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Econometric Analysis of Pricing and Operational Strategies

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Abstract
This dissertation contains three essays. The first essay, entitled *"Pricing and Production Flexibility: An Empirical Analysis of the U.S. Automotive Industry,"* uses a detailed dataset of the U.S. auto industry to examine the relationship between production flexibility and responsive pricing. Our analysis shows that deploying production flexibility is associated with a reduction in observed discounts and with an increase in plant utilization. Our results allow quantifying some of the benefits of production flexibility. The second essay, entitled *"An Empirical Analysis of Reputation in Online Service Marketplaces,"* uses a detailed dataset from a leading online intermediary for software development services to empirically examine the role of reputation on choices and prices in service marketplaces. We find that buyers trade off reputation and price and are willing to accept higher bids posted by more reputable bidders. Sellers primarily use a superior reputation to increase their probability of being selected, as opposed to increasing their prices. Our analysis shows that the numerical reputation score has a smaller effect in situations where there exists a previous relationship between buyer and seller, when the seller has certified his or her skills, when the seller is local, or in situations that prompt higher interpersonal trust. The third essay, entitled *"The Effects of Product Line Breadth: Evidence from the Automotive Industry,"* studies the effects of product line breadth on market shares and costs, using data from the U.S. automotive industry. Our results show a positive association between product line breadth and market share and production costs. Beyond the effects on production costs, we study the effect of product line breadth on mismatch costs, which arise from demand uncertainty, and we find that product line breadth has a substantial impact on average discounts and inventories. Our results also show that platform strategies can reduce production costs and that a broader product line can provide a hedge against changes in demand conditions.

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has given up on too many things to make my dream come true. She has been a constant source of support and inspiration and she is the most wonderful partner one can hope to have. Our son Pau was born during my doctoral studies and brought joy and fun to the last years of this adventure. As I am writing these lines, even more fun awaits us. Without Maria's company and love, this journey would have not been possible. I dedicate my work to her.

ABSTRACT

ECONOMETRIC ANALYSIS OF PRICING AND OPERATIONAL STRATEGIES

Antonio Moreno-Garcia

Christian Terwiesch

This dissertation contains three essays. The first essay, entitled *"Pricing and Production Flexibility: An Empirical Analysis of the U.S. Automotive Industry,"* uses a detailed dataset of the U.S. auto industry to examine the relationship between production flexibility and responsive pricing. Our analysis shows that deploying production flexibility is associated with a reduction in observed discounts and with an increase in plant utilization. Our results allow quantifying some of the benefits of production flexibility. The second essay, entitled *"An Empirical Analysis of Reputation in Online Service Marketplaces,"* uses a detailed dataset from a leading online intermediary for software development services to empirically examine the role of reputation on choices and prices in service marketplaces. We find that buyers trade off reputation and price and are willing to accept higher bids posted by more reputable bidders. Sellers primarily use a superior reputation to increase their probability of being selected, as opposed to increasing their prices. Our analysis shows that the numerical reputation score has a smaller effect in situations where there exists a previous relationship

between buyer and seller, when the seller has certified his or her skills, when the seller is local, or in situations that prompt higher interpersonal trust. The third essay, entitled "*The Effects of Product Line Breadth: Evidence from the Automotive Industry*," studies the effects of product line breadth on market shares and costs, using data from the U.S. automotive industry. Our results show a positive association between product line breadth and market share and production costs. Beyond the effects on production costs, we study the effect of product line breadth on mismatch costs, which arise from demand uncertainty, and we find that product line breadth has a substantial impact on average discounts and inventories. Our results also show that platform strategies can reduce production costs and that a broader product line can provide a hedge against changes in demand conditions.

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Chapter 1

Introduction

This dissertation contains three independent essays that contribute to the empirical literature in operations and information management.

The first essay, entitled *"Pricing and Production Flexibility: An Empirical Analysis of the U.S. Automotive Industry,"* examines the benefits of production flexibility in the automotive industry. Although the costs of deploying production flexibility are typically known to the firms, the benefits of flexibility are often more elusive. The main objective of this essay is to understand the interplay between pricing and production flexibility and to quantify the benefits of production flexibility. While there is a vast theoretical literature on production flexibility with endogenous pricing (e.g., Van Mieghem and Dada, 1999; Chod and Rudi, 2005; Goyal and Netessine, 2007), no previous work has empirically studied how flexibility affects prices. This essay combines several proprietary datasets of the U.S. automotive industry that provide production, sales and pricing information between 2002 and 2009. During this period, multiple vehicle models experienced changes in the flexibility with which they were manufactured (from inflexible to flexible or vice versa). This gives an identification strategy to examine the effect of flexibility. The analysis shows that deploying production flexibility is associated with reductions in observed discounts, as a result of an increased ability to match supply and demand. Under the market conditions observed between 2002 and 2009, flexibility accounts for average savings in discounts of $200 to $700 per vehicle. The deployment of flexibility has effects on plant utilization, too. Jordan and Graves (1995) suggest a positive association between flexibility and capacity utilization when prices are exogenous. The ability to use responsive pricing does not alter this positive association, and the results empirically support the claim that the deployment of flexibility is associated with an increase in plant utilization (4% higher in the analyzed period).

The second essay, entitled *"An Empirical Analysis of Reputation in Online Service Marketplaces,"* is concerned with a recent phenomenon of increasing economic importance. Technology has reduced the transaction costs associated with outsourcing tasks, and markets that match service buyers (firms or individuals who post work they would like to procure) and service sellers (firms or individuals who bid for the jobs posted by buyers) have proliferated. These markets have the potential to significantly affect the way service procurement is conducted, but they present novel challenges because buyers have little information about bidders and little control over their work, which leads to increased adverse selection and moral hazard problems, and to a higher uncertainty regarding the outcome of the collaboration. In this context, reputation systems are likely to play an important role in the service procurement process, but their impact in this setting has not been studied in the literature – unlike with product markets like eBay, where there has been extensive research (e.g., Bajari and Hortacsu 2004). This essay uses a detailed dataset from a leading online intermediary for software development services to empirically study reputation in online service marketplaces and its effect on prices and market outcomes. The analysis shows that buyers trade off seller reputation and price and are willing to accept higher bids posted by more reputable bidders. Sellers increase their bids with their reputation score, but primarily use a superior reputation to increase their probability of being selected as opposed to increasing their price. The essay also studies how various variables moderate the importance of the reputation score. The reputation score has a smaller effect in situations where there exists a previous relationship between buyer and seller, when the seller has certified his or her skills, when the seller is local, or in situations that prompt higher interpersonal trust.

The third essay, entitled *"The Effects of Product Line Breadth: Evidence from the Automotive Industry,"* studies the effects of product line breadth in the U.S. automotive industry during the period 2002-2009. Theoretical models (e.g., Lancaster 1990) suggest that broader product lines should result in higher firm market shares and in higher production costs. However, as noted by Netessine and Taylor (2007), "empirical researchers have analyzed linkages between variety and production costs, but have arrived at contradicting conclusions." This essay provides new evidence from the U.S. automotive industry, showing the effects of a broader product line on market shares and costs. The results suggest that one additional product in the line is associated with an increase of 0.1% in the market share of an automaker and with an increase of around $175 on the average production costs. In addition to providing evidence from a new industry to the literature on product line breadth, this essays attempts to bridge the gap between some theoretical notions that have been developed in the operations management and product development communities and the existing empirical literature on the effects of product line breadth. For example, Fisher (1997) discusses two types of costs in supply chains: *physical costs* are the costs of production, transportation and inventory storage, while *market mediation costs* arise "when supply exceeds demand and a product has to be marked down and sold at a loss or when supply falls short of demand, resulting in lost sales opportunities and dissatisfied customers." The literature on product line breadth has focused on the first type of costs, but has not considered the second type, which are a consequence of demand uncertainty and can be generically referred to as mismatch costs. In the automotive industry, mismatch costs can be observed in the form of discounts and inventories. The effects of product line breadth on mismatch costs are found to be substantial, with an additional product in the line being associated with an increase of around $100 in average discounts and with carrying three additional days of supply in the average inventory of the models offered by the firm. On the other hand, it has been suggested that product platforms (Robertson and Ulrich 1998) allow offering a broad product line while controlling production and development costs. Consistent with this view, data from the U.S. automotive industry shows that using platform families decreases the production costs. Finally, the essay develops an attribute-based measure of product line breadth that captures the range of fuel economy levels offered by an automaker, and shows that automakers who offer a broader range of fuel economy levels increase their market share and reduce their average discounts as gas prices increase, suggesting that choosing the right type of product breadth can provide a hedge against changes in demand.

While the three essays are independent and self-contained studies, each of them focusing on specific research questions, there are some common themes that are present in all of them, which broadly characterize the general contribution of this dissertation.

One common theme is that these three essays study questions that can be broadly characterized as pertaining to *operations strategy* (Van Mieghem 2008). The first essay is concerned with the strategic decision of deploying manufacturing flexibility (Van Mieghem 2008, Chapter 5) and the upsides of this decision in terms of pricing power and increased resource utilization. The second essay is concerned with the strategic decision of sourcing (Van Mieghem 2008, Chapter 7). In the setting of the second essay, sourcing is done through an online marketplace, and the focus of the work is to understand how buyers weigh seller reputation in their procurement strategy. The third essay is concerned with product line strategy and its effects on market shares and costs. The settings in which these questions are analyzed are complementary. Essays 1 and 3 focus on a manufacturing setting (the automotive industry), while the second essay focuses on a service context (software development).

The second common theme that the three essays touch on is *pricing*. The first essay analyzes how the deployment of product mix flexibility affects pricing power. The second essay analyzes the tradeoffs made between price and reputation by buyers and sellers of services in an online marketplace. The third essay provides evidence on how product line breadth affects price discounts.

A third common theme that is relevant to the three studies is the theme of *flexibility*. Flexibility is typically defined as the ability to adjust and respond to new information (Van Mieghem 2008), and it can take multiple forms. In the first essay, the main type of flexibility of concern is the ability to produce multiple products using the same resources. Firms can adjust to new conditions by adjusting their production mix and/or by using responsive pricing. The setting of the second essay could be characterized as one where workforce capacity is flexible. As opposed to maintaining a dedicated workforce, buyers can use online service marketplaces to tap into the global talent pool on an on-demand basis. On the other hand, there is flexibility on the seller side as well, since workers do not depend on a particular employer and can decide when to work. In the third essay, we consider a specific type of shock to which companies may want to adjust: changes in gas prices that change the relative demand for different products. Firms can respond to those changes by changing the production mix (as in Essay 1) or they can hedge against those changes by offering a broad product line (Essay 3).

Finally, on the methodological side, a common feature that is shared by the three essays is that they are all *empirical* studies. The three studies use *observational* data that comes from *proprietary* sources. For the first and the third essays, we have collaborated with TrueCar.com, a market research company specialized in new car pricing, and we have gained access to an extensive dataset on prices and incentives in the U.S. auto industry. We have combined this pricing data with other more widely available data about the U.S. automotive industry, including sales, production and plant data that comes from Ward's Automotive and Automotive News. For the second essay, we have partnered with vWorker (formerly rentacoder.com), one of the leading intermediaries for software development projects, who has given us access to the entire history of transactions conducted on the site, including more than 1,800,000 bids corresponding to more than 250,000 projects that were posted in between May 2001 and November 2010. Actually, one by-product of this dissertation is the compilation of these two novel datasets in the space of automotive pricing and online service marketplaces. These datasets can be used to study multiple questions in operations management and other related fields, beyond the essays included in this dissertation.

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Chapter 2

Pricing and Production Flexibility[1]

Abstract

Despite the abundant theoretical literature on production flexibility, price postponement and dynamic pricing, there exists limited empirical evidence on how production flexibility affects pricing decisions. Using a detailed dataset of the U.S. auto industry, we examine the relationship between production flexibility and responsive pricing. Our analysis shows that deploying production flexibility is associated with reductions in observed discounts, as a result of an increased ability to match supply and demand. We estimate that, under the observed market conditions between 2002 and 2009, flexibility accounts for average savings in discounts of \$200 to \$700 per vehicle. This is equivalent to savings of about 10% of the total discounts provided in the industry. We also demonstrate that list prices and plant utilization increase after the deployment of flexibility, providing additional sources of benefit from flexibility adoption. To the best of our knowledge, our paper provides the first piece of empirical evidence on how the deployment of production flexibility affects firms' pricing behavior.

[1] This chapter is based on Moreno, A., C. Terwiesch. 2011. Pricing and Production Flexibility. An Empirical Analysis of the U.S. Automotive Industry. Working Paper.

2.1. Introduction

Flexibility is typically defined as the ability to adjust and respond to new information (Van Mieghem 2008). Flexibility can take multiple forms. 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 (including yield management and revenue management; see Bitran and Caldentey 2003 for an overview). Flexibility can also exist with respect to a firm's production decisions (production flexibility). Typically, such changes in production take the form of different production quantities (volume flexibility, see Sethi and Sethi 1990) and different product mixes (mix flexibility, see Fine and Freund 1990).

The objective of this paper is to understand the interplay between pricing flexibility and production 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 towards more fuel efficient vehicles. The responses to this market shift varied substantially across automotive manufacturers. To illustrate this variation, consider two comparable vehicles in the mid-size SUV segment, the Ford Edge and the Honda Pilot. Both vehicles have the same fuel economy (17 mpg in the city and 23 mpg on the highway). Figure 2.1 shows how Ford and Honda reacted to the shift in demand towards more fuel efficient vehicles, away from SUVs. Figure 2.1 (left) displays monthly production levels. Production volumes for the Ford Edge remained relatively constant, while production volumes for the Honda Pilot were reduced as gas prices increased. Figure 2.1 (right) displays the average incentives the two manufacturers provided. We will provide a careful definition of incentives at a latter point. For now, observe that the incentives provided by Honda did not change with fuel prices, while incentives for the Ford Edge increased significantly over 2007. In other words, Ford relied on its ability to adjust prices (by providing incentives), while Honda relied on its ability to adjust production volume.

One of the essential aspects of production flexibility in the auto industry is given by the number of vehicle types that can be manufactured in a production facility. This is what the operations literature typically calls mix flexibility. Prior literature (e.g. Jordan and Graves, 1995) has identified some of the benefits of mix flexibility and has recognized that partial flexibility in the allocation of products to plants can yield most of the benefits of full flexibility. Our definition of flexibility (developed in Section 4) captures this notion of partial mix flexibility and is based on the ability of a plant to manufacture multiple platforms. According to our definition of flexibility, in 2007, the Honda Pilot was produced in flexible plants. We therefore consider it a "flexible model" for that time period. In contrast, the Ford Edge was produced in plants that could only produce this one SUV platform. We thus define it as an "inflexible model" for that time period. The two models in our motivating example also differ in a number of other aspects beyond flexibility, and no conclusion about the effect of flexibility can be drawn from the example alone. The rest of this paper explores systematically how companies adjust to changes in demand. In particular, the paper studies the relationship between production flexibility and 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, from now on "MSRP") for new vehicles are relatively easy to find. However, manufacturers constantly apply incentives that result in discounts and transaction prices that are significantly below the MSRP. These incentives and thus the actual transaction prices are much harder to obtain. The absence of pricing data has limited prior research to studying sales volume as opposed to analyzing the underlying demand dynamics. These demand dynamics, including the demand volatility, however, are essential when analyzing the benefits associated with flexibility.

We have collaborated with TrueCar.com, a market research company specialized in new car pricing, and we have gained access to a proprietary data set on prices and 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 consumer demand, changes in consumer demand, and manufacturer's responses to these changes, be it in the form of price adjustment or in the form of production adjustment. This allows us to empirically analyze the relationship between flexibility and pricing. Our main identification strategy exploits the fact that in our sample there are models that change their flexibility level from flexible to inflexible and vice versa. This unique dataset, together with our econometric approach, allows us to make the following three contributions:

First, we show how production flexibility affects incentives. Short run price adjustments in the automotive industry occur mainly through discounts from the MSRP that are implemented using incentives from the manufacturer. We provide evidence that deploying flexibility allows manufacturers to reduce the use of incentives, typically by between $200 and $700 per vehicle. To the best of our knowledge, this is the first empirical evidence supporting 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 2011).

Second, we analyze the effect of flexibility on plant utilization. Jordan and Graves (1995) suggest a positive association between flexibility and capacity utilization when prices are exogenous. The ability to use responsive pricing does not alter this positive association, and we empirically support the claim that the deployment of flexibility is associated with an increase in plant utilization. Our measure of flexibility is built on Jordan and Graves's chaining model, emphasizing the benefits of partial mix flexibility. We show that partial mix flexibility increases plant utilization by about 4%.

Third, we introduce a novel approach to measuring demand volatility. In presence of endogenous pricing, a measure of sales variance would be affected by the firm's discounting behavior, and would therefore be an unsuitable measure of volatility. Our measure is based on a structural choice model that includes the actual transaction prices. This enables us to estimate counterfactuals (what would have been demand had there been no discounts?). Using this structural model of demand volatility, we develop a cross-sectional analysis in which we show how demand volatility affects discounts. We show that models with lower demand volatility give lower discounts, regardless of production flexibility. This suggests that firms that can design vehicles that are not exposed to substantial demand volatility can avoid price discounts even when they do not rely on flexible production. Our demand model identifies Mini, Porsche, Smart, and Lexus as makes that were able to have a consistent demand pattern in an industry that was otherwise plagued by volatility.

The rest of the chapter is organized as follows. Section 2 discusses the underlying theory and related literature and also develops our main hypotheses. Section 3 describes our dataset. Section 4 describes our measures of production flexibility and demand volatility. Section 5 introduces the econometric specification and describes the identification strategy. In Section 6, we present our main results, followed by Section 7 which conducts several robustness checks and also explores alternative explanations. Finally, Section 8 concludes and points at some areas of current and future research.

2.2. Theoretical Context and Hypotheses

The literature on flexibility and the literature on dynamic pricing and revenue management provide the theoretical context for our work. Within the literature on flexibility, there exist a number of studies that have modeled the flexibility and production postponement decisions, to which our work is related. The earlier work in this research stream models the flexibility investment decision under uncertainty in product demand (Fine and Freund, 1990). Jordan and Graves (1995) introduced the concept of partial flexibility and demonstrate that partial flexibility can yield most of the benefits of full flexibility. Both of these studies, as well as many others not mentioned here, assume prices to be exogenous. In contrast, the literature on dynamic pricing and revenue management has largely focused on developing models that let firms adjust prices when capacity is exogenous. Gallego and Van Ryzin (1994) is a seminal paper in this line of research; see Bitran and Caldentey (2003) and Elmaghraby and Keskinocak (2003) for comprehensive overviews. 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 with respect to the demand uncertainty, in particular production and price postponement, 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 2011. Despite these careful analytical studies of dynamic pricing and production flexibility, the empirical evidence in this area remains scarce, which is one motivation of the present study.

A topic in the manufacturing strategy literature that has been empirically studied more extensively is what one might call the opposite of mix flexibility, focus. Focus has been shown to improve operational performance in some settings (e.g. Huckman and Zinner 2008, Kc and Terwiesch 2011). Our empirical analysis shows evidence of some positive benefits of producing multiple product lines in one facility (and thereby be unfocused) and thus speaks to the flexibility vs. focus debate.

The Marketing literature on promotions is also related to our work. This literature has mainly focused on quantifying the effect of promotion on sales (e.g. Gupta 1988) and other related issues (for a comprehensive review, see Neslin 2002). To our knowledge, no paper in this line of work has studied how decisions related to flexibility and utilization affect promotions and so we only mention this field for the sake of completeness.

