

# A New Vehicles Transaction Price Index: Offsetting the Effects of Price Discrimination and Product Cycle Bias with a Year-Over-Year Index<sup>\*</sup>

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## Abstract

A number of the factors drive regular patterns in the pricing of a vehicle over its product life cycle. These pricing dynamics, discussed in detail in Copeland, Dunn, and Hall (2011), have implications for price measurement. Aizcorbe, Bridgman, and Nalewaik (2010) identify consumer heterogeneity as one factor driving price change over the life cycle of a vehicle model. Exploitation of consumer heterogeneity through intertemporal price discrimination may explain the continuous, downward movement observed in monthly, matched-model price indexes for new vehicles. Similar price movements are often attributed to “chain drift,” but we dismiss this explanation using methods developed in Ivancic, Diewert, and Fox (2011). We show that intertemporal price discrimination violates the assumptions necessary for measuring cost-of-living and that the methods currently used by the Bureau of Labor Statistics to address product cycle issues are not valid when used with a dynamically weighted index formula. We attempt to measure price change by making price comparisons at similar points in a product’s life cycle. Specifically, we compare each vehicle to its prior model year equivalent, 12 months ago. Given an assumption of stability in the pattern of model year introduction, the year-over-year measure gives a measure of price change free from product cycle effects but does not convey information about short-run fluctuations in new vehicle prices.

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# 1. Introduction

This paper presents research behind the first index based on transaction data proposed for incorporation into the Consumer Price Index. Transaction data provide real-time weighting information necessary to calculate a superlative index, which approximates a cost-of-living index, the conceptual objective of the CPI.<sup>1</sup> Previous research on new vehicle pricing has shown a product life cycle where prices tend to decline during the model year. This pattern complicates the measurement of price change. Aizcorbe, Bridgman, and Nalewaik (2010) suggest that intertemporal price discrimination (IPD) might explain this pattern. A variety of other explanations for the product cycle's pricing behavior have been proposed going back at least to Pashigian, Bowen, and Gould (1995), who attributed the pricing pattern to fashion effects. Aizcorbe et al. (2009) conclude with the suggestion that year-over-year (YOY) price indexes could be used to hold the characteristics of buyers constant. We analyze transaction-level data from JD Power and confirm one of the regularities seen in prior research: the tendency for substantial declines in prices over the course of a model year and reject chain drift as the source of this movement. We discuss implications of intertemporal price discrimination (IPD) in terms of cost-of-living theory and the difficulties it creates for constructing a "representative consumer." The current CPI uses item replacement to offset within model year price change to mitigate these effects, but we show this method does not work well with dynamically weighted data. We consider a YOY index to achieve a measure of long-run price change that avoids complications from the product cycle regardless of whether the underlying source of these patterns is IPD or other effects. Our final index shows a nearly 6% increase since December 2007 compared to an almost 8% increase in the CPI for new vehicles, a difference in the annual rate of about 0.24%.

The remainder of the paper is organized as follows. Section 2 provides a literature review that contextualizes our index within the larger body of work on transaction data, price indexes, and quality adjustments. Section 3 describes the JD Power data and documents observations on the behavior of vehicle prices and quantities. Section 4 discusses the standard formulation of price indexes and how the data are seemingly inconsistent with standard theory. Section 5 discusses how a year-over-year price index can resolve these deviations from standard theory. Section 6 develops the methodology of our proposed a year-over-year price index while Section 7 details the behavior of the resulting price index. Section 8 concludes.

## 2. Background Review

Previous research has studied the price and sale dynamics of new vehicles—several papers have even used data from JD Power. None of this research, however, has produced a long-term, monthly price index series from transaction data. Furthermore, while this research has documented the tendency for prices to fall within a model year, explanations for falling prices during the model year vary. Common explanations for this pattern of price change in the product cycle include IPD and fashion effects.<sup>2, 3</sup> Two papers identify year-over-year relatives as a method of price change measurement that are immune to the dynamics of the new vehicle product cycle.

Copeland, Dunn, and Hall (2011); Corrado, Dunn, and Otoo (2006); and Aizcorbe, Bridgman, and Nalewaik (2010) use aggregated transaction data from JD Power's "PIN Explorer." Our data comes from the same source, but we have access to the transaction-level data that underlies the aggregated data

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<sup>1</sup> "Chapter 17. The Consumer Price Index," p 2-3.

<sup>2</sup> See Copeland, et al., 125 for discussion of examples.

<sup>3</sup> Pashigian, et al. (1995).

in PIN Explorer. We also receive details of every transaction including finance terms and trade-in information.

In addition to JD Power data, Aizcorbe et al. (2010) also use survey data from NOPWorld. Aizcorbe et al. matched self-reported consumer information from NOPWorld to the sales data from JD Power in order to look at the consumer demographics behind the vehicle purchases in JD Power. Aizcorbe et al. find evidence of IPD with higher income consumers buying vehicles early in the model year while lower income, presumably more price-conscious consumers tended to delay their purchases well into the model year.

Copeland, Dunn, and Hall (2011) focus on inventory patterns' role in vehicle pricing dynamics. In addition to JD Power, Copeland et al. (2011) use data from Ward Communications on vehicle inventories. The inventory data only cover American manufacturers, so their results do not necessarily apply to the entire, American consumer market. Copeland et al. (2011) create a model that explains the hump shaped curve that we see in expenditures over the model year (a pattern the authors also see in their inventory data). Copeland et al. (2011) claim dealers and manufacturers intentionally keep prices high at the beginning of the year to accumulate inventory. Dealers maintain a high inventory to sales ratio in order to offer customers variety and maintain high prices at the beginning of a model year rather than lose stock. Only in the later part of the model year do demand shifts<sup>4</sup>—such as IPD and fashion effects—drive downward price movement.

Corrado, Dunn, and Otoo (2006) use JD Power data to investigate price change with a focus on the impact of incentives. Corrado et al. (2006) analyze within model year price declines and the impact of accounting for rebates and interest rate subvention (concessionary finance).<sup>5</sup> They attribute the price declines to a “seasonal” pattern driven by obsolescence, or a loss of newness, and note that these drops do not reflect persistent change in the “actual price of new vehicles.”<sup>6</sup> Their long-run measure of price change looks at the year-over-year price change from one December to the next between two model years, but they do not create a monthly price index.<sup>7</sup>

Bils (2009) examines how the CPI treats quality change during substitutions for a variety of durable goods. For his analysis of new vehicles, he supplements CPI data with quantity data from Ward's. Bils (2009) argues that the CPI misses quality growth and overstates inflation. He argues that inferences can be made about relative price change and quality growth based on relative demand for replacement versus old models, and whether a replacement model maintains a persistently higher price following a substitution, suggesting quality improvement, or reverts to the previous price level, suggesting a transient demand shock or intertemporal price discrimination. Using these principles, Bils estimates that one-third of price change at model substitution can be attributed to transitory demand changes while the remaining two-thirds is due to increased quality.<sup>8</sup> Bils's discussion of price change offers an insightful look at how substitution relatives should be calculated. However, his study does not deal with creating substitutions on a transaction dataset. His work also elucidates the treatment of transitory and non-transitory price change. Treating non-transitory price increases as quality improvements may not always be justified since, as Bils mentions, non-transitory price increases could indicate inflation instead of quality

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<sup>4</sup> Copeland, et al., 122.

<sup>5</sup> We did not consider adjustments for interest rate subvention on the basis of an existing policy set forth in a November 20, 1995 memo, “Deletion of Automobile Finance Charges from the CPI,” from John S. Greenless to Kenneth V. Dalton. The treatment of financing in the new vehicle index may be evaluated in later work.

<sup>6</sup> Corrado, et al., 18.

<sup>7</sup> Corrado, et al., 33.

<sup>8</sup> Bils (2009), 640.

improvement if sellers use model changes to introduce higher prices.<sup>9</sup> Bils's work supports the argument that cross model year price change should be taken into account, even if the transitory effects on within model year price change can be accurately accounted for.

All of the previously discussed research suggests that intertemporal price discrimination accounts for at least a portion of the price decline over the course of a model year. Copeland et al. (2006) suggest that four-tenths of the decline can be explained by changes in inventory stock, but note that a model with dynamic demand might attribute some of that decline to price discrimination and other factors.<sup>10</sup> Corrado et al. (2010) note that early purchases by "fashion-oriented" or "price-inelastic" consumers might explain within model year price declines, but they find no evidence that there is a declining pattern in consumer age, their proxy for income.<sup>11</sup> Aizcorbe et al. (2010) focus on the change in income of customers over the course of a model year but do not quantify the effects on price change. We find additional evidence supporting consumer heterogeneity consistent with intertemporal price discrimination.

The background literature is consistent in finding strong, persistent within model year price declines. Each paper focuses on a different explanation for these declines: price discrimination in Aizcorbe, et al., inventory management in Copeland, et al., and "newness" in Corrado, et al. There is no reason to assume that any single explanation is exclusive and all three papers suggest factors that should not be reflected as cost-of-living declines over the long term. Two of the papers, Aizcorbe et al. (2009) and Corrado et al., measure long-run change by calculating year-over-year price change, a method that should exclude transient price declines due to any of the aforementioned effects. The twelve month, or year-over-year, price change provides a measure of long-run price change that does not require directly estimating effects of price discrimination, inventory control, fashion effects, or obsolescence of a model year over time.

### 3. Data

The BLS purchased transaction-level data from the JD Power Group. JD Power receives vehicle transaction records from participating dealerships across the United States. These records provide the raw information for JD Power's aggregated "Power Information Network" (PIN) analytics.<sup>12</sup> The data used in this paper covers the time period between January 2007 and March 2015 and represent about a third of the new vehicle purchases in the United States. Data coverage improves over time with increasing dealership participation. Each observation in the dataset includes a transaction price as well as a set of 40 variables showing the value of manufacturer rebates, vehicle characteristics, information on finance terms, and, sometimes, the cost of the vehicle to the dealer.

Most of the characteristic information in the data are indicated and derived from the squishvin. The squishvin is a shortened version of the vehicle identification number (VIN) commonly used for vehicle registration. VIN numbers are based on an international standard, ISO 3779, that allows certain features of a vehicle, such as its make, model, and origin, to be determined from standardized usage of certain digits. We only receive a "squishvin," the shortened portion of the VIN that identifies features and

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<sup>9</sup> Bils (2009), 639.

<sup>10</sup> Copeland, et al., 145.

<sup>11</sup> Corrado, et al., 14-15.

<sup>12</sup> Disclaimer from J.D. Power: "The information supplied by Power Information Network, a business division of J.D. Power and Associates ("PIN") is based on data believed to be reliable but is neither all-inclusive nor guaranteed by PIN. Without limiting the generality of the foregoing, specific data points may vary considerably from other information sources. Any opinions expressed herein reflect the judgment of the authors at this date and are subject to change."

omits the serial number identification component of the VIN and the ninth “check digit.” The fourth through eighth digits identify vehicle attributes, but the specific meaning of these digits varies by manufacturer. For example, one manufacturer might use the seventh digit to denote drive train type while another might use the fourth.

Generally we have found that the squishvin identifies vehicles down to the trim level and usually provides some additional information on major equipment packages. The specificity of the squishvin varies by manufacturer. Some manufacturers use squishvins that seem to denote a specific vehicle model and equipment configuration and others use a single squishvin to describe a set of vehicles with different packages and transmissions.

