Dynamics of Expenditures on Durable Goods: the Role of New-Product Quality[*]

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June 2021

Abstract

We document that new-product quality largely accounts for the dynamics of durable-goods expenditures around the Great Recession. To this end, we assemble a rich dataset on US new-car markets during 2004-2012, combining transaction-level data on prices with detailed information about vehicles' technical characteristics. During the recession, car manufacturers introduced new models of low quality. In turn, a reallocation of expenditures away from high-quality new models accounts for a significant decline in the dispersion of expenditures. The drop in new-model quality induced a persistent decline in the technology embodied in vehicles, and likely contributed to the slow recovery of expenditures.

[*]We thank David Berger, Francesco Bianchi, Russell Cooper, Sara Moreira, Sergio Rebelo, and Juan Carlos Suárez Serrato for helpful comments. Javier Fernandez provided excellent research assistance. Alessandro Gavazza gratefully acknowledges support from the European Research Council (ERC-Consolidator grant award no. 771004).

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1 Introduction

Households adopt new technologies by purchasing new durable goods, such as vehicles. During the Great Recession of 2008-09, consumer expenditures on durable goods dropped by approximately 15 percent, or almost 200 billion dollars. Expenditures on motor vehicles—which constitute approximately 35 percent of durable expenditures—accounted for more than half of this decrease and remained persistently low during the recovery.

The goal of this paper is to empirically investigate the role of newly introduced models in this decline and in the subsequent slow recovery. Our descriptive analysis suggests that during the Great Recession, manufacturers introduced new models that were cheaper and of lower quality relative to those introduced before the recession. In turn, households reallocated their purchases of new cars toward continuing models—which tend to be cheaper and of lower quality than new models—or delayed their purchases.

Cars represent an ideal object for our analysis for two main reasons. First, they are a large and procyclical component of durable-goods expenditures. Second, detailed information about car markets allows us to measure price and quality dynamics, thus providing empirical evidence on the importance of new products. To this end, we assemble a rich dataset on US new-car markets, combining two data sources. The first dataset contains the universe of transactions on new vehicles in several US states between 2004 and 2012 and reports transaction *prices* as well as some car features, such as the make and model. The second dataset contains detailed information on the technical *characteristics* of each vehicle model sold in the US during the same period, and—most notably—whether the model is newly introduced or a continuing model.

We exploit these data to provide several novel facts about the distribution of expenditures on new vehicles and the evolution of vehicle *quality* around the Great Recession. Our empirical analysis proceeds in four steps, gradually moving from car expenditures to car characteristics, with each step yielding a new finding.

In the first step, we show that during the Great Recession, the right tail of the new-car expenditure distribution declines substantially more than its left tail, thereby depressing the average and the standard deviation of new-car expenditures.

In the second step, we document that the dispersion of new-car expenditures declines during the recession almost exclusively because of the decline in the between-model variation in prices, which in turn is due to the decline in the expenditures on newly introduced models. Moreover, the share of transactions on new models and the fraction of new models among all models on sale do not overshoot during the recovery, suggesting that car manufacturers did not respond to the recession by delaying the introduction of high-quality models; rather, a generation of new products seems to be "missing", likely contributing to the slow recovery of expenditures on new cars.

These findings on the dynamics of the distribution of expenditures prompt us to investigate the connection between car prices and car characteristics. Hence, in the third step of our analysis, we use hedonic regressions to construct a measure of vertical quality that summarizes the main vehicle characteristics (Griliches, 1961). This measure of quality tracks well the dynamics of prices before and during the recession, indicating that compositional changes in the characteristics of cars sold accounts for the drop in between-model price dispersion during the recession. However, a striking finding of this analysis is that this measure of quality, based on pre-recession hedonic prices, displays no growth after the recession, whereas actual prices grow approximately 2 percent per year after the recession. This decoupling between prices and quality suggests that the hedonic prices of key quality characteristics increased substantially after the Great Recession, which buttresses the argument that quality dynamics partially account for the slow recovery in new-car sales.

In the fourth step of our analysis, we focus on the level of technology embodied in vehicles by exploiting only data on car characteristics. We document that new models introduced during the Great Recession featured a significantly worse trade-off between their main attributes—e.g., size, horsepower, and fuel efficiency—than models introduced in other years. Moreover, this slowdown in the level of technological introductions had persistent effects throughout the recovery.

Overall, our empirical analysis suggests that the quality of new products is a quantitatively important margin of adjustment to shocks for households and for manufacturers. Our findings have several implications. Most directly, the motor vehicle industry experienced a deep crisis in 2008-2009, which likely contributed to a slowdown in technological progress. Employment in this industry fell by approximately one-third during the Great Recession, leading to government bailouts for automakers. Moreover, because of the centrality of the motor vehicle industry in the US production structure, the effects of the drop in vehicle expenditures spread across different sectors.[1] Thus, understanding the micro dynamics of expenditures on vehicles is an important step toward a full account of the Great Recession and the slow recovery.

[1] Atalay (2017) and vom Lehn and Winberry (2021) document that the auto industry plays a central role in the US production network and business cycles.

Moreover, our findings contribute to several strands of the literature. First, a recent literature shows that downward adjustment in the quality of consumption is an important margin in the Great Recession (Jaimovich, Rebelo, and Wong, 2019; Argente and Lee, 2021).[2] A related literature emphasizes product reallocation—i.e., the entry and exit of products—as an important margin for the evolution of technology around the same period (Argente, Lee, and Moreira, 2018; Jaravel, 2019; Granja and Moreira, 2020).[3] To our knowledge, these studies focus on services and nondurable goods, or rely on survey data for durables. Our main contribution is to analyze in depth one of the most important household durable goods—cars—by focusing on the dynamics of its quality, building on the insights of Bils and Klenow (2001) and Bils (2009).

Second, durable goods provide a natural connection between quality changes during the Great Recession and the subsequent slow recovery. Because technology is, to an important extent, embodied in durable goods, changes in the quality of new products have persistent implications on the evolution of technology. Thus, our evidence on the introduction of low-quality new durables is consistent with significant medium-run technological effects of large recessions (e.g., Benigno and Fornaro, 2018; Anzoategui, Comin, Gertler, and Martinez, 2019; Bianchi, Kung, and Morales, 2019; Vinci and Licandro, 2020).

Finally, a large literature studies the business-cycle dynamics of durable goods, dating at least to the seminal contributions of Mankiw (1982); Bernanke (1985); and Caballero (1993). Several recent papers combine models of adjustment costs with data on household expenditures (Berger and Vavra, 2015; Dupor, Li, Mehkari, and Tsai, 2018; Attanasio, Larkin, Ravn, and Padula, 2020; Gavazza and Lanteri, 2021; McKay and Wieland, 2021).[4] We contribute to this literature by providing descriptive evidence on the role of new-product quality in accounting for the dynamics of durable-goods expenditures.

2 Data

Our empirical analysis exploits two datasets on new-car transactions and model characteristics, respectively. We introduce them in this section.

[2]Relatedly, Fisher, Johnson, and Smeeding (2013) and Meyer and Sullivan (2013) find that consumption inequality declined during the Great Recession.

[3]Broda and Weinstein (2010) documents that product creation is procyclical during the period 1999-2003.

[4]These papers build on Eberly (1994) and Attanasio (2000), which abstract from business-cycle shocks. Relatedly, Adda and Cooper (2000); Adda and Cooper (2006); and Gavazza, Lizzeri, and Roketskiy (2014) develop quantitative models of car replacement.

New-car Prices, Dominion Dealer Solutions (2019). This dataset (henceforth Dominion dataset) reports the universe of new-car sales in five states—Colorado, Idaho, North Dakota, Ohio, and Texas—for the period 2004-2012. For each sale, the dataset reports the transaction price, the month of the transaction, and the make, model, body type, and trim of the vehicle. The dataset contains more than 18 million vehicle transactions.[5]

New-car Model Characteristics, IHS Markit (2020). This dataset (henceforth IHS dataset) reports detailed characteristics of all new passenger-car models sold during 2003-2012, including make, model, trim, body type, generation year, dimensions, as well as engine attributes, such as size and horsepower, fuel type, fuel consumption, transmission, and turbo injection.[6]

The dataset also reports the aggregate number of US sales for each model at annual frequency during 2003-2012. The dataset includes sport utility vehicles, but does not have comprehensive information about pick-up trucks. Hence, we exclude pick-up trucks from our analysis.

The product life cycle of cars typically features the replacement of a "generation" of a car model with a new generation every approximately 5 years. For example, all 2007-2011 Toyota Camry models belong to the 2007 generation. Whereas only minor changes happen at annual frequency, a new generation features a major redesign. Hence, we define a vehicle model in the IHS data as a triplet of make, model, and generation. We further define a new model in year t as a model for which we observe the first transaction in year t or $t-1$, to account for the fact that the first transaction on a new model tends to appear in the second half of the year. This definition of a new model also includes entirely new model names.[7]

Based on this definition in the IHS data, we merge the Dominion and IHS datasets by matching vehicle models across the two datasets and allocating each transaction in the Dominion dataset to a model generation in the IHS dataset. Appendix A describes in more detail our model definition, as well as our procedure in merging the datasets.

We thus obtain a rich dataset on car sales that combines information on prices and

[5]The states in the Dominion dataset account for approximately 7 percent of national sales of new vehicles. For North Dakota, prices are reported for 2008-2012 only.

[6]Information about weight is missing in approximately 40 percent of models. Thus, we use all models for which we observe their weight to estimate a log-linear relationship between weight and other physical dimensions: wheelbase, width, height, and number of seats. This regression has an R^2 of 0.93. We use its predicted values to impute the weight whenever we do not observe it.

[7]A new model name sometimes is a slight redesign of an existing model, similar to a new generation.

technical characteristics. Throughout the paper, we refer to a car model as a make-model-generation triplet. According to this industry-wide definition, our merged dataset contains over 500 car models.

3 Empirical Patterns

In this section, we describe several patterns of our dataset. Specifically, (i) we document the dynamics of the distribution of expenditures on new cars around the Great Recession; (ii) we decompose the dispersion in expenditures and emphasize the role of new models; (iii) we relate the dynamics of expenditures to underlying car characteristics; and (iv) we analyze the level of technology embodied in new models.

3.1 Dynamics of the Distribution of Expenditures on New Vehicles

We begin our analysis by describing the evolution of the distribution of expenditures on new cars in the Dominion dataset. Figure 1 displays the main features of this distribution during 2004-2012. The transactions in this dataset provide a representative account of the dramatic aggregate effects of the Great Recession on US car markets. Specifically, the top-left panel shows that the total number of new-car sales drops by approximately 30 percent during the recession and only returns to pre-recession levels in 2012, similar to the corresponding aggregate dynamics for the US (e.g., Gavazza and Lanteri, 2021).[8]

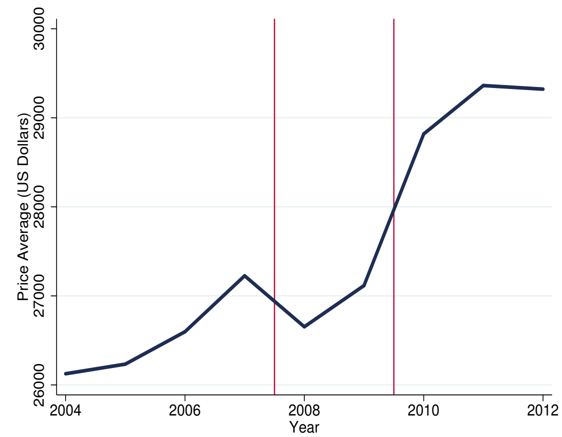
We thus exploit the dataset to analyze the micro dynamics of the distribution of expenditures. The top-right panel of the figure plots the average transaction price; the bottom-left panel the standard deviation; and the bottom-right panel the 10th, 50th, and 90th percentiles of the distribution, all normalized to equal zero in 2007 to facilitate comparison.

