Measuring Growth from Better and Better Goods

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June 2004

Abstract

Using micro CPI data, I show that much of inflation for durable goods since 1988 reflects, not increases in price for a given set of products, but rather shifts to a newer set of product models that display higher prices. I examine how these price differences should be divided between quality growth and price inflation based on how consumer spending responds to product substitutions. For all goods examined (cars, other vehicles, televisions, and other consumer electronics), buying shifts to the newer models despite their higher prices. This suggests that quality growth for durables has averaged at least 5.8% per year, more than double the rate implied by CPI measurement.

*This work was conducted while I was visiting the Bureau of Labor Statistics (BLS) under the IPA (Intergovernmental Personnel Act) agreement. A number of persons at the BLS have been extremely helpful. I want to particularly thank David Johnson, Teague Ruder, Paul Liegey, Michael Hoke, and Walter Lane. Any interpretations presented are clearly my own, and should not be associated with the BLS. I also thank Pete Klenow for his comments; this paper initiated from our discussions. The research is supported by a grant from the National Science Foundation.

Much of economic growth occurs through growth in quality as new models of consumer goods replace older, sometimes inferior, models. Moulton and Moses (1997) estimate that Bureau of Labor Statistics (BLS) methods allowed for perhaps as much as 1% average quality growth in goods in 1995. It is often argued, however, that the Bureau of Labor Statistics (BLS) methods miss much of the growth in goods' quality. (Hausman, 2003, and Pakes, 2003, are two recent examples.) The Boskin Commission Report (1996) suggests that the BLS overstates inflation by perhaps 1% per year. Unmeasured growth in quality of goods is put forth, based on examining a fairly limited set of goods, as the most important component contributing an overstatement of inflation of 0.6% per year.[1]

To calculate the CPI the BLS tracks a large set of prices, with each price specific to a particular product at a particular outlet. The products followed change for two principle reasons. At regular sample rotations, roughly every four years, the BLS draws a new sample of stores and products within a geographic area to better reflect current consumer spending. I refer to these as scheduled substitutions. In addition, a store may stop selling the particular product being priced. The BLS agent then substitutes another model of that brand or of a similar product. These (forced) substitutions occur on average about once every three years for all non housing CPI items. They occur much more frequently, nearly once per year, for consumer durables.

I employ the *CPI Commodities and Services Survey*, the monthly micro data underlying the Consumer Price Index, to show that both scheduled and forced substitutions are associated with important increases in the unit prices of durable goods. How these price increases are attributed to quality growth versus measured inflation dramatically affects long-term measures of inflation, growth, and productivity growth for durables. Although the price increases accompanying scheduled and forced substitutions largely reflect the same economic phenomenon--newer versions of goods sell at higher prices than old, BLS methods treat them very differently. Current methods implicitly treat the increases in goods' unit prices associated

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[1] Shapiro and Wilcox (1996) review much of the evidence on CPI bias. In Bils and Klenow (2001) we find that measured CPI inflation is faster for goods that we predict will display faster quality growth. This suggests that an important part of quality growth is not captured by the CPI.

with sample rotations as reflecting quality growth. Therefore, the National Income and Product Accounts (NIPA) will interpret that part of the upward trend in unit prices as real growth. By contrast, the price increases from forced substitutions *within* sample rotations have been largely attributed to price inflation, not quality growth.[2]

In the next section I calculate that BLS methods implied quality growth for consumer durables, excluding computers and related equipment, on the order of 2.7% per year for 1988 to August 2003. More than 70% of this quality growth reflects price increases across scheduled substitutions. Suppose counter factually that the BLS measured inflation based only on price changes for matched models, that is, models available in consecutive periods. This omits for one period the price changes accompanying forced substitutions, paralleling the treatment of price increases with scheduled substitutions. I calculate this would have yielded 3.1% faster quality growth for durables, with growth at 5.8% per year.

Much of the discussion of possible biases in measured inflation has been motivated by perceived feedback from measured inflation to monetary or fiscal policies (e.g., social security payments). But it should be kept in mind that most consumption deflators for the National Income and Product Accounts (NIPA) are based on BLS's measures of CPI inflation. The NIPA derive real growth measures by subtracting measured inflation from nominal spending growth for each category of good. Thus any measurement error in CPI inflation will lead to an opposite error in rates of real growth. If we cannot accurately attribute the price changes from model substitutions between quality growth and price inflation then it is not possible to ascertain rates of growth in real consumption or productivity. To illustrate, TFP growth for motor vehicles and other transportation sector (SIC 37), reflecting BLS price measurement, averaged 1.1% per year for 1987 to 2001 (from Bosworth and Triplett, 2003). But suppose that forced substitutions for motor vehicles should be treated the way scheduled substitutions are treated, with price changes across models viewed as quality upgrades. I calculate then that both quality growth and

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[2] This statement applies to nondurables as well. For instance, Moulton and Moses calculate that for 1995 forced item substitutions account for perhaps 30 percent of inflation, even excluding apparel from the calculation.

productivity growth are understated by 4.4% per year. If, on the other hand, the treatment of price changes for forced substitutions should actually be applied to scheduled substitutions then both quality and productivity growth are overstated by 1.8% per year. The implied range for TFP growth for motor vehicles varies dramatically from -0.7% to 5.5% per year.

How to allocate the price increases associated with product substitutions between quality change and inflation is an open question. Suppose inflation from one month to the next were measured based solely on price increases for models available in both months. This implicitly assumes that substituted models exhibit the same rate of change in consumer surplus as those models matched across months. As just stated, this approach would have yielded much faster quality growth than measured by past practices. Pakes (2003) suggests that even this is likely to understate quality growth because goods that exit the market are obsolete and, absent the substitution, were likely to experience a relative fall in price. By contrast, Triplett (1997), among others has argued that sellers use periods of model turnovers to increase price more than justified by quality improvements. In principle, hedonic pricing equations, as introduced by Court (1939) and developed by Griliches (1961) and Adelman (1961), might be used to split goods' rates of unit-price inflation between quality growth and true declines in purchasing power. But in practice the exacting detail on product characteristics this requires is rarely collected.[3]

I show how quality growth can be judged by the response of consumer purchases to model changes. Consider estimating the price inflation, net of quality growth, associated with replacing one television model with another. Suppose that we observe time series for prices and sales for each model; and suppose further that we know the price elasticity of market demand across models. Then, knowing the change in market share that accompanies a model change, we can

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[3]Hausman (2003) discusses practical limitations of hedonics given that the analyst typically possesses a quite small number of relevant characteristics. These include the fact that the shadow prices of characteristics are notoriously unstable and sometimes even appear perverse in sign. For instance, hedonic equations for automobiles can exhibit a negative coefficient for gasoline mileage (miles per gallon), presumably reflected a negative correlation between miles per gallon and unmeasured quality characteristics. The use of hedonic price equations by the BLS in constructing the CPI is fairly limited. Computer equipment is one good where data on several relevant characteristics is collected (e.g., RAM, processor speed) and hedonic prices play an important role. But even here, hedonics are only employed if across the substitution it is possible to match brand and all but a small number of characteristics to the base-period product.

multiply this change by the (negative) elasticity of demand to get the quality-adjusted change in price relative to the rate of increase for goods without model turnovers. In practice we typically do not know the elasticity of demand. However, if relative quantity movements are not too large, then it is possible to limit the plausible range for relative effective price movements for new models.[4] To this end, section 3 presents a model in which consumers choose both variety and quality for a broad set of durable goods. Section 4 employs the model to construct an estimator of inflation based on the price changes of matched models (those available in consecutive periods) and on what happens to the market share of matched goods.

Section 5 returns to the data to examine the question: If we measured price inflation based only on the price changes for matched goods, would this measure be biased upward or downward? I examine how market share responds to model substitutions for motor vehicles by linking substitution rates by vehicle model in the *CPI Commodities and Services Survey* to sales data by model from *Ward's Automotive*. I similarly examine changes in market share for video, audio, and telecommunications products based on scanner data. These goods generate about 75 percent of the price increases from model substitutions for durables (weighting goods by expenditure shares). For all these goods, I find a declining market share for matched models relative to those with model turnovers. This suggests that even measuring inflation based on matched-model inflation may overstate inflation and understate quality growth. Section 5 additionally examines how prices for continuing (matched) models respond to frequent model changes for competing products.

The final section summarizes the findings. I conclude that average quality growth for durables has likely been understated by 3 percent per year, or more, during the past 15 years. This is about three times the bias for durables underlying the Boskin commission report. The final section also discusses extending the results beyond durables.

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[4] A product should be priced in the elastic portion of its demand. So, if appearance of a new model creates a drop in relative quantity of 5 percent, we can assume that its relative price increase is less than 5 percent. Relatedly, Hausman (2003) argues that proper construction of a price index requires that the BLS collect data on quantities. I attempt to recover much of the needed information for durables from available information on quantities.

2. *The Quality Measurement Problem*

The problem of measuring quality growth can be viewed as allocating the rate of growth in unit prices of consumer goods ($\pi_{unit-price}$) to that reflecting quality growth ($g_{quality}$) and that reflecting true inflation, that is, the growth in prices holding quality constant ($\pi_{constant\,quality}$)

$$\pi_{unit-price} = g_{quality} + \pi_{constant\,quality} \; .$$

Implicit are subscripts denoting a particular good and time period. It is also implicit that these variables reflect averages over the population. Not all consumers will face the same rate of growth in unit price for good *i*; and a good's model change can present a greater quality improvement for some consumers than others. $\pi_{constant\,quality}$ is the required change in nominal expenditure to achieve a certain base-year level of welfare, given changes over time in prices and qualities of goods. The next section provides a setting where $g_{quality}$ and $\pi_{constant\,quality}$ have clear model interpretations.