When BLS collects data for the Consumer Price Index, we utilize statistical methods to draw a sample with the goal of creating a representative sample for our survey. In contrast, JD Power’s objective is not to select a representative sample of the market, but to capture as many sales as possible. Despite this difference the BLS survey and JD Power’s convenience sample, internal comparisons of JD Power and CPI data show similar market shares by brand and a similar geographic distribution of vehicles sales. Publicly available information indicates there has been a shift to trucks away from cars in the past several years.<sup>13</sup> As of December 2017, the CPI’s sample was evenly split between cars and trucks with a slight majority of trucks. The JD Power was much closer to other publicly available sources that indicate trucks outsold cars two-to-one (in terms of number of vehicles not expenditures).<sup>14</sup> CPI’s breakdown may be due to a lag in sample rotation that reflects this market shift. The JD Power data may not be designed as a representative sample, but the data appear to provide a similar level of representativeness when compared to the CPI while giving a more timely picture of the current state of the market.

In the CPI survey, prices are observed at the dealer level and price relatives reflect price change within a dealership. In JD Power, dealerships are not identified and our analysis reflects consumer activity across dealerships within a geographic area. The methodology currently used by the BLS relies, in part, on outlet level weights. The JD Power data do not tell us the specific point-of-sale for a transaction, so the BLS’s exact methodology cannot be applied.

## Data behavior

Our analysis of the JD Power data reproduced the fundamental patterns seen in previous research on vehicle prices. Over the course of a model year we observe that a typical vehicle’s price declines steadily while its expenditures rise at first and then decline after the vehicle has been on the market about seven months. The within model year price behavior leads to problems in measuring long-run price change.

## Expenditures

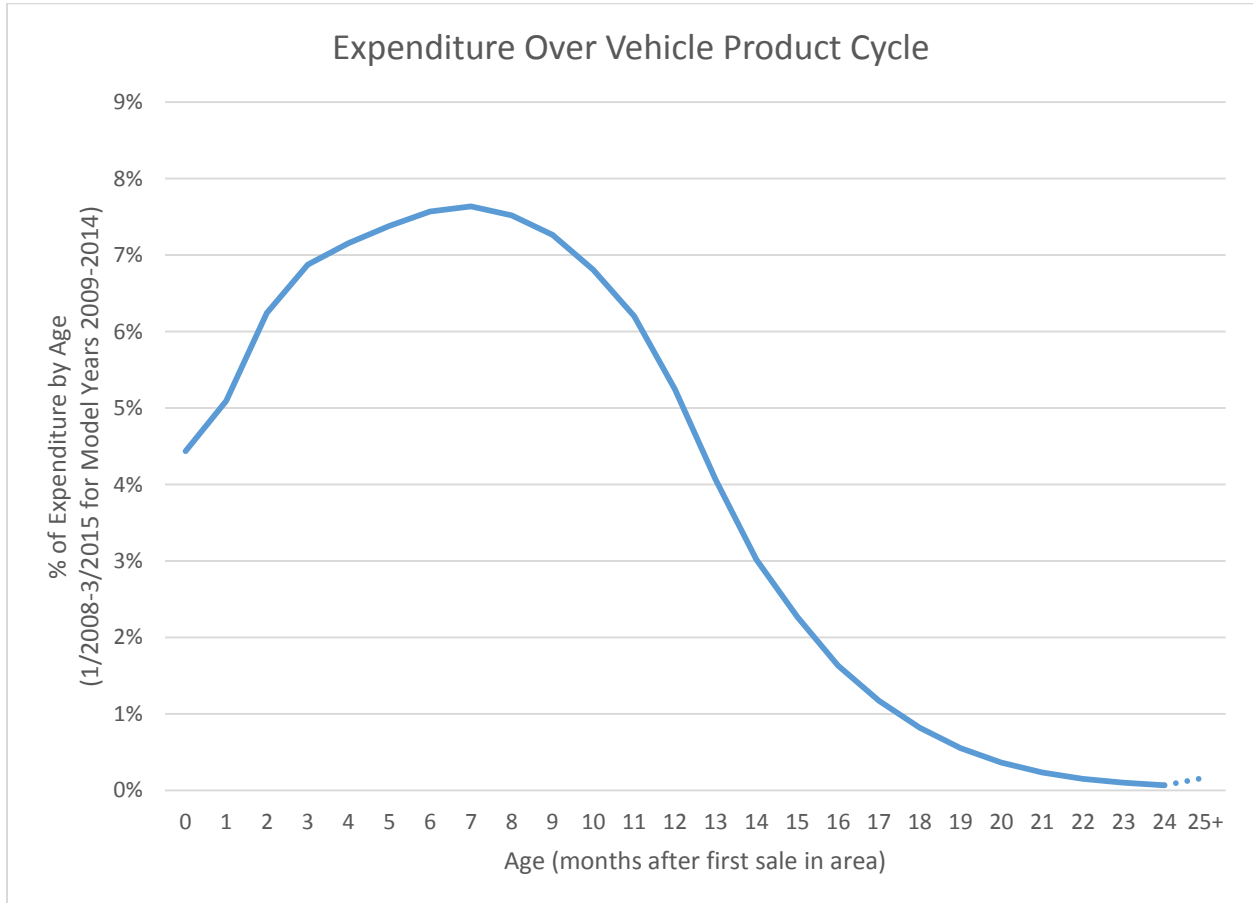
We observe a humped pattern in the sales of vehicles over the course of a model year. Upon being introduced to the market, a typical vehicle’s sales increase until reaching a peak about seven months after introduction. Sales steadily decrease thereafter with few vehicle sales occurring 24 months or more after a vehicle’s first sale in a geographic area. Copeland, Dunn, and Hall (2011) find a similar pattern in their analysis of older JD Power data. They attribute the pattern to an initial production ramp up and dealership inventory accumulation process followed by a managed end of life strategy for late

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<sup>13</sup> “What’s Moving: US Auto Sales.” *Wall Street Journal*. 5 December 2017.  
[http://www.wsj.com/mdc/public/page/2\\_3022-autosales.html](http://www.wsj.com/mdc/public/page/2_3022-autosales.html).

<sup>14</sup> “Sales and Share of Total Market By Manufacturer.” *Wall Street Journal*. 5 December 2017.  
[http://www.wsj.com/mdc/public/page/2\\_3022-autosales.html](http://www.wsj.com/mdc/public/page/2_3022-autosales.html).

model vehicles that remain in inventory as new model year vehicles arrive. This pattern contrasts with the static weighting of the CPI, and, as further discussed in later sections, leads to complications when trying to offset within model year price decline with cross model year price change. Details of creating such a month-to-month index are covered in the companion article, “A New Vehicles Transaction Price Index: High-Frequency Component Extraction and a Trend Corrected Price Index.”

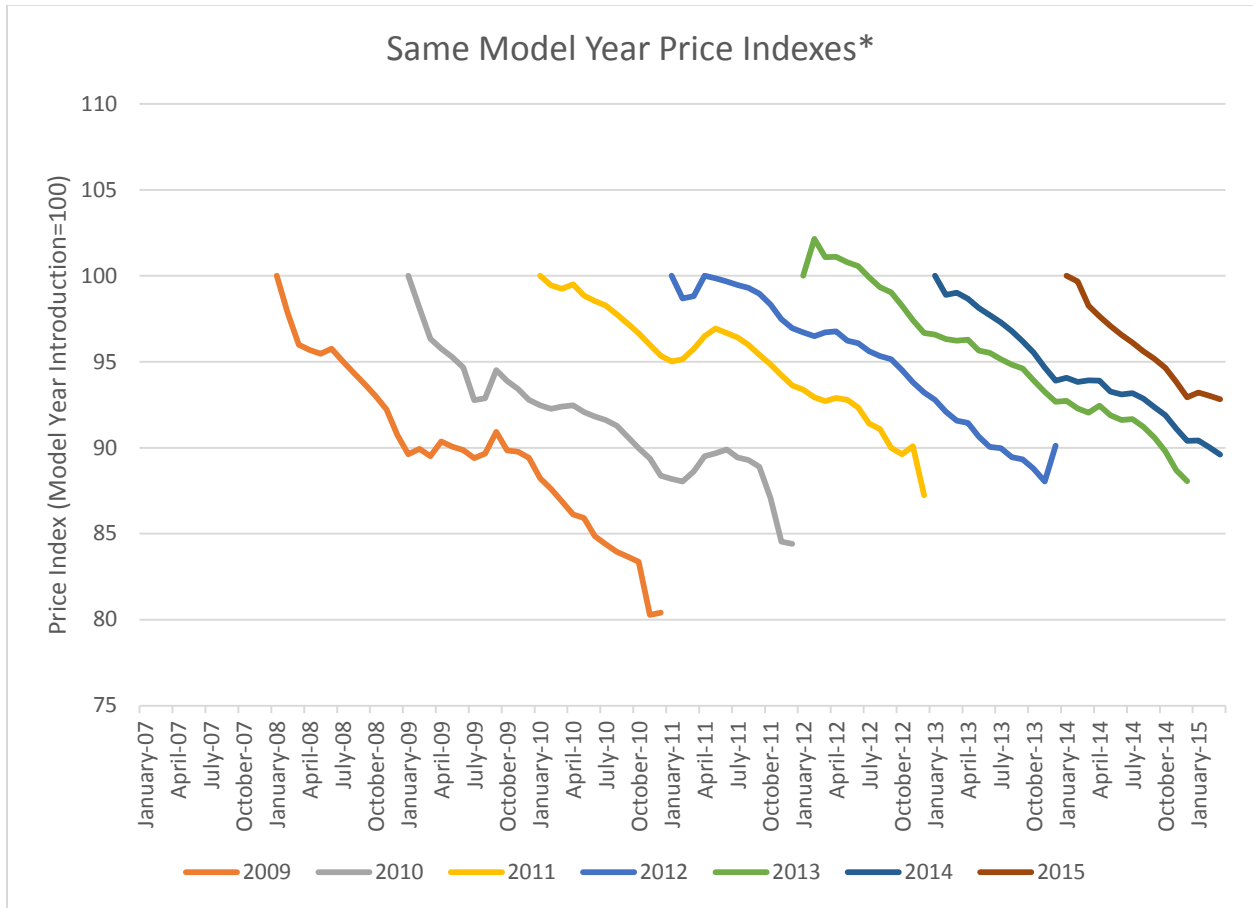


## Prices

A price index can be constructed using JD Power’s data by simply plugging prices and quantities (or expenditure shares) into a price index formula; however, this would ignore the price dynamics at the entry and exit points of a model’s life cycle. We have found that the life cycle dynamics of a vehicle’s price show steady downward movement within a model year. Prices have the strong tendency to decline from the point when a model enters the market to the point where it exits, consistent with previous analysis discussed in the background literature. When a price index constructed on this data only shows matched-model price change (and never a change between model years), the index will reflect a decline.

Our analysis of the data finds that within model year price change tends to be strongly negative. The chart below, covering model years 2008-2015, shows Tornqvist indexes reflecting price change within a given model year. Indexes are based on 100 at the beginning of the model year. The chart below shows the first 36 months of matched-model price change for all models in a given model year. A few models may have sales after 36 months, but, at this point, three years into a model year, extremely few

transactions occur. Our results are very similar to a chart in Corrado et al. (Chart 5, p, 38) that shows the price change for model years 1990-2004.