Both the first and second moments of the expenditure distribution display an increasing low-frequency trend. On average, transaction prices increase by 1.6 percent annually between 2004 and 2012. However, during the Great Recession, we observe a decline in the average price and an even larger decline in the dispersion of prices. Notably, the average transaction price, which equals $27,226 in 2007, displays a peak-to-trough decline of approximately 2 percent. The standard deviation, which equals $13,614 in 2007, declines by

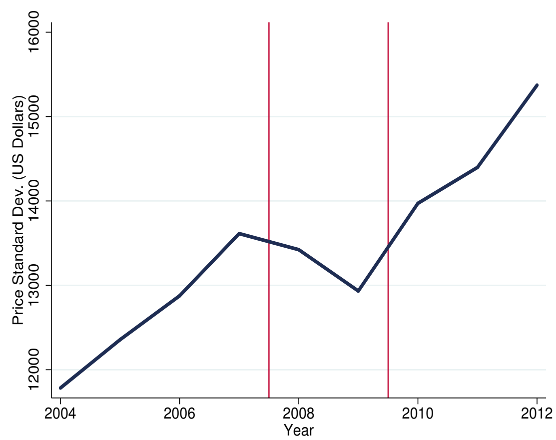
[8] Figure B1 in Appendix B displays the dynamics of aggregate expenditures on durable goods and on vehicles during the Great Recession.

Figure 1: Dynamics of New-Vehicle Expenditures

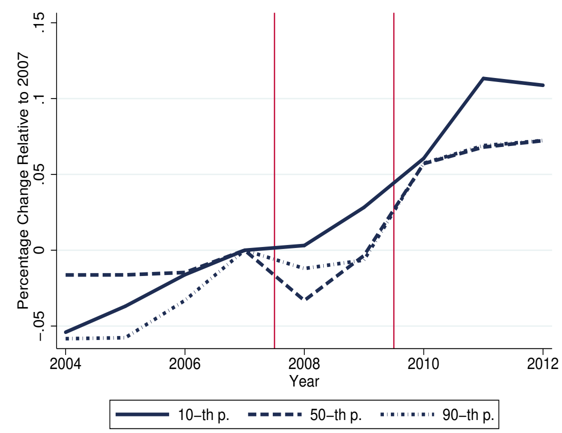
(a) Number of Transactions



(b) Average Transaction Price



(c) Standard Deviation of Prices



(d) Percentiles of Prices

Notes: The figure displays the number of new-car sales (top-left panel), the average (top-right panel), the standard deviation (bottom-left panel), and three percentiles—10th, 50th, and 90th—(bottom-right panel) of the distribution of transaction prices from the Dominion dataset. Horizontal axes report years (2004-2012); vertical lines highlight recession years (2008 and 2009).

approximately 5 percent. Relative to their respective trends, the average price drops by approximately 3 percent and the standard deviation by approximately 6 percent during the recession. In summary, the decrease in dispersion during the recession is about twice as large as the decrease in average expenditures.

The evidence on the first two moments of the distribution suggests that households reallocated their expenditures away from expensive vehicles during the recession. To confirm this pattern, we analyze the dynamics of different percentiles of the distribution of prices.

Consistent with the low-frequency dynamics of average prices, all percentiles increase over time between 2004 and 2012. However, the median and the 90th percentile undergo a significant decline during the recession, in both absolute terms and relative to their trend. In contrast, the 10th percentile remains on its trend throughout the recession. This analysis suggests that the leftward shift in the right half of the support of expenditures—i.e., a drop in expenditures on intermediate- and high-quality cars—accounts for the decline in the average and the dispersion of expenditures.[9]

These dynamics of the expenditure distribution are broadly consistent with the evidence on overall consumer expenditures based on the Consumer Expenditure Survey. Meyer and Sullivan (2013) documents a low-frequency increase in consumption inequality in the same period, as well as a decrease in dispersion during the Great Recession, with lower percentiles of expenditures displaying a smaller decline than higher percentiles. Relative to this evidence, however, a key advantage of our dataset is that we can now take further steps to connect the distribution of expenditures with salient features of the goods that households purchase.

3.2 Decomposing the Dispersion of Expenditures

We perform several decompositions of the variance of transaction prices to investigate the drivers of the cyclical dynamics of the distribution of expenditures on new cars. We find that reallocation of expenditures *between* car models—specifically a drop in expenditures on newly introduced models with high price—accounts for the compression in the distribution of expenditures in the Great Recession. In contrast, average prices conditional on vehicle model do not display significant changes relative to their trend.[10]

3.2.1 Between versus Within Models

We decompose the total variance of expenditures on new vehicles in year t, V_t, as follows:

$$V_t = V_t^B + V_t^W + Cov_t^{B,W},$$

[9]In Appendix B we report two robustness checks of these facts. First, during July and August of 2009, the Car Allowance Rebate System, commonly known as "Cash for clunkers," subsidized the replacement of highly polluting cars with new ones, potentially affecting the pool of new-car buyers (Hoekstra, Puller, and West, 2017). Nevertheless, we find that the dynamics of the distribution of expenditures are unchanged when we remove the months of July and August from all years in our dataset (Figure B2). Second, we verify that the empirical patterns are not significantly affected when we exclude fleet sales (Figure B3).

[10]Figure B6 in Appendix B displays the average transaction price of ten popular new-car models.

where V_t^B denotes the between-models component of the total variance, V_t^W denotes the within-model component, and $Cov_t^{B,W}$ denotes the covariance. Formally, we have

$$\begin{aligned}
V_t &\equiv \frac{1}{N_t}\sum_{i\in M_t}\sum_{j\in X_{it}}\left(p_{ijt}-\overline{p}_t\right)^2, \\
V_t^B &\equiv \sum_{i\in M_t} s_{it}\left(\overline{p}_{it}-\overline{p}_t\right)^2, \\
V_t^W &\equiv \frac{1}{N_t}\sum_{i\in M_t}\sum_{j\in X_{it}}\left(p_{ijt}-\overline{p}_{it}\right)^2, \\
Cov_t^{B,W} &\equiv \frac{2}{N_t}\sum_{i\in M_t}\sum_{j\in X_{it}}\left(p_{ijt}-\overline{p}_{it}\right)\left(\overline{p}_{it}-\overline{p}_t\right),
\end{aligned}$$

where $i \in M_t$ denotes models sold in year t, $j \in X_{it}$ denotes individual transactions on model i in year t, with market share s_{it}; N_t is the total number of transactions in year t; p_{ijt} are individual transaction prices; $\overline{p}_{it}$ is the average price of model i in year t; and $\overline{p}_t$ is the overall average transaction price in year t.

The top-left panel of Figure 2 displays the total variance V_t (solid line) and its components—between models V_t^B (dashed line), within models V_t^W (dashed-dotted line), and covariance $Cov_t^{B,W}$ (dotted line). The between-models component accounts for almost 80 percent of total variation in prices before the recession, whereas dispersion in transaction prices for a given model accounts for approximately 20 percent of total variation.[11] Most notably, the between-models component accounts for the entire reduction in the overall dispersion during the recession. In contrast, during the same period we do not observe significant changes in the dispersion of prices within models, and the magnitude of the covariance term is negligible. Hence, this evidence establishes that households reallocated their expenditures toward models with a typical price close to the average.

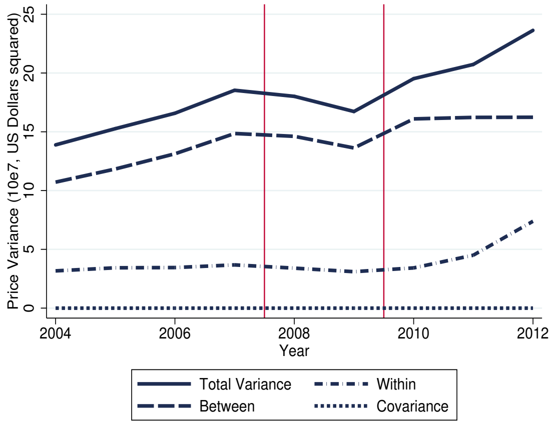
3.2.2 New versus Old Models

The reallocation of expenditures away from expensive models and toward average models prompts us to analyze the expenditures on newly introduced models. The reason is that new models tend to be more expensive than continuing models, which in the long run fuels the growth in average expenditure shown in the top-right panel of Figure 1.

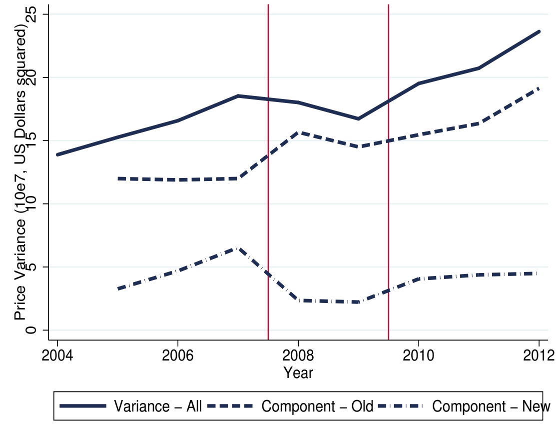
Based on our definition of a new model of Section 2, we find that new models play a

[11] Variation in prices within models is mostly due to different trims within each model. The fact that this variation does not appear to be relevant for the cyclical dynamics suggests that our approach, of merging the Dominion and IHS datasets at the model level, captures the most relevant features of the data.

