Does Adding Inventory Increase Sales? The Billboard and Scarcity Effects in U.S. Automobile Dealerships

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Abstract

Beyond the obvious stockout effect (you cannot sell a car you don't have) what is the relationship between inventory and sales? Inventory might signal a popular, and therefore a desirable, product, thereby increasing sales (a billboard effect). Or, inventory might encourage a consumer to continue her search (on the theory that she can return if nothing better is found), thereby decreasing sales (a scarcity effect). We seek to identify these effects in U.S. automobile sales. Our primary research challenge is the endogenous relationship between inventory and demand - dealers influence their inventory in anticipation of demand. Hence, our estimation strategy relies on weather shocks at upstream production facilities to create exogenous variation in downstream dealership inventory. We find that the impact of adding a vehicle of a particular model to a dealer's lot depends on which cars the dealer already has. If the added vehicle expands the available set of sub-models (e.g., adding a four-door among a set that is exclusively two-door), then sales increase. But if the added vehicle is of the same sub-model as an existing vehicle, then sales actually decrease. Hence, expanding variety should be the first priority when adding inventory - adding inventory without expanding variety is actually detrimental. Based on this insight, given a fixed set of cars, vehicles should be allocated among a group of dealers so as to maximize each dealer's variety. Our data indicate that the implementation of this strategy could increase expected sales by about 2% without changing the total number of vehicles in the market, which vehicles are produced or the number of vehicles at each dealership.

1 Introduction

In early 2008, before the financial crisis, car dealerships in the United States (U.S.) held enough vehicles to cover sales for 75 days (WardsAuto market data). However, immediately following the financial crisis automakers began drastic reductions in their inventories. By January 2010, days-of-supply for the industry had dropped to less than 49, leading many dealers to complain that their low inventories were negatively affective sales (AutomotiveNews (2010)). Were those complaints justified?

Clearly sales could fall if a dealer does not have any inventory - it is hard to sell a car if there is no car to sell in markets, like the U.S., where customers are accustomed to purchase directly from units on the lot rather than a make-to-order process as is more common in Europe. But beyond this stockout effect, does carrying more or less inventory influence sales? Traditional inventory theory assumes the answer is "no": demand is generally taken to be independent of inventory, so while sales varies in inventory (due to the stockout effect), demand does not. But in some product categories, including automobiles, there is reason to believe that demand may indeed depend in part on the amount of inventory carried, thereby creating a link between inventory and sales beyond the stockout effect. For example, seeing many cars on a dealers lot might cause a customer to infer that the car is popular (a dealer carries many cars only if the model is popular), thereby making the car more desirable to the customer and increasing the chance the customer purchases the vehicle. In contrast, ample inventory could create the opposite inference: if there are many cars, then demand must be slow because the car is not popular, and it must not be popular for a reason, so the customer becomes less likely to purchase. In general, we use the label "billboard effect" for any mechanism that assigns a positive relationship between inventory and demand, and "scarcity effect" for any mechanism with a negative relationship. Our objective is to empirically evaluate the strength of these effects in the U.S. auto industry.

While it is possible to identify several mechanisms that lead either to a billboard or to a scarcity effect, estimating the relationship between inventory and sales is complex primarily because it is reasonable to believe that inventories are endogenously chosen. For example, a simple plot reveals a positive relationship between the amount of inventory a dealer carries and the dealer's average weekly sales. But dealers that operate in larger markets are expected to carry more inventory and have higher sales even if inventory has no influence on demand merely because a firm rationally needs to carry more inventory when it serves more demand. To overcome this selection effect, we estimate the influence of inventory using only observed variation within dealer-model pairs rather than variation across dealerships and models. This approach is valid given the assumption that a dealer's market conditions are reasonably constant in our six-month study period (e.g., there is little change in local factors like demographics, population, or the degree of competition the dealer faces). However, even within a dealer-model pair, there is a concern that a a dealer may change her inventory level in anticipation of changes in demand. For example, the dealer may build inventory due to a planned promotion. In that situation it is incorrect to conclude that the larger inventory caused the higher sales. To overcome this issue, we exploit shocks to dealers' inventories due to weather disruptions in upstream

production. Extreme weather disrupts production via a number of mechanisms (e.g., delays in inbound or outbound shipments, worker absenteeism, etc.) and also is independent of dealer demand (as production generally occurs a considerable distance from the dealership), thereby providing a valid instrument that allows us to estimate the causal impact of inventory on sales. Given our results, we are then able to estimate the increase is sales that could be achieved if vehicles were allocated differently across dealerships.

2 The stockout, billboard and scarcity effects

Focusing on a single item with q units of inventory and stochastic demand, d, that is independent of q, as inventory increases, so does expected sales, E[min(q,d)], simply because a stockout occurs when d > q. Hence, the stockout effect suggests that sales increase with inventory even though demand is independent of inventory. However, the magnitude of the effect also diminishes with inventory, i.e., the effect is small when q is large.

There are also various mechanisms that we collectively label as billboard effects because they create a positive relationship between demand (the likelihood a customer wants to buy) and inventory, which is observed as a positive relationship between inventory and sales (see Balakrishnan et al. (2004)). Variety is one example. Suppose a retailer stocks similar items that differ in several attributes (e.g., engine size, body style) and consumers have heterogeneous preferences over those attributes. Increasing inventory may also increase the breadth of attributes available to consumers, thereby increasing demand (because consumers are more likely to find an item that matches their preference), and in turn this leads to higher expected sales. This is similar to a stockout effect in which each possible variant is considered separately. There is an extensive literature on consumer choice that offers a number of approaches for modeling variety (e.g., multinomial logit, nested logit, etc.). See Train (2009) for an overview. There is also work that combines the inventory choice decision with one of these consumer choice models (see Talluri and van Ryzin (2004), Smith and Achabal (1998)).

Continuing to hold preferences constant, inventory could increase sales by influencing a consumer's engagement in the purchasing process. For example, if a consumer is not aware of an item, the consumer cannot even consider purchasing it - as with a literal billboard, a large inventory may increase awareness. Or, a consumer may infer that a large inventory implies a low price (e.g., the item must be on promotion or the dealer will be willing to negotiate a good deal), thereby motivating the consumer to include the item in her consideration set (see Zettelmeyer et al. (2006) for a study on the effect of dealership inventory on prices). Finally, if search is costly, then consumers are more likely to visit (and therefore buy from) a dealer that has a reputation for higher inventory - nobody likes to go to a store only to find out that the desired item is unavailable (e.g., Dana Jr. and Petruzzi (2001)). Alternatively, inventory could influence demand by directly influencing preferences. For example, a consumer might infer from a large inventory that the item has good quality (why else would the dealer have so many), thereby making the item more desirable to the

consumer - a good quality item has useful features and durability.