The BLS collects prices on about 90,000 non-housing goods and services per month to calculate the CPI. About half of goods are priced monthly, with the others priced bimonthly. Prices are collected from about 22,000 outlets in 87 Primary Sampling Units across 45 geographic areas.[5] These prices, and other information related to the constructing the non-housing components of the *CPI*, are contained in the BLS' *CPI Commodities and Services Survey*. This is the data employed in this section and in much of the empirical work in Section 5. As discussed above, the specific products priced by the BLS change over time through both scheduled sampling changes and forced substitutions. Scheduled substitutions occur every four

[5] The BLS chooses outlets probabilistically based on household point-of-purchase surveys, and choose items within outlets based on estimates of their relative sales. The BLS divides consumption into 388 categories called Entry Level Items (ELIs). The BLS sampling methods are described in detail in Armknecht, et al. (1997) and the BLS Handbook of Methods (1997).

years.[6] For durables forced substitutions occur, weighting by importance of good, about once every 14 months.

Unit-price inflation can be broken into three parts: Inflation calculated for continuously-followed models, the extra unit-price increases across forced substitution of new versions, and thirdly the unit-price inflation associated with sample rotations.

$$(1) \qquad \pi_{unit-price} = \pi_{same\text{-}model} + s(\pi_{substitution} - \pi_{same\text{-}model}) + \pi_{sample\,rotations} \,.$$

I express the unit-price inflation associated with forced substitutions as the share of quotes with forced substitutions (*s*) multiplied by the excess inflation rate for these substitutions compared to those without substitutions ($\pi_{substitution} - \pi_{same\text{-}model}$).

I examine the importance of each of these three components for 50 separate categories (BLS Entry Level Items--ELI for short) of consumer durables using information from the *CPI Commodities and Services Survey* for years 1988 to August 2003. My focus is on durables because forced substitutions are much higher for durables. However, the approach proposed for exploiting quantity and price information can potentially be applied to other goods. Goods with a strong seasonal fashion cycle tend to be exhibit large price reductions as the seasons change. I exclude apparel to limit the importance of fashion changes. I exclude other goods with important seasonal or fashion cycles such as motor boats or entertainment CD's. I also exclude used cars, which are priced based on auction data. The categories of consumer durables are listed in Table 1. The table's third column provides the number of quotes used in analyzing price changes. The final column provides the weight of each durable in calculating the CPI for 1997. The combined share for the 50 goods is about 10 percent of the CPI. Vehicles make up about half of this share.

I observe a total of 829,364 price changes within sample rotations for the 50 durables. 95.2% reflect price changes observed over one or two months. The average duration applying to

[6] These rotations occured every 5 years historically, including much of my sample period. The BLS has moved to even more frequent sample rotations for consumer electronics.

the price changes is 1.7 months. (I exclude price changes that are measured, due say to repeated stock outs, over a period of more than 6 months.) 90.0% of price quotes reflect following the same version, whereas 10.0 % reflect forced substitutions. For the remainder of the paper I present weighted statistics--I construct mean values by expenditure category (ELI), then arrive at an aggregate number by weighting the individual categories by their shares in the 1997 CPI.[7] Weighting increases the share of forced substitutions to 12.9%.

BLS treatment of price changes associated with model changes for computers is dramatically different than for other durables. So including them with the bulk of durables hides a good deal of information. Unless noted otherwise, the statistics to follow are for the 49 durables excluding computer equipment, with results for computers and equipment presented separately.

I calculate the rate of increase in unit prices ($\pi_{unit-price}$) as follows. For each year for each category of good (ELI) I construct the average natural log price. I then regress this average price on a time trend separately for each good. Results for the separate ELI's are then weighted by each category's consumer expenditure share for 1997. Unit prices for these durables increased at an annual rate of 2.5% for January 1988 to August 2003.

The size of unit-price increases for good without and with forced substitutions are reported in the second column of Table 2. For goods with no item substitutions the average price change was actually quite negative, equaling -0.5%. This translated into an average annual inflation rate within versions, that is $\pi_{same\text{-}model}$, equal to -3.3%.[8] By contrast the price increases calculated solely for forced substitutions averaged 4.0%, or 4.5% greater than for price quotes without product substitutions. Although these forced substitutions constituted only 12.2

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[7] The BLS selects outlets proportionally to their importance in a somewhat wider product category than an ELI, for instance, based on men's clothing, not the specific ELI men's shirts. In constructing ELI-level statistics I weight by the percentage of sales within the broader category at the outlet corresponding to that ELI. The BLS refers to this percentage as the percent of pops category. The BLS Handbook of Methods, 1997, gives more detail. To be more exact, I also first construct year-ELI means then time aggregate to obtain the ELI's mean. Otherwise recent years would often be weighted more heavily as the number of quotes collected has risen.

[8] In creating the annualized inflation rate I weight the quote's inflation rate per unit of time by the duration covered since the BLS previously sampled the item (usually one or two months).

percent of the price quotes, the excess of their rate of price increase over $\pi_{same\text{-}model}$ added 3.8% annual inflation to unit-prices.

The top panel of Table 3, Column A, breaks down unit-price changes according to equation (1). The overall growth rate in unit prices, 2.5%, reflects the sum of the rate of inflation within sample rotations plus the contribution from rotations. The average annual rate of price increase within rotations equals 0.5%; this equals the -3.3% calculated based on goods without substitutions, plus the 3.8% annual unit-price inflation contributed by the excess price increases associated with forced substitutions. The rate of increase in prices across rotation samples is obtained by subtracting 0.5% from the total unit-price trend of 2.5% per year. The implied contribution from sample rotations is considerable, equaling 2.0% per year.

How these unit-price changes are divided into quality growth versus inflation defines overall quality growth for durables. For example, if we were to base quality-adjusted inflation simply on price changes for goods without model substitutions, then measured inflation would be -3.3%, with quality growth equaling 5.8% per year.

How do BLS methods treat the components of price changes? The matched-model rate of inflation, -3.3%, is obviously treated as part of CPI inflation. The price increases associated with sample rotations, 2.0% per year, are implicitly treated as quality growth. For time period *t* prices are collected for both the outgoing and incoming samples. The rate of inflation for *t-1* to *t* is based on price changes for the outgoing sample of products; the rate for *t* to *t+1* is based price changes for the incoming products. As there is no direct comparison of products' prices across the two samples, price increases from sample rotations have no impact on measured inflation. By contrast, for many forced substitutions the BLS does compare prices of the new version of products to that of the discontinued item.

The BLS follows several different procedures for dividing the price increases from forced substitutions between CPI inflation and quality growth. These are described in detail by Armknecht and Weyback, 1989. Faced with a forced substitution, an analyst examines brief written descriptions of the old and new goods provided by the field agent to determine which procedure to apply. Table 2 shows the prevalence of each procedure for treating quality growth for forced substitutions for durables for January 1988 to August 2003.

Often the new good is judged to be strictly comparable to the model that dropped out. This occurred for a little over one third of substitutions for durable goods (weighting goods by expenditure shares). It is even more common outside of durables, being employed in 58% of substitutions for all goods and services in 1997. With this procedure the new model's price is compared directly to that of the older model in calculating inflation, with quality growth across the model change set to zero. For these substitutions price was, on average, 2.6% higher for the new model than for model priced before, with all of this increase allocated to CPI inflation.

The BLS's other common method for durables is to make an explicit or direct quality adjustment based on comparing the characteristics of the old and new models. These can reflect applying hedonic pricing equations or employing information on production costs for new features. This procedure was also employed in a little over a third of substitutions for durables. (It is much less common for non durables.) Prices increased on average by 4.3% for these substitutions. BLS direct quality adjustments for these substitutions averaged only 0.5%; so much of the average price increase across these substitutions was treated as CPI inflation.

Other adjustments refer to two other procedures, called return-from-sale and class-mean, that make an indirect adjustment for quality. Together they accounted for nearly 20 percent of substitutions. Neither procedure directly compares the new model's price to the replaced model's. The return-from-sale procedure adds back inflation equal to price reductions that the replaced item exhibited during sales prior to disappearing. The class-means procedure assigns for that quote the average CPI inflation rate exhibited within that category of goods by substitutions treated as comparable or treated with direct quality adjustments.[9] Goods treated with these two types of adjustments exhibited unit-price increases across the substitutions of 7.3%. Because

[9] Over the 1988 to 2003 period use of the return-from-sale procedure has been sharply reduced for durables, whereas use of the class-means procedure has grown in importance.

these substitutions were assigned average CPI inflation of 5.1%, they were implicitly treated with average quality growth of only 2.3%.

Finally, for only 10 percent of forced substitutions the BLS omitted the price change entirely in calculating CPI inflation. This is referred to as the deletion method. This approach implicitly treats the price change from the old to new model, net of measured inflation for other price quotes, as the quality growth across models. This parallels the treatment of model changes associated with regular sample rotations. These quotes exhibited price increases of 2.2%. Quotes treated by the deletion method indirectly are assigned the inflation rate measured for all other price quotes in their category. Because this rate averaged nearly zero, the price increases associated with these forced substitutions translated into average quality growth of the same magnitude.

Across all forced substitutions prices increased on average by 4.0%. (By comparison, with no substitution prices fell by 0.5% on average.) Overall only 20 percent of the price increases that accompanied forced substitutions were allocated, explicitly or implicitly, as quality growth. Appendix 1 reexamines the impact of forced substitutions on unit-price and BLS defined inflation using regression analysis. There I examine to what extent the big price increases across forced substitutions are offset by smaller than usual price increases in the periods preceding or following the substitution. There is a predictable fall in prices for the observations directly preceding a forced substitution. But this cut is fairly small relative to the price increase accompanying the substitution. Examining a larger window in time around the forced substitutions reduces their impact on price changes by only about 20 percent in magnitude.