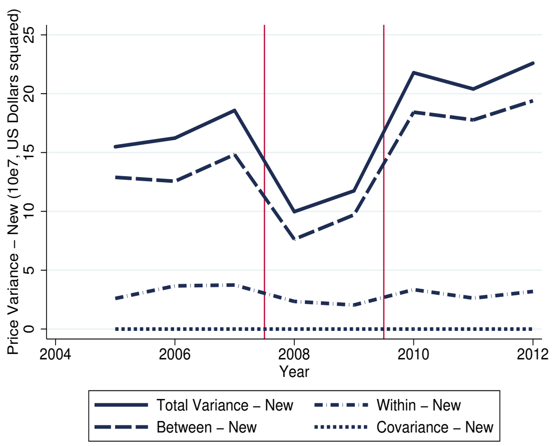
Figure 2: Variance Decomposition



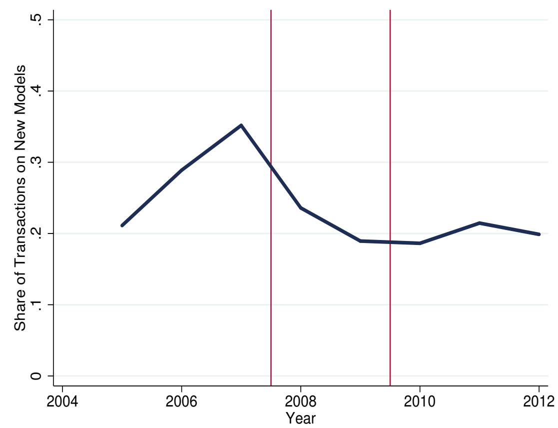
(a) Variance of New-Car Prices, Between and Within



(b) Variance of New-Car Prices, New and Continuing



(c) Variance of Newly Introduced Models



(d) Shares of Newly Introduced Models

Notes: The figure displays several decompositions of the variance of transaction prices in the Dominion dataset. The top-left panel displays the decomposition of the variance of new-vehicle transaction prices V_t (solid line) into the following components: between models V_t^B (dashed line); within models V_t^W (dashed-dotted line); and covariance term $Cov_t^{B,W}$ (dotted line). The top-right panel displays the decomposition of the variance V_t (solid line) into two components: new models $s_t^N V_t^N$ (dashed-dotted line) and old models $(1 - s_t^N)V_t^O$ (dashed line). The bottom-left panel displays the variance of expenditures on new models V_t^N (solid line) and its decomposition into between-models component $V_t^{N,B}$ (dashed line), within-models component $V_t^{N,W}$ (dashed-dotted line), and covariance term $Cov_t^{N,B,W}$ (dotted line). The bottom-right panel displays the share of transactions on new models s_t^N. Horizontal axes report years (2004-2012); vertical lines highlight recession years (2008 and 2009).

prominent role in the dynamics of the distribution of expenditures. Strikingly, between 2005 and 2007, the average transaction price for new models is \$28,080, which is higher than the average for old models, \$26,144.[12] However, in 2008, the average price of new models drops to \$25,764, which is lower than the average for old models, \$26,972.

We use our definition of new models to understand the contributions of new models to the variance of expenditures. Formally, we decompose the total variance as follows:

$$V_t = s_t^N V_t^N + (1 - s_t^N) V_t^O,$$

where s_t^N is the share of transactions on new models in year t, V_t^N is the variance of expenditures on new models, and V_t^O is the variance of expenditures on old models. In turn, these variances equal:

$$\begin{aligned} V_t^N &\equiv \tfrac{1}{N_t^N} \textstyle\sum_{i \in M_t^N} \sum_{j \in X_{it}} \left(p_{ijt} - \overline{p}_t\right)^2, \\ V_t^O &\equiv \tfrac{1}{N_t^O} \textstyle\sum_{i \in M_t^O} \sum_{j \in X_{it}} \left(p_{ijt} - \overline{p}_t\right)^2, \end{aligned}$$

where M_t^N and M_t^O are the sets of new and continuing models in year t, and N_t^N and $N_t^O = N_t - N_t^N$ are the respective number of transactions.

The top-right panel of Figure 2 displays the decomposition of the total variance of expenditures V_t into the components of expenditures on new models, $s_t^N V_t^N$, and on old models, $(1 - s_t^N) V_t^O$. The figure shows that the component due to new models displays a sharp drop during the recession, fully accounting for the drop in the overall variance. This pattern arises for two concurring reasons. First, the dispersion of prices of new models drops dramatically, by nearly one-half, during the recession. The bottom-left panel of Figure 2 portrays the dynamics of the variance of expenditures on new models V_t^N, showing that the drop in this variance is accounted for by its between-model reallocation, consistent with the decomposition of the total variance of expenditures.[13]

Second, the share of transactions on new models s_t^N decreases sharply during the recession, from a peak in 2007 of approximately 35 percent to less than 20 percent in 2009, as the bottom-right panel of Figure 2 shows, despite the fact that new models were cheaper

[12] We exclude 2004 from our analysis of new models because this is the first year in the Dominion dataset, and thus we cannot cleanly identify new models.

[13] In Appendix B we verify that these results are not affected by excluding the months of July and August from all years to remove the effects of "Cash for clunkers" (Figure B4) or by excluding fleet sales (Figure B5).

during the recession.[14] This pattern suggests a drop in the quality of new models during the recession, which is thus the focus of our analysis in the following subsections. Nonetheless, we do not observe large changes in the variance of expenditures on old models, V_t^O, relative to its trend, suggesting that households did not substitute the "missing" new models of high quality with old models of high quality—most likely delaying their purchases. Hence, the term $(1 - s_t^N)V_t^O$ depicted in the top-right panel of Figure 2 (dashed line) displays a moderate increase in 2008, because of the decrease in the share s_t^N, but the effect of this change on the total variance V_t is dominated by the drop in the variance of expenditures on new models, V_t^N.

In the aftermath of the recession, the dispersion of expenditures on new models V_t^N returns to its pre-recession trend. However, Figure 2, as well as Figure B7 in Appendix B, show that neither the share of transactions on new models s_t^N nor the fraction of new models on sale display signs of overshooting during the recovery. This evidence suggests that car manufacturers did not simply respond to the recession by delaying the introduction of high-quality new models; rather, there was a missing generation of new products, likely contributing to the slow recovery of expenditures.

3.3 Dynamics of the Distribution of Quality

Our decompositions establish that the heterogeneity between models and, critically, new models are the main drivers of the dynamics of the distribution of new-car expenditures. Moreover, quality differences between new and continuing models were lowest during the Great Recession. These patterns spur us to focus on vehicle characteristics to further examine the dynamics of quality.

To this end, we use hedonic regressions to estimate the function that maps vehicle characteristics to prices (for a seminal contribution, see Griliches, 1961). Formally, let the average price p_{it} of car model i in year t equal:

$$p_{it} = h_t(X_{it}, W_{it}, \eta_{it}),$$

where $h_t(\cdot)$ is the hedonic function; X_{it} are observed continuous vehicle attributes, such as fuel efficiency, horsepower, engine size, weight, and wheelbase; W_{it} are observed discrete

[14] The 2007 peak in the market share of new models is due to the simultaneous introduction of new generations of three popular models: Toyota Camry, Nissan Altima, and Chevrolet Tahoe. Figure B7 in Appendix B displays the time series of the number of transactions on new models N_t^N, as well as the share of models we classify as new.

attributes, such as indicator variables for make, four-wheel drive, number of gears, manual transmission, turbo injection, number of cylinders, diesel, number of seats, and number of doors; and η_{it} are unobserved determinants of prices. We transform all continuous variables in logarithms and assume that the log of the hedonic function $h_t(\cdot)$ is linear:

$$\log p_{it} = \beta_t \log X_{it} + \gamma_t W_{it} + \eta_{it}, \tag{1}$$

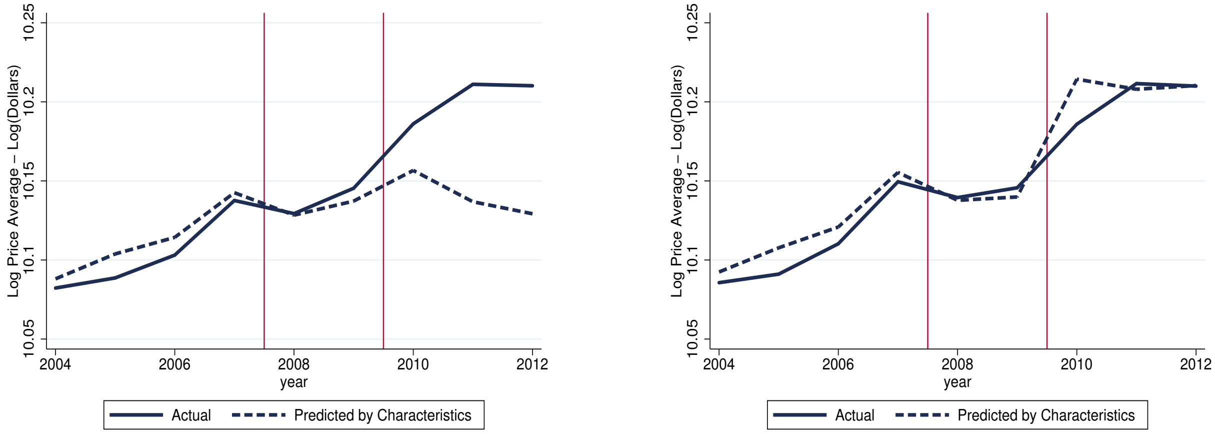
where β_t and γ_t are the vectors of coefficients, or "hedonic prices" of car characteristics.

To perform this analysis, we face the challenge that we observe detailed characteristics of different trims of each model in the IHS dataset, whereas we only observe transaction prices at a coarser level of aggregation—namely car models—in the Dominion dataset. To overcome this challenge, we aggregate all continuous characteristics of different trims of each model, weighting different trims according to their transaction shares in the IHS dataset, whereas we consider different discrete characteristics as different observations, or, equivalently, different models. Appendix B reports on robustness analyses with alternative aggregations of continuous and discrete characteristics of different trims of each model.

We consider three subsamples: pre-recession (2004-2007), recession (2008-2009), and post-recession (2010-2012), assuming the coefficients are constant within each subsample but potentially differ across subsamples. We use these hedonic regressions to implement decompositions between the differences in the mean characteristics of vehicles over time and the differences in the hedonic prices of these characteristics over time (Oaxaca, 1973; Blinder, 1973). Column (1) in Panel A of Table 1 reports the hedonic prices of the main continuous attributes X_{it} in the pre-recession subsample. We leverage these estimates to track the evolution of the distribution of quality, by assigning a predicted value based on characteristics to each model. Formally, given the estimated hedonic prices $\hat{\beta}_{2004-2007}$ and $\hat{\gamma}_{2004-2007}$, we measure the quality of vehicle j in year $t = 2004, 2005, ..., 2012$ as $\hat{\beta}_{2004-2007} \log X_{jt} + \hat{\gamma}_{2004-2007} W_{jt}$. This prediction represents the value of the bundle of characteristics contained in model j in year t, based on the dollar value of these characteristics implicit in pre-recession prices.

The left panel of Figure 3 displays the dynamics of the average transaction price and the average of our measure of quality. The panel shows that they grow at a similar rate until the recession and, crucially, quality predicts the decline in the average price during the recession. In fact, the decline in average quality between 2007 and 2008 is slightly larger than the decline in the average price. To relate the dynamics of prices to the dynamics of

Figure 3: Hedonics and Vehicle Quality



(a) Constant Hedonic Prices (b) Time-varying Hedonic Prices

Notes: The figure displays the dynamics of average (log) transaction price in the merged Dominion-IHS dataset (solid lines) and the average (log) value predicted with a hedonic regression—equation (1)—(dashed lines). Each model is weighted according to its transaction share in the IHS dataset. The left panel refers to constant pre-recession hedonic prices (2004-2007); the right panel to time-varying hedonic prices, estimated in three subsamples: pre-recession (2004-2007), recession (2008-2009), and post-recession (2010-2012). Horizontal axes report years (2004-2012); vertical lines highlight recession years (2008 and 2009).

selected characteristics during the recession, we analyze the evolution of several variables that are significantly associated with high quality based on our hedonic regressions, such as wheelbase, horsepower, and engine size. For all of these characteristics, we observe a decline in the average during the recession, which suggests a pattern of reallocation of expenditures toward smaller and less powerful cars, consistent with the dynamics of the distribution of prices displayed in Figure 1.

