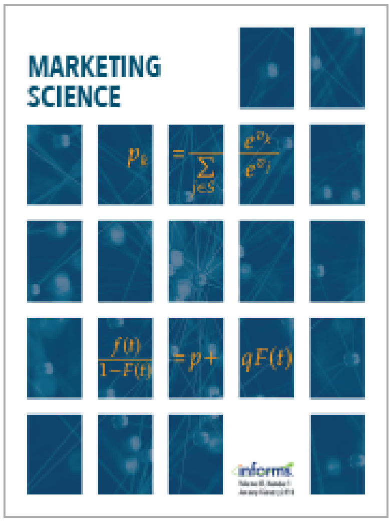

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The Effects of Product Line Breadth: Evidence from the Automotive Industry

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Abstract. Using a detailed data set from the U.S. automotive industry, we enrich the existing literature on product line breadth with new results that highlight previously unexplored operational aspects of its benefits and costs. We find that expanding product line breadth has a significant effect on increasing mismatch costs arising from the increased demand uncertainty associated with product proliferation. These mismatch costs are manifested through additional discounts and inventories. The effect of product line breadth on mismatch costs is comparable in magnitude to the effect on production costs, suggesting that the operational benefits of inventory pooling achievable by rationalizing product lines can be very substantial. Furthermore, we quantify the benefit of using a platform strategy to mitigate the effects of a broad product line on production costs. Finally, we propose an additional, attribute-based measure of product line breadth and find that product line breadth can work as a hedge against changes in demand conditions. For example, automakers that offer a broader range of fuel economy levels increase their market share and reduce their average discounts as gas prices become more volatile.

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1. Introduction

Product proliferation is pervasive in many industries. Consumers willing to buy a car in 2002 in the United States could choose among some 192 models, each of which had multiple configuration options. Certainly that is a broader choice set than the black Ford Model T available to consumers in 1908 but not very impressive if we compare it with the 274 models that were available in 2013. On average, individual automakers have been broadening their product lines over the last few years. This paper studies the effects of *product line breadth* (measured by the number of different models an automaker offers) in the U.S. automotive industry.

Previous literature in marketing has been concerned with the drivers and effects of product line breadth. Theoretical models (e.g., Lancaster 1990) suggest that broader product lines should result in higher firm *market share*, since customers are more likely to find products that are closer to their taste, and in higher *production costs*, due to the loss of economies of scale. These aspects have been empirically studied by marketing researchers (e.g., Kekre and Srinivasan 1990, Bayus and Putsis 1999).

However, there are other costs associated with increased product line breadth that have been ignored by the previous marketing literature. An important source of cost is related to the impact of demand uncertainty. As firms expand their product lines, forecasting demand for each product becomes more difficult. It is well established in the operations management literature that as demand becomes more fragmented, it is necessary to carry more safety inventory to account for the increase in relative demand uncertainty (Eppen 1979).[1] Carrying additional safety inventory is associated with increased inventory holding costs, and the extra inventory eventually may have to be disposed of via price discounts. We label these costs arising from mismatches between supply and demand due to demand uncertainty "*mismatch costs*."[2] The main objective of this paper is to empirically study how product line breadth affects mismatch costs and how the magnitude of this effect compares to the previously studied effects that product line breadth has on production costs.

The second objective of this paper is to investigate how firms can mitigate the costs of product line breadth. Researchers in operations management have investigated ways of reducing those costs by pooling inventories and components across different products. In the automotive industry, this is accomplished via sharing *platforms*.[3] These ideas, developed primarily in the operations management community, have not been considered previously in the empirical literature studying the effects of product line breadth. In this paper, we estimate the economic impact that the strategy of sharing platforms across different models and makes has on the costs of product line breadth. Another way in which firms can mitigate the costs of product line breadth—in particular, the aforementioned mismatch costs in the presence of unexpected demand shifts—is by broadening the *range of options* along an attribute associated with those potential demand shifts. In the case of the automotive industry, gas prices are a big source of uncertainty that results in demand shifts. We study how covering a broader spectrum of fuel economy in a firm's product line can provide a hedge against uncertainty that can offset some of the costs of carrying a broader product line.

Our empirical setting is the U.S. automotive industry during the period 2002–2009. Besides being a very important industry, the automotive industry provides a suitable setting to study the effects of product line breadth, particularly some of the aforementioned issues. It is an industry where the number of firms is relatively low and product platforms are used extensively. Furthermore, decisions that automotive manufacturers make follow a specific sequence of events, allowing us to measure supply-demand mismatch costs separately from production costs, since firms set list prices annually, then make production decisions (before demand is realized), and, finally, offer discounts or carry inventory (after demand is realized).

Through collaboration with a recognized automotive pricing and information company, we gained access to a detailed proprietary data set that covers pricing in the U.S. automotive industry. This data set includes information about the list prices firms set at the beginning of the model year as well as manufacturer incentives (discounts or other favorable conditions manufacturers offer to dealers or customers). These manufacturer incentives are determined after the production decision has been made and demand has been realized. Since models typically are marketed over several years, we can observe data for the same models in different contexts of product line breadth. Methodologically, this allows us to control for model fixed effects and to estimate how observed variation in product line breadth impacts the two types of price information that we observe (list prices and discounts), which are related to different types of costs.

Our methodology, combined with the rich data set on the U.S. automotive industry that we compiled, allows us to build on the results of previous research in marketing and operations management and to make the following main contributions:

First, we document the effect of product line breadth on mismatch costs, which had not been considered by previous literature. We find that besides the well-known effects on production costs, product line breadth also has a substantial impact on supply-demand mismatch costs. In the automotive industry, mismatch costs are manifested in the form of discounts and inventories. We find that an additional product in the line is associated with an increase of around $100 in average discounts for each vehicle sold and with carrying extra days of supply in average inventories for the make. This suggests the (previously ignored) effect of product line breadth on mismatch costs is comparable in magnitude to the (previously studied) effect on production costs. Our results indicate the costs of product line breadth are substantially larger than what has been shown before.

Second, we study the effect of platforms on production costs. We find that, consistent with the theoretical literature on platforms, using platform families decreases production costs. On average, for every 100,000 vehicles produced in a year for other models based on the same platform, production costs per vehicle are reduced by a substantial amount, which we estimate in the range of $33 to $87 per vehicle. To our knowledge, no previous work has empirically examined the effects of platform families on production costs. Our results show how the loss of economies of scale arising from product proliferation can be mitigated by the use of a platform strategy.

Third, we propose a complementary attribute-based measure of product line breadth and we show that a broad span in attributes in which demand is uncertain can help hedge against this uncertainty. In our specific example, we focus on the range of fuel economy levels offered by an automaker as a measure of *product line span*, in addition to conventional measures of product line breadth (which we define as the number of different models an automaker offers). We find that for the same median fuel economy, automakers offering a broader range of fuel-economy levels increase their market share and reduce their average discounts as gas prices become more volatile.

In addition to those contributions, a byproduct of our analysis is to update and extend to the U.S. automotive industry the analysis of previous studies that explore the trade-off between the benefits and costs of product line breadth, focusing on its effects on market share and production costs.[4]

The remainder of the document is organized as follows: Section 2 discusses the underlying theoretical models and develops the main hypotheses. Section 3 describes the setting, data, and variables used in this study. Section 4 presents the econometric models, with the results of the estimation described in Section 5. Finally, Section 6 concludes by discussing some limitations of our study and some implications of our findings.

2. Theoretical Foundations and Hypotheses Development

2.1. Background

Previous work in marketing and operations management has been concerned with product line strategies and their effects on revenues and costs, both analytically and empirically. Among the relevant analytic modeling work, several papers have explored aspects related to product line breadth, such as the trade-off between component commonality and product differentiation (Desai et al. 2001), and the impact of modularity and delayed differentiation (Hopp and Xu 2005, Swaminathan and Tayur 1998), production technology (Netessine and Taylor 2007), or channel structure (Liu and Cui 2010) on product line decisions.

Among the empirical papers, the operations management literature has studied the challenges associated with managing product variety (see Ramdas 2003 for a review). However, the focus has been mainly at the plant level (e.g., Fisher and Ittner 1999 and MacDuffie et al. 1996 analyze the effect of product variety on work-in-process inventory, productivity, and quality). By contrast, the marketing literature has been concerned with trying to understand the effects of product line breadth at the market level. One of the first papers to study the effects of product line breadth was Kekre and Srinivasan (1990). They use self-reported survey data across industries to study the market benefits and cost disadvantages of broader product lines and find that broader product lines are associated with higher market shares. However, they do not find a positive association between broader product lines and production costs. By contrast, Bayus and Putsis (1999) analyze the personal computer industry and find an association between product line breadth and market shares and prices, which they assume to be a proxy for production costs.[5] Note that these papers have not incorporated the theoretical ideas developed by the operations management community.

We start our analysis by developing two hypotheses, which have been tested in the literature, dealing with the effect of product line breadth on market shares (Section 2.2) and on production costs (Section 2.3). The objectives of these two hypotheses are to relate our paper to previous work, to validate previous results in the context of the U.S. automotive industry, and to provide a baseline for the costs and benefits of product line breadth on market shares and production costs. We use a measure of product line breadth that is consistent with previous work (e.g., Bayus and Putsis 1999). We define product line breadth as the *number* of different products (vehicle models, in our empirical setting) that a firm (an automaker, in our empirical setting) offers at a given time.

