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Pricing and Production Flexibility: An Empirical Analysis of the U.S. Automotive Industry

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We use a detailed data set from the U.S. auto industry spanning from 2002 to 2009 and a variety of econometric methods to characterize the relationship between the availability of production mix flexibility and firms' use of responsive pricing. We find that production mix flexibility is associated with reductions in observed manufacturer discounts, resulting from the increased ability to match supply and demand. Under the observed market conditions, mix flexibility accounts for substantial average savings by reducing price discounting by approximately 10% of the average industry discount. We test three supplementary hypotheses and find that the reduction in discounts for vehicles manufactured at flexible plants is (1) higher for higher demand uncertainty, (2) higher for vehicles coproduced with vehicles that belong to a different segment, and (3) lower in situations with higher local competition.

Keywords: empirical operations management; flexibility; pricing; automotive industry
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1. Introduction

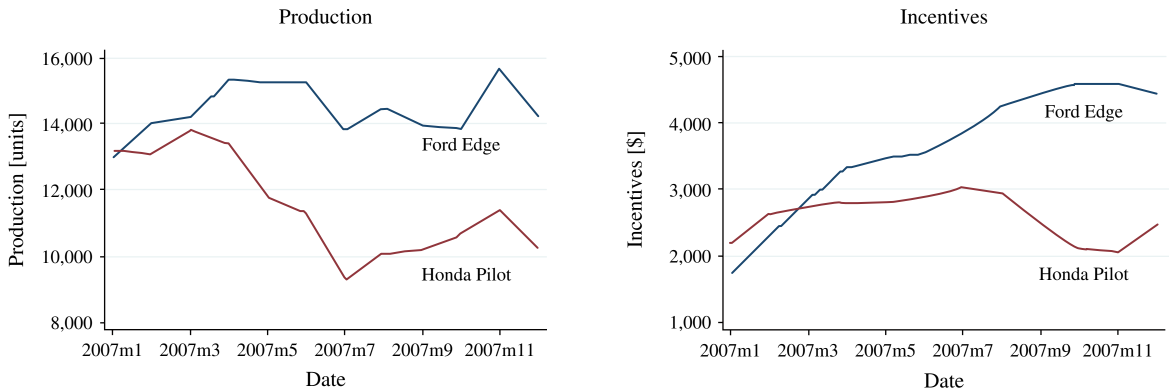
Flexibility is typically defined as the ability to adjust and respond to new information (Van Mieghem 2008), and it can take a variety of forms among manufacturers. Flexibility can exist with respect to a firm's pricing decisions (pricing flexibility), as has been demonstrated in a large body of literature on dynamic pricing. Flexibility can also exist with respect to a firm's production decisions (production flexibility). Typically, such changes in production take the form of adjustable production quantities (volume flexibility) or adjustable product mixes (mix flexibility).

The objective of this paper is to understand the interplay between pricing flexibility and production flexibility—in particular, mix flexibility. To motivate this choice of research objective, consider the automotive industry and its market dynamics in 2007. Over the first six months of 2007, fuel prices in the United States increased by roughly 50% (from $2 per gallon to $3 per gallon), creating a significant (and exogenously triggered) shift in demand toward more fuel-efficient vehicles. Manufacturers' responses to this market shift varied substantially.

To illustrate this variation, consider two comparable vehicles in the mid-size SUV segment, the Ford Edge and the Honda Pilot, which have the same fuel economy (17 mpg in the city and 23 mpg on the highway). Figure 1 shows how Ford and Honda reacted to the shift in demand toward more fuel-efficient vehicles and away from SUVs. Figure 1 (left) displays monthly production levels. Production volumes for the Ford Edge remained relatively constant, whereas production volumes for the Honda Pilot declined as gas prices increased. Figure 1 (right) displays the average incentives (money spent by the manufacturers to encourage sales by offering discounts that reduce the cost to the dealer or to the customer) provided by the two manufacturers. The incentives provided by Honda did not change as fuel prices increased, while incentives for the Ford Edge increased significantly over that same time period. In other words, Honda relied on its ability to adjust the number of Honda Pilots that were produced, whereas Ford relied on its ability to adjust prices (by providing incentives) as a response to changes in gas prices.

One of the essential aspects of production flexibility in the automotive industry is the number of vehicle types that can be manufactured in a given production facility. This is what the operations literature typically calls *mix* flexibility. In our example, Honda was actually able to reduce the production of the Honda Pilot without sacrificing plant utilization because other types of vehicles (e.g., the more fuel-efficient Honda Civic) were produced in that same plant. Our definition of mix flexibility (developed in §4) is based on the ability of a plant to manufacture

Figure 1 (Color online) Production (Left) and Incentive (Right) Data for Ford Edge vs. Honda Pilot



multiple platforms. According to this definition of mix flexibility, in 2007 the Honda Pilot was produced in *flexible plants* able to produce multiple platforms. In contrast, the Ford Edge was produced in *inflexible plants* that could only produce a single platform at the time. The two models in our motivating example also differ in a number of other aspects beyond flexibility, and, although the example suggests that mix flexibility may affect companies' use of responsive pricing to react to changes in demand, no conclusion about the effect of flexibility can be drawn from the example alone. The rest of this paper systematically explores the relationship between mix flexibility and responsive pricing suggested by the motivating example.

The link between pricing and production flexibility has not been empirically studied in the existing literature. This might be partially explained by the difficulty of obtaining adequate data. In our empirical setting, the U.S. automotive industry, list prices (manufacturer suggested retail prices (MSRP)) for new vehicles are relatively easy to obtain, but manufacturers constantly apply varying incentives that result in discounts to dealers and final customers, which can make transaction prices substantially lower than MSRP. Data on these discounts, and thus the actual transaction prices, are harder to obtain. The unavailability of adequate pricing data has restricted prior research to studying sales volume as opposed to analyzing the underlying pricing dynamics.

We have collaborated with TrueCar.com (http://www.truecar.com), a market research company specializing in new car pricing, and we have gained access to a proprietary data set on prices and manufacturers' incentives in the U.S. auto industry. We have combined this pricing data with other data about the U.S. automotive industry, including sales, production, and plant data. Combining these data sets, we are able to model manufacturer production and price responses to changes in market conditions. This allowed us to empirically analyze the relationship between production mix flexibility and pricing. Our main identification strategy exploits the fact that, in our sample, the mix flexibility with which a particular model is produced changes over time.

Our unique data set, together with our econometric approach, allows us to make the following two main contributions:

First, we show how production mix flexibility affects discounts. Short-run price adjustments in the automotive industry occur mainly through discounts from the MSRP implemented using incentives from the manufacturer. We provide evidence that deploying mix flexibility allows manufacturers to reduce this discounting. This finding occurs both at the plant level and at the model level, and it is robust to using multiple different methods. The specific magnitude of the estimate of the effect depends on the method used, but it exceeds 10% of the average industry discounts.

Second, we explore three moderators of the effect of flexibility on discounts. Based on existing theory, we hypothesize that the reduction in discounts enabled by flexibility will increase with demand uncertainty and with the existence of models manufactured in the same plant that are subject to different demand patterns. We also hypothesize that the reduction in discounts enabled by flexibility will be lower in situations where there is more local competition. We find support for these hypotheses in our empirical setting.

To the best of our knowledge, this paper provides the first piece of empirical evidence complementing the theoretical literature on production flexibility with endogenous pricing (e.g., Van Mieghem and Dada 1999, Chod and Rudi 2005, Goyal and Netessine 2007, Ceryan et al. 2013).

2. Theoretical Context and Hypotheses

Several studies have modeled the adoption of production flexibility and production postponement decisions. The earlier work in this stream models the flexibility investment decision under uncertainty in product demand (Fine and Freund 1990). More recently, empirical work has studied the drivers of manufacturing flexibility in the context of the automotive industry (Goyal et al. 2012). Unlike that stream of work, our paper does not look into what drives flexibility, but into *the effects flexibility has on pricing*. A related topic in the manufacturing strategy literature that has been empirically studied more extensively is what one might call the opposite of mix flexibility, namely specialization. Specialization has been shown to improve operational performance in some settings (e.g., Huckman and Zinner 2008, KC and Terwiesch 2011). Our empirical analysis explores some of the positive benefits that result from producing multiple product lines in one facility and thus speaks to the flexibility versus specialization debate. Finally, within the literature on production flexibility there is also substantial work that has been concerned with measuring the flexibility of a system. For example, Jordan and Graves (1995) developed a framework for evaluating the amount of flexibility in a system and demonstrated that partial flexibility (an allocation of products to plants such that not all products can be produced in all plants) can yield most of the benefits of full flexibility. The objective of our work is different, since we attempt to assess the value of mix flexibility, measured at the plant level, in terms of reducing discounts.

These studies, as well as many others not mentioned here, assume prices to be exogenous. In contrast, some of the more recent literature on flexibility and postponement has endogenized the pricing decision in models where firms also choose capacity. For example, Van Mieghem and Dada (1999) study how the timing of decisions—in particular production and pricing—with respect to the demand uncertainty affects the strategic investment decision of the firm and its value. Other recent papers that analyze flexibility in the presence of responsive or dynamic pricing are Chod and Rudi (2005), Goyal and Netessine (2007), and Ceryan et al. (2013). Despite these careful analytical studies of dynamic pricing and production flexibility, the empirical evidence in this area remains scarce, which is one of the main motivations of the present study.