A number of empirical operations papers have studied various aspects of the automotive production process, including MacDuffie et al. 1996, Fisher and Ittner 1999, and Fisher et al. 1999. Closest to our work, Cachon and Olivares (2010), study the drivers of inventory in the U.S. downstream automotive supply chain. Our paper is concerned with understanding the drivers of observed pricing, rather than the drivers of inventories, but we share their interest in the role of flexibility. Also, Goyal et al (2006), empirically study the drivers of manufacturing flexibility in the automotive industry. Our paper does not look into what drives flexibility, but into the effects flexibility has on pricing.

A key novelty of our paper is the fact that we consider the manufacturer's pricing. Very few empirical papers in operations management have examined the role of prices. An exception is Gaur et al. 2005, which investigates the correlation of inventory turnover and gross margin. Including prices also allows us to build a rich model of the demand dynamics, including an appropriate measure of demand volatility.

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 (can produce both types of vehicle) and inflexible (can only produce one type of vehicles). Following an increase in gas prices, demand for fuel inefficient vehicles decreases. The manufacturer can respond by offering more incentives (higher discounts from the MSRP) for fuel inefficient vehicles or by reducing the production volume of fuel inefficient vehicles. By definition, for a manufacturer with an inflexible plant, a reduction in production volume of the fuel inefficient vehicle implies a reduction in plant utilization. This leads to an increase in the average cost per vehicle in the plant, because the plant's fixed costs are spread over a lower number of units. Higher average costs result, all else being equal, in lower average profits per car. If the manufacturer with the inflexible plant decides to maintain high production volume (and thus high plant utilization), incentives are needed to avoid vehicles accumulating in inventory. In this case, the revenue per vehicle sold decreases, which also results in lower average profits.

A manufacturer with a flexible plant can shift production of the fuel efficient model to the plant that is presently producing the less attractive fuel inefficient vehicle. 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 go down. However, some pooling benefits exist even at modest levels of positive correlation and so the manufacturer with the flexible plant is less affected by the exogenous demand shock. Note that after adjusting the product mix, the manufacturer with the flexible plant might still decide to reduce plant utilization (at the expense of a higher average cost) or to increase incentives (at the cost of foregoing revenue). The optimal decisions will be a result of manufacturers playing a complex game in which the equilibrium decisions with regards to production volumes and incentives provided will depend 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 flexibility and incentives under the demand patterns observed during our period of analysis. The exact magnitude of the effect of flexibility will depend on the shape of the cost and demand curves as demonstrated in the recent modeling work by Ceryan et al (2011). Since flexibility allows manufacturers with a flexible plant to adjust the mix, these manufacturers have an additional tool they can use before engaging in giving costly incentives. We thus hypothesize:

Hypothesis H1. *The deployment of flexibility is associated with a reduction of the average incentives*

In addition to confirming that the direction of the effect is the one we hypothesize, we also seek to quantify the magnitude of the impact of flexibility on discounts for the US automotive market during the period covered by our data (2002-2009).

Next, we turn our attention to the relationship between flexibility and plant utilization. Firms can offer incentives to encourage sales. These incentives are hypothesized to be higher for inflexible plants and thus the relationship between flexibility and utilization depends on the actual cost and demand curves. In absence of a complete equilibrium model, we follow the Jordan and Graves (1995) argument that flexibility allows firms to change the production mix and thus provides them with an alternative to reducing plant utilization:

Hypothesis H2. *The deployment of flexibility is associated with an increase in plant utilization*

Again, rather than merely validating that the effect goes in the hypothesized direction, we are interested in providing an estimate of the magnitude of the effect of flexibility on plant utilization.

Our primary hypothesis H1 refers to effects of flexibility on incentives, but flexibility is not the only way in which firms can avoid giving incentives. Some manufacturers seem to be able to design and market vehicles that are not subject to substantial demand volatility. Understanding the causal pathway of how these manufacturers are able to limit demand volatility is beyond the scope of this paper. Instead, we restrict our last hypothesis to the effect of demand volatility on incentives:

Hypothesis H3. *Firms give lower incentives for vehicles with low demand volatility*

2.3. Empirical Setting and Data

Our empirical analysis focuses on the U.S. automotive industry, covering the section of the supply chain that spans from the manufacturers to the final consumers. There are three main reasons why we decided to choose the automotive industry as our empirical setting. First, the automotive industry is important on its own. The U.S. automotive industry is responsible for more than 3 million jobs in the U.S and contributes 5% of the total U.S. GDP (Ramey and Vine 2006). Second, it is an industry where operations and supply chain management play a major role, and companies are known to follow different operational strategies. Third, there is a limited amount of manufacturers in the market and their final product is comparable using a reduced number of attributes. The methodology that we use can be easily 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 a number of prices that govern the transactions between manufacturers, dealers and customers. The manufacturer sets the *MSRP*. Vehicles are typically allocated to dealers before they are produced. Manufacturers charge dealers the *invoice price* when the vehicle is released for transportation. The final *transaction price* is usually obtained after some haggling between the consumer and the salesperson. At predetermined times (typically quarterly), the manufacturer reimburses a percentage of the invoice price (or the MSRP, depending on the manufacturer), known as the *holdback*. This common practice explains how the dealers can profitably sell cars below the invoice price.

In addition to discounts, a manufacturer can offer *trade incentives* at various times. Incentives 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 loans in favorable conditions or other initiatives of financial nature.

In this paper we focus on the manufacturer's pricing decisions. To respond to changing market conditions, manufacturers offer varying levels of incentives to dealers and/or consumers. In 2009, auto companies reportedly spent more than $28 billion in incentives. Table 2.1 shows the average incentives offered by each manufacturer. This includes incentives given by the manufacturers to both dealers and final consumers, and includes the cost of financial incentives (e.g. 0% interest loans). However, it does not include the holdback, which is relatively stable over time and typically does not change with market conditions.

There exist systematic differences in the incentives that firms give. The Big Three are among the companies who offer the highest incentives, and Toyota and Honda are among the companies who offer the lowest incentives. Our analysis explains part of this observed variation through variables such as production flexibility and demand volatility. We will use firm (and model) level fixed effect to ensure that we truly identify the effect of flexibility as opposed to picking up firm level effects.

Our data covers the vehicles marketed in the U.S. in the period of 2002-2009. We have information on the 348 distinct *models* (e.g. Chevrolet Malibu) marketed in the U.S. during the period. Our analysis uses monthly data and we have a total of 20,052 model-month (e.g. Chevrolet Malibu, February 2003) observations. We combine three sources of data: volume data, pricing data and vehicle-level data.

Volume data. The volume data is obtained from WARDS automotive and includes monthly sales and domestic production (if applicable). Domestic production refers to vehicles produced in the U.S., Mexico or Canada. If a car is imported from outside this region, we label it as not domestic. We have information about the platform on which each of the domestically produced models is based and the segment to which they belong. We observe how domestic production is distributed across different plants, and also across different facilities within the plant (e.g. Fremont 1 and Fremont 2). We have also obtained data on the annual capacity of U.S. plants, which allows us to calculate the plant utilization.

Pricing data. We have obtained incentive data from TrueCar. TrueCar is a market information company that provides prospective car buyers with real transaction price data of new cars (www.truecar.com). TrueCar obtains data directly from car dealers, respected dealer management system (DMS) providers, and well-known data aggregators within the automotive space. We have collaborated with TrueCar and we have obtained access to some of their historical data. In this paper we focus on the incentives given by manufacturers. As are sales and production data, incentive data is available at the model-month level and indicate the average amount spent by the manufacturer for each vehicle sold in that month. The measure includes incentives given to the dealers and to the final consumers, and it also includes incentives of financial nature (e.g. credit in favorable condition), which are converted to their equivalent monetary values. The incentive figure does not include holdbacks, since these are not used to respond to market conditions. Not all the incentives are necessarily passed-through to the consumer (see Busse et al 2006), yet incentives always represent an additional cost to the manufacturer.

Vehicle level data. Our model of demand volatility uses data on vehicle attributes, which we also obtain from WARDS Automotive. The attributes we focus on are weight, horsepower, fuel economy, length, height, wheel base and MSRP. These attributes remain constant within the model year. Combining fuel economy with gas prices (obtained from the Energy Information Administration), we can generate a measure of miles per dollar, which varies monthly for every 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, because our sales, inventory and incentive data is 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. We also run some robustness checks using the minimum and the maximum of the attributes instead of the median.

2.4. Measures of Flexibility and Volatility

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. We refer the reader to the review by Sethi and Sethi (1990) that identifies over 50 ways to operationalize flexibility.

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 following the automotive industry. For example, the Prudential Report, a third party evaluation of the financial outlook of the various US car manufacturers, uses the number of nameplates manufactured in a production line as the criteria to define a plant as flexible. Lines producing more than one nameplate are considered flexible, while lines producing a single nameplate are considered inflexible.

We use a binary variable to code flexibility. We define a production facility as flexible if it produces more than one platform. We choose the number of platforms as opposed to the number of products 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" products can just be branded versions of the same vehicle). As an example, Figure 2.2 shows the allocation of platforms to plants for Nissan and Ford in the end of 2010. According to our measure, the four plants that Nissan has in North America were flexible in the end of 2010, while only five out of the thirteen North American plants that manufacture Ford vehicles were flexible. The figure is just a snapshot, as flexibility has evolved over time. With substantial investments, an inflexible plant can become flexible. In some rare 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.

Since our sales and incentive data are at the model-month level, we assign a flexibility score to every model on a monthly basis. A model is given a high flexibility score in a given month if it has at least some production in a domestic (North American) flexible facility. Previous research has shown that partial flexibility can go a long way in achieving the benefits of full flexibility (Jordan and Graves 1995). This insight has been extended to multi-stage supply chains (Graves and Tomlin 2003), queuing settings (Bassamboo et al. 2008), and newsvendor settings (Bassamboo et al. 2010). Model flexibility changes over time, since a model 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.

We consider fully imported models not flexible. Transportation adds a lead time of at least 4 to 6 weeks to the production time, meaning that firms have a limited ability to quickly adjust production to match changes in demand. The inability to adjust to demand because of poor mix flexibility and because of long lead times can have different effects. In order to make sure that our decision to code fully imported models as inflexible does not drive the results, we perform additional analyses without the fully imported models. Our results do not change qualitatively.

Using our definition of flexibility, we can perform a simple comparison between the incentives given for models manufactured with flexibility and for models manufactured without flexibility. The average incentive for models that are produced with flexibility was $2,691 in 2007, while the average incentive for models that are produced without flexibility was $3,411 in the same year. Not all the difference between the two groups ($720) comes necessarily from differences in flexibility. It could be, for example, that Japanese firms are more flexible and that Japanese firms also provide systematically lower discounts for reasons different from flexibility. A more refined econometric analysis is needed.

Our flexibility measure is based on the demonstrated ability to produce a mix, but a plant could have this flexibility and choose not to use it. Moreover, a plant can produce multiple products but have each product allocated to an independent production line without mix flexibility. To strengthen our measure of flexibility, we also created flexibility scores of the plants based on the subjective assessment of an industry expert. Ron Harbour is widely acknowledged as a leading expert in understanding the US automotive industry. He has visited every single plant in the US automotive industry and has been the producer of the Harbour reports (now published through Oliver Wyman). We compared his subjective assessment that he kindly provided to us with our measure and found them to largely be consistent. We also performed our empirical analysis using his evaluation as the flexibility measure and found the results to be similar. To allow future research to replicate our results and build on our work, the remainder of this paper is based on the objective flexibility measure that we previously defined.

Estimation of the demand system

A crude measure of demand volatility could be defined based on sales volatility. However, monthly sales depend on the incentives that are given. Ideally, we would like to measure the volatility of demand in absence of incentives. Since this is not possible, we have to create a structural model that models the underlying demand dynamics. We then can evaluate the counter-factual sales at non-discounted prices. Based on these sales data not polluted by price discounts, we can then generate our measure of volatility.

We start by estimating the parameters of the demand curve $D_{iym}(p)$, which gives the demand for vehicle i in year y and month m. This demand depends on the price of vehicle i, attributes of vehicle i, the prices of all vehicles in the market other than i, and the attributes of all vehicles in the market other than i.

The choice model that we use to estimate the demand system is a nested multinomial logit model. As in other multinomial models, each alternative (vehicle model) is defined as a bundle of attributes and consumers choose the one that gives them the highest utility or the outside option of not buying.

The nested multinomial logit model has the advantage that it allows reasonable substitution patterns and avoids the independence of irrelevant alternatives problem present in multinomial logit models, which imply proportional substitution patterns between alternatives (for more details, see Train 2009). With respect to other similar models like the random coefficients logit (Berry et al. 1995), it has the advantage that it is more parsimonious and that we do not need to specify a distribution for the heterogeneity of consumer preferences. The flexibility in the substitution patterns is given by the nests. In the nested logit model, the set of alternatives is partitioned into subsets. Substitution patterns are proportional within nests, but can vary across nests. We use the combination of vehicle segment and luxury indicator variables in the construction of the nests (for example, a nest contains "luxury SUVs").

To estimate the model, we follow the transformation described in Berry (1994) and write :

$$\ln\left(s_{jt}\right)-\ln\left(s_{0t}\right)=x_{jt}\beta+\alpha p_{jt}+\sigma\ln\left(s_{jt|g}\right)+\xi_{jt} \tag{2.1}$$

where s_{jt}, s_{0t} and $s_{jt|g}$ are, respectively, the market shares of model j in time t, the share of the outside good (no purchase) in time t and the share of the nest g to which model j belongs in time t; x_{jt} are the product characteristics, and ξ_{jt} is a shock unobserved to the econometrician. We do not observe the actual price p_{jt} faced by the consumer in time t. We approximate it as the list price minus the average incentive for model j at time t. As product characteristics, we use the vehicle size variables, a proxy for acceleration given by horsepower/weight and the miles per dollar, which depends on the current gas price and the MPG of the vehicle. We also include segment-time dummies.

We use instrumental variables to account for price endogeneity. The instrumental variables that we use are based on Berry et al. (1995). We include the characteristics of the other models of the same manufacturer and the characteristics of the rest of the vehicles on the market (for more details, see Berry et al. 1995). Changes in the choice set (introduction and removal of models), changes in vehicle attributes, changes in gas prices, and segment trends captured by the dummy variables allow us to identify the coefficients of the demand model. Table 2.A1 reports the estimates of the demand system.

Evaluation of counterfactual sales at reference prices

Once we have estimated the demand model, we can calculate counterfactual measures. We define $CSALES_{iym}=D_{iym}(p)$ as the counterfactual sales that we would expect to observe for model i in year y and month m, if the vehicles were priced at a price vector p. For the choice of the vector p, we can use a reference price level that is not affected by the incentive behavior. We propose using the list prices, but other alternatives are also possible (e.g. using the average prices).

The method allows us to construct an alternative series of counterfactual sales over the entire period of analysis. This series gives a measure of the underlying demand that is not contaminated by the incentives that the firms decided to give.

Generation of volatility measure

Based on the counterfactual sales $CSALES_{iym}$ at a vector of reference prices, we compute demand volatility VOL_m for a model as the coefficient of variation of this series:

$$VOL_m = \frac{stdev(\mathrm{CSALES}_{iym})}{mean(\mathrm{CSALES}_{iym})} \tag{2.2}$$

This gives a measure of demand volatility for each of the models in our dataset that is not contaminated by the incentive behavior.

2.5. Econometric Specification and Identification

Automotive manufacturers play a complex game in which the equilibrium decisions with regards to flexibility deployment, production and incentive will depend on their demand and cost curves and those of their competitors. One potential approach to analyze their decisions would be to fully characterize the problem that firms are solving and to structurally estimate the model primitives. However, the lack of cost data and the number of interdependent decisions that firms are making limit the appeal of such an approach. Our approach is instead to focus on the equilibrium average relationship between flexibility and incentives under the demand patterns observed during our period of analysis. We start by modeling the impact of flexibility on discounts (incentives).

We use a family of reduced form specifications that model discounts as:

$$DISCOUNT_{it} = \beta_0 + \beta_1 FLEX_{it} + CONTROLS_{it} + \mu_i + \gamma_{s(i)t} + u_{it} \tag{2.3}$$

where i is the model, t is the month and $s(i)$ is the segment to which model i belongs. All specifications include $FLEX_{it}$, the demonstrated flexibility measure described in Section 4; μ_i, a model fixed effect; $\gamma_{s(i)t}$, a variable that controls for segment-time interactions; and u_{it}, the error term. The set of additional controls includes the variables $DISCOUNT\_COMP_{it}$, the MPD_{it}, AGE_{it}, $INTRODUCTION_{it}$, $PHASE\_OUT_{it}$ and $DESIGN\_CHANGE_{it}$, described in Table 2.2.

Hypothesis H1 (the deployment of flexibility is associated with a reduction of the average incentives) holds if $\beta_1 < 0$, with β_1 giving the magnitude of the impact of flexibility on discounts.

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 features that do not change over time). The identification of the coefficients, including that of flexibility, will be based on temporal variations of the level of discounts for a given model. The identification of the coefficient of flexibility is achieved from vehicles that change from flexibility to inflexibility or vice versa. During our period of analysis, around 25% of the models experience some change in their flexibility score.

As an example of the variation that helps to identify the coefficient of flexibility, Figure 2.3 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 the average incentive is similar for both vehicles before that. In September 2004, the Nissan Pathfinder started to be produced in the flexible Smyrna Plant, making the model flexible according to our definition. After that, the average incentive for the Nissan Pathfinder dropped considerably, compared with the average incentive given for the GMC Envoy. Our econometric analysis does a more rigorous job by controlling for additional variables that may play a role before and after the deployment of flexibility. For example, in the period shown in Figure 2.3 there were also changes in MSRP. Therefore not all the difference in observed incentives comes from flexibility.

Using flexible technology to produce a model is clearly an endogenous decision, since firms choose which models to produce with flexible technology and when. 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.

Model fixed effects reduce the extent of the problem, because they account for any potentially ignored cross-sectional variable that might affect discounts and might be correlated with the adoption of flexibility. For example, labor practices that do not vary much during our period of analysis. If there existed a labor practice (e.g. union status) that would be correlated with the error term (i.e. it would affect incentives once controlling for everything else we observe) and would be correlated with flexibility, not controlling for labor practices would lead to biased estimates. Adding fixed effects deals with omitted variables (e.g. labor practices) that are constant over time for a given model.

The potential endogeneity concern is further attenuated if we control for additional variables. In particular, some of 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. Also, all our specifications include segment-time dummies. They account for any temporal shocks that affect all models of a given segment. This includes any temporal trends in discounts at the segment level as well as any global industry trends.

In order to be protected against any remaining source of flexibility endogeneity, we use instrumental variables. A good instrumental variable for the flexibility with which a 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 make 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. We have also used variations of the instrument (for example, excluding models that are manufactured in the same plant as the model of interest in the calculation of the average flexibility) without substantial changes in the results

The unit of observation for the specification described above is the model-month. Since the subjective assessment provided by the expert is at the plant level, we replicate the analysis at the plant level. In order to do that, we compute the production weighted incentive given at every plant. The econometric specification is the following:

$$DISCOUNT_{pt} = \beta_0 + \beta_1 FLEX_{pt} + CONTROLS_{pt} + \mu_p + \gamma_t + u_{pt} \tag{2.4}$$

where $DISCOUNT_{pt}$ is the production weighted average incentive, $FLEX_{pt}$ is the plant flexibility measure, $CONTROLS_{pt}$ include any 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 measure of demonstrated mix flexibility or the subjective flexibility measure provided by the expert.

