A Test of Hedonic Price Indexes for Imports

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Sourcing patterns for many types of imported products have changed dramatically over the past two decades as emerging economies have become major producers of the manufactured products consumed in the US. In addition, goods with regular quality improvements due to new or improved technology have also increased their representation in US imports. The US export and import price indexes are constructed using a "matched model" approach that is likely to miss price reductions for imports that occur when sourcing shifts from high cost countries to low cost countries of origin and changes in quality-adjusted prices that occur when new models enter that embody improved technology. Hedonic methods for quality adjustment could help to resolve these problems. This paper demonstrates the feasibility of applying these methods to import price index data by estimating hedonic indexes for two products that have experienced changes in sourcing and technological progress, televisions and consumer cameras. The hedonic indexes imply that significant upward bias in matched model import indexes for these products arose both changes in sourcing and from new technologies.

Why Study Hedonic Indexes for Imports?

An important element of globalization is the growth of export-oriented manufacturing industries in emerging economies, bringing with it expanded opportunities to source imports from new locations where costs are lower. Since the mid-1990s, shifts in sourcing to emerging economies have become more common for a wide range of consumer products and intermediate inputs, including electronic goods, and textiles and apparel. Such shifts in sourcing create measurement challenges for price statisticians because direct price comparisons of the items from the new and previous source countries are usually not possible.

Another element of globalization has been the rapid growth imports by countries like the US of types of products for which technological improvements are an important phenomenon, such as electronic goods. For products with evolving technologies, comparisons of new models to previous model may again be impossible without a way to do a quality adjustment, but omitting new and existing models will cause bias if the new models tend to enter with lower-quality adjusted prices.

Changes in source country and changes in technological characteristics both present a risk of bias for the US import price index (MPI) because the Bureau of Labor Statistics (BLS) International Price Program (IPP) constructs its indexes as matched model indexes. In a matched model index, only continuing items (models that match) are used in the index calculation. Changes in sample composition resulting from item replacements or sample rotations are handled by linking the incoming items into the index. Linking means that any item that is not present in both the initial and the comparison period is excluded from the calculation of the change in the index. Linking therefore prevents the MPI from capturing any cost savings that an importer enjoys by switching suppliers. Any remaining gap that exists between the inflation-adjusted price of the old supplier and the price of the new supplier is, in effect, attributed to quality change. The bias in the MPI from failing to capture price reductions caused by shifts in sourcing resembles the phenomenon of outlet substitution bias in the consumer price index from consumers switching to low priced outlets like Wal-Mart (Reinsdorf, 1993).[1]

A matched model index avoids making possibly specious comparisons of items that may be of differing quality. Rather than omitting price changes that occur during item replacements, as the matched model method does, hedonic price indexes adjust for quality differences in a way that allows these price changes to be taken into account. Hedonic methods therefore offer a potential solution to the biases created by globalization. Indeed, by using other kinds of data as a proxy for US import data, hedonic techniques have already been applied to these or related problems. In particular, Grimm (1998) used proprietary data on worldwide markets for semiconductors to construct hedonically adjusted deflators for exports and imports of semiconductors in the US

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[1] For a recent study with estimates of outlet substitution bias, see Greenlees and McClelland (2011)

national income and product accounts (NIPAs) for the years 1981 to 1997. To our knowledge, however, no one has yet applied hedonic regression techniques to trade data directly.

Literature on Bias in Import Price Indexes

Changes in sample composition can also occur in the import index for reasons other than sourcing changes and technological progress. Recent research finds that an important part of overall price change for exports and imports occurs at times of product entry and exit. Nakamura and Steinsson (2012) analyze a sample of the micro data that the US Bureau of Labor Statistics (BLS) used 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). A high proportion of price changes must therefore 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 significantly flatter than it should be.[2]

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. For these kinds of goods, even a matched model index that is trending downward might have an upward bias because the changes in quality-adjusted prices at times of item replacements are smaller than the average price change of continuing items. Erickson and Pakes (2011) provide evidence that unmeasured price changes associated with item replacements tend to be systematically smaller than the measured price changes when a product is undergoing improvement as a result of technological progress.[3]

The lower prices that import buyers have obtained by sourcing from China and other emerging economies have also been topics of several papers. Thomas, Marquez, and Fahle (2008) inferred

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[2] 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).

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

the size of the price reductions that importers in the US realized by substituting sources to emerging economies on the basis of purchasing power parity data from the Penn World Tables. More recent, Byrne, Kovak, and Michaels (2012) directly looked at prices from traditional sources of semiconductors and from new sources in China and found that the China price was 17 percent lower for an identical semiconductor. Finally, Reinsdorf and Yuskavage (2013, table 1) show that changes in import sourcing to countries like China could plausibly have resulted in an upward bias in the MPIs for consumer durable goods including computers but excluding motor vehicles of up to almost 1 percent per year.[4]

An indirect method for estimating the bias in a matched model import price index from new and disappearing varieties was introduced by Feenstra (1994). In applying the method, varieties are usually distinguished on the basis of source countries. The model underlying this method implies that a variety may be bought in limited quantities just because it is different, but market shares are inversely proportional to quality-adjusted prices, so for a variety to sell well, it must have a low quality-adjusted price. If the post-entry share of the entering varieties is greater than the pre-exit share of the exiting varieties, the estimated bias in the matched model index will be 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, with new countries of origin treated as new varieties. They find an average bias of about 0.6 percent per year, indicating substantial net gains in market share by new supplying countries. This estimate reflects a combination of several factors, including entry of low-priced producers in emerging low cost locations, lower quality-adjusted prices made possible by technological progress, and a general broadening of the available range of varieties as markets thicken.

Finally, Houseman, Kurz, Lengermann and Mandel (2011) and Mandel (2007, 2009) focus on price effects due to the offshoring of production from the US to lower cost locations. Offshoring substantially reduces the price paid by buyers of intermediate inputs, yet this price reduction cannot be captured either in the MPI or in the producer price index. Alterman (2009 and 2013) proposes a buyer's price index for intermediate inputs as a way of capturing the effects of substitution from local to offshore production. Note, however, that if the buyer's price index 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 because the offshored version of the product may not be matched with the previous local version of the product. Hedonic methods are likely to be needed to enable the buyer's price to fully measure the effects of changes in source countries.

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[4] For motor vehicles, the upper bound estimate for the bias from import sourcing changes is a bit smaller, at about 0.7 percent per year, while for apparel it is about one-quarter percent per year.

Hedonic Price Indexes for Imports

Hedonic price indexes do not exclude observations that are only present in one time period from the index calculation. They are based on hedonic regressions that model the effects of items' characteristics on the price.

The history of hedonic price index research extends back for more than 80 years and in the years since the Stigler commission report included Griliches's (1961) chapter applying this method to autos, 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 approaches give numerically similar estimates when rates of entry and exit are low, or when observations are at high frequency and changes in characteristics occur gradually over time

One traditional specification of a hedonic regression model includes dummy variables for time periods along with a set of characteristics variables. If the dependent variable is log price, the coefficient on a time period's dummy variable is the logarithm of its price index. Another common approach uses fitted coefficients from a regression using data from time period s to predict the price that an observation from the other time period, say time period t, would have had had it been present in period s. An analogous regression run for period t is then used to predict the prices of items that only existed in period s. The predicted prices can then be included in the calculation of the index.

Recently, Erickson and Pakes (2011) have developed a modification of this hedonic technique that accounts for the selection bias caused by exiting goods supplanted 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. In principle, the method should work well for handling the data limitations faced by IPP, as it does not require that a large number of characteristics be observed. Unfortunately, a key assumption is not met: Erickson and Pakes assume that for given set of characteristics, the marginal cost is the same across sellers. This assumption does not hold in our data

Despite the high degree of interest in the questions that hedonic methods might help to answer, to our knowledge, this paper is the first to estimate a hedonic import price index using data collected from importers by a statistical agency. Data limitations are probably the main reason for the lack of research on hedonic indexes for import prices. Many countries construct most of their export and import indexes as unit value indexes from customs data values and volumes for detailed classes of items, such as the 10-digit categories of the Harmonized System (which is an internationally agreed upon classification scheme for traded commodities). A unit value in these

indexes will typically cover a range of varieties whose characteristics vary, so no particular set of characteristics can be ascribed to an observation.

The US no longer uses unit values for its export and import indexes except in special cases: the BLS began to produce complete sets of specification-based price indexes for goods imports in 1982 (Alterman, 1991, p. 113). This means that the observations in the US import index sample have well-defined characteristics. Nevertheless, detailed characteristics information can be difficult to collect from the respondents to the IPP surveys, so the import price index data base often lacks full information.