To motivate our research hypotheses, consider again our example from the introduction. To keep the example simple, assume two types of vehicles, "fuel-efficient" and "fuel-inefficient," and two types of plants, "flexible plants" (which can produce both types of vehicles) and "inflexible plants" (which can only produce one type of vehicle). Following an increase in gas prices, demand for fuel-inefficient vehicles decreases. The manufacturer can respond by using a combination of readjusting production volumes (i.e., reducing the production volume for fuel-inefficient vehicles) and by offering more incentives (higher discounts from the MSRP) for fuel-inefficient vehicles.

Note that, for an inflexible plant, a reduction in production volume of fuel-inefficient vehicles necessarily implies a reduction in plant utilization. This leads to an increase in the average cost per vehicle from that plant, because the plant's fixed costs are spread over a lower number of units. All else being equal, higher average costs result in lower average profits per car.

In contrast, a flexible plant can shift production capacity from the less attractive, fuel-inefficient vehicle, to the more attractive, fuel-efficient model. Total factory production and utilization need not decline if demand is merely shifting from one vehicle type to the other. Depending on the level of correlation between demand for fuel-efficient and fuel-inefficient vehicles, overall demand for the manufacturer might go down or not. However, some pooling benefits exist even at modest levels of positive correlation, and after readjusting production the manufacturer with the flexible plant is less affected by the exogenous demand shock than a manufacturer with inflexible plants.

Note that, after adjusting the product mix, the manufacturer with the flexible plant might still decide to increase discounts. Pricing and production decisions result from manufacturers playing a complex game that depends on their demand and cost curves and those of their competitors. Rather than estimating the parameters of those curves, we are interested in the equilibrium average relationship between mix flexibility and discounts under the demand patterns observed during our period of analysis. The exact magnitude of the effect of mix flexibility will depend on the shape of the cost and demand curves, as demonstrated in the recent modeling work by Ceryan et al. (2013).

In any case, when choosing the combination of production adjustments and price adjustments to react to changes in demand, inflexible plants face higher costs associated with changing production than flexible plants, given that for flexible plants, the reduction of production for one type of vehicle does not directly translate to a reduction in utilization of the plant. Consequently, we hypothesize that manufacturers using flexible plants will use more production adjustments and less price adjustments, relative to manufacturers using inflexible plants. Note that incentives can be applied to reduce prices when demand for a vehicle decreases, but not to increase prices when demand for a vehicle increases—the price paid by final customers very rarely goes above MSRP. Therefore, we expect average discounts to be lower for vehicles manufactured in plants that have mix flexibility. We formalize this notion in the following hypothesis, which is the main hypothesis of this paper:

Hypothesis 1. *Mix flexibility is negatively associated with discounts.*

In addition to our main hypothesis regarding the effect of mix flexibility on discounts, we explore how that effect varies with three different dimensions that we expect might change the value of flexibility and consequently the impact of flexibility on incentives.

The first of these supplementary hypotheses concerns the role of demand uncertainty. It is well known that higher demand uncertainty results in higher supply–demand mismatches and, as a consequence, higher mismatch costs (Cachon and Terwiesch 2009). Mix flexibility allows companies to reduce supply-demand mismatches arising from demand uncertainty by reallocating production capacity from one model to another. The analysis that evaluates Hypothesis 1 quantifies the value of flexibility in the presence of the average demand uncertainty encountered during the period of analysis. We supplement that analysis by focusing on how the effect of flexibility on discounting changes when demand uncertainty is particularly high:

Hypothesis 2. *Mix flexibility decreases discounts by more when demand uncertainty is high.*

In addition to describing the importance of demand uncertainty, the flexibility literature has highlighted the importance of demand correlation between products. Flexibility is more valuable if demand correlation is low (Fine and Freund 1990, Chod and Rudi 2005, Goyal and Netessine 2007, Goyal et al. 2012). If the correlation is negative, mix flexibility enables the company to easily switch from the product with declining demand to the complementary product with increasing demand (e.g., as in our hypothetical example of consumers switching from fuel-inefficient to fuel-efficient vehicles), and even if the correlation is zero or slightly positive, risk-pooling effects may result in flexibility having some value. Based on this literature, we hypothesize that the effect of flexibility on discounts will be stronger when the demands for products that are coproduced in the same plant have lower correlation. This happens, for example, when the vehicles coproduced in the same plant belong to different segments. This is formalized in the following hypothesis:

Hypothesis 3. *Mix flexibility decreases discounts by more when demand correlation is low.*

Finally, we study how local competition limits the extent to which mix flexibility allows companies to reduce discounts. In the end, customers choose the products that maximize their utility. In a perfectly competitive market, it would not be possible for firms to sustain a premium simply based on their production technology if it does not result in different product attributes that customers derive value from. If products had the same attributes, in a competitive market they should be priced very similarly regardless of how they are produced. In practice, there is variation in the local competitive pressure that affects the automotive industry in different regions, and manufacturers can factor this in when they allocate incentives to dealers in different regions. Empirical research has shown that competition increases inventory holdings and service level (Olivares and Cachon 2009). In markets where there is more competitive pressure, customers will have easier access to a broader assortment of vehicles that are produced with and without flexibility. The existence of more options for the customers will limit the ability of manufacturers to use flexibility to sustain higher prices—for example, if there are competitors that are forced to discount their prices because of their lack of flexibility. Consequently, we hypothesize that

Hypothesis 4. *Mix flexibility decreases discounts less when local competition is high.*

3. Empirical Setting and Data

Our empirical analysis focuses on the U.S. automotive industry, covering the section of the supply chain that spans from vehicle manufacturers to the final consumers. There are three reasons why we chose the automotive industry as our empirical setting. First, the automotive industry is itself very important. The U.S. automotive industry provides more than three million jobs in the United States and contributes 5% of the GDP. Second, it is an industry in which operations and supply chain management play major roles, and companies are known to follow different operational strategies. Third, there is a limited number of manufacturers in the market and, using a reduced number of attributes, their final products are comparable. The methodology that we use can be adapted to study the impact of flexibility on prices in other industries and also to study the impact of other operational decisions besides the deployment of flexibility.

In the auto industry there exist different prices that govern the transactions between manufacturers, dealers, and customers. In this paper we focus on the *manufacturer's pricing decisions*. For each model year, the manufacturer sets the MSRP, which is the list price that serves as a reference level for the final retail price paid by the customer. Consumers very rarely pay a price above the MSRP. To respond to changing market conditions, manufacturers discount the effective price of the vehicle by offering varying levels of incentives to dealers and/or consumers. These discounts include any costly action undertaken by the manufacturer to reduce the net cost of purchasing a vehicle, and they can be targeted to the dealer or to the final customer. These incentives sometimes take the form of favorable loan conditions or other financial initiatives.

The amount spent in price discounting via incentives in the automotive industry is very substantial—in 2009, manufacturers spent more than $28 billion. Our data suggests that there exist systematic differences in discounting by firms. The Big Three are among the companies who offer the deepest discounts, and Toyota and Honda are among the companies who offer the lowest discounts. Our analysis shows that variations in production mix flexibility explain part of the observed variation in discounts. Note that our analysis will use firm (and model) fixed effects to ensure that we truly identify the effect of flexibility, as opposed to picking up between-firm effects.

Our data covers vehicles marketed in the United States over the period 2002–2009. The automotive industry went through a period of substantial turmoil in 2008–2009, which generated heavy intervention with potentially asymmetric impacts on the different brands and models. As a consequence, our main analysis is run on the entire period of interest as well as excluding those two years. We have information on the 327 distinct vehicle *models* (e.g., Chevrolet Malibu) marketed in the United States during the period. Our analysis uses monthly data, and we have a total of 18,166 model-month (e.g., Chevrolet Malibu, February 2003) observations. We combine four sources of data: production/sales data, pricing data, vehicle-level data, and geographic-level data.

Production/sales data: Monthly sales and domestic production data for each model were obtained from Ward's Automotive (http://www.wardsauto.com/). Domestic production refers to vehicles produced in the United States, Mexico, or Canada. We focus on vehicles that have at least some domestic production, which leaves us with 11,043 model-month observations. We have information about the vehicle design platform on which domestically produced models are based and the segment to which they belong. We observe how domestic production is distributed across different plants, as well as across different facilities within the plant (e.g., Fremont 1 and Fremont 2). We obtain the number of assembly lines of each plant from the Harbour Report (now published through Oliver Wyman; see https://www.theharbourreport.com), which is the authoritative information source for automotive plant productivity. We have also obtained data on the annual capacity of U.S. plants.

Pricing data: We have obtained manufacturers' incentive data from TrueCar. TrueCar is a market information company that provides prospective car buyers with real transaction price data on new cars. TrueCar acquires data directly from car dealers, respected dealer management system (DMS) providers, and well-known data aggregators in the automotive space. In this paper we focus on the discounting via incentives given by manufacturers. We calculate the average discount per vehicle by adding the total amount spent by the manufacturer to incentivize sales of a particular model and month and dividing it by the number of vehicles of that model sold in that month. We have an aggregate measure that includes incentives given to the final consumers and to the dealers. Note that not all incentives are necessarily passed through to the final consumer (Busse et al. 2006), yet incentives always represent an additional cost to the manufacturer. The measure includes indirect incentives such as manufacturer-provided financing in favorable conditions, which are converted to their equivalent monetary values (e.g., the cost to the manufacturer to provide credit at below-market interest rates). We have also obtained a used-price index at the month and segment level from Manheim Consulting (http://www.manheimconsulting.com/). We use this as a control variable to account for the competition between the new and used vehicle markets.

