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

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We use a detailed dataset from the U.S. auto industry spanning 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 co-produced with vehicles that belong to a different segment; and 3) lower in situations with higher local competition.

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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 US 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 towards more fuel-efficient vehicles and away from SUVs. Figure 1 (left) displays monthly production levels. Production volumes for the Ford Edge remained relatively constant, while 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, while Ford relied on its ability to adjust prices (by providing incentives) as a response to changes in gas prices.

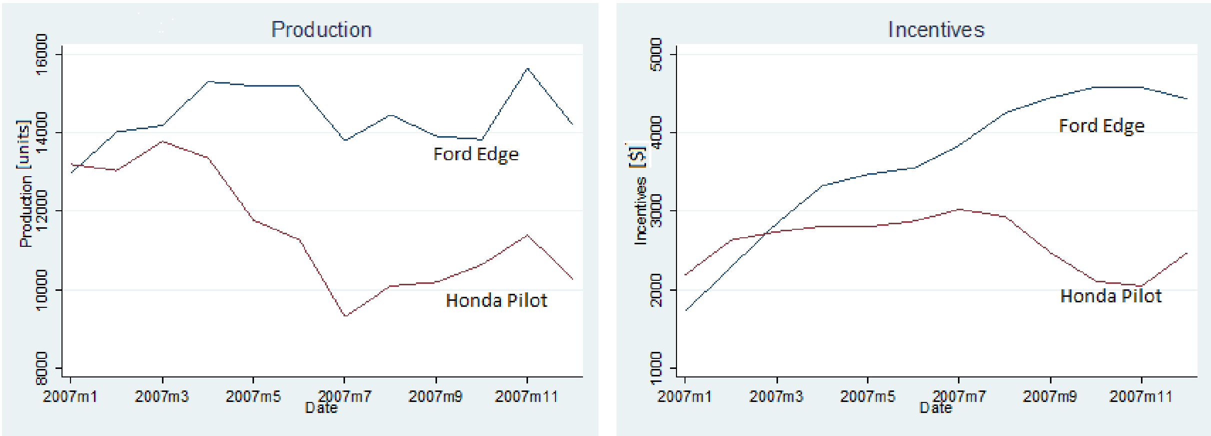

Figure 1 Production (left) and incentive (right) data for Ford Edge vs Honda Pilot

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 plat 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 Section 4) is based on the ability of a plant to manufacture 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, or *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*, a market research company specializing in new car pricing, and we have gained access to a proprietary dataset 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 datasets, 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 dataset, 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 is found 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. 2006). 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 vs. 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 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.

In order 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 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 et al. 2006, Goyal and Netessine 2007). 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 co-produced in the same plant have lower correlation. This happens, for example, when the vehicles co-produced 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 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 3 million jobs in the U.S. 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

Table 1 Variables and Summary Statistics

Variable	Description	Mean	Standard deviation			N
			Total	Between	Within	
$DISCOUNT_{it}$	Average incentive given for model i in month t in USD.	3145	1988	1660	1182	11043
$FLEX_{it}$	Binary variable that indicates if model i is manufactured in at least one flexible plant in month t, according to the measure described in Section 4.	0.38	0.48	0.40	0.28	10535
$DISC\_COMP_{it}$	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.	2758	890	768	537	11039
$MSRP_{it}$	Median list price of the model i in USD, constant during the model year.	30120	9914	10609	1919	11043
MPD_{it}	Miles per dollar. The evolution of gas prices changes the attractiveness of some models and incentives might respond to that. We define $MPD_{it} = MPG_i/gasprice_t$.	9.10	3.16	2.55	2.32	10923
AGE_{it}	Number of years since the model was first introduced.	3.20	2.24	1.77	1.79	11043
$INTRO_{it}$	Dummy variable that is 1 in the model year when the model is introduced.	0.08	0.27	0.20	0.23	11043
$PHASE\_OUT_{it}$	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	11043
$DESIGN\_CHNG_{it}$	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	11043
$INVENTORY_{it}$	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	11043
$PRODUCTION_{it}$	Amount of units of model i produced in month t.	9468	12597	9591	5790	11043
P_FLEX_{pt}	Binary variable that indicates if plant p is flexible in month t, according to the measure described in Section 4.	0.23	0.42	0.32	0.25	7705
$P\_FLEX\_REC_{pt}$	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	7705
P_AGE_{pt}	Number of years since the plant was opened.	37.17	25.66	27.58	2.12	7581
$UTIL_{pt}$	Average utilization of plant p in month t. It is calculated as the total production of the plant divided over $1/12_{th}$ of the annual capacity.	0.83	0.77	0.46	0.69	6780
$PRODUCTION_{pt}$	Total number of vehicles produced in month t in plant p.	14865	9217	7610	5614	7705
$NPRODS_{pt}$	# of different vehicles produced in month t in plant p.	2.31	1.16	1.02	0.53	7705