However, the left panel of Figure 3 shows that a striking pattern emerges from 2009 onward. Specifically, the average price grows at a rate of approximately 2 percent per year, whereas the average value implied by car characteristics undergoes a protracted decline, diverging from the average price until the end of our sample. Most notably, average quality shows no growth in the period 2007-2012, whereas the average price grows by 7 percent in the same period.

This apparent decoupling between prices and predicted quality, based on pre-recession prices, indicates that the post-recession hedonic prices of some characteristics are higher than their pre-recession values. Different car attributes or brands may have different costs or may be valued differently over time, implying that changes in the state of the economy likely affect hedonic prices (Pakes, 2003). Accordingly, we re-estimate equation (1) separately in the three subsamples, and use these different estimates to compute a second measure of average quality. Columns (2) and (3) in Panel A of Table 1 report the hedonic prices of the main continuous attributes X_{it} in the recession and post-recession subsamples, respectively. The right panel of Figure 3 displays the dynamics of this second measure of average quality, based on time-varying hedonic prices. The panel shows that this measure of average quality tracks the average price closely in all sub-periods.

The difference between our first and our second measures of quality confirms that the hedonic prices of some characteristics increased over time. As Panel A of Table 1 reports, comparison of the coefficients of the continuous attributes across the three subsamples reveals that the hedonic prices of two important characteristics—wheelbase and horsepower—increased by over 20 percent in the post-recession sample relative to the pre-recession sample.[15] In contrast, other hedonic coefficients, such as fuel efficiency, are relatively stable across subsamples, though noisier.[16,17] Changes in the hedonic prices of some characteristics associated with high quality have different potential explanations; nevertheless, because vehicle sales remained persistently depressed after the recession (as Figure 1 shows), the contemporaneous increase in the hedonic prices of wheelbase and horsepower suggests a relative scarcity of models in the most expensive segments. Hence, the increase in these hedonic prices may partially account for the slow recovery in new-car sales after the Great Recession.

Our hedonic regressions are also well suited for accounting for the dispersion of expenditures. Panel A of Table 1 reports the R^2 coefficients of several regressions that indicate that car characteristics capture a large share of the between-model variance in prices: R^2 coefficients of the hedonic regressions exceed 0.93 in all subsamples.

Critically, pre-recession hedonic prices accurately predict the dynamics of expenditures on new models during the recession. Panel B of Table 1 shows that the hedonic regression accounts for approximately 98 percent of the observed drop in between-model dispersion of

[15] Table B1 in Appendix B reports that we obtain similar results when we focus exclusively on new models.

[16] Table 1 shows that the coefficients of some attributes, most notably engine size, are not precisely estimated. The reason is that our regression equation (1) includes some discrete characteristics W_{it}, such as indicator variables for the number of cylinders, which absorb almost all variation in engine size. Hence, the residual variation in engine size is minimal and its coefficient estimate is noisy.

[17] We also investigated any differential effects between US carmakers and foreign carmakers. While the hedonic regressions show that the point estimates of US carmaker fixed effects are lower than those of Asian and European carmakers, respectively, the estimates do not show any differential changes across subsamples.

Table 1: Hedonic Regressions

Panel A: Coefficient Estimates of Continuous Attributes

	(1) Pre-Recession	(2) Recession	(3) Post-Recession
Log(Wheelbase)	1.138	1.273	1.495
	(0.133)	(0.168)	(0.162)
Log(Horsepower)	0.487	0.488	0.612
	(0.039)	(0.051)	(0.051)
Log(Weight)	0.090	0.153	0.035
	(0.060)	(0.078)	(0.077)
Log(Fuel Efficiency)	-0.080	-0.058	-0.062
	(0.051)	(0.044)	(0.047)
Log(Engine Size)	0.095	0.028	-0.038
	(0.051)	(0.066)	(0.064)
Observations	2,055	1,084	1,671
R^2	0.939	0.958	0.950

Panel B: Quality of New Models

	(1) Data	(2) Constant Prices	(3) Time-Varying Prices
Average 2008 − Average 2007	-0.044	-0.052	-0.059
St. Dev. 2008 − St. Dev. 2007	-0.073	-0.072	-0.072

Notes: Panel A reports the estimated coefficients of the log of continuous characteristics X_{jt} in equation (1), with standard errors in parentheses, in three subsamples: column (1) refers to the pre-recession subsample (2004-2007); column (2) to the recession subsample (2008–2009); and column (3) to the post-recession subsample (2010–2012). Panel B reports the peak-to-trough dynamics of expenditures and quality of newly introduced models, weighted according to their transaction shares in the IHS dataset. Column (1) reports the difference between the average log price of new models in the 2008 and the average log price of new models in 2007 (first row) and the difference between the standard deviation of log prices of new models in 2008 and the standard deviation of log prices of new models in 2007 (second row). Column (2) reports the difference between the average (first row) and the standard deviation (second row) of predicted log prices, based on constant hedonic prices estimated in the pre-recession subsample, applied to new models introduced in 2008 and to new models introduced in 2007. Column (3) reports the difference between the average (first row) and the standard deviation (second row) of predicted log prices, based on recession hedonic prices applied to new models introduced in 2008 and pre-recession hedonic prices applied to new models introduced in 2007.

new-model prices, though it slightly overpredicts the decrease in their average price. These results confirm that reallocation across different levels of quality accounts for the dynamics of the distributions of expenditures on all and new models.

Overall, our hedonic regression analysis highlights some striking dynamics in the quality of vehicles and confirms a reallocation in expenditures on new models away from high quality. In the next subsection we present a complementary analysis that focuses on technological trade-offs in the set of models available on the market, abstracting from information on prices. This analysis allows us to address some potential limitations of the hedonic methodology, such as the difficulty of disentangling changes in marginal costs from changes in markups and in preferences for different models, that may occur around the recession.

3.4 New Models and Technological Progress

We now analyze the level of technology embodied in vehicles and document a sharp drop in the quality of new models introduced during the Great Recession.

We follow Knittel (2011) to measure the technological trade-off between fuel efficiency, weight, and engine power, and to estimate its evolution over time. This methodology posits a marginal-cost function that depends on vehicle attributes and estimates the level sets of this function, including time fixed effects to capture the evolution of the technological frontier. Specifically, the marginal cost function for vehicle i in year t equals:

$$c_{it} = c_t^1(mpg_{it}, hp_{it}, w_{it}, Z_{it}^1) + c_t^2(Z_{it}^2),$$

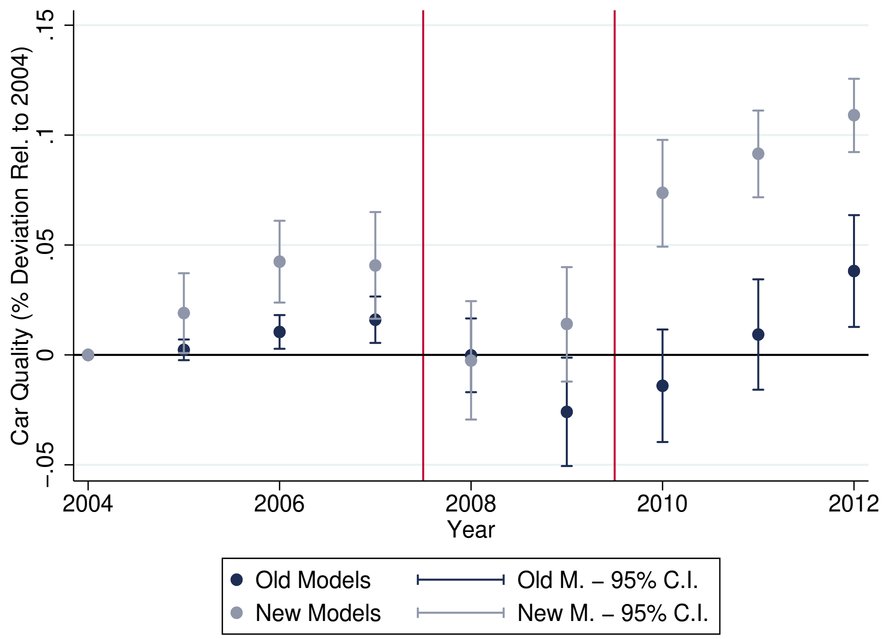
where $c_t^1(\cdot)$ is the component of marginal cost related to fuel economy, which depends on fuel efficiency mpg_{it}, horsepower hp_{it}, weight w_{it}, and a subset of characteristics Z_{it}^1 that are relevant for the trade-off of interest; $c_t^2(\cdot)$ is the component of the marginal cost that depends on other characteristics that are less related to fuel efficiency, Z_{it}^2.[18] Relevant characteristics Z_{it}^1 include vehicle attributes such as make, indicator functions for diesel engine, turbo injection, manual transmission (also interacted with a time trend), and whether a model is introduced in year t.

We further assume that vehicle attributes enter the marginal-cost function $c_t^1(\cdot)$ in a log-linear form—i.e., the cost function is Cobb-Douglas—and that time t affects this function in multiplicative form—i.e., technological progress is input neutral.[19] Under these assumptions, we can estimate the level sets of the marginal cost $c_t^1(\cdot)$ with the following

[18] Our dataset does not contain information about torque; thus, we measure engine power with horsepower.

[19] Appendix B reports similar results using a translog cost function.

Figure 4: Technology of New and Old Models



Notes: The figure displays the estimated average level of technological efficiency for new models (clear markers) and old models (dark markers), measured as the estimated time fixed effects in regression equation (2). The horizontal axis reports years (2004-2012); vertical lines highlight recession years (2008 and 2009).

specification:

$$\log mpg_{it} = \alpha_1 \log hp_{it} + \alpha_2 \log w_{it} + \delta Z^1_{it} + T_t + T_t \times \mathcal{I}^N_{it} + \varepsilon_{it}, \tag{2}$$

where T_t is a year fixed effect; $\mathcal{I}^N_{it}$ is an indicator variable for new models; $T_t \times \mathcal{I}^N_{it}$ is their interaction, which allows the regression (2) to flexibly capture a differential effect of the recession on new models; and ε_{it} are unobservables. We estimate equation (2) without weighting models by the number of transactions.[20] Hence, whereas the hedonic approach combines the reallocation of demand and changes in the supply of quality, this marginal-cost estimation likely captures quality changes that originate on the supply side of the market.