The annual rates of quality growth implied by alternative treatments of forced substitutions are presented in the bottom panel of Table 3. The average BLS quality-adjustment associated with forced substitutions averaged only about 0.7% per year. Adding to this the 2.0% annual growth in unit prices contributed by sample rotations, I calculate total quality growth implicit in BLS methods on the order of 2.7% per year. By contrast, had price inflation been based solely on matched-model inflation, quality-growth associated with forced substitutions would have been 3.8% per year, with total quality growth equaling 5.8% per year.

These results hide important differences across the 49 goods. Based on the analysis of market shares to follow, I separate out two sets of durables: (i) vehicles, and (ii) consumer electronics (video, audio, and telephone equipment). This is done in Columns B and C of Table 3. Both vehicles and consumer electronics display much higher forced-substitution rates than the other durables. The substitution rate is 15.8% for vehicles and 15.1% for consumer electronics. (For the balance of the 49 durables it is 7.1%.) Unit-price inflation is much lower for consumer electronics, reflecting rapid deflation of nearly 10% per year for goods without substitutions. If inflation had been based solely on same-model inflation, I calculate that quality growth would have been 4.4% higher per year for vehicles and 2.9% percent higher for consumer electronics.

Table 3 shows that measured quality growth depends crucially on how much of the increase in prices across substitutions is assigned to quality growth. Consider measuring inflation based only on price changes for products available at consecutive observations (matched-model inflation). This treatment has intuitive appeal. When products are replaced, either by scheduled or forced substitutions, it treats the increase in price for the newer models, relative to increases for the continuously observed goods, as a measure of quality change. It roughly corresponds to Gordon's (1990) approach to measuring durables goods prices by following catalogue prices for similar items over time. Table 3 shows that this measure of inflation implies quality growth of 5.8% per year for durables (excluding computing equipment). Again, even this could be too low; it is quite conceivable that new products provide quality enhancements that more than justify their higher, on average, prices (Hausman, 2003, Pakes, 2003).

BLS methods, by my calculations, implied quality growth of 2.7% per year for these durables. But most of this, 2.0%, is from implicitly assigning price increases from sample rotations to quality growth. It seems unlikely that the product and price upgrades associated with sample rotations could be all associated with quality growth, while the product and price upgrades associated with ongoing item substitutions reflects relatively little quality growth. For illustration, suppose we assume the BLS methods applied to forced substitutions should also be applied, approximately, to scheduled substitutions as well. Then the rate of quality growth should be only 1.1% per year (0.7% within rotations plus 0.4% across rotations). Thus, without further evidence, the plausible range for quality growth is at least as wide as from 1.1% to 5.8% per year. Over the nearly 16 year period, 1988 to August 2003, quality would accumulate by less than 19% with an annual growth rate of 1.1%, but by a very dramatic 148%, if growing by 5.8% per year.

The calculations above omit computers and computing equipment--BLS methods for treating substitutions for computers differ dramatically from that typical for other durables. Table 4 considers the importance of substitutions calculated purely for computing equipment. The substitution rate for computing equipment is 27.0%, twice as high as for other durables. Ignoring substitutions, the average price quote shows a significant decline of -2.7%. The substitutions, by contrast, are associated with jumps up in price of 5.4 percent, and for non-comparable substitutions it is on the order of 10%. Unlike other durables, for computers these price increases do not translate into CPI inflation. The BLS uses hedonics extensively for computing equipment and price changes are much more likely to be omitted (deletion method). My calculations suggest that BLS methods imputed on average about 10.2% quality growth for forced substitutions.

Column D of Table 3 presents annualized rates of quality growth for computers and equipment. I calculate that BLS methods yielded about 18.5% annual quality growth from forced substitutions for computing equipment for January 1988 to August 2003. This is not quite a complete picture. As discussed above, price changes associated with sample rotations are implicitly treated as quality growth. For computers, these changes are negative on average, equaling -1.3%. So the implied overall rate of quality growth for computers equals 17.2% per year, 18.5% within rotations minus 1.3% across rotations. If the BLS had based CPI inflation simply on matched-model inflation, I calculate that quality growth would have actually been 1.8% lower for computers, at 15.4% per year. Columns A and D of Table 3 suggest the importance of computing equipment in measured quality growth for durables. Although computing equipment constituted only 5% of the CPI for the 50 durables in 1997, adding computers more than doubles the annual rate of quality growth from forced substitutions from 0.7% to 1.6%. The picture is considerably different when the quality growth implicit in the BLS treatment of sample rotations is added. Including computer equipment raises this broader measure of BLS quality growth from 2.7% to 3.4%; so computing equipment contributed only about 20%.

3. *Quality Choices*

This section draws a model of household quality choices for consumer durables. The following section uses the model to judge relative price changes for products experiencing substitutions based on the growth in their relative market share. This provides a gauge of quality growth across product substitutions.

Household preferences

At time 0, household *h* maximizes lifetime utility given by

$$U_{h0} = \sum_{t=0}^{\infty} \beta^t \tilde{c}_{ht}^{1-1/\sigma}.$$

β is the discount factor. $\tilde{c}_{ht}$ denotes effective consumption during t. I assume this effective consumption reflects a Cobb-Douglas function of non-durable consumption, c_o, and consumption of J distinct categories of durable goods.

$$\tilde{c}_{ht} = c_{0ht}^{1-\alpha} \prod_{j=1}^{J} c_{jht}^{\alpha/J} .$$

The share parameter α is the same for all durables for ease of exposition. Consumption of the (composite) non durable is divisible. The J durables are consumed indivisibly--a household enjoys consumption from at most one television, one sofa, and so forth. Given the utility function, all households will in fact consume each of the J durables.

Household *h*'s consumption for durable *j* depends on two aspects of the good as follows

$$c_{jht} = q_{jht} v_{jht} \ . \tag{2}$$

q reflects a pure quality component; variations in *q* are evaluated commonly across consumers. Measuring the average growth in q is the purpose of the empirical work. I treat q as a continuous choice variable. This captures the idea that for each good households face a menu of quality-price combinations. As an example, for sofas q might reflect factors such as fabric quality. Treating q as a continuous choice variable abstracts from the possibility that increased variety in quality choices over time might allow consumers to better match themselves with an optimal level of quality. Here consumers will always be choosing their optimal degree of quality *q*.[10]

v captures how well a household's specific taste in product characteristics match those for a particular *variant* of j. Following Hotelling (1929), Lancaster (1966, 1971), and many others, I represent preferences over good attributes by particular addresses in a characteristics space. In addition to quality *q*, a good has *K* distinct attributes. A household's preferences reflect its ideal bundle of characteristics for the good. The factor v_{jh} associated with consuming a particular variant depends on how well its characteristics align with the household's ideal bundle. For an arbitrary variant with vector of attributes $\underline{z}$ (with elements z_k), this is specified as

$$Ln\, v_h(\underline{z}) = -\phi \sum_{k=1}^{K} (z_k - z_{kh})^2 \ . \tag{3}$$

The good *j* and time t indices are implicit. This quadratic form is used widely in address models

[10] The choice by consumers of quality *q* here parallels consumers choosing the quantity, as well as variety, of a good in Anderson, de Palma, and Thisse (1993) and Feenstra (1995).

of product differentiation, particularly as applied to discrete consumer choices (e.g., d'Aspremont, et al., 1979, Horstman and Slivinski, 1985, Anderson, et al., 1992).

Household *h*'s period *t* budget constraint is given by

$$c_{0ht} \; + \; \sum_{j=1}^{J} \Omega_{jht} x_{jht} \; = y_{ht} \; .$$

The price of the non durable is normalized to one. Household *h's* total expenditure equals y_{ht}, which is the household's income plus any dissaving in *t*. Ω_{jht} is 1 if household *h* purchases durable *j* in period *t*, and 0 otherwise. x_{jht} is the *unit price* paid by household *h* for good j.

Durable *j* is assumed to depreciate stochastically and completely with probability δ_j. The empirical tests below do not hinge on this. Consumers do not sell used durables. I assume a depreciation rate sufficiently high relative to the growth rate in quality that only a negligible set of consumers would choose to discard a working durable in order to upgrade its quality.[11]

Product varieties

On the supply side each durable *j* is produced and sold by N_j competing variants, with $N_j \leq K_j + 1$. Each seller faces a marginal and average cost of w_{jt} per unit of quality q_j. Following Archibald, Eaton, and Lipsey (1986), Anderson, et al.(1993), among others, the N_j sellers are assumed to be located symmetrically in the space of characteristics so that

(4) $$z_{jn}^{k} \; = \begin{cases} \eta_j \;\; if\, k = n, \;\; for\; k = 1,...., K; \; n{=}1, ..., N{-}1 \\ \quad -\eta_j \; otherwise \qquad . \end{cases} \qquad .$$

$$z_{jN}^{k} \; = \; -\, \eta_j \quad for\, k \; = \; 1, ..., K \; .$$

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[11] For instance, for a durable with an annual depreciation rate of 15% and quality growth of 3% per year, less than half of one percent of the durable would last sufficiently long to be discarded while working. For a 5% growth rate this fraction is about 3.9%. Certain depreciation at some point, for example after 15, could be entertained without altering the analysis below except slightly modifying certain constant terms.

From here on, I set η equal to $\frac{1}{2}$, so that distance between variants equals one. This is a normalization, as the impact of parameter η can be encompassed in the preference parameter ϕ.