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 U.S. over the period of 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 U.S. 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 for each model were obtained from WARDS automotive. Domestic production refers to vehicles produced in the U.S., 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 Reports. We have also obtained data on the annual capacity of U.S. plants.

Pricing data: We have obtained manufacturers' incentive data from TrueCar (www.truecar.com). 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 is converted to its 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. 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 WARDS 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 price changes 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 4dr 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: While most of our analysis uses a dataset with monthly model observations aggregated at the national level, for the purpose of testing Hypothesis 4, we have obtained an additional dataset that allows us to exploit the geographic variation on incentives and level of competition. The dataset also comes from TrueCar and includes a sample with around 1 million new vehicle purchases corresponding to 2009 and all brands sold in 2009. This covers 10% of the vehicle purchases in the US 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 dataset, which is not present in the other datasets 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 dataset 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 (for example, 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, while 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. In order 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 America plants were flexible at the end of 2010, while only five out of Ford's thirteen 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

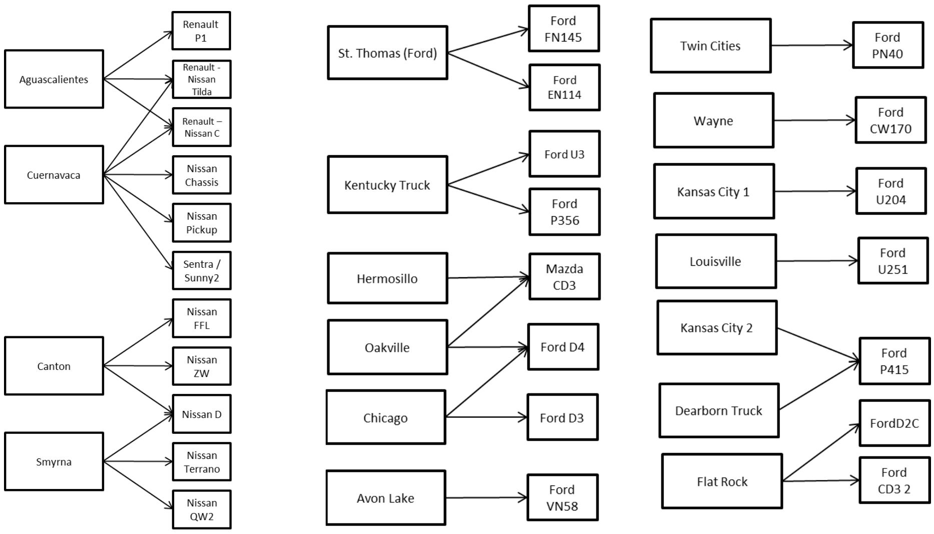

Figure 2 Allocation of platforms to North American plants at Nissan (left) and Ford (right)

notion that "a little flexibility can go a long way," we use a binary score and we give model i a high flexibility score in a given month t ($FLEX_{it}$=1) if it has at least some 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 which 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 Section 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, while 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 Section 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 6 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 (now published through Oliver Wyman, see https://www.theharbourreport.com), which is the authoritative information source for automotive plant productivity. 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.

