Alternative Data Sources and Hedonic Price Indexes for High-Tech Products in the U.S. Consumer Price Index

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This paper summarizes recent research conducted by the Bureau of Labor Statistics to use alternative data sources and methods to improve price change measurement for high-tech goods and services in the U.S. Consumer Price Index.

Abstract

The Bureau of Labor Statistics has a goal of transitioning a portion of the U.S. Consumer Price Index market basket from traditional data collection to non-traditional or alternative data sources and collection modes. This paper explores the use of alternative data sources and methods for adjusting price indexes for quality change. We combine web-collected and household survey data to estimate hedonic regression models. We examine price estimation methods that consider the valuation of both observable and unobservable characteristics at the time of product turnover. A superlative index formula is used in the estimation of experimental price indexes for wireless telephone services and televisions.

1. Introduction

The Bureau of Labor Statistics (BLS) has a goal of transitioning a portion of the Consumer Price Index (CPI) market basket of goods and services from traditional data collection to non-traditional data sources and collection modes.[2,3] Using non-traditional data is not a new concept for the CPI program; secondary source data has been used since the 1980s to develop sample frames, to serve in benchmarking analysis, and to supplement collected data to support hedonic modeling and sampling. However, outside of a few notable exceptions like postage, gasoline, used vehicles, and new vehicles, non-traditional data has not directly replaced traditional data collection for most of the CPI market basket. As non-traditional data sources improve and become more suitable for use in price index construction, BLS plans to pivot from using non-traditional data as a supplementary

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[1] This paper is released to inform interested parties of ongoing research and to encourage discussion of work in progress. This paper reports the results of research and analysis undertaken by Bureau of Labor Statistics staff. It has undergone more limited review than official publications.

[2] See the BLS Strategic Plan – Strategy 3. https://www.bls.gov/bls/bls-strategic-plan-2020-25.htm

[3] Konny et al. (2019) provides a concise summary of traditional data collection in their overview of the CPI (section 2.2). For additional details, see the BLS Handbook of Methods for the Consumer Price Index, specifically, the section on data sources, for a description of current (i.e., traditional) data collection methods. https://www.bls.gov/opub/hom/cpi/data.htm

tool to using it as the very basis for CPI calculation where it is deemed appropriate and cost-effective to do so. As this transformation occurs, BLS must innovate the infrastructure it uses to calculate the CPI and reimagine several foundational principles if it is to succeed. Practically, this means reducing the BLS's reliance on full probability sampling as the basis of its data collection processes for the CPI and adopting a stance of greater flexibility in terms of adhering to historical methodologies.

In framing the motivation for pursuing nontraditional or new alternative data sources, Konny, Williams, and Friedman (2019) note several challenges that arise in calculating the CPI using traditional data collection, namely (1) the difficulty of maintaining constant quality price change for products and services where product turnover is frequent, (2) the importance of incorporating new goods in a timely manner, and (3) the need to reduce sampling error.[4] The authors highlight that new alternative data sources and methods provide BLS with an opportunity to address these challenges and may lead to more accurate measures of price change. Specific cited examples relevant to the research presented later in this paper include (1) BLS's use of secondary source data to aid data collectors in the selection of representative telecommunications samples and (2) BLS's use of secondary source data to assist in quality adjusting the prices of smartphones.

Since 2019, research has continued and, in some cases, non-traditional data and new index methods have been adopted. Brown, Sawyer, and Bathgate (2020) provide a summary of innovations focused on high-tech products experiencing rapid and complex quality change. Specifically, the examples of smartphones and residential telecommunications services (landline telephone, internet, and cable and satellite television) are explored in detail. For these product categories, secondary source data were used in the estimation of hedonic regression models used to indirectly estimate quality adjusted price changes when a unique item is replaced in the CPI survey. The authors also address ongoing research using alternative data and methods for these and other related product categories such as wireless telephone services for which, at the time, BLS was exploring the time dummy hedonic approach. Hedonic methodologies, like time dummy, where indexes are calculated completely from model estimated prices, are more feasible with increased access to alternative data.

Recognizing the prospect of future modernization challenges, BLS commissioned the Committee on National Statistics (CNSTAT) of the National Academy of Sciences to convene a panel of price index experts. This panel provided guidance to the agency as it plans for and progresses through its transition to increased reliance on alternative data for calculating the CPI. The panel assessed new opportunities created by the availability of alternative data sources and its findings were released in 2022. Chapter 2 (The Potential of Alternative Data Sources to Modernize Elementary Indexes) is most relevant to the topics discussed in this paper. Of particular focus is Recommendation 2.6, which encourages BLS to research and assess the potential of alternative data sources for quality change adjustments. The panel suggests that initially this work could be

[4] Konny et al. (2019) classifies the CPI's alternative data sources into three main categories: (1) *Corporate supplied data* from CPI survey respondents, (2) *Secondary source data* compiled by a third party and purchased by BLS, and (3) *Web-collected data* which are data collected by BLS using either web-scraping or application programming interfaces (APIs).

part of an effort to replace price quotes from traditional data but notes that the use of new alternative data will likely result in a call for new methodologies for adjusting for quality change. The panel also advises BLS to pay close attention to products where rapid quality changes are common, such as for high-tech items. Large datasets containing high-quality product specification information of high-tech items offer opportunities for improving price change measurement, especially when used with hedonic methods (Recommendation 2.6). The panel suggests that BLS explore creating indexes with the hedonic methods developed by Erickson and Pakes (2011), specifically Recommendation 2.5 and Appendix 2B. These methods are novel because they can adjust for unobservable characteristics and can correct for sample selection effects. Finally, the panel advised BLS that implementation of the methodological improvements suggested in Recommendation 2.6 could be consequential for high expenditure items. In concluding its recommendation, the panel cited telecommunications goods and services as good examples of products to prioritize, thereby offering some confirmation of BLS's research agenda in this area.

In this paper we review the background and issues with calculating price indexes for televisions and wireless telephone services, particularly those related to quality change and quality adjustment, describe alternative data sources that were used in our research, and define our research methodology. Our research indexes are presented in the results section. We conclude with final observations and remarks.

2. Background

In a recent paper, Williams (2021) provides a systematic accounting of the impact of quality adjustments and other item replacement imputations on the U.S. CPI since 1999. Williams found that quality adjustments reduce the rate of CPI growth by 0.04 percent per year, and that the largest contributors to this trend are indexes with unambiguous, vertically differentiated product attributes. However, Williams adds that the hedonic adjustments used by the BLS do not always have a clear relationship with hedonic theory. In his conclusion, Williams notes that BLS has attempted to make improvements to address several well-known measurement issues stemming from the item replacement process, but also offers that several of the issues could be better addressed in other ways, outside the item replacement process. Williams specifically claims that the introduction of new goods need not be directly tied to the exit of another product as the current BLS methodology imposes. Rather, it may be more appropriate to apply methods for imputing prior period prices for new goods or current period prices for exiting goods outside of the traditional item replacement process. Finally, Williams recommends that BLS explore methods for capturing changes in consumer welfare based on demand modeling, adding that the increased availability of transaction data and other non-survey data may aid BLS in this endeavor.

BLS has a long history of quality adjusting television prices through the traditional item replacement process. Starting with Moulton, LaFleur, and Moses (1998), hedonic models have been applied in the production of the CPI for televisions. Moulton et al. found the impact of these adjustments to be rather small and the direction of the effects were mixed. Two decades later, Williams' analysis found an annualized difference of -1.38 percent between the published index and a strict matched model counterfactual index where the later fell faster than the former, and offered that this difference could be due to unaccounted for quality change that is shown as a price increase at item replacement (despite the BLS's best efforts to remove the bulk of quality change through the combination of current hedonic adjustment methods and analyst judgements).[5] If true, Williams asserts that BLS would be better off implementing a strict matched model index for televisions rather than maintaining its current quality adjustment methods.

Compared to televisions, BLS has a much shorter history of quality adjusting the prices of wireless telephone service plans. Since 2017, the CPI for wireless telephone services has been calculated using prices that have been quality adjusted whenever the amount of data included in a service plan change at item replacement.[6] As Williams (2021) notes, hedonic adjustments have made large differences for item categories like telecommunication services, where prices are stable within a product's lifecycle and quality improvements are introduced at the time of product turnover. For services like these, price changes outside of item replacements are rare.

When considering the instructive comments of Williams, we evaluated how non-traditional data sources and methods could be leveraged to improve BLS's handling of quality change for televisions and wireless telephone services. Recent methodological advances in adjusting for quality change put forth by academia, like Redding and Weinstein (2020), focus on demand-based modeling. This approach requires expenditure information that BLS does not currently collect in its survey data. While a few data sets from alternative sources we have investigated come close to meeting the data requirements for this approach, we have yet to identify a robust, reliable source for this information.[7] Moreover, as noted in Appendix 2B of the CNSTAT (2022) report, statistical agencies do not use demand-based methods because a price index that relies on the assumptions about consumer utility functions would not be reliable enough for official purposes.

Another approach to quality change uses hedonic regressions to predict prices. This approach interprets the hedonic coefficients as not being tied to any underlying consumer preferences and may not necessarily have an intuitive interpretation. In this approach, the primary purpose of a hedonic regression is to predict prices, in which case choices about the specification are motivated by the predictive power of the regression, not the sign and magnitude of the coefficients (CNSTAT, 2022). This approach is like the "imputation method" and has been studied for a long time (see Berndt, 1991 and Pakes, 2003). Recent innovations to the imputation method by Erickson and Pakes (2011) allow for accounting of changes in unobserved characteristics.

