A Test of Hedonic Price Indexes for Imports

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May 15, 2013

Reliance on linking causes problems of artificial rigidity in imports indexes (Nakamura and Steinsson, 2012) and of failure to reflect price reductions for imports that occur when production shifts to from high cost countries of origin to low cost countries of origin (Reinsdorf and Yuskavage, 2013).

Hedonic methods for quality adjustment are an alternative to linking that could help to resolve these problems. Hedonic methods will also be needed if a buyer's index for intermediate inputs is developed as a solution to the offshoring bias problem discussed in Mandel (2007, 2009) and Houseman et al (2011). Hedonic quality adjustment has not been attempted using data collected from importers for purposes of constructing an import price index. In this paper, we attempt to develop approaches for implementing hedonic or other quality adjustment methods that would be feasible for import price indexes despite these well-known difficulties. We then test these methods in an attempt to quantify the amount of product replacement bias present in the official import price indexes for some representative products such as televisions.

* We would like to thank Taylor Blackburn and Marisa Gudrais for excellent research assistance. The views expressed in this paper are solely those of the authors and not necessarily those of the U.S. Bureau of Labor Statistics or the U.S. Bureau of Economic Analysis.

The Need for an Alternative to Matched Model Indexes for Imports

The US Bureau of Labor Statistics uses matched model indexes to measure price change for exports and imports. In a matched model index, changes in sample composition resulting from item replacements or sample rotations are handled by linking the incoming items into the index calculation. This means that items that are not present in both the initial and the comparison period are excluded from the calculation of the change in the index. Although holding the sample constant in this way keeps spurious comparisons of different quality items from influencing the estimate of price change, any true changes in quality-adjusted prices that occur at the time of item replacements or sample rotations are excluded from the estimate of the rate of price change.

Complicating matters is increasing globalization. With globalization, new source countries have entered and changes in source country have become more frequent. Although quality might decline when sourcing switches to a lower cost country, any genuine cost saving that import buyers realize by changing source countries is likely to be linked out of the change in the import price index. When linking is used to handle a change in source country, all of the change in the price paid by the buyer is attributed to changing quality, but frequently only a portion of the price change is a result of quality change.

Recent research finds that price developments associated with changes in sample composition are important components of overall price change for exports and imports. Nakamura and Steinsson (2012) analyze a sample of the micro data that the US Bureau of Labor Statistics (BLS) uses to compile the imports and export price indexes. They find that items in the sample tend to be subject to frequent replacement and tend to have rigid prices during their lifespan in the sample (44.3 percent of the items in import price samples never have a price change). These patterns imply that high proportions of price changes must occur at the time of item replacements.

In the Nakamura-Steinsson paper, the sign of the bias in the matched model index depends on whether the index has an upward or downward trend; if the price index is trending downward, excessive flatness of the matched model index means that it has an upward bias. The assumption that changes in quality-adjusted prices at times of item replacements are, on average, the same as the observed price changes for continuing items implies corrections to estimated changes in the index for non-oil imports that raises the standard deviation of quarterly log changes from 1.1 percent to 1.6 percent. This implies that the matched model index for imports is much flatter than it should be.[1]

[1] Gagnon, Mandel, and Vigfusson (2012) prefer different assumptions and find smaller effects of omitted price changes for exiting and entering items than those found by Nakamura and Steinsson (2012).

The assumption that quality-adjusted price changes associated with item replacements have the same mean as price changes for continuing items may, however, be unrealistic for products undergoing rapid technological progress or entry by new producers in low wage countries that have cost advantages. As emphasized in Erickson and Pakes (2011), unmeasured price changes associated with item replacements could be systematically smaller for categories of goods undergoing rapid technological progress. The matched model index may then have an upward bias even if it is trending upward because the changes in quality-adjusted prices at times of item replacements are smaller than the average price change of continuing items (including those whose price stays constant).

Although declines in quality-adjusted prices caused by technological progress for high technology goods could be a source of bias in the producer price index (PPI) and the CPI, the import price index faces the additional measurement problem of shifts in production to lower cost countries.[2] Since the mid-1990s, production shifts to emerging economies have occurred for a wide range of products, including electronic goods, textiles, and other consumer durables and intermediate inputs. The upward bias from linking in new models of goods with rapidly improving technology could then be further compounded in the import price index by shifts in production toward lower cost host countries.[3] An indirect method for estimating the bias in a matched models import price index from the entry of new varieties and exit of incumbent varieties was introduced by Feenstra (1994). The bias estimate is a function of the post-entry expenditure share of the new varieties, the pre-exit expenditure share of the exiting varieties, and an elasticity of substitution parameter that must be greater than one, so that higher expenditure shares correspond to lower quality-adjusted prices. If the post-entry share of the entering varieties is greater than the pre-exit share of the exiting varieties, then the bias in the matched model index is positive. Feenstra, Mandel, Slaughter and Reinsdorf (2013) use this method to estimate the bias associated with variety entry and exit in the deflator for non-petroleum imports in the US national accounts, where new countries of origin are treated as new varieties. They find an average bias of about 0.6 percent per year. This estimate reflects a combination of several factors, including entry of low-priced producers in emerging low cost locations, gains from technological progress, and a general broadening of the range of varieties that are available as markets thicken.[4]

Houseman, Kurz, Lengermann and Mandel (2011) and Mandel (2007, 2009) focus on shifts of production from the US to low-cost offshore locations, finding that such shifts substantially

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[2] Unmeasured reductions in the price paid for an imported product that occur when the buyer switches to a new supplier in a low cost country resemble the problem of outlet substitution bias in the CPI, however. See Reinsdorf (1993) and Greenlees and McClelland (2011).

[3] For example, Byrne, Kovak and Michaels (2012) show that new producers in China supply identical quality semiconductors at prices that are on average 17 percent lower. Thomas, Marquez, and Fahle (2008) attempt to measure price reductions from substitution to low cost countries for a wider range of products.

[4] Note that availability of a broader range of varieties makes buyers better off, as they can better match their specific needs to product characteristics.

reduced prices paid by US manufacturers for intermediate inputs. This line of research implies a need for alternatives to a pure matched model index for two reasons. First, a matched model import price index will fail to account for the entry of lower-priced items from new producers in low cost offshore locations. Second, if the proposed buyer's price index for intermediate inputs is developed to capture the effects of substitution from local to offshore production, some of the changes in sourcing location are likely to involve substitutions of items with differing characteristics. If the buyer's index for intermediate inputs relies exclusively on the matched model approach to handle quality change, it may miss some of price changes associated with changes in where the intermediate inputs are produced.

Hedonic Price Indexes for Imports

The evidence on the existence of significant bias in a pure matched model import price index implies that indexes that directly measure the price effects of entry and exit of varieties and producers would be extremely valuable for products in dynamic markets. Hedonic indexes do not exclude observations that are only present in one time period from index calculation, so they can potentially account for the changes in quality adjusted prices that occur at times of item substitutions or sample updates.

The history of hedonic price index research extends back for more than 80 years, and since Griliches's (1961) chapter on this method appeared in the Stigler commission report, there have been innumerable empirical applications of this technique to the consumer or producer price indexes. Aizcorbe, et al. (2003) explore conditions under which matched model and time-dummy hedonic quality adjustment techniques lead to comparable measures of prices. They find that the two methods give estimates that are numerically similar when turnover is low, or when a high frequency of observations allows new models to be brought in promptly and characteristics are relatively constant over time. More recently, Erickson and Pakes (2011) develop new hedonic methods in order to account for the selection bias caused by exiting goods that are replaced by more technologically advanced goods. Their technique accounts for unobserved price-determining characteristics by making use of the information in the residuals from the standard hedonic regression.

Nevertheless, in spite of the voluminous literature on hedonic indexes, applications of hedonic techniques to export or import price indexes have been limited. Hedonic price indexes based on data from industry sources or from producer price index surveys have occasionally been used to deflate trade flows in the national accounts.[5] But to our knowledge, no one has estimated a hedonic import price index using data collected from importers by a statistical agency.