After that, we proceed to develop and test a set of novel hypotheses arising from the operations management literature. Section 2.4 analyzes the effect of product line breadth on supply-demand mismatch costs, including discounts (H3A) and inventories (H3B). Section 2.5 develops hypotheses related to the effectiveness of potential strategies firms can use to reduce the costs of carrying a broad product line; these include platform sharing (H4) and increasing the span of a product line as a strategy to hedge against possible changes in demand (H5).

2.2. Effect of Product Line Breadth on Market Share (H1)

The view that product variety increases market share is generally accepted and described in marketing textbooks (e.g., Kotler and Keller 2011). Consumers have heterogeneous preferences and, using a spatial analogy where products are represented in a space in which each dimension corresponds to a product attribute, the broader the product line, the more likely consumers are to find products that are close to their individual preferences. As firms broaden their product lines, they increase their appeal relative to their competition. Thus, we hypothesize the following:

Hypothesis 1 (H1)**.** *An increase in product line breadth is associated with an increase in market share.*

This hypothesis has received support in previous empirical literature (Kekre and Srinivasan 1990, Bayus and Putsis 1999). Beyond just validating that the effect goes in the same direction in the automotive industry, we are interested in quantifying the magnitude of the increase in market share.

Since our data are available both at the make (e.g., Toyota) and model (e.g., Corolla) levels, it is important to define the level at which we hypothesize the effects to occur. In the case of Hypothesis 1, we expect the effect to happen at the make level. If Toyota adds a new model to its product line, that model will trigger new demand that will increase Toyota's total market share. We do not hypothesize this effect at the model level because, although a newly introduced model will trivially increase its market share, the market share of the existing models is likely to decrease if the new model cannibalizes some of their sales. The average effect at the model level will depend on the substitution patterns.

2.3. Effect of Product Line Breadth on Production Costs (H2)

Product variety comes at a cost. As noted by Lancaster (1990), greater product variety brings decreased economies of scale. Higher product variety results in a lower demand per model, which generates diseconomies of scale, higher overhead, and, in short, higher average unit production costs. Thus, we hypothesize the following:

Hypothesis 2 (H2). *An increase in product line breadth is associated with an increase in average production costs.*

This hypothesis has also been studied in previous empirical literature, with mixed conclusions. For example, Kekre and Srinivasan (1990) find that broader product lines are associated with lower production and inventory costs, whereas Bayus and Putsis (1999) find a positive association between product line breadth and production costs. By testing this hypothesis in our data, we can provide additional evidence in one or the other direction and we can quantify the effect of the cost increase that can be attributed to variety in the U.S. automotive industry.

Note a more suitable approach to this hypothesis is at the model level, since each of the models has different costs and each model will be subject to loss of economies of scale after a new model is introduced. If we analyzed this at the make level, the introduction of a new inexpensive model could actually reduce the average production costs for the make, obscuring the effects from the loss of economies of scale. At the model level, we can include model fixed effects to account for a model's time-invariant characteristics.

2.4. Effect of Product Line Breadth on Mismatch Costs (H3A and H3B)

The literature that has empirically studied the cost consequences of product line breadth has focused largely on its impact on production costs. However, as Fisher (1997) notes, it is important to differentiate between the physical costs (including production, transportation, and inventory storage) and market mediation costs that arise as a consequence of supply-demand mismatches (such as markdowns, excess inventories, and shortages). We refer to these as mismatch costs and, to our knowledge, no previous work has empirically studied the effects of product line breadth on them. In an empirical context, it is important to understand whether one of the two types of costs dominates and how variety affects them both. Following the terminology introduced in Fisher (1997), if variety affects mainly mismatch costs, firms willing to offer broad product lines should adopt market-responsive supply chains (e.g., use local production), whereas if variety affects mainly production costs, firms offering broad product lines should adopt physically efficient supply chains.[6]

Several researchers have recognized the importance of the separation between production and sales in the presence of demand uncertainty. For example, Desai et al. (2007, p. 151) observe that "marketing researchers have not devoted much effort to this separation between production and marketing in the face of demand uncertainty. Yet ... this is a very real problem that has effects that persist even after the uncertainty is resolved." Although some recent work has studied the effect of some strategic decisions on mismatch costs (e.g., Moreno and Terwiesch 2015 study the effect of production flexibility on discounts), to our knowledge there is no available evidence regarding the direction and magnitude of the effect of product line breadth on mismatch costs and its importance relative to the previously analyzed effects on production costs. We hypothesize that increasing product line breadth is associated with higher mismatch costs because, as Ramdas (2003) notes, higher variety can increase demand variability and forecast errors, thereby increasing mismatch costs. This is an "*unpooling*" argument, since fragmentation exacerbates the uncertainty faced by the firm. This is the logic behind stockkeeping unit (SKU) rationalization practices (see Alfaro and Corbett 2003). The argument can be developed mathematically following Eppen (1979), who shows that consolidating demand will reduce mismatch costs through reduced aggregate uncertainty. To see this, consider the following simple model: A firm that manufactures two different products (vehicles), denoted by A and B, sells through a retailer (dealer) in a single sales period. Demand during the sales period for each product is *independent*, normally distributed with mean μ and standard deviation σ. The optimal quantity Q to stock is given by the critical fractile $F^{-1}(c_u/(c_o+c_u))$, where F^{-1} is the inverse cumulative distribution of the demand, c_u is the cost of understocking the realized demand by one unit (lost sale), and c_o is the cost of overstocking demand by one unit.[7] For a normal distribution, this quantity is $Q=\mu+z\sigma$, where z is the value for which $P(Z\leq z)=c_u/(c_o+c_u)$, with $Z\sim N(0,1)$. The expected leftover inventory for each product will be $Q-\mu=z\sigma$, increasing in σ. In total, the expected leftover inventory for the firm will be $2z\sigma$.

Consider now that the firm decides to rationalize its product line and offer only one product, AB, which appeals to buyers of both A and B. Demand will be distributed normally, with mean 2μ and standard deviation $\sqrt{2}\sigma$. If the firm orders the optimal quantity, the order amount will be $Q=2\mu+\sqrt{2}z\sigma$ and the leftover inventory will be $\sqrt{2}z\sigma$, which is lower than the leftover inventory in the case with two products. In other words, the total mismatch costs will be lower when selling only AB than when selling A and B. This stylized model can be generalized, but we simply use it to build intuition to support the following general hypothesis:

Hypothesis 3 (H3). *An increase in product line breadth is associated with an increase in mismatch costs.*

Our empirical setting—the automotive industry—provides two main pieces of information that are directly related to mismatch costs: discounts and inventories.[8] Automotive manufacturers set list prices before demand is realized, and they can use discounts to correct supply-demand mismatches. (Obviously, firms can also use discounts for other purposes, as discussed below.) The effect of product line breadth on mismatch costs can be manifested through an increase in discounts or inventories, or a combination of both. Continuing with our stylized model, a manufacturer selling only the single product AB will carry less inventory on average than if it sells both A and B. Similarly, the fact that leftover inventory is higher when selling both A and B may prompt the manufacturer to offer higher discounts to unload these leftovers.

All else being equal, higher product variety will result in more demand uncertainty and in more significant supply-demand mismatches requiring discounts. Similarly, higher demand uncertainty will result in greater average inventories. Thus, we can formulate the following two hypotheses, which we test to validate Hypothesis 3:

Hypothesis 3A (H3A). *An increase in product line breadth is associated with an increase in average discounts.*

Hypothesis 3B (H3B). *An increase in product line breadth is associated with an increase in average inventories.*

Note that Hypotheses 3A and 3B might simultaneously hold. It is an empirical question which of those effects is more important. Although the logic of the increase in mismatch costs with product line breadth holds both at the make and model levels, we do not directly observe mismatch costs and this can distort the analysis at some levels of aggregation. Discounts and inventories are correlated with mismatch costs, but it is important to note that not all discounts and inventories denote mismatches. There are examples in the literature where discounts are provided for different reasons. For example, Bruce et al. (2005) study trade promotions for durable goods (such as automobiles) where manufacturers provide incentives to dealers for exceeding specific sales targets, and Bruce et al. (2006) identify situations where a durable goods manufacturer gives customers a cash rebate to offset the burden of customers who have to pay off negative equity because the market value of their current used vehicle is lower than their outstanding loan amount. Our goal is not to explain or predict discounts but to understand to what extent they are positively correlated with extensions of product line breadth that increase mismatch costs.

The existence of other reasons to give discounts or hold inventory may challenge our ability to observe the hypothesized effects at certain levels of aggregation. For example, consider an increase in the number of products a firm makes. Average mismatch costs, represented by expected leftover inventories, will increase. However, given that there is a plausible demand cannibalization from a new product, the firm could decide to reallocate production capacity from some of the cannibalized products to the new product. This may not affect total inventories but could reduce average model-level inventories, resulting in an ambiguous effect for model-level inventories. As a consequence, it is reasonable to test H3A and H3B at both the make and model levels, but we should be careful with the interpretation of each single case. Failing to find significant effects at certain levels of aggregation does not provide evidence against the hypothesis of association between product line breadth and mismatch costs.