We found that for items that have a make and model number, the problem of missing characteristics information could be largely overcome by performing internet searches on the make and model number of the sampled items. Except for the items that exited before the internet became pervasive, we were generally able to find good product description information using this method from owner's manuals or other product literature.

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 use the description field in the IPP database to assemble data sets on imports of consumer televisions, consumer cameras, and bananas.[5] Bananas are intended 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 is also the basis for the quality variables that we construct for each product type. The variables used in the hedonic models cover the characteristics that are well documented in the description portion of the IPP database, although even for these variables blanks sometimes have to be filled in via internet searches on make and model number. See Appendix Table A1 for the list and description of quality characteristics that we are 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 become 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

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[5] 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.

the official import and export price indexes. Thus, we also use the net prices. Also, for certain commodities, the BLS allows reporters to give "index" prices.[6] 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 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 Prices that are Intra-firm

	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.[7] 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.

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

[7] Almost 12% of the televisions experience these temporary exits, as opposed to about 6% for bananas.

[8] When using the cell-relative method, the missing value is determined by the change in the index value for the non-missing values in a particular class. When using the class-mean method, the missing value is determined by the mean of the non-missing values for a particular class. IPP also sometimes uses linear interpolation to impute prices.

Table 2. Share of Prices that are Imputed

	Televisions	Cameras	Bananas
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 at back of paper), while cameras moved away from Japanese imports to imports from China and Thailand (Figure 2). The growth in television screen sizes over our sample period is also noteworthy (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. Mean Share of Items Experiencing Permanent 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

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[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.

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 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 (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 sets of hedonic price indexes, we calculate two baseline measures of price change. The first of these simply tracks the change in the geometric average price of the sample. The average price index should exhibit similar behavior to a unit value index: like a unit value index, it does not hold the sample composition constant when comparing time periods. (We cannot calculate true unit value indexes because we do not have the necessary data on quantities.) 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 our hedonic price indexes. The matched model indexes of the MPI include item weights in a Laspeyres-like index formula.[11] We do not have the item weight information needed to replicate these Laspeyres matched model indexes, so our matched model indexes are calculated as modified Jevons indexes of the prices of the continuing items in which less detailed weights based on customs data are used.[12] A matched model Laspeyres index is calculated as a share-weighted arithmetic average of price relatives of continuing items, while the logarithm of our weighted, matched model Jevons index is a share-weighted average of logarithms of these same price relatives. We also include weights for observations in all of the indexes that we calculate so that

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[11] The Laspeyres indexes used by BLS are more precisely described as Lowe indexes because their weights are based on values from a previous year that have been updated for price change. From 1997 to 2001 the weights in the MPI came from 1995. After 2001 the weights began to be updated annually and with a lag of two years.
[12] The standard definition of a Jevons index is an unweighted geometric mean of price relatives. Within any given classification group our Jevons indexes are, indeed, unweighted, but weights are applied when we aggregate over the classification groups comprised by a Jevons index. These weights come from the same year used for the official index and reflect trade values in that year.

the overall weight for each source country is proportional to its importance in the trade data for the product in question.

BLS policies on disclosure of non-public data allow us to report only publication-level indexes. We are not unable to report indexes at the level of the individual products comprised by a publication level index, nor can we report coefficient estimates that would allow someone to reproduce one of these unpublished indexes. Therefore, besides calculating matched model indexes for the three products of interest, we calculate matched model Jevons indexes for the other products contained in the published index and then aggregate up to the level of the published index. For example, for bananas, we simulate the relevant published index for Edible Fruit and Nuts ((Harmonized System Code 08, or HS 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.

Despite these limitations, we can 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 simplest 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:

$$p_{it} = \alpha_t + X_{it}\beta + \varepsilon_{it} \tag{1}$$

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 α_{t-1}.

As a more flexible alternative to the pooled hedonic regression, we also estimate a set of overlapping hedonic regressions that use a moving window of just 24 months for their sample. The time periods covered by these regressions have 12 month overlaps so that a cumulative price index from the beginning of the overall sample can be constructed via a sequence of transitive comparisons. Ideally, we would have run these regressions on monthly data, but, in practice, to get around sample size problems we had to pool the observations for each quarter. The moving

window approach has the advantage of allowing the coefficients on characteristics to change over time if evolving technologies and market conditions alter the hedonic relationships.[13]

We fit these models both including and excluding country dummies from the set of variables in X_{it} in equation (1). 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.

Rather than leaving the country dummies out of the hedonic regression, a hedonic index that includes price changes due to changes in source country can instead be calculated by adding back the part of the hedonic index's quality adjustment coming from changes in source countries. Using the pooled hedonic index as an example, let $\hat{\alpha}_t$ be the fitted coefficient on the time dummy for period t (with the time dummy omitted in the base period), $\Delta\overline{p}$ be the change in the average log price, and ΔX be the change in the average characteristics including the country dummies. The log hedonic index with country dummies included equals the raw price change minus a quality adjustment equal to the predicted effect of the average characteristics change:

$$\hat{\alpha}_t = \Delta\overline{p} - (\Delta X)\hat{\beta}. \tag{2}$$

Now break X into a physical attributes part and a country mix part:

$$\hat{\alpha}_t = \Delta\overline{p} - (\Delta X_{PA})\hat{\beta}_{PA} - (\Delta X_{CM})\hat{\beta}_{CM}. \tag{3}$$

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

$$\tilde{\alpha}_t = \hat{\alpha}_t + (\Delta X_{CM})\hat{\beta}_{CM}. \tag{4}$$

Empirical Results

HS 8528 and Televisions

The first set of hedonic indexes that we estimate are for imported televisions. BLS disclosure policies prevent us from showing research indexes that would correspond to an unpublished level

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[13] In future research we plan to test the method of full hedonic imputation. This method uses the estimated coefficients from the comparison period regression to predict prices of items that were present in the base period, and the estimated coefficients from the base period to predict prices of items present in the comparison period.

of detail, so we show indexes at the lowest published level that includes televisions, HS code 8528. HS 8528 covers televisions and other video devices.[14]

Comparisons of the official index with our hedonic indexes would be affected by more than just the differences in compilation methods that we want to investigate, so we construct a matched model import index of our own for use in these comparisons. The key feature of the official import index is its use of the matched model index. Our matched model index replicates that feature, but it differs in the choice of aggregation formula. Whereas the official index has a modified Laspeyres formula, we use a Jevons (geometric means) index formula to combine the matched model indexes for televisions with that for other video devices. Also, whereas the usual Jevons index is as an *unweighted* geometric mean of price relatives, our Jevons indexes include country weights that reflect the relative importance of different source countries in the trade data. Note, however, that our weights do not precisely match the weights used for the official index.

Our matched model Jevons index with country weights closely tracks the official matched model index for HS 8528 most of the time (Figure 5). It also has a similar long run trend. Over the whole period of January 2000 to December 2010, our matched model index falls at an average rate of 5.7 percent per year, close to the official index's 6 percent per year rate of decline. On a few occasions the indexes diverge, however. In May of 2001, August-September of 2005, and April of 2008, our index has a higher rate of change than the official index, while in August-September of 2008 and April-May of 2009 our index measures lower inflation.

Televisions and video devices experienced rapid increases in quality over the period covered by the sample, including the displacement of CRT screens by superior flat screen technologies (plasma, LCD, and, finally, LED) and an increase in the average screen size. These quality improvements substantially affected the average price of a television. The difference between the growth rate of the average price and the growth rate of the matched model index reflects the value of the quality improvements. In contrast to the rapidly falling matched model indexes, the weighted average price *rises* at an average rate of 5.6 percent per year. Assuming, for the sake of argument, that the matched model Jevons index correctly measures the pure price change, we can infer that quality improvements added more than 11 percent per year to the annual growth rate of the average price of televisions and other video devices over the period that we study.

Next, we check the accuracy of the matched model index by comparing it to hedonic indexes. To estimate the effects of the entry of new source countries whose prices may be lower, one

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[14] 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.

alternative is to include physical characteristics of televisions, but not source countries, in the hedonic model. Including dummy variables for country of origin in the hedonic regression would cause the hedonic index to include country effects in its quality adjustments.

A weakness of this approach is, however, that it is vulnerable to omitted variable bias. If characteristics and countries are correlated, some of the effects of the omitted country variables could be reflected in the coefficients on the physical characteristics. This may then cause effects of changes in country mix to be embedded in the coefficients on the physical characteristics.