In contrast to the billboard effect, there are several mechanisms that lead to a scarcity effect in which more inventory actually lowers sales. This could happen if consumers infer that an item with ample inventory is unpopular or low quality - there must be many units because nobody is buying the item (e.g., Balachander et al. (2009),Stock and Balachander (2005)). Or, a consumer might prefer an item that is perceived to be exclusive or rare, as in a collectible (e.g. Brock (1968); Brehm and Brehm (1981); Worchel et al. (1975)). This may apply to some specialty vehicles in the auto industry, but probably not to the sample of mainstream vehicles we consider.

If it is costly for consumers to consider all possible options, then low inventory may imply a low variety of options and higher confidence that a good option has been identified. Similarly, high inventory and high variety may create confusion or frustration (too many options to know where to begin), thereby leading to lower demand and sales (e.g. Iyengar and Lepper (2000), Schwartz (2004), Kuksov and Villas-Boas (2010)).

A large inventory may indicate that a product will be available later on at a good price (because the dealer may need to discount the item), thereby encouraging consumers to wait before buying (which lowers current sales). In contrast, with a low current inventory consumers not only anticipate that the price will not fall, they also anticipate that the item may not be available in the future. This can lead to a "buying frenzy" in which the low current inventory creates a sense of urgency among consumers to buy immediately (DeGraba (1995), Qian and van Ryzin (2008)). A similar effect can materialize in search behavior. Say a consumer finds a vehicle that she likes at a dealership. If the dealer has only one of that type of car, she may be inclined to stop her search and just buy the car - if she continues her shopping at other dealers, then she risks not finding a better car and losing the current car to another customer. But if the dealer has several of her desired cars, she may be more inclined to continue her search, and that search may lead her to make a purchase from some other dealership (See Cachon et al. (2008) for a model in which variety influences the degree of consumer search.).

To summarize, there are several mechanisms that lead to a billboard effect (ample inventory enables a better preference match, increases awareness, signals popularity, indicates availability and suggests the potential to obtain a good price) while other mechanisms lead to a scarcity effect (ample inventory signals an unpopular vehicle, creates overwhelming choice, suggests that prices will soon be lowered, and reduces the urgency to purchase immediately while encouraging additional search).

3 Data Description and Definition of Variables

As a general reference, during the period of our study six car companies accounted for about 90% of sales in the U.S. auto market. The company we focus on, General Motors (GM), captured 25% of the market. This market share was distributed across several different brands: Chevrolet, GMC, Pontiac, Buick, Saturn, Cadillac and Hummer.

The data used in our analysis can be separated in two groups. The first group includes the inventory and sales information for the dealers in our sample. The second group includes geographic location, weather information for all the GM dealers in our sample and all GM plants located in the U.S. and Canada.

3.1 Dealer's sales and inventory data.

We obtained, via a web crawler, daily inventory and sales data from a website offered by GM that enables customers to search new vehicles inventory at local dealerships. The data collection was done from August 15, 2006 to February 15, 2007, and includes a total of 1,289 dealers in the following states: California, Colorado, Florida, Maine, Nebraska, Texas and Wisconsin. These states are geographically dispersed and somewhat geographically isolated - they may border with Mexico or Canada or have a substantial coastline. They represent approximately 10% of all GM dealers in the U.S. for the period under analysis.

The crawler collected specific information for each vehicle at a dealer's lot, such as its trim level, options, list price and Vehicle Identification Number (VIN). Our sample of GM vehicles includes all cars and a large portion of light-truck models manufactured and sold in the U.S. and Canada. VINs uniquely identify all vehicles in the U.S. Thus, they provide three key pieces of information. First, the VINs allow us to identify when a new car arrived at a dealer and when a sale happened (a vehicle is removed from a dealer's inventory). Second, the VIN code identifies the particular plant where the vehicle was produced even if the model is manufactured at multiple plants. Finally, the VINs provide us with information regarding dealer transfers—we can observe when a vehicle is removed from one dealer's inventory and added to another dealer's inventory within the state.¹

We removed from our sample a limited number of dealerships that opened or closed during the period under analysis.

3.2 Geographic location and weather data

For each dealer and all 22 GM plants supplying vehicles in our sample (located in the U.S. and Canada), we obtained their address and exact geographic location (longitude and latitude) from GM's website.

We identified the closest weather station to each plant and each dealer. The selected weather stations are close to our plants with a mean and median distance of 12 and 10 miles, respectively. No plant is further than 32 miles from its corresponding weather station. To assess whether a station's weather is likely to be similar to the weather at its nearby plant, we constructed a sample of weather stations that are between 30 and 60 miles apart. In this sample, the correlation in our weather variables is no less than 95%, suggesting

 $^{^{1}}$ If a vehicle leaves a dealer in week t and does not reappear in another dealer's inventory in week t+1, then we code this as a sale. Otherwise, it is coded as a transfer. For example, car A is transferred from dealer 1 to dealer 2 and then sold at dealer 2, a sale is counted only at dealer 2. We can only observe transfers between dealerships within the same state. We anticipate that we observe the majority of transfers because transfers probably occur in a limited geographic area. In our sample the ratio between transfers and sales is 2.5%.

that the weather reported at the nearby weather station is representative of the weather at the plant².

Using the website from the National Weather Service Forecast Office (NWSFO) and www.wunderground.com, we obtained daily weather information for every dealership and plant location in our sample for the period August 15, 2006 to February 15, 2007. The weather variables include for each day the maximum, mean and minimum value for temperature, wind speed, humidity, pressure, visibility, dew point, cloud cover (the portion of the sky cover with clouds), the type of weather event (rain, thunderstorm, snow, etc.) and total precipitation (measured in inches).

Table 1 summarized the number of dealers in each state and Figure 2 shows the geographic location of GM plants and the dealers in our sample.

4 Model Specification

We seek to estimate the impact of inventory and variety on sales. The available data was used to construct a panel data-set where the unit of analysis is the sales of a particular vehicle model i at a specific dealership j during a week t ($Sales_{ijt}$). Expected sales during a week are influenced by the total number of vehicles available at the dealership during the week ($Inventory_{ijt}$), the number of varieties of the model that where available ($Variety_{ijt}$, to be described in more detail shortly), plus other factors that could influenced the demand for vehicles at the dealership. Figure 1 illustrates the relationship between the key variables in our analysis – sales, inventory and variety.