2.5. Mitigation Strategies: Platform Sharing (H4) and Hedging Benefits (H5A and H5B)

One of the broad issues we study is how firms can mitigate the costs of product line breadth. One possibility is to pool inventories and components across different products. In the automotive industry, this is accomplished via *platform sharing*. We build on the literature on component sharing and product platforms to study the effect of platform strategies on production costs. Automotive manufacturers use product platforms to share intellectual and material assets across a family of products (Robertson and Ulrich 1998, Krishnan and Gupta 2001). Component commonality and platform strategies have been suggested to reduce the diseconomies of scale associated with offering broad product lines (Robertson and Ulrich 1998). Economies of scale can be achieved by producing higher volumes of common parts. Consequently, we hypothesize the following:

Hypothesis 4 (H4). *Average production costs for a model decrease with the production volume of other models based on the same platform.*

Some empirical literature has studied component commonality, but this research has focused mostly on understanding what drives it (e.g., Fisher et al. 1999) or its effects on aspects other than costs, such as reliability (e.g., Ramdas and Randall 2008). To our knowledge, empirical work has not studied the effects of product platforms on reducing diseconomies of scale and lowering average unit production costs.

Since platform affiliation is a model characteristic, Hypothesis 4 is only meaningful at the model level. Note that the hypothesis considers only the volume of *other models* based on the same platform. If we did not exclude the specific model's volume, there would be a risk of capturing cost reductions based purely on the model's scale rather than the platform strategy.

If we find support for Hypothesis 3—that is, if we find evidence that product line breadth results in higher mismatch costs arising from demand uncertainty—a related issue is whether breadth can be added to a product line in a manner that mitigates the effect of this demand uncertainty. So far, our discussion has considered product line breadth as the number of products a firm offers. We now propose a complementary attribute-based measure of product line breadth. Since we are interested in understanding how product line breadth interacts with demand uncertainty, we measure breadth along a dimension that we know presents substantial uncertainty in our empirical context: gas prices. Gas prices are a big source of demand uncertainty in the automotive industry. If gas prices are high, customers prefer fuel-efficient vehicles (e.g., compact cars). If gas prices are low, the same customers might prefer other types of cars (e.g., sport utility vehicles).

Our complementary measure of product line breadth is based on the range of fuel economy offered by an automaker, relative to the range of fuel economy offered by the entire industry. We call this attribute-based measure "product line span" (distinguishing it from the "product line breadth" measure based on the number of products). Note that product line breadth and product line span are complementary measures. A make can have very few models (e.g., two models) and cover a wide range of fuel economy (e.g., from a highly fuel-efficient model to a very fuel-inefficient model). Similarly, a make can have many models but cover a very narrow range of fuel economy (e.g., by having models of similar fuel economy).

Because of the long design cycles, firms do not have very accurate demand information when they design their product lines. Firms that offer a broader product line span in terms of fuel economy might benefit from internal substitution when gas prices change, increasing their market share relative to firms that have a more limited product line span. Furthermore, having a broader product span allows firms to reallocate production to more appealing products in the medium-run, which could result in lower mismatch costs when the demand environment has substantially changed from what was anticipated at the beginning of the product design cycle. We formulate the following hypothesis:

Hypothesis 5 (H5). *A broader product line can provide a hedge against changes in demand.*

We break down Hypothesis H5 into two complementary hypotheses that more precisely define what we mean by hedging against changes in demand:

Hypothesis 5A (H5A). *When gas prices are more volatile, product lines that cover a broader range of fuel economy levels increase market share.*

Hypothesis 5B (H5B). *When gas prices are more volatile, product lines that cover a broader range of fuel economy levels have lower mismatch costs.*

This analysis is related to Busse et al. (2013), who study the effect of gas prices on the prices and market shares of new and old vehicles, and to Langer and Miller (2013), who study how gas prices affect automakers' short-run responses. Our focus is to study how product line breadth affects the changes in market shares and discounts for a given average level of fuel economy.

Our analysis also shares some features with Randall et al. (1998), who study how the presence of premium products in a product line enhances brand equity, in their case, analyzing the U.S. mountain bike industry. Their analysis supports the hypothesis that firms with high-quality products in their lines have higher brand premiums; in other words, they find spillovers from the highest-quality models in the product line. Like them, we also study product line attributes that go beyond the mere number of products in the product line. In our study, we look at how the range of fuel economy levels a firm offers affects the firms' ability to cope with uncertain demand.

3. Empirical Setting, Data, and Variables

3.1. Empirical Setting: The U.S. Automotive Industry

The empirical setting for this project is the U.S. automotive industry in the period between 2002 and 2009. The U.S. automotive industry is very important on its own (it accounts for 5% of total U.S. gross domestic product (GDP); see Ramey and Vine 2006) and it is especially appealing for the type of analysis considered in this paper. In particular, its structure allows us to create separate measures of average production costs and mismatch costs. In this industry, manufacturers set list prices (MSRP) for a model year before demand is realized. When they set list prices, they take into account their expected production costs, among other considerations. Manufacturers decide on production quantities during the model year and, when demand is realized, they offer discounts (referred to as "incentives" in the industry) to dealers or final customers for those vehicles that are selling worse than expected. Observed discounts thus provide an indication of the supply-demand mismatch. In other words, although many factors drive list prices and discounts, each (list prices and discounts) is affected by a different source of costs. List prices are affected mainly by production costs (the online appendix describes how production costs can be estimated from list prices) and discounts are affected mainly by supply-demand mismatches.

There are other aspects that make the automotive industry appealing for our analysis. In the automotive industry, product platforms—another one of our constructs of interest—are used extensively. Automotive platforms are sets of common designs, as well as engineering and production practices, that allow sharing components across the multiple vehicles belonging to a platform.[9] Also, it is an industry with a limited number of automakers that market vehicles comparable to each other using a reduced set of attributes. Firm entry and exit are not very important during our period of study, and models typically are marketed over several years, which allows us to observe the same models in different contexts of product line breadth.

3.2. Data Sources

For our analysis, we combined three types of automotive data from different sources: market data, vehicle-level data, and production data. Our market data comes from TrueCar (http://www.truecar.com), an online automobile information and communications platform that provides information to consumers and dealers. Through collaboration with TrueCar, we obtained access to some of its historical proprietary data, including total U.S.-wide monthly data on sales, end-of-month inventory, and average discounts at the model level. Average discounts are calculated by adding the total amount a manufacturer spends to incentivize sales of a particular model in one month, including the cost of financial incentives, such as favorable credit terms, and dividing it by the number of vehicles of that particular model sold in the month. The amount includes incentives given directly to the customer and those given to dealers, which may or may not be passed through to customers (see Busse et al. 2006). Although the actual prices customers see may vary, all incentives represent a cost to manufacturers that can be affected by mismatches exacerbated by product line breadth. We also have access to the same information at the make level by month. Our market-level data is aggregate and we do not have customer-level data. The transaction price that every customer pays is negotiated on a case-by-case basis, and the dealer may offer additional discounts. We do not have access to that information.[10]

We obtained vehicle-level data and production data from Ward's Automotive. Vehicle-level data contains information about vehicle attributes (including weight, horsepower, fuel economy, length, height, wheel base, and MSRP) that is available at the year level. Vehicle attributes are available at a more granular level than the model. A model may be offered in various trim levels, which denote different configurations of standard equipment and amenities. For example, "Chevrolet Malibu" is a model available in different trim levels, such as "Chevrolet Malibu LS" and "Chevrolet Malibu 1LT," which can have slightly different attributes. Since our market-level data are only available at the make and model levels (e.g., "Chevrolet Malibu"), we match every model with the median of the attributes across the different trim levels in which a model is available.

Production data indicate the quantities produced for each model and month for the models manufactured (at least partially) in the United States as well as information about the plant where models are produced and the platform on which they are based, allowing us to compute total production for each platform.

3.3. Definition of Variables

Dependent Variables. We measure market share of make j in month t ($MKTSHR_{jt}$) as the total number of sales of make j in month t divided by total sales in month t. Although this measure can be defined at the model level as well, our Hypothesis H1 is established at the make level. Our focus is on studying how make market share increases when new products are introduced and not how the introduction of new models cannibalizes part of specific previously existing models' market share.