Figure 4 displays the estimated year fixed effects for new models (clear markers) and

[20]For consistency with our hedonic-regression analysis of Section 3.3, we aggregate all continuous characteristics of different trims of each model at the model level, weighting different trims according to their transaction shares in the IHS dataset, and we consider different discrete characteristics as different observations. Appendix B reports that the results are robust to different levels of aggregation of car characteristics.

old models (dark markers), relative to their pooled baseline value in 2004, normalized to zero. Typically, new models have superior technology, and the fixed effect for new models is thus significantly higher than those for old models. However, during the Great Recession, the quality of new models declines sharply: In 2008, the estimated quality of new models is almost identical to the quality of old models, which implies an abrupt halt in technical progress. Quantitatively, the coefficients displayed in Figure 4 mean that the average level of technology of new models, measured in miles per gallon conditional on all observable car attributes, declined by almost 5 percent between 2006 and 2008.[21]

Although the technological level of new models recovers sharply from 2010, the low quality of new models introduced during the recession persistently drags the average level of technology for the continuing models, which remains on a lower path throughout the recovery. Overall, the technological level of old models breaks its pre-recession 2007 level only at the end of our sample, as models introduced during the recession are gradually replaced.

4 Conclusions

We emphasize the role of quality dynamics for the cyclicality of the distribution of expenditures on durable goods. Our empirical analysis points to an important margin of adjustment for durable-goods producers in recessions: the endogenous quality of new products. During the Great Recession, automakers introduced models of low quality, consistent with a reallocation of expenditures away from expensive models, thereby inducing a persistent decline in the level of technology.

[21] In Appendix B, we report the results of regressions that weight observations by their number of transactions.

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APPENDICES

A Data and Measurement

In this appendix, we describe our procedure for merging the Dominion dataset and the IHS dataset and explain our definitions of vehicle models.

A.1 Merging Dominion and IHS Datasets

For each transaction in the Dominion dataset, we observe a string for make name—e.g., "TOYT" for Toyota—and a string for model name—e.g., "Camry"— as well as the corresponding model-year, which may or may not correspond with the calendar year in which the transaction takes place because new models marketed as model-year t are often introduced in year $t-1$.

For each vehicle model in the IHS dataset, we observe a string for make name—e.g., "Toyota"—and a string for model name—e.g., "Toyota Camry"— as well as a variable named generation-year, which allows us to identify different generations of a same model—e.g., first generation, second generation, etc. Moreover, we also observe the total number of US transactions by calendar year.

1. In the Dominion dataset we identify all strings corresponding to make and model names.

2. We perform the same step, identifying make and model names in the IHS dataset.

3. For all make-model names in the Dominion dataset (point 1), we find a single corresponding make-model name in the IHS dataset (point 2). Whenever we do not find a match for the make-model name (approximately 16 percent of cases), we assign as model name the combination of make name and the first word of the model string from the Dominion dataset.

4. For each make-model name in the Dominion dataset, we identify the corresponding set of model-years for which we observe a positive number of transactions. For example, in the case of the Toyota Camry, these model-years are 2003, 2004, ..., 2013.

5. For each make-model-generation in the IHS dataset, we identify the first model-year with a positive number of transactions in the IHS dataset. If the first year with a

positive number of transactions of a make-model-generation is year t, we infer that the first model-year for that make-model-generation is year $t+1$, to account for the fact that vehicles marketed as model-year t are typically first introduced in the market in year $t-1$.

6. We merge the dataset of Dominion make-model-years (point 4) with the Dominion-IHS matched list of make-model names (point 3).

7. We assign each make-model-year from the Dominion dataset (point 6) to the corresponding make-model-generation (point 5) as follows: Toyota Camry model-years 2007-2011 are assigned to the generation-year 2007 and Toyota Camry model-years 2012 through 2013 are assigned to generation-year 2012.

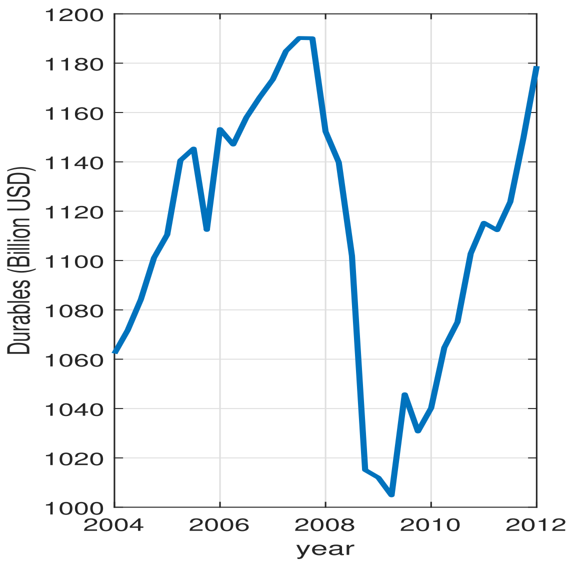
A.2 Model Definitions

We define a vehicle model as a triplet of make, model, and generation obtained following the merging procedure described above—e.g., Toyota Camry generation-year 2007.

We define a new model in year t as a model for which we observe the first transaction in year t or in year $t-1$, to account for the fact that the first transaction on a new model tends to appear in the second half of the year. Specifically, this implies that we consider a model as new whenever its model year in the Dominion dataset corresponds with its generation year, and possibly also whenever we observe a transaction for this model that occurs in a calendar year preceding its model year. Thus, this definition includes new model names as the first generation of a model, as well as new generations of existing model names.

We should point out that because we observe transaction prices at the model level in the Dominion dataset and, thus, we merge information from the Dominion dataset and the IHS dataset at the model level, there remains some residual heterogeneity in vehicle characteristics across different trims of each model in the IHS dataset. To deal with this heterogeneity, in our analyses of car characteristics in Sections 3.3 and 3.4, we average all continuous car characteristics across different trims of each model using their respective transaction shares in the IHS dataset, whereas we treat vehicles with different values of discrete characteristics—such as diesel, or turbo injection—as different models. In Appendix B we consider an alternative approach, aggregating both continuous and discrete characteristics at the model level using their transaction shares. As Figures B8 and B9 show, our main findings are robust to this alternative approach, suggesting that

Figure B1: Consumer Expenditures on Durable Goods and on Motor Vehicles



Notes: Personal Consumption Expenditures on Durable Goods (left panel) and on Motor Vehicles and Parts (right panel) during 2004-2012.

the level of aggregation of car characteristics, as well as the exact number of models, do not affect our results.

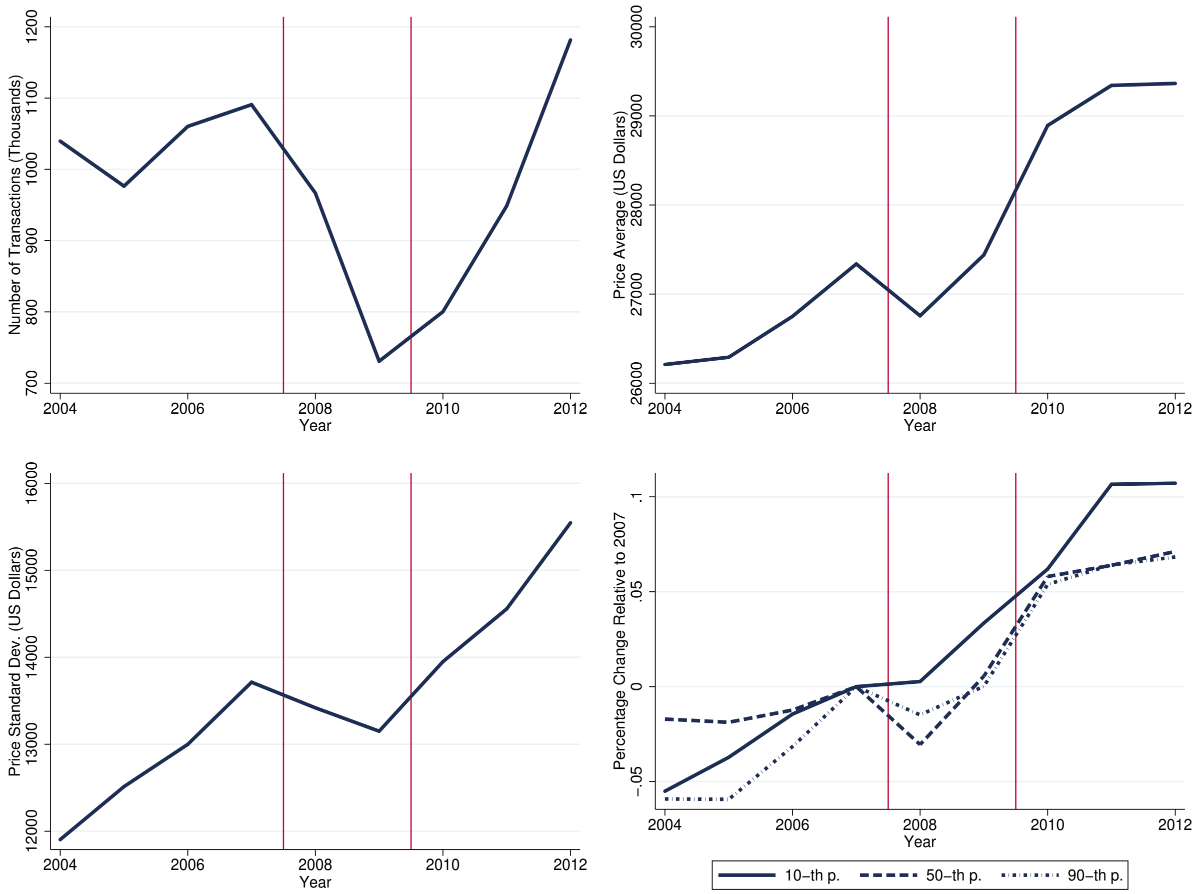
B Additional Empirical Evidence

In this appendix, we provide additional empirical evidence and document several robustness checks.

B.1 Dynamics of the Distribution of Expenditures

Figure B1 displays aggregate consumer expenditures on durable goods (left panel) and on vehicles (right panel) during 2004-2012. Figure B2 reproduces the findings displayed in Figure 1, but excluding the months of July and August in each year to show that the patterns of the distribution of expenditures on new vehicles are not significantly affected by the Cars Allowance Rebate System—commonly referred to as "Cash for clunkers"—which was implemented during July and August of 2009. Figure B3 displays the same variables, but excludes fleet sales—which account for approximately 5 percent of transactions—to show that our main findings are unchanged if we restrict attention to consumer sales only.