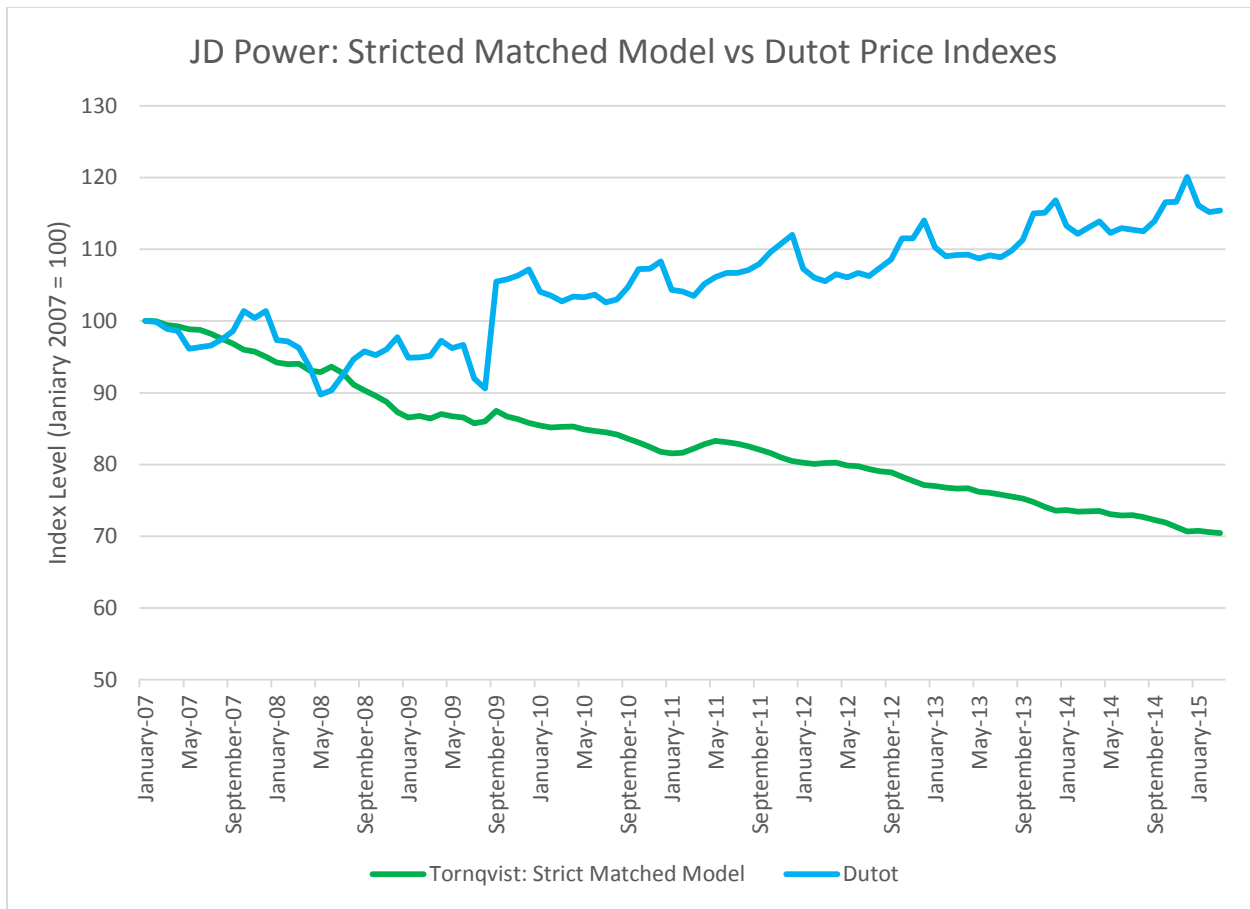


\* First 36 months of model year sales (Tornqvist)

Over the course of the lifespan of a model year, vehicle prices generally decrease more than 10% over a three-year span. When a simple matched-model index is constructed where matches are only made within the model year (i.e. there are no “item replacements” where the relative would reflect price change between different model year iterations of the same vehicle), the index drops precipitously. Over the entire course of the dataset, a Tornqvist, matched-model index drops almost 30%.

The results of the matched model index seem suspect given a clear increase in nominal new vehicle prices over the same time frame. The Dutot price index in the figure below represents the percentage change in average prices in the JD Power dataset. The Dutot price index shows prices increasing more than 15% over the same time frame in which the matched-model drops 30%. The Dutot price index reflects the change in average price between the vehicles sold in time  $t$  and  $t-1$ :

$$P_{Dutot,t} = \frac{\frac{1}{N_t} \sum_j^{N_t} Price_j}{\frac{1}{N_{t-1}} \sum_i^{N_{t-1}} Price_i}$$



The divergence between the unit value and strict matched-model indexes could reflect changing quality in vehicles. Consumers might be paying more in nominal terms, but getting more, in terms of shifting purchases to higher end cars or getting improved cars across the board and paying more for the additional features, but other factors could be at play. Intertemporal price discrimination could lead to continuously declining price relatives. Matched-model indexes in the presence of IPD are susceptible to downward bias since indexes show the drop in price for a given model over time as prices are cut to attract more price sensitive consumers and never show upward price movement when a new model is introduced and sold to high willingness-to-pay consumers. More generally, this matched-model index only reflects price change as a specific version gets older. Any aging effects will be comingled with actual price change, and there is no chance for a comparison of an end-of-life vehicle to a new one to offset within model year declines.

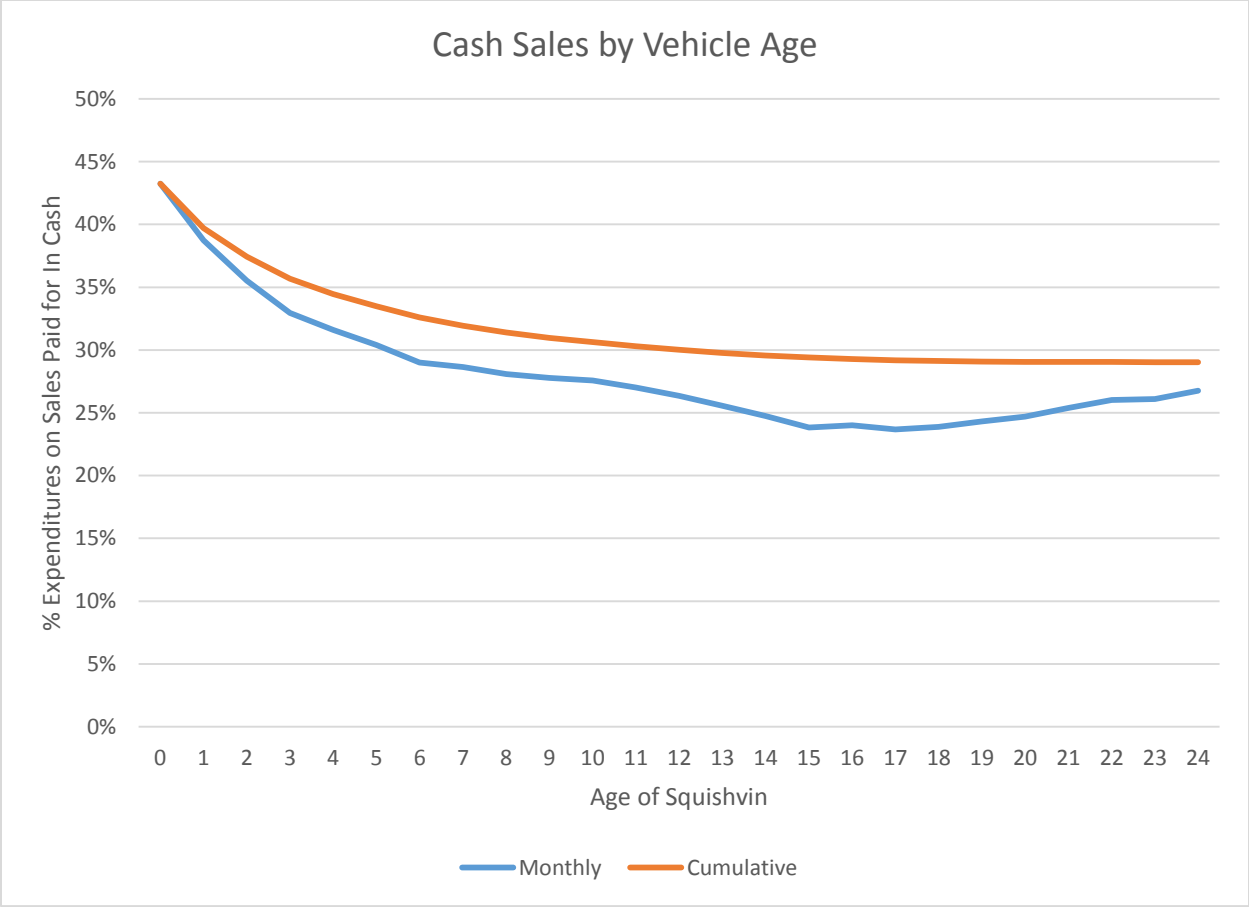
Given a pure “matched-model” approach, the index will not have the chance to show any price change from one iteration of a model to the next. Price increases generally only appear in comparisons across model years. In order to show price increases from one model year to the next, the matched-model approach must be adapted to show price change from an old model year to its successor. In the current CPI, an item replacement or “changeover” process is used in a monthly index to incorporate this price change across model years. For our index based on JD Power data, we use a year-over-year measure discussed in Section 5.



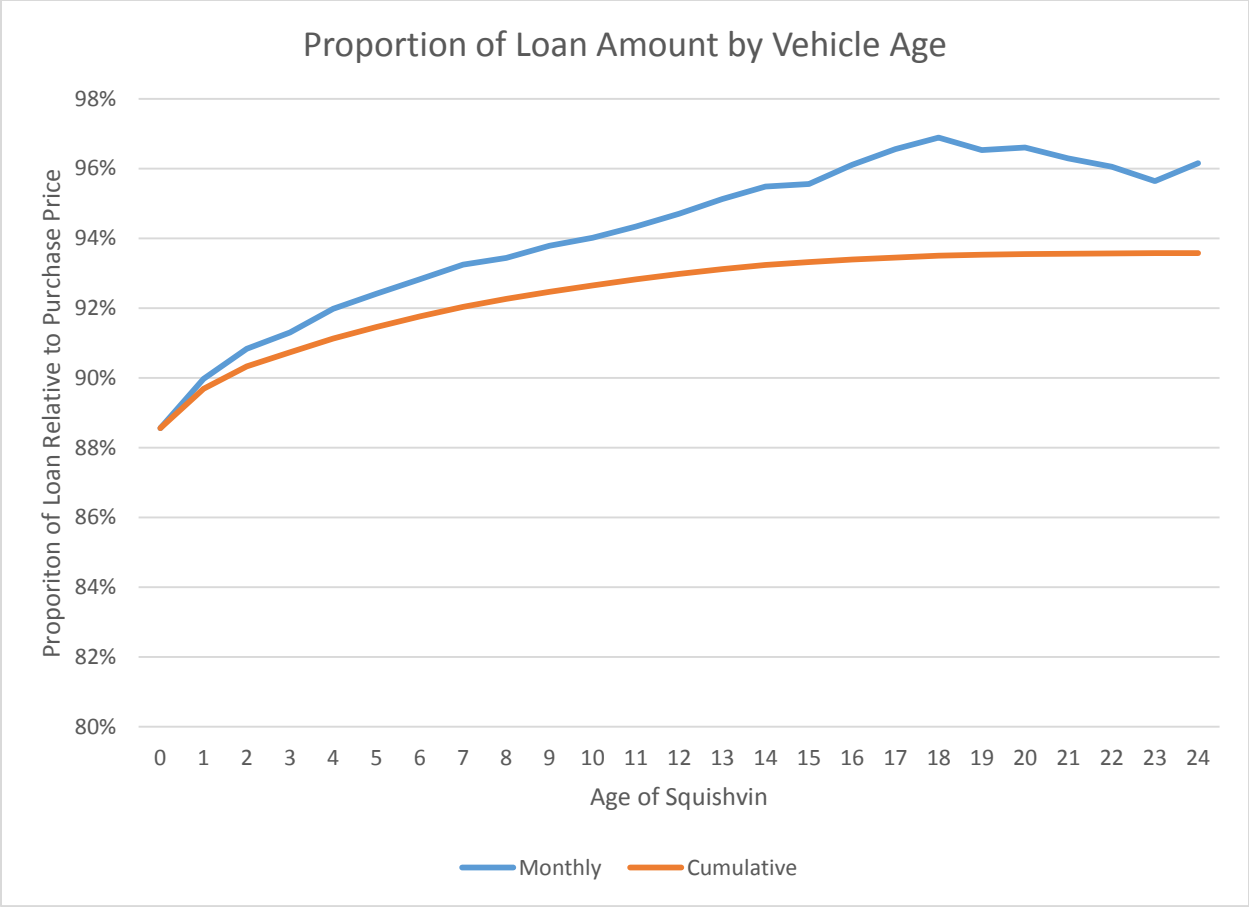
## Consumer heterogeneity

We find evidence of consumer heterogeneity that would be consistent with IPD influencing the price dynamics of new vehicles. This evidence supports the more direct evidence of IPD found in Aizcorbe et al. (2010). Unlike Aizcorbe et al., we have no measure of consumer income, but the JD Power transaction data include certain details on how an individual purchase was paid for and financed. We analyze the changes over the model year in several financing variables: the portion of cash versus financed transactions, the portion of the vehicle cost that is financed, and the APR of the loan. These are charted below in terms of the “age of squishvin,” the number of months since a squishvin first appeared. We observe that the ratio of vehicle transactions that are paid for in cash rather than financed decreases through the model year, and, of those transactions that are financed, the portion of the transaction financed (generally, the amount of a financed deal not covered by a down payment) tends to increase. APR rates have a more complicated relationship with vehicle age. Percentiles for APR diverge over a vehicle lifespan as the most qualified buyers receive 0% financing incentives for older vehicles while, at the same time, lower-credit consumers appear to enter the market later in the model year, which drives up the higher level APR percentiles.