Vehicle-level data: Some parts of our analysis also use data on vehicle attributes, which we have obtained from Ward's Automotive as well. We include some vehicle attributes as control variables. For example, fuel economy is an important attribute because it affects the sensitivity of a model's demand to changes in gas prices that cause the manufacturer to adjust production volumes or price discounting. We also use vehicle attributes to identify possible major changes in design that might explain changes in prices of a given model. The vehicle attributes are specific to the trim level (e.g., Chevrolet Malibu LS four-door sedan) and model year. This poses some integration challenges; our sales, inventory, and incentive data are available at the model level (e.g., Chevrolet Malibu), and we do not observe the breakdown of sales for the different trims of a model (or for different model years that might be sold simultaneously). Our solution is to match every model with the median of the attributes across the different trims in which a model is available. Using the minimum of the maximum of the attributes instead of the median does not change the results.

Geographic-level data: Whereas most of our analysis uses a data set with monthly model observations aggregated at the national level, for the purpose of testing Hypothesis 4, we have obtained an additional data set that allows us to exploit the geographic variation on incentives and level of competition. The data set also comes from TrueCar and includes a sample

Table 1 Variables and Summary Statistics

Variable	Description	Mean	Standard deviation Total	Between	Within	N
$DISCOUNT_{it}$	Average incentive given for model i in month t in USD	3,145	1,988	1,660	1,182	11,043
$FLEX_{it}$	Binary variable that indicates if model i is manufactured in at least one flexible plant in month t, according to the measure described in §4	0.38	0.48	0.40	0.28	10,535
$DISC\_COMP_{it}$	For every model, we compute the average incentive per car in USD given by the competitors in models of the same segment and luxury level	2,758	890	768	537	11,039
$MSRP_{it}$	Median list price of the model i in USD, constant during the model year	30,120	9,914	10,609	1,919	11,043
MPD_{it}	Miles per dollar; the evolution of gas prices changes the attractiveness of some models and incentives might respond to that (we define $MPD_{it} = MPG_i/\text{gasprice}_t$)	9.10	3.16	2.55	2.32	10,923
AGE_{it}	Number of years since the model was first introduced	3.20	2.24	1.77	1.79	11,043
$INTRO_{it}$	Dummy variable that is 1 in the model year when the model is introduced	0.08	0.27	0.20	0.23	11,043
$PHASE\_OUT_{it}$	Dummy variable that is 1 for observations that correspond to the last year in which a model is produced and for observations after production for the model has stopped	0.03	0.17	0.21	0.13	11,043
$DESIGN\_CHNG_{it}$	Dummy variable that is 1 when there has been a change in vehicle characteristics that might relate to changes in design with respect to the previous model year	0.33	0.47	0.26	0.44	11,043
$INVENTORY_{it}$	Days of supply for model i in month t; when used for a plant p, it denotes the total amount of finished units of the models manufactured in the plant	95	53	33	45	11,043
$PRODUCTION_{it}$	Amount of units of model i produced in month t	9,468	12,597	9,591	5,790	11,043
P_FLEX_{pt}	Binary variable that indicates if plant p is flexible in month t, according to the measure described in §4	0.23	0.42	0.32	0.25	7,705
$P\_FLEX\_REC_{pt}$	Binary variable with the maximum value of P_FLEX_{pt} observed for plant p in the last n months (we use $n = 6$)	0.25	0.44	0.33	0.26	7,705
P_AGE_{pt}	Number of years since the plant was opened	37.17	25.66	27.58	2.12	7,581
$UTIL_{pt}$	Average utilization of plant p in month t; it is calculated as the total production of the plant divided over 1/12th of the annual capacity	0.83	0.77	0.46	0.69	6,780
$PRODUCTION_{pt}$	Total number of vehicles produced in month t in plant p	14,865	9,217	7,610	5,614	7,705
$NPRODS_{pt}$	Number of different vehicles produced in month t in plant p	2.31	1.16	1.02	0.53	7,705

with around one million new vehicle purchases corresponding to 2009 and all brands sold in 2009. This covers 10% of the vehicle purchases in the United States in 2009. For each of those transactions, we observe the model that was purchased, the date and state where the transaction took place, and the average incentive that was available for that model for customers and dealers in that particular state and on that date. An important feature of this data set, which is not present in the other data sets used in the analysis described above, is that it gives us geographic variation in the discounts, which we use to analyze the moderating role of competition on the impact of flexibility on discounts.

We enrich this transaction-level data set with a state-based measure of competition intensity of the automotive market. This measure is calculated as the number of dealers in the state divided by the state population. We proxy the number of dealers in the state with the number of dealers that posted at least one transaction during the Car Allowance Rebate System of 2009 (popularly known as "Cash for Clunkers" program). We obtain state population from the U.S. Bureau of the Census. States with more dealers per inhabitant are considered to have a more competitive automotive market and, following Olivares and Cachon (2009), we assume they will offer a better service level. Hence, consumers will have easier access to broader assortments in those states.

Table 1 includes a description of the main variables we use and their summary statistics.

4. Measures of Flexibility

The review by Sethi and Sethi (1990) identifies more than 50 ways to operationalize flexibility. Our objective is not to identify the specific contribution of each of the types of flexibility identified in the previous literature but to define a simple measure that embodies the most important dimensions of flexibility at the strategic level in the auto industry.

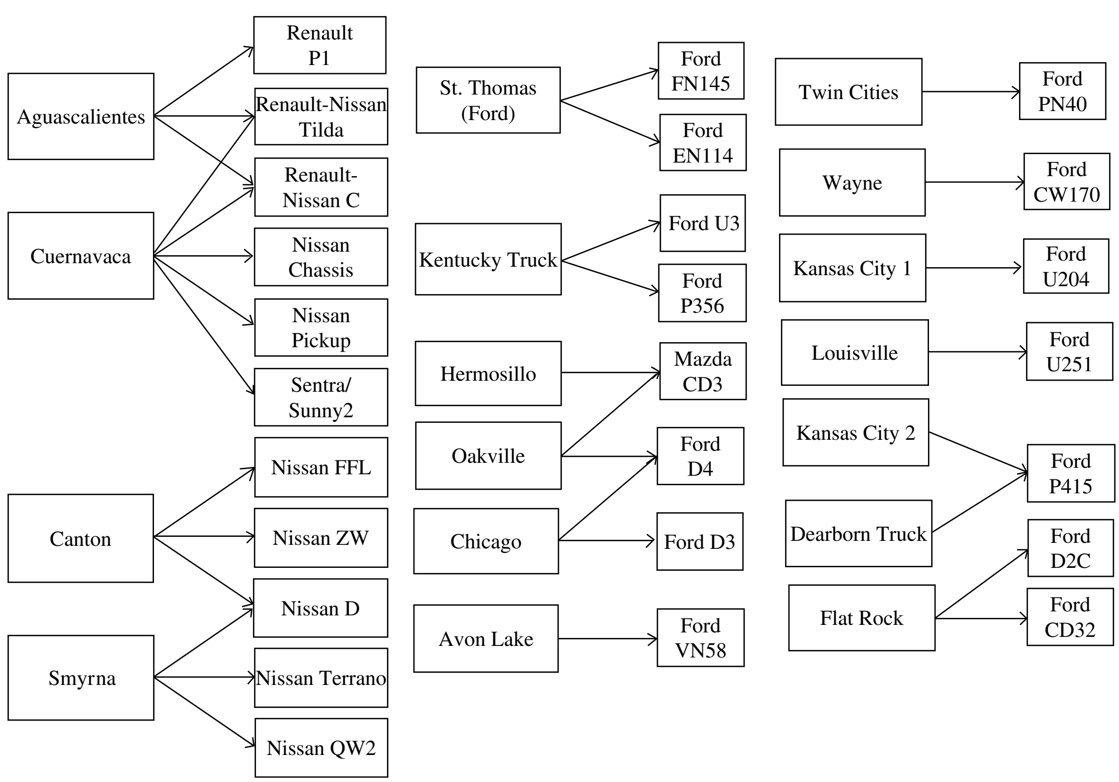
Our primary measure of flexibility is an objective measure based on the demonstrated ability of a plant to produce multiple products in the same facility. This is what has been called *mix flexibility* or product flexibility in some taxonomies (e.g., see Parker and Wirth 1999). Mix flexibility has been used in prior academic studies and is also used by analysts who follow the automotive industry. For example, the Prudential Report, a third-party evaluation of the financial outlook of the various U.S. car manufacturers, uses the number of different models manufactured in a production line as the criteria to define a plant as flexible; lines producing more than one model are considered flexible, whereas lines producing a single model are considered inflexible.