The number of product varieties is treated as constant over time. Expansion in the number of variants could lead to additional welfare gains. My focus, again, is on measuring the contribution of quality growth. Measuring gains from an increase in product varieties is an active parallel line of research (e.g., Hausman, 2003, Berry, et al., 2002).[12]

Household choice of quality

Assume that firms set unit prices proportional to quality. So, for seller *n* of good *j*

$$x_{jnt} = p_{jnt} q \ . \qquad (5)$$

Since costs of producing the unit are proportional to *q*, this corresponds to a proportional markup that is independent of the quality chosen. I examine seller's pricing decisions below and find this pricing does maximize profits, given that other sellers price in this fashion. Pricing as in (5) constitutes a Nash equilibrium in pricing schedules (Wilson, 1993, Rochet and Stole, 2002).

Consider household *h*'s choice of quality, conditional on choosing to purchase variant *n* of durable *j*. The price of increasing the quality purchased of durable *j*, that is relative to the price of the non durable, is simply p_{nt}. The household should equate this relative price to the ratio of the marginal utility gained from possessing a better quality of durable *j* versus having more non durable consumption. Reflecting the durability of good *j*, this condition is

$$\frac{\frac{\alpha}{J} q_{nht}^{-1} \sum_{\tau=0}^{\infty} (\beta(1-\delta))^{\tau} \left(\frac{\tilde{c}_{ht+\tau}}{\tilde{c}_{ht}}\right)^{1-\frac{1}{\sigma}}}{(1-\alpha) c_{ht}^{-1}} = p_{nt} \ .$$

[12] The specification of locations in equation (4) makes variety grow proportionately with entry. This is perhaps objectionable for estimating variety benefits from increased market entry (see Berry, et al., 2002, and Ackenberg and Ryslin, 2002); but it is not so directly relevant for the exercise here.

The good index *j* is implicit. Also the household's consumption of the non durable c_{oh} is labeled simply as c_h. Recall that $\widetilde{c}_{ht}$ denotes the household composite of consumption of all goods from equation (1). Allowing for a steady growth rate of *g* in real consumption, and rearranging, yields

$$(6) \qquad q_{nht} = \frac{\alpha}{J(1-\alpha)(1-(1-\delta)\beta(1+g)^{1-\frac{1}{\sigma}})} \frac{c_{ht}}{p_{nt}} .$$

Thus quality displays elasticities of one and minus one respectively in response to increases in household non durable consumption and the relative price of the durable.[13] Consider a growing economy. Absent relative price changes, households increase the quality of, and expenditures on, durables at the same rate as the non durable. We should anticipate the durable's quality growing even faster if its price controlling for quality, p_{jt}, is falling reflecting, for instance, faster technological advances than for other goods.

Household choice of brand

Now consider the household's choice of which variant to purchase. Given spending based on (6), this choice has no impact on the expenditure on non durables or choices for other durables. Therefore, the problem reduces to maximizing effective consumption of good *j*.

$$(7) \qquad \max_n \; -Ln(p_{nt}) - \phi \sum_{k=1}^{N-1} (z_{kn} - z_{kh})^2 + Ln(\psi_n) .$$

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[13] It is more common to express demands in terms of expenditure and prices. If the number of durables is large, so there is negligible uncertainty in how many durables are replaced during *t*, then expenditures on nondurables and on the representative durable (given it is purchased) can be expressed compactly as

$$c_{ht} = (1 - \widetilde{\alpha})y_{ht} ,$$

$$p_{nt}q_{nht} = \frac{\widetilde{\alpha}}{\delta J} y_{ht} ,$$

where:

$$\widetilde{\alpha} = \frac{\alpha}{\alpha + \frac{1-\alpha}{\delta}(1-(1-\delta)\beta(1+g)^{1-\frac{1}{\sigma}})} .$$

Good index *j* is implicit. Although the good has *K* (≥*N-1*) attributes, from (4) only the first *N-1* are relevant for the household's choice, as the variants share the same address on *N* through *K*. The term $Ln(\psi_n)$ allows for unequal market shares by making, everything else equal, some variants more popular in all households' eyes. This could be derived by slightly modifying the specification of addresses in (4) so that brands have different addresses on one or more of attributes *N* through *K*, with households sharing a common ideal point for these attributes. Potential shifts in households' demand across variants can be captured by changes in ψ_n. Note that the decision implicit in (7) does not depend on the household's income.

Let households' ideal points for the vector $\underline{z}$ of attributes be distributed according to the continuous density $g(\underline{z})$. Then the share of households purchasing variant *N*, as an example, is

$$s_N = \int_{-\infty}^{\frac{1}{2\phi}Ln(\frac{\psi_N p_1}{\psi_1 p_N})} \cdots \int_{-\infty}^{\frac{1}{2\phi}Ln(\frac{\psi_N p_{N-1}}{\psi_{N-1} p_N})} g(z_1, \ldots, z_{N-1}) dz_{N-1} \cdots dz_1 \ .$$

A distribution for $g(\underline{z})$ often used in discrete-choice models is the Type-1 extreme value. The market shares then have the closed-form

(8) $$s_n = \frac{(p_n/\psi_n)^{\frac{-1}{\mu\phi}}}{\sum_{i=1}^{N}(p_i/\psi_i)^{\frac{-1}{\mu\phi}}} \quad for\, n = 1, \ldots, N \ ,$$

where μ is a dispersion parameter for the distribution. These demands mirror the CES demand function for divisible commodities. The elasticity of demand is smaller if products are poor substitutes, ϕ large, or if consumers are diffusely distributed in their preferences, μ large. Since these two parameters always enter multiplicatively in describing product demands, for the balance I set the distribution parameter μ equal to one for convenience.

Pricing

Using equations (6) and (8), profits for seller *n* are

$$\textit{Profits}_n = \frac{\alpha\bar{c}}{J(1-\alpha)(1-(1-\delta)\beta(1+g)^{1-\frac{1}{\sigma}})} \frac{(p_n/\psi_n)^{\frac{-1}{\phi}}}{\sum_{i=1}^{N}(p_i/\psi_i)^{\frac{-1}{\phi}}} \frac{1}{p_n}(p_n - w) \ ,$$

where $\bar{c}$ equals mean non durable consumption; time subscripts are suppressed.

The profit maximizing net price markup can be expressed as

$$\frac{p_n^* - w}{w} = \frac{\phi}{1 - s_n} \ . \qquad (9)$$

where s_n is firm n's market share given in (8). The markup is higher if consumers have strong brand preference--ϕ large. The markup is increasing in the firm's market share, and indirectly its relative demand through ψ_n. For the symmetrical case (all ψ_i's equal), the markup is $(\frac{N}{N-1})\phi$.

4. ***Using Growth in Matched-Models' Market Share to Measure Inflation***

The goal is to measure the rate of inflation in a price index for a good despite potential quality changes across product substitutions.

$$\pi = \sum_{n=1}^{N} s_n \pi_n = \sum_{n=1}^{M} s_n \pi_n + \sum_{n=M+1}^{N} s_n \pi_n \ .$$

Good *j* and time subscripts are implicit. π_{nt} equals $ln(p_{n,t}/p_{n,t-1})$. Weighting by expenditure shares corresponds to the BLS's primary current practice for weighting product models within an ELI (geomeans weighting). Number the product models so that the first *M* correspond to those products that experience no model substitution. Products *M*+1 to *N* are those for which substitutions are made. The right-hand-side of the second equation breaks the inflation rate for good *j* into the contributions from these two sets of products. The first component is measured by following the unit prices of the matched models. For the second set it is necessary to somehow deduct quality growth from inflation in unit prices.

Let S_m equal the combined share of the matched models ($S_m = \sum_{n=1}^{M} s_n$). The inflation rate for the product models with substitutions can be gauged, relative to that measured for matched models, by what happens to S_m. Intuitively, if the inflation rate for products with substitutions, net of quality growth, exceeds that for matched models, then S_m will increase. More exactly, from equation (8) changes in S_m can be related to the changes in the relative prices of matched models plus shifts in demands (ψ_n's). Substituting in the above equation yields

$$\text{(10)} \qquad \pi = \sum_{n=1}^{N} s_n \pi_n = \sum_{n=1}^{M} (\tfrac{s_n}{S_m}) \pi_n + \phi \frac{dS_m}{S_m} + \xi ,$$

$$\text{where} \qquad \xi = \sum_{n=M+1}^{N} s_n \frac{d\psi_n}{\psi_n} - (\tfrac{1-S_m}{S_m}) \sum_{n=1}^{M} s_n \frac{d\psi_n}{\psi_n} .$$

The inflation rate has three components. The first is the rate of inflation for the matched products. I reported this in Section 2 as the matched-model rate of inflation. The second term requires multiplying the growth rate in the market share of the matched products times the parameter ϕ. The final term is an error term that is positive if preferences systematically shift between *t-1* and *t* toward those products that experience product substitutions between *t*-1 and *t*.

Product substitutions are triggered by a product being discontinued at an outlet. Decisions to replace product lines presumably take at least several weeks to implement. Given the high frequency of the data, monthly or bimonthly, this suggests that product substitutions between *t-1* and *t* are predetermined with respect to innovations to ψ between *t-1* and *t*. As a special case, if disturbances to ψ_{nt} follow a random walk, then the expectation of ξ is zero. Furthermore, given the large number of goods and months aggregated in the empirical work, the variability to measured inflation contributed by ξ should be extremely small. Of course, shifts in preferences need not follow a random walk; but it is not necessary to assume this in the empirical work, as it is possible to condition on past market shares.