In order to assess the impact of flexibility on utilization, we perform the analysis at the level of the manufacturing plant. We use the following specification:

$$UTIL_{pt} = \beta_0 + \beta_1 FLEX_{pt} + CONTROLS_{pt} + \mu_p + \gamma_t + u_{pt} \tag{2.5}$$

where $UTIL_{pt}$ is the plant utilization of plant p in month t, $FLEX_{pt}$ is the plant flexibility and $CONTROLS_{pt}$ include any plant level controls. The model includes plant fixed effects and time effects. Again, the identification of the effect of flexibility comes from temporal variations in plant flexibility. Hypothesis H2 (the deployment of flexibility is associated with an increase in plant utilization) holds if $\beta_1 > 0$, with β_1 giving the magnitude of the impact of flexibility on discounts.

Finally, in order to test Hypothesis H3 (firms give lower incentives for vehicles with low demand volatility), we focus on the cross-sectional variation, and we compute discount and volatility measures for each model. Our objective is to assess whether some of the cross-sectional differences between model discounts can be attributed to differences in demand volatility. Define:

$$\overline{DISCOUNT_i} = \theta_0 + \theta_1 VOL_i + \varepsilon \tag{2.6}$$

where $\overline{DISCOUNT_i}$ is the average discount given for model *i* during our period of analysis, and VOL_i is the volatility of demand of model i during the period of analysis, calculated using the model described in Section 4. Note that this specification does not account for those variables affecting the average discount that were considered in our model described in Equation 2.3, such as flexibility and other controls. To incorporate the effect of those variables, we can use the model fixed effect μ_i from (3) as the dependent variable. The model fixed effect represents the persistent model level shock in discounts, net of the effect of the other variables of the model. Define:

$$\mu_i = \theta_0 + \theta_1 VOL_i + \varepsilon \tag{2.7}$$

Hypothesis H3 holds if $\theta_1 > 0$. Note that in this specification the analysis is cross-sectional, and we have only one observation per model. Equation 2.7 links the coefficient of variation of demand over the entire period with the model-fixed effect on the incentives.

2.6. Results

We begin by estimating the models characterizing model level discounts (Equation 2.3). Table 2.3 shows the estimates using OLS. The first three columns focus on vehicles with some domestic production (that is, excluding fully imported vehicles), while Columns 4, 5 and 6 show the estimates using all the vehicles marketed in the U.S., including those that are fully imported.

Columns 1 and 4 show the estimates including the flexibility and the competitor discounts variables and segment time interactions, but without any other controls and without including fixed effects. In both groups the flexibility coefficient is negative and significant, suggesting that flexibility is associated with lower discounts. However, in these cases endogeneity is a serious concern - flexible vehicles might have other characteristics that result in the observed lower discount activity.

Columns 2 and 5 incorporate model fixed effects, which account for persistent unobserved variables at the model level. The effect of flexibility is still negative and significant when we add the model fixed effects (-202.4 for the models with domestic production and -300.5 for all the models). Columns 3 and 6 incorporate additional controls for some variables that change over time. The flexibility estimate remains almost constant across these models, which suggests that flexibility adoption is not correlated with those observed variables. Columns 3 and 6 are our preferred specifications in Table 2.3, as they include all controls. We observe an estimated effect of flexibility on discounts of -215.5 for vehicles with domestic production and -$293.8 for all vehicles. 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. Standard errors are robust and clustered by model. The results of Table 2.3 show that the effect of flexibility is both statistically and economically significant. Flexibility explains about 10% of the average discount. Discounts of the competitors in the segment are partially matched (around $0.25 per dollar of competitor discounts, when including the controls).

Despite our extensive set of controls, the OLS specification estimated in Table 2.3 can still suffer from an endogenous vehicle-to-flexibility assignment as described in Section 5. Table 2.4 shows the estimates when we use the average flexibility of the rest of the models of the same make as an instrument for flexibility and then estimate the model using 2SLS. Again, we separately report the results for the vehicles with domestic production (Columns 1 and 2) and for all vehicles (Columns 3 and 4).

The estimates displayed in Table 4 show that the coefficient of flexibility is even more negative when using the instrumental variable estimation. The rest of coefficients remain largely unchanged. Our preferred specifications are the ones given in Columns 2 and 4, which include all the control variables, besides the model fixed effects and the segment-time dummies. These columns suggest an effect of -699 and -1295 for the vehicles with domestic production and for all vehicles, respectively. Both the OLS and the 2SLS results show support for H1. In other words, the adoption of flexibility is associated with a reduction of discounts. In the IV model, the point estimates, which quantify the average effect of flexibility on discounts, change significantly compared to the OLS estimates. The Durbin-Wu-Hausman test allows us to reject the hypothesis that the flexibility is exogenous (e.g. $p=0.0054$ for the specification shown in Column 2) and therefore the 2SLS method is suitable. However, as often is the case with IV estimation, we have to acknowledge that our instrument might have problems related to the violation of the two conditions, instrument exogeneity and relevance.

The IV model assumes that the discounts given for a model are not affected by the flexibility of the other plants. This instrument exogeneity condition is not testable in our case, because we only have one instrument. We are thus in the just-identified case. If the relevance condition is satisfied only weakly, it is well known that instrumental variables can have a small sample bias (for example, see Angrist and Pischke 2009). The instrument is correlated with the endogenous variable and the first stage for Column 2 has an adjusted R-squared of 0.744, but the Partial R-squared is 0.06, which seems somewhat low, suggesting that we should be cautious because we might have a weak instrument. Another potential problem could be that the instrument might affect a particular subpopulation more significantly, and it also might be picking up additional effects, such us portfolio effects that might or might not be related to flexibility.

Altogether, these potential problems with the instruments suggest that we should not take the 2SLS estimates at face value. But this does not mean that they are useless. The results of the instrumental variable estimation suggest that our OLS estimation, if biased, is probably biased upwards, and that the effect of flexibility on discounts is stronger than the effect estimated by OLS. Thus, we can consider our OLS results as a lower bound on the effect of flexibility.

The modeling literature can offer some guidance in interpreting our findings and in understanding in what direction our OLS estimates are likely to be biased. Demand uncertainty has been identified as one of the key drivers of flexibility adoption (Fine and Freund 1990, Swaminathan and Lee 2003). We can argue what the likely direction of the bias would be if flexibility is adopted as a response to increased expected uncertainty for the demand of one model. 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 will probably result in higher average discounts. To see that, note that 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. Since the upward price increases are capped by the list price, we expect the average effect to result in higher discounts. If the flexibility adoption 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. Therefore the OLS coefficient of flexibility would be biased upwards. This is consistent with the results that we find with our instrumental variable specification.

In summary, our results indicate that under the observed market conditions between 2002 and 2009, flexibility accounts for average savings in discounts of between $200 and $700 per vehicle, for cars with domestic production. The results of the analysis using the subjective measure of flexibility are qualitatively similar and are shown in Table 2.A2 in the Appendix.

Turning our attention to the effect of flexibility on utilization, Table 2.5 shows the estimates of the specification given by equation 5, for which the unit of observation is the plant-month. The model includes plant fixed effects and time effects. Columns 1 and 2 use the mix flexibility variable described in Section 4. Columns 3 and 4 use a modified version based on the highest flexibility that a plant has had in the past. This modified version assumes that a plant that has become flexible stays flexible.

All specifications have a positive coefficient for flexibility, supporting H2. Columns 1 and 3 do not include plant fixed effects. Columns 2 and 4 control for plant fixed effects and provide lower estimates for the effect of flexibility. Column 2 uses our regular measure of plant flexibility, and the OLS estimate of the magnitude of the effect of flexibility on utilization is 9.8%. Since the flexibility measure captures the demonstrated flexibility rather than the potential flexibility, there exists a potential endogeneity problem. A plant that is able to produce multiple platforms might only do so when demand for them is high. We also expect high utilization when demand for the products manufactured in a plant is high. Therefore, the effect attributed to flexibility might be actually related to unobserved demand shocks. In order to attenuate this potential problem, Column 4 shows the estimates when we build the plant flexibility variable based on historical data. We assume that a plant that has ever produced more than two platforms at the same time in the past remains flexible, even if the firm might decide not to use that flexibility. When doing that, the effect of flexibility on utility is attenuated, and is estimated to be around 4%. In all cases, the results support our Hypothesis H2. The average plant has the capacity to produce around 15,000 vehicles per month. Increasing utilization by 4% is roughly equivalent to producing a total of 600 more vehicles per month. If the fixed costs of operating the plant do not increase, adopting flexibility results in lower fixed costs per vehicle sold and more efficient capital investments.

Finally, we estimate the specifications (2.6) and (2.7). For these specifications, the unit of observation is the model (one observation for the entire period). The two specifications differ in the dependent variable, but both analyze how the demand volatility of a model (calculated as described in Section 4) affects the incentives. Table 2.6 shows the results. In Column 1, the dependent variable is the mean incentive for the model. In Column 2, we use the model fixed effect of specification (3) as the dependent variable, and we analyze how the demand volatility of a model affects the part of the incentives that is unexplained by the variables included in specification (3).

We use a log transformation for our volatility variable. We see that the coefficient of demand volatility is positive in both cases, and therefore Hypothesis H3 holds. We conclude that firms give lower incentives for vehicles with low demand volatility. Figure 2.4 plots the model fixed effect vs the log of the demand volatility. The first subplot shows the data at the model level and suggests the positive association between flexibility and incentives that we observe in Table 2.6. The second subplot shows the aggregation of the data at the make level. Again, we see a positive association.

A couple of makes stand out in Figure 2.4 (Smart, Mini, Lexus and Porsche) as they have unusually low fixed effect on the incentive and unusually low demand volatility. These are makes that are able to avoid giving incentives regardless of their flexibility, thanks to their low underlying demand volatility. This suggests that besides using flexibility, there are other tools that firms can use control incentives, and that some makes are "robust by design" against shocks in demand.

2.7. Robustness Checks and Alternative Explanations

Our main measure of flexibility, the measure based on the demonstrated mix flexibility described in Section 4, has several potential shortcomings. In Section 4, we have presented an alternative subjective measure based on an expert assessment, and we have shown above that the results obtained with such a measure were qualitatively similar. We find that the measures based on the demonstrated flexibility and the flexibility measures based on the expert's assessment are highly correlated (>0.8). Besides validating our results with the subjective measure, we have performed a series of robustness checks to our analysis with the demonstrated flexibility measure.

One of the potential shortcomings of our demonstrated flexibility measure is the fact that it is based on what the plants choose to product, rather than what the plants can produce. For example, we have noticed that in some (infrequent) cases a flexible plant produces only one model during a short period of time. In order to address this, we have redefined our flexibility measure as the maximum flexibility observed over the last n months (with n=3 and n=6), finding estimates that are consistent with the results that we have described. In the plant level analysis, we have also used the "record" flexibility, that is, the maximum historical flexibility for the plant (see Table 2.5), again, with qualitatively similar results.

Another potential shortcoming of our measure is that we do not have production data at the line level but at the plant level. However, having multiple platforms produced in independent lines of the same plant is not much different from having independent plants. This could result in an overestimation of the available flexibility in some cases. To address this potential problem, we have identified the cases where this could have been an issue by examining the number of lines per plant. We obtain that information from the Harbour Reports. Our results are robust to excluding those observations.

We have also tested for alternative definitions of our incentive variable. For example, in specification 2.3 we used the monetary amount of the discounts, but our results are robust to using log transformations and also to using a relative measure of discounts, expressing them as a percentage of the list price.

The analysis shown in Section 6 focuses on short run pricing given by discounts from the MSRP. The effect of flexibility on prices depends on the effect of flexibility on MSRP. It could be the case that after deploying flexibility lower discounts are accompanied by lower list prices. This would result in an ambiguous effect on final transaction prices and on manufacturer revenue per car. The relation between flexibility and list prices is given by the following specification:

$$MSRP_{it} = \beta_0 + \beta_1 FLEX_{it} + CONTROLS_{it} + \mu_i + \gamma_{st} + u_{it} \qquad (2.8)$$

Table 2.7 shows the impact of flexibility on MSRP, according to specification 2.8, where the unit of observation is the model-month. Columns 1 and 2 show OLS estimates, columns 3 and 4 show the 2SLS estimates using the same instruments as for Table 2.4. All columns include model fixed effects and segment time interactions. Except for the OLS estimation with all vehicles, the coefficient of flexibility in all regressions is positive and significant and we conclude that flexibility is not associated with lower list prices.

Having established that prices and average revenue per car increase after deploying flexibility, it is interesting to analyze whether this is at the expense of sales. We have conducted several tests on whether flexibility is associated with a sales decrease, but this hypothesis can be rejected (see Table 2.A3). Therefore, our estimates for the effect of flexibility on discounts provide lower bounds on the average effect of flexibility on revenues per car.

Regarding the explanation of the phenomenon we are describing, our preferred one is that flexibility allows to better match supply and demand, and having fewer and less important supply-demand mismatches allows to avoid using incentives. An alternative explanation would be based on cost. Lower discounts could be also derived from the fact that the marginal costs of production are higher with flexibility. However, observe that sales do not decrease after flexibility is deployed. It is difficult to explain why customers would be willing to buy more and at higher prices.

2.8. Conclusion and Discussion

In this paper we have illustrated some of the benefits of deploying production flexibility. We have shown that the deployment of production flexibility is associated with savings in discounts of between $200 and $700 per vehicle during our period of analysis, 2002-2009. We have shown that list prices (MSRP) increase with the use of flexibility, and therefore both transaction prices and manufacturer revenue per car increase when vehicles are produced with flexibility. Flexibility is not the only lever that firms can use to avoid using discounts. Designing products that are robust to shocks in demand is an alternative strategy, as suggested from the fact that vehicles with low demand volatility engage less often in discounting activity. We have also shown that flexibility is associated with higher utilization, 4% more on average. All the rest being equal, achieving higher utilization allows firms to reduce the fixed cost per vehicle, and therefore to increase average profits.

To see the managerial importance of flexibility and the results presented in this paper, consider the following, back-on-the-envelope calculation. Ford sells about 150K vehicles per month. If, through flexibility, Ford could reduce its discounts by the most conservative amount we estimated ($200), our model suggests incremental profits of 150K*$200=30M$ per month. This does not include the benefits of higher plant utilizations and potentially increased sales (see our results of Tables 2.5 and 2.A3). Of course, 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 nowadays very 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 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 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 convenience of investing in flexibility.

As far as the implication for the academic community is concerned, we believe that the models that we present in this paper open up several opportunities for future research. We have developed a model of customer demand rather than relying on sales as a proxy for demand. This allows us to integrate the pricing decision into the analysis, something that has been done in the modeling literature, but not in prior empirical work. Within the realm of flexibility, one potential extension using a similar approach could be to analyze the flexibility investment decision jointly with the demand system. More generally, future research can estimate the impact of other operational variables, including product variety, fuel efficiency or the timing of new product launches. 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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2.10. Tables.

Table 2.1: Average Trade Incentives (2003-2009)

Company	Mean	as % of MSRP
Porsche	809	1.10%
Honda	1,024	4.00%
Toyota	1,083	4.30%
Daimler	2,469	4.80%
BMW	2,691	5.80%
Subaru	1,470	5.80%
Volkswagen	2,041	7.30%
Nissan	2,170	8.30%
Mazda	2,040	8.60%
Hyundai Group	2,252	11.00%
Mitsubishi	2,776	12.00%
Chrysler	3,682	13.00%
Ford	3,585	13.00%
General Motors	3,587	13.00%

Table 2.2: Variables

Variable	Description
$DISCOUNT_{it}$	Average incentive given for model *i* in month *t*
$FLEX_{it}$	Binary variable that indicates if model *i* is flexible in month *t*, according to the measure described in Section 4
$DISCOUNT\_COMP_{it}$	For every model, we compute the average incentive per car given by the competitors in models of the same segment and luxury level
$MSRP_{it}$	Median list price of the model, constant during the model year.
MPD_{it}	Miles per dollar. The evolution of gas prices changes the attractiveness of some models. Incentives might respond to that. We define MPD=MPG/gasprice. This variable changes over time for a given model according to the evolution of gas prices.
AGE_{it}	Number of years since the model was first introduced
$INTRODUCTION_{it}$	Dummy variable that is 1 in the model year when the model is introduced
$PHASE\_OUT_{it}$	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
$DESIGN\_CHANGE_{it}$	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

Table 2.3: OLS estimates

VARIABLES	(1) Only Domestic	(2)	(3)	(4) All Vehicles	(5)	(6)
FLEX	-676.9***	-202.4***	-215.5***	-196.5***	-300.5***	-293.8***
	(37.80)	(43.90)	(42.69)	(34.07)	(43.52)	(42.51)
DISCOUNT_COMP	0.161***	0.368***	0.238***	0.154***	0.388***	0.267***
	(0.0436)	(0.0357)	(0.0341)	(0.0320)	(0.0300)	(0.0305)
MODEL FIXED EFFECTS	No	Yes	Yes	No	Yes	Yes
SEGMENT-TIME DUMMIES	Yes	Yes	Yes	Yes	Yes	Yes
ADDITIONAL CONTROLS	No	No	Yes+	No	No	Yes+
Constant	1,790***	690.4***	-2,588***	1,148***	436.3***	-2,211***
	(196.3)	(91.65)	(276.2)	(136.1)	(73.31)	(248.9)
Observations	10,043	10,043	9,929	17,166	17,166	17,052
R-squared	0.169	0.721	0.747	0.133	0.690	0.707

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

+ indicates the following controls: *INTRODUCTION, PHASE_OUT, AGE, MPD, MSRP, DESIGN_CHANGE*

Table 2.4: IV estimates

VARIABLES	(1) 2SLS Only domestic	(2)	(3) All Vehicles	(4)
FLEX	-576.9***	-699.0***	-1,280***	-1,295***
	(187.7)	(177.7)	(233.9)	(226.1)
DISCOUNT_COMP	0.388***	0.264***	0.373***	0.250***
	(0.0356)	(0.0338)	(0.0297)	(0.0302)
MODEL FIXED EFFECTS	Yes	Yes	Yes	Yes
SEGMENT-TIME DUMMIES	Yes	Yes	Yes	Yes
ADDITIONAL CONTROLS	No	Yes+	No	Yes+
Constant	1,273***	767.3	1,202***	806.0*
	(224.4)	(492.6)	(363.6)	(461.8)
Observations	10,034	9,923	17,064	16,953
R-squared	0.719	0.743	0.679	0.695

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
+ indicates the following controls: *INTRODUCTION, PHASE_OUT, AGE, MPD, MSRP, DESIGN_CHANGE*

Table 2.5: Flexibility and plant utilization

VARIABLES	(1) OLS UTIL	(2) OLS UTIL	(3) OLS UTIL	(4) OLS UTIL
FLEX	0.138***	0.0980***		
	(0.00837)	(0.0121)		
FLEX_RECORD			0.113***	0.0377***
			(0.00858)	(0.0136)
PLANT FIXED EFFECTS	No	Yes	No	Yes
CONSTANT	0.522***	0.481***	0.392***	0.379***
	(0.0394)	(0.0321)	(0.0350)	(0.0261)
Observations	7,606	7,606	7,606	7,606
R-squared	0.193	0.520	0.190	0.517

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

Table 2.6: Incentives and demand volatility

VARIABLES	(1) Mean Incentive	(2) Model Fixed Effect
L_VOL	2,030***	1,368***
	(189.6)	(253.2)
Constant	3,981***	731.1***
	(131.8)	(175.9)
Observations	325	296
R-squared	0.262	0.090

Table 2.7: MSRP and flexibility

VARIABLES	(1) OLS Only domestic	(2) OLS All vehicles	(3) 2SLS Only domestic	(4) 2SLS All vehicles
FLEX	274.9***	72.27	2,104***	1,370***
	(56.78)	(68.75)	(282.0)	(304.7)
Constant	27,501***	29,877***	12,052***	10,527***
	(103.0)	(85.04)	(241.3)	(259.5)
Observations	10,044	17,167	10,035	17,065
R-squared	0.979	0.986	0.976	0.985

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
All columns include the following controls: *INTRODUCTION, PHASE_OUT, AGE,DESIGN_CHANGE*

Table 2.A1: Estimates of the Demand System

VARIABLES	(1) IV Nested Logit MS
MODEL_PRICE	-9.30e-05***
	(1.13e-06)
SIZE	0.000208***
	(5.58e-06)
HPWT	18.63***
	(0.700)
MPD	-0.0354***
	(0.00358)
L_MKSHIINSEG	0.805***
	(0.0145)
CONSTANT	-3.700***
	(0.186)
Observations	17,683
R-squared	0.729

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Includes segment-time interactions

Table 2.A2: Subjective assessment of flexibility

	(1)	(2)	(3)	(4)
VARIABLES	AVG_INC	AVG_INC	AVG_INC	AVG_INC
MIX_FLEX	-772.8***	-218.0***		
	(55.17)	(59.22)		
HARBOUR_FLEX			-448.2***	-821.7***
			(129.5)	(180.1)
PLANT FIXED EFFECTS	No	Yes	No	Yes
Constant	2,822***	2,871***	3,607***	3,945***
	(209.6)	(112.1)	(326.1)	(229.5)
Observations	4,427	4,427	1,221	1,221
R-squared	0.075	0.698	0.027	0.730

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

Columns 1 and 2 show the effect of the demonstrated mix flexibility on plant level average incentives. We observe that those effects are similar to the ones found at the model level. Columns 3 and 4 show the effect of the subjective assessment of flexibility on plant level average discounts. We observe that they are also negative and statistically and economically significant.

