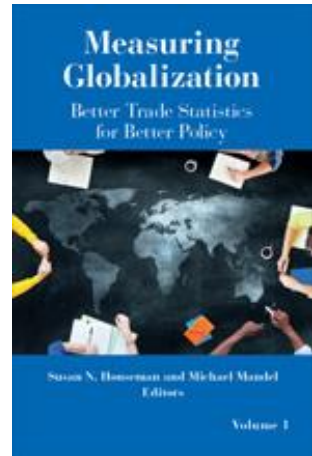

Upjohn Institute Press

The Impact of Globalization on Prices: A Test of Hedonic Price Indexes for Imports

Mina Kim
Bureau of Labor Statistics

Marshall B. Reinsdorf
International Monetary Fund



Chapter 9 (pp. 293-330) in:

**Measuring Globalization: Better Trade Statistics for Better Policy, Volume 1,
Biases to Price, Output, and Productivity Statistics from Trade**

Susan N. Houseman and Michael Mandel, eds.

Kalamazoo, MI: W.E. Upjohn Institute for Employment Research, 2015

DOI: 10.17848/9780880994903.vol1ch9

9

The Impact of Globalization on Prices

A Test of Hedonic Price Indexes for Imports

Mina Kim
Bureau of Labor Statistics

Marshall B. Reinsdorf
International Monetary Fund

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 United States. In addition, goods with regular quality improvements due to new or improved technology have also increased their representation in U.S. imports. The U.S. 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. The matched-model approach is also likely to miss changes in quality-adjusted prices that occur when new models that embody improved technology enter the market. Hedonic methods for quality adjustment could help to resolve these problems. This chapter 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 arises both from 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 variety of consumer products and intermediate inputs, including electronic goods, textiles, and apparel. Such shifts in sourcing create measurement challenges for price statisticians since 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 in imports by countries like the United States 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 models 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- (or higher-) quality-adjusted prices.

Changes in source country and changes in technological characteristics both present a risk of bias for the U.S. 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 Walmart (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 U.S. import data, hedonic techniques have already been applied to these or related problems. In particular, Grimm (1998) uses proprietary data on worldwide markets for semiconductors to construct hedonically adjusted deflators for exports and imports of semiconductors in the U.S. 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 microdata that the BLS used to compile the import 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). They conclude that a high proportion of price changes must therefore occur at the time of item replacements.

In Nakamura and Steinsson (2012), 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. With the matched-model index, there is an 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. This assumption implies corrections to estimated changes in the index for nonoil

imports that raise the standard deviation of quarterly log changes from 1.1 percent to 1.6 percent. This in turn would imply 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 for 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 lower than the measured price changes when a product is undergoing improvement as a result of technological progress.³

The lower prices that import buyers obtain by sourcing from China and other emerging economies have also been topics of several papers. Thomas, Marquez, and Fahle (2008) infer the size of the price reductions that U.S. importers realize by switching to sources from emerging economies on the basis of purchasing-power parity data from the Penn World Tables. More recently, Byrne, Kovak, and Michaels (2013) have directly looked at prices from traditional sources of semiconductors and from new sources in China and find that the China price is 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 that because market shares are inversely proportional to quality-adjusted prices, 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

et al. (2013) use this method to estimate the bias associated with variety entry and exit in the deflator for nonpetroleum imports in the U.S. 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 et al. (2011) and Mandel (2007, 2009) focus on price effects that are due to the offshoring of production from the United States 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 Chapter 10 of this volume) 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 the 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.

HEDONIC PRICE INDEXES FOR IMPORTS

Hedonic price indexes do not exclude from the index calculation observations that are only present in one time period. 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, Corrado, and

Doms (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 employs 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 being 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 the 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 a given set of characteristics, the marginal cost is the same across sellers. This assumption does not hold true in our data.

Despite the high degree of interest in the questions that hedonic methods might help to answer, to our knowledge this chapter 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 variety of items whose characteristics vary, so no particular set of characteristics can be ascribed to an observation.

The United States 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 U.S. import index sample have well-defined characteristics. Nevertheless, detailed characteristics information can be difficult to collect from respondents in IPP surveys, so the import price index database 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 existed 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 from the International Price Program (IPP) Research Database (Blackburn, Kim, and Ulics 2012). 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 through Internet searches on make and model number. (See Appendix Table 9A.1 for

the list and description of quality characteristics that we are able to pull from the database.)

The data set for televisions and bananas covers 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, the 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. In addition, 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 intrafirm “transfer” prices in our study to keep sample sizes from becoming too small. We do, however, include a dummy variable for intrafirm 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 intrafirm pricing strategy is the same across firms and time throughout this study. As shown in Table 9.1, the share of intrafirm prices is high for cameras and bananas.

Table 9.1 Share of Prices That Are Intrafirm 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

SOURCE: Authors’ calculations.

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, the 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 9.2 reports the share of missing values that are imputed for each subset considered.