Suppose the BLS had measured inflation simply based on matched models. From Section 2, this would have resulted in about 3% faster quality growth per year for durables (excluding computing equipment) for 1988 to August 2003. The primary question I pursue is whether measuring inflation based just on matched models would overstate quality growth. From equation (10), the answer is yes if, for those goods matched between *t-1* and *t*, market share is declining. The intuition is straightforward. The inflation rate for matched goods understates inflation if the new product models provide less consumer surplus than the products replaced, given their respective prices. But from equation (10), this implies the market share of the matched products should increase from *t-1* to *t*. Alternatively, a decline in market share of the matched models implies that even the low rate of inflation based on matched models is overly high.

Note that these qualitative tests do not require knowing the parameter ϕ in equation (10). It is based just on the result that if inflation for the matched products is less than for the substituted products then consumers should shift toward these products. It is also not particularly sensitive to assuming the extreme value distribution for $g(\underline{z})$. In discrete choice models all varieties are gross substitutes. So if we see consumers moving away from the matched products, this robustly suggests that their relative price has not declined.

With knowledge of ϕ and information on $\frac{dS_m}{S_m}$ one can obtain, by substituting for $\phi\frac{dS_m}{S_m}$ in equation (10), a more precise estimate of inflation. This is related to Hausman's argument that constructing an accurate price index requires information on quantities and knowing demand elasticities. Note, however, that convincingly estimating demand elasticities from data on prices and quantities for a large set of goods, given problems of identification, could be as daunting as constructing reliable hedonics estimates.

It is possible, however, to further constrain the reasonable range of values for inflation. From the previous section, for the symmetric case (common ψ's) the markup equals $(\frac{N}{N-1})\phi$.

This implies a value for ϕ of $(\frac{N-1}{N})(\frac{p_n^*-w}{w})$, which is strictly smaller than the percent markup of price over marginal cost. This suggests values for ϕ should be considerably less than one. For instance, even if we accept the plausibility of a 100 percent markup, this still implies a value importantly less than 1, unless *N* is large. But the presence of a large number of competitors together with markups of 100 percent would seem implausible. The upshot is that, if realizations for $\frac{dS_m}{S_m}$ are not too large in magnitude, it is possible to state narrow bounds for the rate of inflation and, implicitly, the rate of quality growth.

The next section examines sales data by product model for cars, other vehicles, televisions, audio equipment, telephones, and other related consumer electronics. These goods represent about three-quarters of the impact of forced substitutions on unit prices for the durable goods. Because market-share information is not readily available for a number of durables, I finish this section by discussing how price responses for matched products might proxy for market-share information. Intuitively, if product substitutions are associated with price increases greater than justified by quality, an increase in *p* in the notation above, then we might expect the matched products to face less competition, justifying an increase in their prices.

From equation (10), we need a measure for $\phi\frac{dS_m}{S_m}$. In lieu of quantity information, note that the ϕ-weighted individual share changes can be related from the pricing equation (9) to seller *n*'s change in price and marginal cost. Evaluated near the case of equal market shares

$$\frac{\phi ds_n}{\mathrm{s}_n} = \frac{p_n}{w}\Big(\frac{N-1}{N}\Big)^2\Big[\frac{dp_n}{p_n} - \frac{dw}{w}\Big].$$

Aggregating yields

$$\text{(11)} \qquad \phi\frac{dS_m}{S_m} = \frac{\sum_{n=1}^{M} s_n(\frac{\phi ds_n}{\mathrm{s}_n})}{S_m} = \Big(\frac{N-1}{N}\Big)^2\frac{\sum_{n=1}^{M}\frac{p_n}{w}s_n(\frac{dp_n}{p_n})}{S_m} - \Big(\frac{N-1}{N}\Big)^2\Big(\frac{\overline{p}}{w}\Big)\frac{dw}{w}.$$

$\frac{\overline{p}}{w}$ denotes the average gross price markup. For exposition, I have treated the firms as having common growth in marginal cost.

$\phi \frac{dS_m}{S_m}$ reflects two terms. The first is the weighted average of inflation rates for the matched models, but the inflation rates are multiplied by the factor $\left(\frac{N-1}{N}\right)^2 \frac{p_n}{w}$. This factor should not much exceed one--it can only significantly exceed one in the odd scenario of a large price markup in conjunction with a large number of competitors. Therefore this first term can be qualitatively captured by the matched-model rate of inflation. The second term reflects the impact of marginal cost changes on prices of the matched products--a price increase for the matched products does not imply their share has risen if it is in response to a rise in marginal cost.

To augment information on quantities, I examine whether a durable's rate of matched-good inflation is higher than usual at times when its rate of product substitution is high. If yes, this suggests that the substituted products have become less competitive, implying their unit-price inflation exceeds their quality growth. Conversely, if high substitution rates are associated with lower than usual matched-good inflation, this suggests the substituted products are perhaps more competitive than those replaced. This inference requires that periods with high substitutions not be periods of particular high or low growth in marginal cost for the matched models, or times that markups change for reasons other than market share. These are much stronger assumptions than needed to exploit equation (10) based on market shares. Therefore, I treat the price reactions of matched goods as a diagnostic statistic, rather than providing structural information.

5. *How Market Shares Respond to Product Substitutions*

The ideal exercise would be to examine market sales data collected at the same outlets for the same products at the same times as the price data collected to construct the CPI. Such data do not exist. I am able, however, to examine sales data for major components of consumer spending on durables. In particular, in the next subsection I examine for the last 15 years how market sales for automobiles, vans, pickup trucks, and SUV's that experienced a spike in forced substitutions behaved relative to sales for models not experiencing substitutions. Secondly, I present results based on scanner data on sales for televisions, audio goods, and other consumer electronics. The results suggest that market share declines noticeably for matched models (those available in consecutive periods). This suggests measuring inflation based just on matched models, which yields much higher quality growth than current practices, may still understate quality growth. Together the vehicles and consumer electronic goods make up more than 50 percent of consumer spending on all the durables detailed in Table 1. Because substitution rates are skewed toward these goods, they constitute about 75 percent of price increases accompanying forced substitutions for durables, weighting by spending share. The final subsection examines how the rates of inflation for products that do not experience substitutions respond to periods of rapid product turnover as measured by forced substitutions.

Model substitutions and changes in market shares for automobiles and other vehicles

Data on monthly unit sales by car, van, and pickup model are available from compilations by Ward's for their *Automotive Yearbook*. I obtained this data for January 1988 to June 2003. It is then necessary to match this information to statistics on substitutions rates from the CPI data. I construct a data table of substitution rates by vehicle model from the CPI data.[14] Combining this table with the Ward's data provides a panel data set with nearly 27,000 observations on forced substitution rates, price increases, and sales growth by model.[15]

Table 5 presents results on how prices and sales for car models respond to the rate of forced substitutions. Results are presented separately for automobiles and other light vehicles.

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[14] The BLS field agent records some descriptive information for an item at the time it is selected for pricing. I am able to identify the vehicle model for 97.5% of price quotes for automobiles and 96.2% of other vehicles. For automobiles the forced substitution rate is 15.1%, for other vehicles 16.2%. 88.7% of substitutions for cars, and 87.0% for other vehicles, are accompanied by a model-year change. Less than 1% of quotes result in a change in the vehicle model being priced. These are not reflected in the substitution rates in the regressions below.

[15] Only quotes in the CPI data covering one or two months are included. For quotes of two-month duration, I allocate inflation equally between the months. For two-month quotes with substitutions I allocate slightly over one half substitution to each month. The amount over one-half reflects the probability of exhibiting substitutions in consecutive months estimated from quotes that are monthly in duration.

Observations are weighted by the number of monthly observations underlying the substitution rate. The regressions include time-period dummies; so the coefficients should be interpreted as the growth rate in prices or units sold for models that experienced a 100 percent rate of forced substitutions for that month relative to the growth rate for models experiencing no substitutions.[16] The first two rows show the impact of substitutions on unit-price inflation and unit-price inflation net of the BLS adjustment for quality growth. The findings are consistent with the results reported in Section 2. For cars substitutions are associated with 4.8% greater price increases with only about one-sixth of this captured by the quality adjustment. For vans, pickups, and SUV's substitutions are associated with a 3.9% greater price increases with only about one-tenth captured as increased quality.

Row (3) shows the impact on market share. For automobiles forced substitutions are associated with a considerable increase in market share of units sold of 15.1% (with standard error of 2.1%). I also examined results separately by several classes of vehicle (e.g., compact); the positive impact of substitutions on market share is quite consistent across classes.[17]

The results for cars suggest that quality growth accompanying substitutions is even larger than the large impact observed for unit prices. That is, the 4.8% typical increase in price for forced substitutions for cars is more than rationalized by quality growth. How much more? From equation (10), it is necessary to add the positive impact on market share multiplied by the parameter ϕ. This impact is potentially important. Suppose ϕ is equal to 0.1; in the model this is associated with a mark up of $\frac{N}{N-1}$ times 10 percent for the symmetric case. This implies that

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[16] The tables show that substitutions are associated with a marked increase in market share for automobiles and at least no decrease for other vehicles. It is not the case, however, that aggregate sales are high in months with many substitutions. Counter results for relative sales, months with high rates of substitution are associated with considerably lower sales. This largely reflects considerably lower sales growth in the fall season, at the same time substitution rates are high.