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 (Section 5.1) and a model-level panel data (Section 5.2). As we will show, both analyses provide evidence of the hypothesized negative relation between flexibility and discounts. In order 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 (Section 5.3), and an additional endogenous treatment effect specification that allows for the treatment to be based on unobservables (Section 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 dataset with monthly information of each of the North American plants. Recall that discounts are defined at the model level. In order 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:

$$DISCOUNT_{pt} = \mu_p + \beta_1 P\_FLEX_{pt} + CONTROLS_{pt} + \gamma_t + u_{pt} \tag{1}$$

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. 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 H1. Table 2 shows the results of the estimation using 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 due to the turmoil in the automotive industry during those years, and the fact that 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 -240.50 USD. Note that the coefficient of flexibility barely changes from Column 2 to Column 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

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

Robust standard errors in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$
$^+$ indicates the following controls: $PRODPLANT, PLANTAGE, UTIL, NPRODS, MODEL\_INV$
Column 1 does not include plant fixed effects but includes a constant.
Columns 4 does not include years 2008 and 2009.

magnitude of the effect when excluding those years. We explicitly study the moderating role of uncertainty in Section 6.

As discussed above, 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. In order 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 6 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 from the fact that 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 while 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 Section 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 1 USD 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 (for example, 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,

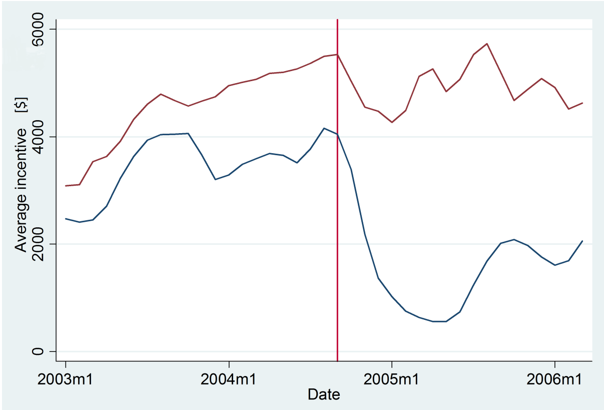

Figure 3 **Average incentive for GMC Envoy (top) and Nissan Pathfinder (bottom)**

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 given 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, and therefore not all the difference in observed discounts comes from flexibility.

Hypothesis H1 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. Column 1 and Column 2 both use the definition of flexibility described in Section 4. The difference between Column 1 and 2 is that Column 2 includes an extensive set of controls on top of 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).

Table 3 Flexibility and Incentives: Model Level Analysis

	DISC (1)	DISC (2)	DISC (3)	DISC (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

Robust standard errors in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$
All columns report the effect of flexibility on incentives and include model fixed effects and $DISC\_COMP$.
$^+$ indicates the controls $INTRO, PHASE\_OUT, AGE, MPD, MSRP, DESIGN\_CHNG, USED\_INDEX$
(3) uses an alternative flexibility definition (requires at least 20% produced in flexible plant).
(4) excludes observations of 2008 and 2009.

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, 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 Column 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 (Section 5.3) or unobserved (Section 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 above. These analyses are based on the "potential outcomes" framework (Rubin 2005). We have a sample of subjects (in our case, vehicle models), some of which receive a treatment ("being manufactured in a flexible plant") and some of which 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 dataset, 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 Section 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 the fuel economy (in highway and city), the horsepower, the engine displacement, the weight, the height, the width, the length and the 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):

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

where Z includes the aforementioned variables. The estimates of the treatment equation are provided in Section 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 2 or 3 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).