Including country dummies in the hedonic regression makes the coefficients on the physical characteristics less likely to include effects of changes in source countries that are correlated with changes in physical characteristics. The coefficients on the country dummies can be used to adjust the hedonic index so that it includes the price effects of changes in country mix, as shown in equation (4). (Note, however, that a problem of collinearity between countries and characteristics may not be completely solved by this technique because if the sample size is not large enough such collinearity would likely lead to high variances for the coefficient estimates.) The difference between the adjusted hedonic index and the matched model index will then include the price effects of changing source countries that are missed by the matched model index. If the adjustment is not made, the difference between the raw hedonic index that includes country dummies and the matched model index will estimate the amount of quality change from improvements in physical attributes due to technological advances that is missed by the matched model index.

Of the two types of hedonic indexes that we estimate for televisions, the moving window hedonic index is probably more reliable than the pooled hedonic index. In the pooled hedonic regression, a single set of coefficients on the quality characteristics and country dummies (if included) is estimated for the entire time interval covered by the sample, so a characteristic's effect on the logarithm of a TV price is constrained to be constant over a long interval. On the other hand, the moving window approach allows the slope coefficients to evolve over time by estimating separate sets of hedonic coefficients for overlapping pairs of years. Over longer time intervals, technological progress is likely to significantly alter the shadow value of at least some television characteristics, and changes in prices and income could change the demand for characteristics in ways that affect their shadow values. Suppose, for example, that the price differential for large screens declines over the course of the period covered by the sample, and that near the end of the sample period imports from China start to grow rapidly with a specialization in smaller screen sizes. The pooled hedonic regression would then tend to underestimate relative quality of the Chinese televisions in the period when they are growing and hence tend to overestimate the quality-adjusted price level of televisions from China.

Another advantage of the moving window regression approach is that one can see what the bias estimate would have been if the analysis had stopped earlier than December 2010. Differences

between the matched model index for HS 8528 and indexes for HS 8528 that incorporate moving window hedonic price indexes for televisions are shown in figure 6. The growth rate gap between the matched model index and the adjusted moving window hedonic index is not uniform over time; some earlier stopping points would have implied larger estimates of the bias in the matched model index. Adjusting the hedonic index for the changes in source countries lowers its growth rate by 0.016 log points and brings the estimate of the bias in December 2010 of the matched model index up to 0.042 log points. The unadjusted moving window hedonic index for HS 8528 is about 0.026 log points lower than the matched model index in December of 2010, suggesting that incomplete measurement of the gains from improved technology adds about 0.026 to the matched model index.

Omitting the country dummies implies a slightly smaller estimate of the bias in the matched model index of 0.032 log points in December 2010. This implies that the bias in the matched model index due to failure to capture price declines from changing source countries is only about 0.006 log points in December 2010. The difference between the hedonic index that includes country dummies and the hedonic index from regression with the no country dummies may underestimate the country mix effect because of omitted variable bias. The differences between the weighted matched model index and the various hedonic indexes stated in terms of differences in average annual growth rates are shown in table 4.

Table 4: Amounts by which Match Model Index Growth Rate exceeds Moving Window Hedonic Growth Rates for HS 8528
(Percent per year, 2000-2010)

Country dummies included	0.44
No country dummies	0.53
Adjusted for changing country mix	0.72

We also estimate pooled hedonic indexes as a kind of robustness check on the moving window hedonic results. Figure 7 shows the differences between the pure matched model index for HS 8528 and the indexes that incorporate pooled hedonic price indexes for televisions. Like the moving window hedonic indexes, the pooled hedonic indexes all imply positive estimates for the ending bias in the matched model index. Indeed, the pooled version of the unadjusted hedonic index that includes country dummies implies the same estimate of bias from underestimation of gains from improvements in technology as the moving window version, 0.026 log points.

On the other hand, the pooled specification produces a lower hedonic index than the moving window specification in the case when country dummies are omitted from the model, and a slightly higher hedonic index in the case when country dummies are included and an adjustment is made for the effects of changing country mix. Under the pooled specification, the no-country-dummies index is 0.064 log points below the matched model index in December 2010, while the adjusted hedonic index is just 0.034 log points lower than the matched model index. The pooled hedonic index that includes country dummies is 0.026 log points below the matched model index. If that is the bias in the matched model index due to technological progress, with the pooled specification, the adjusted hedonic index implies a bias in the matched model index from changing sourcing of 0.008 log points, while the no-country-dummies hedonic index implies that this bias is 0.038 log points. These differences in average annual growth rates that correspond to these log point differences are shown in table 5.

Table 5: Amounts by which Match Model Index Growth Rate exceeds Pooled Hedonic Growth Rates for HS 8528
(Percent per year, 2000-2010)

Country dummies included	0.44
No country dummies	0.53
Adjusted for changing country mix	0.72

Televisions Component of HS 8528

Even though we cannot show the television component of HS 8528 as a separate index, we can calculate how sensitive the television index is to the choice of method. To find the difference between a matched model index and a hedonic index for televisions, we divide the difference between the logarithmic matched model and hedonic indexes for HS 8528 by the weight of the television component of HS 8528, which is 0.343. The implied difference for televisions in the final period can then be converted into an average annual growth rate over the 11 years covered by the sample.

The growth rate of the matched model index for televisions is 2.2 percent per year above that of the adjusted moving window hedonic index (table 6). Subtracting the 1.3 percentage points

coming from unmeasured technological improvements (measured by the unadjusted hedonic index) leaves 0.9 percentage points of the bias in the matched model index growth rate to be attributed to changing source countries.

To gauge the robustness of the results to the estimation method, we show in table 6 the estimates of the bias in the matched model index that would be implied by taking a hedonic index with no country dummies or a pooled hedonic index to be the true measure of price change. Subtracting the number in the last column from numbers in the middle two columns shows that the various alternatives imply bias estimates ranging from 0.5 to 2.1 percent per year for the effect of changing source countries.

Table 6: Estimates of Bias in Matched Model Index for Televisions implied by Different Specifications of the Weighted Hedonic Regression

Type of Hedonic Regression	From hedonic regression with no country dummies	From using country's coefficients to adjust for change in country mix	From hedonic regression with country dummies (under measurement of technology-related quality change)
Moving window	1.6 percent/year	2.2 percent/year	1.3 percent/year
All years pooled	3.4 percent/year	1.8 percent/year	1.3 percent/year

HS 90 and Cameras

Besides televisions, we also investigate differences between hedonic and matched model indexes for cameras. Cameras are a component of the published import index for HS 90, "Optical, photographic, measuring and medical instruments", so we show indexes for HS 90 that incorporate matched model and hedonic indexes for cameras. Even though fewer than 4 percent of the observations classified in HS 90 are for cameras during the period we examine (January 2000-March 2006), the HS 90 index is sufficiently sensitive to the choice of method for its cameras component to produce interesting results.

The baseline for the comparisons with hedonic indexes is again a matched model index meant to simulate the official methodology. Most of the time our weighted matched model Jevons index has virtually the same rate of change as the official index for HS 90 and it exhibits similar turning points (figure 8). However there are two episodes when our matched model index is flat

or slowly rising at the same time that the official indexes are falling. The first episode occurs in June-September of 2001, and the second occurs in January-March of 2006.

An index of the weighted average price is also shown in figure 8. A notable decline in the average price relative to the matched model index occurs between June 2001 and April 2002. The growing gap between the matched model and the average price indexes implies that the average quality of imported cameras was declining over that time interval. An alternative explanation could, of course, be that the matched model index is upward biased. Part of the relative decline in average price comes from the emergence of inexpensive digital cameras as a popular camera type and another part of the decline seems to be due to changes in source countries. Such collinearity between physical changes in characteristics and changes in source countries tends to reduce the precision with which independent slope coefficients for these two kinds of effects can be identified in a hedonic regression.

The moving window hedonic index with country dummies assumes that price differentials between countries reflect quality differences. According to this index, the matched model index has a cumulative bias of zero up to January, 2004 (figure 9). In other words, the adjustments for declining quality that are implicit in the matched model procedure are deemed to be correct, on average, up to 2004. Over the subsequent two years, however, changes in physical characteristics embodied in new camera models do appear to cause declines in quality-adjusted prices that are missed by the matched model index.

Adjusting the moving window hedonic index so it includes effects of country sourcing changes gives a different picture. In fact, this adjusted hedonic index behaves much like the index of the average price up to 2004. Figure 8 shows that in early 2002, the average price index dropped precipitously relative to the matched model index so the matched model index considerably overstates price change in early 2002 according to the adjusted moving window hedonic index. Thereafter, the cumulative bias in the matched model index implied by the adjusted hedonic index rises slowly but consistently until the end of the sample period.

The implication that physical changes in cameras between 2000 and 2004 did not affect their average quality level seems questionable. The low slopes coefficients on physical characteristics in the model with country dummies could reflect the imprecision caused by collinearity and small sample sizes. In fact, the hedonic index with no country dummies implies that roughly half of the large decline in the average price index relative to the matched model index is caused by falling quality due to changes in physical characteristics. This quality adjustment results in a smaller estimate of the total bias in the matched model index than is produced by the adjusted hedonic index.