[5] For example, using proprietary data on worldwide markets for semiconductors Grimm (1998) constructed hedonic price indexes for semiconductors that were used to deflate exports and imports of this product in the US national

Unavailability of data is the main reason for the lack of research on hedonic indexes for import prices. Although the US has produced complete sets of specification-based price indexes for goods imports since 1982 (Alterman, 1991, p. 113), many countries continue to calculate unit value indexes for foreign trade prices based on values and volumes from customs data. Furthermore, even in the case of BLS, the database used to construct the export and import indexes often has insufficient information on the characteristics of the sampled items to construct a hedonic model of price behavior.

In this paper, our strategy for filling in the missing product characteristics data is to perform an internet search on the model number provided by the respondent. We were frequently able to find product description information from manufacturers or product reviewers using this method.

Data Description

To construct experimental hedonic indexes and benchmark matched model indexes for imports, we use three subsets of the import price data collected for BLS's International Price Program (IPP). In particular, we used the description field in the IPP database to assemble data sets on imports of consumer televisions, consumer cameras, and bananas.[6] Bananas were selected as a kind of control group. Unlike televisions and cameras, they are relatively homogeneous (though besides the main Cavendish variety, the sample also contains some specialty varieties.)

The description field in the IPP database was also the basis for the quality variables that we constructed for each product type. The variables included in the hedonic models cover the characteristics that are well documented in the description portion of the IPP database; however we did fill in some blanks by means of internet searches on make and model numbers. See Appendix Table A1 for the list and description of quality characteristics that we were able to pull from the database.

The data set for televisions and bananas cover the months between January 2000 and December 2010. Unfortunately for cameras the data on quality and monthly prices became too sparse after March 2006, so our camera indexes end at that point.

The IPP database contains two types of prices: reported prices and net prices. To derive the net price, BLS adjusts the reported price as needed for discounts, duties, freight charges, and the exchange rate. The net prices are estimates of actual transaction prices in dollars and are used for the official import and export price indexes. Thus, we also use the net prices. For certain

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income and product accounts (NIPAs) from 1981 to 1997. Also, Kravis and Lipsey (1971) used industry data to estimate hedonic indexes of relative price levels received by producers in different countries for selected products.

[6] We focus on color televisions sized 13 inches or larger and exclude television/VCR combinations. We do not include plantains in the analysis of bananas.

commodities, the BLS also allows reporters to give “index” prices.[7] These types of prices, which were reported for some of our banana items, are excluded from our analysis.

We include intra-firm “transfer” prices in our study to keep the sample sizes from becoming too small. We do, however, include a dummy variable for intra-firm prices in our hedonic regressions because these prices behave differently from arm’s length prices; they are characterized by less stickiness, less synchronization, and greater exchange rate pass-through, as found in Neiman (2010). For tractability, we assume that the intra-firm pricing strategy is the same across items and time throughout this study. As shown in Table 1, the share of intra-firm prices is high for cameras and bananas.

Table 1. Share of intra-firm prices in each month

	Televisions	**Cameras**	**Bananas**
Mean	0.41	0.89	0.85
Min	0.15	0.72	0.62
Max	0.64	1.00	1.00

In the IPP database, many items are repriced less often than every month, so monthly prices are often temporarily missing. Temporarily missing prices can also occur because the respondent fails to report a price one month. We experimented with two ways of imputing temporarily missing prices. The simple method of carrying forward the last observation to fill in the missing prices is a standard practice in research using IPP data (see, for instance, Nakamura and Steinsson, 2012, and Gagnon, Mandel, and Vigfusson, 2012). Given that for many products in the IPP long periods of price rigidity are common, this method is a reasonable approximation.

On the other hand, for official price indexes, BLS generally imputes missing values by adjusting the last observation to reflect an estimate of the subsequent price change using either “cell-relative” imputation or “class-mean” imputation.[8] We found that our results were insensitive to whether we used cell-relative imputation or the simple carry-forward method favored by researchers, so below we will focus on indexes that include carry-forward imputations. Table 2 reports the share of missing values that are imputed for each subset considered.

Table 2. Share of imputed prices in each month

	Televisions	**Cameras**	**Bananas**

[7] When respondents are concerned about disclosure, they can give an index price that approximates the behavior of the actual price instead of an actual transaction price.

[8] IPP also sometimes uses linear interpolation to impute prices.

Mean	0.03	0.04	0.00
Min	0.00	0.00	0.00
Max	0.32	0.50	0.12

Both televisions and cameras exhibit a great deal of cross-sectional variation in price level. Television prices vary 300-fold, while camera prices vary 500-fold. Television prices are much less sticky than camera prices. In the television sample, items change price an average of 6.4 times during their time in the sample, while in our camera sample items on average have only 1.6 price changes in between entering and exiting.[9]

Source countries shifted for both televisions and cameras over our sample periods; televisions shifted from Mexican imports to Chinese imports (see Figure 1), while cameras moved away from Japanese imports (see Figure 2). It is also true that televisions got larger over our sample period (see Figure 3). Televisions experience slightly more sample entry than sample exit throughout the period that we study. Cameras, on the other hand, experience almost one and a half times more exits than entries of items into the sample. On average about 4.7 percent of televisions in a given month are no longer present in the next month, while for cameras the hazard rate for sample attrition is 5.6 percent per month (see Table 3 for a summary of exit reasons). The mean duration of a television in the sample is 18.1 months (with a standard deviation of 12.9 months). This is slightly shorter than the 21 months that would occur if the hazard rate for exit were constant. On the other hand, mean duration of an item in the camera sample, at 17.8 months (with a standard deviation of 11.6 months) is consistent with a constant hazard rate for sample exit.

Table 3. Share of exit in each month by reason (mean)

	Televisions	Cameras	Bananas
Refusal	0.01	0.00	0.01
Out of business	0.00	0.00	0.00
Out of scope[10]	0.02	0.04	0.00
Out of scope, replaced	0.01	0.01	0.01

Bananas behave very differently from televisions and cameras. Prices for bananas only vary six-fold, reflecting their greater homogeneity. Moreover, bananas change prices very frequently

[9] In calculating these average durations and price change frequencies we included items for which the observable lifespan was truncated because they entered before January 2000 or exited after the end of our sample (December 2010 for televisions or March 2006 for cameras). Correcting for truncation bias will raise our estimates slightly.

[10] Out of scope items are items that are no longer traded. Reporters sometimes are able to give a quote for a replacement item. Other times, there is no replacement.

compared to televisions and cameras; on average, a banana quote changes price 19.3 times during the time that it is in our sample. Banana imports in our dataset primarily come from Guatemala, Honduras, Costa Rica, Colombia, and Ecuador. Colombia, Ecuador and Guatemala have increased their representation in the import price index sample, while the share of the sample from Honduras has fallen (see Figure 4). On average about 1.9% of bananas in each period are no longer present in the next period. The mean duration of an item in the banana sample is substantially longer than those of televisions or cameras, at 32.2 months (with a standard deviation of 23.9 months).

Baseline Non-hedonic Measures of Price Change

Before calculating alternative versions of hedonic price indexes, we calculate two baseline measures of price change. The first of these is not a true price index because it simply tracks the change in the geometric average price of the sample. Since we do not have usable information on quantities at the level of individual items, we cannot calculate unit value indexes. Indexes of average prices behave like unit value indexes because they do not hold the sample composition constant when comparing across time periods. Changes in sample composition are likely to alter the average quality level represented in the sample, so the behavior over time of the average price reflects both price and quality developments. Deflating the average price index by a price index that holds quality constant yields an index of quality change.

Second, we construct matched model indexes to use as benchmarks to compare to hedonic price indexes. The matched model indexes of the IPP include item weights in a Laspeyres index formula. We do not have the item weight information needed to replicate the Laspeyres matched model indexes of the IPP, so our matched model indexes are calculated as Jevons indexes of the prices of the continuing items. (Jevons indexes use unweighted geometric means.)

For disclosure reasons, we are unable to report indexes at the level of individual products. Therefore, besides calculating matched model indexes for the three products of interest, we calculated matched model Jevons indexes for the other products contained in the most detailed published index that include these three products, and then combined these indexes. For example, for bananas, we simulate the relevant published index for Edible Fruit and Nuts (Harmonized System (HS) Code 08) by combining our index for bananas with an index for other edible fruits and nuts with weights based on the number of items in each category.