[17] The sales data compiled by Ward's combines leased vehicles with regular sales. Leased vehicles are not incorporated into the *CPI Commodities and Services Survey* until 1998, and then only gradually. Furthermore, lease quotes are not readily separated between cars and other vehicles. Therefore, my analysis of substitution rates, here as well as in section 2, is based on purchased vehicles. Note, however, that market-share results are very similar for the early and later parts of the sample period. The estimated impact on sales is 15.7% (with standard error 2.8%) for the first eight years and 14.4% (with standard error 3.2%) in the latter seven-and-a-half years. (For vehicles other than cars, discussed next, the estimates are 4.4%, with standard error 3.0%, for the first eight years and 1.8%, with standard error 3.6%, for the latter seven-and-a-half years.) This strongly suggests that vehicle leasings, much less important in the first half of the sample, are not driving the results.

substitutions are associated with an effective price cut of 1.5% relative to inflation for matched products. Adding this to unit-price growth would bring the estimated typical impact of a substitution on quality growth up from 4.8%, to 6.3%. (Given the substitution rate for cars, the implied annual rate of quality growth would also be on the order of 6%.)

These results, it is important to note, do not imply that manufacturer's model-year changes are typically associated increases in quality of this magnitude. Over the course of a year buyers will be increasing quality of a given vehicle by incorporating more and more-expensive features. This quality deepening is reflected in the model above by equation (6). Therefore, by triggering a forced substitution, the model-year change will alter the vehicle being priced, not only to a new model year, but also to one encompassing higher-value features.

There are one or more caveats to this picture. Separate from quality, a possible advantage to the next-year model, if the vehicle is later sold used, is that it can be dealt as a year-later model (assuming the used buyer does not know the car's exact age). My calculations suggest this might explain some of the increase in market share accompanying model substitutions.[18] One might argue that part of the willingness to pay more, everything else equal, for the next-year model reflects, akin to a fashion statement, a desire to have the most recent model. Willingness to pay for this might not reflect aggregate quality upgrading as arrival of the new-year model creates a loss to owners of cars that were formerly the most-recent model year. Several points of evidence suggest this is not the primary factor in the results in Table 5.[19] But based partly on these

[18] Bluebooks for used cars suggest the typical impact of an added year on resale value. But this measure reflects, in addition to a pure age effect, reductions in value due to mileage, observed wear, and obsolecence (from this paper of about 6% per year). Netting these effects from the one-year impact on blue-book value (calculated from several popular models) suggests that a newer model year car, truly everything else equal, will sell for only a few percent more at the time of resale. To get the impact on original-purchase willingness to pay, it is necessary to discount these few percent by the ratio of expected resale price to original price, as well as for foregone interest over the time the car is held. Based on a reasonable expectation for age at resale for non-leased cars (see Genesove, 1993, for some related data), the implied discounted effect on willingness to pay at initial purchase is likely well less than 1 percent. For this alone to explain the 15 percent faster growth in market share from substitutions would require an extremely high product demand elasticity and relatedly, an extremely low price markup.

[19] Firstly, the positive impact on market share is very consistent across class of vehicles. If it reflects importantly a fashion statement, it should be more important for upscale vehicles than economy cars. Secondly, I report below that growth in market share remains above average for several months after a substitution. If the increase in market share reflects desire to have the most-recent available car model, separate from quality, I would expect the impact on sales to be more concentrated at the time of introduction. Finally, it is important to keep in mind that cars are a very durable good. So the benefit of having the most-recent model year is limited to a quite short period of the asset's life.

caveats, I do not interpret the market-share results aggressively as showing that forced-substitutions generate increases in consumer surplus relative to matched models. I read the results more conservatively as showing that measuring inflation based on the matched-model prices does not importantly bias measured inflation downward.

For other light vehicles the estimated impact of substitutions on the rate of growth in market share is positive, but much lower in magnitude than for automobiles, equaling 3.0%. It is not statistically significant. I also estimated separately for vans, pickups, and SUV's, but results look extremely similar across these categories--small positive, but statistically insignificant, estimated impact of substitutions on growth in market share.[20]

Nearly half of forced substitutions for vehicles are concentrated in the two fall months of October and November. The timing of these forced substitutions might be viewed as more exogenous. I re estimated allowing a differential impact for these two months. For both cars and other vehicles the impact on market share of a substitution is even more positive for October and November: For cars a fall substitution increases market share by 19.2% (standard error 3.3%); for other vehicles market share is increased by 7.0% (standard error 3.7%). But for cars substitutions in other months still have a large and statistically significant impact on market share of 12.5% (standard error 2.7%). For other vehicles the effect of a substitution outside of October and November is positive, but small and insignificant.[21]

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to have the most recent model, holding quality constant, is important, then it should be more important for leased cars, because the first few months is a more important part of the life of a lease (which has been averaging 3 years) than for the overall life of a vehicle. But I see no evidence of this. For the years after 1998 I can compare the impact of model substitutions on unit prices of leased vehicles to the effect for purchased vehicles. Although model-substitutions are associated with an important increase in price for price quotes on leased vehicles, it is actually statistically significantly smaller than the impact on purchased vehicles.

[20] The model's equation (10) suggests examining market share of sales revenue, rather than market share of units sold. Given unit prices increase predictably with forced-substitutions (Table 5, row 1), substitutions clearly are associated with an increase in market share. This effect can be seen by summing the coefficients in the first and third rows of Table 5. For cars substitutions increase market share by about 20%, for other vehicles by about 7%.

[21] I also used this seasonality in substitutions to estimate by instrumental variables. I instrument for a model's rate of forced substitutions by its rate 11, 12, and 13 months prior. (Again all regressions, first and second stages, include time-period dummies.) This actually yields a more positive impact of substitutions on market share; but standard errors for the estimates are much larger. The estimated impact on market share is 43.5% (standard error 18.3%) for cars and 9.0% for other vehicles (standard error 20.6%).

Table 6 presents results for a specification that allows growth in a vehicle's market share to depend on its past growth rates, as captured by four monthly lags. The data do strongly reject a random walk in market shares. These regressions also allow for an impact of past substitution rates by including the model's substitution rate for the previous 4 months. The first column presents results for automobiles. The substitution rates, as a group, are statistically very significant, though the contemporaneous rate is easily the most important. The estimated response to a substitution is an initial increase in market share of 16.6%, growing to 19.6% by the third month, and 23.4% in the sixth. Thus the faster growth in market share accompanying a model substitution is not offset in the subsequent few months, as might be expected if it reflected a burst of advertising at the time of substitution, instead continuing to build.[22]

The second column of Table 6 gives results for the dynamic specification for vans, pickups, and SUV's. Here the results suggest, more clearly than in Table 6, that model substitutions lead to an increase in market share, though considerably less in magnitude than for cars. The increase in market share is largely concentrated in the month after a substitution. The substitution rates, as a group, are statistically significant with a p-value less than .01. The estimated response to a substitution is a very small decrease in market share of 1.3% in the first month, but an increase of 8.0% as of the third month, and 6.6% in the sixth.[23]

Model changes and expenditures for video, audio, and telecommunications products

For two years, March 2000 to February 2002, I examine monthly scanner data on prices and expenditures for video, audio, and telecommunications goods by product model. The scanner

[22] There might also be concern that sales the month prior to substitutions are a bad reference point, if dealers provide poorer selection of model features at that time. The data do not suggest this. Monthly growth in model sales are somewhat higher than usual the month prior to substitutions for cars; it is little different than usual for other vehicles. Related to this, if the regressions reported in Table 5 are estimated over a two-month window, rather than one, the results are very similar. The impact of substitutions on rates of price inflation are slightly smaller, with the impact on market share a little larger.

[23] I also estimated expanding the specification to include six lags in both market share and substitution rates. The estimated impact of substitutions, especially the estimated impulse response function, remains very similar.

data are collected by the company NPDTechworld.[24] I present results for 18 categories of goods. These categories are listed in Table 7, together with the number of observations and expenditure shares. Color televisions are notably the most important good, with an expenditure share of 38.6 percent of the sample. The table also presents the monthly entry and exit rates for each good. That is, on average, what fraction of products appears for the first time and what fraction appears for the last time. These rates are quite high--the median is about 4%. By comparison, the forced substitution rate for these goods in the CPI is 15%, which would translate into a monthly rate of almost 9%. It is not surprising that the forced substitution rate is considerably higher--a forced substitution is generated by a product no longer being carried at an outlet, whereas the exit rate for the scanner data is generated by the product dropping out of all outlets.

The first column of Table 8 presents the average rate of inflation for each of the 18 categories based just on product models that can be matched across months (matched-model inflation). It shows quite rapid deflation; the median rate is close to that for televisions of -1.1% per month. This is quite consistent, however, with the rate from the *CPI Commodities and Services* survey data of -9.9% per year, especially considerably that inflation rates for years 2000 and 2001 are lower than typical for the past 15 years.

The second and third columns of Table 8 present the average price and units sold for products entering the scanner data relative to those exiting. For each good price is significantly higher for entering goods, for instance, 62% higher for color televisions. At the same time the entering models exhibit considerably higher sales than exiting models (though smaller than typical for continuing models). As a result, the market share of the matched goods declines for each of the 18 categories of goods, typically by about 2% per month (Table 8, Column 4).[25]

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[24] I was kindly provided access to this data as a visitor of the BLS under the IPA (Intergovernmental Personnel Act) agreement. The data are compiled at a variety of types of retailing outlets. For the most part national coverage rates are reasonably high. For instance, coverage is about 95% for electronic appliance stores, though only about 60% at more general mass merchandisers.

[25] This decline in share for the matched goods does not just reflect an expanding number of models. I also examined what happened to average size, in terms of sales, of the matched goods relative to all models. With the exception of two goods with very rapid entry rates, DVD players and telephone headsets, this relative size always declines, typically by one-and-half to two percent per month.