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***	-310.0***
		(41.03)	(47.47)
Nearest neighbor	NN=1	-354.6***	-402.6***
		(37.04)	(43.89)
Nearest neighbor	NN=1, bias adjusted	-366.2***	-357.9***
		(36.35)	(43.26)
Nearest neighbor	NN=1, exact	-336.8***	-382.3***
		(36.35)	(43.69)
Nearest neighbor	NN=1, bias adjusted, exact	-339.0***	-294.9***
		(35.76)	(43.41)
IPW		-467.8***	-364.5***
		(32.28)	(37.96)
RA		-429.1***	-389.8***
		(33.42)	(39.77)
IPWRA		-410.3***	-356.2***
		(32.46)	(38.35)

Robust standard errors in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$

The results for nearest neighbor matching analysis (NN) are displayed in Table 4 (rows 2 to 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 Tabe 4 (rows 6-8) indicate the results for inverse-probability weighting (IPW) methods (e.g., see Hirano et al. 2003), regression adjustment (RA), and inverse-probability-weighted regression-adjustment (IPWRA) estimators. These methods also give qualitatively very similar results to the methods described above.

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 Section 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 Section 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. In order to make sure 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):

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

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

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. The first column 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 Section 5.3. The second column of Table 5 excludes observations from the years 2008 and 2009 from the sample, and obtains an effect of a smaller magnitude, but still negative and statistically significant (-324.4). As discussed in Section 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 Section 6.

Table 5 Endogenous Treatment Effects

	All sample DISC (1)	Excluding 2008 and 2009 DISC (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

Robust standard errors in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$
$^{+}$ indicates the following controls: $INTRO, PHASE\_OUT, AGE, MPD$, $MSRP, DESIGN\_CHNG$, $USED\_INDEX$

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 (Section 5.1) and at the model level (Sections 5.2-5.4), using different models including panel data models (Section 5.2), matching methods (Section 5.3) or an endogenous treatment model (Section 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 due to 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 to that. 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 suggests that our results do not critically depend on these values or even on the forecasting model used to predict sales. In order 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:

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

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 H2, with the coefficient of the interaction between

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

	Demand Uncertainty		Model Complementarity
	DISC	DISC	DISC
	(1)	(2)	(3)
$FLEX_{it}$	-85.17*	-69.85	130.1
	(44.73)	(47.65)	(80.31)
$HIGH\_UNCERTAINTY$	-327.5***		
	(43.10)		
$FLEX_{it} \times HIGH\_UNCERT$	-131.2*		
	(67.59)		
$SD\_GASPRICE$		-3.541	
		(2.324)	
$FLEX_{it} \times SD\_GASPRICE$		-3.567**	
		(1.589)	
$COMPLEMENTARY_{it}$			-283.1***
			(53.09)
$FLEX_{it} \times COMPLEMENTARY_{it}$			-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

Robust standard errors in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$
$^{+}$ indicates the following controls: $INTRO, COMPINCENTIVE, PHASE\_OUT, AGE, MPD, MSRP, DESIGN\_CHNG, USED\_INDEX$

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. While unlikely (since the firm usually sets discounts levels with some information based on hard sales), this could result in a circularity that would make potential biases hard to asses. In order to make sure 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 Section 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. 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:

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

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.

6.2. The Moderating Role of Product Complementarity

We now explore how the effect of flexibility depends on whether a model is co-produced 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 co-produced 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:

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

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 co-produced 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 H4 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 dataset 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:

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

where γ_{mt} and δ_{st} account for time effects at the brand and at the state level, respectively. A negative and significant value of α_3 would provide evidence supporting H4. While 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 H4. The difference between high local competition levels (75th percentile) and low competition levels (25th percentile) results in a difference of 48 USD 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 H4 is supported in all cases. We also obtain support for H4 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.

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

	DISC (1)	DISC (2)	DISC (3)	DISC (4)	DISC (5)	DISC (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

Robust standard errors in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$
The columns without model fixed effects [i.e., (1) and (4)] include a constant

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 in 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 co-produced in the same plant belong to different 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. While 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 have to also 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. But 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. It is therefore difficult to give a universal measure for the costs of flexibility. As a reference point, consider Ford's plans to retool its Wayne (MI) 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 in order 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. In order to be able 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.

While 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 Section 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 homogenous 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 homogenous 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.

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A. Online Supplement: Additional Robustness and Alternative Explanations

A.1. Robustness Analysis

Here we expand on the robustness checks mentioned in Section 5 and describe additional robustness analyses. We discuss the impact of using alternative definitions of flexibility and discounts, and we propose another way to address any remaining endogeneity concerns using an instrumental variable approach.