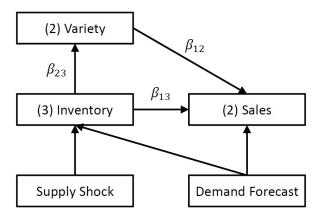


Figure 1: Relationship between Sales, Inventory and Variety

Figure 1 shows multiple effects between the three key variables. First, there is a direct effect of inventory on sales (labeled with the coefficient β_{13}). An example of this effect is when low levels of inventory signal low future availability of the vehicle model and lead to a "buy frenzy" behavior, or when high levels of inventory signals lower prices and therefore increases sales. Therefore, the sign of β_{13} is ambiguous. Second, there is a

²The locations consider for this analysis were: Marysville, Ohio and Columbus, Ohio; Washington DC and Baltimore, Maryland; Kansas City, Missouri, and Topeka, Kansas; Lansing, Michigan and Grand Rapids, Michigan

direct effect of variety on sales (labeled by β_{12}), as when more variety leads to a better match of customer preferences, thereby increasing sales. Higher variety could also lead to more confusion in choosing among too many options, lowering sales. Hence, the sign of β_{12} is also ambiguous. Third, there is an indirect effect of inventory on sales through variety (labeled β_{23}): adding inventory can lead to an increase in variety, which in turn could affect sales.

The estimation can be viewed as a system of simultaneous equation with three endogenous variables - $Sales_{ijt}$, $Variety_{ijt}$ and $Inventory_{ijt}$. Let Sales, Variety and Inventory be vectors containing the observations for these three variables, respectively (indexes i, j, t are therefore suppressed). The system is given by:

$$Sales = \beta_{12} Variety + \beta_{13} Inventory + \gamma_1 Z + \varepsilon_1$$
 (1)

$$Variety = \beta_{23}Inventory + \gamma_2 Z + \varepsilon_2$$
 (2)

$$Inventory = +\gamma_3 Z + \delta_3 W + \varepsilon_3 \tag{3}$$

The matrix of covariates Z is a set of exogenous controls to be specified in detail later. The matrix of covariates W is a set of weather shocks at the plant that produces a specific model. The error vectors $\{\varepsilon_g\}_{g=1,2,3}$ represent unobservable factors that affect each of the endogenous variables. Throughout we assume that Z and W are predetermined in the three equations, in the sense that $E(\varepsilon_g|Z,W)=0$, for g=1,2,3. Next, we discuss identification of the system of equations (1)-(3).

The error term ε_1 represent factors that affect sales which are unobservable in the data. Dealerships and manufacturers may predict some of these factors in advanced and use them in their demand forecast to choose inventory levels (see Figure 1 for an illustration). Hence, ε_1 and ε_3 are likely to be positively correlated, making *Inventory* endogenous in the sales equation (1).

W is excluded from the sales equation but included in the inventory equation. If weather at the plant affects its productivity, then weather shocks at the plant affect the inventory level at the dealerships; this effect is captured by the coefficient δ_3 in equation (3). A dealer's local weather is included in Z, but because most of the plants are located far away from the dealerships in our study, weather shocks at the plants should be unrelated to the local demand for autos. Hence, W is excluded from equation (1). Consequently, the explanatory variables in W are valid instrumental variables for Inventory in equation (1).

Nevertheless, this exclusion restriction on W is insufficient to identify the parameters of the system of equations; in fact, the parameters of the first equation are not identified without additional assumptions. The reason is that, since inventory also affects variety (Inventory is an explanatory variable in equation (2)), Variety is also endogenous in equation (1). Hence, Variety has to be instrumented to obtain consistent estimates of the coefficient in equation (1). Note that although W affects inventory, it does not have any further effect on the variety of vehicles; that is, W is excluded from equation (2) (i.e., $\delta_2 = 0$). Weather at the plant is a productivity shock that affects total production at the plant but not the mix of vehicles that

are produced at the plant. Hence, W is not a valid instrument for Variety.

In the absence of further exclusion restrictions of the exogenous variables (Z, W), identification of the system (1)-(3) requires assumptions about the covariance structure of the errors $(\varepsilon_1, \varepsilon_2, \varepsilon_3)$. As previously mentioned, it is likely that ε_1 and ε_3 are positively correlated due to inventory endogeneity. However, it is reasonable to assume that ε_1 and ε_2 are uncorrelated, that is, $E(\varepsilon_1\varepsilon_2) = 0$. Although dealerships can control to some extent the number of vehicles of a particular model that they receive, they typically have little control on the exact sub-models that are allocated to them. Therefore, the variations in variety after controlling for inventory levels should be unrelated with the demand forecasts or other unobservable factors related to demand. Moreover, it is also reasonable that $E(\varepsilon_2\varepsilon_3) = 0$: because dealers can only control variety through their inventory levels, other factors that induce variation in variety (captured by ε_2) should be unrelated to factors that affect inventory. These assumptions are sufficient for identification, as shown next.

Proposition 1. If $E(\varepsilon_g|Z,W)=0$, for all $g\in\{1,2,3\}$, $E(\varepsilon_1\varepsilon_2)=0$ and $E(\varepsilon_2\varepsilon_3)$, then all the parameters of the system of equations (1)-(3) are identified.

The proof of the proposition can be found in the appendix.

We need instrumental variables to estimate the parameters of equation (1) because Variety and Inventory are endogenous. As noted earlier, the exogenous plant weather variables W are excluded from (1) and can therefore be used as instruments for inventory. Moreover, under the assumption $E(\varepsilon_1\varepsilon_2) = 0$, the residual of equation (2) can be used as an instrument for variety in equation (1). This requires a consistent estimator of ε_2 . Under the assumption that $E(\varepsilon_2\varepsilon_3)$, the residual of the OLS regression of (2), denoted \hat{e}_2 , is a consistent estimator of ε_2 . Thus, the following method can be used to obtain consistent estimates of the coefficients of equation (1):

- 1. Estimate regressions (2) and (3) via OLS.
- 2. Compute the fitted values $Inventory = \hat{\gamma}_3 Z + \hat{\delta}_3 W$ and the residuals $\hat{e}_2 = Variety \hat{\beta}_{23} Inventory \hat{\gamma}_2 Z$.
- 3. Estimate equation (1) via Two-Stage Least Square using \hat{e}_2 and Inventory as instrumental variables for the endogenous variables Variety and Inventory.

Controls

Z includes model-dealership fixed-effects which control for the invariant characteristics of each dealer: each dealer location, the average popularity of a model at a particular dealership, the intensity of competition a model faces at each dealer, the average discount policy a dealer offers for a particular model, etc. Z also includes a seasonality dummy variable to account for changes in the sales across weeks. This is implemented by grouping dealers into four geographic regions: {Florida, Texas}, {Colorado, Nebraska}, {Maine, Wisconsin}, and {California}. Let r(j) be the region containing dealership j. We include the set of dummy

variables $Seasonal_{r(j)t}$ to control for different seasonal patterns across geographic regions, e.g., a different weekly sales pattern in Texas than in Wisconsin. Finally, as already mentioned, Z includes measures of local weather at each dealership to control for the effect of local weather on sales and demand forecasts. (See Steele (1951) and Murray et al. (2010) for examples of how local weather affects retail sales. There is also anecdotal evidence of this relationship in the public press, e.g. BloombergTV (2012)).