The pooled approach to fitting the hedonic regression may also help with the problem of collinearity and small sample size. The magnitude of the adjustment for country mix is

significantly smaller using the pooled regression model, and the behavior of all three hedonic indexes is plausible (figure 10).

The growth rate differences between the matched model index and the various moving window approach and the pooled hedonic indexes are summarized in table 7. The two approaches agree on the total size of the bias in the matched model indexes, but the moving window hedonic implies that a larger portion of this bias comes from changing source countries.

Table 7: Differences in Average Growth Rate between Matched Model Index and Hedonic Indexes for HS 90

	Moving Window Hedonic	Pooled Hedonic
Country dummies included	0.21	0.31
No country dummies	0.29	0.33
Adjusted for changing country mix	0.36	0.36

Cameras Component of HS 90

The weight of cameras within the HS 90 aggregate is about one-thirtieth, so we infer the effects of hedonic adjustment on the cameras index by scaling up the effects on the logarithmic HS90 index by a factor of 30.   Table 8 shows the implied differences in average annual growth rates. The first two rows are based on the last date available for each individual time series, while third the row of table 8 uses the ending date for the pooled hedonic indexes that is used for the moving window hedonic indexes. (The pooled hedonic indexes in figure 10 end three months later than the moving window hedonic indexes in figure 9.) If the same ending date is used, the moving window and pooled approaches imply similar estimates of the total bias in the matched model index of about 11.5 percent per year. On the other hand, if a longer period is used for the pooled hedonic regression, the pooled indexes are all 0.9 percentage points below the comparable moving window hedonic index.

According to the moving window indexes, the bias in the matched model index caused by declines in quality-adjusted prices associated with new technology amounts to 6.7 percent per year, while based on the pooled hedonic indexes, this bias amounts to just 5.8 percent per year. The latter figure is consistent with prior literature: moving window estimates from an earlier study by Manninen (2005) also imply a bias of 5.8 percent per year in a matched model index for digital cameras from Q4 of 1999 to Q4 of 2002. (Manninen used consumer prices, so the matched model index in that study may have captured the price declines caused by changing source countries.)

The adjustment for the price effect of changing country mix is 4.7 percent per year both for the moving window hedonic regressions and for the full sample pooled hedonic regression. On the other hand, using the shorter time period, the pooled hedonic regression attributes just 2.3 percent per year of the total bias to changes in source country. The hedonic regressions with no country dummies (using either the moving window or the full sample for the pooled index) also imply a bias of 2.3 percent per year from changes in source country.

The sample period for the camera indexes is only about six years long and the variances of the moving window coefficient estimates tend to be high because of problems of small sample size and collinearity between changes in physical characteristics and changes in source country. Imposing additional restrictions can be a way of reducing the variances of regression coefficient estimates, and holding the coefficients constant over our relatively short panel data set on cameras does not seem highly restrictive. Thus, in this case, the pooled approach may produce more reliable estimates of the hedonic model than the more flexible moving window approach.

Table 8: Estimates of Bias in Matched Model Index for Cameras implied by Different Specifications of the Weighted Hedonic Regression

Type of Hedonic Regression	Estimate from hedonic regression with no country dummies	Estimate from adjusting for change in countries using country coefficients	Estimated unmeasured technology-related quality change from hedonic regression with country dummies
Moving window	9.0 percent/year	11.4 percent/year	6.7 percent/year
All years pooled	8.1 percent/year	10.5 percent/year	5.8 percent/year
All years pooled, same ending month as for moving window	10.1 percent/year	11.6 percent/year	9.3 percent/year

Bananas

As a check on whether our hedonic indexes for televisions and cameras could be producing spurious measures of the effects of evolving technology, we calculate the same sort of hedonic indexes for bananas. We would not expect to find evidence of unmeasured gains from technological progress for this product, nor is there a reason to expect that large cost savings have been realized by changing source countries for this product. However, as noted above, bananas have had changes in source country, so price effects from changes in source country may not equal 0.

Bananas have a weight of about one-fifth in the publication level import index for HS 08, edible fruits and nuts. After excluding "index prices" (which are reference prices report by respondents who prefer not to provide an actual transaction price), our matched model index for HS 08, edible fruits and nuts, usually tracks the shorter term movements of the official index for HS 08, and over the longer run it shows very similar growth to official index (figure 11). Its average growth rate over the whole sample period is 0.73 percent, compared with 0.65 percent per year for the official index. The average price index, on the other hand, has a long run growth rate of 1.18 percent per year.

The hedonic indexes for bananas behave very differently from those televisions and cameras. In contrast to the estimates of upward bias in matched model import indexes for televisions and cameras, they imply that some price increases are missed by the matched model index (figure 12). Thus, in this case there is no evidence of unmeasured price declines from factors such as technological progress. However, this difference in the sign of the matched model index's bias is consistent the hypothesis that matched model indexes tend to be too flat, missing increases when prices are generally rising and decreases when prices are generally falling. The indexes for televisions and cameras have a downward trend, while banana prices have an upward trend. Furthermore, comparing the unadjusted hedonic index that includes country dummies to either the index with no country dummies on the index that was adjusted to treat price differential between countries as true price differences rather than quality differences shows that sourcing for bananas had a slight tendency to migrate to more expensive countries. The unadjusted hedonic index that includes country dummies grows on average at 1.28 percent per year, whereas the adjusted index grows at 1.19 percent per year. In contrast, for televisions and cameras, sourcing had a strong tendency to migrate to less expensive countries.

Conclusion

The import and export price indexes are constructed as matched model indexes. If new entrants have lower quality-adjusted prices than incumbents and incumbents either exit or fail to adjust their prices to match those of the incumbent the matched model index will be upward biased, other things being equal. Thus, when technological progress leads to frequent entry of new models with lower quality-adjusted prices, matched model indexes can easily suffer upward bias. Furthermore, the movement of production to lower cost foreign locations can also lead to price reductions that would not be measured by a matched model import index, because sourcing an item from a new country usually results in its being treated as a new item. Hedonic index methods are a possible way to address these concerns, but they have not been viewed as feasible for import price indexes because of the data set used for these indexes has limited information on product characteristics, and, in some cases, samples that are rather small for purposes of estimating a hedonic regression model.

One goal of this paper is to disprove the view that hedonic indexes are not feasible for imports. Our results show that hedonic methods indeed are a realistic alternative for at least some of the imported produces that have experienced technological progress and changes in sourcing. Our results also provide evidence on the existence and size of the biases in a matched model type import index for two of these products, televisions and cameras. They support the hypothesis that technological progress and changes in source countries have led to reductions in quality-adjusted prices that are incompletely reflected in the matched model import price index. In the case of televisions, our preferred adjusted moving window hedonic regression implies a bias in the matched model index of 2.2 percent per year, of which 1.3 percentage points comes from under measured gains from new technology, and 0.9 percentage points comes from unmeasured price savings from country substitution. For cameras, our preferred pooled hedonic regression specification implies a total bias in the matched model index of 10.3 percent per year, of which 5.8 percentage points come from under measured gains from new technology and 4.7 percentage points come from country substitution.

References

Aizcorbe, Ana, Carol Corrado, and Mark Doms. 2003. "When Do Matched-Model and Hedonic Techniques Yield Similar Price Measures?" Federal Reserve Bank of San Francisco Working Paper 2003-14.

Alterman, William. 1991. "Price Trends in U.S. Trade: New Data, New Insights." In *International Economic Transactions: Issues in Measurement and Empirical Research*. Studies in Income and Wealth Vol. 55, Hooper, Peter and Richardson, David, eds., pp. 109-143. Chicago: Univ. of Chicago Press.

Alterman, William. 2013. "Producing An Input Price Index." Working paper. Presented at the Upjohn Institute conference on Measuring the Effects of Globalization. Accessed at: http://www.upjohn.org/MEG/papers/Alterman_input_price_index.pdf .

Byrne, David. Brian K. Kovak and Ryan Michaels. 2012. Price and Quality Dispersion in an Offshoring Market: Evidence from Semiconductor Production Services. December. Accessed at: www.andrew.cmu.edu/user/bkovak/BKM_semicon.pdf .

Erickson, Tim and Arial Pakes. 2011. "An Experimental Component Index for the CPI: From Annual Computer Data to Monthly Data on Other Goods." *American Economic Review* 101 (August): 1707–1738.

Feenstra, Robert C. 1994. "New Product Varieties and the Measurement of International Prices." *American Economic Review* 84 (1): 157–77.