Table 9.2 Share of Prices That Are Imputed in Each Month

	Televisions	Cameras	Bananas
Mean	0.03	0.04	0.00
Min.	0.00	0.00	0.00
Max.	0.32	0.50	0.12

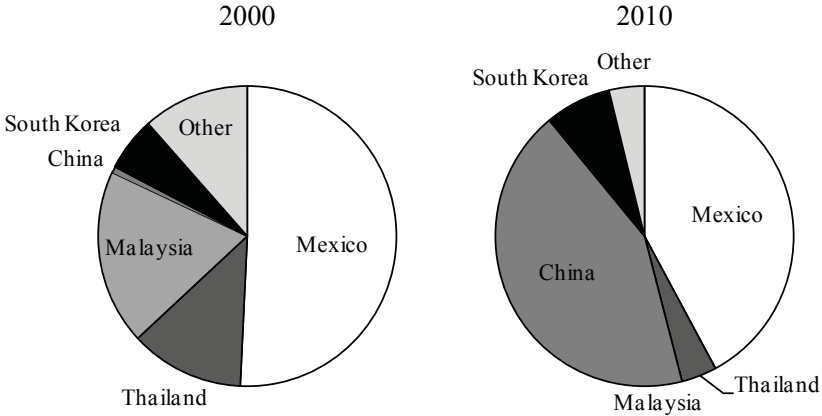
SOURCE: Authors' calculations.

Both televisions and cameras exhibit a great deal of cross-sectional variation in price levels. 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 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 9.1), while cameras moved away from Japanese imports to imports from China and Thailand (Figure 9.2). The growth in television screen sizes over our sample period is also noteworthy (Figure 9.3).

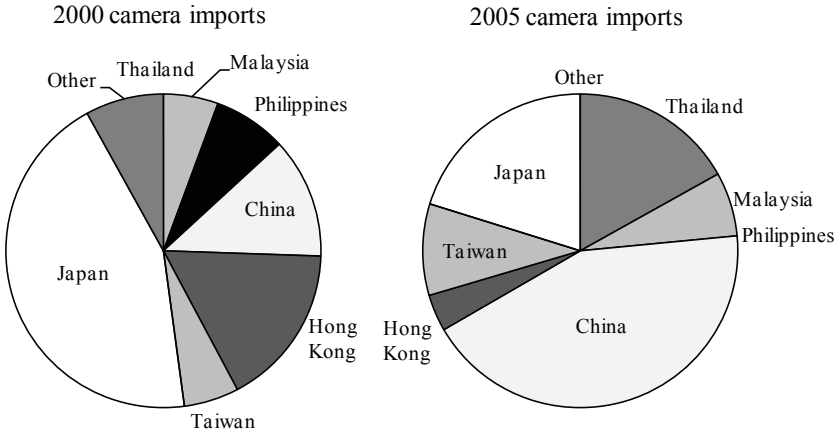
Televisions experience slightly more sample entry than sample exit throughout the period that we study. Cameras, on the other hand, experience almost one and a half times more exits than entries of items into the sample. On average about 4.7 percent of televisions in a given month are no longer present in the next month, while for cameras the hazard rate for sample attrition is 5.6 percent per month (see Table 9.3 for a summary of exit reasons). The mean duration of a television in the

Figure 9.1 Change in Share for the Source Country for Television Imports, 2000–2010



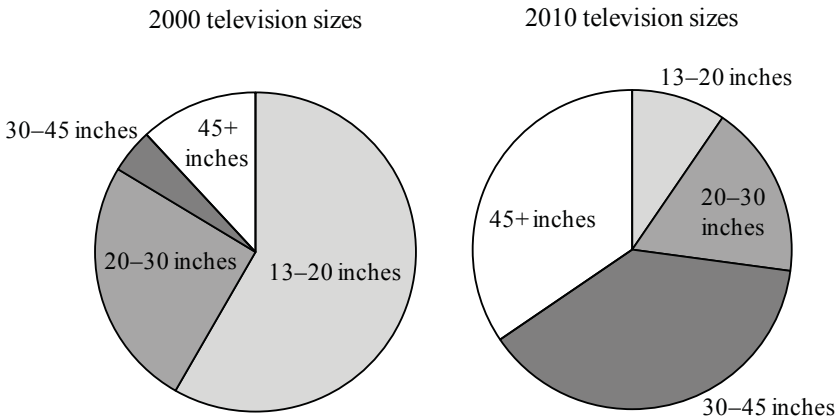
SOURCE: Authors' calculations.

Figure 9.2 Change in Share for the Source Country for Camera Imports, 2000–2005



SOURCE: Authors' calculations.

Figure 9.3 Change in Share for Imported Television Sizes, 2000–2010



SOURCE: Authors’ calculations.

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.

Bananas behave very differently from televisions and cameras. Prices for bananas only vary sixfold, reflecting their greater homogeneity. Moreover, bananas change prices very frequently compared to

Table 9.3 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	0.02	0.04	0.00
Out of scope, replaced	0.01	0.01	0.01

NOTE: “Out of scope” items are items that are no longer traded. Reporters sometimes are able to give a quote for a replacement item. At other times, there is no replacement.