We use a binary variable to encode flexibility. We define a production facility p as flexible ($P\_FLEX_{pt} = 1$) if it produces more than one platform in month t. We choose the number of platforms as opposed to the number of models for our measure of mix flexibility because the number of platforms is more related to the necessary technological and managerial complexity in the plant (two "different" models can just be branded versions of the same vehicle), but our qualitative results still hold if we take a vehicle model-based measure. To avoid characterizing as flexible those plants where different platforms are manufactured in different (inflexible) lines within the facility, we only code as flexible those plants that produce a higher number of platforms than their number of lines. For robustness, we have also conducted the analysis restricting our attention to those plants that only have a single line, and our results are qualitatively consistent.

As an example of our mix flexibility notion, Figure 2 shows the allocation of platforms to plants for Nissan and Ford at the end of 2010. According to our measure, all four of Nissan's North American plants were flexible at the end of 2010, whereas only 5 out of Ford's 13 North American plants were flexible. The figure is just a snapshot, because mix flexibility changes over time. With substantial investments, an inflexible plant can become flexible. In some cases, a flexible plant can become inflexible. This can happen, for example, when one of the models manufactured in the plant is discontinued and leaves the plant with a single allocated platform.

Because our sales and discount data are at the model-month level, we also assign a flexibility score to every model on a monthly basis. Previous research has shown that partial flexibility can go a long way in achieving the benefits of full flexibility (Jordan and Graves 1995). Motivated by the notion that "a little flexibility can go a long way," we use a binary score and give model i a high flexibility score in a given month t ($FLEX_{it} = 1$) if it has at least some

Figure 2 Allocation of Platforms to North American Plants at Nissan (Left) and Ford (Right)



production in a domestic (North American) flexible facility. Model flexibility changes over time, because a given model's production can (a) be shifted from a flexible to an inflexible plant, (b) be shifted from an inflexible to a flexible plant, or (c) remain at a plant that changes its flexibility level because of changes in other models. This variation in model flexibility over time is essential for our identification strategy, as we discuss in §5.

Using our definition of flexibility, we can perform a simple comparison between the discounts given for models manufactured with flexibility and for models manufactured without flexibility. The average discount for models that are produced with flexibility was $2,842 in 2007, whereas the average discount for models that are produced without flexibility was $3,308 in the same year. Not all the difference between the two groups comes necessarily from differences in flexibility. It could be, for example, that Japanese firms are more flexible and also provide systematically lower discounts for reasons different from flexibility. A more refined econometric analysis to evaluate the actual effects of flexibility is needed (see §5), but this raw comparison of the average discount suggests that the use of flexibility may be associated with a reduction in the discount.

We propose two additional measures of flexibility that address some shortcomings associated with the mix flexibility variable described above. First, the flexibility measure described above is based on the demonstrated ability to produce a mix, but a plant could have this flexibility and choose not to use it at certain periods of time. To address potential problems arising from this fact, we also define a "record" measure ($P\_FLEX\_RECORD_{pt}$), which captures the maximum flexibility observed in the last six months. Second, we also created flexibility scores of the plants based on the subjective assessment of an industry expert. We obtained the assessment of the flexibility of all the North American plants at two points in time from the editor of the Harbour Report. The results obtained using these alternative measures are qualitatively consistent with the results found using the objective flexibility measure described above. To allow future research to replicate our results and build on our work, the main analysis of this paper uses the objective flexibility measure that we previously defined. We report the results with the "record" and subjective measures in the online supplement (available as supplemental material at http://dx.doi.org/10.1287/msom.2015.0534).

5. Econometric Analysis of the Impact of Flexibility on Discounts

We focus on the equilibrium average relationship between mix flexibility and discounts under the demand patterns observed during our period of analysis. Recent work in operations has followed a similar approach. For example, Cachon and Olivares (2010) study the drivers of inventory in the U.S. downstream automotive supply chain using panel data. More recently, Gopal et al. (2013) analyze the impact of new product introduction on plant productivity, and Moreno and Terwiesch (2015) study the impact of product line breadth in the automotive industry.

We start by studying the average effect of flexibility on discounts during the period of analysis. To do that, we combine results from an analysis of plant-level panel data (§5.1) and a model-level panel data (§5.2). As we will show, both analyses provide evidence of the hypothesized negative relation between flexibility and discounts. To evaluate the robustness of this relation, and to account for the fact that flexibility is not randomly assigned in our sample, we conduct a series of quasi-experiments, including matching analyses that model treatment assignment using observable covariates (§5.3), and an additional endogenous treatment effect specification that allows for the treatment to be based on unobservables (§5.4).

One important caveat is that the goal of our analysis is not to fully characterize discounts and their drivers. The objective is to understand the effect of mix flexibility on them. As a consequence, we are only concerned with missing some of the drivers of discounts to the extent that they may be correlated with the adoption of flexibility, because that could generate bias in the flexibility coefficient. If the unobserved covariates that affect discounts are not correlated with flexibility, then they will not cause problems in our estimates of the effect of flexibility on discounts.

5.1. Plant-Level Analysis

Because flexibility is a plant-level measure, we start by analyzing the overall impact of flexibility on discounts at the plant level. For this purpose, we generate a data set with monthly information of each of the North American plants. Recall that discounts are defined at the model level. To obtain plant level discounts for a month, we compute the average discount of the models produced in the plant for that month, weighted by their production.

We use econometric specifications of the following family:

$$DISCOUNT_{pt} = \mu_p + \beta_1 P\_FLEX_{pt} + CONTROLS_{pt} + \gamma_t + u_{pt}, \qquad (1)$$

where $DISCOUNT_{pt}$ is the production-weighted average manufacturer's incentive, P_FLEX_{pt} is the plant flexibility measure, $CONTROLS_{pt}$ include any additional plant level controls, μ_p is a fixed effect, γ_t is a set of time dummies, and u_{pt} is the error term.

Table 2 Flexibility and Incentives: Plant Level Analysis

	(1)	(2)	(3)	(4)
P_FLEX_t	-579.2^{***} (46.28)	-253.8^{***} (48.01)	-240.5^{***} (50.88)	-125.6^{*} (67.39)
Plant fixed effects	No	Yes	Yes	Yes
Time controls	Yes	Yes	Yes	Yes
Other controls	No	No	Yes^{+}	Yes^{+}
Observations	6,427	6,427	6,168	4,677
R-squared	0.054	0.667	0.674	0.689

Notes. Robust standard errors in parentheses. Column (1) does not include plant fixed effects but includes a constant. Column (4) does not include years 2008 and 2009.

$^{+}$Indicates the following controls: *PRODPLANT, PLANTAGE, UTIL, NPRODS, MODEL_INV.*

$^{*}p < 0.1$; $^{***}p < 0.01$.

Based on this specification, we can use either the objective plant measure of demonstrated mix flexibility (P_FLEX_p) or other transformations of this variable, such as the maximum of this variable over a certain period.

A negative and significant coefficient of β_i would support Hypothesis 1. Table 2 shows the results of the estimation using ordinary least squares (OLS). Column (1) does not include plant fixed effects or plant-level controls and is provided for reference purposes only. Column (2) includes plant fixed effects, and column (3) adds a rich set of plant-level controls, including the total monthly production of the plant, the age of the plant (number of years since it was opened), the plant utilization, the number of products manufactured in the plant, and the inventory (measured in days of supply) of the models manufactured in the plant. Column (4) is the equivalent of column (3) but excludes observations belonging to 2008 and 2009, which could be subject to different dynamics because of the turmoil in the automotive industry during those years and because there was heavy exogenous intervention with potentially asymmetric impacts (e.g., cost shocks to some manufacturers).

The estimated effect of flexibility on discounts is, in all cases, negative and significant. In our preferred specification (column (3), which includes all the plant-level controls), the estimated effect is USD −240.50. Note that the coefficient of flexibility barely changes from columns (2) to (3) where the controls are added, which suggests that the omission of those controls does not generate a substantial bias in the estimate of the coefficient of flexibility. Also, note that excluding years 2008 and 2009 results in a lower estimate of the effect of flexibility. An explanation for this is that the effect of flexibility on discounts was more important during years 2008 and 2009 because those were years with very substantial economic volatility in the automotive industry, hence the lower magnitude of the effect when excluding those years. We explicitly study the moderating role of uncertainty in §6.

As previously discussed, one of the potential shortcomings of our demonstrated flexibility measure is the fact that it is based on what the plants chose to produce rather than what the plants could have potentially produced. For example, we have noticed that in some (infrequent) cases a flexible plant may produce only one model during a short period of time despite being able to produce multiple products. To address this, we conduct two robustness checks. First, we redefine our mix flexibility measure as the maximum flexibility observed for the plant in the last six months ($P\_FLEX\_RECORD_{pt}$). Second, we use a subjective assessment of the actual flexibility of each plant, provided by an expert. We describe these analyses, which yield qualitatively similar results, in the online supplement.

One potential concern with the analysis presented in this section arises because flexibility is not randomly assigned to plants. If plants with particular (observed or unobserved) characteristics are more likely to adopt flexibility, and plants with those characteristics are also more likely to eschew discounts, then an analysis along the lines used in this section may attribute to flexibility some effects on discounts that are partially a consequence of the other characteristics. Plant fixed effects and additional controls (which we are including in our estimation) help attenuate this issue, but we defer a more detailed discussion of this issue and our proposed solutions to our model-level analysis.