Feenstra, Robert C., Benjamin R. Mandel, Marshall B. Reinsdorf, and Matthew J. Slaughter, "Effects of Terms of Trade Gains and Tariff Changes on the Measurement of US Productivity Growth", *American Economic Journal: Economic Policy 2013, 5(1): 59–93.*

Gagnon, Etienne, Benjamin R. Mandel, and Robert J. Vigfusson. 2012. "Missing Import Price Changes and Low Exchange Rate Pass-Through." Board of Governors of the Federal Reserve System International Finance Discussion Papers Number 1040.

Greenlees, John and Robert McClelland. 2011. "New Evidence on Outlet Substitution Effects in Consumer Price Index Data." *Review of Ecomomics and Statistics.*

Grimm, Bruce. "Price Indexes for Selected Semiconductors, 1974–96." *Survey of Current Business* 78 (February): 8-24.

Houseman, Susan, Christopher Kurz, Paul Lengermann, and Benjamin Mandel, 2011. "Offshoring Bias in U.S. Manufacturing, *Journal of Economic Perspectives*, 25 (2): 61-80.

Irving B. Kravis and Robert E. Lipsey, 1971. *Price Competitiveness in World Trade.* New York: Columbia University Press for the NBER.

Linz, Stefan, Timm Behrmann and Ulf Becker, 2004. Hedonic Price Measurements for IT Products Federal Statistical Office of Germany, Wiesbaden.

Mandel, Michael. 2007. "The Real Costs of Offshoring." *Business Week*, June 18. http://www.businessweek.com/magazine/content/07_25/b4039001.htm

Mandel, Michael. 2009. "Growth: Why the Stats Are Misleading." *Business Week*, June 3. http://www.businessweek.com/magazine/content/09_24/b4135000594984.htm

Manninen, Kari. 2005. "The Effects of the Quality Adjustment Method on Price Indices for Digital Cameras", BEA Working Paper WP2005-01.

Nakamura, Emi and Jon Steinsson. 2012. "Lost in Transit: Product Replacement Bias and Pricing to Market". *American Economic Review* 102 (December): 3277–3316.

Neiman, Brent, 2010. "Stickiness, synchronization, and passthrough in intrafirm trade prices," *Journal of Monetary Economics* 57(April): 295-308.

Reinsdorf, Marshall. 1993. "The Effect of Outlet Price Differentials in the U.S. Consumer Price Index." In *Price Measurements and Their Use*, Murray F. Foss, Marylin E. Manser, and Allan H.Young, eds., 227–254. Chicago: University of Chicago Press.

Reinsdorf ,Marshall and Robert Yuskavage. 2013. "Unmeasured Declines in Import Prices for Final Consumption Goods." Manuscript, US Bureau of Economic Analysis.

Thomas, Charles P., Jaime Marquez, and Sean Fahle. 2008. "Measuring U.S. International Relative Prices: A WARP View of the World." International Finance Discussion Papers No. 917.
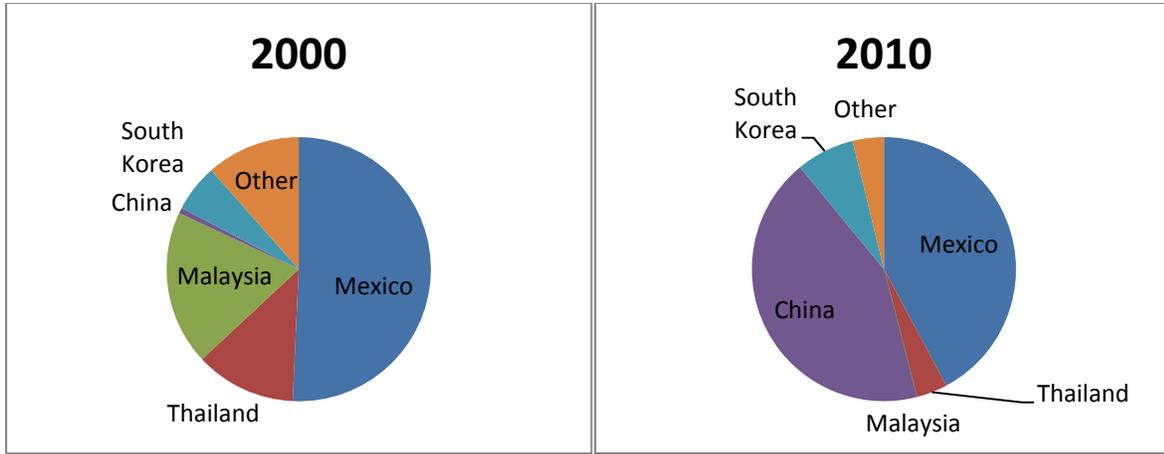
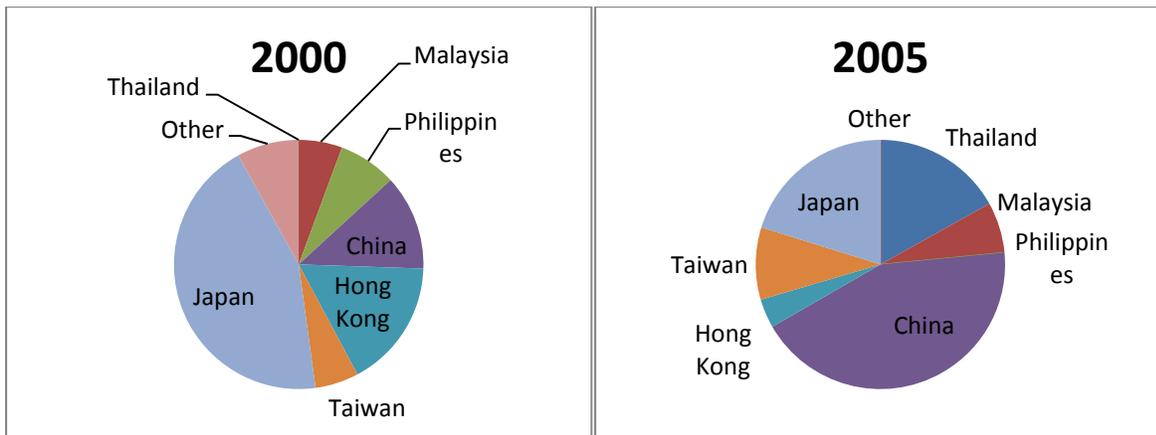**Figure 1. Change in the source country for television imports**