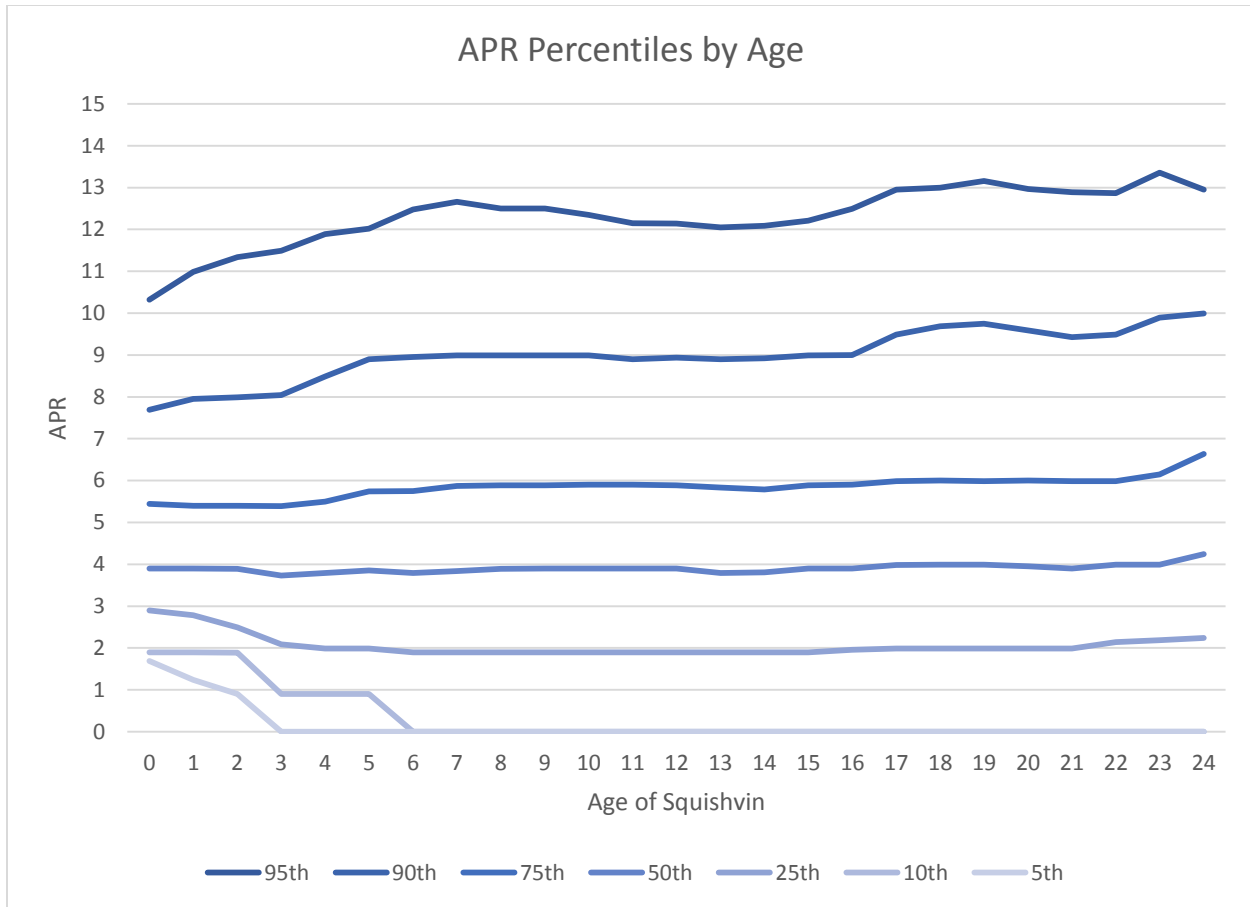
The JD Power data show that buyers of newly debuted vehicles are more likely to pay in cash. These buyers may actually be obtaining financing from a non-dealer source, but show up in the data records as “cash” purchasers. Whether or not a customer brings third party financing or actually pays cash straight from their bank account, a cash sale is indicative of a customer with greater access to financial resources who would be expected to pay more under an IPD regime. Analyzing data from January 2009 to March 2015, cash transactions accounted for 43% of expenditures during the debut month of vehicle. The portion of expenditures represented by cash transactions falls as a vehicle gets older and reaches a nadir of 23% at 17 months. At this point, in a vehicle’s lifespan the vast majority of expenditures have occurred, and further sales are sporadic. The cumulative portion of cash transactions (the portion of cash transaction up to the month in question) stays around 29%.



In cases where customers take dealer financing, JD Power offers data indicating how much of a transaction was covered with financing (the amount of a financed transaction not covered by the down payment). Early purchasers tend to put more money down, so less of the remainder of their expenditure is financed. In the first sales month of a vehicle, about 89% of the vehicle price is financed. As a vehicle ages, customers tend to borrow more or put less money down relative to the purchase price. A peak is reached 18 months into a vehicle’s life cycle when 97% of the transaction is financed.



Age has a more complicated relationship with APR than it does with the other variables analyzed here. The central tendency for APR remains mostly flat at 4% over the time period examined (January 2009 to March 2015); however, APR percentiles reveal a more complex story. They show a divergence in APR rates as customers become more heterogeneous through the model year. Consumers with good credit ratings get lower interest rates. A few months after introduction, those who qualify for concessionary interest rates often get zero percent financing, an effective price cut. The 5<sup>th</sup> and 10<sup>th</sup> percentiles for APR are zero for much of the model year. At the other end of the APR distribution, interest rates increase steadily as the model gets older, which is consistent with consumers with fewer financial resources entering the market later in the model year.



#### 4. Product Cycle Theory

A variety of factors may explain why we see persistent price declines like those in the strict matched-model index discussed in the earlier “Data behavior” section. From a certain point of view, this index could reflect a real decline in consumers’ cost-of-living. The within model year price change show actual declines in vehicle prices, and the tendency for new model year vehicle prices to exceed those of their predecessors could indicate a price premium on the features and quality of newer vehicles. Given the large difference between behavior of vehicle average prices and price relatives, we do not think the strict matched-model index reflects the true change in cost-of-living. These declines could be an artifact of price index construction known as “chain drift.” Other explanations for these apparent price declines include IPD and other factors related to the product cycle, the pattern of behavior from the introduction to the exit of a version of a product.

##### Chain drift

Chained price indexes often experience “drift” in one direction. As usually defined, chain drift arises from frequent price oscillations or “bouncing.”<sup>15</sup> The vehicle prices we see here actually tend to be relatively stable compared to the extreme price changes often observed in retail scanner data. The drift appears to arise from consistent downward price change within model year rather than oscillating prices.

<sup>15</sup> Ivancic (2011), 27.

Greenlees and McClelland (2010) observed similar behavior in apparel prices and found that “the relentless downward march of prices completely overwhelm the chain drift issue” in their data.<sup>16</sup>

We find further support in dismissing conventional chain drift in the results of the RYGEKS index (Rolling year GEKS, index named for Gini, Eltetö, Köves, and Szulc). Ivancic, Diewert, and Fox (2011) proposed the RYGEKS index as a means of reducing chain drift. The pure GEKS index eliminates chain drift associated with non-transitivity.<sup>17</sup> The RYGEKS is a more practical adaptation of the GEKS. The GEKS is recalculated completely as new data are introduced over time. The RYGEKS starts with a base GEKS calculated over one year and then updated with a “chain link.” The RYGEKS is not fully transitive, but it reduces chain drift from non-transitivity.<sup>18</sup>

Our RYGEKS formula starts with a thirteen-month GEKS index (Ivancic, et al. use a 13 month rolling window for their RYGEKS):

$$\text{GEKS}_{0,12} = \prod_{l=0}^{12} \left( \frac{P_{0,l}}{P_{12,l}} \right)^{1/13}$$

For the thirteenth month the GEKS is updated with a “chain link”:

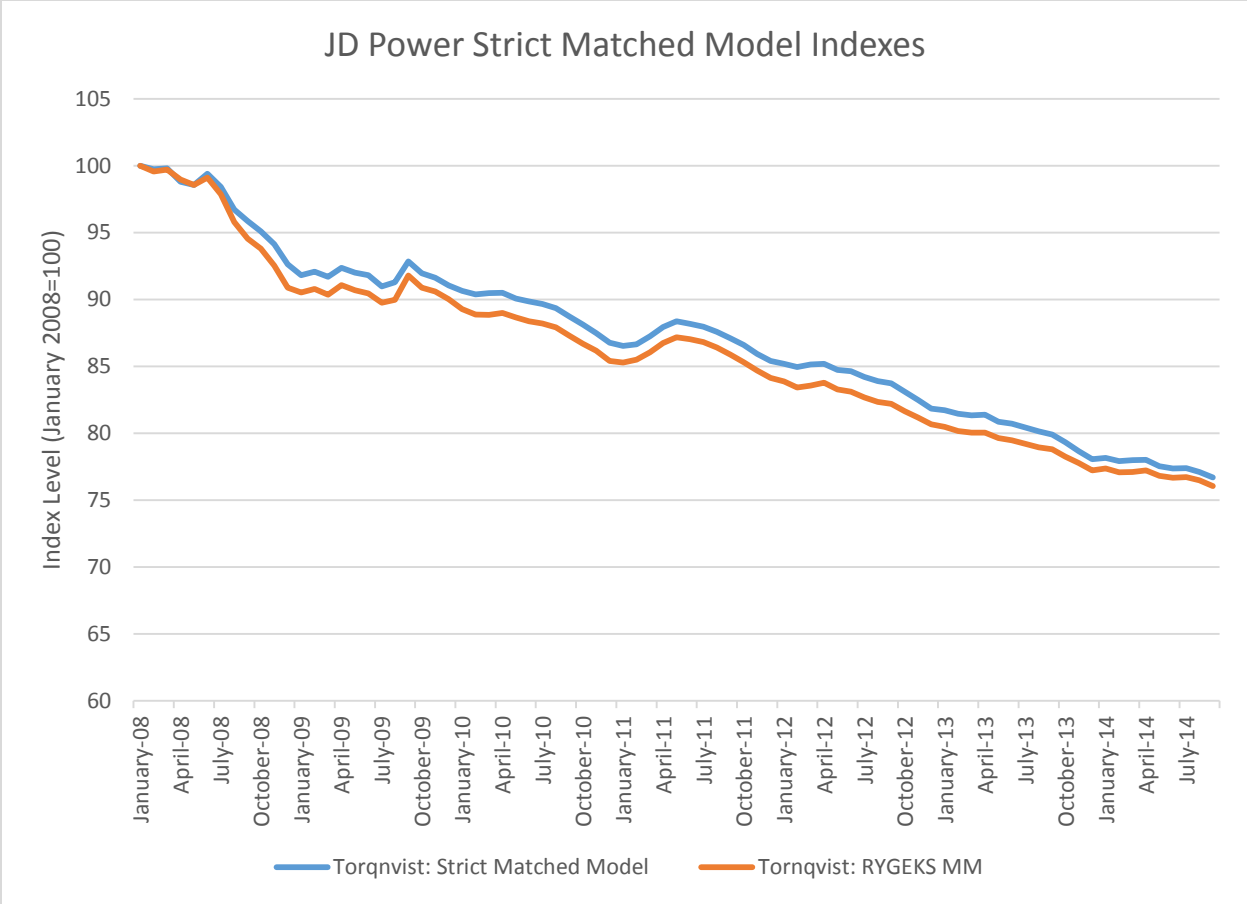
$$\text{RYGEKS}_{0,13} = \text{GEKS}_{0,12} * \prod_{t=1}^{13} \left( \frac{P_{12,t}}{P_{13,t}} \right)^{1/13}$$

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<sup>16</sup> Greenlees and McClelland (2010), 6.