We use the difference between the aggregated matched model indexes with the aggregated hedonically adjusted indexes to infer the effects of the quality adjustment on the products of interest. In particular, we divide the change in the logarithm of the more aggregate index by the weight of televisions or cameras in that index to find the implied change in the logarithm of the index for televisions or cameras.

Hedonic Indexes

Sample size limitations affect what kinds of hedonic models we can investigate. The first specification we try is the pooled time dummy hedonic regression, which assumes that the effect of quality characteristics on the log price is constant over the whole span of time covered by the sample. The general form of the pooled time dummy regression equation is:

$$p_{it} = \alpha_t + X_{it}\beta + \varepsilon_{it}$$

where p_{it} is the log price of item *i* at time *t* and X_{it} is a vector of quality characteristics such as the television's screen size and screen type. The price index comparing time *t* to *t*-1 is then just the exponential difference between α_t and $\alpha_{t\text{-}1}$.

We fit this model both with and without country dummies from the set of variables in X_{it}. The specification that includes country dummies assumes that price differences between countries of origin are due to quality differences between these countries, while the specification that omits the country dummies assumes that price level differences between countries of origin are real. The truth probably lies in between these alternatives—ease of doing business and quality assurance may vary by country, but on the other hand, the large gains made by countries offering lower prices suggest that the value of the quality differences is small in comparison with the price differentials.

Another way to include price changes due to changes in source country in the hedonic index is to leave the country dummies in the set of explanatory variables but add back the quality adjustment made in connection with the changes in source country mix. If $\hat{\alpha}_t$ is coefficient on the time dummy, $\Delta\overline{p}$ is the change in the average log price, and ΔX is the change in the average characteristics including the country dummies, the log hedonic index equals the raw price change minus a quality adjustment equal to the predicted effect of the average characteristics change:

$$\hat{\alpha}_t = \Delta\overline{p} - (\Delta X)\hat{\beta}.$$

Now break *X* into a physical attributes (PA) part and a country mix (CM) part:

$$\hat{\alpha}_t = \Delta\overline{p} - (\Delta X_{\mathrm{PA}})\hat{\beta}_{\mathrm{PA}} - (\Delta X_{\mathrm{CM}})\hat{\beta}_{\mathrm{CM}}\,.$$

The index that includes the effect of source country changes in the measure of price change is:

$$\tilde{\alpha}_t = \hat{\alpha}_t + (\Delta X_{\mathrm{CM}})\hat{\beta}_{\mathrm{CM}}.$$

The next specification we estimate is the moving window hedonic regression, where the coefficients on the characteristics are held constant for only 24 months with each regression overlapping by 12 months. The moving window approach has the advantage of allowing the coefficients on characteristics to change over time as evolving technologies and market conditions alter the hedonic equation. The price index is constructed by chaining the coefficients on the time dummies from the moving windows.

Our final hedonic alternative is full hedonic imputation, which uses the estimated coefficients from the comparison period regression to predict the price of each item that was present in the base period. (These are not reported in the present draft of the paper, as we intend to implement a Fisher version of hedonic imputation in the next draft of this paper, in which base period coefficients are used to impute base period prices for the items present in the sample in the comparison period.) The comparison period regression is:

$$p_{it} = \alpha_t + X_{it}\beta_t + \varepsilon_{it}$$

Ideally, we would have run this regression on monthly data. However, to get around sample size problems, we had to pool observations for each quarter.

Accurate hedonic price indexes generally require that all the important quality characteristics be included in the model. Erickson and Pakes (2011) argue that in most applications of hedonic regression techniques, there are unobservable characteristics affecting whether an item exits or continues, or whether an item enters. Since standard hedonic specifications cannot account for price differences due to unobservables, Erickson and Pakes (2011) derive an alternative hedonic method making use of the information in the residuals from the standard hedonic regressions. Their procedure is specifically designed for goods that improve over time, such as televisions or camera. In principle, the method should work well for handling the data limitations faced by IPP, as it does not require a large number of observed characteristics to be effective. This part of the analysis has yet to be completed at the time of this writing.

Empirical Results

Televisions

Televisions and other video devices are combined in the published import price index for HS 8528.[11] To simulate the formula used for the official index, we constructed a matched model index for televisions and a matched model index for the other video devices in HS 8528 using the Jevons index formula. Each component index was then weighted by its share of the observations in HS 8528 to arrive at the combined Jevons index. For televisions, this share is

[11] For national accounts purposes it would be helpful to have separate data on values and prices of imported televisions and video monitors. Televisions are mostly used for final consumption, but video monitors have significant uses as investment goods. Because of the way investment is measured in the US national accounts, an inaccurate split between imports of final consumption goods and imports of investment goods could affect the measurement of GDP.

around 0.343, so the weight of the log index for televisions (which we are unable to report for reasons of confidentiality) in the index for HS 8528 (which we can report) was approximately 0.343.

Our matched model index generally tracks the official Laspeyres-type matched model index for HS 8528 quite closely (see Figure 5). Occasionally, however, they diverge: in May of 2001, May-September of 2007, and August of 2010, our matched model index measures higher inflation than the official index; and in April 2007 and September 2008, it measures lower inflation. Our matched model index falls by about 46 percent over the 119 month period ending in December 2010, compared with a fall of 49 percent in the official index.

The behavior of the average television price over the sample period implies a large amount of quality improvement: replacing the matched model index with the average price index results in an increase of 25 percent in the index for HS 8528. If the matched model index correctly measures the pure price change in televisions, the gap between the matched model index and the average price index implies that quality improvements contribute more than 8.5 percent per year to the annual growth rate of the average price of a television in the IPP sample. Among the important quality advances over the time period in our sample were the replacement of CRT screens with plasma, LCD, and LED flat screens and an increase in screen sizes.

Rather than assuming that the matched model index is an exact measure of pure price change, we hypothesize that the matched model index is too high because it misses the price effects of the entry and exit of countries with different levels of production cost and misses reductions in the quality-adjusted price due to entry of new models embodying more advanced technology. To calculate price indexes that can account for these effects, we estimate hedonic price indexes that exclude dummy variables for country of origin.[12] Hedonic price indexes that include country dummy variables would treat price level differences between countries as quality differences.

Because the hedonic index for televisions must adjust for large amounts of quality change, the results may be sensitive to the specification of the hedonic pricing model. Figure 6 shows the differences between the matched model index for HS 8528 and three different specifications of the hedonic price index for televisions. The specification that groups screen sizes into bins results in the smallest estimate of the bias in the matched model. In December 2010, the size bin hedonic index (solid line with no markers in figure 6) is 1.5 percentage points lower than the matched model index. As explained above, to solve for the effect on the log of the television index component of HS 8538, we must divide the effect on the log of the index for HS 8538 by 0.343. After doing this and converting the effect over the 119 months ending in December 2010 into a average annual growth rate, we find that the annual growth rate of the matched model

[12] See Appendix Table A2 Models C and D for the significance levels of the coefficients for the pooled hedonic regression.

index is 0.9 percent per year higher than the growth rate of hedonic index for televisions, as shown in table 4.

Table 4: Estimates of Bias in Growth Rate of Matched Model Index implied by Alternative Specifications of the Hedonic Regression

Specification of Hedonic Regression:		
Pooled, size grouped in bins	**Pooled, continuous size variables**	**Moving window, continuous size variables**
+0.9 percent/year	+2.8 percent per year	+2.5 percent per year

Specifying the model to include screen size and screen size squared raises the estimate of the bias in the matched models index for HS 8528 to 4.6 percentage points over 10 years, which implies a bias of about 2.8 percent per year in the matched model index for televisions. Finally, fitting separate hedonic regressions for moving 24 month windows (again with the screen size and screen size squared) implies a difference in the HS 8528 index of 4 percentage points over ten years, and a bias in the matched model index for televisions of about 2.5 percent per year.

One advantage of the moving window regression approach is that it is possible to see what the bias estimate would have been if the analysis had stopped at an earlier point than December 2010. As is evident in Figure 6, the growth rate gap between the matched model index and the moving window hedonic index is not uniform over time, and some earlier stopping points would have implied larger estimates of the bias, while others would have implied no bias.