5.2. Model-Level Analysis

Expanding the analysis to the model level is particularly interesting because, whereas mix flexibility is determined mainly by plant technology, discounts occur at the model level. Also, our model-level analysis allows us to introduce a set of additional model-level controls that can address potential issues with unobserved heterogeneity that a plant-level analysis may miss. Furthermore, it allows us to perform a matching analysis that pairs vehicle models manufactured in flexible plants with very similar models manufactured in inflexible plants (more on this in §5.3).

We start by modeling the effect of flexibility on discounts (incentives) at the model level using conventional panel data methods. We use the following family of reduced-form specifications:

$$DISCOUNT_{it} = \mu_i + \beta_1 FLEX_{it} + CONTROLS_{it} + \gamma_{it} + u_{it}, \quad (2)$$

where i is the model and t is the month. All specifications include $FLEX_{it}$, which is 1 if the model is manufactured at a flexible plant and 0 otherwise; μ_i, a model fixed effect; a set of dummy variables γ_{it} that control for systematic temporal variations in discounts (including brand-year and segment-month dummies); and u_{it}, the error term. A model-level analysis allows us to consider a rich set of control variables, including variables that control for competitive aspects, such as the level of discounts offered by competitors in the segment ($DISC\_COMP_{it}$) and the average prices of used cars in the same segment (*USED_INDEX*), the number of miles that can be driven with USD 1 of gas (MPD_{it}), the number of years since the model was introduced (AGE_{it}), and indicators of whether the product is being introduced, phased out, or if it has experienced substantial design changes with respect to the previous model year ($INTRO_{it}$, $PHASE\_OUT_{it}$, and $DESIGN\_CHNG_{it}$, respectively).

Model fixed effects capture the contribution to discounts of any model characteristics that do not change over time (e.g., being a model produced by a Japanese firm, being a Ford, being a Toyota Corolla, or being an SUV are such features). The identification of the coefficients, including that of flexibility's effect on discounts, is enabled by temporal variations of the level of discounts for a given model. Because some vehicle models change from flexibility to inflexibility or vice versa, it is possible to identify the effect of flexibility even when we have model fixed effects.

As an example of the variation that helps to identify the coefficient of flexibility, Figure 3 shows the evolution of incentives for two similar vehicles, the GMC Envoy and the Nissan Pathfinder. Both vehicles were manufactured in inflexible plants until September 2004. The evolution of discounting in terms of the average incentive was similar for both vehicles before that. In September 2004, the Nissan Pathfinder started to be produced in the flexible Smyrna Plant, making $FLEX_{it} = 1$ according to our definition. After that, discounting for the Nissan Pathfinder dropped considerably, compared with that for the GMC Envoy. Note that our econometric analysis controls for additional variables that may play a role before and after the deployment of flexibility. For example, in the period shown in Figure 3, there were also changes in MSRP for the Nissan Pathfinder; therefore, not all the difference in observed discounts comes from flexibility.

Hypothesis 1 holds if $\beta_1 < 0$, with β_1 giving the magnitude of the effect of flexibility on discounts. Table 3 shows the estimates for some specifications of the family obtained using OLS. In all four columns, the dependent variable is $DISCOUNTS_{it}$, and all specifications include model fixed effects and controls for brand-year and segment-time. Columns (1) and (2) both use the definition of flexibility described in §4. The difference between columns (1) and (2) is that column (2) includes an extensive set of controls in addition to the variables included in column (1). The flexibility coefficient is negative and significant in both cases (−88.21 and −113, respectively), suggesting that flexibility is associated with lower discounts. These coefficients can be interpreted as the average dollar savings in discounts that are obtained by switching a model from an inflexible facility to a flexible one. For the preferred specification (column (2)), the results are statistically significant with $p < 0.01$ ($p < 0.05$ if we use Driscoll-Kraay standard errors, which are robust to potential autocorrelation of the residuals). Columns (3) and (4) show some additional robustness checks. In column (3), we use an alternative definition of flexibility in which *FLEX* is 1 only if at least 20% of the monthly production of the model occurs in flexible plants. The estimate obtained for this more-restrictive flexibility definition is very similar to the one shown in column (3). Finally, column (4) presents the same estimation as in column (2) when we drop the observations of years 2008 and 2009, which may be subject to some idiosyncratic patterns. The estimated effect of flexibility on discounts barely changes when restricting our attention to our pre-2008 observations (i.e., we cannot reject the hypothesis that the coefficient resulting from a sample that only includes pre-2008 observations is equal to the coefficient resulting from using the entire sample).

Overall, the evidence presented in Table 3 supports our hypothesis that flexibility is negatively associated with discounts, with a magnitude that is both statistically and economically significant. However,

Figure 3 (Color online) Average Incentive for GMC Envoy (Top) and Nissan Pathfinder (Bottom)

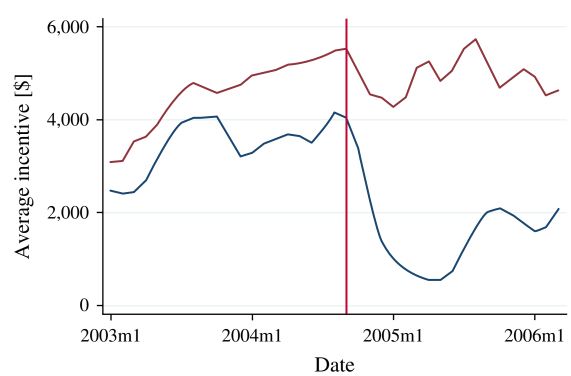


Table 3 Flexibility and Incentives: Model Level Analysis

	DISCOUNT (1)	*DISCOUNT* (2)	*DISCOUNT* (3)	*DISCOUNT* (4)
$FLEX_t$	−88.21* (45.88)	−113.0*** (43.73)	−94.29** (45.55)	−117.7** (52.81)
Model fixed effects	Yes	Yes	Yes	Yes
Segment-time dummies	Yes	Yes	Yes	Yes
Brand-year dummies	Yes	Yes	Yes	Yes
Additional controls	No	Yes+	Yes+	Yes+
Observations	10,531	10,411	9,743	7,393
R-squared	0.779	0.792	0.799	0.830

Notes. Robust standard errors in parentheses. All columns report the effect of flexibility on incentives and include model fixed effects and *DISC_COMP*. (3) uses an alternative flexibility definition (requires at least 20% produced in flexible plant). (4) excludes observations of 2008 and 2009.

+Indicates the controls: *INTRO, PHASE_OUT, AGE, MPD, MSRP, DESIGN_CHNG, USED_INDEX*.

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

these estimates may be subject to endogeneity bias. Using flexible manufacturing technology to produce a model is an endogenous decision, because firms choose which models to produce with flexible technology and when to produce them. This decision might be based on factors that also affect the discount policy for the vehicle, and the specification shown above could result in biased estimates if the use of flexibility is correlated with any unobserved variable captured by the error term. Note, however, that the decision to invest in plant flexibility or the decision to assign a model to a plant are made long before incentive levels are decided. Model fixed effects also reduce the extent of the problem, because they account for any potentially ignored time-invariant variable that might affect discounts and might be correlated with the adoption of flexibility. Also, all our specifications include segment-time dummies and brand-year interactions. They account for any temporal shocks that affect all models of a given segment or a given brand. This includes any temporal trends in discounts at the segment level as well as any global industry trends. Including additional controls (as we do in column (2)) reduces the effects of unobserved heterogeneity. For example, our specifications control for the vehicle list price (MSRP), which is adjusted yearly. Unobserved changes in the demand conditions expected by the firm for a year, which can be potentially correlated with the adoption of flexibility, can be accounted for by observed changes in the list price. Note that the flexibility coefficient does not change substantially if we add these additional controls (i.e., the effects are similar in columns (1) and (2)), which suggests that flexibility adoption is not very correlated with those observed variables.

The next set of analyses that we present account more explicitly for the fact that flexibility is selected by the firm, assuming that selection is based on covariates that are observed (§5.3) or unobserved (§5.4) to us. This allows us to study the extent to which any remaining endogeneity might be affecting the estimates shown in this section.

5.3. Matching Analysis

This section provides a series of analyses that address some of the concerns that could arise with a regression-based model such as the one presented earlier. These analyses are based on the "potential outcomes" framework (Rubin 2005). We have a sample of subjects (in our case, vehicle models), some that receive a treatment ("being manufactured in a flexible plant") and some that do not. We are interested in measuring the effect of the treatment on an outcome, which in our case is the level of discounts. Consider a vehicle model that did not receive the treatment at a given point in time. We call Y_0 the outcome (discounts) when this model does not receive the treatment (flexibility). This is observed in our data set, because this model did not receive the treatment. We call Y_1 the potential outcome if the subject had received the treatment, i.e., the level of discounts that we would have observed for this vehicle if it had been manufactured in a flexible plant. We are interested in the mean of the difference $Y_1 - Y_0$, i.e., the average treatment effect. We cannot simply take the difference between the sample means for treated and untreated subjects because some covariates can affect both the outcomes and the treatment. The methods that we use account for the fact that, for every subject and time, we only observe one of Y_0 and Y_1. In this section we assume we observe enough covariates so that after we condition on them, any remaining influence on the treatment is not correlated with the outcomes. We relax this assumption in §5.4.