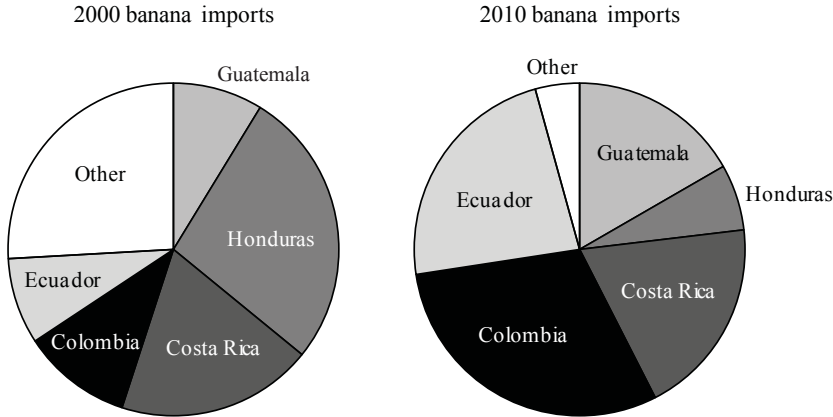
SOURCE: Authors’ calculations.

televisions and cameras; on average, a banana quote changes price 19.3 times during the time that it is in our sample. Bananas in our data set primarily are imported 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 and the one from Costa Rica has remained about the same (Figure 9.4). On average, about 1.9 percent 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 NONHEDONIC 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

Figure 9.4 Change in Share for Source Country for Bananas, 2000–2010



SOURCE: Authors' calculations.

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.¹⁰ 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, for which less detailed weights based on customs data are used.¹¹ 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 our calculated weights for observations in all of the indexes that we calculate so that 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 nonpublic data allow us to report only publication-level indexes. We are unable to report indexes at the level of the individual products that make up 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 fruits 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 and 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

$$(9.1) \quad p_{it} = \alpha_t + X_{it}\beta + \varepsilon_{it},$$

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 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 from 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.¹²

We fit these models by both including and excluding country dummies from the set of variables in X_{it} in Equation (9.1). 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 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{a}_t be the fitted coefficient on the time dummy for period t (with the time dummy omitted in the base period), $\Delta\bar{p}$ 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:

$$(9.2) \quad \hat{a}_t = \Delta\bar{p} - (\Delta X)\hat{\beta}.$$

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

$$(9.3) \quad \hat{a}_t = \Delta\bar{p} - (\Delta X_{PA})\hat{\beta}_{PA} - (\Delta X_{CM})\hat{\beta}_{CM}.$$

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

$$(9.4) \quad \tilde{a}_t = \hat{a}_t + (\Delta X_{CM})\hat{\beta}_{CM}.$$

EMPIRICAL RESULTS

HS 8528 and Televisions

The first set of hedonic indexes that we estimate are for imported televisions. As explained above, BLS disclosure policies prevent us from showing research indexes that would correspond to an unpub-

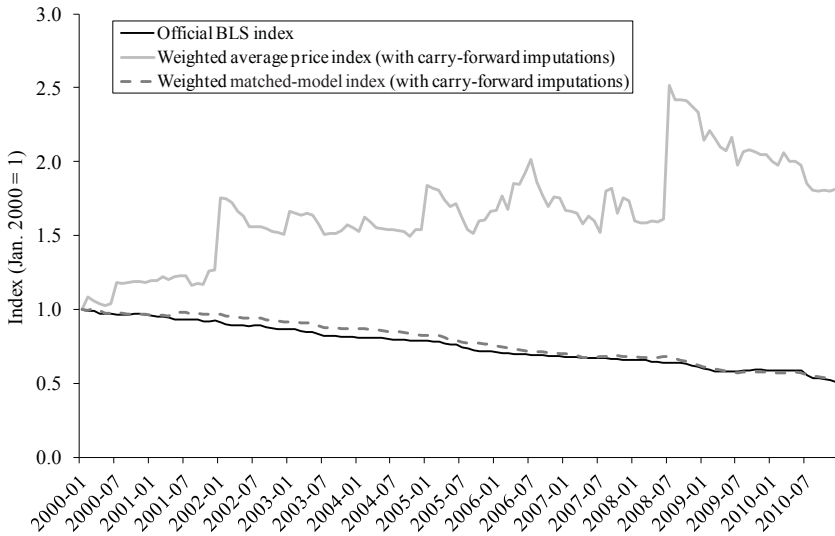
lished level of detail, so we show indexes at the lowest published level that includes televisions, HS code 8528. HS 8528 covers televisions and other video devices.¹³

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 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 9.5). 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

Figure 9.5 Matched-Model and Average Import Price Indexes for HS 8528: Televisions and Other Video Devices



SOURCE: Bureau of Labor Statistics and authors' calculations.

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 alternative is to control for 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.