Measuring production costs is more involved, since we do not observe them directly. We consider production costs at the model level and define $COST_{it}$ as the average production costs for model i during month t. We take two different approaches to ensure our qualitative results do not critically depend on our particular modeling choice. In the first approach, we simply use the (observed) list price ($MSRP_{it}$) instead of the unobserved production cost. A similar approach is used by Bayus and Putsis (1999), who proxy costs using prices. The logic of the approximation is that list prices can be expressed as a combination of the production costs plus some markup, and the variation in list prices will capture some of the variation in those production costs. On the other hand, list prices are determined before actual demand is observed and they typically remain constant during the entire vehicle year; in other words, they are not affected by mismatches between supply and demand. Since using list prices as a proxy for unobserved production costs can present potential problems, we propose a second approach that estimates the equilibrium markup using a demand model. We use an aggregate nested logit model to characterize demand (Berry 1994) and we back up the costs that rationalize the observed pricing behavior. The procedure is explained in detail in the online appendix. This gives us an estimation $\widehat{COST}_{it}$ that we can then use as a dependent variable in our analysis.[11]

For the mismatch costs, we consider two different variables that capture the effects on incentives and inventories. At the make level, we define $DISCMAKE_{jt}$ as the average incentive offered by the manufacturer for a vehicle of make j, calculated as the total amount spent in manufacturer incentives for make j divided by the total sales of make j in month t; we use $INVMAKE_{jt}$ to denote the make's average inventory of vehicles, measured as the average number of days of supply in finished products of the models marketed by make j. We also define the counterparts of these variables at the model level: $DISCMODEL_{it}$ is the average incentive the manufacturer offers for a vehicle of model i, calculated as the total amount spent in manufacturer incentives for model i divided by the total sales of model i in month t; $INVMODEL_{it}$ denotes the number of days of supply in finished products of the models i in month t.

Key Independent Variables. Our main measure of product breadth, PLB_{jt}, is constructed by counting the number of different models (e.g., Malibu) marketed by a make (e.g., Chevrolet) in a given month. This variable changes when models are introduced or phased out. Although the total number of vehicles in the market presents an increasing trend, individual automakers had their product lines expanded or reduced at different points during our period of analysis (see the evolution of this variable for the top-selling makes in Figure 1).

We generate a measure of product line span, $MPGSPAN_{jt}$, based on the range of fuel economy levels a make offers, relative to the industry. This measure is calculated as the interquartile range of fuel economy offered by the models of make j in month t over the interquartile range of the fuel economy offered by the entire industry in month t. These interquartile ranges are based on model availability, regardless of sales. For example, for a make that only offers one level of fuel economy, the interquartile range would be 0. For a make that has the same interquartile fuel economy as the entire industry, this ratio would be 1. This ratio can be larger than 1 if a make has an interquartile fuel economy range that exceeds the industry's. This measure complements our measure of product line breadth. A make can have many products but a narrow span of fuel economy, or few products that span a wide range of fuel economy options.

For our study of Hypothesis 4 on how using platforms can reduce production costs, we define $PLATVOLUME_{pt}$ as the total annual production of vehicles of platform p during year t.

Control Variables. Besides the outcome variables and the key independent variables discussed above, we use an extensive set of control variables in our analysis. For reference purposes, Table 1 shows all of the variables used in the analysis, including our control variables, along with a short description and some summary statistics.

Our data set contains 328 models with 18,166 model-month observations.

4. Econometric Models

4.1. Make-Level Analysis

We start by describing the set of equations that govern the behavior of the variables of interest at the make level. Note the hypotheses that we have established at the make level are concerned with the relationship between product proliferation and make market share (H1), the relationship between product proliferation and mismatch costs in the form of incentives (H3A) and inventories (H3B), and the hedging value of a broad

Figure 1. (Color online) Variation in Product Line Breadth for the 12 Top-Selling Makes

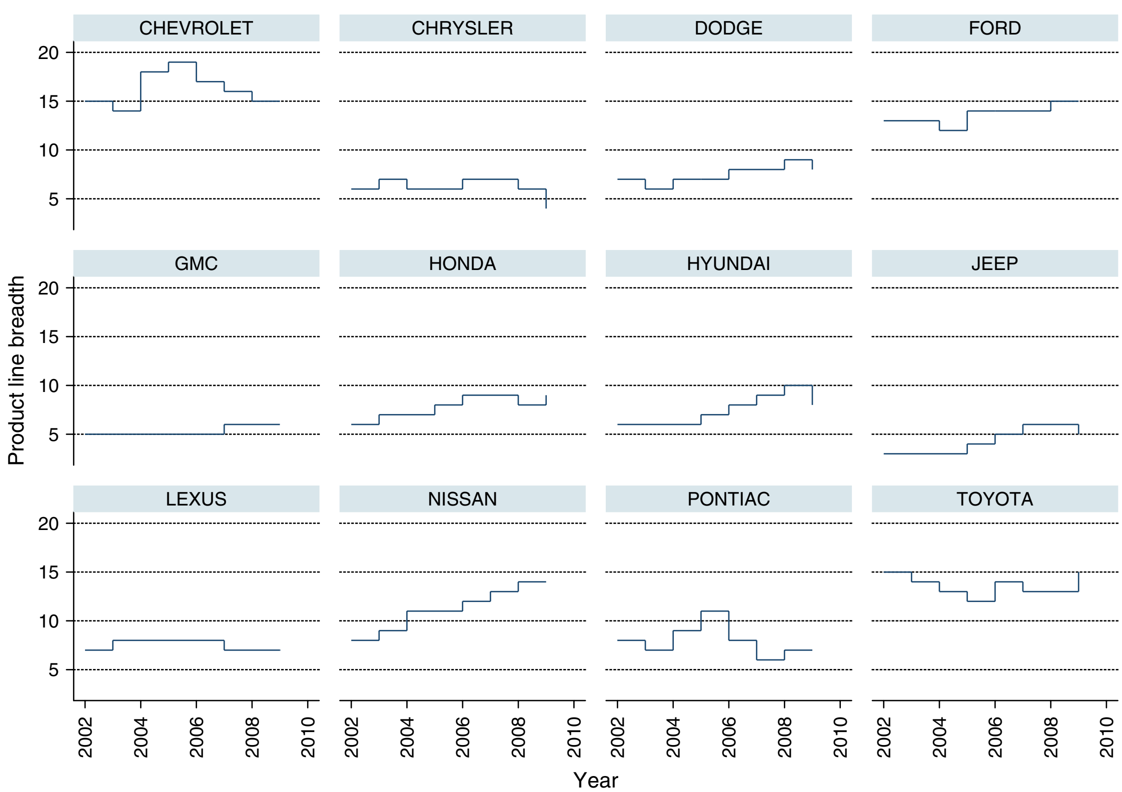

Table 1. Variables and Summary Statistics

Variable	Mean	Std. Dev	Median	Count	Description
Dependent variables					
MKTSHR	0.05	0.057	0.02	18,166	Make market share
MSRP	32,795	13,500	29,780	18,166	List price
DISCMODEL	2,822.52	2,080.08	2,499	18,166	Average discount for model
DISCMAKE	2,848.11	1,464.61	2,760	18,160	Average discount for make
INVMAKE	86.77	35.67	84.78	18,166	Average days of supply for models of make
INVMODEL	90.10	49.67	81.50	18,166	Model days of supply
Key independent variables					
PLB	8.21	4.22	7	18,166	Product line breadth (number of products of a make)
MPGSPAN	0.94	0.465	0.89	18,134	Range of fuel economy levels offered by make, relative to market
PLATVOLUME	211,981.8	695,610.4	158,544	18,166	Annual production of vehicles of the same platform
Model attributes					
LAUNCHED	0.08	0.27	0	18,166	1 if model just launched
PHASEDOUT	0.027	0.16	0	18,166	1 if model to be phased out
NEWDESIGN	0.34	0.48	0	18,166	1 if model has changed attributes substantially
AGE	3.15	2.18	3	18,166	Years since model introduction
SIZE	13,879.8	1,756.8	13,757	18,166	Size of vehicle
HPWT	0.059	0.01	0.057	17,803	Horsepower/weight
MPG	21.05	4.72	20.59	18,046	Miles per gallon
Additional control variables					
GASPRICE	240.78	65.24	231.6	18,166	Gas price (obtained from the Energy Information Administration)
GASVOL	12.57	11.07	8.84	18,166	Volatility of gas prices. For each week, we compute the standard deviation of the weekly gas prices during the last 12 weeks, and we average the values for the month.
MEDMPGMAKE	20.68	2.28	20.59	18,134	Median fuel economy level offered by make
FLEX	0.25	0.43	0	17,167	1 if model produced in a plant that can produce different platforms (mix flexible) (see Moreno and Terwiesch 2015)
COMPDISC	2,697.63	956.12	2,806.09	18,162	Average discount given by competing models (same segment and luxury level)

product line span to increase market share (H5A) and reduce mismatch costs (H5B) under demand volatility. We will therefore need an equation to describe the evolution of the make's market share (*MKTSHR*) and one equation for each of the variables associated with mismatch costs—that is, incentives (*DISCMAKE*) and inventories (*INVMAKE*).