If different countries produce televisions of different quality levels, the omission of country dummies from the hedonic regression could bias the coefficient estimates on the quality characteristics. In particular, if televisions are produced in lower cost countries are of lower quality, the hedonic indexes that omit country dummies could be too low.

To estimate a hedonic index that treats different countries as different qualities, we add dummy variables for country of origin to the set of characteristics in X_{it}.[13] Including country dummies in the hedonic model with size bins raises the estimate of the hedonic index for HS 8528 in December 2010 by 2.8 percentage points. This effect on the HS 8528 index implies the country-mix effect to be +1.6 percent per year on the growth rate of the hedonic index for televisions. In the hedonic regression with continuous size variables, the effect on the HS8528 index is 2.1 percentage points over ten years, implying an effect of +1.3 percent per year on the growth rate

[13] See Appendix Table A2 Models A and B for the significance levels of the coefficients for the pooled hedonic regression.

of the hedonic index for televisions. Thus both specifications imply that changes in the country mix substantially reduced prices paid for televisions.

Including country dummies but then subtracting the quality adjustment that is implied for the changes in the country mix is another way of treating price changes associated with changes in source country as true price changes. Multiplying the fitted coefficients on the country dummies by the changes in country shares yields a "quality adjustment" for changing country mix equal to the predicted price effect of the changes in source countries. In the specification with size bins, the predicted price effect of changing country mix based on the coefficients on the country dummies is 0.4 percent per year, which is about a quarter of the overall difference between the hedonic indexes with and without country dummies included. Using the coefficients from the continuous size variables regression, the effect of changes in the country mix is slightly greater than 0.4 percent per year, or about a third of the gap between the hedonic indexes that do and do not include country dummies.

After adjusting the hedonic indexes that include country dummies to remove the quality adjustment for changes in country mix, we obtain higher estimates of price change for televisions compared to excluding the country dummies. Indeed, the adjusted hedonic index with size bins has virtually the same growth rate as the matched model index, implying that the matched model has a bias of zero. The adjusted hedonic index with continuous size variables has a slightly lower growth rate than the one with size bins, however. It implies that the matched model index for televisions has bias of 1.8 percent per year, which is a percentage point lower than the estimate from comparing the hedonic indexes with and without country dummies. Also, after subtracting the predicted effect of changes in country mix, the moving window regressions with continuous screen size imply a bias in the matched model index of just 1.5 percent per year.

Adding country dummies to the regression equation alters the estimates of the coefficients on the variables in the original regression, which cover the physical characteristics of the televisions. Countries with lower price levels tend to produce televisions that are smaller or less advanced, so when country dummies are included the estimates of the coefficients on the physical characteristics are generally smaller in magnitude. Smaller adjustments for improvements in television characteristics then result in higher estimates of the hedonic index even after subtracting the predicted effect of changes in country mix.

A possible reason for the smaller estimated coefficients on the physical characteristics including country dummies in the model is the influence of omitted quality attributes that are correlated both with country shares and with the included physical characteristics. When the country dummies are absent, the physical characteristics in the model proxy for the omitted quality attributes, but the country dummies pick up some of effects of the omitted quality attributes when they are present. Under this interpretation, the true effect of quality improvements is larger than predicted by the coefficients on the physical characteristics in the regression that includes country dummies, but smaller than the one predicted by the regression that excludes country dummies.

The omitted quality change effects appear to be less important using the continuous screen size variables, suggesting that continuous variable model is better specified than the size bins model. The estimates of the bias in the matched model index implied by the continuous screen size regressions range from 1.5 percent per year in the regression with country dummies to 2.8 percent per year in the pooled regression with no country dummies.

Cameras

Cameras are included in the published import index for HS 90, "Optical, photographic, measuring and medical instruments." During the period we examine, which ends in March 2006, between 3 and 4 percent of the observations classified in HS 90 are for cameras. Assuming that the weight of cameras within the HS 90 aggregate is about one-thirtieth, if substituting a hedonic index for cameras for a matched model index for cameras reduces the growth rate of the camera index by 3 percent per year, the effect on the HS 90 index will be about 0.1 percent per year. For reasons of confidentiality we can only report the HS90 index. The effect on the HS 90 index of using an alternative formula for cameras must therefore be multiplied by 30 to find the effect on the camera index.

The matched model Jevons index that we calculate using continuing items tracks the official index for HS 90 well (figure 7). However the index of average prices also resembles the official index, and at the end of our sample period in March 2006 these two indexes agree precisely. This suggests that the net effect of quality changes in cameras over the period that we examine was negligible.

Measuring the bias in the matched model index by the gap between it and the hedonic index with no country dummies gives a bias estimate in the index for HS 90 of 1.2 percent points over 74 months, implying a difference in growth rates of 0.2 percent per year. The estimate is not sensitive to whether a pooled hedonic model or a moving window hedonic model is used or to the stopping point of the analysis. Because the weight on the camera component of HS 90 is low, a bias of 0.2 percent per year in the HS 90 index implies a bias of 6 percent per year in the matched model camera index.

Using the pooled regression specification, the hedonic index that includes country dummies is higher than the one that omits the country dummies, but the gap is small.[14] The effect of including country dummies on the hedonic index for cameras is only 0.7 percent per year. The moving window hedonic specification implies a larger effect of adding country dummies,

[14] See Appendix Table A3 Models A and B for the significance levels of the coefficients for the pooled hedonic regression.

however. The growth rate of the moving window hedonic index with county dummies is about 3.6 percent per year faster than the growth rate of the matched model index. Thus changes in source country are estimated to have reduced the growth rate of import prices for cameras by 0.7 percent per year or 3.6 percent per year depending on whether a pooled or moving window specification is used.

Bananas

As a check on our interpretation of the hedonic indexes for televisions and cameras measuring the effects of shifts in source countries and evolving technology that are missed by the matched model indexes, we calculated the similar indexes for bananas, which are a homogeneous product not subject to shifting technology. As noted above, however, bananas have been subject to changes in source country.

After excluding "index prices" (which are reference prices that respondents report when they prefer not to provide a true transaction prices), our matched model index for HS 08 (Edible fruits and nuts) shows similar growth to the official index for HS 08 over the longer run. Furthermore, the residuals between our matched model index and the official index are smaller than the residuals between an index of average prices and the official index (figure 9). Nevertheless, the fit is not as good as was the case for HS 8528 and HS 90. In individual months the two indexes can differ by as much as 10 percent percentage points.

The hedonic index results for bananas are very different from the results found for televisions and cameras. The hedonic index for bananas generally tends to be similar to the average price index of a banana item, so the difference between the matched model index for HS08 and the hedonic index for HS08 tends to resemble the difference between matched model index and the index of the average banana item price (see figure 10). Furthermore, in contrast to the results for televisions and cameras, in the case of bananas the matched model index is lower than the hedonic index. The matched model index thus implies that quality has declined in ways that the hedonic index fails to measure. In addition, including country dummies in the hedonic model does not change its behavior, suggesting that changes in source countries had little effect on banana prices.

Conclusion

The official import and export indexes use a matched model approach to handle the entry and exit of items from the sample. Changes in quality-adjusted prices associated with changes in sample composition are not measured by matched model indexes, so in cases when technological progress leads to new models with lower quality-adjusted prices, matched model indexes are likely to suffer upward bias. Furthermore, in the case of an import price index, the movement of production to lower cost locations can also lead to price reductions that would not be measured by a matched models index. Items from new source countries are generally treated as new items in a matched model import price index.

Price changes due to technological progress and migration of production to lower cost locations could be measured if hedonic price indexes could be estimated for imported products. This paper shows that hedonic indexes are feasible to estimate for at least some of the products in the import price index. For the two non-homogenous products that we investigate, televisions and cameras, our results generally support the hypothesis that technological progress and changes in source countries have led to reductions in quality-adjusted prices, which are incompletely reflected in a matched model index. The alternative specifications that we investigate for televisions imply grow rates for the hedonic index that differ from the growth rate of the matched model index by between 0 to –2.8 percent per year. For cameras, the hedonic indexes have growth rates that are 3.6 to 6 percent per year lower than that of the matched model index. Although further research on improving these hedonic indexes is needed, the results suggest that hedonic indexes are a promising route for measuring the price effects from changes in source countries and entry of more technologically advanced.