Measuring variety

To identify which of the main effects of inventory on sales described earlier dominates, we identify separately the impact of our two measures of availability – inventory and variety. For example, a negative effect of $Variety_{ijt}$ would suggest that the confusion effect dominates the impact on sales. Although $Inventory_{ijt}$ can be objectively defined as the number of vehicles available for a model, variety could be defined in many different ways, depending on the relevant product characteristics that are considered by customers when making their purchase decision. For example, a customer wanting to buy a Chevrolet Malibu may consider two vehicles with different horsepower as two different products, but could be indifferent on the color of the car. To measure Variety, it is necessary to define a set of attributes that describes relevant differences across vehicle options within a model. See Hoch et al. (1999) for a framework on how customers perceive variety.

The VIN of a vehicle contains information about vehicle characteristics, including the model, body style, engine type, restraint type, among others. We use all the relevant characteristics reported in the VIN to define the different possible variants of a model and we refer to each variant as a sub-model. The variable $AvailVar_{ijt}$ is the number of sub-models of a model i available at dealership j during week t.

Table 2 summarizes the number of different sub-models observed in our data and the average $Variety_{ijt}$ observed at the dealerships for a sample of models. The table reveals that there is variation in the number of sub-models available across the set of models. Hence, it is plausible that the impact of variety is different across models: for example, adding one more sub-model of a Cobalt (which has many sub-models) can have a smaller impact than adding one more sub-model of an Equinox (which has fewer available sub-models). To account for this, the amount of available variety can be measured relative to the number of sub-models that exist for that model. Denote $MarketVar_j$ as the number of sub-models available for model j (this is measured for model-year 2007). Our main measure of variety is defined as:

$$Variety_{ijt} = \frac{AvailVar_{ijt}}{MarketVar_{j}}.$$
(4)

For robustness, we considered other definitions of variety; for example, we used $AvailVar_{ijt}$ and its logarithm as alternative measures. The results using these alternative measures, discussed in Section 5, were similar.

Weather Instrumental Variables

Our instrument can work in several ways. Bad weather can affect the supply of parts to the production line slowing the production process. In addition, weather conditions can affect employee behavior both in their task performance and by increasing absenteeism. Alternatively, weather can delay shipments of vehicles to dealers. Consistent with these mechanisms, Cachon et al. (2011) provide evidence that weather in the vicinity of an assembly plant affects its productivity.

Our weather variables are defined as in Cachon et al. (2011) and are described in detail in Table 3. We included Wind, Fog, Rain and Snow variables because each of these weather events may influence travel to and from a plant. Cloud could proxy for other inclement weather and could influence employee behavior. High Temp is included because it could influence ambient temperature within the plant or employees that must work outside (e.g., loading docks). Low Temp may proxy for hazardous road conditions (e.g. ice). Some of the variables, such as Wind and Cloud, directly capture weather shocks. For other measures—specifically for Fog, Rain, High Temp, Low Temp and Snow—we estimated specifications including multiple levels of the variable to capture potential non-linear effects on production.

Some of these weather variables have a weak impact on dealership inventory, in part because of the high correlation between the many alternative measures of weather that we considered. Using a large number of instruments in a two-stage least square estimation can induce bias on the estimates (Buse (1992)). There is also a rich literature that discusses other challenges that can arise when dealing with multiple instruments, in particular when some of these instruments might be weak (Bekker (1994), Donald and Newey (2001), Chao and Swanson (2005)).

Kloek and Mennes (1960) proposed a practical solution to solve the shortcomings of dealing with a large number of (possibly weak) instruments. The idea is to use a reduced number of principal components of the original set of instruments as the instrumental variables in the estimation. We follow a similar approach.

The thirteen weather variables were reduced to five principal components. By capturing more than fifty percent of the variance on the original variables, the components obtained contain a good portion of the information in our instruments. The OLS regression of equation (3) shows that the five principal components coefficients are significant with an average p-value for the five factors of 12. In addition, to validate the strength of our instrument, we observe that both the R-squared (0.9) of this regression and the F-test (195) of join significance of the instruments exceed the usual standards to rule out weak instruments. For robustness, we also estimated our model using all of the the original weather variables as instruments in W, and all the main results continued to hold.

Although plant productivity is affected during the same week of a weather incident (as reported in Cachon et al. (2011)), the impact on dealership inventory is lagged due to delivery lead-times. We used a one-week lag based on anecdotal evidence reporting one-week delivery lead-times, but we also tested other specifications and obtained similar results.³

³ Another specification assumed there is no lead-time, hence we include contemporaneous weather. Finally, we considered another specification that included a specific lead-time for each vehicle to the dealers depending on the distance between the dealer and the plant where a particular model was manufactured. When this distance is less than 600 miles we consider that the vehicle will arrive within the week (zero lag). When the distance is between 600 and 1200 miles we consider that the vehicle will arrive with a lead time of one week and when the distance is more than 1200 miles we consider a two weeks lead-time.

An alternative estimation approach of the overall effect of inventory

Proposition 1 establishes sufficient conditions to estimate the system of equations (1)-(3) consistently. This requires assumptions about the covariance structure of the error terms $\{\varepsilon_g\}_{g=1,2,3}$. However, it is possible to estimate the overall effect of inventory on sales – which corresponds to the direct effect β_{13} plus the indirect effect through variety, $\beta_{12}\beta_{23}$ (see figure 1) – under weaker assumptions. To see this, replace Variety from equation (2) into equation (1):

$$Sales = (\beta_{13} + \beta_{12}\beta_{13})Inventory + \gamma_1'Z + \varepsilon_1', \tag{5}$$

where $\gamma_1' = \beta_{12}\gamma_2$ and $\varepsilon_1' = \varepsilon_1 + \beta_{12}\varepsilon_2$. Under the exogeneity assumption $E(\varepsilon_g|Z,W)$, $g \in \{1,2,3\}$, the coefficient $\beta_{13}' \equiv \beta_{13} + \beta_{12}\beta_{13}$ can be estimated via instrumental variables, instrumenting *Inventory* with the weather variables W. This provides an alternative estimate of the overall effect inventory on sales without making assumptions about the covariance structure of the error terms $(\varepsilon_1, \varepsilon_2, \varepsilon_3)$. The drawback of this approach is that it doesn't identify separately the effect of inventory and variety on sales. In particular, this precludes analyzing the counterfactuals described in section 6.