Matching estimators are based on the comparison of models that are as similar as possible, with the exception that one receives the treatment (is manufactured in a flexible plant) and one does not (is not manufactured in a flexible plant). Our main analysis is based on propensity score matching (PSM), which was first proposed by Rosenbaum and Rubin (1983). The propensity score is the estimated probability of receiving treatment. For every observation, we calculate the propensity score. We then compare the outcomes for vehicles that belong to the treatment group (manufactured in flexible plants) and vehicles that belong to the control group (manufactured in inflexible plants) that have a similar propensity score.

There are different variants of this method depending on the model used to estimate the probability of treatment (e.g., logit, probit) and maximum number of units that can be matched to a single observation (e.g., 1:1, 1:2, 1:3). Prior research suggests that a parsimonious model for the treatment assignment can lead to reasonably good results (Dehejia and Wahba 2002, Gopal et al. 2013). We include year, month, and a number of vehicle characteristics, including fuel economy (in highway and city), horsepower, engine displacement, weight, height, width, length, and wheelbase distance. Similar attributes have been used in classic studies in the automotive industry such as Berry et al. (1995). We use the following logit model (note that we have also run a similar analysis using probit, with no substantial differences in the results):

$$Pr(FLEX=1 \mid Z)=\frac{1}{1+e^{-\beta Z}}, \tag{3}$$

where Z includes the aforementioned variables. The estimates of the treatment equation are provided in §A.3 in the online supplement.

Table 4 displays the results of the treatment effect. The first row corresponds to the analysis using propensity score matching, allowing only one control observation to be matched to every treated observation. The effect is negative and significant, providing further support for Hypothesis 1. The magnitude of the effect is even bigger (−400.9) than the magnitude we found in the preceding sections, suggesting that, if anything, our regression analysis underestimates the effect of flexibility. There are no qualitative differences in the results if we allow two or three control observations to be matched to every treated observation.

Besides propensity score matching, we use four alternative families of methods to measure the average treatment effect, and in all cases we find remarkably consistent estimates. These families are nearest neighbor matching (NN), inverse-probability weighting (IPW), regression adjustment (RA), and "doubly robust" methods that combine regression adjustment and inverse probability weighting (IPWRA). The reader is referred to Guo and Fraser (2009), Wooldridge (2010), and StataCorp (2013) for more detailed information about these methods. Similar methods have been used in the operations management literature (e.g., Gopal et al. 2013).

The results for NN are displayed in Table 4 (rows 2–5). They include estimates of the treatment effect using one single neighbor, with and without bias adjustment (see Abadie and Imbens 2002), and with and without exact matching for month and year. In all displayed cases we use the same variables as with the propensity score matching. (We have found similar results for different sets of covariates and also allowing more neighbors.) The results using nearest neighbor matching are similar to the ones obtained using propensity score matching. They are in all cases negative and significant, providing additional support of Hypothesis 1, and range between −336.8 to −366.2. The remaining rows in Table 4 (rows 6–8) indicate the results for IPW methods (e.g., see Hirano et al. 2003), RA, and IPWRA estimators. These methods also give qualitatively very similar results to the methods described above.

Table 4 Quasi-Experimental Analysis

Technique	Comments	(1) Mean effect All sample	(2) Mean effect Excluding 2008 and 2009
Propensity score matching	NN = 1	−400.9*** (41.03)	−310.0*** (47.47)
Nearest neighbor	NN = 1	−354.6*** (37.04)	−402.6*** (43.89)
Nearest neighbor	NN = 1, bias adjusted	−366.2*** (36.35)	−357.9*** (43.26)
Nearest neighbor	NN = 1, exact	−336.8*** (36.35)	−382.3*** (43.69)
Nearest neighbor	NN = 1, bias adjusted, exact	−339.0*** (35.76)	−294.9*** (43.41)
IPW		−467.8*** (32.28)	−364.5*** (37.96)
RA		−429.1*** (33.42)	−389.8*** (39.77)
IPWRA		−410.3*** (32.46)	−356.2*** (38.35)

Note. Robust standard errors in parentheses.
***$p < 0.01$.

The evidence presented in column (1) of Table 4 presents strong support for Hypothesis 1. This analysis has been replicated at the plant level using the available plant level controls with qualitatively similar results (see §A.3 of the online supplement). As we did before, we also reproduce the analysis for a sample that does not include 2008 and 2009, to make sure that the results are not exclusively driven by the turmoil of those years. Column (2) of Table 4 presents the results excluding those years. The effects are still negative and significant, suggesting that they are not driven by idiosyncratic aspects of those years. The point estimates of the effects obtained when we exclude those years are slightly lower, which suggests that flexibility actually had a higher value (in terms of avoiding discounts) during 2008 and 2009.

5.4. Endogenous Treatment Effects Model

The results presented in §5.3 assume selection on observables. In other words, they rely on the assumption that, after conditioning on observed covariates, the treatment can be considered to be randomly assigned. If we observe enough covariates, this is a reasonable assumption. However, it is possible that there are unobserved covariates that affect both treatment and outcome, in which case the conditional independence assumption would be violated. To ensure that the potential existence of unobserved covariates does not critically affect our estimates, we use an endogenous treatment effects model, which allows for selection to be based on unobservables, replacing the assumption of selection on observables with a precise specification of the joint dependence among unobservables.

These types of models were introduced by Heckman (1978), and the derivation of the maximum likelihood estimator for the model we use is given in Maddala (1983). The endogenous treatment effects model has one equation for the outcome (discounts, in our case) and another equation for the binary treatment (flexibility, in our case):

$$DISCOUNT_{it} = \mu_i + \beta_1 FLEX_{it} + CONTROLS_{it} + \gamma_{it} + \epsilon_{it}, \tag{4}$$

$$FLEX_{it} = \begin{cases} 1 & \text{if } \mathbf{z}_{it}\gamma + u_{it} > 0, \\ 0 & \text{otherwise,} \end{cases} \tag{5}$$

where $\mathbf{z}_{jt}$ includes the observed covariates used to model treatment assignment. (In our case, we use a model like the one we used in our propensity score analysis.) This model accounts for potentially unobserved factors affecting the use of flexible plants to manufacture a vehicle model. The error terms ϵ_{it} and u_{it} are assumed to follow a bivariate normal distribution with mean zero and covariance matrix:

$$\begin{bmatrix} \sigma^2 & \rho\sigma \\ \rho\sigma & 1 \end{bmatrix}. \tag{6}$$

The results of the estimation of this model are shown in Table 5. Column (1) uses the entire sample and obtains a negative and significant effect of flexibility on discounts, with a point estimate of −644.9, which is similar in magnitude of the effects obtained using methods that assume selection on observables, such as the ones described in §5.3. Column (2) of Table 5 excludes observations from the years 2008 and 2009 from the sample, and it obtains an effect of a smaller magnitude but still negative and statistically significant (−324.4). As discussed in §5.3, this can indicate that the effect of flexibility on discounts is more pronounced in periods where there is more volatility. We study this more in depth in §6.

Table 5 **Endogenous Treatment Effects**

	All sample	Excluding 2008 and 2009
	DISCOUNT	*DISCOUNT*
	(1)	(2)
$FLEX_{mt}$	-644.9^{***} (181.7)	-324.4^{*} (189.4)
Model fixed effects	Yes	Yes
Brand-year dummies	Yes	Yes
Additional controls	Yes^{+}	Yes^{+}
Observations	10,270	7,393

Note. Robust standard errors in parentheses.
$^{+}$Indicates the following controls: *INTRO, PHASE_OUT, AGE, MPD, MSRP, DESIGN_CHNG, USED_INDEX*.
$^{*}p < 0.1$; $^{***}p < 0.01$.

5.5. Robustness and Alternative Explanations

Overall, the results shown in this section provide strong support for Hypothesis 1. We find these results both at the plant level (§5.1) and at the model level (§§5.2–5.4), using different models including panel data models (§5.2), matching methods (§5.3), or an endogenous treatment model (§5.4). All these analyses make different assumptions and all yield similar results, which we interpret as strong evidence suggesting a negative association between flexibility and discounts. Section A.1 of the online supplement shows some additional robustness checks that further support this result. Section A.3 of the online supplement also includes some additional results that are not included in the main body of the text because of space limitations. These include the first stage of the propensity score matching and the results of the quasi-experimental analyses at the plant level.

Our preferred interpretation of the results is that flexibility allows a better match between supply and demand, decreasing supply–demand mismatches that result in discounts. Section A.2 of the online supplement explores and rules out several alternative explanations for the observed findings, concluding that changes in the evolution of list prices, inventories, or production costs would not explain our findings.

6. Moderators of the Effect of Flexibility on Discounts

Having established robust support for the main hypothesis of this study—the negative association between flexibility and discounts—we turn our attention to the analysis of three situations that can moderate the effect of flexibility on discounts, developed in Hypotheses 2–4.

6.1. The Moderating Role of Uncertainty

As discussed in the development of Hypothesis 2, we expect demand uncertainty to increase the value of flexibility, and, consequently, the ability of firms with flexible plants to sustain lower discounts.