Section 4 discussed how an estimate of the overall inflation rate for a good could be obtained by adding $\phi\frac{dS_m}{S_m}$ to the rate of inflation for matched models. Where ϕ, in turn, should be a number considerably less than one, as pricing in the symmetric case implies ϕ equal to $(\frac{N-1}{N})(\frac{p_n^*-w}{w})$. Given $\frac{dS_m}{S_m}$ is, in all cases, negative, this suggests that the rate of inflation based on the matched models is an overstatement of true inflation for these categories of consumer electronics. In particular, consider color televisions. If we are willing to assume the markup (actually times $\frac{N-1}{N}$) is no larger than 20%, then we can make a more precise statement. This bounds the inflation rate between -1.1% (matched-model inflation) and -1.5% per month.

Table 3 showed that forced substitutions increased unit prices by 5.3% per year for these goods. The results here suggest that these price increases are more than justified by quality--implying quality growth of greater than 5.3% per year for forced substitutions, or more than 2.9% faster than from historic BLS adjustments.

How matched-goods' prices respond to forced substitutions

The sections above show for vehicles and consumer electronics that models experiencing substitutions gain market share. Although these goods make up an important share of durables, and a large majority of forced substitutions for the durables, it would be desirable to have information on changes in market shares for additional durables. As discussed above, with some relatively strong additional assumptions, the price response of matched goods from *t-1* to *t* reflects the impact of product substitutions on matched-goods market share. I examine this response across the sets of goods distinguished in Table 3: Vehicles, consumer electronics, and the balance of 43 other durables, excluding computers and equipment.

First consider vehicles. Estimation is as follows. Separately for cars and other vehicles, I create a monthly time series for average rate of substitution and average rate of price inflation for matched models.[26] The categories are then pooled and the monthly rate of price inflation is

[26] Only quotes covering one or two months are included. For quotes of two-month duration, substitution and inflation rates are allocated between months as discussed in connection to Table 5. The regression includes linear and quadratic time trends and a separate intercept for each goods category.

regressed on the monthly substitution rate, with the two categories weighted by their relative expenditure shares for 1997. Estimation proceeds in a similar manner for consumer electronics and for the remaining set of durables.

Results are presented in Table 9. For vehicles the impact of the substitution rate on matched-model inflation is positive, but quite small in magnitude. (For each percentage increase in the rate of substitutions, matched-model inflation rate is .003% higher.)[27] As noted above, the number of vehicles sold in aggregate is very much lower in those periods with high substitutions. Therefore, it is difficult to argue that time-variation in substitution rates is exogenous to marginal cost or factors beyond market share that might influence markups. Results for consumer electronics appear in the next two columns. Periods with high rates of product substitutions are clearly associated with bigger price declines for matched models. For each additional percentage of forced substitutions, the matched-model inflation rate is .027% lower. This reinforces the picture from scanner sales data that product substitutions reduce the competitiveness of the static, matched models. The final two columns give results for the remaining durables. Inflation for the matched models shows very little response to the rate of forced substitutions.[28] I take this as some support for interpreting the quality increases accompanying these substitutions as of the same order as their associated price increases. By contrast, BLS methods attribute little quality increase to forced substitutions for these goods.

[27] Seasons (months) with predictably high substitutions are associated with a slightly lower rate of matched-goods inflation for vehicles; with this effect not significantly different from zero. But times with unusually high substitution rates, for that month of the year, are clearly associated with larger than usual price increases for static product models (by .018% for each percentage increase in the substitution rate). Results for the other sets of durables do not differ dramatically between the seasonal component in substitutions and other aggregate variations in substitutions.

[28] I also estimated separately for each of these 43 goods. This yields as many goods that show a significantly lower rate of matched-good inflation in periods with high substitutions as show higher inflation. Regardless of seasonal controls, five goods show a significantly negative effect at a p-value less than 0.10 (three at less than 0.05); four goods show a significantly positive effect at a p-value less than 0.10 (two at less than 0.05).

6. *Conclusions*

It is difficult to distinguish quality growth from true price increases for goods, such as consumer durables, that display frequent model changes. I show that one can arrive at vastly different measures of price inflation and real growth under arguably plausible competing assumptions. Hedonic methods have received the bulk of attention for treating these measurement problems. I have tried to make progress on the problem by examining how consumer expenditures respond to product substitutions.

I find the following. For automobiles and consumer electronics, consumer spending moves away from the static goods, that is, those with no model changes. This suggests a true rate of inflation that is even lower than that exhibited by these static goods. For light vehicles other than cars, market share appears to increase only quite modestly with substitutions; but certainly does not show any decline. Although I do not have market share results for the balance of durables, I do observe that prices for static models respond very little to competing product substitutions, suggesting the higher price increases for the product substitutions may largely reflect higher perceived quality.

What do these results suggest for quality growth? For vehicles my results suggest that quality growth has been understated by perhaps as much as 4.4% per year. My results suggest growth for consumer electronics has also been substantially faster than historically measured, by 2.9% or more per year. Finally for the balance of durables, if price inflation is reasonably well captured by the rate of inflation for matched products, then this implies quality growth that is about 1.6 percent faster than suggested by methods underlying BLS measurement of the CPI. Putting it all together, this suggests quality growth that is 3 percent faster per year than has been measured for these durables, with a resulting growth rate of at least 5.8% per year, even with computers excluded. My results suggest much faster quality growth for durables than the Boskin Commission Report, which stated BLS methods understated quality growth for durables by about 1 percent. This derives from two main differences: (1) The Boskin Report assumed no quality bias for a number of durables; (2) The Report assumed no quality growth for vehicles except from greater durability, contributing about 0.6% per year.

Product substitutions are more important for consumer durables than for most consumer goods; so it would not be appropriate to project the magnitudes here to non durables. It is conceivable, however, to extend the approach beyond durables. The key is to obtain information for additional goods on how market share responds to product substitutions. BLS methods potentially provide such information. The outlets and items priced are periodically updated to reflect changes in spending patterns. The shifts in product coverage, as a reflection of changing market shares, could be related to past product substitutions. Furthermore, greater availability of scanner data should gradually provide researchers with market information for a broader set of goods and for longer sample periods.

Appendix 1

The text displays that forced substitutions are associated with significant increases in unit prices, with much of this increase typically attributed to price inflation. Table A1 presents these facts within a regression framework. The data is again from the BLS *Commodity and Services Survey* and reflect 49 categories of consumer durables, with computers and related equipment omitted. The dependent variable is the rate of price increase relative to the previous price collected for that quote. Observations are weighted by the importance of the goods category (ELI) in the CPI for 1997. Consistent with the text results, substitutions are typically associated with a 4.5% higher unit-price increase than no substitution. By my calculations, using BLS methods (column 2), most of this shows up as higher inflation, 3.7% higher, not as quality growth.

The last two columns of Table A1 expand the regression to examine price responses, not only the month of a substitution, but also for the two observations prior to a substitution (variables *substitution (t+2)* and *substitution (t+1)*) and one observations after (variable *substitution (t-1)*). The substitution variables for after the price change display any impact of firms cutting price to sell off inventory prior to a substitution. The last variable is to test if firms cut price after the initial product introduction. (I included a variable to capture the second observation post substitution. But is was empirically unimportant.) Examining this larger window reduces the number of observations considerably. The data do show a tendency for firms to cut price, and presumably markup, in the observation preceding a substitution. But it is not an overly large effect. Unit prices fall by about 0.7% the observation before a substitution, and 0.3% two observations before. Though statistically significant, these cuts only constitute about 20 percent of the magnitude of the price increase associated with the substitution. The pattern for price inflation, by my calculations using BLS methods, gives a parallel picture. The price, and presumably the markup, is cut for the observation that follows the observation with a substitution. But the cut is very small, equaling about 0.1 percent. The sum of effects over the four observations, which covers, on average, about 7 months, is still a very significant increase in unit prices of 3.8% and in calculated inflation of 2.9%.

Table 1: Durable Goods Studied

Good	Observations	Expenditure Share
Watches	22,497	.069
Jewelry	64,919	.401
Personal computers & equipment	11,432	.488
Telephone & equipment	7955	.065
Calculators, typewriters, etc.	3123	.018
Electric personal care products	1882	.014
Luggage	8464	.034
Infant's equipment	1288	.011
Curtains & Drapes	9526	.057
Window coverings	6590	.038
Mattresses & springs	14,438	.146
Bedroom furniture	18,467	.193
Sofa & slipcover	18,485	.291
Living room chairs	11,382	.136
Living room tables	6007	.063
Kitchen & dinning room furniture	15,859	.163
Infant's furniture	3936	.027
Occasional furniture	18,067	.125
Refrigerator & home freezer	12,687	.106
Washers & dryers	13,005	.098
Stoves	5905	.037
Microwaves	10,051	.030
Vacuums	7848	.051
Small kitchen appliances	13,071	.020
Other Electric appliances	5155	.112
Lamps & lighting	4923	.035
Clocks & decorative items	16,112	.225
Dishes	12,248	.066
Flatware	3442	.014
Non-electric cookware	4658	.034
Tableware & non-electric kitchenware	6218	.064
Power tools	7392	.051
Misc. hardware	6001	.096
Non-powered hand tools	2068	.030
Medical equipment for general use	1546	.009
Supportive & convalescent equipment	1609	.013
Televisions	35,548	.269
Other video equipment	19,480	.095
Audio equipment	26,998	.177

Table 1 continued on next page

Table 1 (continued): Durable Goods Studied

Good	**Observations**	**Expenditure Share**
Bicycles	6466	.047
General sports equipment	30,207	.255
Hunting, fishing & camping equipment	7641	.064
Photography equipment	10,491	.042
Sewing machines	3010	.045
Musical instruments & accessories	15,248	.064
New cars	138,108	2.748
Pickups & Vans	34,215	1.953
New motorcycles	14,465	.082
Tires	66,105	.290
Other vehicle equipment accessories	43,127	.245

Data: *CPI Commodities and Services Survey*.