A.1.1. Alternative Definitions of Flexibility and Discounts

We use the two alternative definitions of flexibility described in Section 4 to show that our results do not critically depend on the measure of flexibility that we use. The first one is the "record" measure of flexibility that keeps the highest value of the flexibility variable observed in the last n months (with n=6). Columns 1-4 of Table 8 reproduce the analysis shown in Table 2 for this alternative measure of flexibility.

Table 8 Robustness Analysis: Plant Level

	(1)	(2)	(3)	(4)	(5)
$P\_FLEX\_REC_t$	-578.5***	-290.0***	-291.5***	-251.7***	
	(45.57)	(46.84)	(48.34)	(63.69)	
$P\_FLEX\_HARBOUR_t$					-656.5***
					(136.9)
PLANT EFFS.	No	Yes	Yes	Yes	Yes
TIME CTRLS	Yes	Yes	Yes	Yes	Yes
OTHER CTRLS	No	No	Yes^+	Yes^+	Yes^+
Observations	6,427	6,427	6,168	4,677	1,801
R-squared	0.056	0.668	0.674	0.690	0.704

Robust standard errors in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$
$^+$ indicates the following controls: $PRODPLANT, PLANTAGE, UTIL, NPRODS, MODEL\_INV$
The column without plant fixed effects [i.e., (1)] includes a constant.
Columns 4 does not include years 2008 and 2009.

The second measure of flexibility is a subjective expert assessment. This is captured by the variable $P\_FLEX\_HARBOUR_p$, which is a plant-level score between 1 and 4 that denotes the subjective level of flexibility of the plant. This score is measured in years 2004 and 2007. Column 5 of Table 8 reports the results. Note that the magnitude of the effect is not directly comparable to the results shown in Section 5 because the subjective expert assessment is not a binary variable, and because the analysis is restricted to the points in time in which the subjective assessment is available. However, the results are also negative and significant, supporting our main hypothesis that more flexibility is associated with lower discounts.

In our model level analysis, we also explore the impact of transformations of our dependent variable —the average discounts offered for a model in a given month. We have chosen to report the main analysis in the text using the dollar level of discounts, as opposed to the logs, because this allows for a more intuitive interpretation of the magnitude of the effect in terms of dollar savings in discounts. However, our main hypothesis is still supported if we use a logarithmic transformation of the discount (Table 9, Column 1) or a relative measure of discounts, such as the percentage discount from the MSRP list price (Table 9, Column 2).

Furthermore, we also conduct transformations of the original flexibility measure at the vehicle model level. Columns 3 and 4 of Table 9 use lagged versions of the flexibility variable, because one could argue that lags in the supply chain and production scheduling process imply that mix flexibility might not affect discounts immediately. Again, we find remarkably similar estimates for the effect of flexibility on discounts.

A.1.2. Instrumental Variable Approach

We also present a complementary analysis using an instrumental variable approach to evaluate the importance of any remaining source of bias in our OLS estimates. A good instrumental variable for the flexibility with which a vehicle model is produced should be correlated with the flexibility variable (relevance condition) and uncorrelated with the error term (exogeneity condition). We use the average flexibility of the rest of models of the same brand as an instrument for the flexibility of a model. This instrument satisfies the relevance condition because there exists correlation in the adoption of flexibility for different plants of the same firm. On the other hand, we do not expect the discounts of a model to be affected by the flexibility of the other models of the firm, after including all our controls.