Figure B2: Dynamics of New-Vehicle Expenditures, Excluding July and August of Each Year



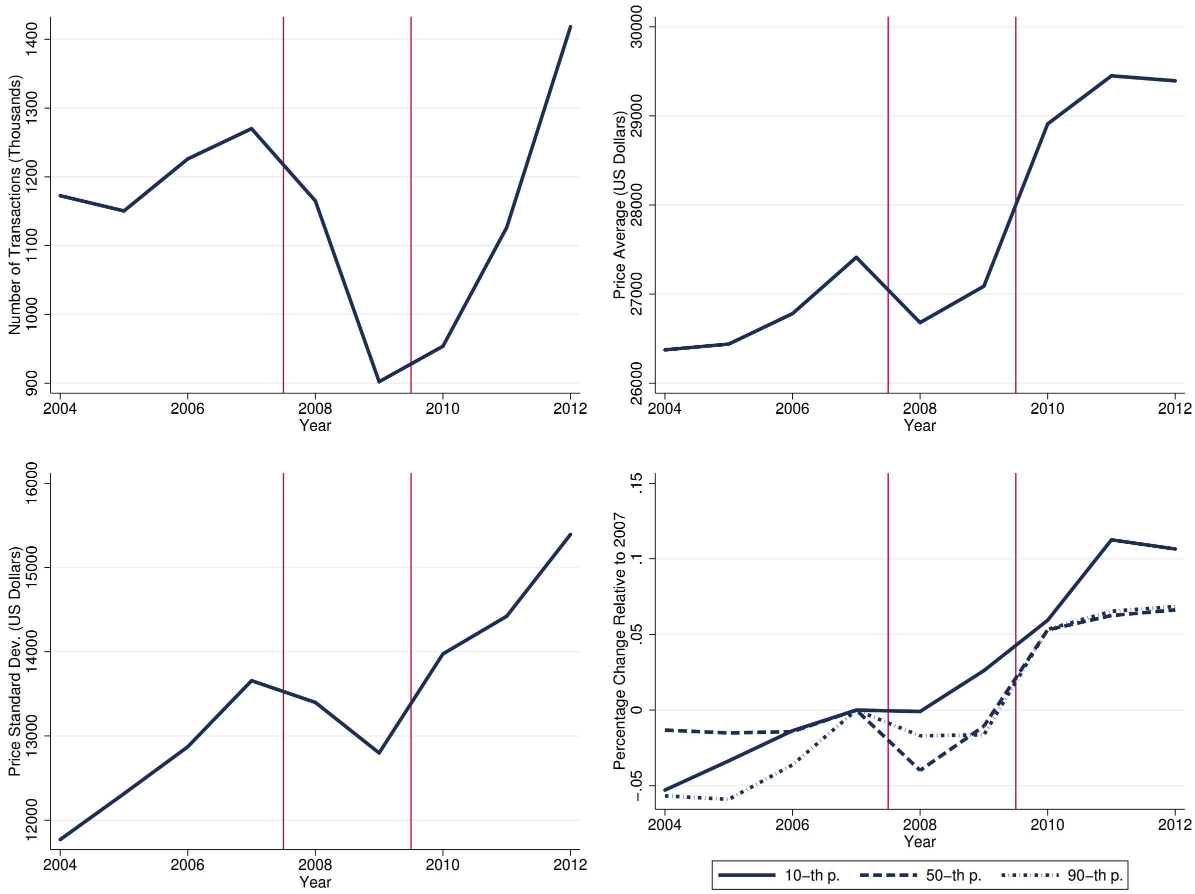
Notes: The figure displays the number of new-car sales (top-left panel), the average (top-right panel), the standard deviation (bottom-left panel), and three percentiles—10th, 50th, and 90th—(bottom-right panel) of the distribution of transaction prices from the Dominion dataset, excluding the months of July and August of each year. Horizontal axes report years (2004-2012); vertical lines highlight recession years (2008 and 2009).

B.2 Decomposing the Dispersion of Expenditures

Figures B4 and B5 reproduce the findings displayed in Figure 2 under the same two robustness checks described above: namely, removing July and August to exclude the effects of "Cash for clunkers" and removing fleet sales, respectively.

Figure B6 portrays the path of the average transaction price for ten popular models. Specifically, we select the five models with the highest sales volume with price below the overall sample median, and the five models with highest sales volume with price above the median. For all of these models, the figure shows that prices did not significantly

Figure B3: Dynamics of New-Vehicle Expenditures, Excluding Fleet Sales

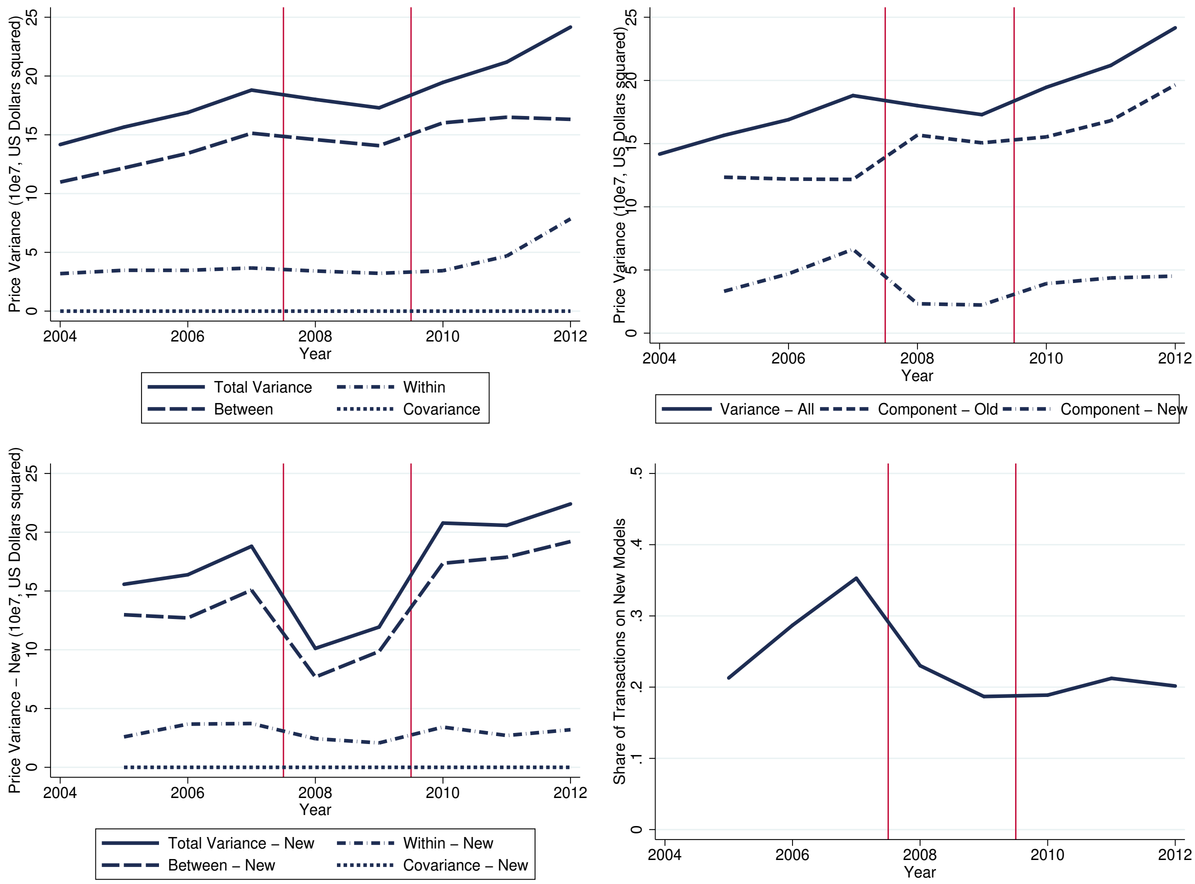


Notes: The figure displays the number of new-car sales (top-left panel), the average (top-right panel), the standard deviation (bottom-left panel), and three percentiles—10th, 50th, and 90th—(bottom-right panel) of the distribution of transaction prices from the Dominion dataset, excluding fleet sales. Horizontal axes report years (2004-2012); vertical lines highlight recession years (2008 and 2009).

deviate from trend during the Great Recession. This confirms that reallocation between models, instead of price changes at the model level, account for changes in the distribution of expenditures during the recession. Consistent with this evidence, Gavazza and Lanteri (2021) show that price changes during the Great Recession were concentrated in used-car markets.

Figure B7 displays the time series of the total number of sales and the number of sales of new models (left panel) and the share of models we classify as new models (right panel). These two figures show that both the share of transactions on new models and the flow of new-product introduction are procyclical, peaking in 2007 and dropping during the Great Recession.

Figure B4: Variance Decomposition, Excluding July and August of Each Year

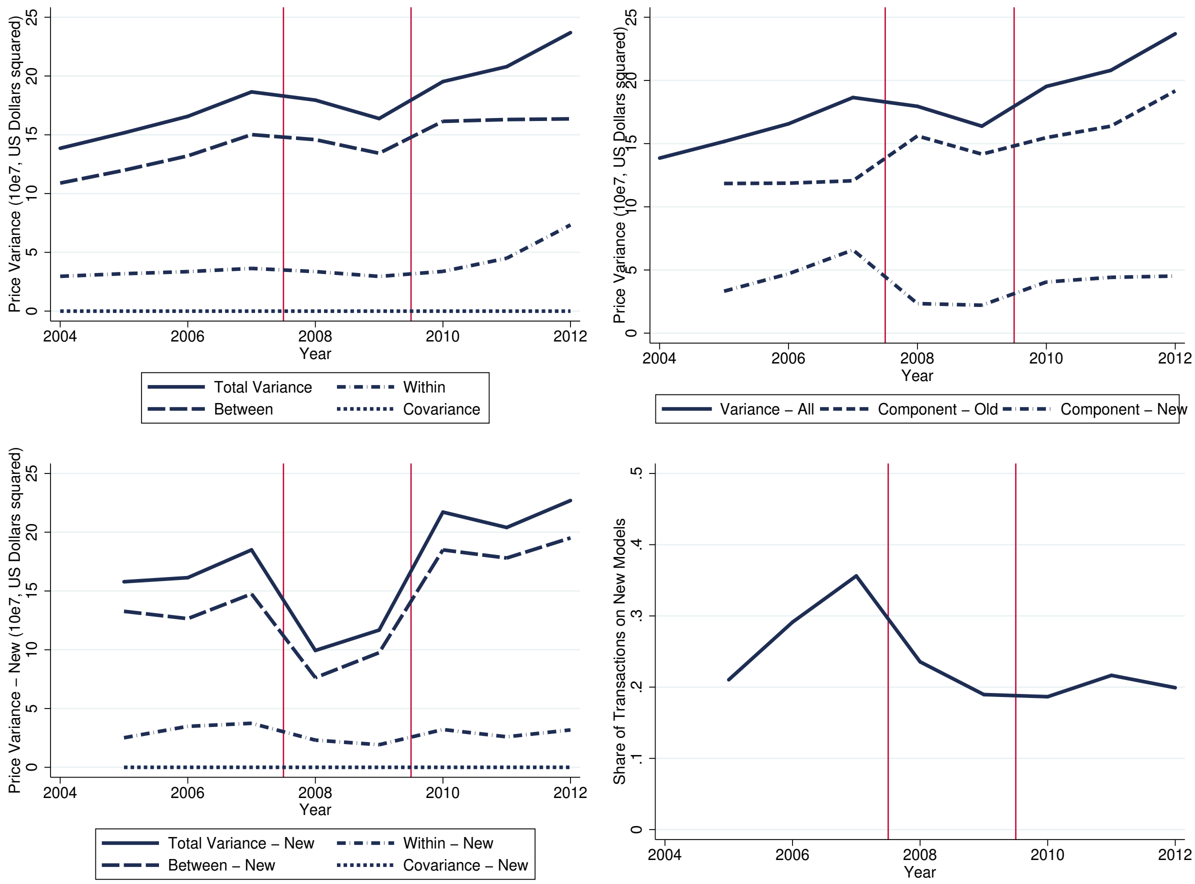


Notes: The figure displays several decompositions of the variance of transaction prices in the Dominion dataset, excluding the months of July and August of each year. The top-left panel displays the decomposition of the variance of new-vehicle transaction prices V_t (solid line) into the following components: between models V_t^B (dashed line); within models V_t^W (dashed-dotted line); and covariance term $Cov_t^{B,W}$ (dotted line). The top-right panel displays the decomposition of the variance V_t (solid line) into two components: new models $s_t^N V_t^N$ (dashed-dotted line) and old models $(1 - s_t^N)V_t^O$ (dashed line). The bottom-left panel displays the variance of expenditures on new models V_t^N (solid line) and its decomposition into between-models component $V_t^{N,B}$ (dashed line), within-models component $V_t^{N,W}$ (dashed-dotted line), and covariance term $Cov_t^{N,B,W}$ (dotted line). The bottom-right panel displays the share of transactions on new models s_t^N. Horizontal axes report years (2004-2012); vertical lines highlight recession years (2008 and 2009).