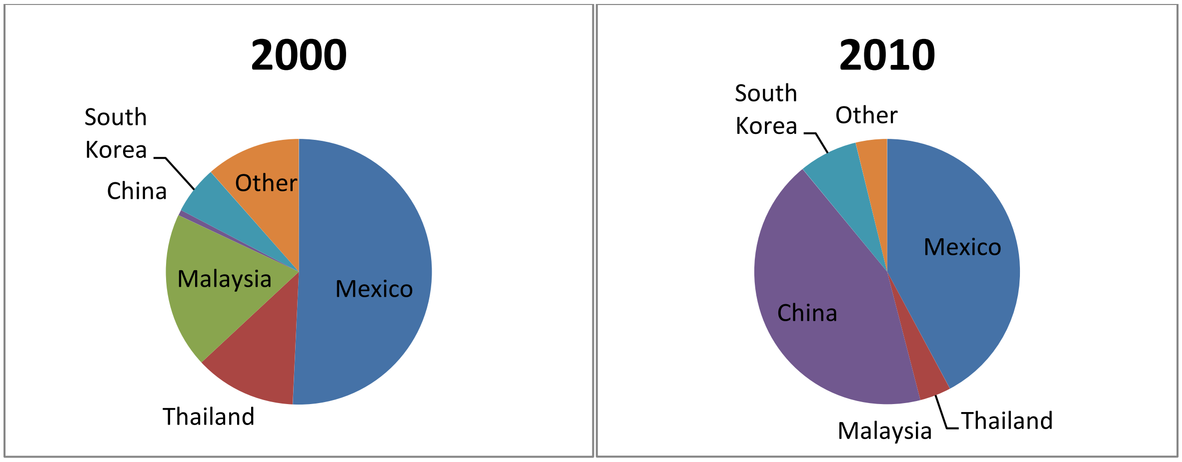

Figure 1. Change in the source country for television imports

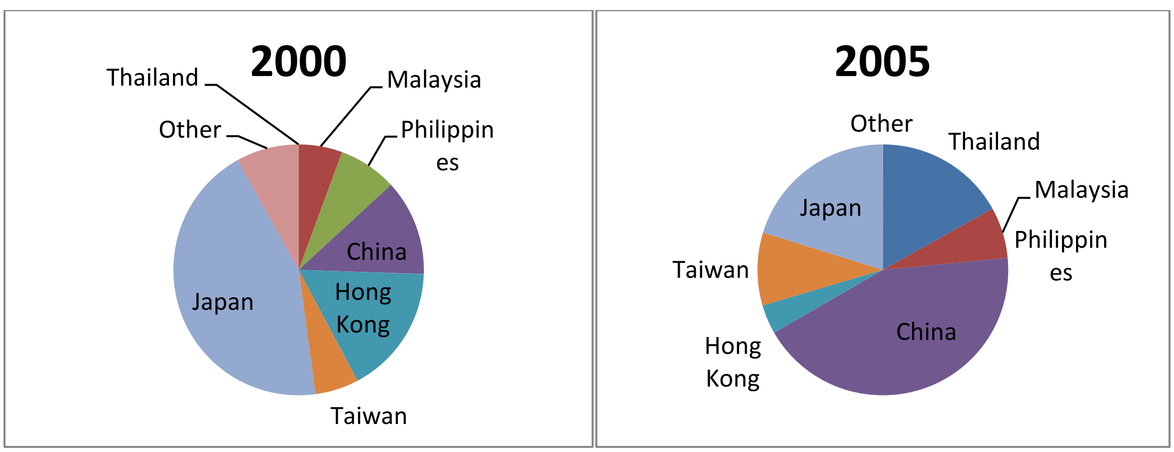

Figure 2. Change in the source country for camera imports

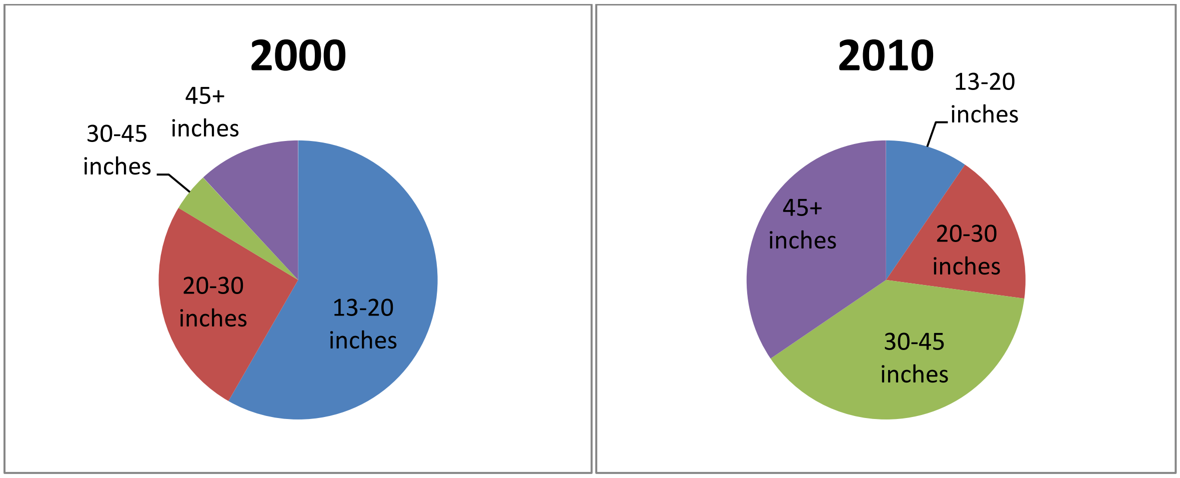

Figure 3. Change in imported television sizes

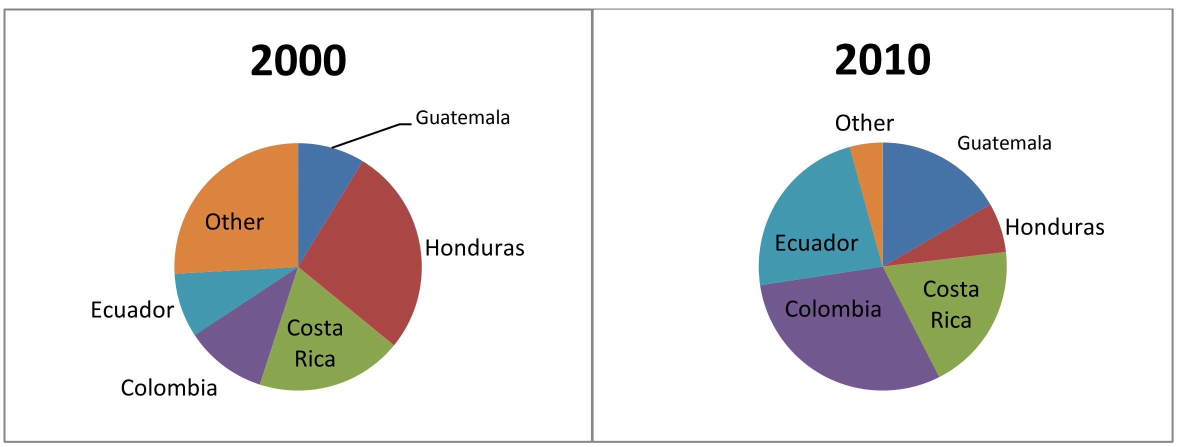

Figure 4. Change in source country for bananas

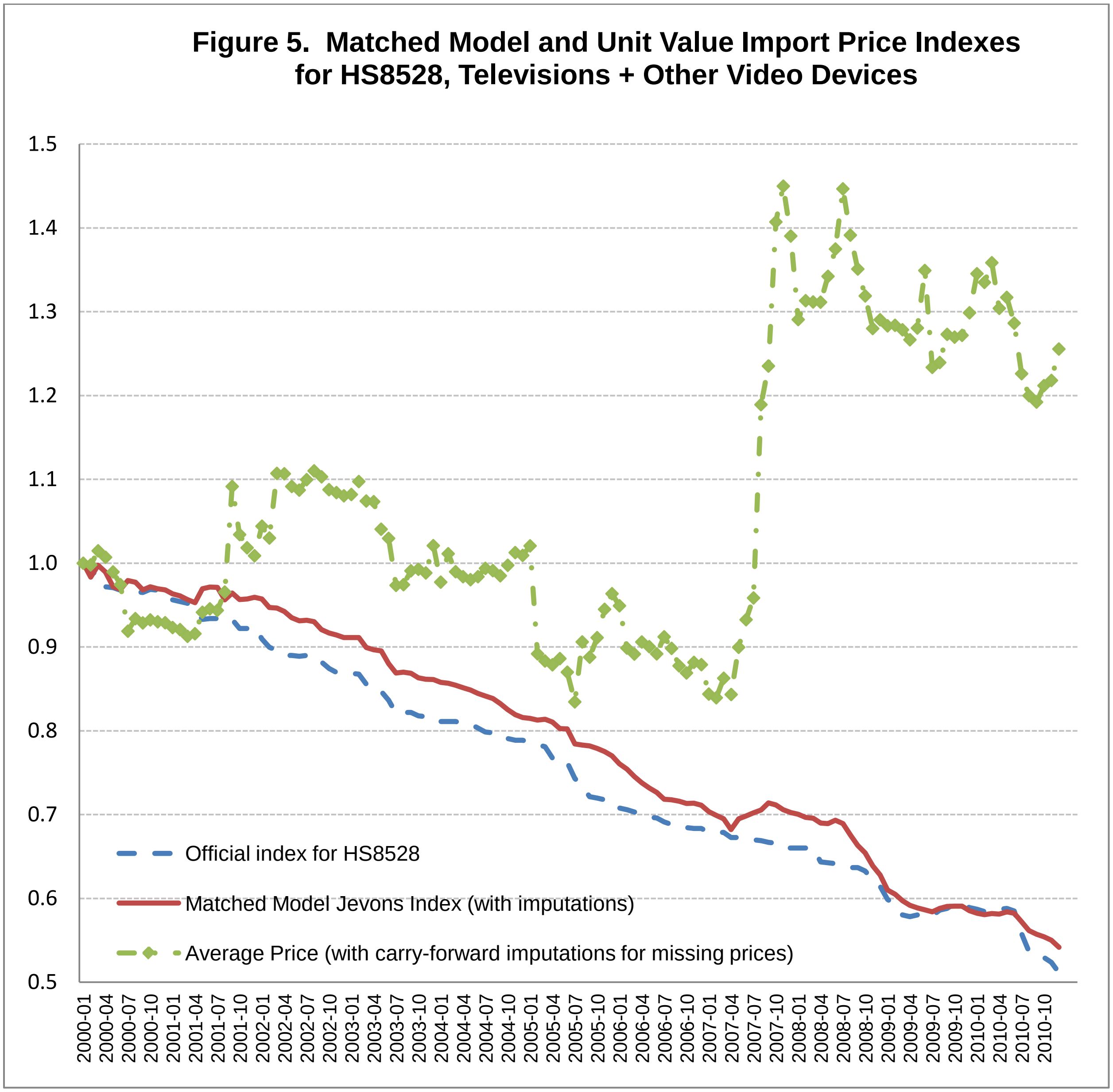
Figure 5. Matched Model and Unit Value Import Price Indexes
for HS8528, Televisions + Other Video Devices
1.5
1.4
1.3
1.2
1.1
1.0
0.9
0.8
0.7
0.6
0.5
Official index for HS8528