<sup>17</sup> Ivancic, et al. (2011), 31.

<sup>18</sup> Ivancic, et al. (2011), 33.



We find little difference between a chained and a RYGEKS matched-model Tornqvist. Both indexes drop precipitously over time. Were chain drift the cause of the drop, we would expect the RYGEKS to moderate the issue. Problems with these indexes seem to stem from the fact that the monthly price relatives for matched-model goods have a strong tendency to be less than one and not from the oscillation issue addressed by the RYGEKS. Chain drift, as conventionally defined, does not appear to explain the downward price tendencies, nor does this appear to be more generally an index formula issue.<sup>19</sup>

<sup>19</sup> Researchers in this field often focus on addressing problems by getting the “right” index formula, but the problem of offsetting within model year price change seems to necessitate a different approach to relative construction. When price  $\frac{P_{i,t}}{P_{i,t-1}}$  relatives overwhelmingly show price declines (having values less than 1), these relatives cannot be weighted to show a price increase (an index relative greater than 1). Consider a matched-model index where a specific model is denoted by the subscript  $i$ , price relatives are constructed as  $\frac{P_{i,t}}{P_{i,t-1}}$  and weights for the relatives are designed as  $w_{i,t,t-1}$  (this formula can encompass several common index formulas depending on how  $w_{i,t,t-1}$  is constructed):

$$P_{Index,t} = \prod_{i=1}^n \frac{P_{i,t}}{P_{i,t-1}} w_{i,t,t-1}$$

In order for predominately declining relatives to produce an increasing index,  $P_{Index,t}$  negative weights would have to be used, an impossibility in conventional price indexes.

## Intertemporal price discrimination

Stokey (1979) identifies several characteristics of markets that could lend them intertemporal price discrimination. Among other cases, she discusses markets where customers lack pricing information or where the seller has limited capacity,<sup>20</sup> both of which fit the new vehicle market. Given the extensive negotiation process generally involved in purchasing a car in America, the new vehicle market lacks transparent pricing. Limited dealer inventory capacity plays an important role in the model developed by Copeland, et al. As discussed in the background literature and data section, Aizcorbe, et al. (2010) found evidence of IPD that is supported by our own findings of consumer heterogeneity. IPD presents a problem for price index calculation from a cost-of-living perspective, and, more specifically, when ignored, leads to an apparent violation of the assumption of homothetic preferences and the ability to represent a market with a representative consumer.

Cost-of-living theory relies on an assumption of stable preferences (i.e. the same utility function persists over time) to justify making statements regarding the cost of obtaining a certain utility level based on observed expenditures and prices. While this assumption is often violated by constantly shifting preferences in the market, IPD leads to systematic shifts that bias indexes downward. IPD can have a pernicious impact on price indexes.

Konüs laid out the original cost-of-living approach to index theory. He defined a cost-of-living index ( $P_{Konüs}$ ) as the ratio of the minimum cost of attaining a certain level of utility,  $u$ , between two time periods given time-specific price vectors,  $p^t$ :<sup>21</sup>

$$P_{Konüs}(u, p^0, p^1) = \frac{C(u, p^1)}{C(u, p^0)}$$

An index of this form qualifies as a cost-of-living index regardless of the choice of a reference level of  $u$ , but  $u$  must be constant between the two time periods. Otherwise, the resulting index reflects both the change in prices and the change in preferences. When sellers practice IPD, they exploit differences in consumer utility function between time periods which necessitates a difference in consumer utility,  $u$ , between the periods. Differences can result due to IPD based on heterogeneous preferences, in which case changes in  $u$  result from differing utility function, or due to differences in consumer budgets, in which case the level of  $u$  differs. Either way, the resulting relative is not necessarily a Konüs index since there is no reference level of utility:

$$\frac{C(u_1^1, p^1)}{C(u_0^0, p^0)}$$

Discrimination based on income would be less of a concern if the consumer preferences are homothetic, meaning that a consumer's preferences over how much of each product to purchase scale linearly with the consumer's income. This would allow us to use either time period as a reference utility.<sup>22</sup> The homothetic preferences assumption is also important for extending cost-of-living theory to a real world use through aggregation by allowing us to create a fictitious representative consumer. Given that cost-of-living theory assumes that all consumers purchase products in the same proportions, a single

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<sup>20</sup> Stokey (1979), 369-370.

<sup>21</sup> See discussion in "The Economic Approach to Index Number Theory: The Single-Household Case." Chapter 17. *Consumer Price Index Manual: Theory and Practice*. 2004.

<sup>22</sup> ILO (2004), 316-317.

consumer (our representative agent) who possesses all of an economy's income also purchases products in these same proportions. In this sense the single consumer represents the preferences of all agents.

The segmentation of purchases by consumer type into different time periods leads to a violation of homothetic preferences, even in cases where the underlying utility function may be homothetic. Given two customer types that vary by income and, correspondingly, willingness to pay for a good  $x$ , customer  $a$  differs from  $b$  by having a higher reserve price, therefore  $p_a > p_b$ . Given perfect IPD, customer  $a$  will consume  $x$  in the first period ( $t_1$ ), and customer  $b$  will consume  $x$  at  $t_2$ . If we try to assume that each period is a snapshot representing the same utility function, the utility function cannot be homothetic. Homothetic utility implies that consumer demands will be proportional to income.<sup>23</sup> When  $b$  demands  $x$  in  $t_2$  and  $a$  has no demand for  $x$ , despite  $a$  having higher income, the utility function implied by only looking at  $t_2$  is not homothetic. No single time period is representative of aggregate consumer behavior because of time-based market segmentation. When markets can profit from differences in consumer's characteristics, consumer heterogeneity better characterizes the reality of consumers' market behavior than a representative consumer can.

The potential ramifications of IPD on measures of price change have not been well explored in the price index literature. Car dealers using IPD exploit differences in consumer preferences by selling to high willingness-to-pay consumers at the beginning of the model year and low willingness-to-pay consumers at the end of a model year's life cycle. Resulting price changes reflect both any change in cost-of-living and changes in customer preferences. IPD always leads to price declines, a possible explanation for the behavior of within model year price.

### Product cycle bias

We consider IPD along with other possible explanations for the new vehicle price cycle behavior generally as "age bias." In the presence of age bias, the nominal price of an item will reflect both change in price due to the aging of a vehicle and any change in the cost-of-living. Let  $P_{ijat}$  be the price of a product  $i$ , with an age  $a$ , at time  $t$ . The price can be decomposed into a time fixed effect  $\theta_t$ , a product fixed effect  $\xi_i$ , an age-characteristic fixed effect  $\kappa_{aj}$ , and a residual  $\tilde{p}_{ijat}$ :

$$p_{iat} = \theta_t + \xi_i + \kappa_{ai} + \tilde{p}_{ijat}$$

The change in price from the period prior to  $t$  can then be expressed in terms of changes to these underlying components with the product fixed effect cancelling out since it is unchanged by definition:

$$\Delta p_{iat} = \Delta \theta_t + \Delta \kappa_{ai} + \Delta \tilde{p}_{ijat}$$

For our price index, we are interested in capturing the price change due to  $\theta_t$ , which means controlling or adjusting for changes in age. If the change in age leads to a change in price, a constructed price relative will be biased. This bias occurs at the formation of the first price relative, so bias is not caused by chaining.

## 5. Addressing Product Cycle Behavior

First, we discuss how the current CPI uses "item replacement" to create cross model year price comparisons that tend to offset the within model year price declines that characterize the product cycle for new vehicles. However, this method relies on a fixed weight index formula that is not compatible with the dynamic weighting used in a superlative index, which would be recommended under a cost-of-living

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<sup>23</sup> Varian (1992), p 147.



approach. We then explore using a year-over-year index to create price comparisons that are robust in the presence of IPD and other age-related factors. The year-over-year methodology is applied to the JD Power in later sections.

### Item replacement

In order to show price change from one iteration of a model to the next in a matched-model price index, a price relative has to be constructed that shows the change from the old to the new model. In the CPI's sampled survey, item replacement is a built-in part of the process to maintain a sample of a certain size as model years come and go from the market, but it also serves to capture price change related to the introduction and exit of goods. For decades, the BLS has seen a general pattern where new vehicle introductions are associated with upward price change relative to flat or decreasing same model year price change. Recognizing this, class-mean imputation was introduced for new vehicles in October 1989 so that discontinued vehicles without comparable replacements would be imputed by price change from other replaced vehicles.<sup>24</sup>