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[5] Williams (2021) defines a "strict matched model index" as one where a product must be observed in *t* and *t-1* periods to be included in the index. The qualifier "strict" is used because only same product version price change is used. This contrasts with the published U.S. CPI, which is often referred to as a matched model index since item replacement can be considered part of the matched model process.

[6] A similar approach to hedonic adjustment was adopted for residential telecommunications services in January 2019. The CPI maintains separate indexes for internet, landline telephone, and television services, though bundled combinations of those services can be included in each of the three categories. Hedonic adjustments in these categories typically account for faster internet download speeds and the number of televisions channels included in package.

[7] We did not estimate demand-based indexes for this paper since alternative datasets for both items only provide observation-level price and specification data. Monthly expenditures must be estimated using lagged 3rd-party survey data. These expenditure estimates are not reactive enough, on a real-time basis, to calculate an accurate demand-based index.

Following the recommendations of Williams and CNSTAT, we believe that BLS's ability to incorporate data from alternative sources into the calculation of the CPI for products that are rapidly changing is best realized through the hedonic imputation approach, as it allows for the introduction of new goods outside of the traditional item replacement process. We find further support for this view in Silver and Heravi (2007) who state that for product areas with high turnover, the use of hedonic indexes is most appropriate because they include the data of unmatched new and old models. Silver and Heravi also show that the hedonic imputation approach is preferred over the time dummy hedonic approach if there is evidence of parameter instability over time. Prior to the availability of large non-traditional data sets, BLS did not have the data necessary to calculate hedonic indexes. In the next section, we will describe the data used in this research.

3. Data

This section provides an overview of the data sources used in this research. We first discuss sources of product prices and characteristics data before discussing the sources of consumer expenditure data used to derive weights.

3.1 Televisions

For televisions, we use price and characteristics data collected through an API (application programming interface) of a national retailer, hereafter referred to as "NCER" (National Consumer Electronics Retailer). Since October 2020, BLS has downloaded price and specification data from NCER's API three times per month. BLS collects item specific datasets for televisions, computers, tablets, smartphones, video game systems, VR headsets, cameras, camcorders, DVD and Blu Ray players, dishwashers, washers/dryers, refrigerators, cooktops, and microwaves. The dataset containing price and characteristics data for televisions contains 96 specification variables per observation, a customer review count tally for each observation, a variable which indicates each item's availability, a regular offer price for the item, and, if applicable, an offered sale price. Each unique observation contains its own stock keeping unit ("SKU") number. On average, the NCER televisions dataset contains approximately four hundred total unique television observations per month. In a typical month, about 90 percent of these observations are available to purchase either in-store or online. The remaining 10 percent of observations in the dataset are listings for out-of-stock items. Our analysis indicates that NCER employs a national pricing strategy, so geographic segmentation of the data is unnecessary.

Each month, we undertake a data cleaning process on the televisions data. First, observations that are not available to purchase either in-store or online by consumers are deleted. Next, observations with certain trigger words in their description are deleted. For example, products that include the word "signage" in their item description tend to be LED signs purchased by businesses, not televisions purchased by consumers. Next, observations with missing price data are eliminated. Finally, for the remaining observations, we take a geometric average of the prices that have been collected throughout the month to determine that observation's singular monthly price. This final group of observations make up the dataset that is used to build our price prediction model.[8]

We use data purchased from a market research firm to estimate observation-level expenditure weights for the dataset described above. The vendor provides BLS with market segmentation information that is derived from surveys issued to American consumers. Survey respondents report an average of 16,400 television purchases per quarter, representing a total expenditure of $8.3 million. Survey respondents are selected to be demographically and geographically representative of the domestic population. While consumers do not report specific UPC or SKU numbers, they do report product specifications like brand, screen size, and resolution. Survey respondents also report the outlet, location of purchase, and whether the purchase was made online or in-store. Expenditure estimates were calculated using weighting data from the same period in which offer prices were collected.

Since surveyed consumers do not directly report model names, SKUs, or UPCs, there is no way to directly merge the expenditure data with NCER's pricing and specification data. Instead, expenditure weights must be estimated using an alternative process which links the expenditure data with NCER data. To estimate expenditure weights for each observation, we use the expenditure data to segment the market by relevant specification variables. For televisions, brand, resolution, and screen size were selected because of their consistent statistical significance in regressions on price. NCER expenditure totals are summated for each unique group of these three specification variables. For example, medium screen size, 4k televisions sold by Brand Y may have accounted for $25,000 among survey respondents during the last four quarters. These expenditure estimates are then merged into the NCER dataset for each observation where specifications match. We use a rolling four quarter average of expenditures to weigh the data, where the most recent quarter includes the index reference month. Finally, to weigh individual observations, we divide the total expenditure estimate in each brand/screen size/resolution group by the proportion of website reviews that an individual observation received during the past month.

3.2 Wireless telephone services

We use price and characteristics data purchased from a market research firm specializing in the telecommunications industry for our analysis of wireless telephone services. The vendor of these data uses both web-scraping and non-automated methods of data collection to monitor and record service plan prices and characteristics offered to new customers by telecommunications providers. While the vendor collects service plan data in nearly every media market in the country, BLS's contract is limited to the markets that align with the CPI's 75 sampling areas. The vendor collects data from nearly all telecommunications providers offering services within a designated market area (DMA). The service categories BLS purchases are land-line telephone, internet access (residential and wireless), television (cable and satellite), bundled service packages of residential telephone, internet, and television, streaming video, premium channels, and wireless telephone.

[8] Our method of calculating a single monthly price from multiple monthly prices replicates the method by Williams and Sager (2019), who also use a geometric mean before ultimately aggregating with a Tornqvist formula.

The focus of this research is wireless telephone services provided by mobile network operators. The service plans and prices for these plans are national and are available in all markets.

Each row or observation in the price and characteristics data is a unique service plan package and its price offered by a specific provider, through a particular sales channel, to a particular type of customer, for a specific contract term length, in a particular month. Additional fields describing the features and characteristics of each package are provided. Many price-related fields are provided in the datasets, and we derive an average monthly price over the term commitment length specified for each service plan, factoring in promotional and standard monthly rates for the duration specified by the contract. We exclude charges for activation, and service fees and taxes are not provided. Nearly all the provider-DMA combinations in the CPI's sample of providers and cities are accounted for in the price and characteristics data for wireless telephone services.

To derive weights for wireless telephone services, we use data purchased from a consumer research, data, and analytics firm. We receive these consumer survey data for wireless telephone services on a biennial basis. The data used in this project are aggregated responses to the household survey on wireless carriers covering the 2018 and 2019 survey periods. The vendor conducts ongoing annual studies of wireless carriers by surveying households regarding their wireless telephone ownership experiences.

We developed a process for summarizing the survey responses to specific questions applicable to the purchase and consumption of wireless telephone service plans into useful groupings. These groupings are based on the payment method (postpaid or prepaid), the number of lines serviced per plan, the amount of high-speed data included with the plan, and the type of service provider (national operators or MVNOs – mobile virtual network operators).[9] We then calculate plan level shares of the consumer reported expenditure by the type of service provider. Finally, we adjust the plan shares by a factor based on the provider's national market share. Those shares are used to weigh individual service plans in the estimation of the hedonic regression models and in the weighting of the plan price relatives when calculating index relatives.

4. Methodology

To construct an accurate cost of living index, statistical agencies must effectively adjust item-level indexes for quality change over time. Practitioners must look beyond traditional matched model price indexes to capture quality change resulting from product turnover. Current BLS methods for the calculation of television and wireless telephone service price indexes include the application of hedonic price adjustments only when an item is replaced. In contrast, our research indexes are not exclusively reliant on item replacement to estimate quality change. Rather, all products are used to build a predictive regression on price which serves as the foundation of index calculation.

[9] The large national wireless providers are sometimes referred to as mobile network operators (MNOs). These providers build and own their wireless networks. Other providers in the market are branded resellers of network capacity that they lease from MNOs. These types of providers are referred to as mobile virtual network operators (MVNOs).

Thus, quality improvements brought about by new goods are immediately and fully integrated into our estimate of constant-quality price change.

4.1 Current index calculations

In terms of relative importance, televisions accounts for nearly 0.14 percent of the CPI market basket, while wireless telephone services represent 1.44 percent of the total weight of the CPI.[10] Currently, indexes for both items are calculated using a traditional matched model with item replacement methodology where representative item categories are defined, item samples are selected, unique items are priced over time, and when a unique item disappears it is replaced by another item of similar quality. BLS has used hedonic regression models to indirectly estimate quality adjusted price changes when a unique item is replaced by an item of dissimilar quality for several decades and began employing this practice in the construction of price indexes for televisions in 1998 and for wireless telephone services in 2017. In cases where a quality-adjusted price change cannot be estimated, class mean imputation is used to impute current period prices. Thirty-two elementary item-area indexes are calculated by a weighted geometric means formula, and then a weighted arithmetic average is taken over each area to obtain a national index for each item category.[11]

4.2 Hedonic function specifications and index estimation

The hedonic imputation methodologies investigated for this study were motivated by the need to account for the effect of unobserved product characteristics in the estimation of the prices of exiting products. Unobserved characteristics are features that improve the quality of the product, but cannot be measured, and thus cannot be included in a hedonic regression on price. Failure to control for the effects of unobserved characteristics may lead to an index with an upward bias, as all quality change introduced by these features is not captured by a standard hedonic index. Erickson and Pakes (2011) propose that it is possible to predict the effect of unobserved product characteristics by using observable characteristics, thereby reducing the omitted variable bias inherent in some hedonic regressions. They propose a two-stage method. In the first stage, the natural log of price (or "ln(price)") for both the current month (t) and previous month (t-1) is predicted by regressing observed characteristics on ln(price). In the second stage, the same set of observed characteristics, plus the month t-1 residual from the first-stage regression, is regressed on the change in first-stage residuals for continuing goods.[12] In our prediction of each observation's month t ln(price), the observation's predicted change in residual is added to its predicted period t ln(price). Like Ehrlich, et al (2023), we extend this technique to entering goods (goods available in the current period, but not the previous period), and assume their t-1 residual is 0.