This analysis requires us to generate a measure of demand uncertainty. We take two approaches. First, we measure demand uncertainty using the prediction error of a sales forecasting model. We propose the following model:

$$SALES_{it} = \mu_i + \sum_{k=1}^{K} \beta_k SALES_{it-k} + \gamma_t + \epsilon_{it}. \tag{7}$$

We estimate the model using our data, and we use it to quantify the relative prediction error every month, $abs((SALES_{it} - \widehat{SALES}_{it})/SALES_{it})$. High values of this expression indicate that predicting the sales value is difficult. To attribute a measure of volatility to each month, we compute a rolling average of the prediction error for the K previous months. In the results shown below we are using $K = 3$, but additional analyses suggest that our results do not critically depend on these values or even on the forecasting model used to predict sales. To make our coefficients more interpretable, we define a binary variable *HIGH_UNCERTAINTY* that indicates whether the volatility measure that corresponds to that month is in the upper quartile.

The equation that we estimate is the following:

$$\begin{aligned} DISCOUNT_{it} &= \mu_i + \beta_1 FLEX_{it} + \beta_2 HIGH\_UNCERTAINTY_{it} \\ &\quad + \beta_3 FLEX_{it} \times HIGH\_UNCERTAINTY_{it} \\ &\quad + CONTROLS_{it} + \gamma_{it} + u_{it}. \end{aligned} \tag{8}$$

We show the results of this analysis in Table 6, column (1). The coefficient of interest is the interaction between flexibility and *HIGH_UNCERTAINTY*. We obtain a negative and significant coefficient, which means that we find support for Hypothesis 2, with the coefficient of the interaction between flexibility and high uncertainty being −131. This means that flexibility is associated to an average reduction of discounts of −85.17 − 131.2 = −216.37 during uncertain periods.

One potential concern with the analysis described above is that demand (and therefore demand uncertainty) could itself be affected by the offered discount. Demand uncertainty could also affect the sales estimates made by the firm, which in turn could affect the discounts allocated by the firm. Although unlikely (since the firm usually sets discount levels with some information based on hard sales), this could result in a circularity that would make potential biases hard to assess. To ensure this does not drive our results, we follow an alternative approach to quantifying uncertainty exploiting the volatility of gas prices. This follows the logic of the motivating example used in §1: when gas prices change, demand for certain vehicles goes up and demand for others goes down. As gas prices become more volatile, demand becomes more uncertain. For every month, we calculate the standard deviation of the weekly gas prices, which we obtain from the Energy Information Administration (http://www.eia.gov/). We interact this measure with our flexibility variable to explore whether in periods with higher gas price volatility the effect of flexibility on discounts is stronger than when gas price volatility is low. This is the equation that we estimate:

$$\begin{aligned} DISCOUNT_{it} &= \mu_i + \beta_1 FLEX_{it} + \beta_2 SD\_GASPRICE_t \\ &\quad + \beta_3 FLEX_{it} \times SD\_GASPRICE_t \\ &\quad + CONTROLS_{it} + \gamma_{it} + u_{it}. \end{aligned} \tag{9}$$

Table 6, column (2) shows that the coefficient of the interaction of interest is negative and significant, which provides further support for Hypothesis 2.

In summary, using two different methods, we find strong evidence in support of the hypothesis that flexibility is associated with a higher reduction in discounts when demand is more uncertain.

Table 6 **Moderators of the Effect of Flexibility on Incentives: Demand Uncertainty and Model Complementarity**

	Demand uncertainty		Model complementarity
	DISCOUNT	*DISCOUNT*	*DISCOUNT*
	(1)	(2)	(3)
$FLEX_{it}$	−85.17* (44.73)	−69.85 (47.65)	130.1 (80.31)
HIGH_UNCERTAINTY	−327.5*** (43.10)		
$FLEX_{it}$ × *HIGH_UNCERT*	−131.2* (67.59)		
SD_GASPRICE		−3.541 (2.324)	
$FLEX_{it}$ × *SD_GASPRICE*		−3.567** (1.589)	
$COMPLEMENTARY_{it}$			−283.1*** (53.09)
$FLEX_{it}$ × $COMPLEMENTARY_{it}$			−236.5** (94.56)
Model fixed effects	Yes	Yes	Yes
Brand-year dummies	Yes	Yes	Yes
Additional controls	Yes+	Yes+	Yes+
Observations	10,411	10,411	10,411
R-squared	0.796	0.793	0.794

Note. Robust standard errors in parentheses.
+Indicates the following controls: *INTRO, COMPINCENTIVE, PHASE_OUT, AGE, MPD, MSRP, DESIGN_CHNG, USED_INDEX.*
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

6.2. The Moderating Role of Product Complementarity

We now explore how the effect of flexibility depends on whether a model is coproduced in the same plant with models belonging to other segments. To operationalize the importance of having vehicles with different demand patterns manufactured in the same plant, we define the notion of complementarity. For each model, we define a binary variable called *COMPLEMENTARITY* that is 1 if the model is coproduced in the same plant with models belonging to other segments. For example, if a compact car model is produced in a plant that produces only compact cars, then *COMPLEMENTARITY* = 0. If a compact car model is produced in a plant that also produces SUV models, then *COMPLEMENTARITY* = 1.

We estimate the coefficients in the following equation:

$$\begin{aligned} DISCOUNT_{it} &= \mu_i + \beta_1 FLEX_{it} + \beta_2 COMPLEMENTARITY_{it} \\ &\quad + \beta_3 FLEX_{it} \times COMPLEMENTARITY_{it} \\ &\quad + CONTROLS_{it} + \gamma_{it} + u_{it}. \end{aligned} \tag{10}$$

If Hypothesis 3 is supported, we would expect to find a negative and significant coefficient for β_3, i.e., when a vehicle manufactured in a flexible plant is coproduced with a complementary product, the reduction of discounts is bigger. The results of this analysis are shown in Table 6, column (3). We find that β_3 is negative and significant, with a value of −236.50. Interestingly, when we introduce this interaction, the direct effect of flexibility becomes insignificant, suggesting that the effects of flexibility on discounts are only achieved if complementary products are manufactured in a plant.

6.3. The Moderating Role of Competition

If Hypothesis 4 is supported, this will limit the manufacturer's ability to implement the reductions in discounts that could arise from flexibility—even if the ability to switch production from one model to another could theoretically allow a firm to reduce the discounts levels, the higher access to competing options in certain regions will moderate the reduction of discounts in those regions.

Using the transaction data, we construct a data set in which each observation corresponds to a model-day-state triad. For each of those triads, we observe the average discounts that were offered by the manufacturer (total for dealer and customer), whether the model was manufactured at flexible plants, and the number of dealers per inhabitant in the state (*LOCAL_COMPETITION*). We use the following specification:

$$\begin{aligned} DISCOUNT_{mt} &= \mu_m + \alpha_1 FLEX_{mt} + \alpha_2 LOCAL\_COMPETITION_{st} \\ &\quad + \alpha_3 FLEX_{mt} \times LOCAL\_COMPETITION_{st} \\ &\quad + \gamma_{mt} + \delta_{st} + u_{mt}, \end{aligned} \tag{11}$$

where γ_{mt} and δ_{st} account for time effects at the brand and state levels, respectively. A negative and significant value of α_3 would provide evidence supporting Hypothesis 4. Whereas the identification in the preceding analysis was enabled by temporal variations in flexibility and discounts, in this case our identification is based on geographic variation. To be specific, variation in competition intensity across states enables the identification of the moderating effect of competition in the relationship between flexibility and discounts. Because changes in flexibility cannot be tracked down to the day level, for each model we use the maximum level of flexibility observed in 2009. This implies that specifications that include vehicle model fixed effects μ_m will not allow to identify the direct effect of flexibility. This is not a problem, because we are interested in the coefficient of the interaction term, which is identified thanks to the differences in state-level competition.

Table 7 shows the estimates. Columns (1)–(3) include all the model-day-state triads. In all cases, the coefficient of interest (interaction $FLEX_{mt} \times LOCAL\_COMPETITION_{st}$) is positive and significant, supporting Hypothesis 4. The difference between high local competition levels (75th percentile) and low competition levels (25th percentile) results in a difference of USD 48 in the average discounts that manufacturers give on their flexible models. Columns (4)–(6) exclude the observations that correspond to the period in which the "Cash for Clunkers" program was active (July 1, 2009, to August 24, 2009). The results are qualitatively very similar, and Hypothesis 4 is supported in all cases. We also obtain support for Hypothesis 4 when we aggregate the data at a different temporal level (e.g., monthly).

Overall, there is substantial evidence supporting the hypothesis that the existence of local competition will attenuate the reduction of discounts that can be achieved using production flexibility.

7. Conclusion and Discussion

In this paper we have shown that automotive companies can use mix flexibility to reduce reliance on discounting as a means of matching supply and demand. The deployment of production mix flexibility is associated with savings in average discounts on the order of 10% of the average discounts during our period of analysis, 2002–2009. These savings in discounts arise from the increased ability to match supply and demand that firms have when they operate flexible plants.