We propose the following family of simultaneous equation models at the make level, where t denotes the month and j denotes the make (e.g., Chevrolet, Toyota, etc.):

$$\begin{cases} MKTSHR_{jt} = \mu_j + \alpha_1 PLB_{jt} + \alpha_2 MPGSPAN_{jt} \\ \qquad + \alpha_3 GASVOL_t \\ \qquad + \alpha_4 MPGSPAN_{jt} \times GASVOL_t \\ \qquad + \alpha_5 DISCMAKE_{jt} + C_{jt} + \gamma_t + \epsilon_{1jt}, \\ DISCMAKE_{jt} = \delta_j + \beta_1 PLB_{jt} + \beta_2 MPGSPAN_{jt} \\ \qquad + \beta_3 GASVOL_t \\ \qquad + \beta_4 MPGSPAN_{jt} \times GASVOL_t + C'_{jt} \\ \qquad + \sum_{k=1}^{K} \eta_k INVMAKE_{jt-k} + \omega_t + \epsilon_{2jt}, \\ INVMAKE_{jt} = \lambda_j + \phi_1 PLB_{jt} + \phi_2 MPGSPAN_{jt} \\ \qquad + \phi_3 GASVOL_t \\ \qquad + \phi_4 MPGSPAN_{jt} \times GASVOL_t \\ \qquad + C''_{jt} + \tau_t + \epsilon_{3jt}. \end{cases} \quad (1)$$

Each of the three equations includes the product line breadth variable (PLB_{jt}) and the variable indicating the span of the product line (*MPGSPAN*), as well as its interaction with gas price volatility (*GASVOL*).[12] All equations include make fixed effects ($\mu_j, \delta_j, \lambda_j$, respectively), which account for any time-invariant effects; time effects ($\gamma_t, \omega_t, \tau_t$, respectively); a set of controls ($C_{jt}, C'_{jt}, C''_{jt}$, respectively) that varies according to the particular specification; and an error term ($\epsilon_{1jt}, \epsilon_{2jt}, \epsilon_{3jt}$, respectively) that captures any unaccounted for effects on the dependent variables.

Besides these common terms, we include other relevant variables. Our goal in choosing these variables is to propose a parsimonious model that allows for simultaneous determination of the variables of interest. The market share of a firm can go up or down for various reasons, including the firm's incentive policy. For example, a firm can temporarily increase its market share by offering aggressive discounts to dealers or customers. Since we observe the average incentives provided by the make ($DISCMAKE_{jt}$), we can include it in the right-hand side of the market share equation. Similarly, the firm can establish its incentive policy as a response to its inventory situation. For example, when inventories are high, the firm may want to stimulate demand by providing higher discounts. To account for this fact, we include the previous K values of the inventory variable ($INVMAKE_{jt}$) on the right-hand side of the incentive equation. This defines a family of specifications, and we can choose the value of K that best fits the data. (In our case, we choose $K = 3$ because that gives the best Akaike Information Criterion (AIC) for $K = 1, 2, 3$.) In summary, we implicitly assume that current discounts are affected by past inventory levels and affect current sales but not current inventory levels.

We can include a series of additional variables under ($C_{jt}, C'_{jt}, C''_{jt}$), which are discussed in Section 5. These include the median fuel economy of the vehicles of the make (*MEDMPGMAKE*), the gas price (*GASPRICE*), and their interaction. This allows us to separately identify the effect of having a broader span from the effect of simply having a portfolio with higher fuel economy.

The system of simultaneous equations in Specification 1 can be estimated using three-stage least squares (3SLS). The 3SLS procedure (see, for example, Wooldridge 2010) accounts for the endogeneity of the jointly determined variables and for potential correlation in contemporaneous error terms (which is important in this case since there are many aspects that we are not able to control for at the make level and that therefore end up being captured by the error terms) and provides consistent and efficient estimates when the system is well specified. The 3SLS procedure allows to specify additional exogenous variables to be used as instruments. We include the number of products manufactured by the rest of the makes as an additional instrument. This (together with many other model-level instruments that we are not able to use at the make level) has often been used as an instrument in previous research in the automotive industry after the work of Berry et al. (1995). Berry et al. (1995) proposed a model in which firms compete on prices and assumed a Bertrand–Nash equilibrium. The equilibrium markup depends on the characteristics of products owned by the same firm and those of products owned by other firms, which determine substitution patterns. These characteristics are assumed to be exogenous because they are defined well before the time vehicles are sold in the market and are therefore uncorrelated with demand shocks. In our particular case, we can use the number of products manufactured by the rest of the makes as an additional instrument because that variable is determined by the participants in the market before any demand shocks occur.

We summarize in Table 2 the expected signs of the coefficients of the system of equations given our hypotheses. The estimation of the system of simultaneous equations using 3SLS is consistent and asymptotically more efficient than single-equation estimation when the model is correctly specified. However, single-equation models can provide more reliable results if the system of equations is not correctly specified. Rossi (2014) notes some potential problems associated with the use of instrumental variables in marketing. To make sure that the support (or lack thereof) of our hypothesis is not a consequence of misspecification of the model or our specific choice of instruments, we conduct a series of single-equation analyses to evaluate the robustness of our findings, including estimation by ordinary least squares (OLS) and two-stage least squares (2SLS). Table 2 summarizes the support using different estimation methodologies. These additional analyses are reported in the online appendix and their findings are summarized in Section 5.

Note that identifying the effect of product line breadth is possible because we have variation in the number of products a given automaker has in the line (makes expand or reduce their product lines at certain times). Figure 1 shows the variation over time of the 12 top-selling makes.

Table 2. Summary of Hypotheses

Hypothesis	Variable of concern	Description	Level	Supported if ...	3SLS	OLS	2SLS
H1	Market share	Product proliferation associated with increase of market share	Make	$\alpha_1 > 0$	✓	✓	✓
H2	Cost	Product proliferation associated with higher costs	Model	$\theta_1 > 0$	✓	✓	✓
H3A	Mismatch—Discounts	Product proliferation associated with higher average discounts	Make	$\beta_1 > 0$	✓	✓	✓
			Model	$\beta'_1 > 0$	✓	✓	✓
H3B	Mismatch—Inventories	Product proliferation associated with higher average inventories	Make	$\phi_1 > 0$	✓	✓	✓
			Model	$\phi'_1 > 0$	—	—	—
H4	Platform use	Platform moderates the increase of costs from product proliferation	Model	$\theta_5 < 0$	✓	✓	✓
H5A	Product line span	Product line span associated with increase in market share under volatility	Make	$\alpha_4 > 0$	✓	✓	✓
H5B	Product line span	Product line span associated with a decrease in mismatch costs under volatility	Make	$\beta_4 < 0$ (discounts)	✓	✓	✓
				$\phi_4 < 0$ (inventories)	—	—	—
			Model	$\beta'_4 < 0$ (discounts)	✓	✓	✓
				$\phi'_4 < 0$ (inventories)	—	—	—

4.2. Model-Level Analysis

We now turn our attention to the model-level data. The hypotheses that we have established at the model level are concerned with the relationship between product proliferation and production costs (H2), the effects of product breadth on mismatch costs in the form of incentives (H3A) or inventories (H3B), the moderating role of platform affiliation in how product proliferation affects production costs (H4), and the hedging value of a broad product line span to reduce mismatch costs (H5B) under demand volatility. Note that for Hypotheses H3A, H3B, and H5B, the effects are defined at both the make and model levels. The model-level analysis allows us to include a more detailed set of control variables that are hard to measure at the make level (e.g., there is no such thing as an *MSRP* at the make level, and we can include all sorts of model-level characteristics, such as *MPG* or *SIZE*, in the model-level specifications). In any case, both make-level and model-level analyses provide complementary evidence when it comes to evaluating the support of the hypotheses, and it is worth exploring both sets of models to construct a bigger picture.

As we did with the make-level analysis, we start by describing a system of simultaneous equations that allow us to explore questions of interest at the model level. Besides the three equations of the make-level system (for market share, discounts, and inventories), we include an additional cost equation, since two of our model-level Hypotheses (H2 and H4) are related to costs.

Let i denote a model marketed by make j, belonging to segment (e.g., compact car, sports utility vehicle, etc.) s and based on product platform p. The following system provides a family of specifications for the simultaneous equations at the model level:

$$\begin{cases} MKTSHR_{it} \\ \quad = \mu'_i + \alpha'_1 PLB_{jt} + \alpha'_2 MPGSPAN_{jt} + \alpha'_3 GASVOL_t \\ \qquad + \alpha'_4 MPGSPAN_{jt} \times GASVOL_t + \alpha'_5 MSRP_{it} \\ \qquad + \alpha'_6 DISCMODEL_{it} + C'_{it} + \gamma'_{st} + \varepsilon_{1it}, \\ COST_{it} \\ \quad = \kappa_i + \theta_1 PLB_{it} + \theta_2 MPGSPAN_{jt} + \theta_3 GASVOL_t \\ \qquad + \theta_4 MPGSPAN_{jt} \times GASVOL_t \\ \qquad + \theta_5 PLATVOLUME_{pt} + C''_{it} + \psi_{st} + \varepsilon_{2it}, \\ DISCMODEL_{it} \\ \quad = \delta'_i + \beta'_1 PLB_{jt} + \beta'_2 MPGSPAN_{jt} + \beta'_3 GASVOL_t \\ \qquad + \beta'_4 MPGSPAN_{jt} \times GASVOL_t \\ \qquad + \sum_{k=1}^{K} \eta'_k INVMODEL_{it-k} + C'''_{it} + \omega'_{st} + \varepsilon_{3it}, \\ INVMODEL_{it} \\ \quad = \lambda'_i + \phi'_1 PLB_{jt} + \phi'_2 MPGSPAN_{jt} \\ \qquad + \phi'_3 GASVOL_t \\ \qquad + \phi'_4 MPGSPAN_{jt} \times GASVOL_t + C''''_{it} + \tau'_{st} + \varepsilon_{4it}. \end{cases} \tag{2}$$

Each of the four equations includes the variable indicating the product line breadth (PLB_{jt}) of the make producing model i on the right-hand side, along with the variable indicating the product line span ($MPGSPAN_{jt}$), as well as its interaction with the volatility of gas prices *GASVOL*.[13] All of the equations include model fixed effects ($\mu'_i, \kappa_i, \delta'_i, \lambda'_i$, respectively), which account for any time-invariant effects, segment-time effects ($\gamma'_{st}, \psi_{st}, \omega'_{st}, \tau'_{st}$, respectively), a set of controls ($C'_{it}, C''_{it}, C'''_{it}, C''''_{it}$, respectively), and an error term ($\varepsilon_{1jt}, \varepsilon_{2jt}, \varepsilon_{3jt}, \varepsilon_{4it}$, respectively) that captures any unaccounted for effects on the dependent variables.