This methodology is appropriate for many high-tech products like televisions; however, this method relies on intertemporal variation in prices for continuing goods, and many telecommunications services experience price movement primarily at the time of product turnover.

[10] Weights are for the CPI-U as of December 2022 and based on U.S. City Average using 2021 weights.

[11] See the BLS Handbook of Methods for the Consumer Price Index, specifically, the section on index calculation, for additional details. https://www.bls.gov/opub/hom/cpi/calculation.htm

[12] The change in first-stage residuals is calculated by finding the difference between month t and t-1 residuals generated by our first-stage price prediction at the observation-level.

Therefore, the two-stage Erickson and Pakes (2011) approach is not recommended for wireless telephone services. Instead, a single-stage hedonic imputation index, as described in Pakes (2003) and which is still state of the art for products with little intertemporal price movement, is applied here to wireless telephone services.

The general form of our log-level hedonic regression model can be specified as:

$$\ln p_{kt} = h_t(Z_k) + n_{kt},$$

where Z_k is a vector of observable characteristics for product k. The function $h_t()$ is estimated with a weighted least squares regression. This hedonic equation varies over time and is estimated each period, allowing the function to pick up changes in consumer valuations of goods and services. With this function, we can utilize hedonic imputation methodology to correct for quality change introduced by product turnover by using observable characteristics to impute the missing prices for entering and exiting goods.

Since weighting data were available in the form of estimated expenditure share-weights, we chose to weigh the regression functions. The effect of using expenditure-weighted hedonic regressions is that the items with the highest expenditure share, i.e., the most popular items, are emphasized in the model and focuses the model on accurately mapping the relationship between prices and characteristics for the mix of items purchased by consumers.

After running a weighted least squares regression, prices are predicted for all goods in the current month (t) and previous time month (t-1). For televisions, the adjustment described in Erickson and Pakes (2011) is applied to period t prices. Additionally, price predictions are extended to exiting goods (goods available in the previous period, but not in the current period), and, as mentioned previously, entering goods (goods available in the current period, but not the previous period). After prices are predicted for time periods t and t-1, price relatives are calculated and then aggregated to a national index using a Tornqvist formula. Estimating current and previous period weights allows us to use a superlative aggregation formula like the Tornqvist. Since NCER employs a national pricing scheme and there is no regional variation in the price of wireless telephone service plans, a single national index is calculated for both items.

$$\frac{P_t}{P_{t-1}} = \prod_{t-1}^{n} \left(\frac{p_{it}}{p_{i,t-1}}\right)^{\frac{1}{2}\left[\frac{p_{i,t-1}q_{i,t-1}}{p_{t-1}q_{t-1}} + \frac{p_{i,t}q_{i,t}}{p_t q_t}\right]}$$

Our resulting hedonic indexes are derived completely from prices predicted by the hedonic regression models. In the literature, this is referred to as “full imputation.” Practically, this means we use prices predicted by our hedonic regressions to calculate relatives for continuing, entering, and exiting items. There are numerous advantages to full imputation indexes. Ehrlich, et al (2023) elegantly summarize these advantages. We spotlight two of these advantages here. First, Pakes (2003) notes that the full imputation form of a hedonic imputation index results in a bound to the exact change in the cost of living under a weaker set of assumptions than those commonly seen in the literature. Ehrlich, et al emphasize that the critical assumption is that consumers have preferences for the characteristics found in the goods, rather than preferences for the goods themselves. Finally, Erickson and Pakes (2011) note that indices other than full imputation are subject to a form of selection bias because they treat the model residuals for continuing, entering, and exiting goods in an asymmetric manner (Ehrlich, et al, 2023). We integrate these insights into our choice of methods.

5. Results

In this section, we present the hedonic imputation indexes calculated for the two product groups we concentrated on: televisions and wireless telephone services. These high-tech product groups are subject to periodic product changes, making them ideal for this kind of analysis, yet they are different in some respects, making them good examples of the types of results we might see with other similar product groups. We also provide analysis of tests conducted to detect the presence of chain drift in our research indexes as chained, superlative index aggregation formulas, such as the Tornqvist method employed in our research, are prone to this phenomenon.

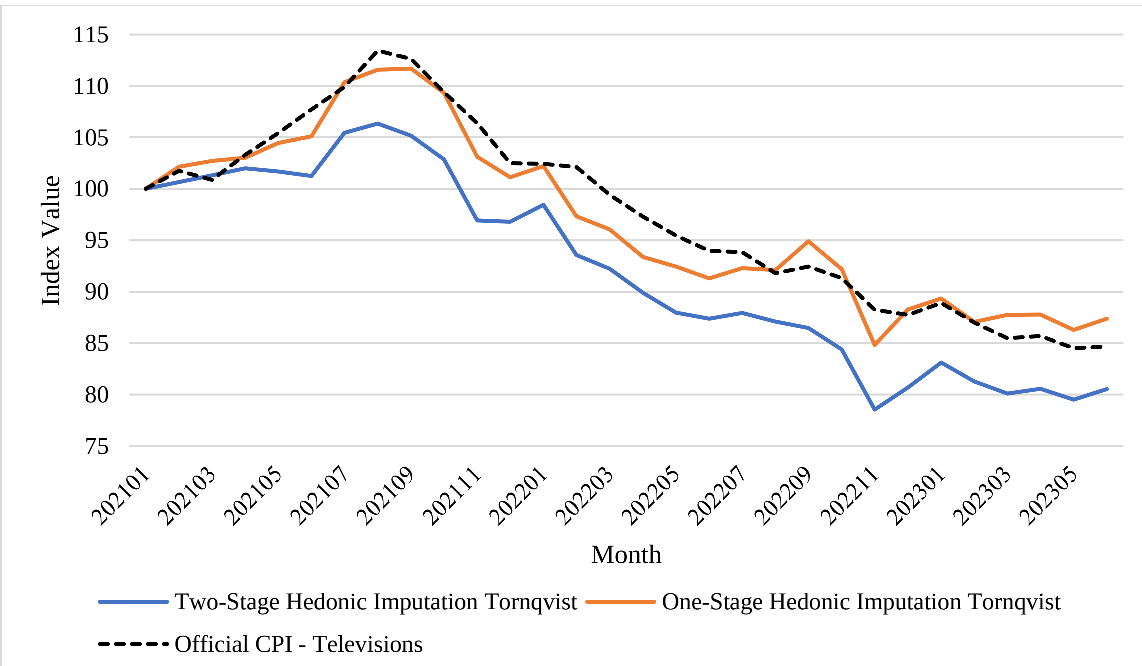
5.1 Televisions

In Figure 1 we compare multiple indexes: a one-stage, "full imputation" index using the NCER data, a two-stage hedonic imputation index which incorporates Erickson and Pakes's (2011) adjustment using the NCER data, and the official, non-seasonally adjusted CPI for televisions. Both hedonic models used in the construction of the research indexes use the same stable, parsimonious model for the entire period. The model does not change between periods. It is important to note that all three indexes reflect the same market trends.

All three indexes rise during the period when the international chip shortage increased production cost for manufacturers (Jan 2021 – Aug 2021). As the chip market began to normalize, all three indexes began to decrease as we would expect under normal market conditions. We expect all three indexes to decline, as rapid technological improvements provide a downward pressure on the index. Additionally, note that the hedonic index may be more reactive to price shocks than the official CPI. Both hedonic indexes drop in November 2021 and November 2022, when NCER (and most similar retailers) begins offering holiday sales on televisions. Both hedonic indexes also increase when holiday sales end in January. The official CPI for televisions was less reactive. There are two possible reasons the CPI may be less reactive to these holiday sale price shocks. First, it's important to understand that the CPI component index contains prices from several retailers, while the NCER indexes only represent a single retailer. NCER may simply implement steeper holiday sales than the market at large. It is also possible that the NCER indexes are more reactive because NCER prices are collected at a much higher frequency than CPI prices. Since all televisions available to purchase were collected three times in November, it is much more likely that the NCER data catches "flash" sales, which may only last a few days. Most CPI observations are only collected every other month, giving each item much more time to go on sale and return from sale between collection dates.

Finally, the two-stage hedonic index shows a more rapid price decline than the official CPI, but the one-stage hedonic index shows a slightly slower rate of price change in the long run. During the period of this study (Jan 2021 – Jun 2023) the official CPI for televisions showed a 15.3 percent decrease, while the one-stage and two-stage hedonic imputation indexes showed 12.6 percent and 19.5 percent decreases respectively. This was expected and replicates the results of Erickson and Pakes (2011) with non-traditional data. The one-stage hedonic index tracks quite closely to the CPI component index for televisions, while the two-stage hedonic index implies larger price declines. We find that the two-stage hedonic imputation index controls the falling residuals phenomenon described further in Appendix I. Controlling for this phenomenon naturally puts negative pressure on our estimation of price change. Since we have found, like Erickson and Pakes (2011), that this phenomenon is at least partially driven by the exclusion of unobserved characteristics, we believe the two-stage method does a better job of accurately measuring cost-of-living change in the market for televisions.