Table 2.A3: Flexibility and sales

	(1)	(2)	(3)	(4)
VARIABLES	SALES	SALES	SALES	SALES
FLEX	495.1***	468.3***	509.7***	282.7**
	(136.9)	(135.6)	(135.1)	(114.5)
INCENTIVE			0.215***	0.305***
			(0.0312)	(0.0278)
PROD				0.267***
				(0.0147)
MODEL FIXED EFFECTS	Yes	Yes	Yes	Yes
SEGMENT-TIME DUMMIES	Yes	Yes	Yes	Yes
ADDITIONAL CONTROLS	No	Yes^{+}	Yes^{+}	Yes^{+}
Observations	10,044	9,930	9,930	9,930
R-squared	0.886	0.888	0.888	0.907

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

2.11. Figures.

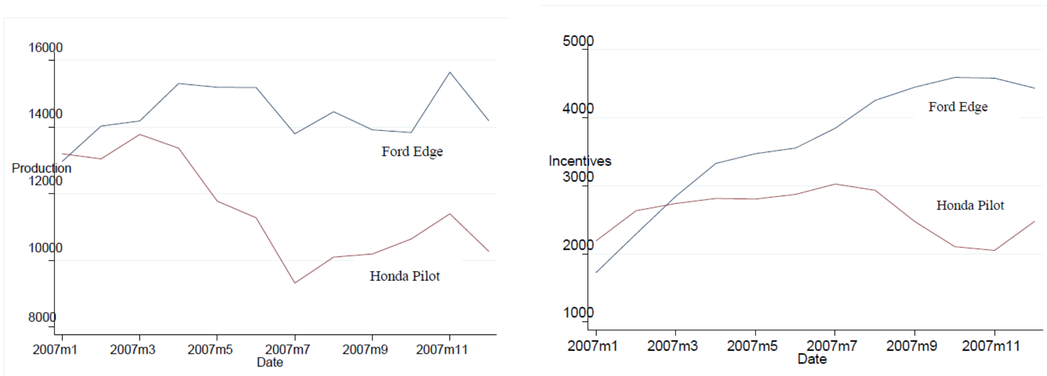

Figure 2.1: Production (left) and incentive (right) data for Ford Edge vs Honda Pilot.

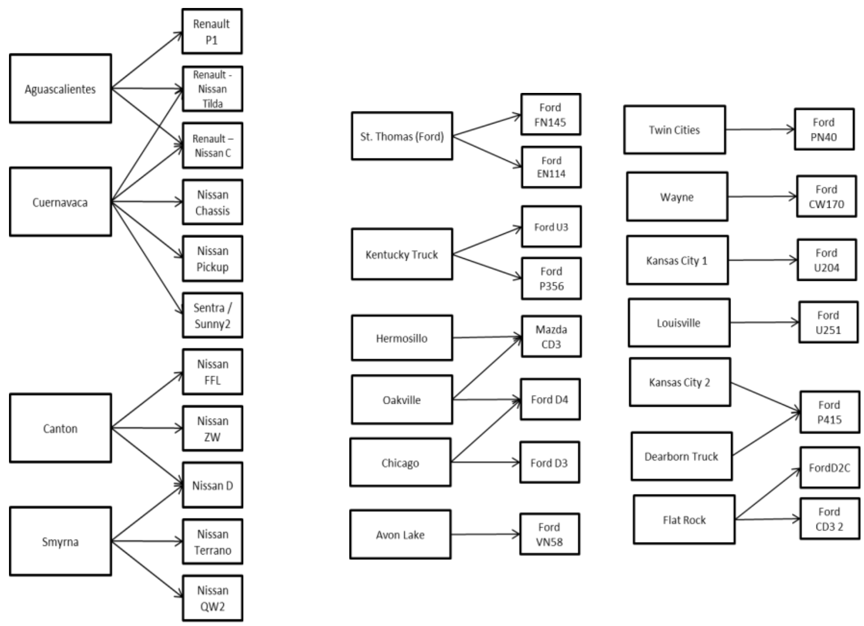

Figure 2.2: Allocation of platforms to North American plants at Nissan (left) and Ford (right)

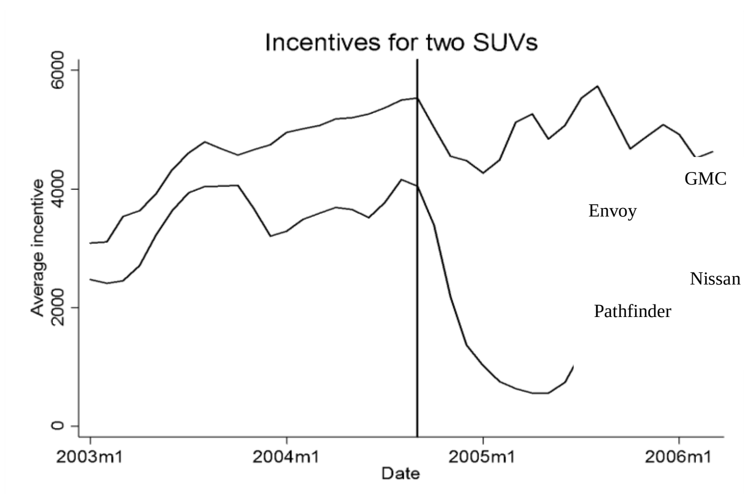

Figure 2.3: Average incentive for GMC Envoy and Nissan Pathfinder

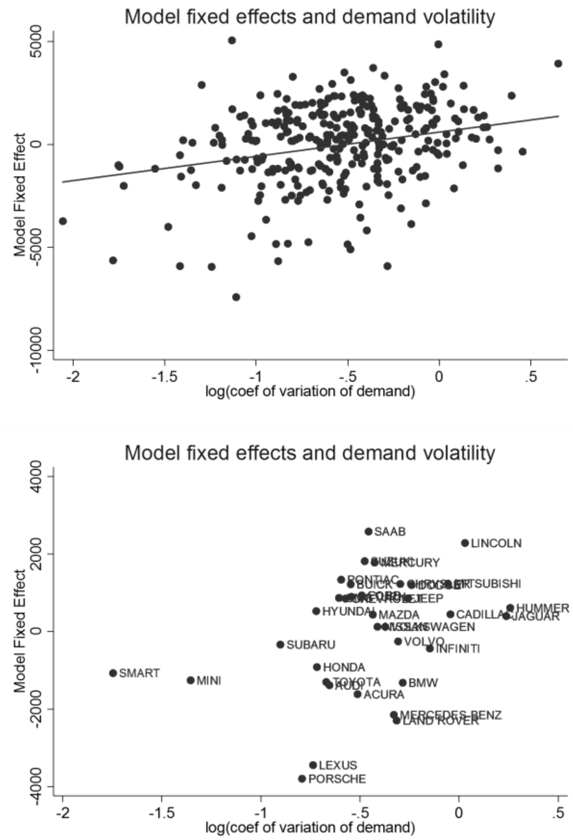

Figure 2.4. Model fixed effects and demand volatility. a) Model level. b) Make averages.

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Chapter 3

Reputation in Online Service Marketplaces[2]

Abstract

Online service marketplaces allow service buyers to post their project requests and service providers to bid for them. In order to reduce the transactional risks, marketplaces typically track and publish previous seller performance as a numerical reputation score. By analyzing a detailed dataset with more than 1,800,000 bids corresponding to 270,000 projects posted between 2001 and 2010 in a leading online intermediary for software development services, we empirically study the effects of reputation on market outcomes. We find that buyers trade off reputation and price and are willing to accept higher bids posted by more reputable bidders. Sellers increase their bids with their reputation score, but primarily use a superior reputation to increase their probability of being selected as opposed to increasing their price. We study how various variables moderate the importance of the reputation score: we observe that the reputation score has a smaller effect in situations where there exists a previous relationship between buyer and seller, when the seller has certified his or her skills, when the seller is local, or in situations that prompt higher interpersonal trust.

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[2] This chapter is based on Moreno, A., C. Terwiesch and E. Krasnokutskaya. 2012. Doing Business with Strangers: An Empirical Analysis of Reputation in Online Service Marketplaces. Working Paper.

3.1. Introduction

Online reverse auctions have been used since the 1990s for procurement in large corporations, but recent technological developments have enabled small- and medium-sized enterprises and even individuals to use similar mechanisms to fulfill their service procurement needs. Platforms offering online service marketplaces matching buyers and sellers of services have proliferated, with some of the leading examples being www.vworker.com, www.elance.com, www.guru.com and www.odesk.com. In the late 2000s, the financial crisis increased the number of self-employed professionals and the need for small firms and entrepreneurs to drive down costs, which resulted in an increase of the use of the most popular service procurement platforms (The Economist 2010, Hipple 2010).

Online service marketplaces are intermediaries that connect buyers and sellers of services. Buyers are firms or individuals who post work they would like to procure (for example, the development of an iPhone application) and request bids for this work. Sellers are firms or individuals (for example, iPhone developers) who bid for the jobs posted by buyers. Such online service marketplaces present distinctive traits in contrast to their offline counterparts. Traditional markets often involve personal relationships that can generate trust, especially when there is repeated interaction. In online service marketplaces, buyers have little information about bidders, and little control over their work, which leads to increased adverse selection and moral hazard problems, and to a higher uncertainty regarding the outcome of the collaboration. In such an uncertain environment, reputation and trust play a crucial role. Reputation creates a link between past behavior and the expectation of future behavior (Mailath and Samuelson, 2006). The intermediary platform typically offers a reputation system that keeps track of the buyers' and bidders' past behavior and facilitates trust (Resnick et al. 2000, Resnick and Zeckhouser 2002, Dellarocas 2003).

Online service marketplaces also differ substantially from online marketplaces for products (e.g., eBay), for which there already exists an impressive amount of research studying the role of reputation (e.g., Bajari and Hortacsu 2003, Houser and Wouders 2005, Resnick et al. 2006, Cabral and Hortacsu 2010). The most important differences are the form of the auction, the service auction's global footprint, and the difficulty to specify the seller's effort. Online service marketplaces as studied in this paper take the form of reverse auctions, where the sellers submit bids in response to buyers' requests for project work. This allows sellers to use their reputation score to increase their pricing power. Moreover, given the multiple bids with varying prices and reputation scores, the buyer faces a multi-attribute auction. Hence, unlike in the commonly studied eBay setting, price alone is not likely to predict the winning bid (in our sample, more than 40% of the projects were not awarded to the lowest bid). In absence of a physical product and the associated shipping needs, online service marketplaces also tend to have a global footprint. This is further accentuated by the opportunity for global wage rate arbitrage. In such global setting, the legal context governing the transaction is highly ambiguous, and thus buyers need to rely on reputation more than on potential litigation. Finally, given the skills of the seller, the accuracy of the specifications, the time it takes to complete the work, and the potential fraudulent seller behavior, the uncertainty associated with the quality of a service transaction is larger than for physical goods. This uncertainty can lead to post-contractual opportunism and thus further increases the importance of reputation.

Despite the growing importance of online service marketplaces and the special importance that reputation plays in them, there exists, to the best of our knowledge, no prior empirical work analyzing the role of reputation in such settings. One explanation for this gap in research relates to the availability of data. eBay transactions are visible to the public, and the product is predictably rewarded to the highest bid. In contrast, in online service marketplaces, the bids are not visible to the public and the multi-attribute nature of the auction makes predicting the winning bid difficult, if not impossible. Through collaboration with vWorker (formerly rentacoder.com), one of the leading marketplaces for software development and other business services, we have obtained access to an extensive proprietary dataset. Our dataset includes more than 1,800,000 bids corresponding to more than 270,000 projects posted between 2001 and 2010 by 122,000 coders. This dataset includes participants from over 80 countries. In fact, more than 85% of the projects have the buyer and the winning seller located in different countries. A unique feature of our data is that we observe *all* the transactions in the market and during a long period of time, so that we are also able to follow buyers and sellers over time. This allows us to study how sellers adjust their bid setting strategy as their reputation changes.

We use a discrete choice framework to study how buyers choose between competing bids from different service providers and how they trade off different attributes, focusing primarily on the role of reputation. Our econometric approach, together with the unique data set we assembled, allows us to make the following contributions.

First, we show that in the multi-attribute auction context created by the online service marketplace we study, buyers trade off the cost of the service with the reputation of the seller. We find a significant and large reputation premium. One additional point in the reputation score (out of 10) has approximately the same effect on bid choice as a reduction by one standard deviation in the bid amount. This extends prior research that has been done on product auctions.

Second, we show that bidders internalize the fact that reputation is valuable to buyers, and adjust their bidding strategy as they accumulate reputation. Bidders start by bidding low when their reputation is low or unestablished, so that they can build reputation. They increase their bids as their reputation improves. However, bidders adjust their bid prices to a lesser extent than the buyers adjust choices. One additional point in the reputation score (in a range 0-10) is associated with an increase in bid equivalent to 1% of the standard deviation of the bids received for a project. In other words, the coders benefit from their increased reputation mostly through higher volume, rather than through higher prices.

Third, we analyze the moderators of reputation. Our data presents significant variation not only in reputation scores but also in other available information and attributes of the coder. This allows us to study how the effect of the reputation score interacts with other variables. We show that reputation is less important for coders who have certified their skills by taking an online test, for coders who are from the same country as the buyer, for coders with whom the buyer has worked before, and for coders who leave cues that prompt interpersonal trust, like posting a picture in their profile. We interpret these findings according to existing economic and behavioral theories.

The rest of the chapter is organized as follows. Section 2 discusses related literature. Section 3 introduces the empirical setting and describes the institutional details of the market. Section 4 develops hypotheses based on previous research. Section 5 describes the data. Section 6 presents the econometric specification and the results of the estimation of the models. Finally, Section 7 concludes by pointing at some of the managerial implications of our findings and at some areas of current and future research.

3.2. Literature Review

Our study of reputation in online service marketplaces has close connections to literature streams in information systems, operations management, economics and management of organizations.

This paper is closely related to the information systems literature that studies reputation in online auctions and its effect on market outcomes. Most of the work in this domain has focused on product auctions, especially in the eBay market (Bajari and Hortacsu 2003, Houser and Wouders 2005, Resnick et al. 2006, Cabral and Hortacsu 2010, among others). Bajari and Hortacsu (2004) reviews some of the most relevant papers, which overall find some evidence supporting the claim that seller reputation has a positive effect on prices in eBay auctions. Some recent work in information systems has focused on the role of online reputation systems and, more generally, online feedback mechanisms. Dellarocas (2003) and Dellarocas (2006) provide comprehensive reviews. Bolton et al. (2004) perform an experimental investigation on the effectiveness of electronic reputation mechanisms. Bakos and Dellarocas (2011) compare litigation and online reputation as quality assurance mechanisms using analytical models. Other papers address some of these issues empirically using observational data. For example, Chevalier and Mayzlin (2006) study the effect of word of mouth on sales, and Dellarocas and Wood (2008) study the feedback mechanism at eBay and the impact of reciprocity and the informativeness of missing reviews. Some recent papers use text mining techniques to study the importance of user feedback and reviews (Ghose at al. 2009, Archak et al. 2011).

The operations management community has devoted considerable efforts to study procurement auctions. Most of the papers describe analytical models (e.g., Elmaghraby 2000, 2004, Tunca and Zenios 2006, Wan and Beil 2009). Pinker et al. (2003) provide a review of the literature related to the management of online auctions. Some recent work has also focused on markets for the procurement of innovation (e.g., Terwiesch and Xu 2008, Yang et al. 2011). Despite the abundance of theoretical models, there is very limited work studying online service marketplaces or procurement auctions empirically. Among those, Gefen and Carmel (2008) study offshoring and global trade in online service marketplaces, Stanton and Thomas (2010) analyze the role of intermediary agencies in screening candidates in online labor markets, Snir and Hitt (2003) study the effects of costly bidding in internet-based procurement of professional services, and Tunca et al. (2011) study online procurement auctions for legal services by General Electric. Our paper complements this literature in procurement auctions by analyzing the role of reputation in markets for service procurement.

The economics literature has provided a significant number of models to analyze reputation. Some general references are Bar-Isaac and Tadelis (2008), Mailath and Samuelson (2006), and MacLeod (2007). The reputation models can be roughly categorized into two frameworks. The first framework deals with reputation as Bayesian updating on a hidden type (Kreps and Wilson 1982, Kreps et al. 1982). Under this framework, the reputation system has predominantly a signaling role – in our particular case, it would give information about the skill and trustworthiness of the coder. The second framework sees reputation as a coordination equilibrium in a repeated game context (Klein and Leffler 1981). Under this framework, reputation has mainly a sanctioning role – in our particular case, the threat of a bad rating would induce high effort on the coder side. In reality, these two frameworks are stylized extremes that allow us to focus on isolated sources of information asymmetry (pure signaling vs. pure moral hazard). In practice, both sources of information asymmetry are important in these markets (see Cabral 2005 and Dellarocas 2006 for a more detailed description of the frameworks). Our paper uses these models to formulate hypotheses about the effect of the reputation score on outcomes and to interpret the results.

Finally, our work is also related to the trust literature in management of organizations. In this literature, trust has been defined as “the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other part,” (Mayer et al., 1995). While the economic literature has discussed trust normatively as arising from the equilibrium of a repeated game (Cabral 2005), the literature in management of organizations literature has followed a more behavioral approach and typically grounds trust in psychological processes analogous to the processes that facilitate collaboration. Trust is a subjective measure that is influenced by the context in which transactions take place and by the individuals’ biases. For example, the literature in organizational psychology has identified situations that prompt interpersonal trust, such as homophily (people are more likely to trust similar people) or familiarity (see Brass 2011), and some research in psychology and in human-computer interface has pointed out the importance of anthropomorphism (people are more willing to trust human agents than nonhuman agents) (see Waytz et al. 2010). Our work discusses the role of some of these behavioral drivers of trust in the choices made by buyers in an online service marketplace and, in particular, we explore how interpersonal trust moderates the influence of the quantitative information provided by the reputation system.