Matched Model Jevons Index (with imputations)
Average Price (with carry-forward imputations for missing prices)
2000-01
2000-04
2000-07
2000-10
2001-01
2001-04
2001-07
2001-10
2002-01
2002-04
2002-07
2002-10
2003-01
2003-04
2003-07
2003-10
2004-01
2004-04
2004-07
2004-10
2005-01
2005-04
2005-07
2005-10
2006-01
2006-04
2006-07
2006-10
2007-01
2007-04
2007-07
2007-10
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2008-07
2008-10
2009-01
2009-04
2009-07
2009-10
2010-01
2010-04
2010-07
2010-10

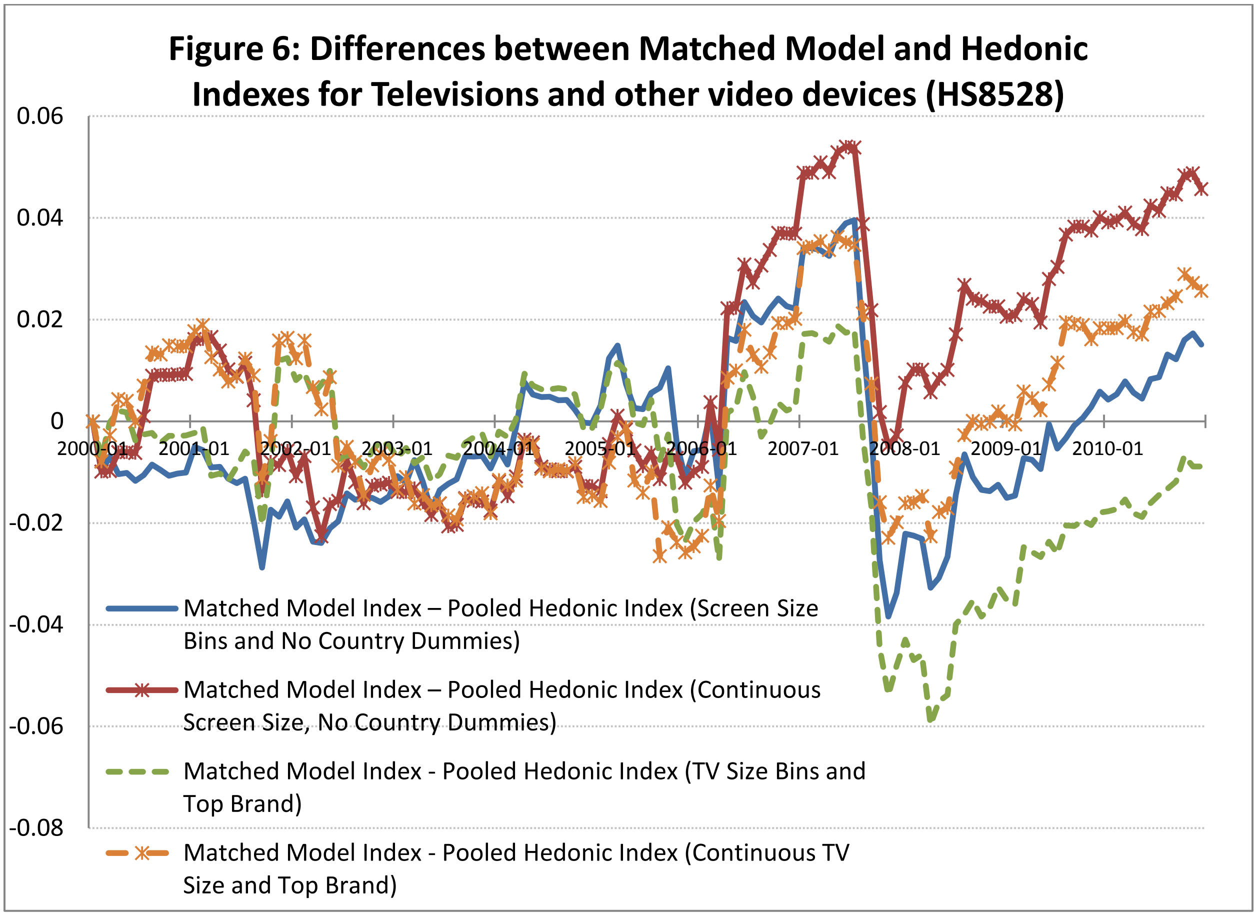
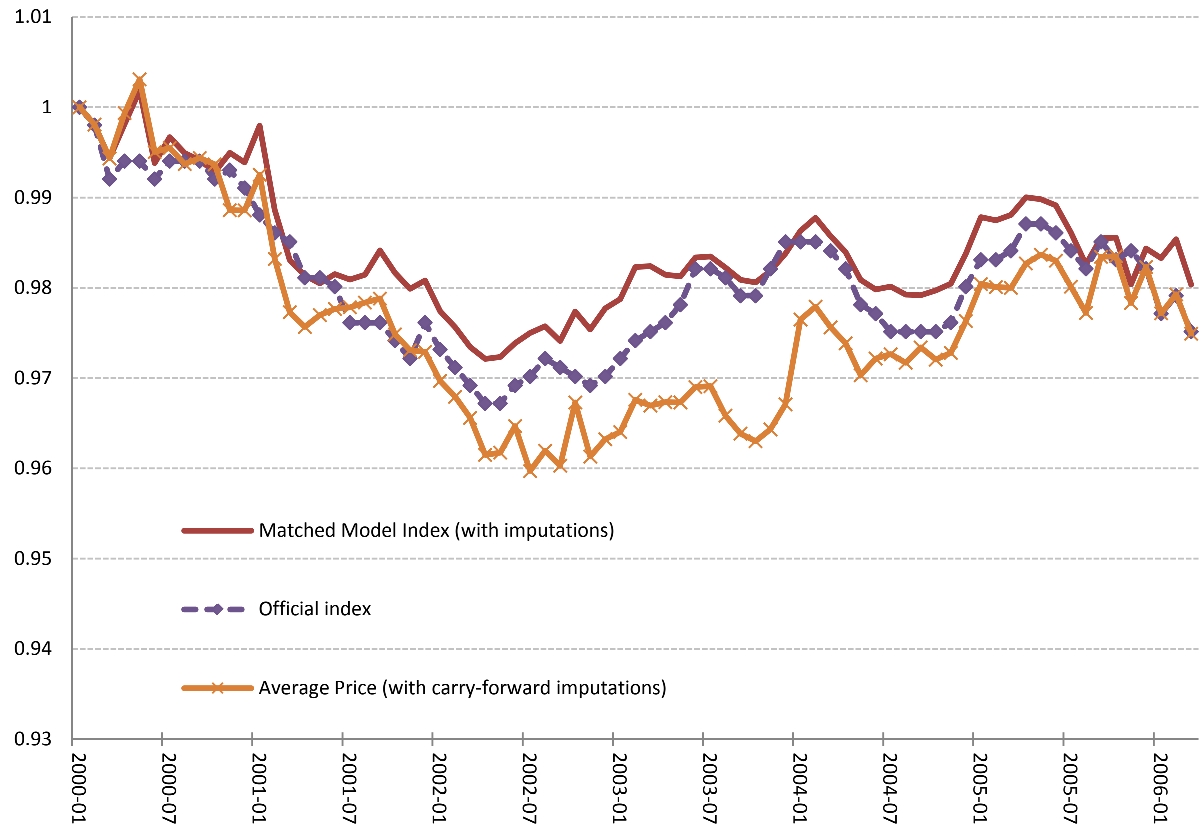