5 Results

Table 4 reports the main estimation results. Column (1) shows the estimates of equation (1), instrumenting the endogenous variables inventory and variety (as defined in equation (4)). The estimates suggest that the direct effect of inventory (β_{13} in Figure (1)) is negative and statistically significant, but the effect of variety (β_{12}) is positive and also statistically significant. This suggests that sales increase if new sub-models are made available to customers, but sales actually decrease if inventory is added to a sub-model that is already available at the dealership.

Given how inventory is allocated to dealerships in our sample, there is a small and positive relationship between inventory and variety: the estimated coefficient is $\hat{\beta}_{23} = 0.0054$, with a standard error $SE(\hat{\beta}_{23}) = 0.0001$. This estimate together with the estimated coefficients of equation (1) can be used to estimate the overall average impact of inventory on variety, which is given by $\beta_{13} + \beta_{12}\beta_{23} = -0.013$ (with a standard error of 0.003, obtained from a bootstrap of 400 samples). Hence, our estimates suggest that, given how vehicles were allocated to dealerships in our sample, the overall impact of inventory on sales is negative and statistically significant - adding inventory increases variety, but not by much, so the negative effect of adding inventory to an existing sub-model dominates the sales benefit of the (limited) expanded variety. However, different vehicle allocation policies can give different results. Figure 3 illustrates the overall impact of inventory on sales with the vehicle allocation policy that maximizes the expansion of variety (black line) compared to the allocation policy that expands inventory without increasing the number of sub-models available (dashed line). As is apparent from the figure, whether adding inventory increases or decreases overall sales depends on how vehicles are allocated to dealerships. For example, with a vehicle allocation

policy that maximizes variety by adding new sub-models to a model's inventory, the overall impact of each additional unit of inventory on sales would be 0.5%. A more precise analysis of alternative vehicle allocation policies is described in Section 6.

Recall that the estimates of column (1) are consistent if the error in equation (2), ε_2 , is uncorrelated with ε_1 and ε_3 . However, the overall impact of inventory on sales can be obtained by estimating equation (5) directly via instrumental variables, without any assumptions on the error term ε_2 (other than the maintained exogeneity assumption $E(\varepsilon_g|Z,W)=0$, for g=1,2,3). Column (2) in table 4 shows these estimates. The coefficient of inventory is -0.014, which is close to our previous estimate based on the coefficients of column (1) (which gave -0.013).⁴ This provides some support to validate the consistency of the estimates of column (1).

To assess the magnitude of the bias induced by the endogeneity of inventory, we estimated model (5) via Ordinary Least Squares (OLS). As mentioned in Section 4, if inventory is set in anticipation of demand, then ε_1 and ε_3 are likely to be positively correlated and therefore the OLS estimate of the inventory coefficient could be biased upward. Column (3) is consistent with this result: in fact, the bias is so severe that the coefficient on inventory changes sign and becomes positive with statistical significance.

Column (4) estimates equation (1) instrumenting *Inventory* but treating *Variety* as exogenous. As inventory increases variety, variety is positively correlated with ε_3 and thereby with ε_1 . Hence, ignoring the endogeneity of variety could also lead to a positive bias on the estimate of coefficient β_{23} , which is what we find: the variety coefficient in column (4) more than doubles that of column (1). This highlights the importance of treating both inventory and variety as endogenous in the estimation.

To repeat, the estimates in column (1) of Table 4 suggest that (i) adding inventory decreases sales if variety is held constant (a scarcity effect), (ii) although increasing inventory expands variety and variety has a positive impact on sales, the overall effect of increasing inventory is negative given the way vehicles are allocated in our sample, and (iii) adding inventory while simultaneously expanding variety can increase sales. Several of the mechanism discussed earlier are consistent with these findings and several are not. For example, our findings are consistent with the notion that more variety improves the match between consumer preferences and the available inventory, thereby increasing the likelihood that a customer makes a purchase. In contrast, the results are not consistent with the notion that more variety creates confusion, thereby reducing demand - in some categories it is possible that the confusion effect is real and sufficiently strong, but with automobiles it appears that consumers are more likely to buy when they have more options to choose from.

Our findings do not suggest that inventory has a strong relationship on how dealer price or how consumers bargains. One would expect that a dealer is more likely to offer a better price when the dealer has an above

⁴A non-parametric bootstrapping method (based on 400 re-samples of the original data) gives an average difference of 0.0008, with standard error 0.0002. Although the difference is statistically significant at the 99%, the difference is quite small in practical terms.

average amount of inventory because the dealer would want inventory to return to a more normal level. But we observe that sales decrease as inventory increases (holding variety constant) - if this is to be explained by pricing, then one needs to be willing to assume that dealers increase their prices when they have more inventory. Similarly, our estimates cannot simply be explained by a stockout effect - if adding inventory prevents stockouts, then coefficient β_{13} should be positive, not negative.

It is possible that the scarcity effect we observe is due to the information inventory conveys to consumers. For example, a consumer might infer that ample inventory is a signal that the car is not popular, possibly due to poor design or quality. For this to explain our data, the inventory signal would have to be at the sub-model level - a consumer would have to believe that ample inventory of two-door Malibus is a bad signal for two-door Malibus, but the overall number of Malibus is not a negative signal. While we cannot rule this out, it does not seem plausible. We suspect that a consumer would infer quality, popularity and design based on the total inventory of a model level rather than based on the inventory of each of various sub-models. If that is the case, then inferences of popularity cannot explain the negative relationship between sales and inventory, controlling for variety.

The scarcity effect we observe is consistent with the notion that inventory influence consumer search. Consumers are likely to desire a particular sub-model. If there is only one unit available of their desired sub-model, then they may discontinue their search for a new vehicle and purchase the vehicle. However, if the dealer has several units that fit the consumer's preference, the consumer may continue her search, feeling confident that if she does not find a better match, she can return to the dealership. If the consumer continues her search, then at the very least it delays the sale, but worse, it risks losing the sale - the consumer might discover a better match at another dealership. Thus, we find evidence that low inventory reduces consumer procrastination and motivate an immediate sale.