To our knowledge, no paper has empirically studied reputation mechanisms in an online service marketplace. Therefore, we contribute to the existing literature by extending the analysis to a new setting of increasing economic importance. Beyond this novel empirical setting, we extend the line of prior work by introducing a set of moderating variables and by taking advantage of repeatedly observing the same seller over time.

3.3. Description of the Empirical Setting

Our data comes from vWorker.com, an on-line intermediary that brings together buyers and sellers of software development services and other professional services. The company began as rentacoder.com, but later expanded the scope of services beyond software.

At vWorker, registered buyers (firms or individuals) submit projects to the intermediary seeking bids from coders. Along with this submission, the buyer provides a project specification, lists the required skills for a successful completion of the project, and sets a targeted deadline. Registered sellers (coders) read the descriptions of the projects. Depending on their relevant expertise and their overall interest in the project, a small fraction of coders then submit bids to the intermediary. Bidders can observe the current number and characteristics of participants in an auction, but they cannot see the competing bids of other coders. At a time pre-determined by the buyer, the intermediary ends the auction and presents a catalog of all bids to the buyer. The buyer sees the bids, including prices, coder location, coder reputation, and the number of projects the coder has completed. With a click on the coder, the buyer can obtain more detailed information on the coder, including a picture of the coder as well as a history of the coder’s prior work alongside with comments and reputation scores posted by previous buyers.

When choosing from the menu, the buyer thus observes all bids and has access to all information about the submitting coders. Based on this information, the buyer awards the project to one coder. At the moment of choice, the buyer potentially faces both adverse selection (are the coders qualified for the job?) as well as moral hazard (will the coders keep their promises?). The intermediary provides a set of measures to reduce these problems. First, the intermediary keeps a rating (reputation score) for each of the participants in the marketplace based on the feedback from historical transactions. Second, the intermediary provides an arbitration system to resolve potential disputes should the service not meet the buyer’s expectations. When the buyer chooses the coder, the buyer submits the funds corresponding to the bid he has chosen to an escrow account managed by the intermediary. The money remains in escrow until the service has been carried out at the satisfaction of the buyer.

Upon completion of the work (or after arbitration), the money (or in the case of arbitration, a fraction of the money) is transferred to the coder. Finally, the buyer has an opportunity to rate the coder, leading to an update in the coder’s reputation score, which is computed as the average of the previous ratings received by the coder. The buyer can also provide verbal comments (positive or negative) for the coder.

Turning our attention to the supply side of this market, coders make several decisions. First, they decide whether to bid for a project or not. If they decide to bid, they decide the amount they want to bid, and if they are awarded the project, they decide the level of effort they exert. Furthermore, coders can take tests on the site to certify their skills (for example, they can take a C++ exam to become a certified C++ coder). These certifications appear in their profiles and can be viewed by buyers. Coders face a dynamic decision problem: they are bidding and working on projects in the near term, but they also have to think strategically about the future. Strategic considerations arise from the fact that the website keeps track of work done by coders and the resulting buyer satisfaction. This makes past coder actions a part of public information in the market. And, as discussed above, future buyers will take this information into account when they choose among competing bids. Coders can also be influenced by their own reputation when setting their bids. Assuming that buyers value coder reputation positively and that buyers trade off reputation and price (which is something that we hypothesize and test in the next sections), a coder, especially one who is new to this marketplace, may bid relatively low in order to accumulate some experience or to build reputation. Experienced coders with good reputation scores, in contrast, may bid relatively high because they know that buyers appreciate their higher reputation score and are willing to pay premium prices for this.

3.4. Theoretical Foundations and Hypotheses Development

We analyze four effects of coder reputation on market outcomes. First, we study how buyers choose among competing bids, focusing on how buyers react to coders' reputation scores. Second, we study how the evolution of coders' reputation scores affects their bids. Third, we study how particular informational situations and characteristics of the coders moderate the effect of the reputation score on buyer choice. And fourth, we analyze how information unobserved to us as researchers, yet potentially public information in the marketplace, complements the structured reputation score created by the intermediary.

In order to develop our hypotheses, we rely mainly on results derived from economic models of asymmetric information as they apply to reputation systems.

Reputation systems are primarily used to reduce moral hazard and adverse selection problems. In online service marketplaces, moral hazard could occur once a project is awarded if the coder engages in post-contractual opportunism by exerting less effort than the one required to deliver what was promised. The reputation mechanism can reduce moral hazard by offering a sanctioning device (Dellarocas, 2006). As noted by Dellarocas (2006), "if the community follows a norm that punishes traders with histories of bad behavior (by refusing to buy from them, or by reducing the price they are willing to pay for their products) and if the present value of punishment exceeds the gains from cheating, then the threat of public revelation of a trader's cheating behavior in the current round provides rational traders with sufficient incentives to cooperate." Klein and Leffler (1981) develop the notion that repetition can induce trustworthiness and contract performance. In our particular case, and focusing on buyer's actions, if such a sanctioning device is in place we would expect buyers to be more likely to award projects to coders with histories of good behavior (e.g., to coders with high reputation) or to be willing to higher bids to coders with a better reputation.

Buyers do not have information about the real ability or intentions of the sellers, creating an adverse selection problem. In such a setting, reputation mechanisms can act as signaling devices. For example, the fact that a coder has received consistently high ratings in a particular type of project may allow the buyer to update his beliefs with respect to the skills of the coder. Assuming that commitment to high effort is a "type" characteristic (e.g., there are coders who are always exert high effort and coders who always exert low effort), the reputation score also gives a signal about the likelihood of the coder exerting high effort. Frameworks dealing with reputation as Bayesian updating on a hidden type are described in Kreps and Wilson (1982) and Kreps et al, (1982).

Dellarocas (2006) describes the distinction between pure moral hazard and pure adverse selection settings in that in the former case, all sellers are assumed to have the same ability level and are capable of the same type of behavior, while in the latter case they have different intrinsic abilities. In pure moral hazard settings, the reputation system is used to constrain behavior, while in pure adverse selection settings the reputation system is used to induce learning.

Our first analysis aims to estimate the effect of coder reputation score on buyer's choice behavior. The two frameworks described above support the hypothesis that higher coder reputation should result in a higher perceived utility for the buyer and thus a higher probability of the bid being chosen. According to a pure moral hazard model, a higher reputation score would induce higher effort by the coder because building reputation is costly for the coders, and a coder with a higher reputation is exposed to a higher potential sanction for a deviation of the expected behavior, and therefore is more likely to cooperate. According to a pure signaling model, a coder with a higher reputation score is more likely to have better skills or to be committed to exerting high effort in the task. Consequently, we hypothesize:

Hypothesis 1. *The probability of awarding a project to a coder increases with the reputation score of the coder.*

Empirical support for this hypothesis would complement prior work in product auctions that have established a price premium of product auctions in these settings (see Bajari and Hortacsu 2004 for a review). Besides confirming that the direction of the effect is the one we hypothesize, we are interested in quantifying the trade-off between price and reputation made by buyers in online service marketplaces.

The second part of our analysis is concerned with how a coder behaves in this market. To the extent that buyers care about reputation (Hypothesis 1), a profit-maximizing coder will take advantage of this preference. Specifically, a coder who achieves a higher reputation can follow one of two strategies. First, the coder can benefit from his reputation by increasing the bid amount and keeping the probability of being chosen constant. Second, the coder can benefit from his reputation by bidding at the same level as before and enjoying a higher probability of winning a given auction. In other words, coders can extract the benefits of higher reputation through price or through volume. It is an empirical question to find how those two (potentially coexisting) mechanisms play out in this market. We thus hypothesize:

Hypothesis 2a. *The bid amounts set by coders increase with their reputation score.*

Hypothesis 2b. *The probability of a coder winning a project increases with the reputation score of the coder.*

Beyond testing these two hypotheses, we are interested in the magnitude of the price adjustment, if such adjustment exists. The comparison between the magnitude of the price effect in coder bidding and the reputation-price tradeoff made by the buyer allows us to interpret whether the coder extracts the reputation premium mostly through price or through volume. These hypotheses also allow us to explore a subtle difference between online service marketplaces and product auctions. Consider an eBay auction for a good with at least one bidder and no reserve price. If there is a reputation premium, we would expect this to be materialized through a higher closing price in the auction. Consider now a project in a service marketplace like ours. Higher reputation of one bidder does not necessarily result in a higher expected transaction price. The reputation premium can be manifested just through an alternative allocation of the project, other than the one that would have occurred if the reputation had stayed the same. For example, the higher reputation can just help this coder gain a project that would have gone to another coder with lower reputation and same price. If coders do not increase their bids with their reputation score (i.e., if Hypothesis 2a is not supported), the reputation premium will result in a different allocation of projects but not necessarily in higher prices. But if coders increase their bids as they increase their reputation (i.e., if Hypothesis 2a is validated), at least some of the reputation premium will reach the market in the form of higher transaction prices.

While the reputation score is an important element to facilitate online transactions, the effect of reputation score on buyer choice is not equally important in every situation. Our third analysis considers variables that moderate the effect of reputation on choice. We develop hypotheses on how the buyer's utility for reputation score interacts with other available informational situations and coder characteristics. Our purpose is not to establish an exhaustive list of all the situations that might interact with reputation, but to offer some representative examples of moderating variables that affect the utility of the reputation score, according to mechanisms that can be explained from available theories drawn from signaling models, sanctioning models, and behavioral models of trust. In particular, we propose hypotheses regarding how the impact of the numerical score on buyer's choice is moderated by four situations that exist in our market but that also have a broader applicability.

First, consider the role of coder certification. Because the reputation score has a signaling function, it is informative to study how its impact changes when there are alternative signals available. Our market provides one feature that allows us to explore this question: vWorker allows coders to certify their skills by taking a timed skill assessment test. For example, coders can take a test to certify their C++ coding skills. The certification information is visible to the buyers in the platform, and they might take it into account when awarding projects. This certification works as a signaling device (Spence 1973): it is costly to obtain (workers must take a test) and the costs of obtaining it are higher for less able coders. We would therefore expect that the buyer's perceived utility increases with the availability of coder certification. How should the availability of additional information affect the impact of the reputation score on buyer's choice? For coders who do not have certification, the reputation score is the only available signal. Coders who have certified skills have another available signal and therefore in those cases the reputation score is a less informative signal overall, and we expect it to have a lower impact on buyer's decisions than when there are no signals other than the reputation score. This is formalized in the following hypotheses:

Hypothesis 3-1a. *The probability of awarding an auction to a coder is higher when a coder is certified.*

Hypothesis 3-1b. *The reputation score has a lower impact on buyer's choice probability when a coder is certified.*

Second, consider the importance of a prior relationship between buyer and seller. From a signaling standpoint, having worked with a coder in the past gives firsthand information on the coder's skills. Analogous to the previous case, we can hypothesize that an additional available signal can reduce the informativeness of the reputation score. But there are also other important behavioral considerations derived from the literature on management of organizations. This literature has studied the aspects that influence perceived trustworthiness and that can induce trust in uncertain transactions. Familiarity between organizations and individuals has been observed to breed trust (Gulati 1995), and therefore we would expect that familiarity with the coder will result in higher valuation for the buyer. Furthermore, perceived trustworthiness can also make up for a lower reputation score. This is formalized in the following hypotheses:

Hypothesis 3-2a. *The probability of awarding an auction to a coder is higher when the buyer has worked with the coder before.*

Hypothesis 3-2b. *The reputation score has a lower impact on buyer's choice probability when the buyer has worked with the coder before.*

Third, consider the effect of location on reputation and trust. It has been noted that similarity between agents simplifies communication and makes trust generation easier (Kossinets and Watts 2009). Therefore, we predict that buyers will prefer coders from the same country, all else being equal. An alternative justification for this hypothesis is that when the buyer and coder are from the same country, there are alternative sanctioning devices. For example, it is easier for the buyer to use the court of law if the project is performed poorly and arbitration is not favorable. The availability of alternative sanctioning devices reduces the appeal of using threats to the reputation score as a sanctioning device, and therefore we would expect the impact of the reputation score to be lower when the coder is local. Furthermore, the increased perceived trustworthiness of a local coder can make up for a lower reputation score. We formalize these notions with the following hypotheses:

Hypothesis 3-3a. *The probability of awarding an auction to a coder is higher when the coder is local.*

Hypothesis 3-3b. *The reputation score has a lower impact on buyer's choice probability when a coder is local.*

Fourth, the last moderator of reputation that we explore is the availability of a coder's picture. Recent research in psychology has demonstrated that people are more willing to punish an agent that they consider mindful (Gray et al., 2007), and it has been suggested that anthropomorphizing agents results in increased trustworthiness (Waytz et al., 2010). Accordingly, we hypothesize:

Hypothesis 3-4a. *The probability of awarding an auction to a coder is higher when the coder has a picture.*

Hypothesis 3-4b. *The reputation score has a lower impact on buyer's choice probability when a coder has a picture.*

3.5. Data

Our dataset includes the 273,837 projects that were posted in vWorker between May 2001 and November 2010. We observe a total of 1,822,705 bids. This amounts to an average of 6.66 bids per project. Most of our data corresponds to the period in which vWorker was called rentacoder.com and the projects are primarily concerned with software development services. The projects are typically small. The mean winning bid is $126.50 (median winning bid is $50). Most of the bids (94.5%) are below $500.

For each project, we compute the number of bids received, the winning bid, and the highest, lowest, mean and median bid. Besides that, we know the date when the bid request was posted, and the rating given to the coder. Table 3.1 shows some summary statistics at the project, bid and coder level.

The participation of the bidders in the market is very heterogeneous. More than half of the coders submitted 3 or less bids. Many of the coders did not win any auction. Actually, only 29,786 of the 122,102 coders (24%) won at least one project during the ten years of our sample. Some features of this market are consistent with the Pareto property: a large number of users are mostly inactive and a small number of users generate a large fraction of the transactions on the site.

3.6. Econometric Specification and Results

3.6.1 Econometric Model of Buyer Choice

The multi-attribute procurement auction can be modeled using a conditional logit specification (McFadden 1974). We assume that the utility that a generic buyer obtains from accepting a bid *b* submitted for project *i* can be expressed as

$$u_{ib}^{*} = X_{ib}'\beta + \varepsilon_{ib} \tag{3.1}$$

where X_{ib} are the attributes of the bids that affect the utility that the buyer receives from choosing that bid. Let *C(b)* denote the coder that submits the bid *b*, *B(i)* denote the buyer that submits the project *i*, *S(i)* denote the set of bids received for project *i* and *D(b)* denote the date when the bid *b* is submitted. These attributes can be broken down into the subvectors $X_{ib}=(X_{project} | X_{bid} | X_{coder} | X_{relation} | X_{bid\text{-}set})$ using the following simplified notation:

- $X_{project}$ are attributes that depend only on the project and are constant for all bids received for the project, such as the number of bids received for the project.
- X_{bid} are attributes that depend only on the bid, such as the bid amount.
- X_{coder} are attributes that depend on the coder, such as the coder's country of origin, and potentially on the time *D(b)* when the bid is submitted, such as the reputation score of the coder at that time.

- $X_{relation}$ are attributes that depend on the relationship between a given coder and a given buyer, and potentially on the time *D(b)* when the bid is submitted. Examples are an indicator of whether the coder and buyer are from the same country or an indicator of whether the buyer has worked with the coder before at the time of bid submission

- $X_{bid\text{-}set}$ are attributes that depend on the bid and on the other set of bids *S(i)* received for the project. One example of this type of variable is whether a bid is the smallest one received for a project.

We do not observe the utility that the buyer obtains from choosing a bid but we do observe which bid $b=1..J$ the buyer chooses, if any. Let $Y_i=b$ if bid b is chosen by buyer for project i, which implies $u_{ib}>u_{ik}$ for all k≠b. If the error ε_{ib} follows a Gumbel (type 1 extreme value) distribution, the probability of choosing a bid has a closed form:

$$\Pr(Y_i = b) = \frac{e^{X'_{ib}\beta}}{\sum_{b=1}^{J} e^{X'_{ib}\beta}} \tag{3.2}$$

Note that the coefficients that correspond to the variables included in $X_{project}$ (i.e., variables that remain constant for all the bids received for a project) cannot be identified from this model, since the conditional logit model requires variation across alternatives.

3.6.2 Reputation and Bid Choice

We start by analyzing how buyers use the available information in their bid choice decision. In particular, we are interested in the effect of reputation on the probability of a bid being chosen. We start with a parsimonious model that allows us to quantify the effect of coder reputation on buyer's choices.

In the bid-specific set of variables X_{bid} we would include the amount of the bid. However, since there is a huge heterogeneity between projects and within bids in a project, we normalize the amount of the bids with respect to the rest of the bids received for the project as:

$$BIDN_{bid-set} = \frac{BID_{bid} - \lambda_{set}}{\sigma_{set}} \tag{3.3}$$

where $set=S(i)$ is the set of bids received for project i, λ_{set} denotes the median bid received for the bid request i and σ_{set} denotes the standard deviation of the bids submitted to the bid request. In other words, we express bid amounts as the distance to the median bid received for the project, measured in number of standard deviations of the bids received for the project. We have tested alternative specifications for the normalization procedure, and the qualitative results do not change. We also include a dummy variable that indicates whether the submitted bid is the smallest, so that we can capture any additional premium that the buyer attributes to the cheapest offer. Therefore $X_{bid-set}$ contains two variables, $BIDN_{bid-set}$ and $SMALLEST_{bid-set}$.

Among the coder-specific variables X_{coder}, we include the number of ratings that the coder has received in the past, the reputation score of the coder when the bid is awarded and a dummy variable to control for those cases in which the coder has received no ratings in the past. We also include region dummies (one for US/Canada, one for Eastern Europe, one for rest of Europe, one for India/Pakistan, one for rest of Asia and one for other location). Therefore X_{coder} contains the variables $NRATINGS_{coder-time}$, $REPUTSCORE_{coder-time}$, $UNRATED_{coder-time}$, and the regional dummies.

Finally, in this specification $X_{relation}$ includes a dummy variable that indicates whether coder and buyer are from the same country.

We estimate the model using maximum likelihood. Table 3.2 shows the estimates (column 1) and the marginal effects evaluated in the median values of the variables (column 2).

We observe that the probability of choosing a bid decreases with the (normalized) bid amount, as we would expect from a buyer who has a positive utility for money. The probability of choosing a bid increases with the number of ratings that the coder has received, which is a proxy for experience.

The smallest bid received in a bid request, and the bids received from coders who are from the same country as the buyer, have a higher probability of being selected. Coders from U.S or Canada (the baseline category) are preferred, all else being equal, although there is no statistical difference with the coders from Western Europe. Coders from India, Pakistan, and the rest of Asia are less preferred.

The positive and significant coefficient for the reputation score allows us to validate Hypothesis 1: the probability of awarding an auction to a coder does increase with the reputation score of the coder. These results are consistent with both the signaling and the sanctioning role of reputation mechanisms. A buyer may prefer to work with a coder with higher reputation because this updates his beliefs on the skills of the worker (adverse selection story) or because he thinks that the coder will have more to lose if he does not perform well, because of the higher cost of a sanction for a coder with higher reputation (moral hazard story).

Besides looking at the signs of the coefficients, it is interesting to analyze the comparative magnitude of their marginal effects, in particular the one of the reputation score. At the median values, one additional reputation point increases the probability of choosing a bid by 0.0054. This is approximately the same effect on success probability as reducing the normalized bid value by one standard deviation. This implies that the reputational effects in this market are economically very important.

We propose a more detailed model in Section 6.4, where we discuss the interactions of the reputation score with other variables, and we observe that the effects that we identify with this parsimonious model do not qualitatively change.