Figure 6: Differences between Matched Model and Hedonic Indexes for Televisions and other video devices (HS8528)
0.06
0.04
0.02
0
-0.02
-0.04
-0.06
-0.08
2000-01
2001-01
2002-01
2003-01
2004-01
2005-01
2006-01
2007-01
2008-01
2009-01
2010-01
Matched Model Index – Pooled Hedonic Index (Screen Size Bins and No Country Dummies)
Matched Model Index – Pooled Hedonic Index (Continuous Screen Size, No Country Dummies)
Matched Model Index - Pooled Hedonic Index (TV Size Bins and Top Brand)
Matched Model Index - Pooled Hedonic Index (Continuous TV Size and Top Brand)

Figure 7: Matched Model and Unit Value Indexes for HS 90:
Cameras + Other Photographic, Measuring and Medical Instruments



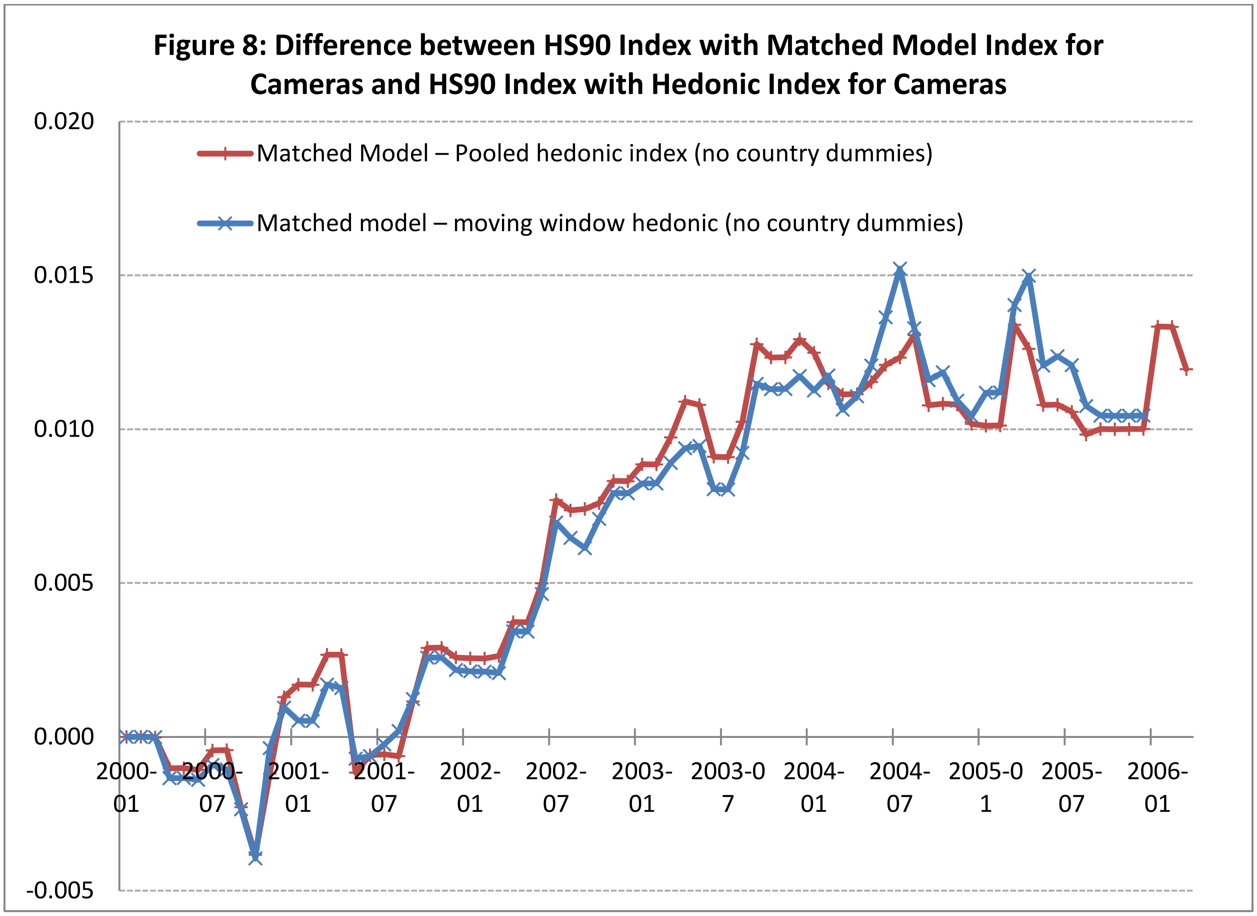


Figure 8: Difference between HS90 Index with Matched Model Index for Cameras and HS90 Index with Hedonic Index for Cameras
Matched Model – Pooled hedonic index (no country dummies)
Matched model – moving window hedonic (no country dummies)
0.020
0.015
0.010
0.005
0.000
-0.005
2000-01
2000-07
2001-01
2001-07
2002-01
2002-07
2003-01
2003-07
2004-01
2004-07
2005-01
2005-07
2006-01