Figure 1: Price Indexes of Televisions, January 2021 – June 2023

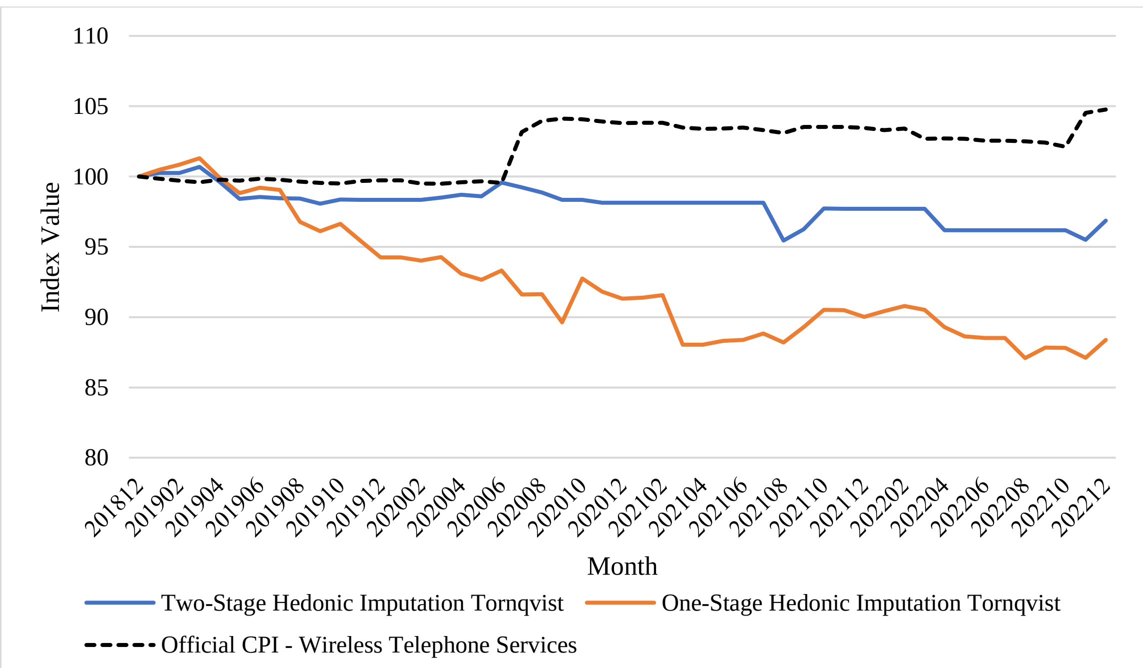


5.2 Wireless telephone services

In Figure 2 we compare the one-stage, "full imputation" hedonic imputation index and a two-stage hedonic imputation index which incorporates Erickson and Pakes's (2011) adjustment to the official CPI for wireless telephone services. We see some notable differences between these series over the analyzed period. During the period of the study, the one-stage hedonic imputation index fell 11.6 percent and the two-stage hedonic imputation index fell 3.1 percent while the official CPI for wireless telephone services increased 4.8 percent. The differences between the official index and the research indexes are exacerbated by a sudden increase in the official index in July 2020. In this month, about a third of the official CPI sample of price observations experienced item replacement and an accompanying price increase after prices were adjusted for quality changes.

Thus, we attribute this index disparity to differences in sample composition and weighting and not to an inability of the hedonic indexes to correctly measure price change. Compared to the one-stage hedonic index, the two-stage hedonic index resulted in only a modest decrease over the four-year period. The opposite result was observed in our research with televisions. To understand this difference, compare the two markets. In the televisions market, we observe discounted prices for older products. Quality change in this market is inherently captured in the price declines of older products that are being obsoleted by higher-tech entrants. Since televisions are a durable product, firms continue to sell older products at typically discounted prices until inventories are depleted. This is not what we observe in the market for telecommunications services, where new, higher quality products replace older, lower quality products, and both old and new products are not typically offered to new customers concurrently. The two-stage methodology relies on the observed price declines of obsoleted products. In the absence of those declines, applying the adjustment diminishes the estimated utility gains to consumers brought about by the introduction of new products leading to an index which shows little cost-of-living change. Therefore, we suggest that a one-stage hedonic imputation methodology is more appropriate for wireless telecommunications services.

Figure 2: Price Indexes of Wireless Telephone Services, January 2019 – December 2022



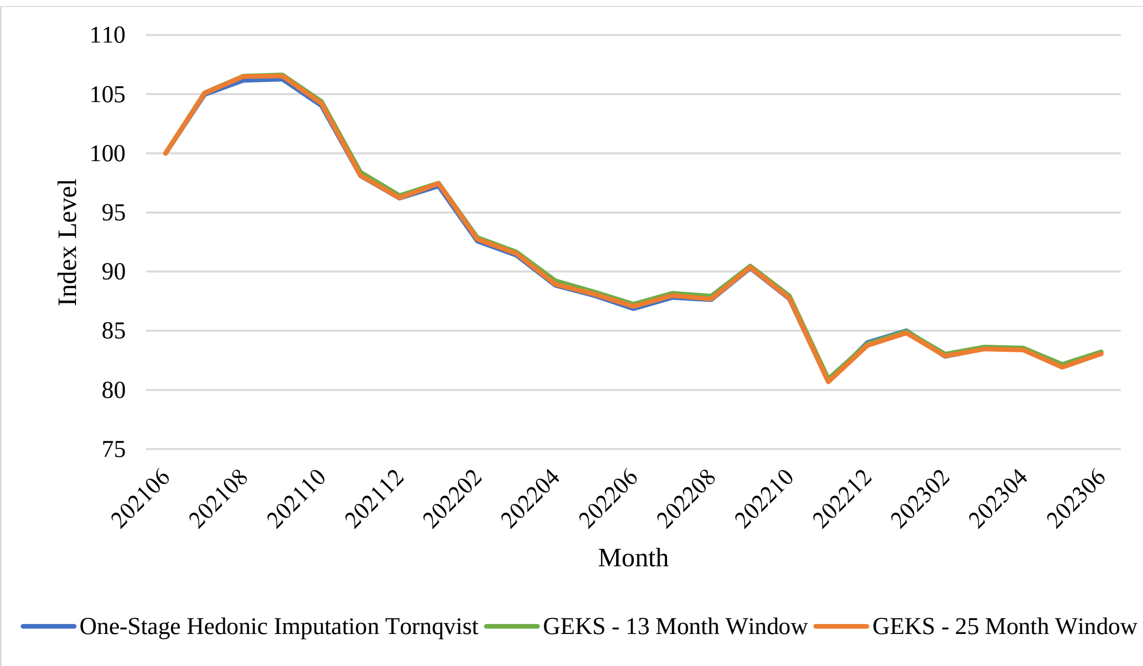
5.3 Chain Drift

Chained, superlative indexes like the hedonic Tornqvist indexes calculated above can be subject to chain drift, which occurs when an index "indicates an overall price change, even though the prices and quantities in the current period have reverted back to their levels of the base period" (von Auer 2019). Chain drift often occurs in indexes built with scanner data because consumers tend to buy more of an item the month the item goes on sale. If consumers purchase a higher quantity of an item the month it goes on sale, the weight given to the observation's negative relative in the sale month will be higher than the weight given to observation's positive relative the month when the item returns from that sale. This will lead to a chained index that shows greater price declines than a direct or multilateral index (see de Haan (2008) and de Haan and van der Grient

(2011)). Life cycle effects can lead to negative chain drift as well. Specifically, Melser and Webster (2021) found that end-of-life runout sales are more heavily weighted in chained indexes than in multilateral indexes because multi-lateral indexes tend to reduce the impact of exiting goods. Chain drift can also occur in the positive direction. Delayed changes in the purchasing behavior of consumers can lead to positive drift as demonstrated by von Auer (2019).

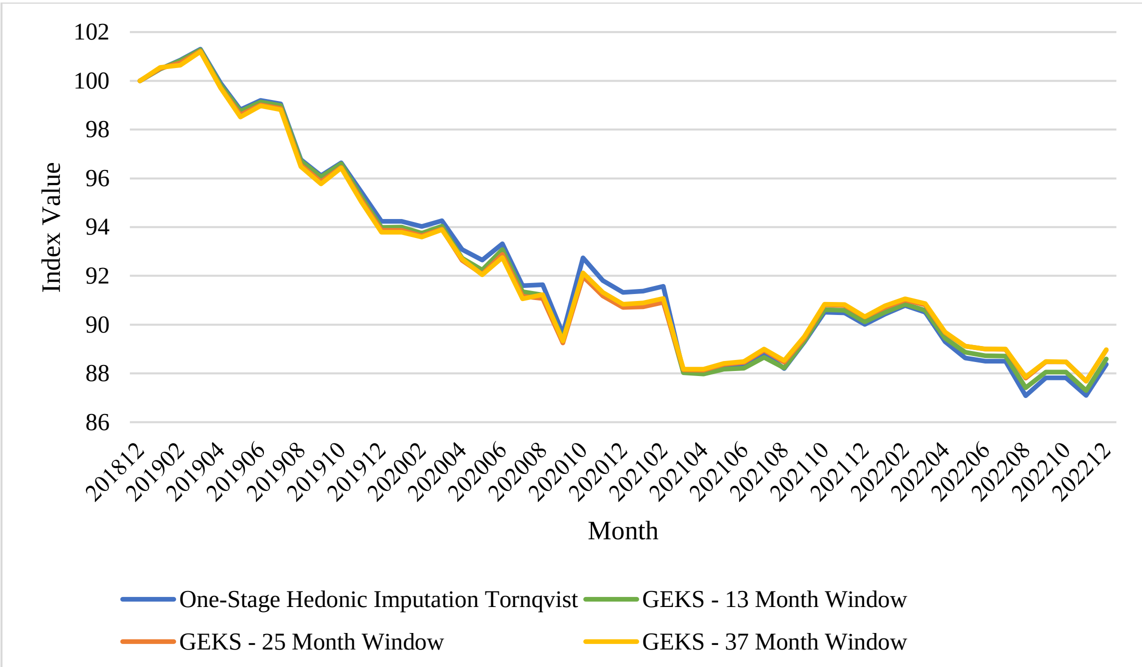
To determine whether our chained hedonic Tornqvist indexes exhibit chain drift, those indexes were compared to GEKS indexes calculated using the same predicted prices and quantities. For televisions, the one-stage hedonic Tornqvist index was used to measure drift. The one-stage hedonic Tornqvist index was compared against GEKS indexes with 25-month and 13-month windows. This test was run over a 25-month period so that the 25-month window GEKS index exhibits zero chain drift. The 13-month GEKS index employs mean splicing. Our research index, the one-stage hedonic imputation Tornqvist, experienced a 25-month percent change of -16.88 percent compared to the 13-month and 25-month GEKS indexes which fell 16.79 and 16.94 percent, respectively. Results are displayed below in Figure 3.