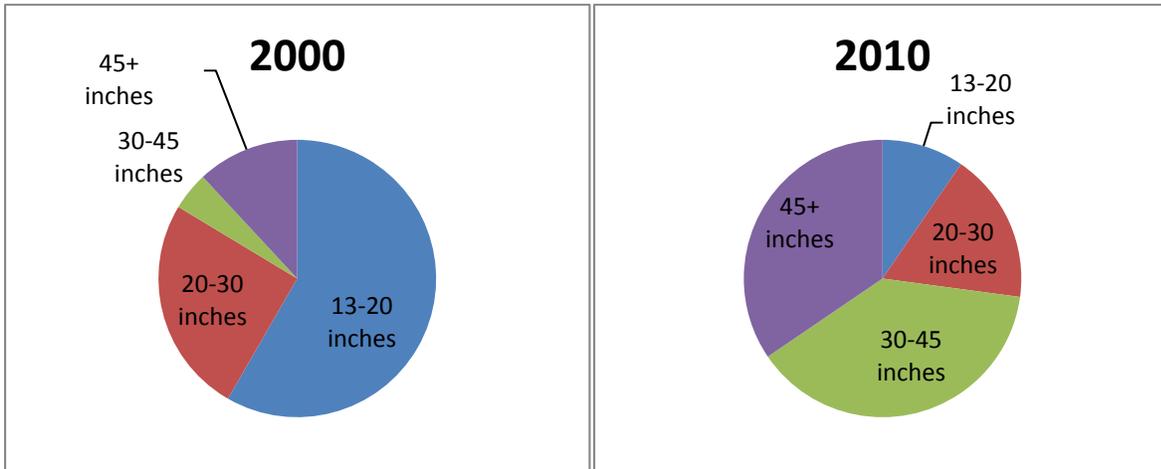**Figure 2. Change in the source country for camera imports**
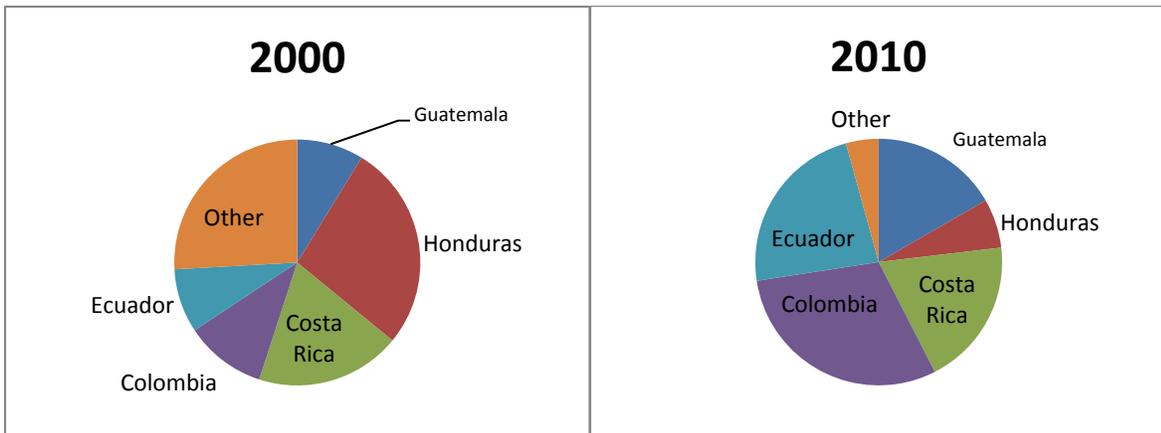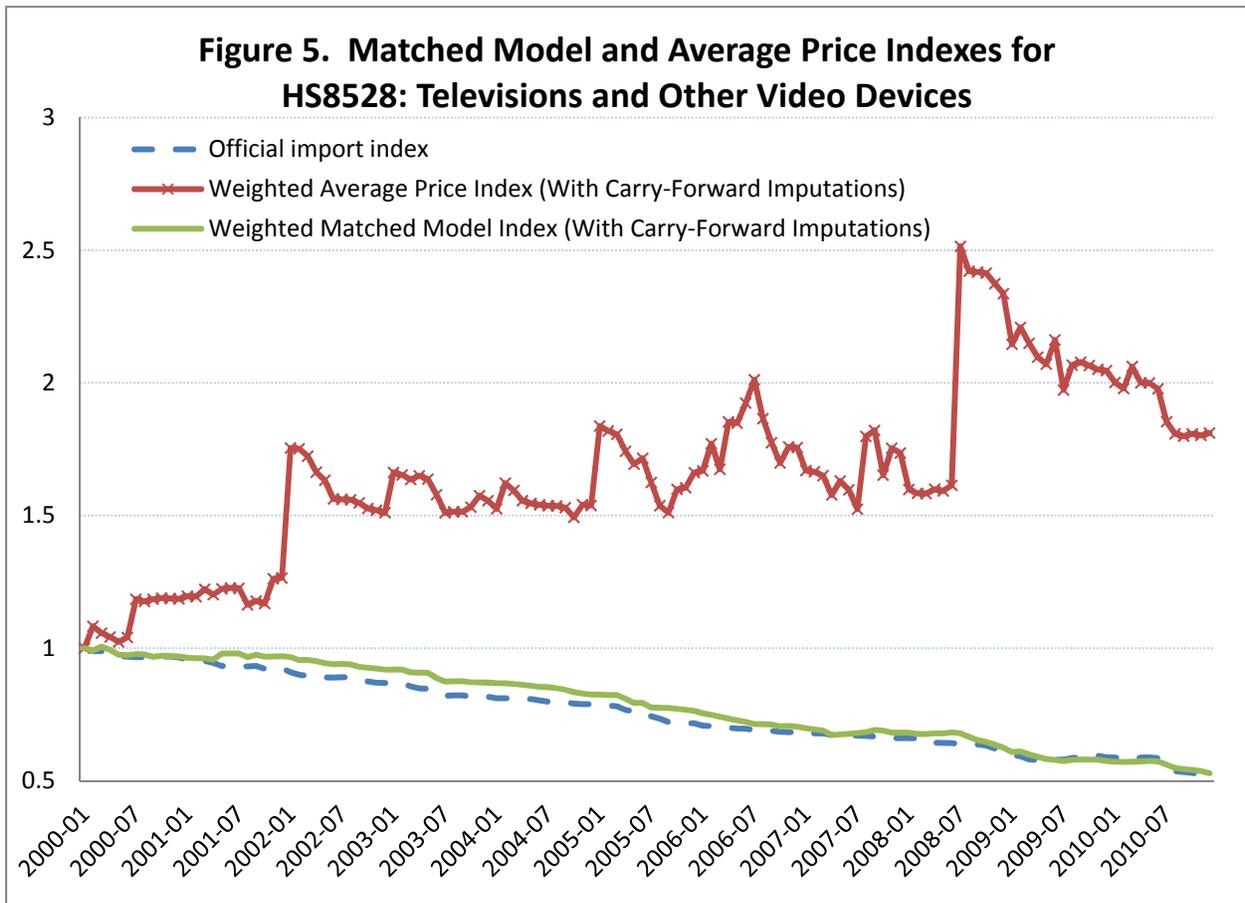
Figure 3. Change in imported television sizes

**Figure 4. Change in source country for bananas**

Figure 5. Matched Model and Average Price Indexes for HS8528: Televisions and Other Video Devices

Figure 6. Differences between Matched Model and Overlapping Hedonic Indexes for HS8528

- – – Matched Model Index – Two-year Overlapping Hedonic Index
- ––□–– Matched Model Index – Two-year Overlapping Hedonic Index, No Country Dummies
- ––– Matched Model Index – Two-year Overlapping Hedonic Index, Adjusted for Changing Country Mix