B.3 Dynamics of the Distribution of Quality

Figure B8 displays the results of robustness analyses of average quality dynamics measured with hedonic regressions. Specifically, while we produce Figure 3 in Section 3.3 by aggregating continuous characteristics of different trims at the model level, but considering trims

Figure B5: Variance Decomposition, Removing Fleet Sales

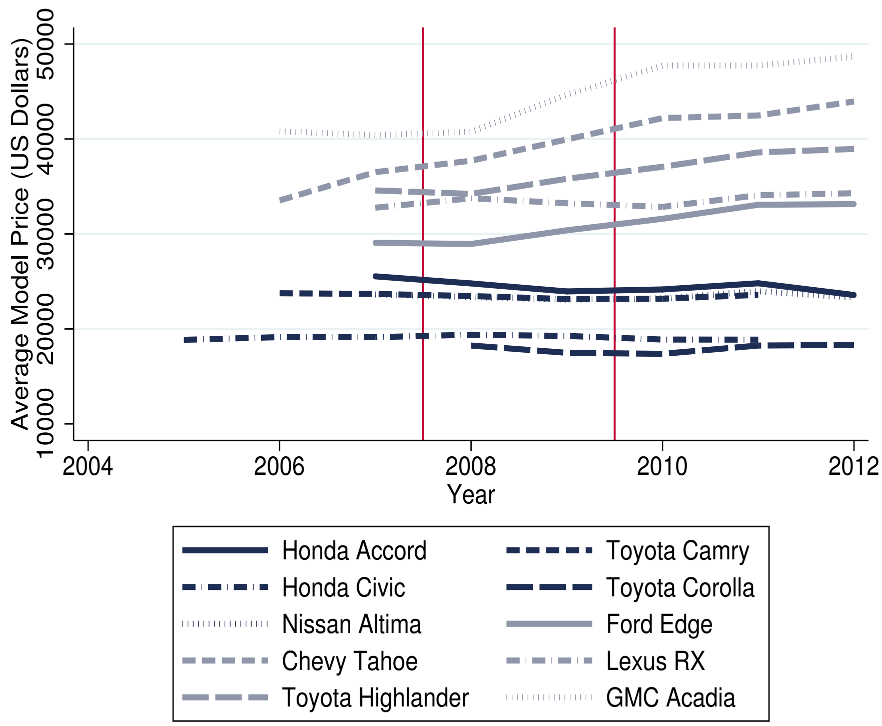


Notes: The figure displays several decompositions of the variance of transaction prices in the Dominion dataset, excluding fleet sales. The top-left panel displays the decomposition of the variance of new-vehicle transaction prices V_t (solid line) into the following components: between models V_t^B (dashed line); within models V_t^W (dashed-dotted line); and covariance term $Cov_t^{B,W}$ (dotted line). The top-right panel displays the decomposition of the variance V_t (solid line) into two components: new models $s_t^N V_t^N$ (dashed-dotted line) and old models $(1-s_t^N)V_t^O$ (dashed line). The bottom-left panel displays the variance of expenditures on new models V_t^N (solid line) and its decomposition into between-models component $V_t^{N,B}$ (dashed line), within-models component $V_t^{N,W}$ (dashed-dotted line), and covariance term $Cov_t^{N,B,W}$ (dotted line). The bottom-right panel displays the share of transactions on new models s_t^N. Horizontal axes report years (2004-2012); vertical lines highlight recession years (2008 and 2009).

with different discrete characteristics—such as diesel, or turbo injection—as distinct models, in these robustness analyses we aggregate both continuous and discrete characteristics of different trims of each model.

We consider two alternative specifications of the hedonic regressions. The first specification (top panels) is more flexible and uses indicator variables for discrete characteristics, as in equation (1). Within each model, we average the discrete characteristics weighting

Figure B6: Average Price of Ten Popular Models

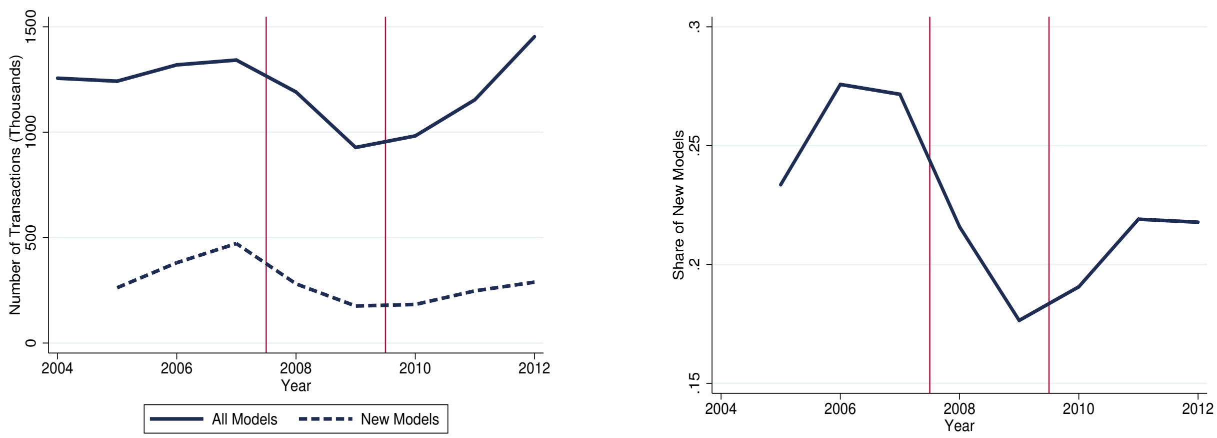


Notes: The figure displays the average transaction price of ten popular models in the Dominion dataset. Specifically, we select the five models with the highest levels of sales and price below the median, and the five models with the highest levels of sales and price above the median. Horizontal axes report years (2004-2012); vertical lines highlight the recession years (2008 and 2009).

different trims according to their transaction shares. We then round the average to the closest discrete value, and set the corresponding indicator variable equal to one. The second specification (bottom panels) treats all characteristics that vary across trims—including discrete ones—as continuous variables and assumes a log-linear relationship between prices and all of these characteristics. Within each model, we average the discrete characteristics weighting different trims according to their transaction shares and treat the average as the value of a continuous characteristic. Because make and body type do not vary across trims within each model, we control for these two attributes with indicator variables as in equation (1).

The first specification has an overall better fit, because the indicator variables better capture the nonlinearities in the relation between discrete attributes—such as the number of cylinders—and prices, whereas the second specification features a finer measurement of discrete variables—as it does not rely on rounding—but imposes a linear relation between

Figure B7: Transactions and Share of New Models



(a) Number of Transactions

(b) Share of New Models

Notes: The left panel displays the number and compositions of new-car sales in the Dominion dataset during 2004-2012. The solid line refers to all sales; the dashed line refers to sales of new-car models only. The right panel displays the time series of the share of models we classify as new models. Horizontal axes report years (2004-2012); vertical lines highlight the recession years (2008 and 2009).

all attributes and prices.

Critically, in both cases we find that quality growth is stagnant after the Great Recession when we measure it with pre-recession hedonic prices (left panels), whereas average quality tracks the average price more closely when we use time-varying hedonic prices (right panels). These results suggest that the level of aggregation of car characteristics, as well as the exact number of models, do not affect our main findings.

Table B1 reports selected coefficients of our hedonic regressions, with the same level of aggregation as in Section 3.3, when we focus exclusively on new models. Consistent with our baseline specification that pools all models (top panel of Table 1), we measure an increase in several hedonic prices of characteristics associated with high quality between the pre-recession and the post-recession periods.

B.4 New Models and Technological Progress

Figure B9 reports several robustness checks of our estimates of the technology level for new and old models. Specifically, the top-left panel reports the results we obtain by replacing the variable weight with three geometric dimensions—wheelbase, width, and height—in regression equation (2). Estimates of the technology level for new and old models are

Table B1: Hedonic Regressions, New Models

	(1) Pre-Recession	(2) Recession	(3) Post-Recession
Log(Wheelbase)	1.375	2.456	1.815
	(0.272)	(0.456)	(0.511)
Log(Horsepower)	0.409	0.324	0.483
	(0.084)	(0.142)	(0.112)
Log(Weight)	0.340	0.933	0.554
	(0.143)	(0.205)	(0.216)
Log(Fuel Efficiency)	0.051	0.307	-0.253
	(0.083)	(0.118)	(0.131)
Log(Engine Size)	0.006	-0.288	-0.135
	(0.104)	(0.166)	(0.130)
Observations	457	215	306
R^2	0.965	0.969	0.982

Notes: The table reports the estimated coefficients of the log of continuous characteristics X_{jt} in equation (1), with standard errors in parentheses, using data on new models only in three subsamples: column (1) refers to the pre-recession subsample (2004-2007); column (2) to the recession subsample (2008–2009); and column (3) to the post-recession subsample (2010–2012).

remarkably similar to the ones we show in Figure 2.

The top-right panel of Figure B9 portrays the level of technology embodied in new and old models estimated with regression equation (2), when we weight observations by their transaction share in the IHS dataset. In this case, the drop in quality in 2008 appears larger than in the unweighted case we display in Figure 4: New models introduced in 2008 display a lower level of technology than previously introduced models.

The bottom-left panel of Figure B9 displays our estimates of the technological level of new models and old models under the assumption of a translog cost function. Under this assumption, we recover the path of technological progress by estimating the following regression equation:

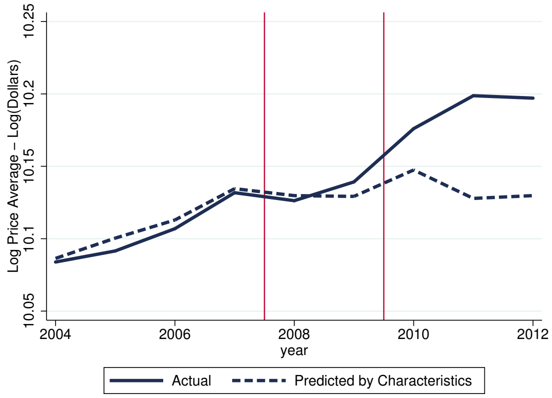
$$\begin{aligned} \log mpg_{it} &= \alpha_1 \log hp_{it} + \alpha_2 \log w_{it} + \delta Z^1_{it} + T_t + T_t \times \mathcal{I}^N_{it} \\ &\quad + \alpha_{11}(\log hp_{it})^2 + \alpha_{22}(\log w_{it})^2 + \alpha_{12} \log hp_{it} \times \log w_{it} + \varepsilon_{it}. \end{aligned} \tag{B1}$$

The results are qualitatively and quantitatively similar to those we obtain in Figure 4 under the assumption of a Cobb-Douglas cost function.