Robustness analysis

In our first robustness analysis we want to study to what extent our results are affected by competition among dealers of the different GM brands. As mentioned earlier the dealer model fixed effects included in our main specification account for the average competition intensity for a particular model at a dealer. However, inventory level for a model at the dealers vary from one week to another and this variation can potentially change the competitive landscape for the dealers. To explore the impact of these changes we estimate our main model with a subsample of dealers that don't face competition in their local market. This requires definining the relevant market of a dealer. Albuquerque and Bronnenberg (2012) conduct a study of dealership's demand for autos and show that a 15 mile radius covers most of the relevant market of a dealership. Hence, we defined a sub-sample of dealers with no competing GM dealer, of each particular brand, within a 15 mile radius. The analysis with this sub-sample is reported on the first column of Table 5. This result is consistent with the results obtained with the complete sample and suggests that our main results are not confounded by the impact of competition patterns between GM dealers.

To evaluate how robust our analysis is to different specifications of the variety variable, we replicated the analysis described on the previous section considering two alternative measures of variety: (i) $AvailVar_{ijt}$, the total number of different sub-models carried by a dealer on each week (instead of the relative measure of variety considered before); and (ii) the logarithm of $AvailVar_{ijt}$. The results for these two alternative specifications are reported in columns (2) and (3) of table 5. First, we note that the coefficient of inventory barely changes (compared to that of Table 4 column (1)). Second, the coefficient of variety is positive and significant in both specifications.

Another potential estimation issue is that *Sales*, our main dependent variable, is a count variable with frequent zeroes (about 60% of the weekly model sales were zero). A negative binomial regression, which accounts for the counting nature of sales, could increase the model fit and therefore lead to more precise estimates. We argue, however, that our estimation strategy – which is consistent under weaker assumptions – already provide precise estimates of the coefficients of interest. Nevertheless, we estimated a model of sales via a negative binomial regression, including inventory as independent variable. We used a control function approach to account for the endogeneity of inventory (see Wooldridge (2010) and Hilbe (2011) for details on the implementation of the control function approach in negative binomial regressions). The results are presented in column (4) of table 5. The overall effect of inventory for this model is still negative and statistical significance as in the comparable specification reported in table 4, column (3).

We also considered alternative specification that include inventory with log transformation, variety measured in the actual number of sub-models (as defined by AvailVar rather than Variety), its logarithm, and combinations of these. The results obtained were similar in magnitude and statistical significance.

6 The impact of inventory allocation

Our empirical estimation reveals that adding inventory to a dealer is only beneficial if the added vehicle expands the dealer's set of sub-models - increasing the inventory of a particular sub-model actually lowers sales. This sections explores the potential sales benefit of using this result to better allocate vehicles to dealers. We take two different approaches. The first approach estimates the potential sales improvement from reallocating the existing vehicles among the dealers in a small local area. The second approach considers only the incoming vehicles to a larger region (e.g., a state) and attempts to maximize sales by allocating those vehicles to the dealers in the area while leaving the dealers' existing inventory intact.

Given the size of our data-set (1289 dealers, 30 weeks, etc) we focus our analysis on a particular week (the week with the median number of total cars) and the ten most popular models. These models represent approximately sixty percent of the weekly sales across all the GM models in our sample: Cobalt, Equinox, G6, HHR, Impala, Suburban, Tahoe, TrailBlazer, Saturn, VUE, and Yukon.

6.1 Local reallocation among dealers

This section partitions dealers into reasonably small local markets. For each model we know each dealer's available inventory in our chosen week. Some dealers may have multiple units within a sub-model and other dealers within the same local market might not have any vehicles of that sub-model. Hence, based on our results, both dealers could benefit from a vehicle transfer - moving a vehicle from the dealer with multiple units to the dealer with no units increases sales at both dealers. Thus, we evaluate for each model the total sales gain across all markets that could be achieved by intelligently transferring vehicles so as to maximize the variety each dealer offers and to minimize the duplication of units within sub-models. We do not model the cost of actually transferring these vehicles - any sales improvement from reallocation would have to be compared with the cost of achieving the better balance of variety across dealers.

We group dealers as part of the same local market if they are in the same core based statistical area (CBSA) - a CBSA is a U.S. geographic area defined by the Office of Management and Budget based around an urban center of at least 10,000 people and adjacent areas that are socioeconomically tied to the urban center by commuting. We consider vehicle swaps only between dealers in the same CBSA. Hence, the total inventory within each CBSA remains constant. In addition, we require that each dealer's total inventory remains constant - each dealer that gains a vehicle must also give up a vehicle.

In the selected week, for each CBSA and each model j we solve the following integer non-linear optimization problem:

$$\max_{Q_{ijk}} \left[\sum_{i=1}^{n} \exp \left(C_{ij} + \bar{\beta}_{13} \sum_{k=1}^{m_j} Q_{ijk} + \bar{\beta}_{12} \cdot \text{Variety}_{ij} \right) \right]$$
 (6)

s.t.

$$\sum_{i=1}^{n} \sum_{k=1}^{m_j} Q_{ijk} = \sum_{i=1}^{n} \sum_{k=1}^{m_j} I_{ijk}$$
(7)

$$\forall i \qquad \sum_{k=1}^{m_j} Q_{ijk} = \sum_{k=1}^{m_j} I_{ijk} \tag{8}$$

$$Variety_{ij} = \frac{\sum_{k}^{m_j} \mathbb{I}(Q_{ijk} \ge 1)}{m_j}$$
(9)

$$Q_{ijk} \geqslant 0 \tag{10}$$

where

- n is the number of dealers within a CBSA
- m_i be the total number of sub-models for model j.
- I_{ijk} is dealer i's initial endowment of inventory of model j and sub-model k (i.e., if there is no reallocation)

- Q_{ijk} is the number of vehicles at dealer i of model j and sub-model k after the reallocation of vehicles among the dealers within the CBSA.
- C_{ij} , $\bar{\beta}_{12}$, and $\bar{\beta}_{13}$ are the estimated coefficients from the first column of Table 4.

Constraint (7) ensures that the reallocation does not change the total inventory within the CBSA of submodel k and constraints (8) ensure that dealer i's inventory of model j after the exchanges is identical to its inventory before the exchange. The objective is then to maximize $Variety_{ij}$ (9) while keeping the dealership's model inventory constant.

The first column on Table 6 shows the solution to this math program, measured by the average potential sales improvement for each car model. We find that on average, exchanging inventory among dealers within a CBSA with the objective of maximizing each dealer's offered variety yields an weighted average sales gain of 1.7%.

6.2 State-wide reallocation of vehicles

Instead of swapping vehicles after they arrive at dealerships, we now consider changing the allocation of vehicles after they leave the production facility. At that point in time there may be some flexibility with respect to the final destination of vehicle and this flexibility may come with little incremental cost. In particular, we estimate the sales gain that can be achieved through smarter allocation of vehicles that arrive to a particular state in a given week. With this approach there are no transfers among dealers - each dealer's initial inventory remains with that dealer. However, rather than send sub-model k to a dealer who already has some units of sub-model k, it is better to send that vehicle to a dealer who begins the week without any units of sub-model k.