Figure 7. Differences between Matched Model and Hedonic Indexes for HS8528: Televisions and Other Video Devices
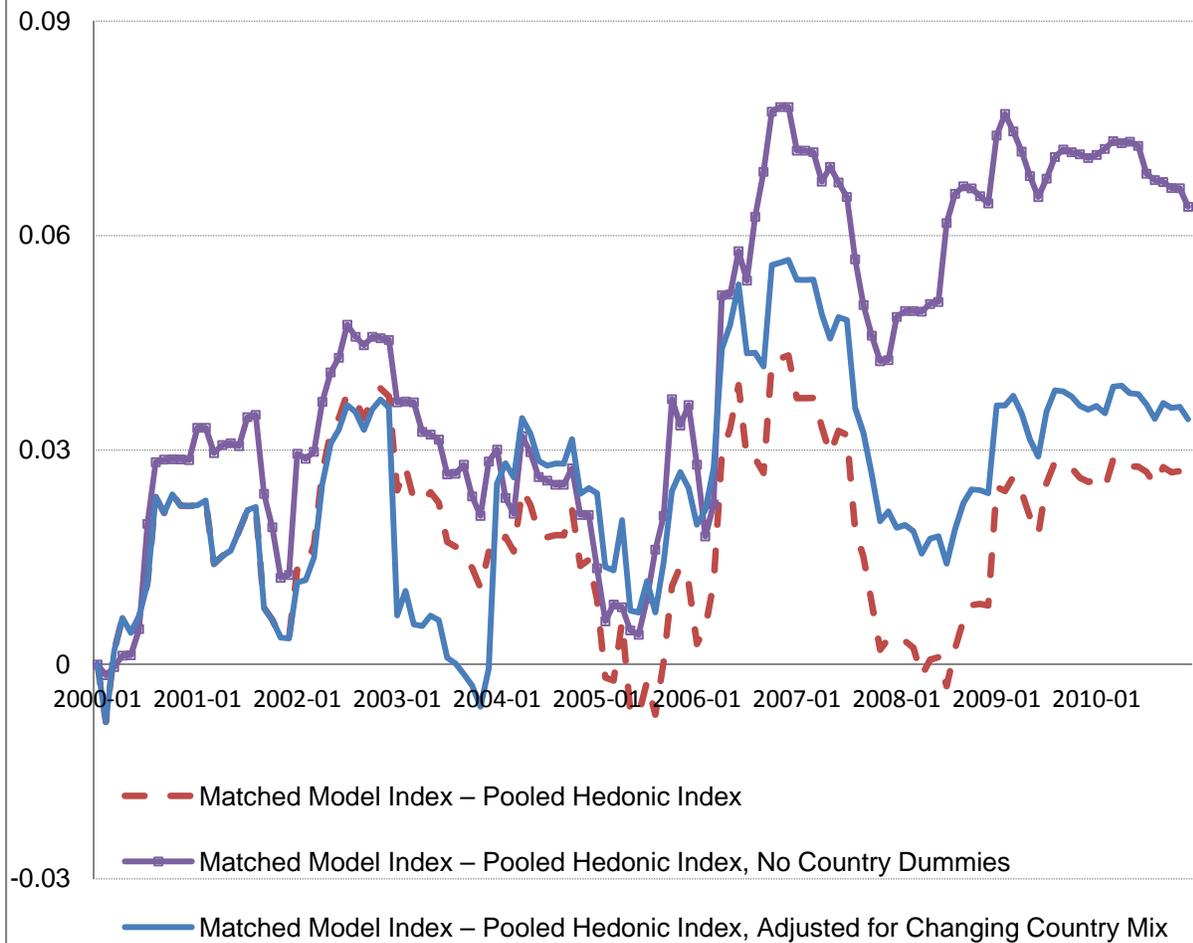
Figure 8. Matched Model and Average Price Indexes for HS 90: Cameras and Photographic, Measuring and Medical Instruments
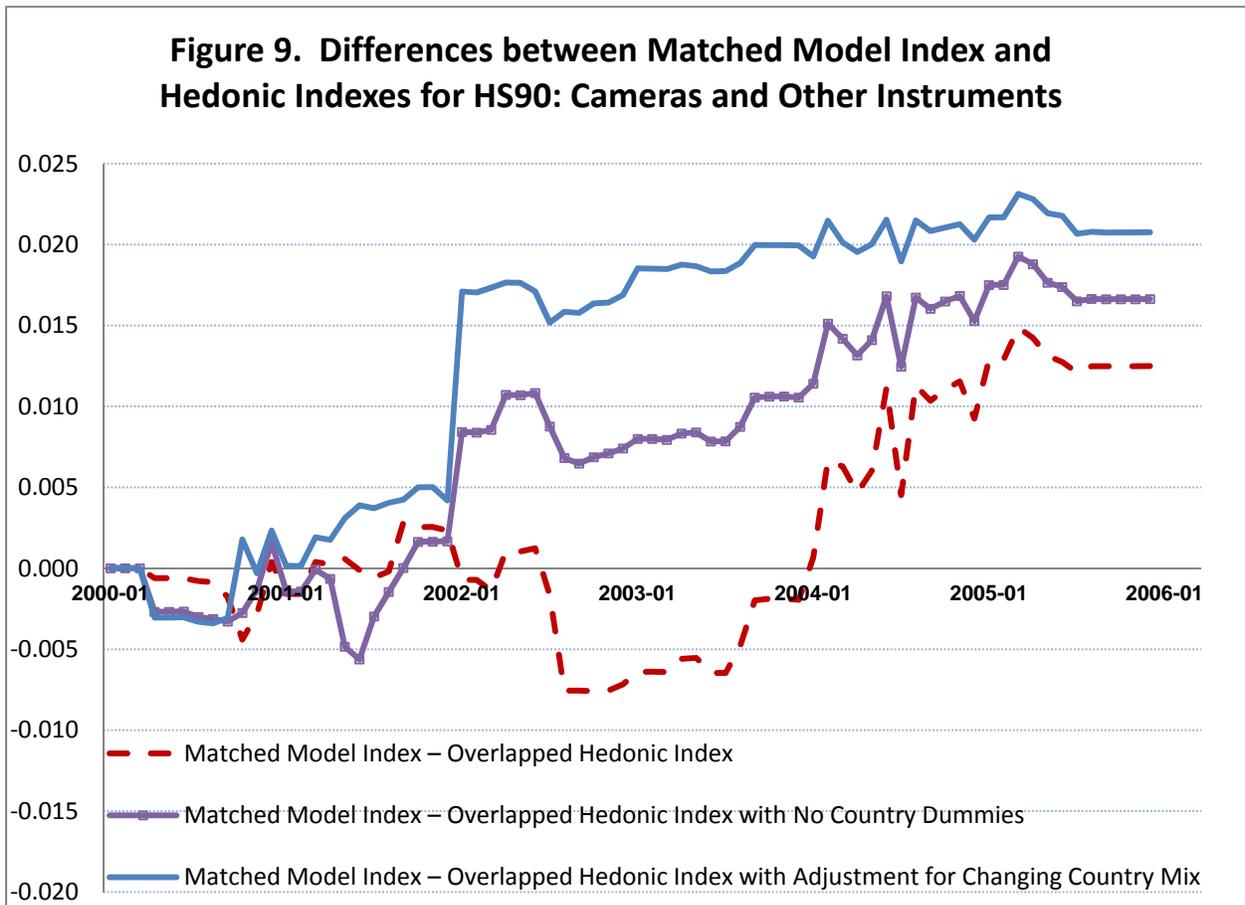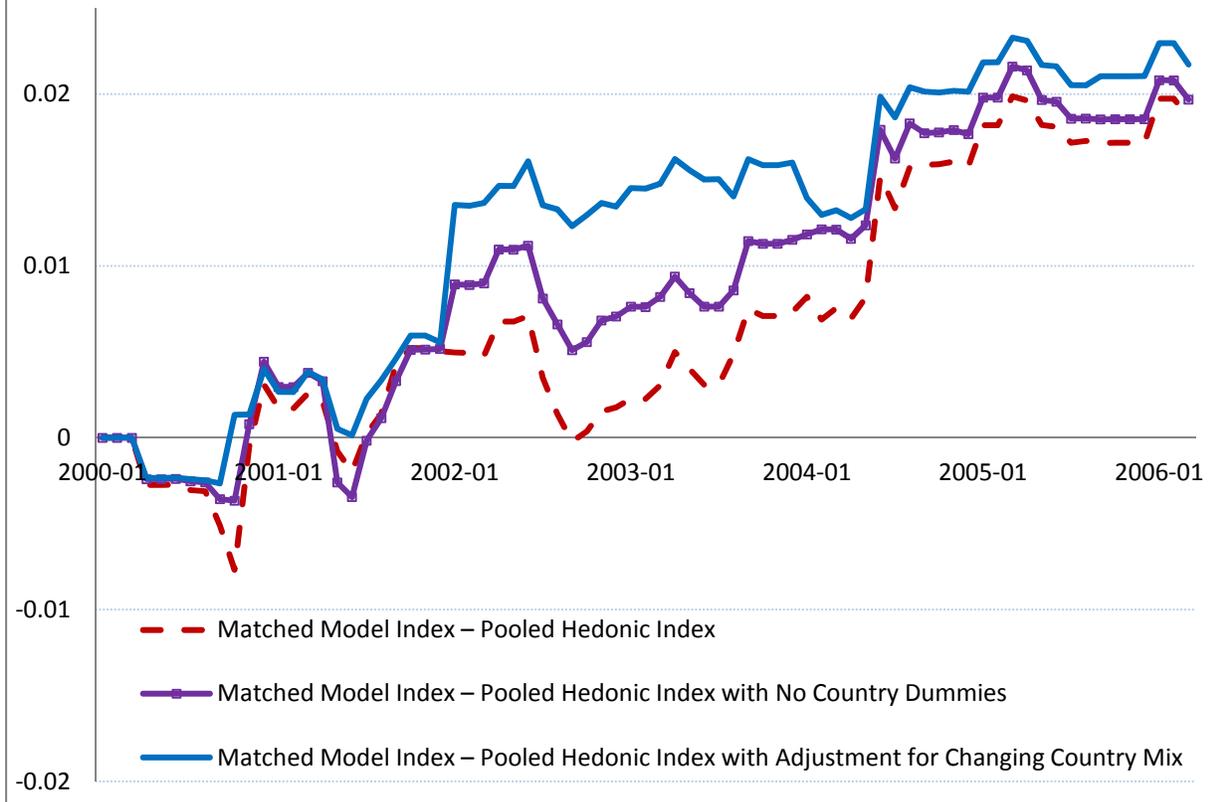
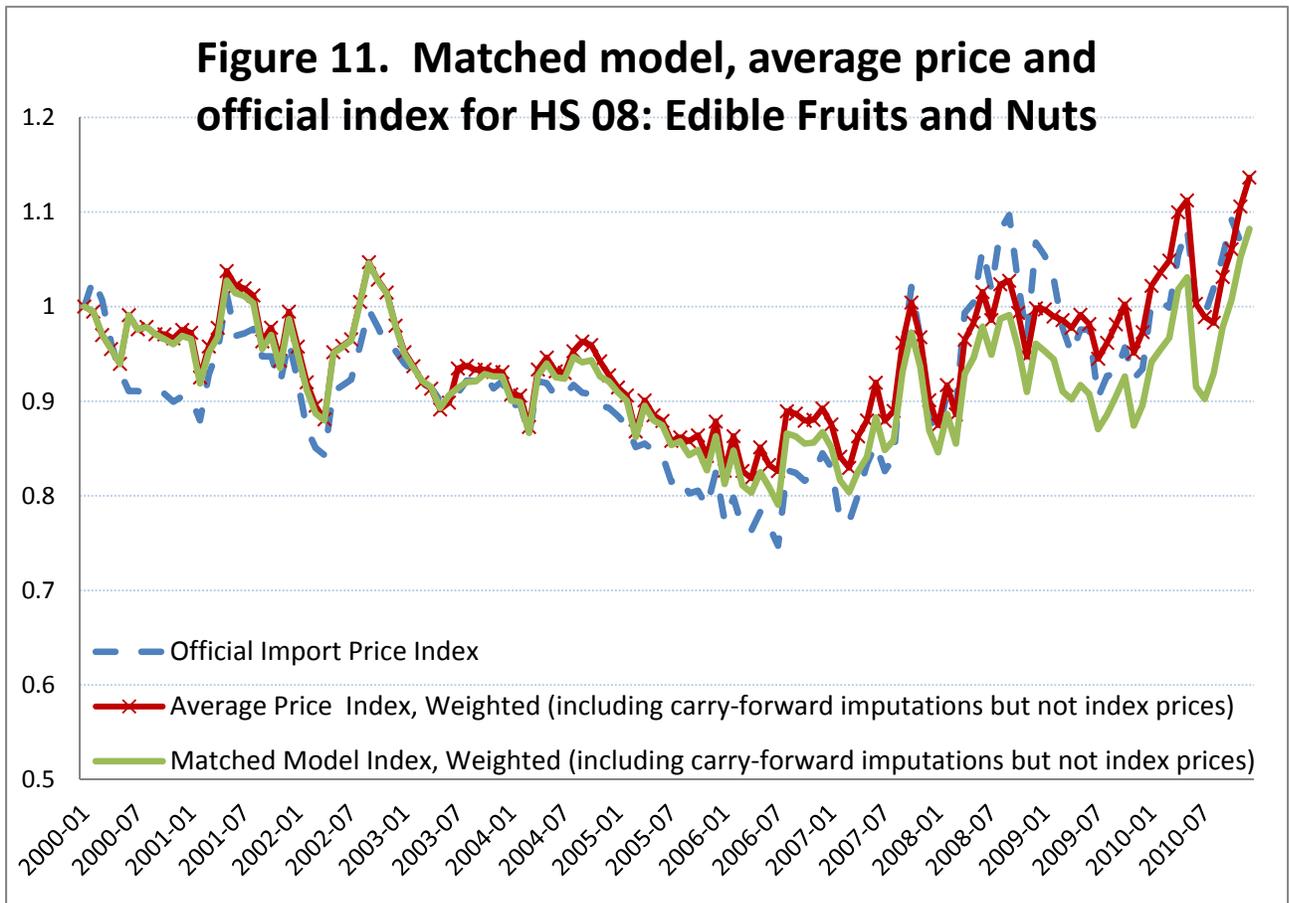Figure 9. Differences between Matched Model Index and Hedonic Indexes for HS90: Cameras and Other Instruments
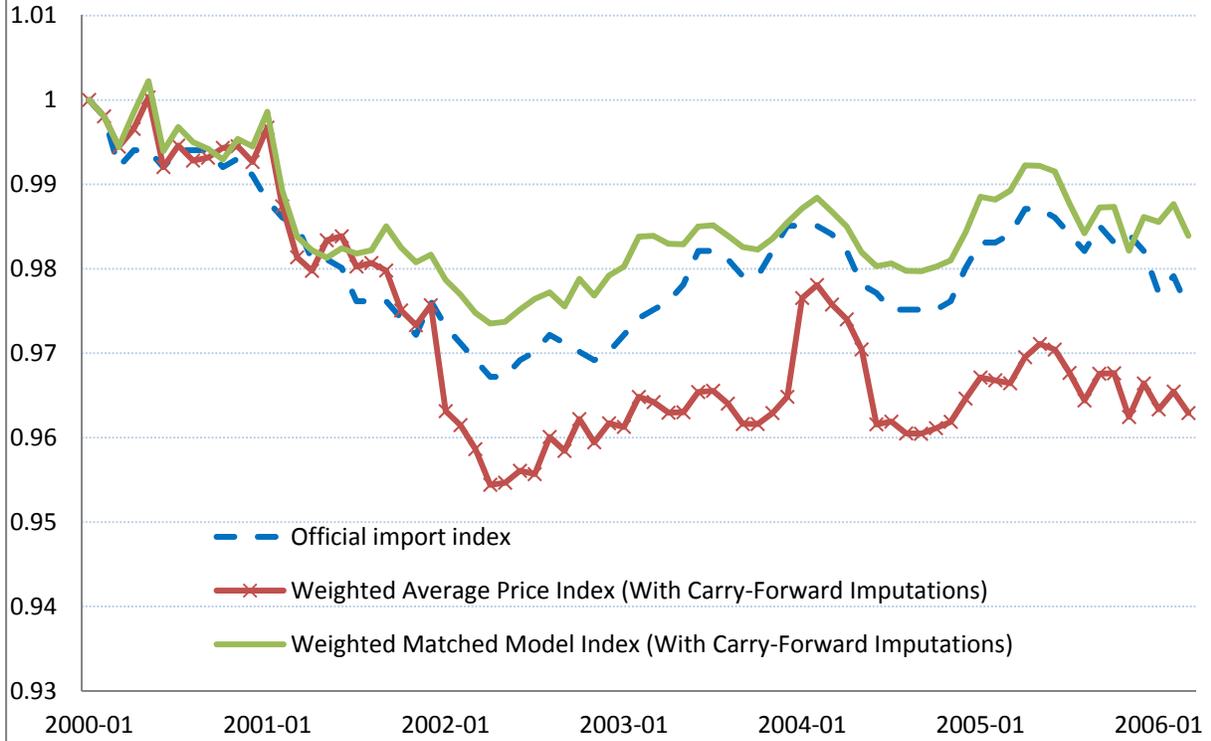
Figure 10. Differences between Matched Model Index and Hedonic Indexes for HS90: Cameras and Other Instruments