3.6.3 Reputation and Bidding Behavior

Having established the effect of reputation on bid choice by the buyer, we now turn our attention to how coders adjust their bidding behavior over time as their reputation varies. Our dataset is unique in that respect, because we can follow coders over time.

If coders are aware of the fact that buyers are willing to pay a significant premium for bids coming from coders with high reputation, they may increase their relative bids as they obtain more reputation. We propose the following specification to estimate the magnitude of the effect:

$$BIDN_{bt} = \mu_j + \alpha_1\ REPUTSCORE_{jt} + \alpha_2\ \ NRATINGS_{jt} + \varepsilon_{jt} \tag{3.4}$$

where j denotes the coder *C(b)* and t denotes *D(b)*, the time at which bid b is placed. The variables have been previously introduced. We include coder fixed-effects to control for time-invariant characteristics of the coder.

If α_1>0 and significant, then our Hypothesis 2a (the bid amounts set by coders increase with their reputation score) is validated. If α_1<0 or if it is not significantly different from 0, our Hypothesis 2a is rejected. The expected effect of $NRATINGS_{jt}$ on price is ambiguous: on one hand, the more projects a coder has won in the past, the more knowledgeable he/she is expected to be. This is valued by the buyer and therefore coders with more previous ratings will be able to charge more while maintaining the probability of being chosen. On the other hand, experience can also reduce cost. If coders who have been awarded projects in the past have lower costs, they could charge lower prices while keeping their expected revenue constant.

We estimate the coefficients by using a fixed-effects estimator (Least Squares Dummy Variable). Table 3.3 shows the estimates.

Column 1 shows the results for the coefficients of the reputation score and the number of ratings. The results show that the bid amount does indeed increase with reputation, and therefore Hypothesis 2a is validated. However, we note that the impact of reputation on bid size for a given coder is significantly smaller than the premium that the buyers are willing to pay for additional reputation. For an additional reputation point, coders increase their bids by 1% of the standard deviation. This suggests that coders could more aggressively try to appropriate the price premium that buyers seem to be willing to pay, which can be quantified as close to one standard deviation of the bids received for a project. In other words, coders receive most of the benefits of their additional reputation by an increase of the probability of being chosen, as opposed to through higher prices. Coders do not cash their reputation mainly through price but through volume. However, there is a slight effect on prices, which means that at least some of the reputation premium will reach the market in the form of higher transaction prices.

Each additional rating also has the effect of increasing the bid slightly. This suggests that the demand-side benefits of an additional rating outweigh the potential cost reduction that could be passed to the bids, and the net effect is positive. One additional rating has a much lower impact than one additional reputation point, but it is important to note that the range that the number of ratings can span is not limited to 10. Therefore, for very active coders, this can result in a significant price increase.

Column 2 adds a dummy variable to control for situations in which the coder has no previous ratings, but this variable is not significant and adding it does not change the other coefficients.

Hypothesis 2b (the probability of a coder winning a project increases with the reputation score of the coder) is tested using a linear probability model with the following specification:

$$\begin{aligned} Y_{ib} = {} & BIDNN\,\beta_1 + SMALLEST\beta_2 + LOCAL\,\beta_3 + REPUTSCORE\beta_4 + NRATINGS\beta_5 \\ & + UNRATED\,\beta_6 + NBIDS\,\beta_7 + \mu_j + \varepsilon_{ib} \end{aligned} \tag{3.5}$$

where $Y_{ib}=1$ if the bid b submitted by coder $j=C(b)$ for project i is accepted, and 0 otherwise. Hypothesis 2b is supported if $\beta_4>0$. This model can be estimated with a fixed effects regression. The results of the estimation, shown in Table 3.4, give support for Hypothesis 2b. In other words, coder yield increases with reputation. Note also that these results give only a conservative estimate of the increase in volume that arises from higher reputation, since coders also submit more bids as they become more reputable.

3.6.4 Moderators of the Effect of Reputation Score on Bid Choice

The model estimated in section 6.1 was a parsimonious model that included only the main effects of the variables that were considered a priori more important. We now develop a richer model that includes additional variables and their interactions with the reputation score. By doing that, we can test the set of Hypotheses 3-1a, 3-1b, 3-2a, 3-2b, 3-3a, 3-3b, 3-4a, 3-4b that we have developed regarding the impact of certification, familiarity, similarity and anthropomorphism in the probability of awarding bids and their moderating effect on the reputation score.

The main variables that we use in the different specifications are described in Table 3.5. We also use interactions between REPUTSCORE and FAMILIARITY, HASCERTS, HASPIC and LOCAL.

Table 3.6 shows the results. The first column reproduces the results of Table 3.4 for comparison purposes. Column 2 adds variables to the baseline specification: HASCERTS is a variable that indicates whether a coder has certified his skills taking an online test; HASPIC is a variable that indicates whether the coder has included a picture in his profile; FAMILIARITY is a variable that indicates whether the buyer has worked with the coder before. Adding these variables improves the fit of the models but does not significantly change the coefficients obtained with the parsimonious analysis presented in section 6.2. Columns 3-6 incorporate the interactions between REPUTSCORE and HASCERTS, LOCAL, HASPIC and FAMILIARITY, respectively, and column 7 presents the full model with all the interactions. All the columns include controls for coder region and an indicator of whether the coder has not been rated yet.

The coefficient of the variable HASCERTS is positive and significant in all the specifications that include it (columns 2-7). This implies that the probability of awarding an auction to a coder is higher when the coder is certified, validating Hypothesis 3-1a. Furthermore, the interaction between HASCERTS and REPUTSCORE is negative and significant. This implies that the reputation score has a lower impact on buyer's choice probability when the coder is certified, which validates Hypothesis 3-1b. In other words, reputation and certification work as substitutes.

The coefficient of the FAMILIARITY variable (which indicates whether buyer and coder have worked together before) is positive and significant in all the specifications that include it (columns 2-7). This implies that the probability of awarding an auction to a coder is higher when the buyer has worked with the coder before, which validates Hypothesis 3-2a. Furthermore, the interaction between FAMILIARITY and REPUTSCORE is negative and significant. This implies that the reputation score has a lower impact on buyer’s choice probability when the buyer has worked with the coder before, which validates Hypothesis 3-2b. Reputation and familiarity with the coder work as substitutes.

The coefficient of the LOCAL variable is positive and significant in all the specifications that include it (columns 1-7). This implies that the probability of awarding an auction to a coder is higher when the coder is local, validating Hypothesis 3-3a. Furthermore, the interaction between LOCAL and REPUTSCORE is negative and significant. This implies that the reputation score has a lower impact on buyer’s choice probability when the coder is local. This validates Hypothesis 3-3b and suggests that reputation and similarity with the coder work as substitutes.

Finally, the coefficient of the variable HASPIC is positive and significant in all the specifications that include it (columns 2-7). This implies that the probability of awarding an auction to a coder is higher when the coder has a picture on the site, validating Hypothesis 3-4a. Furthermore, the interaction between HASPIC and REPUTSCORE is negative and significant. This implies that the reputation score has a lower impact on buyer’s choice probability when the coder has a picture. This validates Hypothesis 3-4b and suggests that reputation and the interpersonal trust enabled by anthropomorphism work as substitutes.

We note that the direction and magnitude of the coefficients of the parsimonious model presented in Section 6.2 do not qualitatively change when we add more variables, suggesting that the parsimonious model is not subject to significant omitted variable bias.

3.7. Conclusions and Future Work

Our results allow us to draw important conclusions regarding the effect of reputation on market outcomes in online service marketplaces. We find that buyers react to coder reputation and are willing to pay a significant premium to award a project to a more reputable bidder. On a representative bid, one additional point in the reputation score has the same effect on the probability of being chosen as a reduction of the bid amount of one standard deviation of the bids posted for that project.

Sellers also take into account their reputation when submitting their bids, and they adjust their bidding strategy as they accumulate reputation. However, they increase their prices more conservatively than what it seems that buyers would be willing to support. This can be interpreted as coders reaping most of the benefits of their reputation through higher volumes, rather than through higher prices.

The reputation score does not live in a vacuum, and buyers do not react to reputation in an absolute way. The context of the transaction is important to determining the impact that reputation will have on choices. We have shown that coder certification reduces the value of reputation, and the same happens with situations that prompt interpersonal trustworthiness, such as familiarity between buyer and coder, common origin of buyer and coder, and coder anthropomorphism. The reputation score happens to be more meaningful in situations where there is no information about the coder, there are limited external sanctioning mechanisms, or in situations where interpersonal trustworthiness is less likely to arise. These results have a broader applicability beyond the setting we study, and suggest that reputation and third-party certification can operate as substitutes. The same phenomenon is observed between interpersonal trust and reputation.

The reputation system is not the only mechanism in place to control moral hazard in online service marketplaces. Most of the online service marketplaces, including vWorker.com, use an escrow system that only releases the funds after the work has been approved. In contrast to a pre-payment scheme, an escrow scheme reduces the likelihood that the coder would want to engage in post-contractual opportunism, because the buyer can threaten not releasing the funds if the coder fails to perform to the specifications of the work. Similarly, the reputation system is not the only mechanism in place to signal quality. Increasingly, platforms like vWorker offer coders the possibility of certifying their skills. Our results on the interplay of reputation score, third-party certification and interpersonal trust are relevant for the design of mechanisms that combine a reputation score with other features to reduce transaction risk.

We conclude by discussing some limitations and areas of ongoing and future work. Our results presented here are based on a descriptive analysis in a reduced form setting. On the buyer side, one limitation of our approach is that we have not considered buyer heterogeneity. Our analysis can be interpreted as revealing the preferences of a representative buyer in this marketplace. We have experimented with random coefficient models that allow for some heterogeneity and our qualitative results do not seem to change, but we believe that fully accounting for buyer heterogeneity could result in additional insights. On the coder side, our model of bid setting estimates the average effect of reputation and number of previous ratings on bid prices. However, there can be important non-linearities. These non-linearities, and more broadly the complex dynamics of coder behavior, could be better captured by using a structural model that endogeneizes the coder's decision to bid for a given project. Such model could also explicitly incorporate forward-looking considerations about pricing and reputation accumulation. There is very little previous work in this space. To our knowledge, only Jofre-Bonet and Pesendorfer (2000) and Jofre-Bonet and Pesendorfer (2003) have modeled repeated participation in auctions, which requires the use of dynamic models. By developing such a structural model, we would be able to run counterfactual simulations to understand how the reputation system affects the market outcomes over time.

Besides incorporating complementary methodologies, there are other questions related to the design of reputation systems for online service marketplaces that could be addressed in future related work. For example, understanding the effect of the amount of information that is shown to participants in the marketplace could lead to managerial insights regarding the design of better reputation systems. If buyers only see a reputation score and number of ratings, then coders can quickly obtain reputation points by bidding for and winning cheap projects and then using the accumulated reputation to obtain better prices in more expensive projects. In order to account for that, vWorker now shows the total dollar amount that has been awarded to a coder to date. Given that some of the online service marketplaces have existed for a few years now, there have been several policy changes like this one. Research on these policy changes could reveal the effect of some decisions in the market outcomes.

With the increasing economic importance of online marketplaces, we believe that these and other related questions will receive more attention in the future.

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3.9. Tables

Table 3.1: Summary Statistics for Project Variables

DESCRIPTION	mean	sd	MED	min	max	count
Project-level summary statistics						
Minimum bid in the bid request	97.83	259.95	30	1	17000	273837
Maximum bid in the bid request	1247.68	230800.8	71.25	1	9.00E+07	273837
Amount of the winning bid	126.53	349.97	50	1	30000	273837
Mean bid	227.47	18413.25	50	1	8333460	273837
Median bid	141.47	1953.34	50	1	1000000	273837
Standard deviation of bids	611.76	83294.5	25.57	0	2.36e+07	139750
Number of bids in bid request	6.67	10.74	2	1	248	273837
Rating to coder	9.78	0.78	10	0	10	128888
Bid-level summary statistics						
Bid amount	192.66	1430.35	70	1	1000000	1822705
Average coder rating	9.34	1.21	9.78	0	10	1256105
Minimum coder rating	6.23	3.73	8	0	10	1256105
Number of previously won projects	33.68	84.40	6	0	1870	1812695
Number of ratings	23.81	62.67	4	0	1697	1812695
Coder-level summary statistics						
# of bids submitted by a coder	14.93	60.77	3	1	2795	122102
# of projects won by a coder	2.25	11.98	0	0	795	122102
# of bid requests posted by buyer	6.11	18.51	2	1	2075	45666

Table 3.2: Bid Choice

	(1)	(2)
VARIABLES	SUCCESS	MFX
BIDNN	-0.457***	-0.00508***
	(0.00486)	(0.000262)
NRATINGS	0.00278***	3.10e-05***
	(4.95e-05)	(1.65e-06)
REPUTSCORE	0.487***	0.00543***
	(0.00563)	(0.000211)
UNRATED	3.439***	0.0109***
	(0.0546)	(0.000536)
SMALLEST	0.185***	0.00189***
	(0.0102)	(0.000134)
LOCAL	0.362***	0.00339***
	(0.0143)	(0.000204)
EASTERN_EUROPE	-0.100***	-0.00117***
	(0.0131)	(0.000171)
INDIA_PAK	-0.532***	-0.00776***
	(0.0126)	(0.000467)
OTHER_ASIA	-0.390***	-0.00528***
	(0.0152)	(0.000367)
OTHER_EUROPE	-0.0104	-0.000116
	(0.0149)	(0.000168)
OTHER_LOCATION	-0.238***	-0.00298***
	(0.0169)	(0.000284)
Observations	1,595,257	1,595,257
Pseudo R2	0.119	
LL	-243323	

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

Table 3.3: Bid Setting

	(1)	(2)
VARIABLES	BIDN	BIDN
REPUTSCORE	0.0102***	0.0112***
	(0.000153)	(0.000676)
UNRATED		0.00941
		(0.00635)
NRATINGS	0.000868***	0.000868***
	(1.47e-05)	(1.47e-05)
Constant	-0.0164***	-0.0256***
	(0.00109)	(0.00631)
Observations	1,799,520	1,799,520
R-squared	0.246	0.246

Table 3.4: Coder Yield

	(1)
VARIABLES	Coder Yield
BIDNN	-0.00881***
	(0.000353)
SMALLEST	0.301***
	(0.000802)
LOCAL	0.0322***
	(0.00126)
REPUTSCORE	0.0113***
	(0.000267)
NRATINGS	0.000370***
	(8.41e-06)
UNRATED	0.0546***
	(0.00234)
NBIDS	-0.00308***
	(1.12e-05)
Constant	0.0536***
	(0.00245)
Observations	1,799,520
R-squared	0.372

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

Table 3.5: Main Variables Used in the Analysis

Variable	Description	Belongs to set…
NBIDS	Number of bids submitted to the project	$X_{project}$
BIDNN	Normalized bid amount	$X_{bid\text{-}set}$
SMALLEST	Indicates that the bid is the smallest received for a project	$X_{bid\text{-}set}$
NRATINGS	Number of ratings received by the coder	X_{coder}
REPUTSCORE	Average rating received by coder in previous projects	X_{coder}
UNRATED	Indicates that the coder has not received previous ratings	X_{coder}
HASCERTS	Indicates whether a coder has been certified on the site	X_{coder}
HASPIC	Indicates whether the coder has a picture on the site	X_{coder}
FAMILIARITY	Indicates whether buyer and coder have worked together before	$X_{relation}$
LOCAL	Indicates that buyer and coder are from the same country	$X_{relation}$

Table 3.6: Moderators of Reputation (2001-2010).

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
BIDNN	-0.457***	-0.457***	-0.456***	-0.457***	-0.456***	-0.456***	-0.456***
	(0.00486)	(0.00496)	(0.00496)	(0.00496)	(0.00496)	(0.00495)	(0.00495)
NRATINGS	0.00278***	0.00220***	0.00222***	0.00220***	0.00221***	0.00221***	0.00223***
	(4.95e-05)	(4.99e-05)	(5.00e-05)	(4.98e-05)	(4.99e-05)	(4.99e-05)	(4.99e-05)
REPUTSCORE	0.487***	0.487***	0.490***	0.492***	0.492***	0.491***	0.503***
	(0.00563)	(0.00588)	(0.00591)	(0.00591)	(0.00594)	(0.00591)	(0.00601)
HASCERTS		0.154***	0.439***	0.157***	0.154***	0.153***	0.424***
		(0.0140)	(0.0505)	(0.0140)	(0.0140)	(0.0140)	(0.0509)
HASPIC		0.125***	0.125***	0.125***	0.220***	0.125***	0.222***
		(0.00687)	(0.00687)	(0.00687)	(0.0158)	(0.00687)	(0.0159)
FAMILIARITY		1.308***	1.308***	1.308***	1.308***	1.428***	1.430***
		(0.00876)	(0.00876)	(0.00876)	(0.00876)	(0.0201)	(0.0202)
LOCAL	0.362***	0.362***	0.363***	0.573***	0.363***	0.362***	0.578***
	(0.0143)	(0.0146)	(0.0146)	(0.0228)	(0.0146)	(0.0146)	(0.0229)
SMALLEST	0.185***	0.205***	0.205***	0.206***	0.206***	0.206***	0.207***
	(0.0102)	(0.0106)	(0.0106)	(0.0106)	(0.0106)	(0.0106)	(0.0106)
REPUT_HAS_CERTS			-0.0314***				-0.0295***
			(0.00539)				(0.00543)
REPUT_LOCAL				-0.0289***			-0.0295***
				(0.00242)			(0.00243)
REPUT_PIC					-0.0120***		-0.0122***
					(0.00181)		(0.00182)
REPUT_FAM						-0.0150***	-0.0153***
						(0.00226)	(0.00227)
Observations	1,595,257	1,595,257	1,595,257	1,595,257	1,595,257	1,595,257	1,595,257
Pseudo R2	0.119	0.163	0.163	0.163	0.163	0.163	0.163
LL	-243323	-231115	-231099	-231045	-231094	-231092	-230982
df	11	14	15	15	15	15	18
AIC	486668.8	462258.6	462227.6	462120	462217.3	462213.3	462000.4
BIC	486803.9	462430.6	462411.9	462304.3	462401.5	462397.6	462221.5
% suc predicted	0.338256	0.386362	0.386301	0.386955	0.386355	0.38667	0.386939
% fail predicted	0.938365	0.94203	0.942026	0.942112	0.942004	0.941928	0.942

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Chapter 4

The Effects of Product Line Breadth

Abstract

Using a detailed dataset from the U.S. automotive industry in 2002-2009, we study the effects of product line breadth on market shares and costs. Consistent with theoretical predictions, we find a positive association between product line breadth and market share (0.1% per additional product) and unit production costs ($175 per additional product). Average unit production costs decrease with the use of platform families (on average, for every 100,000 vehicles produced for other models based on the same platform, unit production costs are reduced by $55). Besides production costs, we study the effect of product line breadth on mismatch costs arising from demand uncertainty, manifested through discounts and additional inventories. An additional product in the line is associated with an increase of around $100 in average discounts and with carrying three additional days of supply in the average inventory of all the models of the line. We propose an additional measure of product line breadth based on the range of fuel economy levels offered by an automaker. We find that automakers who offer a broader range of fuel economy levels increase their market share and reduce their average discounts as gas prices increase, suggesting that product line breadth can work as a hedge against changes in demand conditions.

4.1. Introduction

Product proliferation is pervasive in many industries. Consumers willing to buy a car in 2002 in the United States could choose among some 192 models, each of which had multiple configuration options. Certainly, that is a broader choice set than the black Ford T available to consumers in 1908, but not very impressive if we compare it with the 234 models that were available in 2007, only five years later. On average, individual automakers have been broadening their products lines over the last few years. This paper studies the effects of product line breadth in the U.S. automotive industry.