Figure 3: Hedonic Tornqvist Index vs. Hedonic GEKS Indexes, June 2021 – June 2023: Televisions



For wireless telephone services, the one-stage hedonic Tornqvist index was also used to measure drift. The one-stage hedonic Tornqvist index was compared against GEKS indexes with 37, 25, and 13-month windows. Each GEKS index employs mean splicing. Results are displayed below inf Figure 4.

Figure 4: Hedonic Tornqvist Index vs. Hedonic GEKS Indexes, January 2019 – December 2022: Wireless Telephone Services



Little drift is exhibited by the chained hedonic indexes for either item. For televisions, we observe an annualized difference of only 0.03 percent between the chained Tornqvist and 25-month GEKS indexes, and for wireless telephones services, we observe an annualized difference of only 0.15 percent between the chained Tornqvist and 37-month GEKS indexes. This is to be expected as, unlike the chained indexes generated by de Haan, our indexes use estimated expenditures, not actual expenditure amounts. NCER expenditure estimates are made using third-party market data which represents the last four rolling quarters of expenditure. Wireless Telephone Service expenditure estimates are derived from a single, static year of survey data and revised every two years. These expenditure estimates do not react to sales on a month-to-month basis like scanner data. Additionally, we do not use actual prices like Melser and Webster. Rather, we use predicted prices for all goods in all periods. Thus, we do not observe the drift observed from end-of-cycle sales that were observed in their research. In total, because predicted prices are less subject to transitory price volatility than actual prices (Ehrlich, et al, 2023), and because our weighting scheme estimates relatively stable observation-level expenditures month-to-month, chained hedonic imputation Tornqvist and hedonic imputation GEKS indexes are extremely similar for both televisions and wireless telephone services.

6. Conclusion

The goal of this research is to practically demonstrate how BLS can harness alternatively sourced data in the calculation of hedonic indexes. We see that the data used in this research can support such an application, and, while we did not attempt to mirror the CPI program's production schedule, we believe that the qualities of the data lend itself to being used as described within its strict monthly time constraints. In terms of the implementation of these alternative data sources, the CPI program has multiple possible paths forward. The televisions data from NCER used in this research could be incorporated with traditionally collected data from other retailers of televisions to calculate basic entity level indexes, while the wireless telephone services data is sufficient to represent the entire item level index.

In additional to the practical implications, our research shows that the hedonic imputation methodological approaches described by Pakes (2003) and by Erickson and Pakes (2011) combined with Tornqvist aggregation produce research series that tend to decrease faster than the official indexes for televisions and wireless telephone services that are based on matched model indexes with hedonic price adjustments at item replacement. For televisions, the two-stage hedonic imputation methodology better captures the effects of unobserved characteristics and reacts more quickly to one-month price shocks than does the CPI component index. For wireless telephone service, the use of alternatively sourced data greatly increases the representativeness of the index and the one-stage hedonic imputation methodology results in improved measures of constant quality price change as it allows for the introduction of new goods outside of the traditional item replacement process. We demonstrated that the two-stage Erickson and Pakes (2011) approach is suitable for products like television where prices of old products are discounted as newer products appear in the market but are not recommended for products like wireless telephone services where products are not typically discounted throughout their lifecycle.

Given that our research indexes utilize a chained Tornqvist aggregation formula which can produce indexes that are subject to chain drift, we compared our research series to various GEKS indexes calculated using the same predicted prices and estimated quantities. We found little evidence of extreme drift in the chained hedonic indexes for either item and conclude that this is due to our weights and prices being relatively more stable than weights and prices observed from scanner data.

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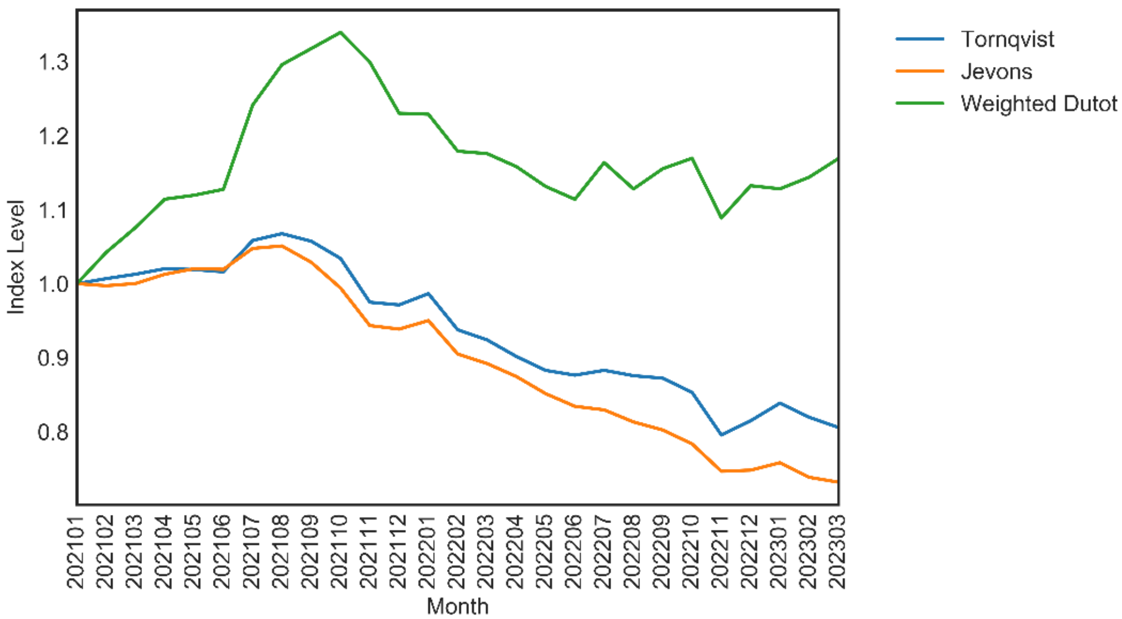
Appendix A

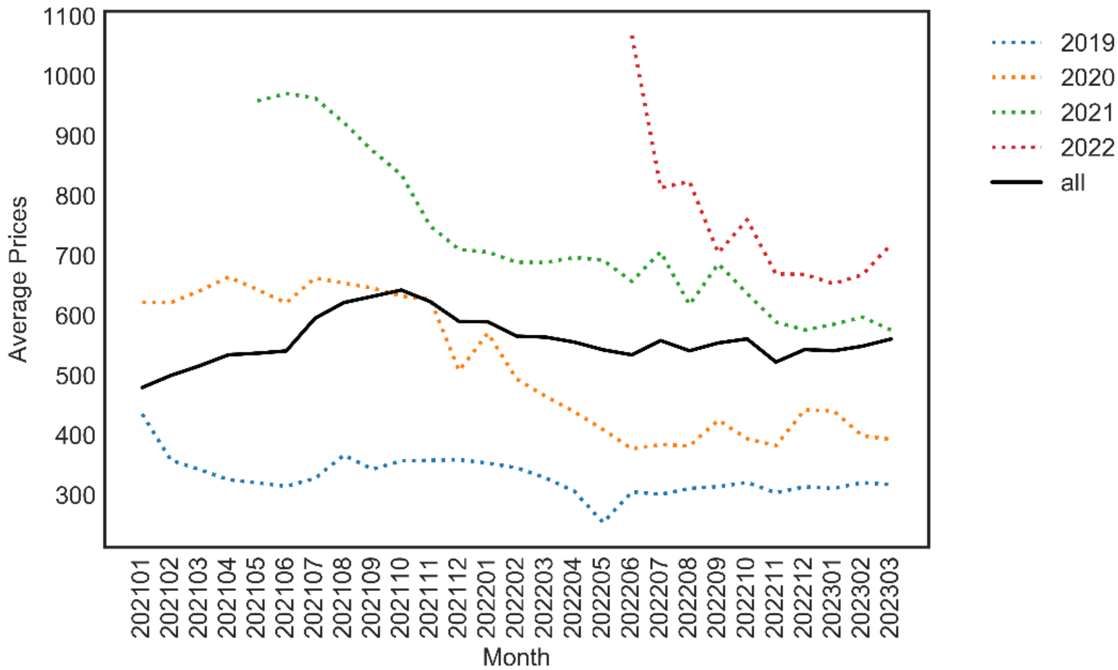
Product life cycle effects must be considered when calculating a true cost of living index. Specifically, in the televisions market, the majority of products enter at the highest price point in their product life cycle, and as their time in the market increases, their price decreases. This phenomenon can be visualized in two ways. First, Figure A.1 compares a weighted Dutot index, which simply tracks weighted average prices in the NCER sample, to strict matched model Tornqvist and Jevons indexes. These strict matched model indexes use no imputation, item replacement, or quality adjustment; they simply match models across time. The chained Tornqvist index uses the weighting mechanism described above to estimate product-level expenditures.