Besides these common terms, we include other relevant variables in each of the equations. The specific choice of variables attempts to capture important variables that might be simultaneously determined with our variables of interest while maintaining a parsimonious model. A model's market share can go up or down for several reasons, such as changes in list prices ($MSRP_{it}$), incentives given for the model ($DISCMODEL_{it}$), or incentives given to other models in the same segment ($COMPDISC_{it}$, which is included among the controls). These variables are observed and included in the right-hand side of the market share equation.

The second equation describes the production costs of a model. Besides fixed effects, segment-time effects, product line breadth, and several other controls that can include product characteristics (such as *LAUNCHED*, *PHASEDOUT*, *AGE*, *NEWDESIGN*, *SIZE*, *HPWT*), we include a variable that accounts for the total annual production of the other models based on the same platform. According to H4, we expect costs to decrease with the number of vehicles produced using the same platform. This variable, labeled $PLATVOLUME_{pt}$, contains the total production of the vehicles j different from i that are based on the same platform as i.

The third equation assumes that the firm can establish its incentive policy for a model as a response to its inventory situation. For example, when inventories are high, the firm may want to stimulate demand by providing higher discounts. To account for this fact, we include the previous K values of the inventory variable for a given model on the right-hand side of the incentive equation because we expect the firm to react with some lag. As in the make-level specification, we choose $K = 3$. We also include the average discount provided for competing models in the same segment ($COMPDISC_{it}$), which is part of the set of additional control variables.

Finally, the fourth equation models the evolution of inventory as a function of product line breadth, plus a number of model-level controls, such as *COMPDISC*, *FLEX*, *LAUNCHED*, *PHASEDOUT*, *AGE*, *NEWDESIGN*.

To evaluate our hypotheses regarding the hedging value of a broad product line span to reduce mismatch costs under volatility, we include additional control variables, such as the model's fuel economy (*MPG*), the gas price (*GASPRICE*), and their interaction, which allows us to separately identify the effect of having a broader span from that of simply having higher fuel economy.

As with the make-level system, the model-level system of simultaneous equations in Specification 2 can be estimated using three-stage least squares (3SLS). However, we need to take an intermediate step because we do not directly observe the variable $COST_{it}$ used in the left-hand side of the system's second equation.

We take two different approaches to make sure our qualitative results do not critically depend on our particular modeling choice: proxying production costs using list prices ($MSRP_{it}$), and estimating the costs using the method described in the online appendix. Rather than particular values of the estimates, we are interested in whether there are systematic changes between both approaches (e.g., are the signs of the effects preserved? Does using *MSRP* result in overestimation or underestimation of the effects?).

Once we have estimated the costs (or proxied them by list prices), we can apply the 3SLS procedure; as mentioned above in the context of the make-level system estimation, this accounts for the endogeneity of the jointly determined variables and for potential correlation in contemporaneous error terms, providing consistent and efficient estimates when the system is well specified. In the model-level specification, we are able to include a more exhaustive set of instruments than in the make-level analysis. Following Berry et al. (1995), we include the sums of the product characteristics for the rest of the make's models and for the rest of the makes. As discussed above, these characteristics are assumed to be exogenous because they are defined well before the time vehicles are sold in the market, and are therefore uncorrelated with demand shocks. In our particular case, we use the sums of each of *SIZE*, *HPWT*, and *MPG* for the rest of a make's products and the rest of makes as instrumental variables, along with the number of products of other makes.

5. Description of Results

5.1. Effect of Product Line Breadth on Market Share (H1)

We start by exploring the effect of product line breadth on market share. As discussed above, this is not the main contribution of the paper because, unlike some of the other analyses, this hypothesis is not novel. We present the results here for completeness, to contrast them with previous results in different settings (e.g., Bayus and Putsis 1999), and as a baseline for our Hypothesis 5A regarding the hedging benefits of product line span, which is novel.

Hypothesis 1 establishes an association between product line breadth and market shares at the make level. The unit of observation is therefore a make-month (e.g., Nissan, February 2007). The results of the system estimation are presented in Table 3. We use the number of products marketed by the other makes as an additional instrument. We obtain a positive and statistically significant estimate for the coefficient of *PLB* (0.001), which supports our Hypothesis 1 regarding the association between product line breadth and market share. As a reference, one additional product in the product line is associated with an average increase of 0.1% points in the make market share. Our single-equation analyses (reported in the online appendix) provide qualitatively consistent results.

Overall, we find strong support for our Hypothesis 1, consistent with previous literature in other empirical settings (Bayus and Putsis 1999, Kekre and Srinivasan 1990). Note that at the model level, the market shares of individual models do actually decrease (see Table 4, where the coefficient of *PLB* in the model market-share equation is negative and significant), consistent with our discussion about potential cannibalization of demand from other models of the same make.

5.2. Effect of Product Line Breadth on Production Costs (H2)

Our hypotheses regarding the effects of product line breadth on production costs are established at the model level. Hypothesis 2 attempts to revisit previous findings obtained in other settings by establishing that production costs will increase with product line breadth. One challenge of this analysis is that we do not directly observe each model's production costs. Using the logic described in Section 4.2, we take two different approaches: (1) proxy costs using list prices and (2) estimate production costs using an equilibrium model. The methodology we use for the estimation is described in the online appendix.

Table 4 shows the estimates resulting from the joint estimation of the model-level equations (market share, production costs, discounts, and inventories) at the model level using 3SLS. Column 1 uses list prices (*MSRP*) as a proxy for production costs, and column 2 uses the estimated costs described above. All specifications use a set of controls that account for vehicle characteristics that can have an impact on production costs (*SIZE*, *HPWT*, *MPG*) and product life cycle variables that can be important, such as the number of years since the model was introduced and whether a model is just being launched, is about to be phased out, or has experienced changes in its design (*AGE*, *LAUNCHED*, *PHASEDOUT*, *NEWDESIGN*). All columns include model fixed effects and segment-time interactions and use additional instrumental variables in the spirit of Berry et al. (1995): the sum of characteristics of the

Table 3. Make-Level System Estimation: Effect of Product Line Breadth on Market Shares, Discounts, and Inventories

	(1) 3SLS
MKTSHR	
PLB	0.000999***
	(0.000210)
MPGSPAN	−0.00105*
	(0.000635)
MPGSPAN × *GASVOL*	8.76e−05***
	(3.35e−05)
DISCMAKE	1.51e−06
	(1.93e−06)
MEDMPGMAKE	−0.00204***
	(0.000247)
MEDMPGMAKE × *GAS*	6.58e−06***
	(1.21e−06)
R-squared	0.968
DISCMODEL	
PLB	64.07***
	(16.66)
MPGSPAN	−93.47
	(61.63)
MPGSPAN × *GASVOL*	−9.184***
	(3.064)
MEDMPGMAKE	38.13
	(24.55)
MEDMPGMAKE × *GAS*	−0.451***
	(0.0862)
$INVMAKE_{t-1}$	−0.282
	(0.798)
$INVMAKE_{t-2}$	1.886**
	(0.941)
$INVMAKE_{t-3}$	2.176***
	(0.806)
R-squared	0.758
INVMAKE	
PLB	1.908***
	(0.502)
MPGSPAN	−4.187**
	(1.859)
MPGSPAN × *GASVOL*	0.0589
	(0.0924)
MEDMPGMAKE	0.345
	(0.742)
MEDMPGMAKE × *GAS*	−0.00258
	(0.00260)
R-squared	0.628
Observations	2,857

Notes. All equations include make fixed effects and month-year controls. *GASPRICE* and *GASVOL* are included as additional controls. We use the number of products of other makes as an additional instrument.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

make's other models (*SIZE*, *HPWT*, and *MPG*), the sum of characteristics of other makes' models (*SIZE*, *HPWT*, and *MPG*), and the total number of products of other makes. The estimates for the coefficient of *PLB* in the cost equation using 3SLS estimation on the system of simultaneous equation varies from

Table 4. Model-Level System Estimation: Effect of Product Line Breadth on Market Shares, Costs, Discounts, and Inventories