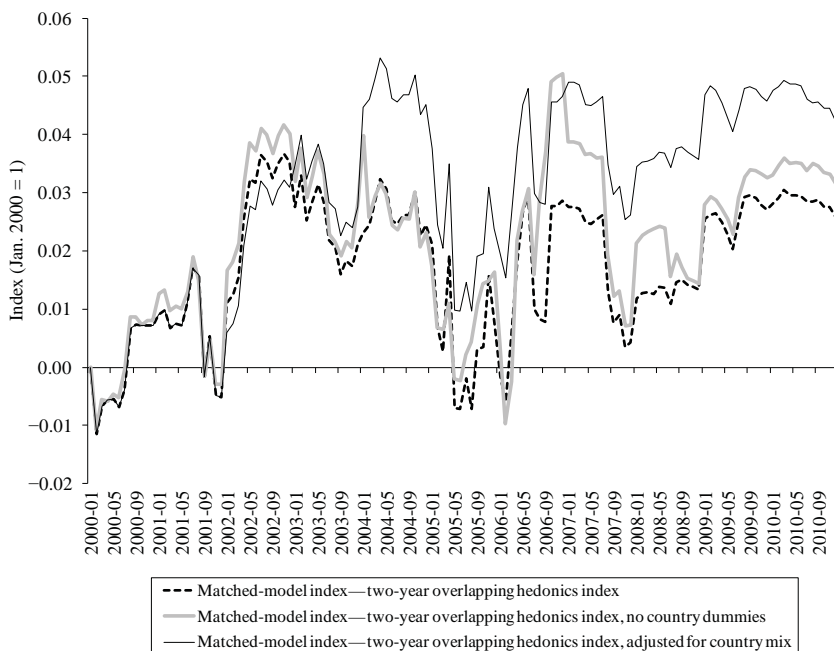
A weakness of this approach is, however, that it is vulnerable to omitted variable bias. If characteristics and countries are correlated, some of the effects of the omitted country variables could be reflected in the coefficients on the physical characteristics. This may then cause effects of changes 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 (9.4). (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 likely to be 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 significantly alters 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 the 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 estimate of the bias 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 9.6. 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 index points and brings the estimate of the bias in December 2010 of the matched-model index up to 0.042 index points. The unadjusted moving-window hedonic index for HS 8528 is about 0.026 index points

Figure 9.6 Differences between Weighted Matched-Model and Weighted Overlapping Hedonic Indexes for HS 8528: Televisions and Other Video Devices



SOURCE: Authors' calculations.

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 index points in December 2010. This implies that the bias in the matched-model index due to the failure to capture price declines from changing source countries is only about 0.006 index points in December 2010. The difference between the hedonic index that includes country dummies and the hedonic index from the regression with 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 9.4.

Table 9.4 Amounts by Which Matched-Model Index Growth Rate Exceeds Moving-Window Hedonic Growth Rates for HS 8528 (% per year, 2000–2010)

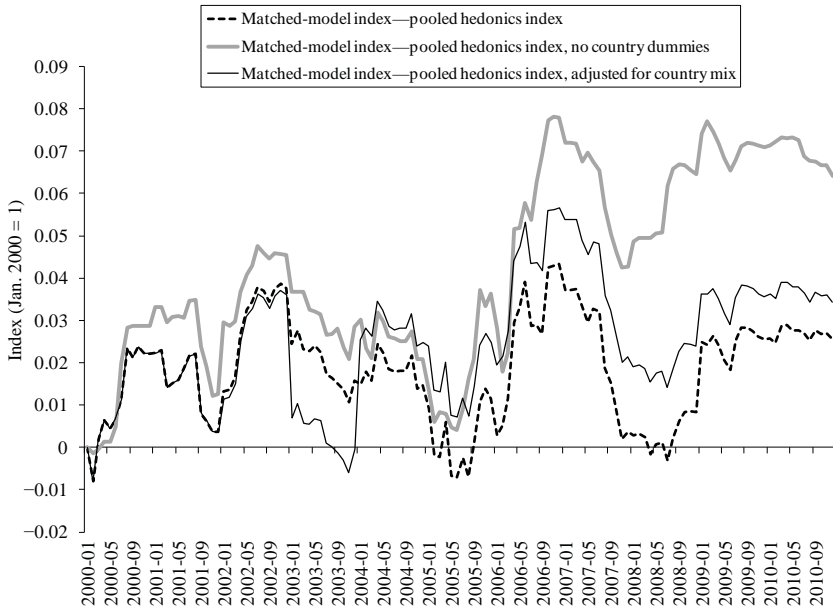
Country dummies included	0.44
Country dummies excluded	0.53
Adjusted for changing country mix	0.72

SOURCE: Authors' calculations.

We also estimate pooled hedonic indexes as a kind of robustness check on the moving-window hedonic results. Figure 9.7 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 owing to underestimation of gains from improvements in technology as the moving-window version, 0.026 index points.

On the other hand, the pooled specification produces a lower hedonic index than the moving-window specification in the case where country dummies are omitted from the model, and a slightly higher hedonic index in the case where country dummies are included and an adjustment is made for the effects of changing country mix. Under the pooled

Figure 9.7 Differences between Weighted Matched-Model and Weighted Hedonic Indexes for HS 8528: Televisions and Other Video Devices



SOURCE: Authors' calculations.

specification, the no-country-dummies index is 0.064 index points below the matched-model index in December 2010, while the adjusted hedonic index is just 0.034 index points lower than the matched-model index. Under the pooled specification, the adjusted hedonic index implies a bias in the matched-model index from changing sourcing of 0.008 index points, while the no-country-dummies hedonic index implies that this bias is 0.038 index points. These differences in average annual growth rates between the pooled hedonic indexes and the matched-model index are shown in Table 9.5.

Table 9.5 Amounts by Which Matched-Model Index Growth Rate Exceeds Pooled Hedonic Growth Rates for HS 8528 (% per year, 2000–2010)

Country dummies included	0.43
Country dummies excluded	1.11
Adjusted for changing country mix	0.58

SOURCE: Authors' calculations.