Figure A.1: Matched Model Indexes vs. Weighted Average Prices: Televisions



While weighted average prices rose significantly in the NCER data, Tornqvist and Jevons indexes fell precipitously. This is because average price increases in the televisions market tend to occur when a product enters the market. De Haan and Diewert found this to be true in the market for televisions (2017). Figure A.2 visualizes this phenomenon in a different way, comparing the weighted average price of all televisions to weighted average prices for each model year. Note that each model year only appears on the chart when at least 50 unique televisions are offered for sale by NCER.

Figure A.2: Average Prices by Model Year vs. All Average Prices: Televisions



While prices within each model year tend to fall over time, particularly during the first six months after introduction, average prices remain stable as consumers shift their expenditures to higher-priced, newly introduced model years. The interaction between falling prices within a model year and expenditure shifts to recently introduced, higher priced televisions keeps average prices for all televisions relatively stable.

Just like actual sales prices, predicted prices also fall for televisions throughout their product life cycle. However, predicted prices tend to fall at a slower rate than actual prices. Additionally, televisions tend to have positive residuals (higher actual prices than predicted prices) at the start of their life cycle, and negative residuals (lower actual prices than predicted prices) at the end of their life cycle. Figure A.3 shows the weighted average residual of a television at different stages of their product life cycle. Figure A.4 displays the mean residual on ln(price) segmented by model year for five selected months. Both figures display the falling residuals phenomenon.

Figure A.3: Weighted Mean Residuals on ln(Price) by Months since Entry: Televisions

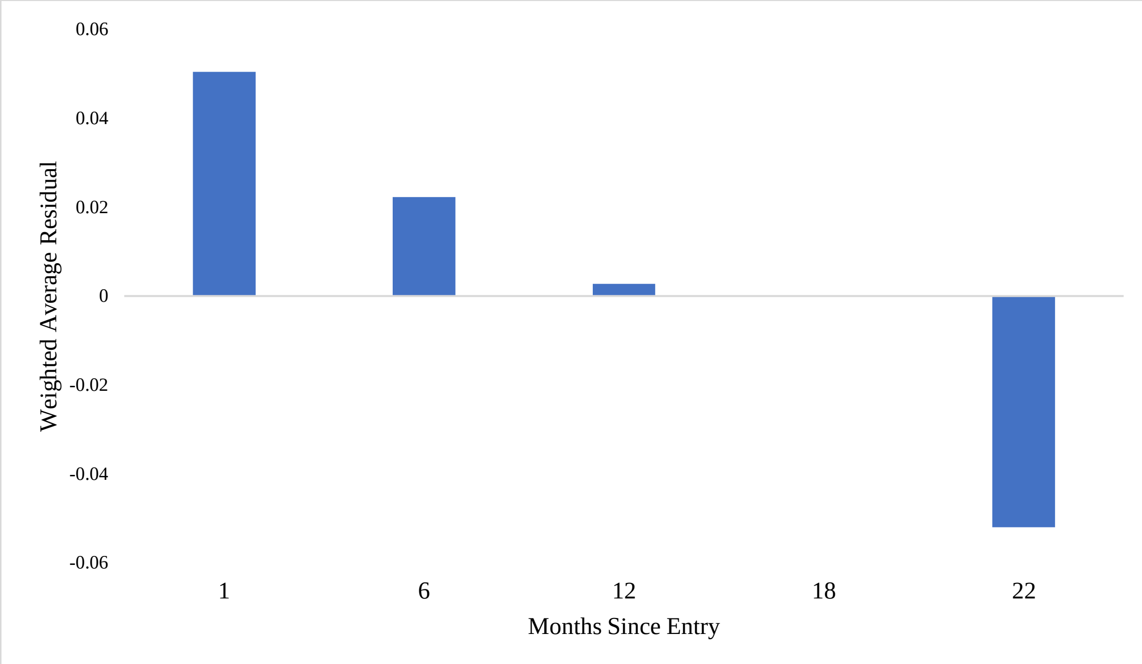


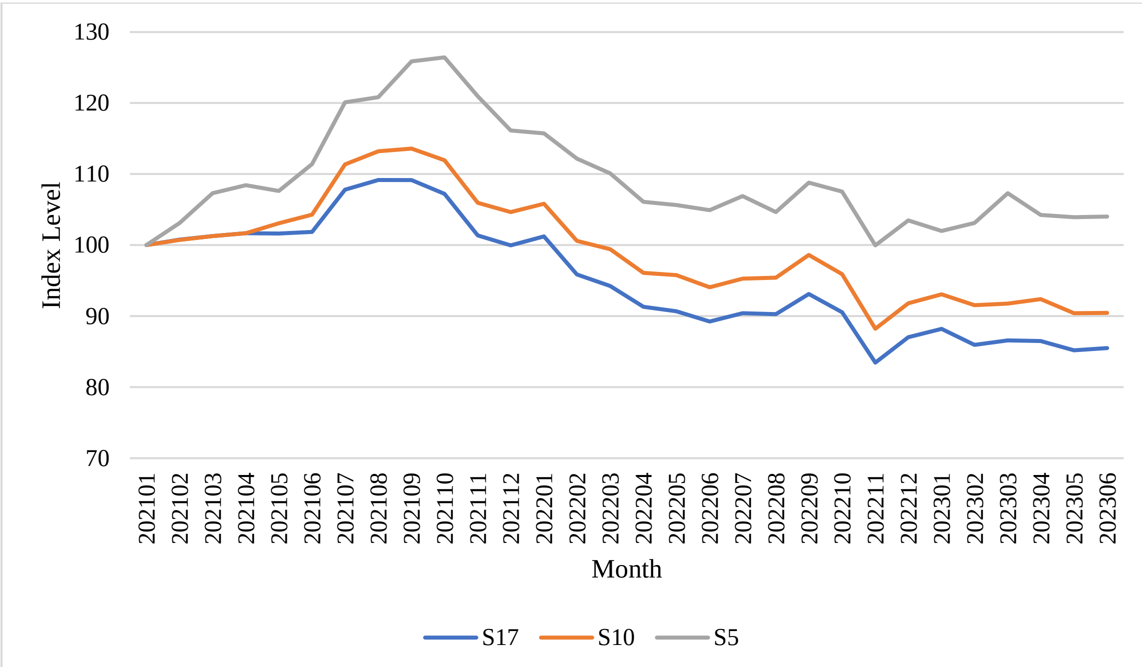
Figure A.4: Weighted Mean Residuals by Model Year: Televisions

There are two possible explanations for this phenomenon. First, firms may be aware that they are marketing towards different consumer groups at the start and end of a product's life cycle. At the beginning of the life cycle, a "price insensitive" group who desire cutting-edge features no matter the price may make up most consumers. At the end of the life cycle, a "price sensitive" group, who wait until prices fall before making a purchase, may make up the majority of consumers. Negative product-level price relatives may exist for a television throughout the duration of its product life cycle not only because it is being obsoleted by higher-tech entrants, but also because the television is marketed to a consumer group with a lower willingness to pay for cutting-edge features. This effect is known as intertemporal price discrimination and has been identified in the vehicles market in previous research (Aizcorbe et al., 2010, Williams and Sager 2019). Since predicted prices only fall if the value of a television's bundle of characteristics falls, the difference between a television's predicted and actual price may capture the markup firms put on early life-cycle televisions regardless of that television's characteristics.

A second possible explanation is offered by Erickson and Pakes (2011). They contend that residuals are falling for products because "unobserved characteristics" exist in the market for televisions. These unobserved characteristics improve the visual or audio quality of a television but are not able to be captured by product specifications, and thus cannot be controlled for in a hedonic regression model. Newly introduced televisions are more likely to contain unobserved characteristics that are novel to the market and increase the value of a television. As a television ages, these unobserved characteristics become more ubiquitous in the market. The television becomes obsoleted by newer model years, and the product's residual falls.

To test whether unobservable characteristics play a role in the falling residual phenomenon, we ran three one-stage, full imputation Tornqvist indexes, each with their own set of regressors. These indexes do not include Erickson and Pakes's (2011) correction for residual change. The first index "S5", contained only dummy variables for three high value brands, screen area, and screen area squared. The second index, "S10", adds five highly predictive technological dummy variables. The final index "S17" adds four less predictive technological dummy variables, and three other brand dummies. In short, the "S5" and "S10" indexes exclude characteristics, which artificially increases the number of unobservable, high-tech features. If the exclusion of unobservable characteristics biases our index upwards, each full imputation index calculated with more features will result in sharper price declines.

Figure A.5: Full Imputation Index Results with S5, S10, and S17 Regressor Sets: Televisions



As Figure A.5 shows, as we increase the number of relevant specifications in our price prediction model, we observe greater price declines in the resulting indexes. This shows that unobserved characteristics drive at least some of the residual change phenomenon described in this section. Erickson and Pakes (2011) ran the same test and saw similar results.

As previously mentioned, Erickson and Pakes (2011) offer a solution to the impact of unobservable characteristics on our estimation of change to the cost of living, previously referred to as the "two-stage" method. Since Figure A.5 shows that the exclusion of unobserved characteristics causes an upwards bias in a one-stage hedonic index, implementing Erickson and Pakes' second stage adjustment would help ameliorate this source of bias in a hedonic index for televisions.

In section 4.2, we stated that the Erickson and Pakes (2011) methodology was most appropriate for products undergoing rapid quality change with the entry of new goods but noted that this method relies on the existence of intertemporal variation in prices for continuing goods. Unlike many consumer electronics devices, most telecommunications services do not change price during their life cycles and indexes for these items experience price movement primarily when products exit and enter the market. Therefore, the two-stage Erickson and Pakes (2011) approach was not pursued for wireless telephone services. Instead, a single-stage hedonic imputation index, as described in Pakes (2003) was applied to wireless telephone services.