Previous theoretical and empirical literature has been concerned with the drivers and effects of product line breadth. Theoretical models (e.g., Lancaster 1990) suggest that broader product lines should result in higher firm market share, since customers are more likely to find products that are closer to their taste, and in higher production costs, due to the loss of economies of scale. However, as noted by Netessine and Taylor (2007), "empirical researchers have analyzed linkages between variety and production costs, but have arrived at contradicting conclusions." For example, Kekre and Srinavasan (1990) find that broader product lines are associated with lower production and inventory costs, while Bayus and Putsis (1999) find a positive association between product line breadth and production costs.

Besides this lack of consensus in the empirical findings, the empirical literature on the effects of product line breadth presents some opportunities for new work. Some important notions developed in the operations management and product development communities have been largely ignored by the empirical literature that studies the effect of product line breadth on costs. For example, Fisher (1997) discusses the two types of functions performed by supply chains: a physical function and a market mediation function, each of which incur in a different type of cost. Physical costs are the costs of production, transportation and inventory storage, while market mediation costs arise "when supply exceeds demand and a product has to be marked down and sold at a loss or when supply falls short of demand, resulting in lost sales opportunities and dissatisfied customers"(Fisher, 1997). The literature on product line breadth has focused on the first type of cost, but has not considered the second type, which we generically label as mismatch costs. Mismatch costs are largely a consequence of demand uncertainty. Other notions such as delayed differentiation (Swaminathan and Tayur 1998) or component commonality and product platforms (Robertson and Ulrich 1998) have been theoretically shown to allow offering a broad product line while controlling production and development costs. However, to the best of our knowledge, the effects of component sharing and platform strategies on production costs have not been empirically studied.

In this paper, we attempt to bridge the gap between these theoretical notions that have been developed in the operations management and product development communities and the existing empirical literature on the effects of product line breadth. In order to do that, we use a detailed dataset of the U.S. automotive industry during the period 2002-2009. Besides being a very important industry, the automotive industry provides a very suitable setting to study the effects of product line breadth and, in particular, some of the aforementioned issues. It is an industry in which product platforms are used extensively, and it has a very particular pricing structure (firms set list prices before demand is realized and offer discounts when demand is realized) that allows us to measure supply-demand mismatch costs separately from production costs. In addition to this, firm entry and exit is not very important (at least in the period of study) and models are typically marketed over several years, which allows us to observe the same models in different contexts of product line breadth.

Using a rich dataset of the U.S. automotive industry and drawing from the results of some previous empirical and analytical research, we make the following main contributions:

First, we study the effect of product line breadth on market share, and find that a broader product line is associated with a higher market share. Carrying one additional product in the line is associated with an increase of 0.1% in the market share of an automaker. This is consistent with findings of previous empirical papers in other settings (e.g., Kekre and Srinivasan 1990, Bayus and Putsis 1999). Using a consumer demand model, we also find that customers experience higher utility when product lines are broader. These findings illustrate the main benefit of having a broader product line.

Second, we study the effect of product line breadth on production costs, and find that a broader product line is associated with higher average production costs, in contrast to Kekre and Srinivasan (1990). One additional product is associated with an increase of around $175 on the average unit production cost. These results are directionally consistent with the results of Bayus and Putsis (1999). An important difference is that Bayus and Putsis (1999) proxy production costs with prices. In the case of the automotive industry, different products might have different markups, and this approach could lead to bias. In contrast, we assume that the observed prices are the result of a pure strategy Nash equilibrium in prices, and use a consumer demand model to recover the markup of each model, which allows us to estimate the production costs.

Third, we study the effect of platform families on production costs. We find that, consistent with the theoretical literature on platforms, using platform families decreases the production costs. On average, for every 100,000 vehicles produced for other models based on the same platform, unit production costs are reduced by $55. To our knowledge, no previous work has empirically examined the effects of platform families on production costs.

Fourth, we study the effect of product line breadth on mismatch costs. Mismatch costs are a consequence of demand uncertainty. Broader product lines are subject to higher demand fragmentation and, following an inverse pooling argument, are more exposed to the consequences of demand uncertainty. In the automotive industry, we observe mismatch costs in the form of discounts and inventories. We find that an additional product in the line is associated with an increase of around $100 in average discounts and with carrying three additional days of supply in their average model inventories.

Finally, we propose a complementary attribute-based measure of product line breadth, capturing the range of fuel economy levels offered by an automaker, and we study how breadth in this measure helps hedge against changes in demand. We find that, for the same median fuel economy, automakers who offer a broader range of fuel economy levels increase their market share and reduce their average discounts as gas prices increase. This suggests that choosing the right type of product breadth can offer a hedge against changes in demand arising, in this case, from changes in gas prices.

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

4.2. Literature Review

Previous work in the operations management and marketing communities has studied product line strategies and their effects on revenues and costs, both empirically and theoretically. Among the empirical papers, one of the first papers to study product line breadth was Kekre and Srinivasan (1990). They use self-reported survey data across industries to study the market benefits and cost disadvantages of broader product lines. They find that broader product lines are associated with higher market shares, but they do not find a positive association between broader product lines and production costs. In contrast, Bayus and Putsis (1999) analyze the personal computer industry and find an association between product line breadth and market shares and prices, which they assume to proxy for production costs. In the same industry, Putsis and Bayus (2001) study the determinants of product line decisions and suggest that firms expand their product lines when there are low industry barriers or when there are perceived market opportunities.[3] The first contribution of our work to the literature is to revisit the linkage between variety and market share and production cost in the context of U.S. automotive manufacturers. We find a positive association between product line breadth and both market shares and production costs.

The operations management community has studied the challenges associated with managing product variety. Ramdas (2003) provides a review of this literature. Some empirical work has studied the effects of product variety in automotive plants. For example, Fisher and Ittner (1999) and MacDuffie et al. (1996) analyze the effect of product variety on work-in-process inventory, productivity and customer-perceived quality. Both papers deal with the effects of variety at the plant level. Our work is complementary to those papers, because we study the effects of product line breadth on market share and on production and mismatch costs.

Some work has looked at product line strategies and their relationship with supply chain and product development decisions. Randall and Ulrich (2001) consider two types of variety: production-dominant variety and mediation-dominant variety (in

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[3] Other papers have studied the competitive dimensions of product line length (Draganska and Jain, 2005), but these competitive aspects are beyond the scope of this paper.

the spirit of market mediation costs described in Fisher 1997); the former is associated with higher production costs (such as direct materials, labor, manufacturing overhead, and process technology investments) and the latter is associated with higher market mediation costs, such as inventory holding costs, product mark-down costs occurring when supply exceeds demand, and the costs of lost sales when demand exceeds supply. They study the association between these types of variety and certain characteristics of a supply chain, such as the production volume and the location of production. They find an association between scale-efficient production and production-dominant variety, and between local production and mediation-dominant variety. Our work is related to their paper, in the sense that we study the empirical relationship between product line strategies and what Randall and Ulrich call market mediation costs, which we label as mismatch costs. To our knowledge, no previous work has empirically studied the effects of product line breadth on mismatch costs. In a related paper, Randall et al. (1998) study how the presence of premium products in a product line enhances brand equity, analyzing the U.S. mountain bicycle industry. Their analysis supports the hypothesis that firms with high-quality products in their lines have higher brand premiums. In other words, they find spillovers from the highest-quality models in the product line. Like them, we also study product line attributes that go beyond the mere number of products in the product line. In our case, we study how the range of fuel economy levels offered by a firm's product line affects the firm's ability to cope with uncertain demand.

Our work also builds on the literature on component sharing and product platforms. Automotive manufacturers use product platforms to share intellectual and material assets across a family of products (Robertson and Ulrich 1998, Krishnan and Gupta 2001). Fisher et al. (1999) study the drivers of component sharing. In our work, we measure the effects of platform affiliation on average production costs.

Some theoretical papers that have studied product line strategies provide context to our work and to the hypotheses that we test with our data. For example, Swaminathan and Tayur (1998) study delayed differentiation, Van Mieghem and Dada (1999) study production postponement, Desai et al. (2001) study the trade-off between component commonality and product differentiation, Hopp and Xu (2005) study the impact of design modularity on the optimal length and price of a differentiated product line, and Netessine and Taylor (2007) study the impact of production technology on the optimal product line design.

A few empirical papers in operations management have studied other aspects of the automobile industry that are related to our work. Cachon and Olivares (2010) study the drivers of finished-goods inventory in the U.S. automobile industry. Among other results, they find that the option content of a model is associated to the inventory of the model. Cachon, Gallino and Olivares (2012) study how inventory affects demand, and they consider the role of the number of options of a given model. Unlike these two papers, our approach to variety is based on the number of products in the product line of an automaker, as opposed to number of options within a model. Moreno and Terwiesch (2011) study the effect of production flexibility on discounts. In this paper, we consider the effect of another strategic decision -- product line breath -- on mismatch costs.

Finally, the unprecedented increase in gas prices has generated a renewed interest in the effects of gas prices on market outcomes in the automotive industry. Our work is particularly related to two papers in this stream. Busse et al. (2011) study the effect of gas prices on prices and market shares of new and old vehicles. Langer and Miller (2012) study how gas prices affect automakers' short-run responses. Our work shows how the range of fuel economy levels covered by a firm's product line affects the ability of firms to cope with uncertain demand, and how manufacturers' reactions to changing gas prices depend on attributes of their entire product line.

4.3. Theoretical Foundations and Hypotheses Development

We build on existing theory to develop the hypotheses that we test with our data. In order to relate our work to earlier studies of product line breadth, we use a measure of product line breadth that is consistent with previous work (e.g., Bayus and Putsis 1999). We define product line breadth as the number of different products (vehicle models, in our empirical setting) that a firm (an automaker, in our empirical setting) offers at a given time. We start our analysis by developing two hypotheses that have been tested in the literature, dealing with the effect of product line breadth on market shares and the effect of product line breadth on production costs.

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

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

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

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

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

This hypothesis has also been studied in previous empirical literature with somewhat contradictory conclusions. By testing it in our data, we can provide additional evidence in one or the other direction, and we can quantify the effect of the cost increase that can be attributed to variety in the U.S. automotive industry.

Component commonality and platform strategies have been suggested to reduce the diseconomies of scale associated with offering broad product lines (Ulrich and Robertson 1998). Economies of scale can be achieved by producing higher volumes of common parts. We hypothesize that:

Hypothesis H3. *Average production costs for a model decrease with the production volume of other models based on the same platform*

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

The existing literature that has empirically studied the cost consequences of product line breadth has largely focused on its impact on production costs. However, as noted by Fisher (1997), it is important to differentiate between the physical costs (costs of production, transportation and inventory storage) and market mediation costs that arise as a consequence of supply-demand mismatches, such as markdowns, excess inventories and shortages. Depending on which type of cost dominates, firms might want to choose between physically-efficient and market-responsive supply chains. Randall and Ulrich (2001) examine the association between supply chain structures and the type of product variety that firms pursue. In an empirical context, it is interesting to understand if one of the types of cost dominates and how variety affects the two types of costs. For example, if variety affects mainly mismatch costs, firms willing to offer broad product lines should adopt market responsive supply chains, whereas if variety affects mainly production costs, firms offering broad product lines should adopt physically-efficient supply chains. As noted by Ramdas (2003), higher variety can increase demand variability and forecast errors, thereby increasing mismatch costs. This is an "unpooling" argument, since fragmentation exacerbates the uncertainty faced by the firm. We formulate the following general hypothesis:

Hypothesis H4. *An increase in product line breadth is associated with an increase in mismatch costs*

Our empirical setting -- the automotive industry -- provides two pieces of information that are directly related to mismatch costs: discounts and inventories. Automotive manufacturers set list prices before demand is realized, and they use discounts to correct supply demand mismatches. Higher product variety will result in higher demand uncertainty and in more significant supply-demand mismatches. Similarly, higher demand uncertainty will result in higher average inventories. Thus, we can formulate the following two hypotheses that we test to validate Hypotheses H4:

Hypothesis H4a. *An increase in product line breadth is associated with an increase in average discounts*

Hypothesis H4b. *An increase in product line breadth is associated with an increase in average inventories*

Figure 1 summarizes graphically our Hypotheses 1 to 4.

If we find support for Hypothesis 4 -- that is, if we find evidence that product line breadth results in higher mismatch costs arising from demand uncertainty -- a related issue is whether breadth can be added to a product line in a manner that mitigates the effect of this demand uncertainty. So far, our discussion has considered product line breadth as the number of products offered by a firm. We now propose a complementary attribute-based measure of product line breadth. Since we are interested in understanding how product line breadth interacts with demand uncertainty, we measure breadth along a dimension in which we know there is substantial uncertainty in our empirical context: gas prices. Gas prices are a big source of demand uncertainty in the automotive industry. If gas prices are high, customers prefer fuel-efficient vehicles (e.g., compact cars). If gas prices are low, the same customers might prefer other types of cars (e.g., sport utility vehicles). Our complementary measure of product line breadth is based on the range of fuel economy offered by an automaker, relative to the range of fuel economy offered by the entire industry. Firms that offer a broader product line in terms of fuel economy might benefit from internal substitution when gas prices change. We formulate the following hypothesis:

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

We break down Hypothesis H5 into two complementary hypotheses that give a more precise definition of what we mean by "hedging against changes in demand":

Hypothesis H5a. *When gas prices increase, product lines that cover a broader range of fuel economy levels increase market share*

Hypothesis H5b. *When gas prices increase, product lines that cover a broader range of fuel economy decrease discounts*

This analysis is related to Busse et al. (2011), which studies the effect of gas prices on prices and market shares of new and old vehicles, and to Langer and Miller (2012), which studies how gas prices affect automakers' short-run responses. Our focus is to study how product line breadth affects the changes in market shares and discounts for a given average level of fuel economy.

4.4. Data and Variables

The empirical setting for this project is given by the U.S. automotive industry in the period between 2002 and 2009. The U.S. automotive industry is very important on its own (it accounts for 5% of the total U.S. GDP, see Ramey and Vine 2006) and it is especially appealing for the type of analysis considered in this paper. In particular, its pricing structure allows us to create separate measures of average production costs and mismatch costs. In the automotive industry, manufacturers set list prices for a model year before demand is realized. When they set list prices, they take into account their expected production costs, among other considerations. During the year, when demand is realized, manufacturers use discounts (incentives, as they are usually referred to in the industry) to dealers or final customers for those vehicles that are selling worse than expected. Therefore, observed discounts provide an indication of supply-demand mismatch. In other words, each of the two pricing levers that the manufacturer has -- list prices and discounts -- is associated with a different source of costs. List prices are related to production costs (Section 5.2 describes how production costs can be estimated from list prices) and discounts are related to mismatch costs. In addition, other aspects also make the automotive industry appealing for our analysis. In the automotive industry, product platforms, another of our constructs of interest, are used extensively. Also, it is an industry with a limited number of automakers who market vehicles that are comparable with each other using a reduced set of attributes. Firm entry and exit is not very important during our period of study, and models are typically marketed during several years, which allows us to observe the same models in different contexts of product line breadth.

For this analysis, we have obtained the gas prices during the period of interest from the Energy Information Administration, and we have combined three types of automotive data from different sources: market data, vehicle-level data and production data. Our market data comes from TrueCar (www.truecar.com), an online automotive information and communications platform that provides information to consumers and dealers. Through collaboration with TrueCar, we have obtained access to some of their historical proprietary data, including U.S.-wide monthly data on sales, end-of-month inventory, and average discounts at the model level. Average discounts are calculated by adding all the amounts spent by the manufacturer to incentivize sales of a particular model in one month (including the cost of financial incentives such as favorable credit terms) and dividing it by the amount of vehicles of that particular model sold in the month. We also have access to the same information at the make-month level.

We obtain vehicle-level data and production data from WARDS Automotive. Vehicle-level data contains information about vehicle attributes (including weight, horsepower, fuel economy, length, height, wheel base, and manufacturer's suggested retail price) that is available at the model-year level. Vehicle attributes are available at a more granular level (e.g., Chevrolet Malibu LS 4dr Sedan vs. Chevrolet Malibu). We match every model with the median of the attributes across the different versions in which a model is available. Production data indicates the amounts produced for each model and month for the models manufactured (at least partially) in the U.S., and it includes information about the plant where they are produced and the platform on which the model is based. We compute total production for each of the platforms.

Our main measure of product breadth, PLB_{it} is constructed by counting the number of different models (e.g., Chevrolet Malibu) marketed by a make (e.g., Chevrolet) in a given month. This variable changes when models are introduced or phased out. We generate an alternative measure of product line breadth, $MPGBREADTH_{it}$, based on the range of fuel economy levels offered by a make, relative to the industry. This measure is calculated as the interquartile range of the fuel economy offered by the models of make i in month t over the interquartile range of the fuel economy offered by the entire industry in month t. These interquartile ranges are based on model availability, regardless of sales. For example, for a make who only offers one level of fuel economy, the interquartile range would be 0. For a make who has the same interquartile fuel economy as the entire industry, this range would be 1. We have experimented with alternative measures of the range of fuel economy level offered by a make and found no substantial qualitative differences in our results. For reference purposes, Table 4.1 shows all the variables used in the analysis, along with a short description and some summary statistics.

Our dataset contains 18,166 model-month observations corresponding to 328 models. Note that some of our specifications in Section 5 are estimated at the make-month level, while other specifications are estimated at the model-month or model-year levels.

4.5. Econometric Analysis and Results

4.5.1 Effect of Product Line Breadth on Market Share

We start by examining the effect of product line breadth on make market shares. We propose the following specification:

$$MKTSHR_{it} = \beta_1 PLB_{it} + CONTROLS + \mu_i + \gamma_t + \varepsilon_{it} \tag{4.1}$$

where i denotes a make (e.g., Chevrolet, Toyota, etc.) and t denotes the month and year of the observation. The specification includes make fixed effects that control for any omitted make-level time-invariant factors. For example, the fact that Chevrolet is an American company is accounted for by the corresponding make fixed effects.

Table 4.2 shows the effect of product line breadth on make market shares. All columns include make fixed effects and time controls. Column 1 provides the baseline specification with no additional controls. The estimate of the product line coefficient β_1 is 0.00106 and it is statistically significant, which gives support to our hypothesis H1. One additional product in the product line is associated with an average increase of 0.1% in the make market share. Column 2 adds the complementary measure of product line breadth based on the range of fuel economy levels covered by the make, which has been described above, and its interaction with gas prices. The coefficient β_1 remains essentially unaltered after including the additional measure, and the coefficients for the fuel-economy-based measure and its interaction with gas prices suggest that automakers who offer a broader range of fuel economy levels increase their market shares as gas prices increase. This supports our Hypothesis H5a. For representative values of gas prices, the net effect of the fuel-economy-based measure is positive, although when gas prices are very low a broader range of fuel economy levels can be associated with lower market shares. Column 3 includes two additional control variables: the median fuel economy of the make and its interaction with gas prices, to make sure that the range variable included in Column 2 is not merely capturing differences in the average fuel economy offering. Adding these controls does not change the results of Columns 1 and 2. Firms with higher median fuel economy have a smaller market share on average, but their market share increases as gas prices go up, as we could expect.

Overall, the results shown in Table 4.2 suggest that an increase in the number of products carried by a make is associated with an increase in the make market share (relating to the role of product lines as a tool for market expansion), and that a product line that covers a broader range of fuel economy levels increases its market share as gas prices increase (thus supporting the hedging role of a broader product line that we have discussed above).