Figure 11. Matched model, average price and official index for HS 08: Edible Fruits and Nuts
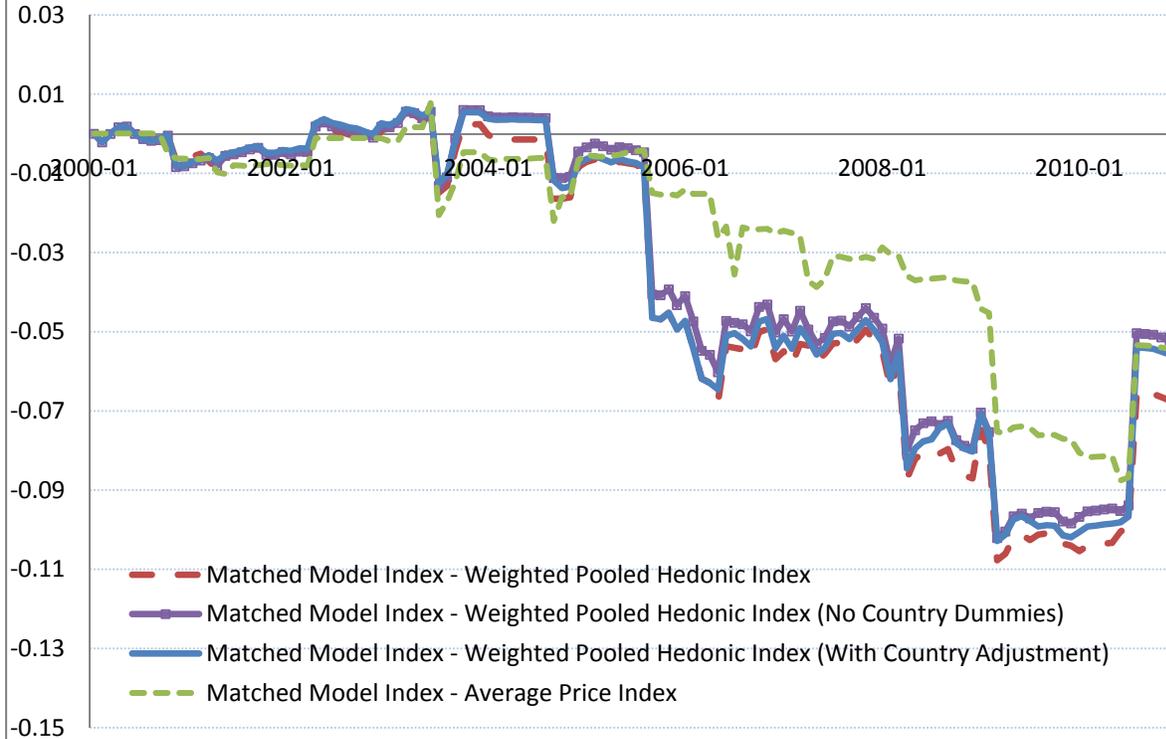
Figure 12. Difference between Matched Model Index and Hedonic Indexes for HS08

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	