For each state and each model j we solved the following integer non-linear optimization problem:

$$\max_{Y_{ijk}} \left[\sum_{i}^{n} \exp \left(C_{ij} + \bar{\beta}_{13} \cdot \sum_{k}^{m_j} Q_{ijk} + \bar{\beta}_{12} \cdot \text{Variety}_{ij} \right) \right]$$
 (11)

s.t.

$$\sum_{i}^{n} Y_{ijk} = A_{jk} \tag{12}$$

$$\sum_{k}^{m_j} Q_{ijk} \le M_{ij} \tag{13}$$

$$Q_{ijk} = I_{ijk} + Y_{ijk} (14)$$

$$Variety_{ij} = \frac{\sum_{k}^{m_j} \mathbb{I}(Q_{ijk} \ge 1)}{m_j}$$
 (15)

$$Y_{ijk} \geqslant 0 \tag{16}$$

where

- n is the number of dealerships in the state
- Y_{ijk} is the number of units dealer i receives of model j and sub-model k during the week.
- A_{jk} is the total number of model j and sub-model k vehicles sent to that state during the week.
- M_{ij} is the maximum number of vehicles dealer i carried of model j across our 30 week sample.

Constraint (12) ensures that the state receives the same number of vehicles of model j and sub-model k as we observed in our data for the chosen week. Constraint (13) ensures that dealer i's inventory of model j after the assignment is not greater than the maximum number of vehicles of model j that dealer i had in any week of our sample. This precludes allocations that result in some dealers having an unreasonable amount of inventory. Equation (14) merely states that a dealer's inventory of a model equals the dealer's initial endowment, I_{ijk} , plus the dealer's allocation, Y_{ijk} .

The second column on Table 6 shows average results for each model in this state-wide allocation problem. On average, we find that routing vehicles to dealers in a state so as to minimize overlap within a dealer's inventory while maximizing variety across dealers yields an average sales increase of 2.5%.

7 Conclusion

We develop an econometric model to estimate the effect of inventory on sales at U.S. automobile dealerships. Theory is ambiguous with respect to the impact of inventory on sales. There are several mechanisms that lead to a billboard effect - a positive relationship between inventory and sales. For example, at a basic level, adding inventory can increase sales by reducing stockouts, or by expanding the variety of sub-models available. However, there are mechanisms that lead to a scarcity effect - a negative relationship between inventory and sales. For instance, adding inventory may encourage additional search

In our sample, we find that an increase in inventory at a dealer actually lowers sales. However, it is important to decompose this effect into two parts: increasing inventory of a sub-model does indeed reduces sales, but if the increase in inventory also expands the number of sub-models available, then sales increase. In short, the benefit of expanding variety can dominate the negative effect of increasing inventory within a sub-model. This is consistent with two mechanisms relating inventory to demand: (i) expanded variety enables a better fit to consumer preferences, thereby increasing demand, and (ii) too many of the same sub-model encourages consumers to procrastinate the purchase decision, thereby lowering sales. To maximize sales a dealer wants to have one unit of each sub-model (to generate an urgency to "buy now before they are all gone") while also having as many sub-models available as possible, to cater to the heterogeneous tastes of consumers.

Our findings emphasizes the importance of careful vehicle allocation. The data suggest that vehicles are allocated in a way that does not maximize the heterogeneity of sub-models available to consumers. Dealers may view one sub-model as particularly desirable and then take actions to increase their inventory in that sub-model rather than to expand the set of sub-models offered. Based on our estimates, an allocation policy that is focused on maximizing variety can increase sales by about 2.5%, without changing the number of vehicles produced or the number of vehicles each dealer carries. In some cases this sales improvement may come with relatively little incremental costs - transportation costs are dominated by the frequency and quantity of deliveries, and less so by the composition of each delivery.

A Appendix

Proof Proposition 1

Starting from a system of the form:

$$Sales = \beta_{12} Variety + \beta_{13} Inventory + \gamma_1 Z + \varepsilon_1$$
 (17)

$$Variety = \beta_{23}Inventory + \gamma_2 Z + \varepsilon_2$$
 (18)

$$Inventory = +\gamma_3 Z + \delta_3 W + \varepsilon_3 \tag{19}$$

If $E(\varepsilon_g|Z,W)=0$, for all $g\in\{1,2,3\}$, $E(\varepsilon_1\varepsilon_2)=0$ and $E(\varepsilon_2\varepsilon_3)$, then all the parameters of the system of equations (1)-(3) are identified.

Proof. The reduced form of the system of equations (1)-(3) is denoted by:

$$Sales = \pi_1 Z + \psi_1 W + u_1 \tag{20}$$

$$Variety = \pi_2 Z + \psi_2 W + u_2 \tag{21}$$

$$Inventory = \pi_3 Z + \psi_3 W + u_3 \tag{22}$$

Because Z and W are exogenous, the coefficients (π_1, π_2, π_3) and (ψ_1, ψ_2, ψ_3) are identified, as well as the covariance matrix of the reduced form error terms (u_1, u_2, u_3) , denoted by Ω .

The triangular structure of the system (17)-(19) facilitates its inversion into the reduced form system (20)-(22). First, equations (19) and (22) are identical, so $\pi_3 = \gamma_3$ and $\psi_3 = \delta_3$. Hence, equation (22) alone identifies γ_3 , ψ_3 and $\Sigma_{33} = Var(\varepsilon_3)$. For equation (21) we have:

$$\pi_2 = \beta_{23}\gamma_3 + \gamma_2 \qquad \psi_2 = \beta_{23}\delta_3$$

so β_{23} and γ_2 are also identified. The variance of u_2 is given by:

$$\Omega_{22} = \Sigma_{22} + \beta_{23}^2 \Sigma_{33}$$

which identifies $Var(\varepsilon_2) = \Sigma_{22}$.

For equation (20):

$$\pi_1 = \beta_{12}\beta_{23}\gamma_3 + \beta_{12}\gamma_2 + \beta_{13}\gamma_3 + \gamma_1$$

$$\psi_2 = \beta_{12}\beta_{23}\delta_3 + \beta_{13}\delta_3 \tag{23}$$

with unknowns β_{12} , β_{13} and γ_1 . Additional identifying equations can be obtained from Ω , the covariance matrix of the reduced form error u. The assumptions $E(\varepsilon_1\varepsilon_2) = E(\varepsilon_2\varepsilon_3) = 0$ imply that:

$$\Omega_{12} = \beta_{23} \Sigma_{13} + \beta_{12} \left(\Sigma_{22} + \beta_{23} \Sigma_{33} \right)$$

$$\Omega_{13} = \Sigma_{13}$$

which together give:

$$\beta_{12} = \frac{\Omega_{12} - \beta_{23}\Omega_{13}}{\beta_{23}(1 - \beta_{23})\Sigma_{33} + \Sigma_{22}}.$$

Replacing in (23) identifies the other parameters.