Television 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 9.6). 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 9.6 some alternative estimates of the bias in the matched-model index. Omitting the country dummies rather than adjusting for the predicted effect of changing country mix reduces the estimate of the total bias implied by a moving-window hedonic index to 1.6 percent per year. Pooling all the years rather than running overlapping regressions on pairs of years reduces the estimate of the total bias based on the model with country dummies to 1.8 percent per year but increases the estimate based on the model with no country dummies to 3.4 percent per year. Subtracting the estimate of the bias from technology-related quality change from each of the alternative estimates of the total gives a range of estimates of 0.5 to 2.1 percent per year for the effect of changing source countries.

Table 9.6 Estimates of Bias in a Matched-Model Index for Televisions Implied by Different Specifications of the Weighted Hedonic Regression

Type of hedonic regression	From hedonic regression excluding country dummies (% per year)	From using country's coefficients to adjust for change in country mix (% per year)	From hedonic regression with country dummies, undermeasurement of technology-related quality change (% per year)
Moving window	1.6	2.2	1.3
All years pooled	3.4	1.8	1.3

SOURCE: Authors' calculations.

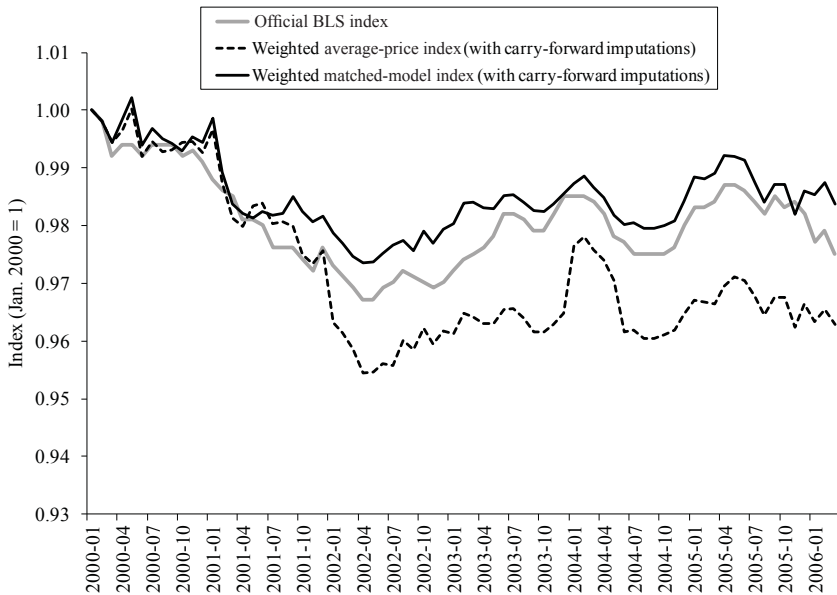
HS 90 and Cameras

Besides televisions, we 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 9.8). However, there are two episodes where 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 9.8. 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 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-

Figure 9.8 Matched-Model and Average Import Price Indexes for HS 90: Cameras and Other Photographic, Measuring, and Medical Instruments



SOURCE: Bureau of Labor Statistics and authors' calculations.

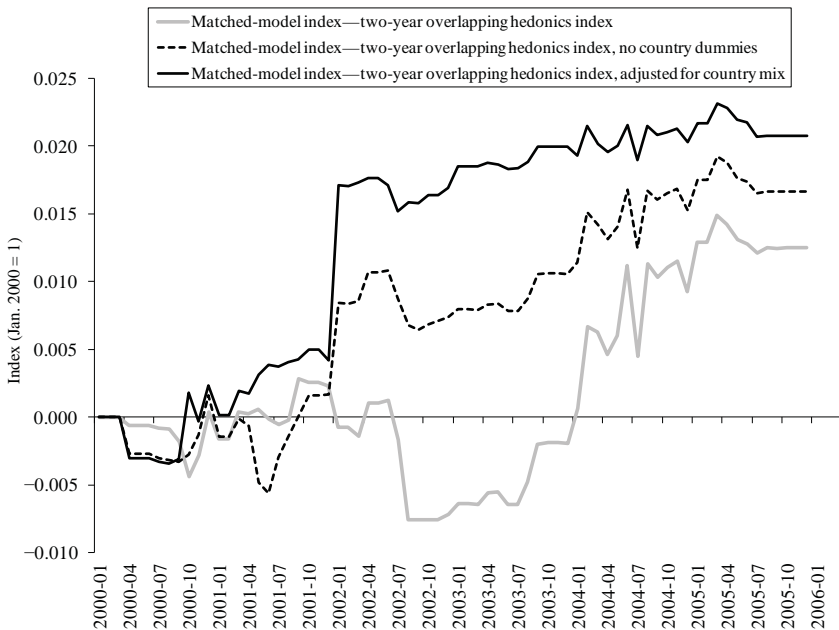
model index is upwardly biased. Part of the relative decline in average price comes from the emergence of inexpensive digital cameras as a popular camera type, and another part of the decline seems to be due to changes in source countries. Such collinearity between physical changes in characteristics 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 9.9). 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 9.8 shows that in early 2002, the average price index dropped precipitously relative to the matched-model index; as a result, 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.

Figure 9.9 Difference between Matched-Model Index and Hedonic Indexes for HS 90: Cameras and Other Photographic, Measuring, and Medical Instruments



SOURCE: Authors' calculations.