We have also shown that the effect of flexibility on incentives depends on different circumstances. When uncertainty is higher, the effects of flexibility on discounts are also higher. When the models that are coproduced in the same plant belong to different

Table 7 Moderators of the Effect of Flexibility on Incentives: Competition

	DISCOUNT (1)	*DISCOUNT* (2)	*DISCOUNT* (3)	*DISCOUNT* (4)	*DISCOUNT* (5)	*DISCOUNT* (6)
$FLEX_{mt}$	-968.8^{***}	-36.96^{***}		-947.8^{***}	11.19	
	(10.20)	(7.353)		(12.09)	(8.899)	
$COMPETITION_{st}$	$4{,}056^{***}$		2,459	$3{,}027^{***}$		2,886
	(134.6)		(2,003)	(156.9)		(1,946)
$FLEX_{mt} \times COMPETITION_{st}$	$4{,}738^{***}$	$2{,}263^{***}$	$2{,}305^{***}$	$6{,}647^{***}$	$2{,}897^{***}$	$2{,}372^{***}$
	(164.4)	(116.8)	(81.32)	(194.0)	(141.6)	(97.66)
Model fixed effects	No	No	Yes	No	Yes	Yes
Brand-time dummies	No	Yes	Yes	Yes	Yes	Yes
State-time dummies	No	Yes	Yes	Yes	Yes	Yes
Observations	932,802	932,802	932,802	655,253	655,253	655,253
R-squared	0.078	0.595	0.815	0.057	0.563	0.805

Notes. Robust standard errors are in parentheses. The columns without model fixed effects, i.e., (1) and (4), include a constant.
$^{***}p < 0.01$.

segments, the effects of flexibility on discounts are also higher. In presence of higher local competition, the effect of flexibility on discounts is lower.

This paper has mainly focused on the benefits of flexibility. Whereas those are very substantial, it is important to keep in mind that the cost side is equally important. When evaluating the deployment of flexibility, firms also have to examine the associated costs. The costs of flexibility depend highly on the current plant and product portfolio of the firm. For newly built plants, the costs of a flexible plant and the costs of an inflexible plant are now similar; however, the capital investment of a new plant is huge, and firms typically update and retool existing plants. The cost of doing that depends on the plant's technology and the models that are going to be manufactured. Therefore, it is difficult to give a universal measure for the costs of flexibility. As a reference point, consider Ford's plans to retool its Wayne (Michigan) plant, which is estimated to require a $550 million investment. Rather than illustrating a cost-benefit analysis for each manufacturer, we have presented our estimates of the average benefit of flexibility based on per-vehicle discount savings. Firms can combine our results and methodology with their detailed information about their cost structure and current capital equipment to evaluate the return on investment in flexibility. It is important to keep in mind that flexibility is only desirable in certain circumstances, and it may make perfect sense for a firm to decide not to invest in flexible plants.

Some limitations of our analysis point at opportunities for follow-up research. For example, an issue we have not addressed is the coordination between manufacturing strategy and product development strategy. To fully enjoy the benefits of mix flexibility, it is necessary to have a portfolio of products that can be jointly produced in the same line. Future research can study how firms can complement the deployment of flexibility in their plants with an adequate product development strategy. Our study focuses on the automotive industry. Clearly, the effects are going to vary from industry to industry. Our results seem more representative of industries with large fixed costs. Automotive plants have huge fixed costs, which motivate vehicle makers to operate at high utilization. In that context, mix flexibility gives manufacturers a very powerful tool to keep utilization high while not flooding the market with undesirable products. In industries with lower fixed costs, firms may simply reduce production as needed without much cost, and mix flexibility may be less attractive. Future research can explore how the effects manifest in other empirical settings.

Whereas we acknowledge that the average effect may vary from industry to industry, we believe that our analysis of the moderators of the effects of flexibility on discounts described in §6 provides us with a set of more generalizable insights. Flexibility will be more valuable in terms of reducing discounting in situations or industries in which demand is more uncertain. Flexibility will be less valuable in terms of reducing discounts in industries with very homogeneous products that are subject to very similar demand shocks. Finally, flexibility will also be less valuable in very competitive environments, because it will not be possible to sustain potential premiums from a better ability to match supply with demand in those cases. Firms operating in markets with relatively low demand uncertainty, very homogeneous products, and fierce competition will not probably gain much—in terms of reducing potential discounting—from adopting flexibility. In contrast, firms operating in a very volatile environment, with very differentiated products and with limited competition, are likely to be able to use flexibility to avoid substantial markdowns.

Besides its managerial importance, we believe that the analysis we have presented has substantial implications for the academic community as well. The analysis presented in this paper complements the modeling literature by estimating the magnitude of some phenomena that have been discussed in previous papers. Our work also opens up opportunities for future research. The present paper focused on the effects of mix flexibility in the automotive industry, but future research could look at the effects of other types of flexibility (e.g., volume flexibility) or the effects of flexibility in other specific industries (e.g., fashion, services, electric power industry). More generally, future research can estimate the impact of other operational variables, including product variety, fuel efficiency, or the timing of new product launches, on pricing behavior. Empirical models of pricing could be particularly fruitful in studying the interplay between pricing and inventory decisions. This area has been the subject of several modeling papers, but there is little empirical research complementing the theoretical results.

Supplemental Material
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References
Abadie A, Imbens G (2002) Simple and bias-corrected matching estimators for average treatment effects. Working paper, National Bureau of Economic Research, Cambridge, MA.

Berry S, Levinsohn J, Pakes A (1995) Automobile prices in market equilibrium. *Econometrica* 63(4):841–890.

Busse M, Silva-Risso J, Zettelmeyer F (2006) 1,000 cash back: The pass-through of auto manufacturer promotions. *Amer. Econom. Rev.* 96(4):1253–1270.

Cachon G, Olivares M (2010) Drivers of finished-goods inventory in the U.S. automobile industry. *Management Sci.* 56(1):202.

Cachon G, Terwiesch C (2009) *Matching Supply with Demand*, Vol. 2 (McGraw-Hill, Singapore).

Ceryan O, Sahin O, Duenyas I (2013) Dynamic pricing of substitutable products in the presence of capacity flexibility. *Manufacturing Service Oper. Management* 15(1): 86–101.

Chod J, Rudi N (2005) Resource flexibility with responsive pricing. *Oper. Res.* 53(3):532–548.

Dehejia RH, Wahba S (2002) Propensity score-matching methods for nonexperimental causal studies. *Rev. Econom. Statist.* 84(1): 151–161.

Fine CH, Freund RM (1990) Optimal investment in product-flexible manufacturing capacity. *Management Sci.* 36(4):449–466.

Gopal A, Goyal M, Netessine S, Reindorp M (2013) The impact of new product introduction on plant productivity in the North American automotive industry. *Management Sci.* 59(10): 2217–2236.

Goyal M, Netessine S (2007) Strategic technology choice and capacity investment under demand uncertainty. *Management Sci.* 53(2):192–207.

Goyal M, Netessine S, Randall T (2012) Deployment of manufacturing flexibility: An empirical analysis of the North American automotive industry. Working paper, available at SSRN: http://ssrn.com/abstract=2077659.

Guo S, Fraser MW (2009) *Propensity Score Analysis: Statistical Methods and Applications*, Vol. 12 (Sage Publications, Thousand Oaks, CA).

Heckman JJ (1978) Dummy endogenous variables in a simultaneous equation system. *Econometrica* 46(4):931–959.

Hirano K, Imbens GW, Ridder G (2003) Efficient estimation of average treatment effects using the estimated propensity score. *Econometrica* 71(4):1161–1189.

Huckman RS, Zinner DE (2008) Does focus improve operational performance? Lessons from the management of clinical trials. *Strategic Management J.* 29(2):173–193.

Jordan WC, Graves SC (1995) Principles on the benefits of manufacturing process flexibility. *Management Sci.* 41(4):577–594.

KC DS, Terwiesch C (2011) The effects of focus on performance: Evidence from California hospitals. *Management Sci.* 57(11): 1897–1912.

Maddala GS (1983) *Limited-Dependent and Qualitative Variables in Econometrics*, Econometric Society Monographs, No. 3 (Cambridge University Press, Cambridge, UK).

Moreno A, Terwiesch C (2015) The effects of product line breadth: Evidence from the automotive industry. Working paper, available at SSRN: http://dx.doi.org/10.2139/ssrn.2241384.

Olivares M, Cachon GP (2009) Competing retailers and inventory: An empirical investigation of General Motors' dealerships in isolated U.S. markets. *Management Sci.* 55(9): 1586–1604.

Parker RP, Wirth A (1999) Manufacturing flexibility: Measures and relationships. *Eur. J. Oper. Res.* 118(3):429–449.

Rosenbaum PR, Rubin DB (1983) The central role of the propensity score in observational studies for causal effects. *Biometrika* 70(1):41–55.

Rubin DB (2005) Causal inference using potential outcomes. *J. Amer. Statist. Assoc.* 100(469):322–331.

Sethi AK, Sethi SP (1990) Flexibility in manufacturing: A survey. *Internat. J. Flexible Manufacturing Systems* 2(4):289–328.

StataCorp (2013) *Stata Treatment-Effects Reference Manual: Potential Outcomes/Counterfactual Outcomes* (StataCorp, College Station, TX).

Van Mieghem JA (2008) *Operations Strategy: Principles and Practice* (Dynamic Ideas, Belmont, MA).

Van Mieghem JA, Dada M (1999) Price versus production postponement: Capacity and competition. *Management Sci.* 45(12): 1631–1649.

Wooldridge JM (2010) *Econometric Analysis of Cross Section and Panel Data* (MIT Press, Cambridge, MA).