Table 1: Dealers by state in our sample

State	Number of Dealers
California	355
Colorado	67
Florida	237
Main	31
Nebraska	50
Texas	366
Wisconsin	183
TOTAL	1,289

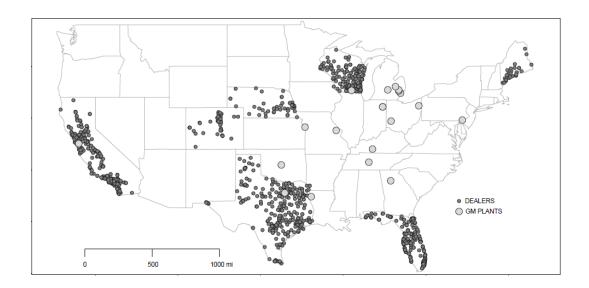


Figure 2: Dealer and plant locations in our sample

Table 2: Model Variety for the top ten selling models

	Total Model Variety (MarketVar)	Average Variety Available (AvailVar)
Cobalt	18	3.5
Equinox	4	2.2
G6	37	6.1
$_{ m HHR}$	4	2.9
Impala	10	3.7
$\operatorname{Suburban}$	18	4.5
Tahoe	13	4.0
TrailBlazer	10	2.1
Saturn VUE	5	4.6
Yukon	30	8.6
AVERAGE	14.9	4.2

Model Variety is the maximum number of variants that could be produced for the model.

Available variety is the number of variants with at least one unit during a particular week.

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Lable 3	Weather	variables	included	in the	empirical	stud v

Variable	Description
Wind	Number of days in which a wind advisory is issued by the National Weather
	Service Forecast Office. A wind advisory is issued when maximum wind speed
	exceeds a threshold for the area which is typical in excess of 40 miles per hour.
Cloud	Average cloud cover during the week $(0 = \text{no clouds}; 8 = \text{sky completely})$
	covered).
Fog 1	Weeks with 1 days with fog during the week.
Fog 2-3	Weeks with 2 or 3 days of fog during the week.
Fog 4-7	Weeks with more than 3 days of fog during the week.
Rain 1-2	Weeks with 1 or 2 days of rain during the week.
Rain 3-5	Weeks with 3 to 5 days of rain during the week.
Rain>5	Weeks with more than 5 days of rain during the week.
Snow 1	Weeks with 1 day of snow during the week.
Snow 2-4	Weeks with 2 to 4 days of snow during the week.
Snow>4	Weeks with more than 4 days of snow during the week.
High Temp 1	Weeks with 1 day of high temperature, above 90 degrees Fahrenheit, during
	the week.
High Temp 2-5	Weeks with 2 to 5 days of high temperature, above 90 degrees Fahrenheit,
	during the week.
High Temp 6-7	Weeks with more than 5 days of high temperature, above 90 degrees
	Fahrenheit, during the week.

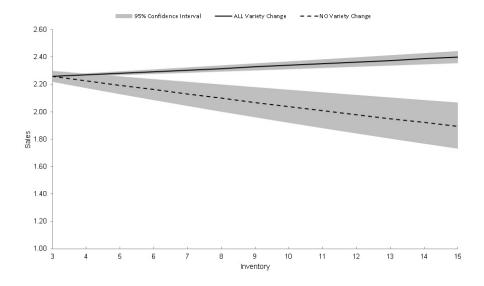
Table 4: Main Model Results - Log Linear Model

	(1)	(2)	(3)	(4)
Inventory	-0.0147***	-0.0140***	0.0130***	-0.0189***
	(0.0030)	(0.0030)	(0.0002)	(0.0034)
Variety	0.2958***			0.7223***
	(0.0094)			(0.0487)
Fixed Effects	YES	YES	YES	YES
Week - Season	YES	YES	YES	YES
Dealer's Local Weather	YES	YES	YES	YES
\overline{N}	293776	293776	293776	293776
N_g	12969	12969	12969	12969

Standard errors in parentheses

- (1) Main estimation results where the estimates are obtained instrumenting the endogenous inventory and variety.
- (2) Estimation results for the overall impact of inventory on sales instrumenting the endogenous inventory.
- (3) Estimation results for the overall impact of inventory on sales *without* instrumenting the endogenous inventory.
- (4) Estimation results where the estimates are obtained instrumenting the endogenous inventory and *without* instrumenting variety.

^{*} p < 0.05 , ** p < 0.01 , *** p < 0.001



The Figure illustrates the overall impact of inventory on sales with the vehicle allocation policy that maximizes the expansion of variety (black line) compared to the allocation policy that expands inventory without increasing the number of sub-models available (dashed line), for a dealer that starts with 3 vehicles of a particular model.

Figure 3: Sensitivity Analysis

<u>_</u>	Table 5: Robustness Checks			
	(1)	(2)	(3)	(4)
Inventory	-0.0171*	-0.0151***	-0.0156***	-0.0752***
	(0.0074)	(0.0030)	(0.0030)	(0.0114)
Variety	0.2847***			
	(0.0123)			
AvailVar		0.0421***		
		(0.0012)		
Log(AvailVar)			0.1310***	
			(0.0034)	
Fixed Effects	YES	YES	YES	YES
Week - Season	YES	YES	YES	YES
Dealer's Local Weather	YES	YES	YES	YES
N	150619	274399	274399	274399
N_g	6803	11879	11879	11879

Standard errors in parentheses

- (1) Analysis excluding dealers that have another GM dealer within a 15 miles radius.
- (2) Analysis including variety as a count of different submodels.
- (3) Analysis including the logarithm of variety as a count of different submodels.
- (4) Analysis considering a negative binomial specification.

^{*} p < 0.05 , ** p < 0.01 , *** p < 0.001

Table 6: The impact of inventory allocation

	Average CBSA Improvement	Average State Improvement	
	Vehicle Swap	Reallocation	
Cobalt	0.7%	2.0%	
Equinox	0.5%	1.5%	
G6	0.5%	2.0%	
$_{ m HHR}$	0.5%	4.8%	
Impala	0.9%	3.9%	
$\operatorname{Suburban}$	1.4%	1.2%	
Tahoe	0.9%	1.7%	
TrailBlazer	0.7%	0.6%	
Saturn VUE	5.6%	3.0%	
Yukon	4.5%	2.6%	
WEIGHTED AVERAGE	1.7%	2.5%	

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