The implication that physical changes in cameras between 2000 and 2004 did not affect their average quality level seems questionable. The low slope 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 that is 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 markedly smaller using the pooled regression model, and the behavior of all three hedonic indexes is plausible (Figure 9.10).

The growth rate differences between the matched-model index and the various moving-window approaches and the pooled hedonic indexes are summarized in Table 9.7. 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 9.7 Differences in Average Growth Rate between the Matched-Model Index and Hedonic Indexes for HS 90

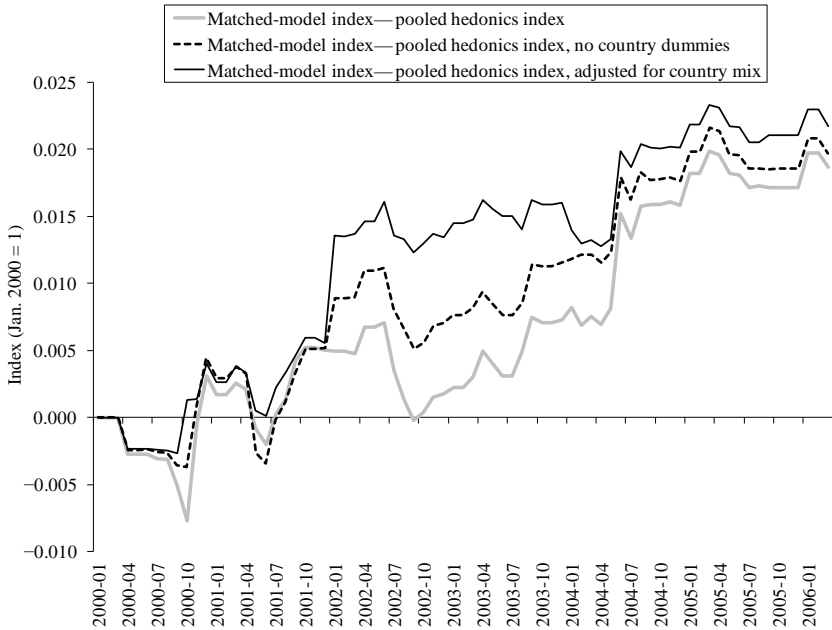
	Moving-window hedonic	Pooled hedonic
Country dummies included	0.21	0.31
Country dummies excluded	0.29	0.33
Adjusted for changing country mix	0.36	0.36

SOURCE: Authors' calculations.

Camera 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 9.8 shows the implied differences in average annual growth rates. The first two rows are based on the last date available for

Figure 9.10 Difference between Matched-Model Index and Hedonic Indexes for HS 90: Cameras and Other Photographic, Measuring, and Medical Instruments



SOURCE: Authors' calculations.

each individual time series, while the third row of Table 9.8 uses the ending date for the pooled hedonic indexes that is used for the moving-window hedonic indexes. (The pooled hedonic indexes in Figure 9.10 end three months later than the moving-window hedonic indexes in Figure 9.9.) 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

Table 9.8 Estimates of Bias in the Matched-Model Index for Cameras Implied by Different Specifications of the Weighted Hedonic Regression

Type of hedonic regression	Estimate from hedonic regression excluding country dummies (% per year)	Estimate from adjusting for change in countries using country coefficients (% per year)	Estimated unmeasured technology-related quality change from hedonic regression with country dummies (% per year)
Moving window	9.0	11.4	6.7
All years pooled	8.1	10.5	5.8
All years pooled, same ending month as for moving window	10.1	11.6	9.3

SOURCE: Authors' calculations.

with new technology amounts to 6.7 percent per year, whereas 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 coeffi-

clients 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.

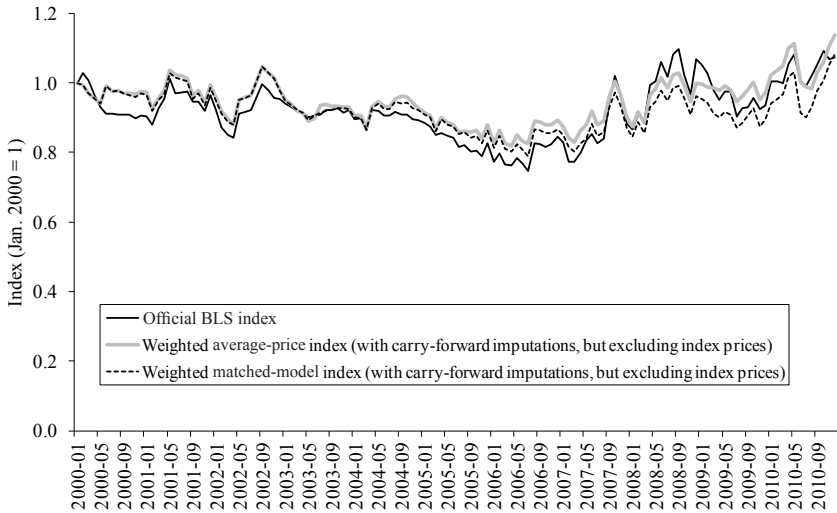
Bananas

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 zero.