	(1) 3SLS	(2) 3SLS
	Using MSRP	Using COST
MKTSHR		
PLB	−0.000282***	−0.000230***
	(2.47e−05)	(2.38e−05)
MPGSPAN	0.000458***	0.000318***
	(8.60e−05)	(8.22e−05)
MPGSPAN × *GASVOL*	2.02e−05***	1.97e−05***
	(3.85e−06)	(3.79e−06)
MSRP	3.51e−07***	−7.77e−09
	(3.74e−08)	(1.40e−08)
DISCMODEL	1.64e−06***	1.39e−06***
	(1.03e−07)	(1.02e−07)
FLEX	0.00110***	0.00102***
	(8.75e−05)	(8.63e−05)
MPG × *GASPRICE*	2.40e−06***	2.27e−06***
	(9.06e−08)	(8.90e−08)
Fixed effects	Model	Model
Time controls	Yes^{+}	Yes^{+}
Additional controls	Yes^{o}	Yes^{o}
R-squared	0.844	0.875
MSRP/COST		
PLB	41.63***	115.3***
	(14.47)	(35.80)
PLATVOLUME	−0.000332***	−0.000871***
	(6.93e−05)	(0.000174)
SIZE	0.681***	0.591***
	(0.0381)	(0.0957)
HPWT	63,909***	16,454**
	(2,984)	(7,489)
MPG	−129.4***	−136.3***
	(13.23)	(32.75)
Fixed effects	Model	Model
Time controls	Yes^{+}	Yes^{+}
Additional controls	Yes^{e}	Yes^{e}
R-squared	0.986	0.920
DISCMODEL		
PLB	145.0***	146.2***
	(9.853)	(9.854)
MPGSPAN	−268.3***	−310.0***
	(39.70)	(39.94)
MPGSPAN × *GASVOL*	−5.587***	−5.004**
	(1.938)	(1.950)
$INVMODEL_{t-1}$	0.490*	0.408
	(0.275)	(0.281)
$INVMODEL_{t-2}$	1.709***	1.816***
	(0.323)	(0.331)
$INVMODEL_{t-3}$	1.580***	2.015***
	(0.272)	(0.277)
FLEX	−351.8***	−325.0***
	(40.15)	(40.40)

Table 4. (Continued)

	(1) 3SLS	(2) 3SLS
	Using MSRP	Using COST
DISCMODEL (Continued)		
MPG × GASPRICE	−0.399***	−0.398***
	(0.0402)	(0.0404)
Fixed effects	Model	Model
Time controls	Yes+	Yes+
Additional controls	Yes°	Yes°
R-squared	0.722	0.722
INVMODEL		
PLB	−0.661*	−0.617*
	(0.339)	(0.339)
MPGSPAN	−4.949***	−5.746***
	(1.376)	(1.380)
MPGSPAN × GASVOL	0.151**	0.161**
	(0.0672)	(0.0674)
FLEX	−1.878	−1.818
	(1.392)	(1.396)
COMPDISC	0.000991	0.00226***
	(0.000688)	(0.000690)
MPG × GASPRICE	−0.0195***	−0.0195***
	(0.00139)	(0.00139)
Fixed effects	Model	Model
Time controls	Yes+	Yes+
Additional controls	Yes°	Yes°
R-squared	0.475	0.475
Observations	15,651	15,651

Notes. All of the columns use additional instrumental variables along the lines of Berry et al. (1995): the sum of characteristics of other models of the make (*SIZE*, *HPWT*, and *MPG*), the sum of the characteristics of the models of other makes (*SIZE*, *HPWT*, and *MPG*), and the total number of products of other makes.

°Indicates *COMPDISC*, *FLEX*, *LAUNCHED*, *PHASEDOUT*, *AGE*, *NEWDESIGN*, *MPG*, *GASPRICE*, *GASVOL*.

eIndicates *LAUNCHED*, *PHASEDOUT*, *AGE*, *NEWDESIGN*, *SIZE*, *HPWT*, *MPG*.

+Indicates Time, Segment, Segment × Time controls.

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

$41.63 USD/vehicle (using *MSRP* to proxy for costs) to $115.30 USD/vehicle (using the cost estimation procedure). In both cases, the estimates are positive and statistically significant, providing support to Hypothesis 2. Our estimates suggest that using list prices may underestimate the effects of product line breadth on production costs.

The analysis using OLS and 2SLS (reported in the online appendix) yields qualitatively similar results. Overall, our results show strong support for Hypothesis 2 (product line breadth is associated with an increase in average production costs). Previous research had provided mixed evidence.

5.3. Effect of Product Line Breadth on Mismatch Costs (H3A and H3B)

Table 3 shows the estimation of the system of simultaneous equations at the make level (Specification 1) using 3SLS. The specification includes model fixed effects, and we use the number of products marketed by the other makes as an additional instrument. If we look at the effects of *PLB* on make-level discounts (*DISCMAKE*), we can see that the effect of *PLB* is positive and statistically significant ($64.07 USD/vehicle). This shows support for Hypothesis 3A at the make level: product line breadth is associated with higher make-level average discounts. The coefficient indicates the average dollar value in discounts associated with adding a new model in a make.

Turning our attention to the effects of *PLB* on make-level inventories (*INVMAKE*), we can see in Table 3 that the effect is positive and significant (1.908). The interpretation of this coefficient suggests that adding a product to the line is associated with an increase in the make's average days of inventory of about 1.908 days of supply. This provides support for our Hypothesis 3B at the make level.[14]

We now move to the model-level analysis. Specification 2 describes the set of simultaneous equations at the model level. An important advantage of the model-level specification is that we can include segment-time controls that account for different discount patterns for vehicles belonging to various segments and also other controls, such as the interaction between gas prices and vehicle fuel economy, which allows us to account for how gas prices differently affect discounts and inventory of models with different fuel economy. Table 4 shows the results of the estimation of the system of simultaneous equations at the model level. As noted above, column 1 uses list prices *MSRP* as a proxy for production costs, and column 2 uses the estimated costs described above. Both columns use a set of controls accounting for model attributes that can have an impact on discounts and could be correlated with product line breadth, such as the flexibility with which a model is manufactured, the discounts given by competitors in the same segment, whether the product is being launched or phased out, the time since the model was introduced, the list price, and whether a model has gone through a substantial redesign. The estimates of the effect of *PLB* on *DISCMODEL* are positive and significant and are very similar across specifications (from $145.00 to $146.20 USD/vehicle). This provides support to Hypothesis 3A. One additional product in the product line of the make that produces one model is associated with an average increase of more than $100 in the average discounts per vehicle given for that model.

Turning our attention to the inventory equation in Table 4, we note that the coefficients of *PLB* in the inventory equation are slightly negative. Therefore, we do not have support of Hypothesis 3B at the model level.

The single-equation approach using OLS and 2SLS (reported in the online appendix) yields qualitatively similar results, although the effects we find for inventory are even bigger (more than three additional days of supply when adding one product to the line, in the make-level analysis). Overall, the results shown in this section suggest a substantial effect of product line breadth on mismatch costs. The order of magnitude of the total effect of product line breadth on mismatch costs is comparable to the effect on production costs. This indicates that the (previously ignored) effects of product line breadth on mismatch costs are quite substantial.

5.4. Mitigation Strategies: Platform Sharing (H4) and Hedging Benefits (H5A and H5B)

Finally, we turn our attention to the issue of how firms can mitigate the costs of product proliferation. We start by considering the effects of platform sharing. Hypothesis 4 establishes that the increase in production costs will be mitigated by the affiliation of a model to a platform with high aggregate production levels. This hypothesis is established at the model level, and the relevant results can be found in Table 4. The coefficient of the variable of interest (*PLATVOLUME*) ranges from −0.000332 to −0.000871. These values would imply that an annual production of 100,000 vehicles of other models based on the same platform is associated with an average cost reduction of $33.20 to $87.10 per vehicle. These savings can be quite substantial, because there are multiple platforms for which more than one million vehicles are manufactured per year (132 of our models are based on platforms that produce more than 100,000 vehicles of other models per year). The results using OLS and 2SLS (reported in the online appendix) yield qualitatively similar results, indicating strong support of our Hypothesis 4.

Our Hypothesis 5 suggests that makes covering a broader range of fuel economy levels will be better hedged against potential changes in demand stemming from unexpected changes in gas prices, all else being equal, by increasing their market share (H5A) and reducing their mismatch costs (H5B) in the presence of demand volatility. H5A is defined at the make level, whereas H5B can be tested at both the make and model levels.

To evaluate support for H5A, we focus on the market share equation of our system of simultaneous equations at the make level (Specification 1). If the coefficient of $MPGSPAN \times GASVOL$ is positive and significant after controlling for the median fuel economy of the make, we will conclude that the product line span provides a hedging benefit against changes in gas prices and our Hypothesis 5A will be supported. Table 3 shows the 3SLS estimates of the system of simultaneous equations at the make level, indicating this is the case. Note that the specification includes additional controls for the make's median fuel economy and its interaction with gas prices, which ensures the effect of $MPGSPAN \times GASVOL_{jt}$ is not simply driven by a make's high average fuel economy.[15]

It remains to be seen whether the complementary measure of product line span based on the range of fuel economy can reduce mismatch costs when demand volatility increases (H5B). The effect might happen through discounts, inventories, or both, and it may be observable at the make or model level. We start analyzing the effect at the make level by looking at estimates of the variable of interest ($MPGSPAN \times GASVOL$) in the make-level discount and inventory equations shown in Table 3. The coefficient is negative and significant (−9.184) in the discount equation and not significant in the inventory equation.