To provide objective evidence to the claim regarding the absence of intertemporal price change for wireless telephone services, Table A.1 compares the percent of price relatives used in the calculation of the research hedonic indexes for televisions and wireless telephone services by type of price change. A small percentage of wireless telephone service plans experienced price changes during their life cycle over the period of this study (January 2019 – December 2022). In contrast, the majority of television observations exhibit a change in price on a month-to-month basis. Nearly 98 percent of wireless telephone service observations exhibit no one-month price change, while only 34.7 percent of televisions exhibit no one-month price change, as displayed in Table A.1.

Table A.1: Percent of Price Relatives by Type of Price Change and Product

Type of Price Change	Televisions	Wireless Telephone Services
Positive	24.3%	0.8%
None	34.7%	97.6%
Negative	41.0%	1.6%

Appendix B

In Appendix B we provide additional information on the different product groups analyzed in this study. A brief overview of the data sets and explanatory variables are described.

Televisions

The price and characteristics data set for the period of study (January 2021 – June 2023) for televisions consists of 10,058 total, usable price observations. An observation is considered usable if it is not eliminated in the data cleaning process and if it receives a non-zero expenditure estimation. There are 831 total eligible, unique SKUs in the dataset. The NCER dataset is rich with characteristic variables, the most relevant of which are described in the table below.

Table B.1: Relevant Specification Variables Provided by NCER: Televisions

Characteristic	Type of Variable(s)	Description
Screen Area	Continuous	Screen Area in Square Inches
Resolution	Categorical	Number of Pixels
Refresh Rate	Categorical	Times/second the TV displays a new image
OLED	Categorical	Organic Light Emitting Diode (leads to clearer, brighter picture)
Brand	Categorical	
Number of HMDI Inputs	Continuous	HDMI Inputs allow TVs to connect with external AV devices like laptops, gaming systems, and Blu Ray players
Number of Digital Optical Audio Inputs	Continuous	Number of inputs for external speakers
HDR	Categorical	High Dynamic Range: Improved contrast and light sensitivity
Smart TV	Categorical	The TV has integrated internet connectivity
Quantum Dot Technology (QLED)	Categorical	Semi-conductor particles that lead to more accurate colors and a larger color gambit
Screen Depth	Continuous	How thin the television is
Local Dimming	Categorical	The TV can backlight only bright parts of an image
Model Year	Continuous	The year the TV was manufactured
Glare Resistance	Categorical	Glare Resistant Coating for Outside Viewing

We use data from the market research company to weigh our observations. Over 150,000 surveys are returned each quarter, with an average of over 16,000 reported television purchases. Data from this firm covers 100 percent of CPI's self-representing areas, and most of its non-self-representing areas.

As noted earlier, the market research company allows users to segment national expenditure by product characteristics. The full list of characteristics that are reported on the surveys include smart TV capability, refresh rate, resolution, brand, and screen area. As mentioned in section 3, brand, resolution, and screen size were selected because of their consistent statistical significance in regressions on price. Since the company also allows users to segment expenditures by geographical location and/or consumer demographics, it would be possible to create unique expenditure weights at the area level.

Wireless telephone services

The price and characteristics data set for the period of study (January 2019 – December 2022) for wireless telephone services consists of approximately 7,700 observations and were purchased by BLS from a market research firm. These data include service plans providing wireless talk, text, and data. Services plans can be either prepaid or post-paid accounts. We limit prepaid plans to observations with less than three serviced lines per plan and we limit post-paid plans to observations with less than six serviced lines per plan. Each observation is a unique combination of service plan name, provider, number of serviced lines per plan, type of customer, contract length, and reference month. Wireless service plans are sold at one price nationally, so there is no need to consider geographic characteristics. We derive an average monthly price over the contract length. The following explanatory variables are available for inclusion in the regression models: plan provider, account type (pre- or post-paid), number of serviced lines per plan, amount of included high-speed data measured in gigabyte (GB) – both the actual and log values, amount of hot spot data included (GB), the type of video quality provided by the plan, and variables for included promotional features such as streaming video subscriptions. The most important quality variables are the number of serviced lines and the amount of high-speed data included per plan. It is important to note that some service plans do not include data and these plans are coded as basic plans. Other plans describe themselves as offering consumers unlimited data when what they offer are large, capped amounts of high-speed data. When the consumer uses their allotted amount of high-speed data, they may continue to use data, but they will be demoted to a slower network. We use the amount of the high-speed data cap in our models. Still other plans claim to offer unlimited data with no caps. These plans are often lower priced than other "unlimited" plans because the consumer is only given access to lower speed networks. We code these unlimited plans differently than plans that offer access to high-speed data.

The data used for weighting observations in the study come from surveys conducted in 2018 and 2019 by a market research firm and were purchased by BLS. The data consist of approximately 30,000 responses to each survey that have been summarized to the service provider, account type, number of serviced lines per plan, and amount of included high-speed data per plan level. The amount of included high-speed data per plan is a categorical variable with three values: No data included, greater than or equal to 1 GB and less than 10 GB, and greater than or equal to 10 GB. Outliers are removed before calculating the expenditure shares. The expenditure shares are calculated in two steps. The first step summarizes by provider, and in the second step we adjust the provider shares by the providers national market share so that all the expenditure shares in the data set sum to 100. An example row in the data set may show that 5 percent of total monthly expenditure is on postpaid, 2-line plans with 1 – 10 GBs of included data from wireless provider XYZ. We combine the weight data with the price and characteristics data by determining which expenditure share category each service plan maps to and then divide the expenditure share of that category equally among all service plans mapped to that category. To illustrate this, if the expenditure share category we just described above with 5 percent of the weight has four service plans that map to it, each of those four plans will receive a final expenditure share of 1.25.

Appendix C

Appendix C provides a short overview of some of the estimation results of the hedonic models used in this research.[13]

Our regression analyses were informed by machine learning feature selection techniques. We used the GLMSELECT procedure in SAS to suggest a parsimonious model for wireless telephone service. The GLMSELECT procedure utilizes a stepwise selection process informed by *k*-fold cross validation to specify a sparse model with high predictive power. LASSO and Random Forest techniques were performed in Python to suggest a highly predictive model for televisions. Feature selection techniques like these will be particularly useful once the BLS adopts these data and methodologies for monthly index calculations. Automating the initial stages of the hedonic model estimation process will allow BLS to maintain a well specified model within its monthly production schedule. Ultimately, the models suggested by the machine learning tools for each item were evaluated by researchers and the specifications were adjusted based on economic knowledge and expertise of the respective markets and datasets.

Televisions

Table C.1: Hedonic Regression Models: Televisions

Month	202101	202306
Dependent variable	ln(price)	ln(price)
Mean square error	0.05417	0.1145
R-Square	0.9668	0.9355
Number of observations	288	394
Variables	**Parameter Estimates**	
Intercept	4.81864***	4.83660***
	(0.12036)	(0.15378)
Screen Area (sq. inches)	0.0051817***	0.00038549***
	(0.00007990)	(0.00008106)
Screen Area Squared	2.385675E-8	3.686463E-8*
	(2.143248E-8)	(2.02819E-8)
Depth (inches)	-0.07664***	-0.07522***
	(0.02658)	(0.02343)
Quantum Dot Technology	0.39060***	0.32852***
	(0.03467)	(0.04035)
OLED	0.71663***	0.65068***
	(0.05369)	(0.04949)
Resolution – 8K	1.35033***	1.18755***
	(0.11150)	(0.14341)
Resolution – 4K	0.50554***	0.48530***
	(0.09759)	(0.14341)
Resolution – Full HD 1080p	0.27660***	0.28763**
	(0.09281)	(0.13291)
Refresh Rate – 120Hz	0.42095***	0.36381***
	(0.03285)	(0.03730)
Brand 1	0.59190***	0.69580***
	(0.03964)	(0.04965)
Brand 2	0.22772***	0.30918***
	(0.03445)	(0.04965)
Brand 3	0.21788***	0.32825***
	(0.04397)	(0.04860)

[13] For Tables C.1 and C.2, note that * = Significant at the 10% level, ** = Significant at the 5% level, *** = Significant at the 1% level, and standard errors are in parenthesis.