Bananas have a weight of about one-fifth in the publication-level import index for HS 08, the category “edible fruits and nuts.” After excluding “index prices” (which are reference prices reported 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 the official index (Figure 9.11). 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 for 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 9.12). 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 with 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.

Figure 9.11 Matched-Model and Average Import Price Indexes for HS 08: Edible Fruits and Nuts



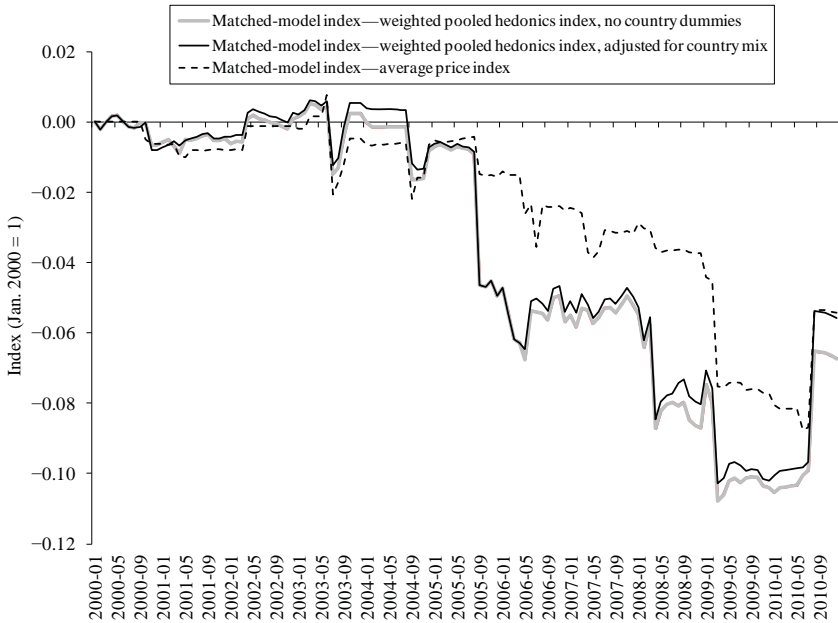
SOURCE: Bureau of Labor Statistics and authors' calculations.

Furthermore, comparing the unadjusted hedonic index that includes country dummies to either 1) the index with no country dummies or 2) the index that was adjusted to treat price differential between countries as true price differences rather than quality differences shows that sourcing for bananas has a slight tendency to migrate to more expensive countries. The unadjusted hedonic index that includes country dummies grows on average 1.28 percent per year, whereas the adjusted index grows 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

Figure 9.12 Difference between Matched-Model Index and Hedonic Indexes for HS 08: Edible Fruits and Nuts



SOURCE: Authors' calculations.

match those of the entrants, the matched-model index will be upwardly 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 that item being treated as a new item. Hedonic index methods are a possible way to address these concerns. Yet they have not been viewed as feasible for import price indexes because of the limited collection of information on product characteristics and, in some cases, small sample sizes for purposes of estimating a hedonic regression model.

One goal of this chapter 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 products 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 come from undermeasured gains from new technology and 0.9 percentage points come 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 10.5 percent per year, of which 5.8 percentage points come from undermeasured gains from new technology and 4.7 percentage points come from country sourcing changes.

Notes

The views expressed in this chapter are those of the authors and should not be attributed to the IMF, its management, or its executive directors; nor do they reflect the views of the Bureau of Labor Statistics.

1. For a recent study with estimates of outlet substitution bias, see Greenlees and McClelland (2011).
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 (2013) 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.
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 0.25 percent per year.
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.

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 percent of the televisions experience these temporary exits, as opposed to about 6 percent for bananas.
8. When using the cell-relative method, the missing value is determined by the change in the index value for the nonmissing values in a particular class. When using the class-mean method, the missing value is determined by the mean of the nonmissing values for a particular class. The International Price Program also sometimes uses linear interpolation to impute prices.
9. In calculating these average durations and price change frequencies, we included items for which the observable life span 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. The Laspeyres indexes used by the BLS are more precisely described as Lowe indexes because their weights are based on values from a previous year; these values have subsequently 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, with a lag of two years.
11. 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 that make up a Jevons index. These weights come from the same year used for the official index and reflect trade values in that year.
12. 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 it uses the estimated coefficients from the base period to predict prices of items present in the comparison period.
13. 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 U.S. national accounts, an inaccurate split between imports of final consumption goods and imports of investment goods could affect the measurement of GDP.

Appendix 9A

Table 9A.1 Quality Characteristics Used in Hedonic Regressions

Product	Characteristics
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	

SOURCE: Authors' compilation.