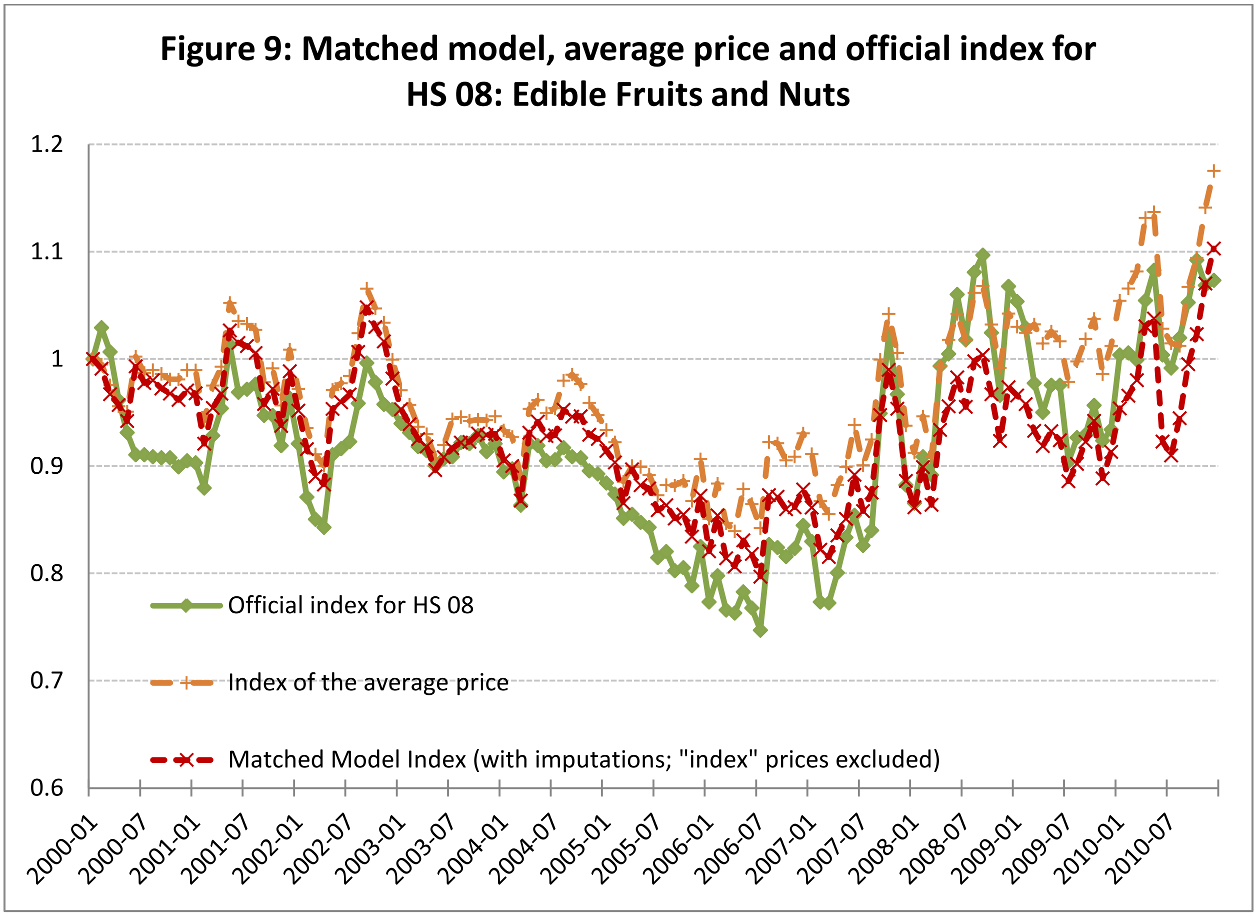
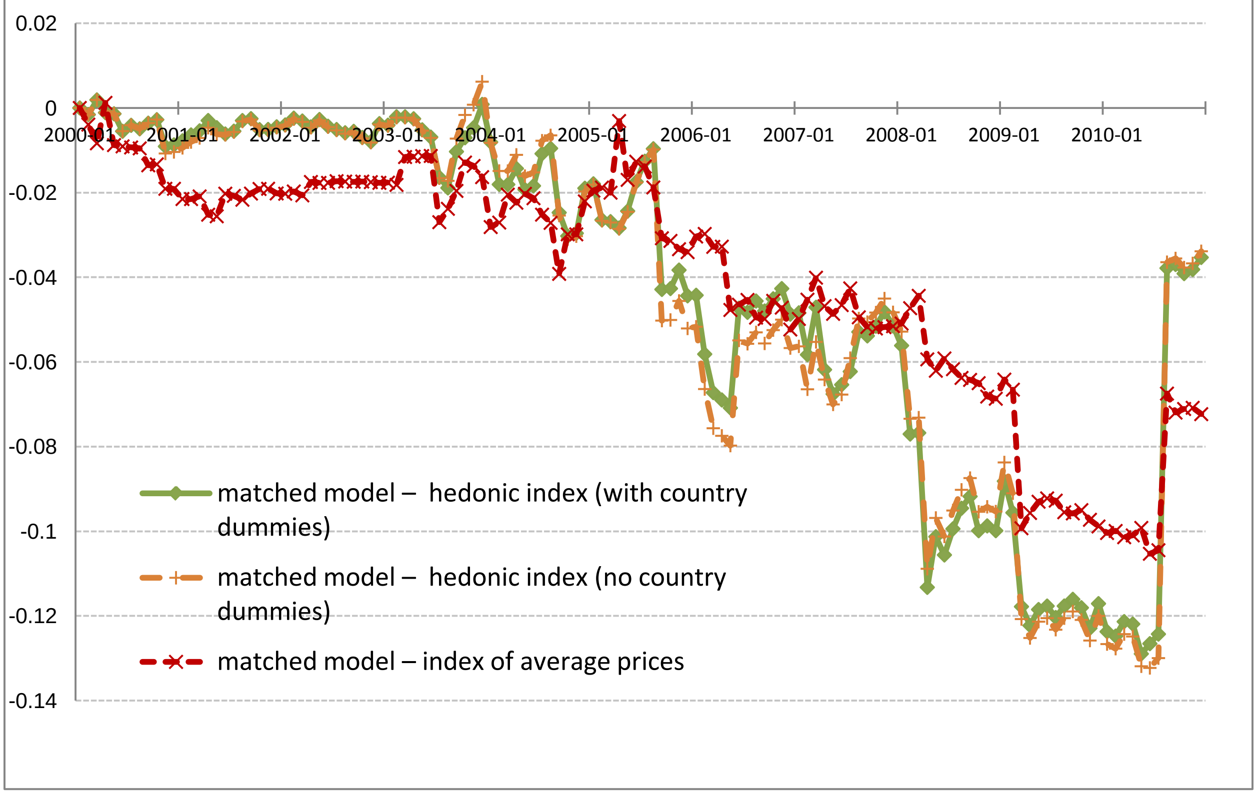


Figure 9: Matched model, average price and official index for
HS 08: Edible Fruits and Nuts
1.2
1.1
1
0.9
0.8
0.7
0.6
Official index for HS 08
Index of the average price
Matched Model Index (with imputations; "index" prices excluded)
2000-01
2000-07
2001-01
2001-07
2002-01
2002-07
2003-01
2003-07
2004-01
2004-07
2005-01
2005-07
2006-01
2006-07
2007-01
2007-07
2008-01
2008-07
2009-01
2009-07
2010-01
2010-07

Figure 10: Difference between Index for HS 08 with Matched Model Index for Bananas and Index for HS 08 with Hedonic Index for Bananas



Appendix

Table A1. Quality Characteristics Used in Hedonic Regressions

Televisions	
Type	Plasma, CRT, LCD, Projection, LED
Size	
Brand	Premium (Sony, Sharp, LG, Samsung, Panasonic) or Other
Intrafirm	
Country of Origin	
Cameras	
Type	Point and Shoot, Polaroid, SLR
Format	Digital, Film
Focus	Autofocus, Fixed Focus, Manual Focus
Brand	Canon, Nikon, or Other
Intrafirm	
Country of Origin	
Bananas	
Type	Cavendish or Other
Grade	Grade 1 or 2
Crate Size	
Intrafirm	
Country of Origin	

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