Figure C.1: Parameter Estimates of Dummy Variables over Time: Televisions

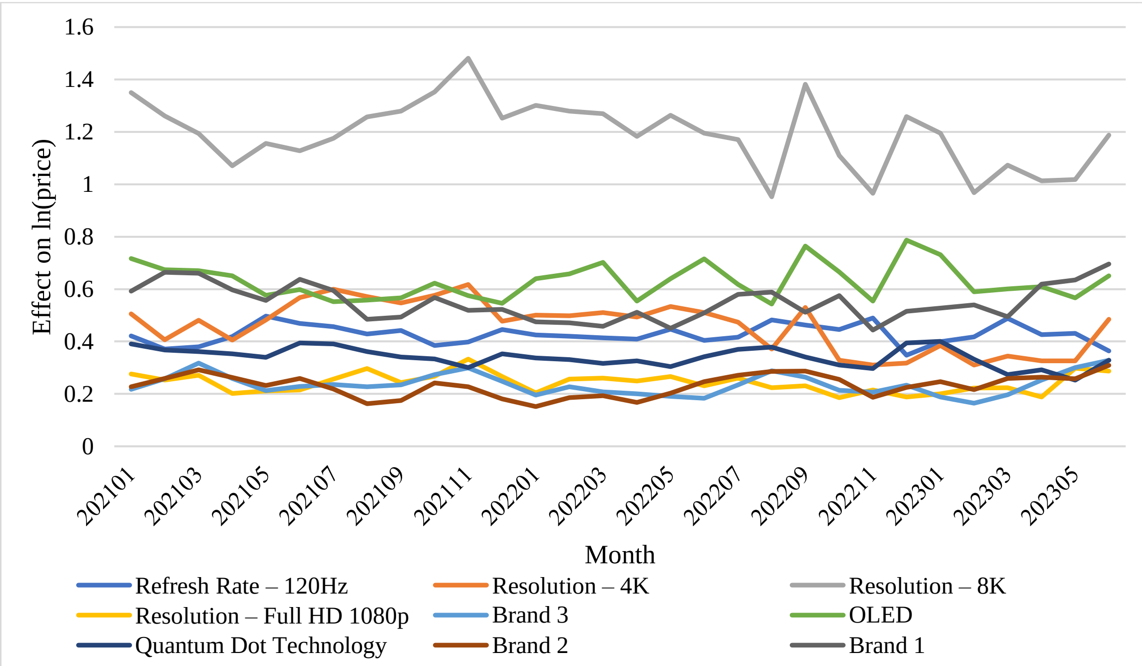


Figure C.2: Parameter Estimates of Continuous Variables over Time: Televisions

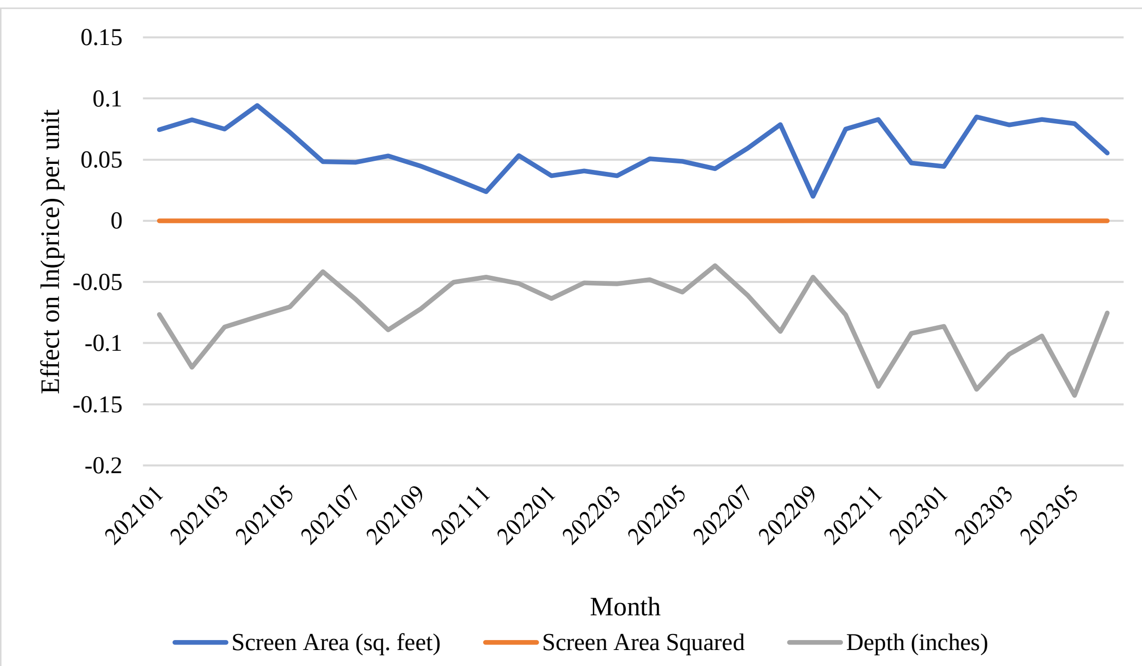
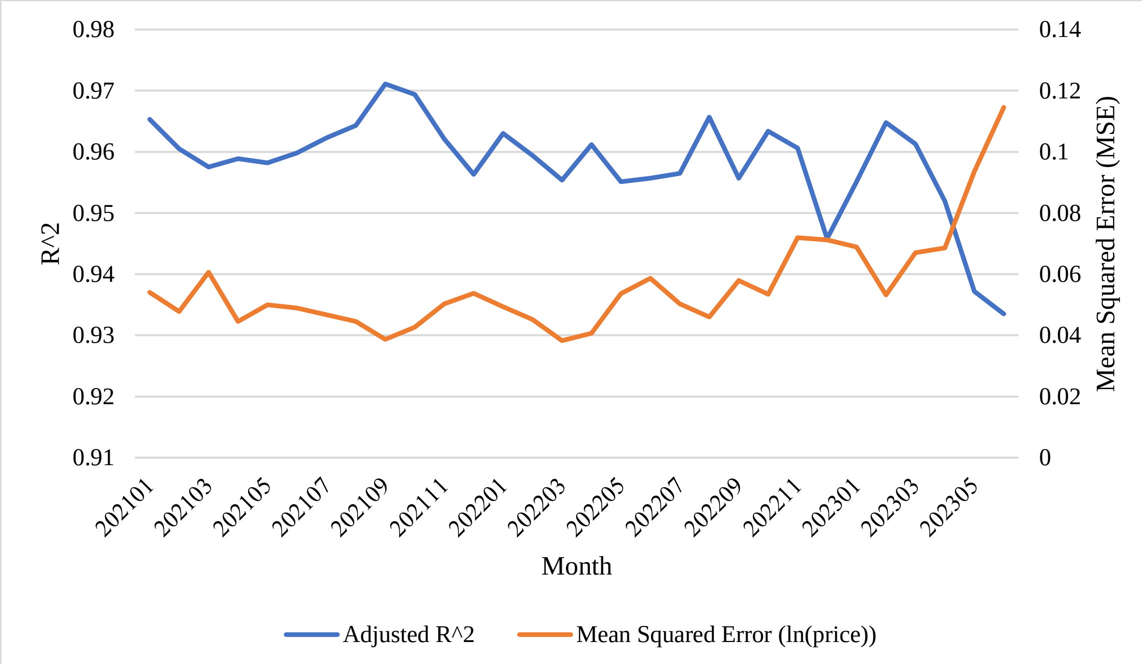


Figure C.3: Fit Statistics over Time: Televisions



Wireless Telephone Services

Table C.2: Hedonic Regression Models: Wireless Telephone Services

Month	**201901**	**202212**
Dependent variable	ln(price)	ln(price)
Mean square error	0.13929	0.15900
R-Square	0.8961	0.8287
Number of observations	148	163
Variables	**Parameter Estimates**	
Intercept	3.67348***	3.49332***
	(0.04562)	(0.06547)
Prepaid Account	-0.48417***	-0.44788***
	(0.04845)	(0.06082)
Number of Lines	0.24354***	0.23527***
	(0.01236)	(0.01519)
ln(Amount of High-Speed Data)	0.17946***	0.19902***
	(0.01335)	(0.02060)
Unlimited Data Plan (low speed)	0.53938***	0.69523***
	(0.06451)	(0.07166)
Provider 2	-0.30195***	-0.36265***
	(0.05152)	(0.05768)

Figure C.4: Parameter Estimates over Time: Wireless Telephone Services

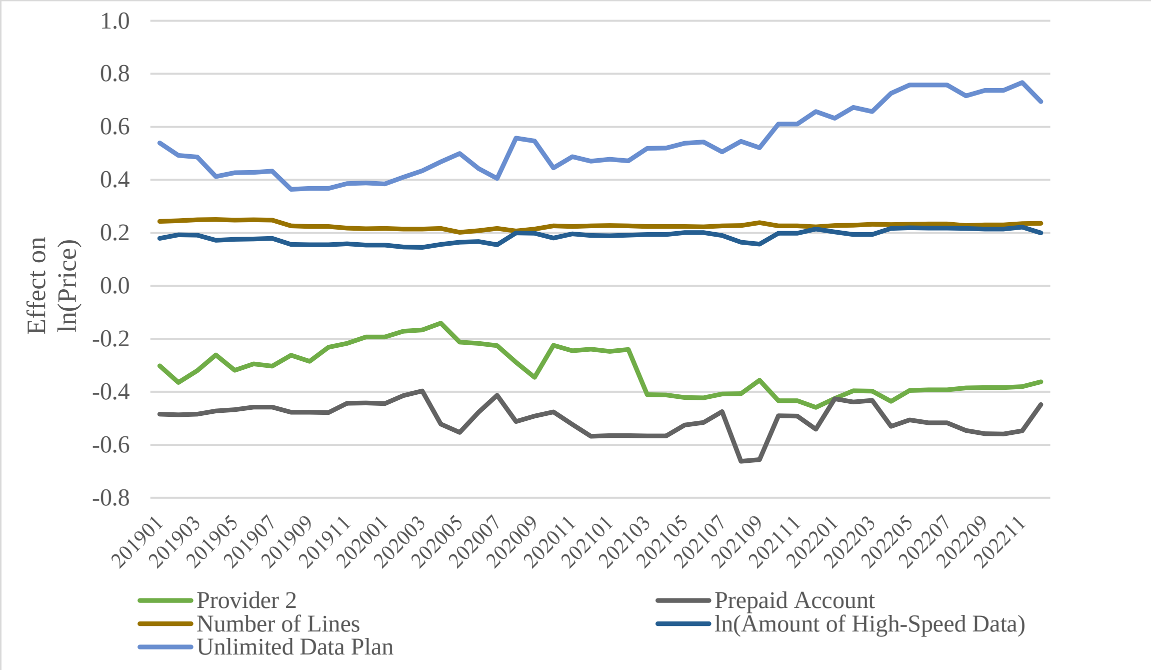


Figure C.5: Fit Statistics over Time: Wireless Telephone Services