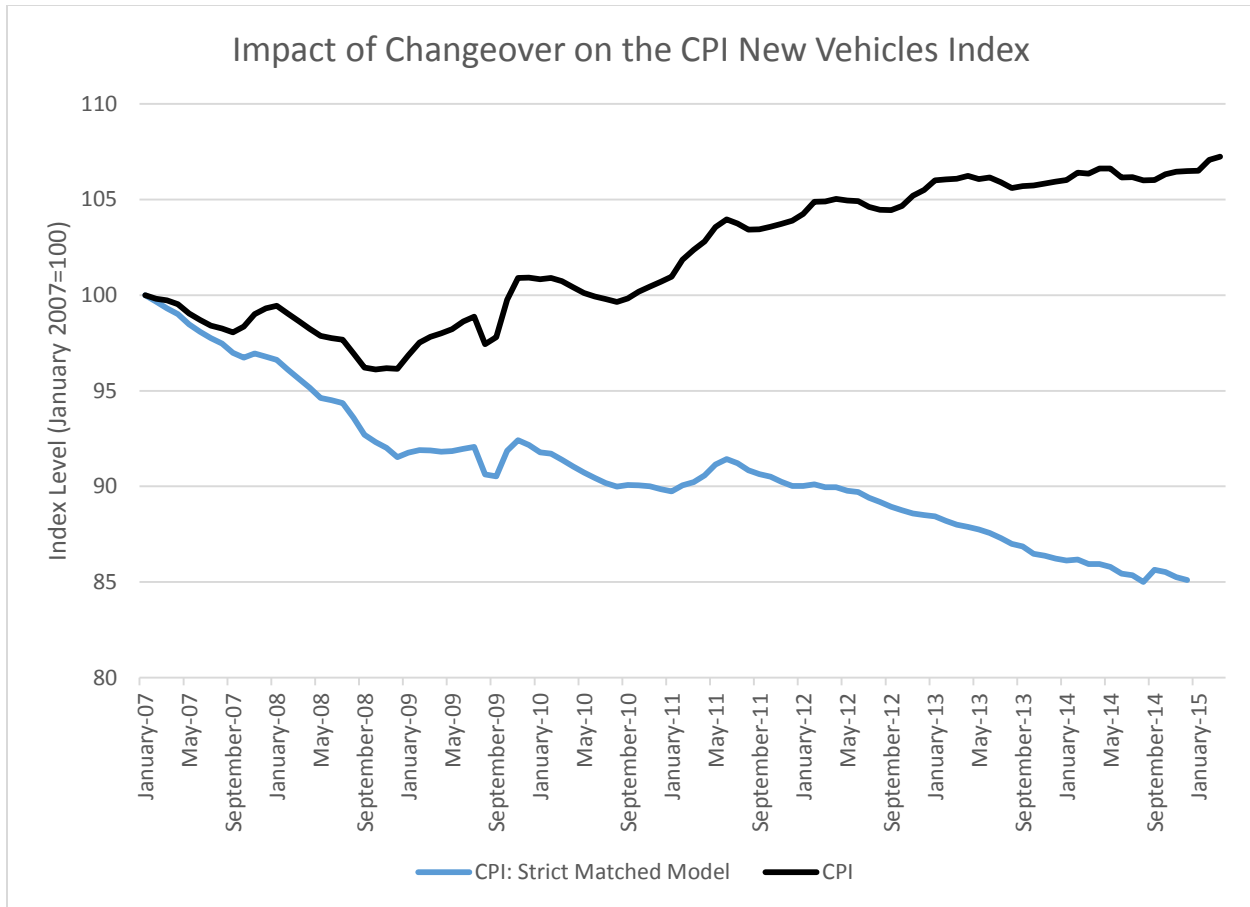
In the current CPI methodology for new vehicles, a “substitution” is made where the old model year is replaced once sales of the new exceeds those of the old. Strongly downward price indexes for new vehicles are avoided by constructing a “changeover” relative,  $\frac{P_{i,MY+1,t+1}}{P_{i,MY,t}}$ , every year that shows the relative price change between a new model year version of a vehicle and its predecessor last month with quality change between model years removed with an adjustment.

An experimental index based on CPI new vehicles data below shows the impact of removing the changeover process from CPI calculations. Like the matched-model index in the “Data behavior” section, the resulting index (in blue) reflects only within model year price change. From January 2007 to December 2014,<sup>25</sup> the index without changeovers decreased 15% while the official increased 6.5%. The decrease is not as substantial as the 30% drop in the matched-model Tornqvist index based on JD Power data, which may be in part due to the difference in index formula. The JD Power-based, matched-model Tornqvist index uses real-time weighting information, while the CPI indexes below follow official CPI procedures and use a statically weighted geomean formula at the lower-level. Both use a Laspeyres formula at the upper level for geographic aggregation using BLS geographic weighting information.

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<sup>24</sup> Reinsdorf, Liegey, and Stewart (1996), p 8..

<sup>25</sup> The research index calculator used to create this index only runs until December 2014 due to changes to our estimation system implemented in January 2015.



The use of real-time weights complicates the use of the changeover process to offset downward bias. Consider the price  $p$ , of a single item  $i$ , in model year  $MY$ , with age  $a$ , in month  $t$ , with a model year lifespan of  $n$  (typically 12). If we consider the component of a price index associated with a specific item with a share weight of  $s_i$ , we can see the result of the changeover process in a fixed weight index. The price change between any two consecutive months may be biased since the comparison reflects a difference in age, but, when a comparison with the next model year iteration  $MY+1$  is forced in month  $n$ , the intervening months cancel and the overall impact of item  $i$  on the index reflects a price comparison between two goods of age  $a$ . As long as there is no quality change between the  $MY$  and  $MY+1$  versions of  $i$ , the resulting relative reflects a measure of price change from month  $t$  to  $t+n+1$  that is not biased by age, but remains biased if the index formula does not accurately capture changes in expenditure consistent with a cost-of-living index.

$$P_{i,Fixed} = \left( \frac{p_{i,MY,a+1,t+1}}{p_{i,MY,a,t}} \right)^{s_i} \times \left( \frac{p_{i,MY,a+2,t+2}}{p_{i,MY,a+1,t+1}} \right)^{s_i} \dots \left( \frac{p_{i,MY,a+n,t+n}}{p_{i,MY,a+n-1,t+n-1}} \right)^{s_i} \times \left( \frac{p_{i,MY+1,a,t+n+1}}{p_{i,MY,a+n,t+n}} \right)^{s_i}$$

$$= \left( \frac{p_{i,MY+1,a,t+n+1}}{p_{i,MY,a,t}} \right)^{s_i}$$

The above situation roughly reflects what we see in the statically weighted, geomean lower-level indexes used for the current CPI (ignoring complicating effects from sample rotation and other practical survey concerns). Once we introduce dynamic weights, such as those used for Tornqvist, Fisher, and other superlative formulas, interpretation of the chained relatives is not as clear:

$$P_{i,Dynamic} = \left( \frac{p_{i,MY,a+1,t+1}}{p_{i,MY,a,t}} \right)^{S_{i,t,t+1}} \times \left( \frac{p_{i,MY,a+2,t+2}}{p_{i,MY,a+1,t+1}} \right)^{S_{i,t+1,t+2}} \dots \left( \frac{p_{i,MY,a+n,t+n}}{p_{i,MY,a+n-1,t+n-1}} \right)^{S_{i,t+n-1,t+n}} \\ \times \left( \frac{p_{i,MY+1,a,t+n+1}}{p_{i,MY,a+n,t+n}} \right)^{S_{i,t+n,t+n+1}}$$

The intervening months no longer cancel and the resulting effects of showing price change between ages is unclear and related to the weights of  $i$  relative to other goods. The “changeover” process for reflecting price change from one model year to the next does not translate well to the dynamic data we have in JD Power. BLS research on the changeover process, such as Reinsdorf, Liegey, and Stewart (1996), did not consider the ramifications of using this procedure in an index with dynamic weights.

Note that the bias is not the result of the typical “chain drift” bias. When age contributes bias (whether the source of this bias is ultimately IPD, fashion effects, or another product cycle effect), the unchained relative  $\frac{p_{i,MY,a+1,t+1}}{p_{i,MY,a,t}}$  already reflects bias. In the case of static weights with model year item replacement, chaining can be seen as a corrective to the age bias. In the case of dynamic weights, the impact on bias of chaining is ambiguous, and bias may be exacerbated rather than attenuated.

### Year-over-year

Year-over-year (YOY) indexes have been used since the nineteenth century to ensure price comparisons reflected true price change instead of seasonal fluctuation.<sup>26</sup> Application of this method to new car data, even JD Power data, is not new. Aizcorbe, et al. (2009) and Corrado, et al. (2006), assess long run price change with year-over-year measures. Prices (and weight information if the index formula uses both current and prior period weights) are compared in one time period (be it a week, month, quarter, etc.) to the corresponding period one year ago. The International Labor Organization CPI Manual chapter on seasonality notes that separability conditions on consumer preferences (Diewert 1996 and 1999) would justify year-over-year indexes from an index number theory perspective.<sup>27</sup> In the article where Konüs introduced cost-of-living theory, he argued that year-over-year treatment of price change may be necessary to measure changes in cost-of-living since “...there is no possibility of comparing standards of living in the summer and winter months of any year since conditions of life differ as between summer and winter. It is possible to compare only the standards of living in the summer months of one year with those of the summer months of another year.”<sup>28</sup>

The new vehicle market does not have a seasonal pattern per se, but an individual vehicle model usually undergoes an annual cycle of price and expenditure patterns related to the annual introduction of new model years. Reasons for the price decline are unclear, but the YOY index helps maintain like-to-like comparisons even in the presence of several of the product cycle drivers discussed in the background literature. Given a relatively stable pattern of new vehicle releases every twelve months, the YOY index compares similar points in a vehicle’s life cycle. For instance, this method helps mitigate fashion effects since the price change reflects the difference in price of vehicles with similar “newness.” The price of a brand new, updated vehicle is compared to the point in the previous model year when the vehicle was at the height of its newness for that model year.

Similarly, the YOY index also helps mitigate the potential effects of IPD. Month-to-month indexes may show the price change between high-willingness to pay consumers at the beginning of a

<sup>26</sup> ILO (2004), p 396.

<sup>27</sup> ILO (2004), p 396.

<sup>28</sup> Konüs (1939), 13.

product cycle and more budget minded consumers who tend to buy models being cleared out of dealer inventory. The YOY relatives reflect price comparisons between transactions made by similar consumer types. Under the assumption that consumer preferences are consistent in the same calendar month from one year to the next, expenditures by like consumer types can be compared in terms of their cost-of-living. We assume  $u^t = u^{t+12}$  so that:

$$\frac{C(u^{t+12}, p^{12})}{C(u^t, p^0)} = \frac{C(u, p^{12})}{C(u, p^0)}$$

Unlike a direct month-to-month comparison, the utility function does not change, so changes in prices can be interpreted as changes in the cost-of-living.

## 6. Transaction Data Index Methodology

In order to find a measurement of price change that is not contaminated by product cycle effects, we construct a year-over-year index. This index captures the long-run price trend but does not show short-run price changes including seasonal patterns and short-term shocks. We aggregate all individual transactions for a squishvin within an area into unit prices and expenditures. Each squishvin-based “model” is matched to its prior model year equivalent. Quality differences introduced between model years are adjusted based on the cost-based estimates of quality currently used in the CPI for new vehicles. These price relatives are then aggregated into area level indexes based on a Tornqvist index formula. A national level index is then created using the same Laspeyres-type formula and geographic weighting system currently used in the CPI.

### Model definition

We define a vehicle model using a “squishvin” that is given with every transaction in the JD Power data. While the squishvin might not fully identify a homogenous item, the squishvin is our best means of defining a “model” in terms of our matched-model requirements. Instead of trying to extract detailed characteristic information from the squishvin, we simply allow the squishvin to define a specific good that we track over time. JD Power also provides additional specification information, some of which is based on interpreting the squishvin, but we choose not to use this in the process of defining a model since the squishvin provides the most accurate means available to us of identifying a consistent set of features to define a constant-quality vehicle.

While the squishvin provides a clear definition of a model within a model year, we also need to match vehicles across model years. We use a system of backward matching where we try to find a match for a vehicle given its model year in the set of vehicles in the previous model year. Finding the corresponding model in the previous model year is not always straightforward. We first search for a current period squishvin by simply changing the eighth digit, the one that corresponds to model year, to the character denoting the previous model year. (For example XXXXXX8X represents a 2008 model, so we would first attempt to match this to the corresponding 2007 model denoted XXXXXX7X). When this process does not succeed, the analyst manually looks at the descriptive information in the JD Power data to find a squishvin in the previous model year that has comparable features, even if there is no match based on squishvin.<sup>29</sup>

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<sup>29</sup> The 2010 model year involved a revision to the VIN standard, so all of the 2010 model year vehicles had to be manually matched to corresponding 2009 vehicles. In addition to this mass recoding based on a change in the squishvin standard, individual manufacturers periodically change how squishvin coding works on their vehicles, which breaks continuity in matching vehicles across model years.

## Unit price

Before we apply a price index formula, we run a first stage aggregation of transactions into a single unit price. Let  $p_{i,t,MY,n}$  be a transaction price for a new vehicle with characteristics  $i$  (defined by squishvin), at date  $t$ , and model year  $MY$ . For any new vehicle of model year  $MY$  with characteristics  $i$  at date  $t$ , there are  $N_{i,t,MY}$  total purchases, which are indexed by  $n = 1, \dots, N_{i,t,MY}$ . Vehicles have a countable number,  $i_t$ , of discernible characteristics at any given date, that are indexed by  $i = 1, \dots, I_t$ . Characteristics include the area in which the vehicle was purchased, the vehicle's make, model, and other detailed characteristics that are recorded by a *squishvin*. The number of characteristics  $I_t$  may change over time as new vehicles enter the market or older models exit.