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 No. 2003-14. San Francisco: Federal Reserve Bank of San Francisco.
- Alterman, William. 1991. "Price Trends in U.S. Trade: New Data, New Insights." In *International Economic Transactions: Issues in Measurement and Empirical Research*, Peter Hooper and J. David Richardson, eds. NBER Studies in Income and Wealth 55. Chicago: University of Chicago Press, pp. 109–143.
- . 2009. "Producing an Input Price Index." Paper presented at the conference "Measurement Issues Arising from the Growth of Globalization," held in Washington, DC, November 6–7. <http://www.upjohninstitute.org/measurement/alterman-final.pdf> (accessed Feb. 19, 2014).
- Blackburn, Taylor, Mina Kim, and Rozi Ulics. 2012. *IPP Research Database*. Washington, DC: Bureau of Labor Statistics.
- Byrne, David, Brian K. Kovak, and Ryan Michaels. 2013. "Price and Quality Dispersion in an Offshoring Market: Evidence from Semiconductor Production Services." NBER Working Paper No. 19637. Cambridge, MA: National Bureau of Economic Research.
- Erickson, Tim, and Ariel Pakes. 2011. "An Experimental Component Index for the CPI: From Annual Computer Data to Monthly Data on Other Goods." *American Economic Review* 101(5): 1707–1738.
- Feenstra, Robert C. 1994. "New Product Varieties and the Measurement of International Prices." *American Economic Review* 84(1): 157–177.
- Feenstra, Robert C., Benjamin R. Mandel, Marshall B. Reinsdorf, and Matthew J. Slaughter. 2013. "Effects of Terms of Trade Gains and Tariff Changes on the Measurement of U.S. Productivity Growth." *American Economic Journal: Economic Policy* 5(1): 59–93.
- Gagnon, Etienne, Benjamin R. Mandel, and Robert J. Vigfusson. 2012. "Missing Import Price Changes and Low Exchange Rate Pass-Through." International Finance Discussion Paper No. 1040. Washington, DC: Board of Governors of the Federal Reserve System.
- Greenlees, John S., and Robert McClelland. 2011. "New Evidence on Outlet Substitution Effects in Consumer Price Index Data." *Review of Economics and Statistics* 93(2): 632–646.
- Griliches, Zvi. 1961. "Hedonic Price Indexes for Automobiles: An Econometric Analysis of Quality Change." In *The Price Statistics of the Federal Government: Review, Appraisal, and Recommendations*, Price Statistics

- Review Committee, ed. New York: National Bureau of Economic Research, pp. 173–196.
- Grimm, Bruce T. 1998. “Price Indexes for Selected Semiconductors, 1974–96.” *Survey of Current Business* 78(February): 8–24.
- Houseman, Susan, Christopher Kurz, Paul Lengermann, and Benjamin R. Mandel. 2011. “Offshoring Bias in U.S. Manufacturing.” *Journal of Economic Perspectives* 25(2): 111–132.
- Mandel, Michael. 2007. “The Real Costs of Offshoring.” *BusinessWeek* 2007(4039): 28–34. http://www.businessweek.com/magazine/content/07_25/b4039001.htm (accessed January 23, 2014).
- . 2009. “Growth: Why the Stats Are Misleading.” *BusinessWeek*, June 3, online version. http://www.businessweek.com/magazine/content/09_24/b4135000594984.htm (accessed January 23, 2014).
- Manninen, Kari. 2005. “The Effects of the Quality Adjustment Method on Price Indices for Digital Cameras.” BEA Working Paper No. 2005-01. Washington, DC: Bureau of Economic Analysis.
- Nakamura, Emi, and Jón Steinsson. 2012. “Lost in Transit: Product Replacement Bias and Pricing to Market.” *American Economic Review* 102(7): 3277–3316.
- Neiman, Brent. 2010. “Stickiness, Synchronization, and Passthrough in Intrafirm Trade Prices.” *Journal of Monetary Economics* 57(3): 295–308.
- Reinsdorf, Marshall. 1993. “The Effect of Outlet Price Differentials on the U.S. Consumer Price Index.” In *Price Measurements and Their Uses*, Murray F. Foss, Marilyn E. Manser, and Allan H. Young, eds. NBER Studies in Income and Wealth 57. Chicago: University of Chicago Press, pp. 227–254.
- Reinsdorf, Marshall, and Robert Yuskavage. 2013. *Unmeasured Declines in Import Prices for Final Consumption Goods*. Washington, DC: 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 Paper No. 917. Washington, DC: Board of Governors of the Federal Reserve System.

Measuring Globalization

Better Trade Statistics for Better Policy

Volume 1

Biases to Price, Output, and Productivity Statistics from Trade

Susan N. Houseman
and
Michael Mandel
Editors

2015

W.E. Upjohn Institute for Employment Research
Kalamazoo, Michigan

Library of Congress Cataloging-in-Publication Data

Measuring globalization : better trade statistics for better policy / Susan N. Houseman and Michael Mandel, editors.

volumes cm

Includes bibliographical references and indexes.

ISBN 978-0-88099-488-0 (v. 1 : pbk. : alk. paper) — ISBN 0-88099-488-6 (v. 1 : pbk. : alk. paper) — ISBN 978-0-88099-489-7 (v. 1 : hardcover : alk. paper) — ISBN 0-88099-489-4 (v. 1 : hardcover : alk. paper)

1. Commercial statistics. I. Houseman, Susan N., 1956- II. Mandel, Michael J.

HF1016.M44 2015

382.01'5195—dc23

2014047579

© 2015

W.E. Upjohn Institute for Employment Research
300 S. Westnedge Avenue
Kalamazoo, Michigan 49007-4686

The facts presented in this study and the observations and viewpoints expressed are the sole responsibility of the authors. They do not necessarily represent positions of the W.E. Upjohn Institute for Employment Research.

Cover design by Alcorn Publication Design.
Index prepared by Diane Worden.
Printed in the United States of America.
Printed on recycled paper.