Column 5 of Table 9 shows the estimates when we use the average flexibility of the rest of the models of the same brand as an instrument for flexibility of each vehicle model and estimate the econometric model using 2SLS. The estimates show that the coefficient of flexibility is even more negative when using the instrumental variable estimation, and therefore our Hypothesis H1 is still supported. This column suggests an effect of -670 USD of mix flexibility on discounts, even more negative than the one obtained using the OLS estimates. It is well known that instrumental

Table 9 Robustness Analysis: Model Level

	L(DISC.) (1)	% DISC. (2)	DISC. (3)	DISC. (4)	2SLS DISC. (5)
$FLEX_t$	-0.100*** (0.0371)	-0.00439*** (0.00123)			-670.0*** (186.8)
$FLEX_{t-1}$			-207.5*** (39.83)		
$FLEX_{t-3}$				-186.0*** (39.69)	
MODEL FIXED EFFECTS	Yes	Yes	Yes	Yes	No
SEGMENT-TIME DUMMIES	Yes	Yes	Yes	Yes	No
ADDITIONAL CONTROLS	Yes$^+$	Yes$^+$	Yes$^+$	Yes$^+$	Yes$^+$
Observations	10,411	10,411	10,177	9,831	9,749
R-squared	0.543	0.684	0.747	0.752	0.743

Robust standard errors in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$
$^+$ indicates the following controls: $DISC\_COMP$, $INTRO$, $PHASE\_OUT$, AGE, MPD, $MSRP$, $DESIGN\_CHNG$, $USED\_INDEX$.

variables can result in a substantial small sample bias, and we should be cautious about taking the 2SLS estimates at face value. However, they are useful at indicating the likely direction of any potential remaining bias, and we can consider our OLS results as a lower bound on the effect of flexibility.

The modeling literature can actually offer some additional guidance in interpreting our findings and in understanding the likely direction of potential bias in our OLS estimates. Demand uncertainty has been identified as one of the key drivers for adopting flexibility (e.g., Fine and Freund 1990). Given that price adjustments in the auto industry are asymmetric (discounts from the list price are offered when demand is low but price premiums over the list price are never charged), a more uncertain demand is likely to result in higher average discounts — because as the variance of the demand distribution increases, the size of the price adjustments downwards (if realized demand is low) or upwards (if realized demand is high) is expected to increase. Because the upward price increases are capped by the list price, we expect the average effect to result in higher discounts. If adopting mix flexibility is correlated with expected uncertainty, our flexibility variable is likely to pick up part of the contribution of uncertainty to discounts, which is expected to be positive. This suggests that a potential correlation between the flexibility variable and the omitted uncertainty is positive and the OLS coefficient of flexibility is likely to be biased upwards. This is consistent with the results that we find with our instrumental variable specification.

A.2. Alternative Explanations

Having established support for our central hypothesis, our preferred interpretation of the results is that mix flexibility allows companies to better match between supply and demand, decreasing supply-demand mismatches that result in discounts. However, there could be alternative explanations to the observed findings. We examine whether changes in the evolution of list prices, inventories, or production costs could explain our findings.

A.2.1. Evolution of list prices

While our analysis focused on short-run pricing behavior given by discounts, this behavior has to be examined in the context of the totality of the pricing decisions made by the firm, and in particular with the annual setting of MSRP (on average, incentives are bigger for vehicles with higher MSRP – the correlation between incentives and MSRP is 0.28). Even if flexibility reduces discounts, the effect of flexibility on final transaction prices and on manufacturer revenue per car is ambiguous. In other words, are savings in discounts really savings? If the savings in discounts that we attribute to flexibility coincide in time with reductions in the list prices that can also be attributed to flexibility, then it could well be that the net effect of flexibility on prices is zero or negative (i.e., vehicles might be sold at a cheaper price after flexibility is deployed). This would go against our explanation that the reduction of discounts comes from a better ability to match supply with demand following the deployment of flexibility. In order to test how flexibility affects list prices, we propose the following specification:

$$MSRP_{it} = \mu_i + \beta_1 FLEX_{it} + CONTROLS_{it} + \gamma_{st} + u_{it} \tag{12}$$

where μ_i are model fixed effects, $FLEX_{it}$ is the flexibility with which vehicle model i is produced in time t, γ_{st} are segment-time dummies and $CONTROLS_{it}$ includes additional control variables, such as $DISC\_COMP$, $INTRO$, $PHASE\_OUT$, AGE, and $DESIGN\_CHNG$.