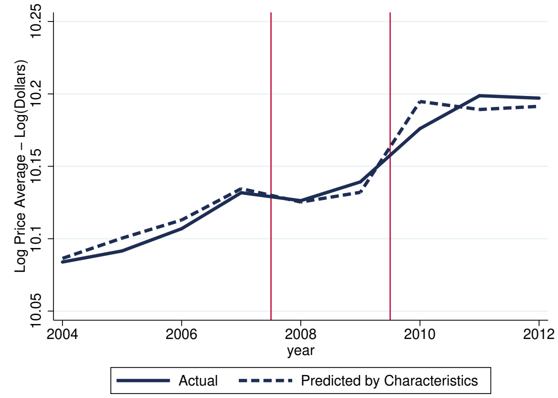
The bottom-right panel of Figure B9 displays our estimates of the technological level of new models and old models when we aggregate both continuous and discrete characteristics of different trims of each model, using their transaction shares in the IHS dataset, consistent with the hedonic analysis displayed in Figure B8. Our results are robust to this different level of aggregation of car characteristics, buttressing our argument that the level of aggregation of car characteristics and the exact number of models do not affect our results.

Figure B10 displays the results we obtain by estimating regression equation (2) without an interaction term between year fixed effects and the indicator function for new models, without sales weights (left panel) and with sales weights (right panel). In this analysis, we effectively pool all models to estimate a common level of technology, and still find a substantial decrease in quality during the Great Recession.

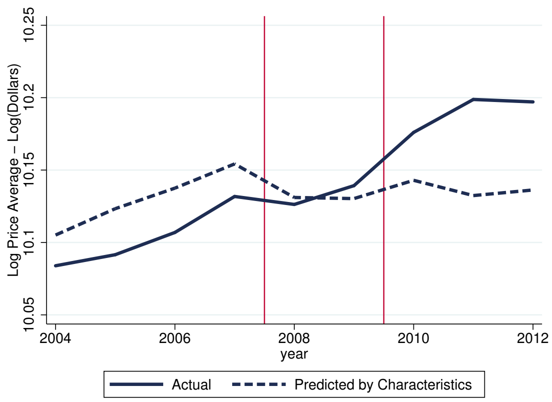
Figure B8: Hedonics and Vehicle Quality, Aggregating All Characteristics



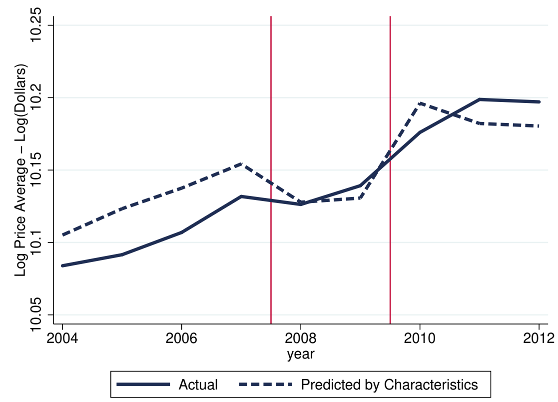
(a) Constant Hedonic Prices, Rounding



(b) Time-varying Hedonic Prices, Rounding



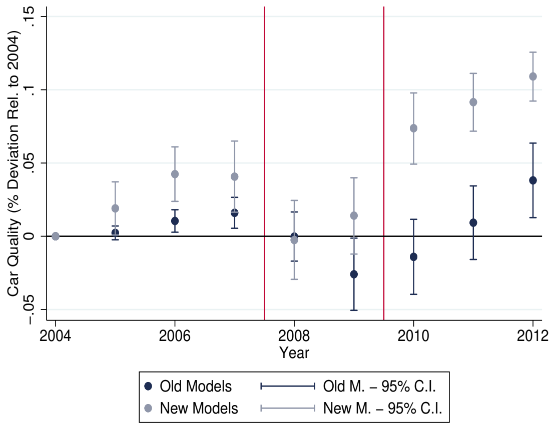
(c) Constant Hedonic Prices, Continuous



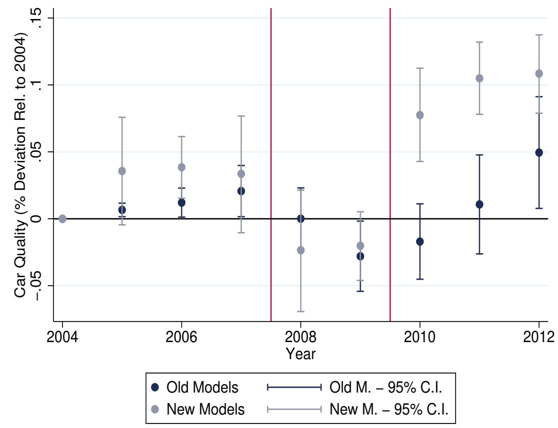
(d) Time-varying Hedonic Prices, Continuous

Notes: The figure displays the dynamics of average (log) transaction price in the merged Dominion-IHS dataset (solid lines) and the average (log) value predicted with a hedonic regression (dashed lines), when we aggregate both discrete and continuous characteristics of different trims at the model level. Top panels refer to a flexible specification with indicator variables for discrete characteristics, as in equation (1). Within each model, we average the discrete characteristics weighting different trims in proportion to their transaction shares. We then round the average to the closest discrete value, and set the corresponding indicator variable equal to one. Bottom panels refer to an alternative specification that treats all characteristics that vary across trims—including discrete ones—as continuous variables and assumes a log-linear relationship between prices and characteristics. Within each model, we average the discrete characteristics weighting different trims in proportion to their transaction shares and treat the average as the value of a continuous characteristic. Because make and body type do not vary across trims within each model, we control for these two attributes with indicator variables as in equation (1). Left panels refer to constant pre-recession hedonic prices (2004-2007); right panels to time-varying hedonic prices, estimated in three subsamples: pre-recession (2004-2007), recession (2008-2009), and post-recession (2010-2012). Horizontal axes report years (2004-2012); vertical lines highlight recession years (2008 and 2009).

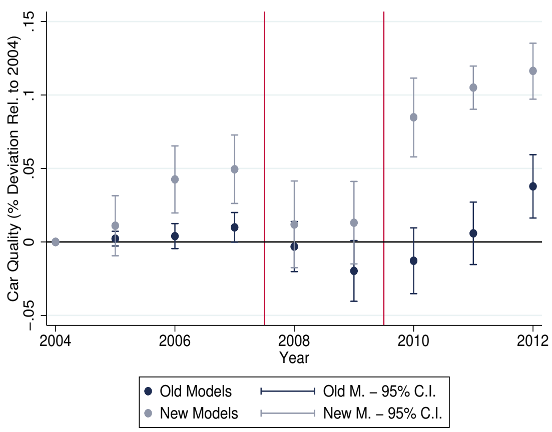
Figure B9: Technology of New and Old Models—Robustness



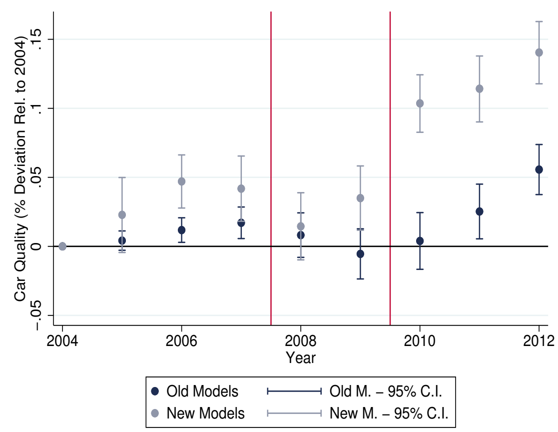
(a) Replacing Weight with Geometric Dimensions



(b) Weighted by Sales



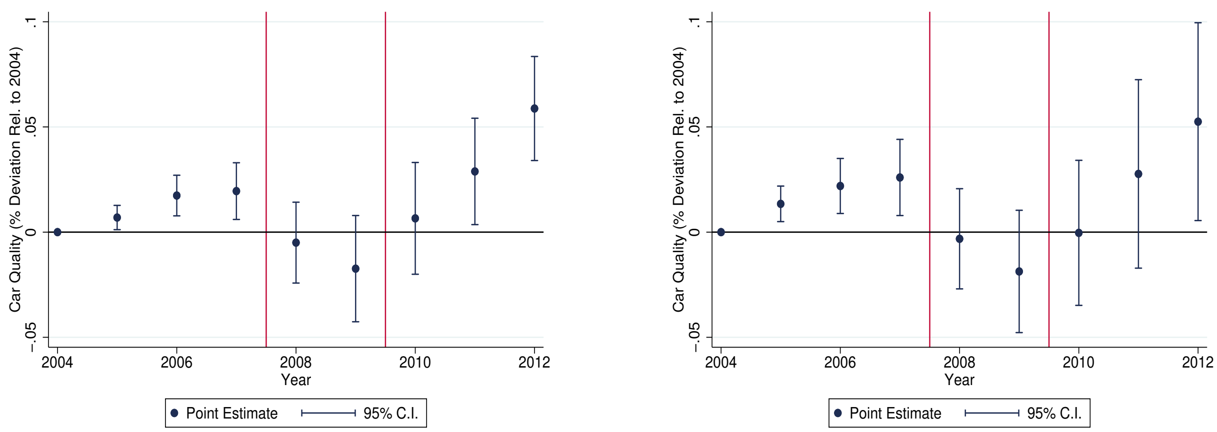
(c) Translog Cost Function



(d) Aggregating All Characteristics

Notes: The figure displays several robustness checks of our measure of technology level for new and old models. Specifically, the top-left panel displays the results we obtain by replacing the variable weight in equation (2) with the variables wheelbase, width, and height. The top-right panel displays the results we obtain by estimating (2), weighting models by number of transactions in the IHS dataset. The bottom-left panel displays the estimates we obtain for regression equation (B1)—i.e., assuming a translog cost function. The bottom-right panel displays the estimates we obtain when we aggregate both continuous and discrete characteristics of different trims of each model using their transaction shares. Horizontal axes report years (2004-2012); vertical lines highlight recession years (2008 and 2009).

Figure B10: Technology of All Models



(a) Not Weighted by Sales

(b) Weighted by Sales

Notes: The figure displays the estimated average level of technological efficiency for all models, based on equation (2), removing the interaction term between new models and time. The left panel refers to a regression without weights, whereas the right panel refers to a regression with weights based on the number of transactions in the IHS dataset. Horizontal axes report years (2004-2012); vertical lines highlight recession years (2008 and 2009).