To construct a price index, we compute unit prices for each vehicle  $i = 1, \dots, I_t$  at each date. Denote such a unit price as  $P_{jt}$ . Unit prices are constructed as the geometric mean across individual transactions:

$$p_{i,t,MY} = \exp\left(\frac{1}{N_{jt}} \sum_{i=1}^{N_{jt}} \ln(p_{ijt})\right)$$

for each  $i = 1, \dots, I_t$  and  $t = 1, \dots, T$ .

## Quality adjustment

Our index uses the same cost-based adjustment that the BLS has used since the early 1960s. The BLS currently receives information on the cost of vehicle quality improvements from manufacturers. Certain vehicle manufacturers provide us with estimates of the cost for feature improvements between model year iterations of their products. We receive cost estimates for changes such as the cost of making electronic vehicle stability control standard or changing the styling of a headlight assembly. We use this information, and a markup factor, to calculate quality adjustments. Mechanically, to quality adjust prices, we first compute the unit cost of production for each new vehicle with characteristics  $i = 1, \dots, I_t$  as a geometric mean over transactions:

$$C_{i,t,MY} = \exp\left(\frac{1}{N_{i,t,MY}} \sum_{n=1}^{N_{i,t,MY}} \ln(C_{i,t,MY,n})\right)$$

Next we compute the retail markup, denoted  $\mu_{i,t,MY}$ , as:

$$\mu_{i,t,MY} = \begin{cases} \frac{P_{i,t,MY}}{C_{i,t,MY}} & \text{If cost data available} \\ 1 & \text{If no cost data available} \end{cases}$$

Lastly, we adjust the price by subtracting the cost-based quality adjustment:

$$p_{i,t,MY} = P_{i,t,MY} - \mu_{i,t,MY} \phi_{i,t,MY}$$

When a completely new vehicle enters, a vehicle is redesigned, or when BLS determines that we do not have information capable of adjusting for large quality improvements between two model years,

the price change is treated as “non-comparable.” For the YOY index, this means the vehicle is omitted from the calculation.

## Second stage aggregation

The CPI-U uses a two stage index aggregation process. The first (elementary) stage is defined as an index for a specific item stratum in a specific geographic area. In the CPI, a geometric mean formula is used for this first stage for most categories—including new vehicles. The second stage aggregates across different items and different geographic areas. Second stage calculations use a Laspeyres-type formula.

The JD Power and CPI indexes discussed here use various elementary level index formulas but all use Laspeyres-type aggregation in the second stage to aggregate across areas to calculate a national level index. In the CPI, weights for these first stage indexes come from the Consumer Expenditure Survey and are used to produce biennial “aggregation weights” found by dividing expenditure estimates for an item type in an area by the respective first stage component price index. The aggregation weights at the second-stage are updated biennially based on the Consumer Expenditure Survey’s estimates of the amount of money spent on new vehicles. We calculate new estimates of the aggregation weight by dividing the “costweight” found in the production by our new index estimates. Area level weights are thus based on the Consumer Expenditure Survey and not derived from JD Power expenditure data. More detail on the two-stage aggregation used in the CPI can be found in Chapter 17 of the BLS Handbook (2018).

## Index formula

This paper focuses on a year-over-year index with a Tornqvist formula. The current new vehicle CPI uses a geometric mean formula, which is exact for a Cobb-Douglas utility function.<sup>30</sup> Lower level indexes, like our area level new vehicles indexes, are commonly considered “elementary indexes,” which typically do not have weights from observed expenditures. The JD Power transaction dataset allows us to weight our indexes with observed expenditures instead of through a formula based on the relatively restrictive assumption of constant expenditure shares. The ILO Manual foresaw this “future” where “scanner data may make it possible to record item-level consumption data... and to use those data in superlative index calculations.”<sup>31</sup>

## Year-over-year index

For each area, the year-over-year (YOY) index shows the annual trend inflation from one calendar year to the next, and one model year to the next. We match each model of vehicle to a similar model in the previous model year. The YOY formula below constructs a price relative ( $p_{rel,i,t,MY}$ ) using the price of given model in the current period ( $p_{i,t,MY}$ ) and matching it to the price of the corresponding model in the previous model year, 12 months ago ( $p_{i,t-12,MY-1}$ ). Once a squishvin match has been made, the twelfth root of the ratio of the matched prices is used as the monthly price relative.<sup>32</sup>

$$p_{rel,i,t,MY} = \left( \frac{p_{i,t,MY}}{p_{i,t-12,MY-1}} \right)^{\frac{1}{12}}$$

These relatives are incorporated into a Tornqvist formula and calculate a final index relative based on the geometric mean of these relatives weighted by the average of their current and prior period

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<sup>30</sup> ILO (2004), 11.

<sup>31</sup> ILO (2004), 212.

<sup>32</sup> A similar method is currently used for the housing component of the CPI. The sixth root of a six-month relative is taken to get a monthly measure of price change. See “Chapter 17. The Consumer Price Index,” p. 21.

(one year ago) expenditure shares. The aggregated expenditures ( $\sum_{MY \in S, i \in n} E_{i, t, MY}$  and  $\sum_{MY \in S, i \in n} E_{i, t-12, MY-1}$ ) only reflect expenditures for price relatives used in the calculation.

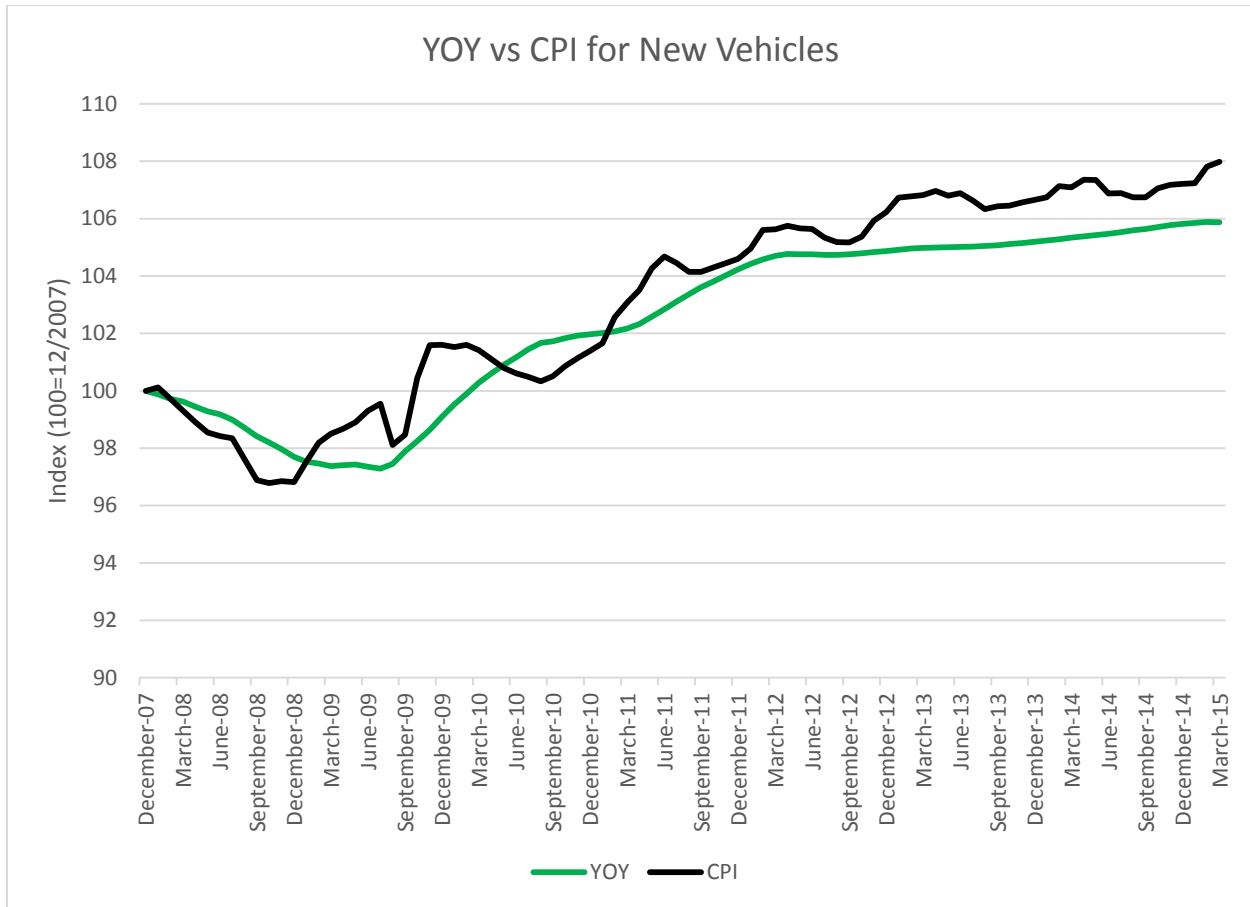
$$W_{i, t, MY} = 0.5 \left( \frac{E_{i, t, MY}}{\sum_{MY \in S, i \in n} E_{i, t, MY}} + \frac{E_{i, t-12, MY-1}}{\sum_{MY \in S, i \in n} E_{i, t-12, MY-1}} \right)$$

Expenditures for vehicles are not counted when their price relatives are not used in index calculation. This excludes expenditures for vehicles without transactions in both  $t$  and  $t-12$  and for vehicles that do not have matches across model years. Thus expenditure shares sum to one. The final index uses the relatives and weights for each of the matched vehicles in time  $t$  into an index for new vehicles in a given area.

$$P_{YOY, t} = \prod_{MY \in S, i=1}^n (P_{rel, i, t, MY})^{W_{i, t, MY}}$$

## 7. Results

From December 2007 to March 2015 the YOY index shows a 5.9% increase in new vehicle prices. This compares with an 8.0% increase in the CPI index for new vehicles over the same period. The YOY index could be expected to run lower than the CPI since it uses real-time expenditure information for weights while the CPI has fixed weighting. As expected, the YOY index presents a very smooth indicator of price change since higher frequency price fluctuations are omitted in YOY calculations. A method for recovering the high-frequency component of price change is discussed in the companion article.



Bootstrapped confidence intervals and standard errors for the index levels suggest the index levels based on the JD Power are estimated with high precision. Looking at the year ending in December 2008, the first year of the YOY index, the bootstrapped standard error for the annual percentage change is 0.012%. According to estimates from BLS’s Price Statistical Methods Division, the standard error for the annual percent change in the CPI for new vehicles for the same period was 0.390%.<sup>33</sup> The variance in the estimator of the CPI price index is calculated using a stratified random groups method<sup>34</sup> that captures the contribution to variance from sampling different geographic localities. Unlike the current CPI, the JD Power data are not sampled and the YOY index is calculated across all available areas. The differences in contributions to and estimates of variance differ between the published CPI for new vehicles and our transaction index. The comparison of standard errors are not directly comparable; however, given the relative size and coverage of the JD Power dataset, we expect a more precise estimate of price change from this transaction data compared to the current production index in the CPI.

Current lower level indexes in the CPI use a geometric mean formula, which approximates a cost-of-living index. The BLS uses the geometric mean formula for lower level indexes because it has not had access to timely expenditure information.<sup>35</sup> The geometric mean approximates a cost-of-living index for a constant expenditure utility function. JD Power data allows us to use real-time expenditure information

<sup>33</sup> Methods for current production estimates of standard error are covered in Chapter 17 of the BLS Handbook pages 37-41.