Table 2: Price increases, inflation, and quality growth by substitution status, Durable Consumer Goods, 1988 to March 2003

	Percent of Quotes (Weighted)	Price Increase	Inflation (BLS methods)	Quality Growth (BLS methods)
All Quotes	100 %	0.06 %	-0.04 %	0.10 %
No Substitution	87.8	-0.5	-0.5	0%
Substitution	12.2	4.0	3.2	0.8
-- treated as same quality	4.3	2.6	2.6	0
-- direct quality adjustment	4.5	4.3	3.8	0.5
-- other adjustments	2.2	7.3	5.1	2.3
-- omitted in calculating Inflation	1.2	2.2	-0.04	2.3

Total number of quotes equals 817,932.

Data: *CPI Commodities and Services Survey*. Computer equipment excluded

Table 3: Annual Price Inflation and Quality Growth — January 1988 to August 2003

		(A) Durables Excluding Computers	(B) Cars, Vans, Trucks, SUV's	(C) Video, Audio, Telephones	(D) Computers and equipment
Panel A	$\pi_{unit\text{-}price}$	2.5%	4.0%	-2.4%	-4.9%
	-- $\pi_{same\text{-}model}$	-3.3	-3.3	-9.9	-20.3
	-- $s(\pi_{substituion} - \pi_{same\text{-}model})$	3.8	5.2	5.3	16.7
	-- $\pi_{sample\ rotations}$	2.0	2.1	2.3	-1.3
Panel B	Δ *quality for forced (BLS)*	0.7	0.8	2.4	18.5
	Δ *quality for forced (BLS)* + $\pi_{sample\ rotations}$	2.7	2.9	4.7	17.2
	$\pi_{unit\text{-}price} - \pi_{same\text{-}model}$	5.8	7.3	7.6	15.4
	Substitution rate	12.2%	15.8%	15.1%	27.0%
	Number of quotes	817,932	172,322	89,981	11,432

Data: *CPI Commodities and Services Survey*

Table 4: Price increases, inflation, and quality growth by substitution status, Computers and Related Equipment, January 1988 to August 2003

	Percent of Quotes (Weighted)	Price Increase	Inflation (BLS methods)	Quality Growth (BLS methods)
All Quotes	100 %	-0.6 %	-3.3 %	2.8 %
No Substitution	73.0	-2.7	-2.7	0%
Substitution	27.0	5.4	-4.8	10.2
-- treated as same quality	9.1	-3.6	-3.6	0
-- direct quality adjustment	8.0	1.9	-8.0	9.9
-- other adjustments	0.5	61.2	14.2	47.0
-- omitted in calculating Inflation	9.4	14.0	-4.3	18.4

Total number of quotes equals 11,432

Data: *CPI Commodities and Services Survey*.

Table 5: Response of Unit-price Inflation, Inflation net of BLS quality adjustment, and Market Share of Units Sold to Substitutions for Cars and other Light Vehicles

Dependent Variable	Automobiles	Vans, Pickups, and SUV's
Δ Unit Price	4.8 (.09)	3.9 (.14)
Δ Unit Price − Δ BLS Quality	4.0 (.08)	3.6 (.12)
Δ Share of Unit Sales	15.1 (2.1)	3.0 (2.4)
Number of model-month observations	19,806	7,587

Data: *CPI Commodities and Services Survey*, 1988 to June 2003. *Ward's Automotive Sales Data*, 1988 to June 2003. Standard errors in parentheses. Regressions include monthly time-period dummies.

Table 6: Dynamic Responses of Market Share to Substitutions for Vehicles

Dependent variable is Δ Share of Sales

	Automobiles	Vans, Pickups, SUV's
Δ Share of Sales (t-1)	-0.22 (.008)	-0.25 (.012)
Δ Share of Sales (t-2)	-0.18 (.008)	-0.18 (.012)
Δ Share of Sales (t-3)	-0.11 (.008)	-0.12 (.012)
Δ Share of Sales (t-4)	-0.05 (.007)	-0.07 (.012)
Substitution Rate (t)	16.6 (2.4)	-1.4 (2.6)
Substitution Rate (t-1)	7.1 (2.5)	7.5 (2.7)
Substitution Rate (t-2)	3.3 (2.4)	3.1 (2.7)
Substitution Rate (t-3)	7.2 (2.4)	1.9 (2.6)
Substitution Rate (t-4)	2.2 (2.2)	0.5 (2.4)
Adjusted R^2	.25	.39
Number of observations	17,779	7,225

Data: *CPI Commodities and Services Survey*, 1988 to June 2003. *Ward's Automotive Sales Data*, 1988 to June 2003. Standard errors in parentheses. Regressions include monthly dummies.

p-value for the set of substitution variables for autos is < .0001. For other vehicles it is < .01. Estimated impulse response in market share to a substitution for autos is 16.6% the first month, 19.6% in month 3, and 23.4% in month 6. For other vehicles the estimated response is -1.3% in month one, 8.0% in month 3, and 6.6% in month 6.

Table 7: Scanner Data—Goods' Shares and Monthly Entry/Exit Rates

Good	Observations	Share	Entry Rate	Exit Rate
Color TV's	19,399	38.6	4.4%	4.2%
Remote controls, web browsers, caller ID	2363	0.7	3.2	3.5
DBS Satellite, TV box-decoders	2089	1.8	3.5	4.6
TV combinations	3361	2.7	4.2	4.1
VCR's	6161	4.5	4.3	6.1
Camcorders, personal video recorders	5420	11.0	4.6	3.4
DVD players	4468	8.6	5.3	2.1
CD players	10,408	5.2	3.5	4.2
Portable radios, radio/cassettes	3493	0.9	3.4	3.5
Portable tape recorders, Solid-state voice recorders	1628	0.4	3.4	2.7
Headset stereos, stereo headphones	6770	1.4	3.8	3.6
Receivers, cassette decks	7490	3.9	4.2	4.1
Home speakers	13,829	4.6	3.9	3.3
Rack or shelf systems	6391	5.0	4.1	4.5
Corded phones	2661	0.9	3.1	3.4
Cordless phones, 2-way radios	6033	5.3	4.8	3.1
Answering devices	3808	4.1	4.0	3.3
Headsets	1821	0.5	7.6	3.0

Data: NPD Scanner data for video, audio, and telecommunications products, Monthly for March 2000 through February 2002

Table 8: Scanner Data—Matched-good Inflation and Share Changes

Good	Matched Inflation (monthly)	$Ln(P_{in}/P_{out})$ (X 100)**	$Ln(Q_{in}/Q_{out})$ (X 100)**	Change in Matched Share
Color TV's	-1.1%	62%	174%	-1.9%
Remote controls, browsers, caller ID	-0.5	87	79	-0.8
DBS Satellite, TV box-decoders	-1.9	68	143	-2.0
TV combinations	-1.0	53	176	-3.1
VCR's	-2.3	26	225	-1.9
Camcorders, video recorders	-2.2	83	210	-2.5
DVD players	-2.1	57	183	-2.9
CD players	-1.0	54	229	-2.4
Portable radios, radio/cassettes	-0.8	46	62	-1.8
Portable tape/voice recorders	-0.6	37	175	-2.0
Headset stereos, stereo headphones	-0.2	17	116	-1.4
Receivers, cassette decks	-1.3	38	240	-1.8
Home speakers	-0.9	36	104	-1.2
Rack or shelf systems	-1.3	42	157	-3.0
Corded phones	-0.8	60	189	-1.3
Cordless phones, 2-way radios	-2.0	46	142	-2.3
Answering devices	-1.7	84	326	-2.1
Headsets	-1.6	12	141	-4.6

Data: NPD Scanner data for video, audio, and telecommunications products, Monthly for March 2000 through February 2002

** P_{in}/P_{out} denotes the ratio of the average price of entering models relative to those exiting; similarly, Q_{in}/Q_{out} denotes the ratio of units sold.

Table 9: Response of Matched-Model Inflation to Substitution Rate

Dependent variable is rate of price increase.

	Vehicles*	Consumer Electronics**	Balance of 43 Durables
Substitution rate	0.32 (.14)	-2.67 (.65)	0.32 (.34)
Adjusted R^2	.26	.11	.03
Number of Observations	372	746	8002

Data: *CPI Commodities and Services Survey*, January 1988 to August 2003.

*Vehicles include cars, vans, pickups, and specialty vehicles.

**Consumer electronics include televisions, other video equipment, audio equipment, and telephones and equipment.

Standard errors in parentheses.

Regressions include good dummies and linear and quadratic trend terms.

Table A1: Responses of Unit-price and Inflation by BLS methods to Substitutions

Dependent variable is rate of price increase.

	(1) Unit-price	(2) Unit-price net of BLS quality adjustment	(3) Unit-price	(4) Unit-price net of BLS quality adjustment
Substitution (t+2)			-0.30 (.051)	-.30 (.043)
Substitution (t+1)			-0.66 (.059)	-.53 (.050)
Substitution (t)	4.50 (.038)	3.69 (.031)	4.80 (.053)	3.83 (.045)
Substitution (t-1)			-.09 (.049)	-.11 (.041)
Sum of coefficients			3.75 (.107)	2.89 (.090)
Adjusted R^2	.021	.022	.024	.023
Observations	817,932		392,075	

Data: *CPI Commodities and Services Survey*, 1988 to August 2003.
(Computer equipment excluded.)

Standard errors in parentheses.

Regressions include time period and good dummies.

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