At the model level, Table 4 shows that the effect of $MPGSPAN \times GASVOL$ on the discount equation is negative and significant (−5.587 and −5.004), and the effect on the inventory equation is positive and significant (0.151 and 0.161). The coefficients for the fuel-economy-based measure and its interaction with gas price volatility suggest that models marketed by makes offering a broader range of fuel economy levels reduce their average discounts as gas prices become more volatile. In other words, a broad span mitigates the mismatch costs associated with product proliferation, as predicted in Hypothesis 5B.[16]

6. Conclusion and Discussion

We find that besides the well-known effects on production costs, product line breadth also has a substantial impact on supply-demand mismatch costs. Mismatch costs arise from the fact that demand is uncertain. Carrying a broader product line leads to higher demand fragmentation and higher relative uncertainty in the demand for each of the products in the line, increasing the chances of mismatch. Mismatch costs manifest primarily in the form of discounts and inventories. We find that an additional product in the line is associated with a significant increase of average discounts and average inventory. The order of magnitude of these effects can be quantified at around $100 increase in average discounts and up to three additional days of supply in inventory for each additional product.

Overall, our results indicate the costs of product line breadth can be even more substantial than previously thought, since previous research has not considered mismatch costs. It is not surprising that firms have developed strategies, such as delayed differentiation and platform-based development, that allow them to offer variety with lower costs. Using our data, we study how platform families help control production costs. We find that production costs for a model decrease with the volume of other models sharing the same platform. In particular, for each 100,000 vehicles produced for other models based on the same platform, production costs are reduced by an amount that in our estimates is in the range of \$33.20 to \$87.10 per vehicle.

Our results also show that product line span can provide a useful hedge against changes in demand. Changes in gas prices provide an exogenous shock to consumer preferences and are an important source of demand uncertainty in the automotive industry. We propose an attribute-based measure of product line breadth that captures a make's range of fuel economy levels, and we find makes that offer a broader range of fuel economy levels increase their market share and reduce their average discounts as gas prices become more volatile. In other words, choosing a product line that spans a broader range of fuel economy levels can offer a hedge against changes in demand arising from changes in gas prices.

Altogether, our analysis allows us to present a more complete picture of the benefits and costs associated with extending a product line. Previous empirical research focused on the increase of market share and production costs, leading to a partial cost-benefit analysis. By introducing the moderating effect of platform strategies on production costs, the effect of product line breath on mismatch costs, and the possibility of hedging against changes in demand with a broader product line, we bring attention to important aspects that have not been studied in the previous empirical literature but that should be considered by firms when deciding on their product portfolio. For situations where demand uncertainty is very important, the cost-benefit analysis based on traditional results can be dramatically different. For example, a company facing substantial demand uncertainty might underestimate the costs of expanding its product line arising from additional mismatch costs.

We acknowledge that the average effects may vary from industry to industry, and we believe some of our findings are generalizable to other industries and product classes. We have pointed out that product proliferation substantially increases mismatch costs, which are a consequence of demand uncertainty. Thus, we expect industries that exhibit high demand uncertainty will be particularly affected when extending their product lines. The automotive industry is an example of such an industry, but it is by no means the only one. Other product categories, like technology or fashion, are subject to very substantial demand uncertainty. In general, industries where commitment to a product line and a set of production quantities is made well before the sales season will be particularly affected (see Desai et al. 2007). This is the case in industries with long product-development cycles or long production lead times. For example, firms operating in the technology space often have to build or contract plant capacity well in advance, and fashion retailers with offshore manufacturing have to commit to their production quantities months before the sales season. Some of these industries could benefit from the mitigation strategies we have described herein. For example, technology firms often use component commonality, and fashion retailers could hedge against uncertain demand by covering a broader span in certain attributes, such as colors, where popularity at the time of sale may be more uncertain.

As with any empirical work, our analysis is not exempt from limitations. Some of these limitations are dictated by data constraints. We have been able to obtain valuable insights from our measures of mismatch costs measured with discounts and inventories, but there are additional sources of mismatch costs that could be studied where appropriate data are available. For example, future research could evaluate the effect of product line breadth on lost sales and stock outs. Similarly, we have studied product line breadth at the make and model levels, but it could be interesting to understand the effects of more granular variety measures, such as a model's option content. On the other hand, we do not have reliable direct measures of production costs and we have to estimate them using a demand and pricing equilibrium model. Direct measures of production costs could provide additional dimensions that cannot be captured from indirect measures. As more data becomes available, we believe that more research opportunities will open in this space.

Finally, we think some of our empirical findings can motivate modeling research in related topics. For example, our results suggesting product line breadth can provide a hedge against changes in demand could be explored further using analytical models.

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Endnotes

[1] This arises from the statistical principle of aggregation, or the fact that the coefficient of variation of the sum of random variables is less than the sum of the coefficient of variations of the individual random variables, unless the random variables are perfectly correlated (see Anupindi et al. 2011). Under conventional models, safety inventories increase with the uncertainty of demand. As a consequence, for the same level of total sales, safety inventories will be higher for broader product lines.

[2] Note that the additional safety inventory may actually be helpful in situations where demand is unexpectedly high. However, in the automotive industry a vehicle is very rarely sold above the MSRP (manufacturer's suggested retail price), which is set for the model

year. In other words, excess inventory is marked down but scarce inventory is not marked up.

[3] "An automobile platform is a shared set of common design, engineering, and production efforts, as well as major components over a number of outwardly distinct models and even types of automobiles, often from different, but related marques. It is practiced in the automotive industry to reduce the costs associated with the development of products by basing those products on a smaller number of platforms. This further allows companies to create distinct models from a design perspective on similar underpinnings." [http://en.wikipedia.org/wiki/Automotive_platform, retrieved July 16, 2014].

[4] On the benefit side, we find that carrying one additional product in the line is associated with an average increase of 0.1% in the market share of an automaker. This is consistent with findings of previous empirical papers in other settings (e.g., Kekre and Srinivasan 1990, Bayus and Putsis 1999). On the cost side, we find that a broader product line is associated with higher average production costs. These results are directionally consistent with the results of Bayus and Putsis (1999) but differ from those of Kekre and Srinivasan (1990). Although the qualitative results regarding the effects of product line breadth on market share and production costs are not completely novel, their magnitude in the context of the U.S. automotive industry has not been previously analyzed, and these findings provide a useful baseline for the rest of the results in our analysis.

[5] In the same industry, Putsis and Bayus (2001) study the determinants of product line decisions and suggest that firms expand their product lines when there are low industry barriers or when there are perceived market opportunities.

[6] Randall and Ulrich (2001) examine the association between supply chain structures and the type of product variety that firms pursue and find an association between efficient-scale production and production-dominant variety and between local production and mismatch-dominant variety.

[7] This is the newsvendor model, which is well known in the operations management community. For more information, see Anupindi et al. (2011).

[8] Another source of mismatch costs comes from shortages. We do not have data on stock outs, and in this paper we focus on discounts and inventories as the main sources of mismatch costs.

[9] For example, the Toyota K platform has underpinned various Toyota and Lexus models from the midsize category upward since 2000, including Toyota's Avalon, Camry, Highlander, and Sienna, and the Lexus EX, among others. This allows Toyota to maintain economies of scale in the production of certain components that are shared across all of the platform's models.

[10] This prevents us from considering some interesting aspects of the customer purchase process that other papers consider, such as the choice of whether to lease or buy (Dasgupta et al. 2007) or how customers make decisions when a trade-in vehicle is involved (Zhu et al. 2008).

[11] The correlation between the costs recovered using this procedure and the list prices is high (0.826).

[12] Note that to ensure that these additional product line span variables do not create any problems in the estimation of the coefficients of our baseline measure of product line breadth (PLB), we estimate alternative specifications that exclude the set of variables related to H5A and H5B, and the results do not qualitatively change.

[13] As in the make-level analysis, we estimate alternative specifications that exclude the set of variables related to H5A and H5B, and the results do not qualitatively change.

[14] To attach a representative dollar value to the increase of average inventories associated with the extension of the product line, note that for a vehicle with production costs of \$20,000, if we assume 20% annual holding costs, holding a vehicle for one additional day has an average cost of $\$20{,}000 \times 0.20 \times 1/360 = \$11.11$. Since our measure of inventory includes vehicles in the dealer lots and finished vehicles that are waiting to be transported, these costs can be thought of as costs incurred by the downstream supply chain. The manufacturer may suffer all of the costs or pass some of those to the dealer.

[15] Although not part of our hypothesis, the coefficients of *MEDMPGMAKE* and $MEDMPGMAKE \times GAS$ suggest that firms with higher median fuel economy have a smaller market share on average, but their market share increases as gas prices go up, as we could expect.

[16] Although not part of our set of hypotheses, it is interesting to note that the coefficient of the interaction between *MPG* and *GASPRICE* is negative (Table 4). This means that as gas prices go up, firms reduce the discounts offered to vehicles with higher fuel economy. A similar result is described in Langer and Miller (2013).

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