The first column of Table 10 shows the impact of flexibility on MSRP, according to specification 12. We can reject the hypothesis that list prices are reduced after flexibility is deployed. In fact, flexibility has a positive, statistically significant association with list prices, which allows us to conclude that the net effect of flexibility on prices is positive. In other words, the savings in discounts afforded by flexibility really are savings.

Table 10 Alternative Explanations: List Prices, Inventories and Sales

	MSRP (1)	DISC. (2)	2SLS DISC. (3)	SALES (4)	SALES (5)	SALES (6)	SALES (7)
$FLEX_t$	363.7***	-199.3***	-159.7***	713.2***	679.6***	724.6***	489.8**
	(52.74)	(39.93)	(77.21)	(132.9)	(132.3)	(132.0)	(115.4)
$INVENTORY_t$		-2.633***	40.46***				
		(0.287)	(6.400)				
$DISCOUNT_t$						0.242***	0.331***
						(0.0296)	(0.0262)
$PRODUCTION_t$							0.282***
							(0.0143)
MODEL FIXED EFF.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SEGMENT-TIME DUM.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ADDITIONAL CONT.	Yes$^{\#}$	Yes^{+}	Yes^{+}	No	Yes^{+}	Yes^{+}	Yes^{+}
Observations	10,415	10,411	10,411	10,535	10,415	10,415	10,415
R-squared	0.979	0.745	0.006	0.877	0.878	0.878	0.901

Robust standard errors in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$
$^{\#}$ indicates the following controls: $DISC\_COMP$, $INTRO$, $PHASE\_OUT$, AGE, $DESIGN\_CHNG$, $USED\_INDEX$, MPD
$^{+}$ indicates the controls in $^{\#}$ plus the additional following controls: $MSRP$

A.2.2. The Role of Inventory

We argue that flexibility has a direct effect on discounts. An alternative explanation is that flexibility does not directly affect discounts; rather, if affects inventories which, in turn, affect discounts. It could be that flexibility affects the level of finished goods inventories (i.e., with models manufactured in inflexible plants having higher inventories), and that vehicles with higher inventories are more likely to offer discounts. Actually, Cachon and Olivares (2010) find an association between flexibility and finished goods inventory. In order to test whether inventory is the channel through which flexibility affects demand, we modify our specification 2 to include an additional control variable, $INVENTORY_{it}$, which contains the days of supply of model i in month t:

$$DISCOUNT_{it} = \mu_i + \beta_1 FLEX_{it} + \beta_2 INVENTORY_{it} + CONTROLS_{it} + \gamma_{s(i)t} + u_{it} \qquad (13)$$

Column 2 of Table 10 includes inventory and other additional controls. We observe that the value of the coefficient of flexibility does not change substantially after controlling for inventory: The direct effect of flexibility on discounts is an average reduction of 199.30 USD per vehicle. Note that inventory is highly endogenous in the discount equations. A high level of inventory can be held in anticipation of a positive future demand shock or as a consequence of a negative contemporaneous demand shock. In Column 2 of Table 10 we observe a negative coefficient of inventory, which would suggest that high levels of inventory are associated to lower discounts. In order to address the endogeneity of inventory and to obtain estimates with a clearer causal interpretation, we use instrumental variables. Cachon and Olivares (2010) report an association between the number of dealers and the amount of finished goods inventory, and between the number of variants of a model and the amount of finished goods inventories. Therefore, both the number of dealers and the number of variants of a model satisfy the relevance condition to be used as instrumental variables. Furthermore, we can argue that they also satisfy the exogeneity condition in the discount equation, because dealer structure and the number of variants of a model are decided long before the determinants of discounts are realized. Column 3 of Table 10 reports the estimates of specification 13 using 2SLS, with the number of dealers that are able to sell model i and the number of variants of model i as instrumental variables for the inventory level. We observe that, again, the effect of flexibility on discounts remains negative and significant. However, now we find a positive impact of inventory on discounts. An additional day of supply is associated with an increase of 40.46 USD in average discounts.

In summary, while inventory does indeed affect discounts, the effect of flexibility on discounts is not an indirect effect through inventories.