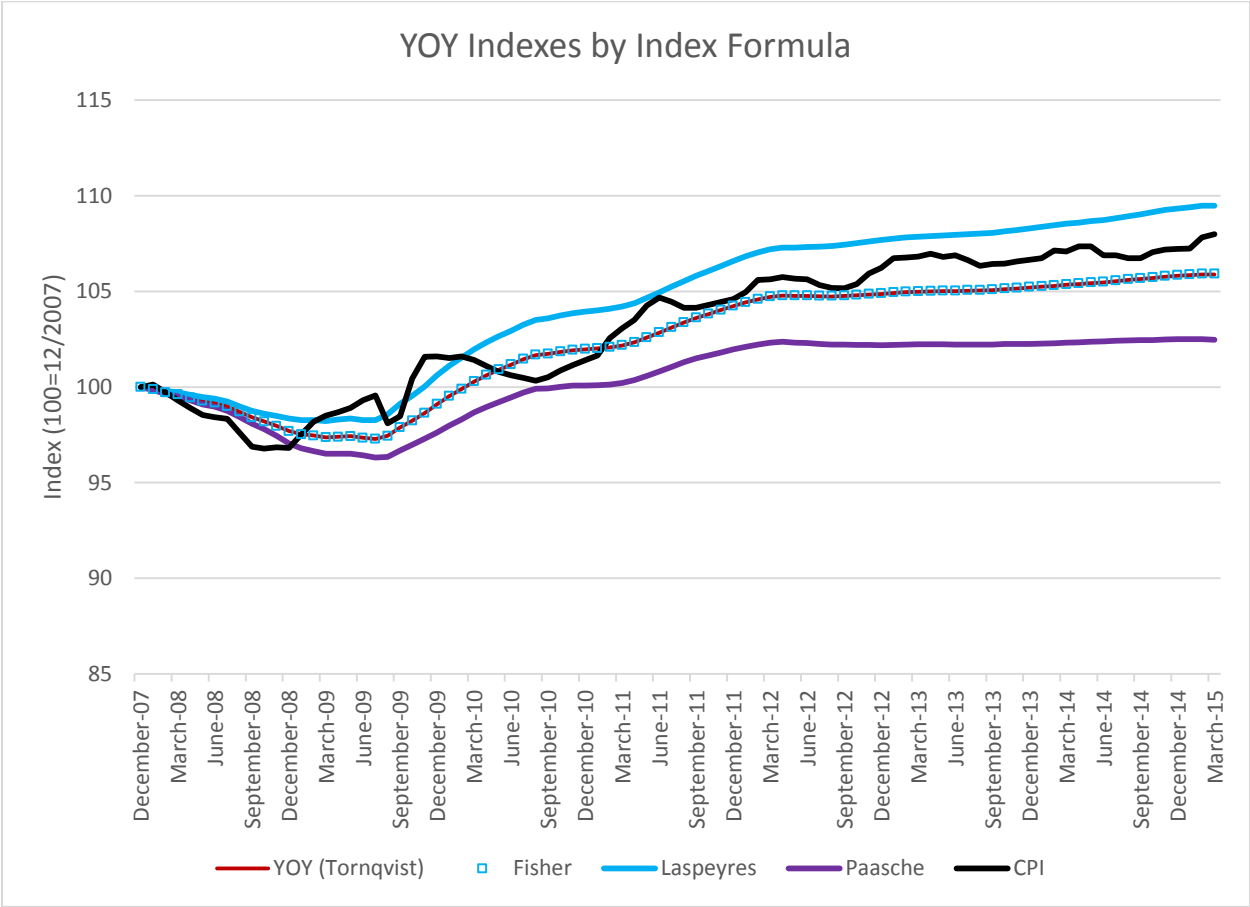
<sup>34</sup> “Chapter 17. The Consumer Price Index,” p. 38.

<sup>35</sup> The Boskin Commission (1996) “..lacking quantity or expenditure information at the lower level, a good approximation to the underlying cost-of-living index is obtained from a geometrically weighted average formula.”

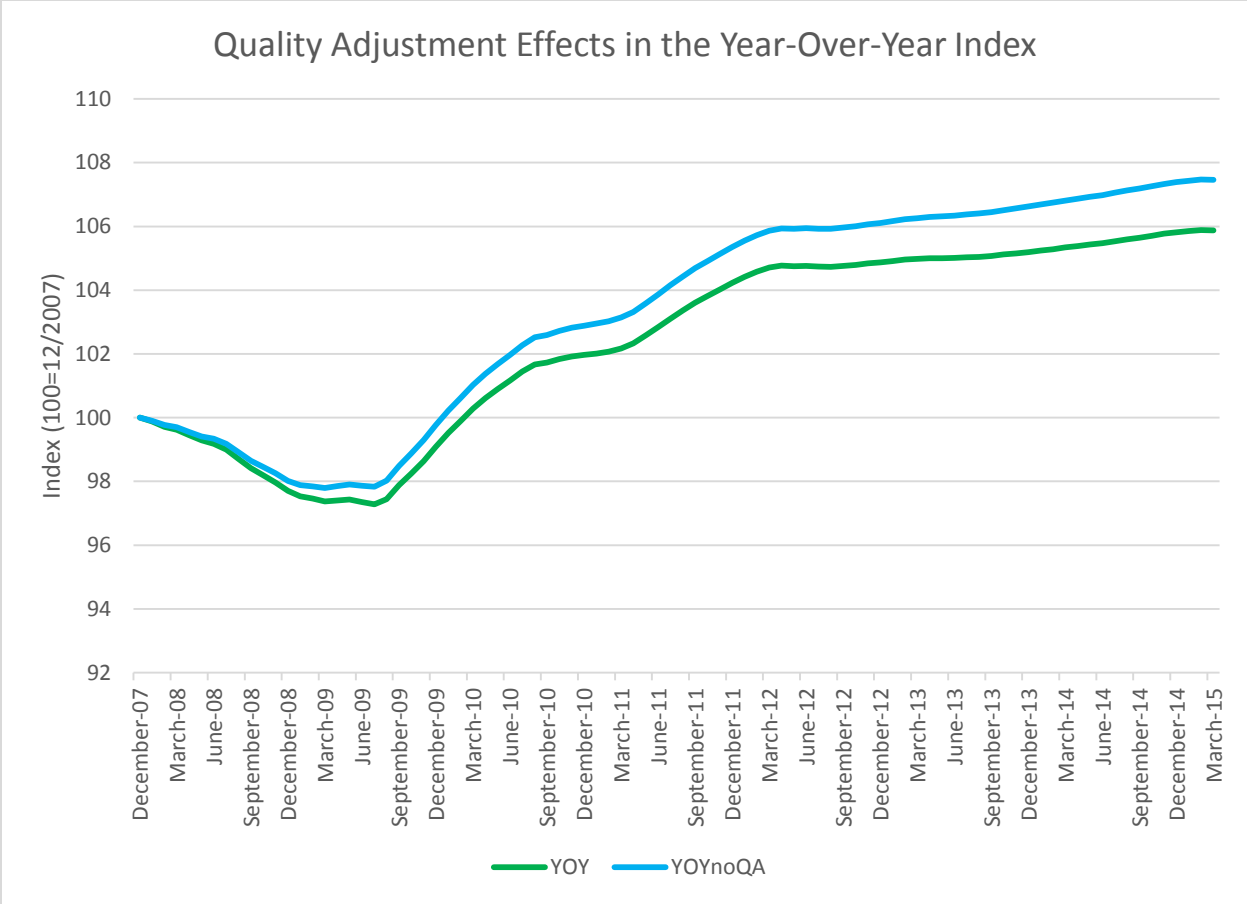


to calculate superlative indexes which approximate cost-of-living across a more general set of utility functions than the Cobb-Douglas function approximated by the geometric mean index.

While we propose a Tornqvist formula for the YOY index, alternative index formulas can be used to construct cost-of-living bounds for the YOY index. The chained Laspeyres index, which does not reflect substitution effects, presents an upper bound according the cost-of-living theory set out by Kónus. The chained Paasche index reflects perfect substitution and forms the lower bound for the true cost-of-living. The geometric average of the Paasche and Laspeyres is a Fisher index. The Fisher index (represented with blue squares in the chart below) almost perfectly overlays the YOY (Tornqvist) index. Over the entire seven plus years examined, the Fisher increases 0.05% more than the Tornqvist.



The impact of quality adjustment was examined by looking at a YOY index where no quality adjustments were made. All quality adjusted relatives were treated as “comparable.” The resulting index might be thought of as an upper bound estimate of the impact of quality adjustments since the analyst would have treated many of the larger quality adjustments as non-comparable and omitted them had quality adjustment values not been available. Over the seven plus years examined, the non-quality adjusted index rose 1.59% more than the YOY index with quality adjustment.



## 8. Conclusion

This work represents one of the first attempts at incorporating transaction data into the US Consumer Price Index. One of the persistent features of the new vehicle market is a product cycle characterized by the tendency for a model year vehicle to be introduced at a high price that then declines throughout the model year. The background literature and our own data analysis suggest that a variety of factors might drive the behavior of vehicle prices over the product life cycle. We pay particular attention to the possibility that intertemporal price discrimination may play a role. The methods currently used in the CPI offset this decline as part of the item replacement process, but this method is not compatible with real-time expenditure weights available in transaction data. When weights vary over time, a changeover relative will not necessarily offset within model year price changes and may lead to an upward bias if the changeover relative weighted too heavily or a downward bias if it is underweighted (See the companion paper). Thus, we proposed an alternative means of measuring price change that is not sensitive to product cycle effects, the year-over-year index.

Consistent with Greenlees and McClelland (2010), we find that transaction price indexes may be susceptible to downward drift that differs from the commonly discussed "chain drift" resulting from high frequency price change. We eliminated weight "bouncing" chain drift as an explanation for the matched-model index's price declines leading us to explore other means of measuring price change. Matched-model price indexes, especially those based on scanner data, often exhibit strong, downward tendencies that appear to be associated with chain drift. Our work suggests apparent "drift" may result from factors

other than weight fluctuations. A distinct product cycle for a product may lead to bias in the index. Intertemporal price discrimination may also explain the tendencies for price decline.

In new vehicles, this drift may be the result of IPD where matched-model price change may reflect differences in consumer characteristics: Showing the price change from the high willingness-to-pay consumers who pay for new model year cars to the budget minded consumers who buy the same car for less at the end of the model year. An index that only reflects the price change from price inelastic to elastic consumers, and, moreover, chaining this price change over several production cycles, will be biased and not reflective of a cost-of-living index. Similarly, the downward price movement over a model year may reflect a change in the perceived value of having a new vehicle versus a late model year one (without necessarily having a change in consumer characteristics). Additional work could be done to see if product cycle impacts can be estimated and their effects directly adjusted. For example, we could adjust for the effects of IPD directly by looking at changes in consumer characteristics over the product cycle.

Instead of directly adjusting for within model year price declines, we focus on a measure of long-term price change that is not susceptible to within model year price a change: A year-over-year index. The year-over-year index represents a general means of ensuring correct price measurement in the presence of price change related to a strong annual product cycle. Regardless of the specific mechanism behind the product cycle behavior of vehicle prices, the YOY method provides a means for measuring accurate price change. More precise corrections should be the subject of future work where the availability of consumer data or more advanced econometric techniques might allow for identifying and adjusting for the effects of IPD, fashion effects, and other factors that drive price change over the product cycle. The YOY provides an accurate measure of long-run price change, but sacrifices information on short-run market conditions. In a follow up article, we explore using time series filtering techniques to combine a cyclical component extracted from a trend biased by product cycle effects with a trend based on the YOY index developed in this paper. This hybrid, year-over-year plus cycle, index could allow us to incorporate transaction data into the CPI and benefit from the enhanced accuracy of a larger dataset, transaction prices, and weights based on real-time expenditure information.

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