	1.02	0.87	2412
	1 or 2 Price Changes			More than 2 Price Changes		
	ERPT	s.e.	N	ERPT	s.e.	N
Reported Prices	0.80	1.21	1677	2.71	1.88	758
Net Prices Exclusive	0.99	1.28	1648	2.94	1.80	764

Note:

- This table reports lifelong ERPT for US imports from China.
- s.e. is the standard error and N is the number of observations.
- The data are monthly observations from June 2005 to July 2008.
- Column “All Prices” includes all prices in our sample. Column “1 or More Price Changes” only includes prices that have at least one change in their lifetime.
- Column “1 or 2 price Changes” includes prices with one or two changes and column “More than 2 Price Changes” includes prices with more than two changes.