A.2.3. Cost explanation

An alternative explanation of the observed pricing behavior is based on a cost story. It could be that the marginal costs of production in flexible plants are higher than the marginal costs of production in inflexible plants. If this were the case, lower discounts could arise merely from the fact that marginal costs of production are higher with flexibility, with part of this cost increase being passed to the customer. If customers were facing higher prices for the same vehicles, we would expect that, all else being equal, sales would decrease. However, observe that sales do not decrease after flexibility is deployed. Columns 4-7 of Table 10 include several specifications of the following form:

$$SALES_{it} = \mu_i + \beta_1 FLEX_{it} + CONTROLS_{it} + \gamma_{st} + u_{it} \tag{14}$$

where μ_i are model fixed effects, $FLEX_{it}$ is the flexibility with which model i is produced in time t, γ_{st} are segment-time dummies, and $CONTROLS_{it}$ denotes additional control variables that vary across the four particular specifications.

We have conducted several tests on whether flexibility is associated with a sales decrease, but this hypothesis can always be rejected (see Table 10, columns 4-7). It would be difficult to explain why customers would be willing to buy more and at higher prices if this was purely a cost story. The observed pattern is more consistent with a superior ability to match supply and demand after the deployment of flexibility. Actually, the effect of flexibility on sales is positive and significant. This finding that flexibility increases sales is consistent with some of the principles described in Jordan and Graves (1995), which associate flexibility with a reduction of expected lost sales.

Therefore, our explanation that the effects on discounts and utilization come from a superior ability to match supply with demand after the deployment of flexibility seems the most plausible one. If anything, sales and list prices also increase, which means that our estimates of the benefits of flexibility through savings in discounts and increase in utilization are only a lower bound of the total benefits obtained from flexibility.

A.3. Additional Results

Due to space limitations, we have not reported in main body of the text the results of the estimation of Equation 3, which predicts the probability of treatment as a function of observable covariates. For completeness, we reproduce the results here in Table 11.

Table 11 Estimation of the probability of treatment

VARIABLES	(1) logit FLEX	S.E.	(2) probit FLEX	S.E.
WBASE_IN	-0.0505***	(0.00658)	-0.0268***	(0.00436)
LENGTH_IN	0.0562***	(0.00507)	0.0304***	(0.00345)
WIDTH_IN	0.0504***	(0.00871)	0.0336***	(0.00555)
HEIGHT_IN	-0.0178***	(0.00666)	-0.0132***	(0.00407)
WEIGHT_IN	0.000382***	(8.82e-05)	0.000266***	(5.32e-05)
ENG_CC	-0.000567***	(5.02e-05)	-0.000346***	(3.06e-05)
HP	0.00551***	(0.000757)	0.00322***	(0.000464)
MPGCTY	0.155***	(0.0199)	0.0901***	(0.0123)
MPGHWY	-0.0445***	(0.0165)	-0.0223**	(0.0102)
Constant	-10.42***	(0.787)	-6.277***	(0.477)
TIME EFFECTS	Year, Month		Year, Month	
Observations	11,252		11,252	

Robust standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

We also report the quasi-experimental analysis of Section 5.3, but conducted at the plant level, in Table 12. The variables that we use for the matching are year, month, the total plant production, the age of the plant, the utilization, the number of products manufactured in the plant, and the average inventory of the models produced in the plant.

Table 12 Quasi-experimental Analysis: Plant Level

Technique	Comments	(1) Mean effect All sample
Propensity score matching	NN=1	-183.9***
		(67.29)
Nearest neighbor	NN=1	-403.5***
		(54.07)
Nearest neighbor	NN=1, bias adjusted	-462.5***
		(55.13)
Nearest neighbor	NN=1, exact	-392.5***
		(54.41)
Nearest neighbor	NN=1, bias adjusted, exact	-371.8***
		(54.39)
IPW		-280.6***
		(78.27)
RA		-449.6***
		(52.37)
IPWRA		-493.5***
		(50.90)

Robust standard errors in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$