We can draw complementary conclusions about the effect of product line breadth on market share using a model of consumer demand. We propose a nested multinomial logit model of consumer demand (McFadden 1978, Cardell 1997). Each vehicle model is defined as a bundle of attributes. We define a nest as a combination of vehicle segment and luxury level (e.g., luxury SUVs). Consumers choose first the nest in which they want to purchase (or the outside option of not buying any vehicle), and then choose the vehicle in the nest that gives them the highest utility. The advantage of this model is that it avoids the problem of independence of irrelevant alternatives of conventional multinomial logit models, without adding too much computational burden. For the model estimation, we follow Berry (1994), which proposes the following transformation:

$$\ln\left(s_{jt}\right)-\ln\left(s_{0t}\right)=x_{jt}\beta+\alpha p_{jt}+\sigma\ln\left(s_{jt|g}\right)+\xi_{jt} \tag{4.2}$$

where s_{jt}, s_{0t} and $s_{jt|g}$ are, respectively, the market shares of model j in time t, the share of the outside good (no purchase) in time t and the share of model j in its nest g at time t; x_{jt} are the product characteristics, and ξ_{jt} is a shock unobserved to the econometrician. We estimate this model with annual data. For the price p_{jt} , we subtract from the manufacturer's suggested retail price (MSRP) of the vehicle the average discount offered by the manufacturer during the year. The product characteristics that we consider include vehicle size variables, a proxy for acceleration given by horsepower/weight, and the miles per gallon. We also include our product line variables and segment-time controls. We account for price endogeneity using instrumental variables along the lines of the variables described in Berry et al. (1995), including the characteristics of the other models of the same manufacturer and the characteristics of the rest of the vehicles on the market (for more details, see Berry et al. 1995). Note that the log of the within group share, $\ln(s_{jt|g})$ is also endogenous, and therefore additional instruments, such as the number of vehicles in the nest and the characteristics of other models in the nest, are necessary. In summary, we use variation in the market shares, choice set (introduction and removal of models), vehicle attributes, and make product line breadth to identify the coefficients of the demand model.

The results, shown in Table 4.A1, suggest that consumers attribute a positive utility to models offered by automakers who have a broader product line. A possible interpretation of these results is that the benefits of a broader product line in terms of market share do not come exclusively from the market share of the new models. With a broader product line, customers are more likely to find products that are closer to their ideal bundle of characteristics, they derive utility from that, and are more likely to choose them.

4.5.2 Effect of Product Line Breadth on Costs

According to our model, product line breadth affects the costs faced by a firm through two different channels: production costs and mismatch costs. None of those types of costs are directly observable to the researchers, but we can estimate them from the available data.

We start by studying the effect of product line breadth on **production costs**. We describe two different analysis strategies to recover cost-related information for the available data. The first one is to simply proxy the unobserved production costs by using the observed vehicle list prices. This is what Bayus and Putsis (1999) do. We expect list prices to be correlated with production costs, because firms are informed about their costs and use their cost information when setting the list prices. On the other hand, list prices are determined before actual demand is observed and they typically remain constant during the entire vehicle year – in other words, they are not affected by mismatch costs. Using list prices as a proxy for unobserved costs has some potential problems. Most important, list prices are affected by the market power of the firm. A firm can choose a high price point for a vehicle not because production costs are high, but because the firm enjoys market power. However, given that the existing empirical literature on product variety has used prices to proxy for costs in the past (e.g., Bayus and Putsis 1999), we include this model as a baseline for reference purposes.

We use the following specification:

$$MSRP_{jt} = \beta_1 PLB_{it} + CONTROLS + \mu_j + \gamma_t + \varepsilon_{jt} \tag{4.3}$$

where i denotes the make (e.g., Chevrolet), j denotes the model (e.g., Chevrolet Malibu) and t denotes the vehicle year. Adding model fixed effects controls for any omitted model-level time invariant factor.

Table 4.3 shows the effect of product line breadth on list prices. All columns include model-fixed effects and segment-year controls. Column 1 provides the baseline specification with no additional controls. The estimate of the product line coefficient β_1 is 297.5 and it is statistically significant, which gives support to our hypothesis H2. One additional product in the product line of an automaker is associated with an average increase of around \$300 in the list prices of the models of that automaker, reflecting a potential change in production costs. Column 2 adds a set of controls that account for vehicle characteristics that can have an impact on production costs (SIZE, HPWT, MPG), and Column 3 includes an additional set of controls that account for situations that can have an impact in the firm's list price setting strategies, such as the number of years since the model was introduced and, whether a model is just being launched, is about to be phased out, or has experienced changes in its design. In both cases, the product line coefficient does not change substantially. Column 4 includes an additional variable with the volume produced for the rest of vehicles that are based on the same platform as the model under consideration. The estimate for this variable is negative and statistically and economically significant. This supports our hypothesis H3. A production of 100,000 vehicles of other models based on the same platform is associated with an average cost reduction of $83.3 on the production costs of a model. Note that the results exclude models that are exclusively exported, since we do not have platform data for vehicles that do not have any production in the United States.

As discussed, list prices are likely to be correlated with production costs, but they are also affected by market power and other considerations that might generate bias in the results. Our second approach to estimating production costs and the effects of product line decisions on them is based on an equilibrium pricing model that arises from the demand model introduced in Section 5.1. Following Berry (1994), we assume that observed list prices are the result of an interior, pure strategy Nash equilibrium in prices. For the nested logit demand model, it is possible to characterize the equilibrium markup for a given model. It can be shown (see Berry 1994) that, for model *j* and time *t*, this markup is:

$$MARKUP_{jt} = \frac{\frac{1-\sigma}{\alpha}}{1-\sigma s_{jt/g}-(1-\sigma)s_{jt}} \tag{4.4}$$

That is, the markup of a model depends on the market share, the within nest market share, the substitution parameter σ and the price elasticity α. The market share and the within-nest market share are observed in our data. The other two parameters are estimated using the model described in Section 5.1 (0.291 and -5.94e-05, respectively).

Each model has a different markup that takes into account the market power considerations that were ignored in the model that proxies production costs with list prices. Using the estimated markup and price for a particular model, we can recover the production costs as $COST_{jt}=PRICE_{jt}-MARKUP_{jt}$. Instead of using list prices, we use the list price minus the average discounts in the cost calculation, since that is the price information that enters the demand model used to calculate the markup (our robustness checks indicate that our qualitative results do not depend on this).

Once we have estimated the production costs, we can conduct an analogous analysis to the one we have presented using list prices. This is the specification:

$$COST_{jt} = \beta_1 PLB_{it} + CONTROLS + \mu_j + \gamma_t + \varepsilon_{jt} \tag{4.5}$$

where i denotes the make (e.g., Chevrolet), j denotes the model (e.g., Chevrolet Malibu) and t denotes the vehicle year.

Table 4.4 shows the effect of product line breadth on estimated production costs. All columns include model fixed effects and segment-year controls. As in Table 4.3, Column 1 is the baseline specification without additional control variables, Column 2 adds a set of controls that account for vehicle characteristics, Column 3 includes an additional set of controls that account for situations that can have an impact on production costs, and Column 4 includes the volume produced for the rest of vehicles that are based on the same platform. The results are qualitatively similar to the ones obtained using list prices as a proxy for costs displayed in Table 3, but the effect of the product line breadth variable seems to be lower, in the $150-200 range. Platform volume is also associated with lower costs, but the magnitude is again smaller (reduction of \$54.70 for a platform producing 100,000 vehicles per year).

Overall, the results presented in Tables 4.3 and 4.4 provide evidence that supports our Hypotheses H2 and H3. On one hand, product line breadth is associated to an increase in average production costs. On the other hand, component sharing across multiple vehicles is associated to a reduction in the production costs that increases with the production volume of the other models based on the same platform.

We now turn our attention to the effect of product line breadth on **mismatch costs**. As with production costs, mismatch costs are not directly observable. But there are two elements in our data that indicate the presence of mismatches: discounts and inventory. Mismatches in the auto industry are typically a consequence of short-run (i.e., within a model year) changes in demand. Although list prices are fixed for the entire model year, firms can react to a negative shock in demand (e.g., a slow-selling vehicle) by offering discounts (dealer or customer incentives, as they are known in the industry). A positive demand shock does not typically have consequences in terms of pricing because firms rarely sell cars above list price (i.e., there are no "negative discounts"). Changes in inventory can also denote mismatches: inventory builds up when supply is higher than demand and depletes when demand is higher than supply.

In order to examine the effects of product line breadth on discounts, we use the following specification:

$$AVGDISCMAKE_{it} = \beta_1 PLB_{it} + CONTROLS + \mu_i + \gamma_t + \varepsilon_{it} \tag{4.6}$$

where i denotes a make, t denotes a month and $AVGDISC_{it}$ is the average discount given by make i in month t (i.e., the sum of all the money spent on discounts in month *t* by make *i* over the number of vehicles sold by make *i* in month *t*). Table 4.5 shows the effect of product line breadth on average incentives given by brands, which measure one type of mismatch cost. All columns include make fixed effects that account for any time-invariant make-level omitted variables. All columns also include time controls (year-month interactions) that account for industry-level temporal patterns in discount behavior. Column 1 is the baseline specification and does not include any additional controls. The estimate of the product line coefficient β_1 is 57.72 and it is statistically significant, which gives support to our Hypothesis H4a. One additional product in the product line is associated with an average increase $57.72 in the average discounts given by the make. Column 2 adds the complementary measure of product line breadth -- based on the range of fuel economy levels covered by the make -- and the interaction of this measure with gas prices. The coefficient β_1 does not change substantially after including the additional measure. The coefficients for the fuel-economy-based measure and its interaction with gas prices suggest that auto makes that offer a broader range of fuel economy levels reduce their average discounts as gas prices increase. This supports our hypothesis H5b. For representative values of gas prices, the net effect of the fuel-economy-based measure on discounts is negative, although when gas prices are very low a broader range of fuel economy levels can be associated with higher discounts. Column 3 includes two additional control variables: the median fuel economy of the make and the interaction of the median fuel economy of the make with gas prices, to make sure that the range variable included in Column 2 is not merely capturing differences in the average fuel economy offering. Adding these controls does not change the results of Columns 1 and 2. Firms with higher median fuel economy offer lower average discounts as gas prices increase, compared to firms with lower median fuel economy.

The previous specification analyzes the effect of make product line breadth at the make level. One could argue that by performing the analysis at the make level, there could be confounding factors that might affect discounts and that could potentially be correlated with product line breadth. If that was the case, our estimates could be biased. In order to understand whether that is a concern, we complement the make-level model with a model-level model with the following specification:

$$AVGDISCMODEL_{it} = \beta_1 PLB_{it} + CONTROLS + \mu_i + \gamma_t + \varepsilon_{it} \tag{4.7}$$

where i denotes a model, t denotes a month and $AVGDISCMODEL_{it}$ is the average discount given by model i in month t (i.e., the sum of all the money spent on discounts in month t for model i over the number of model i vehicles sold in month t). In the model-level specification, a richer set of controls can be used. For example, we can include time-segment controls that account for different discount patterns for vehicles that belong to different segments. Table 4.6 shows the effect of product line breadth on average incentives at the model level. All columns include model fixed effects that account for any time-invariant model-level omitted variables. All columns also include controls for segment, time and segment-time interactions. Column 1 is the baseline specification and does not include any of the additional controls. The estimate of the product line coefficient β_1 is 106.1 and it is statistically significant. One additional product in the product line of the make that produces one model is associated with an average increase of around $100 in the average discounts given for that model. The sign is consistent with the results at the make level, which gives additional evidence supporting our Hypothesis H4a. The magnitude is slightly higher than the effect estimated at the make level (around $75). Column 2 adds a set of controls that account for model attributes that can have an impact on discounts and that could be correlated with product line breadth, such as the flexibility with which a model is manufactured, the discounts given by the competitors, whether the product is being launched or phased out, the time since the model was introduced, the list price, and whether a model has gone through a redesign. The product line coefficient does not change substantially even after introducing these controls. Column 3 adds the complementary measure of product line breadth based on the range of fuel economy levels covered by the make and the measure's interaction with gas prices. Again, the coefficients for the fuel-economy-based measure and its interaction with gas prices suggest that models marketed by makes that offer a broader range of fuel economy levels reduce their average discounts as gas prices increase. This is despite the fact that this column is also controlling for the fuel economy of the model and its interaction with gas prices (i.e., models with a higher fuel economy give lower discounts as gas prices increase). This shows additional support for our hypothesis H5b, also at the model level.

Overall, Tables 4.5 and 4.6 suggest that an increase in the number of products carried by an automaker is associated with an increase in mismatch costs. At the same time, the tables also show that a product line that covers a broader range of fuel economy levels can provide a useful hedge against potential changes in demand arising from changes in gas prices.

In order to examine the effects of product line breadth on inventories, we use the following specification:

$$MAKE\_DS_{it} = \beta_1 PLB_{it} + CONTROLS + \mu_i + \gamma_t + \varepsilon_{it} \tag{4.8}$$

where i denotes a make, t denotes a month and $MAKE\_DS_{it}$ is the average number of days of supply in month t for the models marketed by make i. Table 4.7 shows the effect of product line breadth on average make inventory. All columns include make fixed effects that account for any time-invariant make-level omitted variables. All columns also include time controls (year-month interactions) that account for industry-level temporal patterns in inventories. Column 1 is the baseline specification and does not include any additional controls. The estimate of the product line coefficient β_1 is 3.116 and it is statistically significant, which gives support to our Hypothesis H4b. One additional product in the product line is associated with an increase of three days of supply in the average inventory of the models of the make. Column 2 adds the complementary measure of product line breadth based on the range of fuel economy levels covered by the make and its interaction with gas prices. The coefficient β_1 does not change substantially after including the additional measure. A broader range of fuel economy levels is associated with lower inventories, but the interaction of this variable with gas prices is not statistically significant. Column 3 includes two additional control variables: the median fuel economy of the make and the measure's interaction with gas. Makes with higher median fuel economy carry lower inventories as gas prices increase, compared to firms with lower median fuel economy. In any case, adding them as controls does not change the results of Columns 1 and 2. Finally, Column 4 includes the average discount provided by the make as an additional control. The coefficient of the product line breadth variable is still around 3 after including it.

Overall, results shown in Table 4.7 suggest that an increase in the number of products carried by a make is associated with carrying about three additional days of supply in the average inventory of the models of the make.

4.6. Conclusions

Our analysis shows evidence from the U.S. automotive industry that supports the hypothesis of positive association between product line breadth and market share, which is consistent with some results found by other papers using data from different industries (e.g., Kekre and Srinivasan 1990, Bayus and Putsis 1999). Our estimates suggest that during the period of analysis (2002-2009) carrying one additional product in the line was associated with an increase of 0.1% in the market share of a make.

We also find evidence of positive association between product line breadth and production costs, which we estimate using an equilibrium model of pricing. Previous research addressing this issue had reached somewhat contradictory conclusions. Our estimates suggest that during the period of analysis (2002-2009) carrying one additional product in the line was associated with an average increase of $175 in production costs per vehicle.

Besides contributing new evidence from the automotive industry to the research that has studied the effects of product line breadth on market share and production costs, we also address some important issues that have been unexplored by previous research. In particular, we find that product line breadth also has a substantial impact on supply-demand mismatch costs. Mismatch costs arise from the fact that demand is uncertain. Carrying a broader product line leads to higher demand fragmentation and higher uncertainty in the demand of each of the products in the line, which increases the chances of mismatch. Mismatch costs arise in the form of discounts and inventories, among others. We find that an additional product in the line is associated with an increase of around $100 in average discounts and with carrying three additional days of supply in the average model inventories for this make.

Overall, our results indicate that the costs of product line breadth can be very substantial (one additional product in the line is associated to an average increase of $175 in production costs, $100 in discounts arising from more frequent supply-demand mismatches, and three additional days of supply for the models of the make). Firms have developed strategies, such as delayed differentiation and platform-based development, that allow them to offer variety with lower costs. Using our data, we study how platform families help to control production costs. We find that the production costs for a model decrease with the volume of other models that share the same platform. In particular, for each 100,000 vehicles produced for other models based on the same platform, production costs are reduced by $55.

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

As with any empirical work, our analysis is not exempt of limitations, some of which are opportunities for future research. Product line breadth is obviously an endogenous decision. Our models include controls for make and model fixed effects that account for time-invariant sources of endogeneity, but our dependent variables can be affected by time-variant situations that might be correlated with extensions of product line breadth. The fact that our results are consistent for different specifications at the make and model level that include a rich and diverse set of controls suggests that this might not be a significant problem, but future research could examine the availability of exogenous instruments for product line breadth. Changes in regulation (for example, environmental regulation such as the Corporate Average Fuel Economy regulations) might be good candidates, since they can prompt firms to extend their product lines.

Some other limitations of our work and opportunities for further research are dictated by data availability. We have been able to obtain valuable insight from our measures of mismatch costs measured with discounts and inventories, but there are additional sources of mismatch costs that could be studied if the appropriate data were available. For example, future research could evaluate the effect of product line breadth on lost sales and stockouts. Similarly, we have studied product line breadth at the model level, but it could be interesting to understand the effects of more granular variety measures, such as option content. On the other hand, we do not have reliable direct measures of production costs, and we have to estimate them using a demand and pricing equilibrium model. Direct measures of production costs could provide additional dimensions that cannot be captured from indirect measures. As more data becomes available, we think that more research opportunities will open in this space.

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

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4.8. Tables

Table 4.1. Variable Description and Summary Statistics

	Mean	SD	Median	Count	Description
PLB	8.21	4.22	7	18166	Product line breadth (number of products)
GASPRICE	240.78	65.24	231.6	18166	Gas price
MKTSHR	0.05	0.057	0.02	18166	Make market share
MPGBREADTH	0.94	0.465	0.89	18134	Range of fuel economy levels offered by make, relative to market
MEDMPGMAKE	20.68	2.28	20.59	18134	Median fuel economy level offered by make
PLATVOLUME	35564.25	80271.36	10206.5	9289	Monthly production of vehicles of the same platform
LAUNCHED	0.08	0.27	0	18166	1 if model just launched
PHASEDOUT	0.027	0.16	0	18166	1 if model to be phased out
NEW_DESIGN	0.34	0.48	0	18166	1 if model has changed attributes substantially
AGE	3.15	2.18	3	18166	Number of years since model introduction
SIZE	13879.81	1756.78	13757.14	18166	Size of vehicle
HPWT	0.059	0.01	0.057	17803	Horse power / weight
MPG	21.05	4.72	20.59	18046	Miles per gallon
FLEX	0.25	0.43	0	17167	1 if model produced with flexibility (see Moreno and Terwiesch, 2011)
COMPINCENT~E	2697.63	956.12	2806.09	18162	Average incentive given by competing models (same segment)
MSRP	32795.28	13500.12	29780	18166	List price
AVGDISCMODEL	2822.524	2080.08	2499	18166	Average discount for model
AVGDISCMAKE	2848.116	1464.605	2760	18160	Average discount for make
MAKE_DS	86.76911	35.6747	84.78492	18166	Average days of supply for models of make
N	18166				

Table 4.2. Effect of Product Line Breadth on Market Shares

VARIABLES	(1)	(2)	(3)
PLB	0.00106***	0.000947***	0.000996***
	(0.000187)	(0.000198)	(0.000194)
GASPRICE		9.25e-05	-2.50e-05
		(0.000522)	(0.000517)
MPGBREADTH		-0.00706***	-0.00741***
		(0.00174)	(0.00169)
MPGBREADTH X GAS		2.88e-05***	3.11e-05***
		(7.15e-06)	(6.94e-06)
MEDMPGMAKE			-0.00202***
			(0.000214)
MEDMPGMAKE X GAS			5.65e-06***
			(5.71e-07)
FIXED EFFECTS	Make	Make	Make
TIME CONTROLS	Month-Year	Month-Year	Month-Year
Observations	2,994	2,962	2,962
R-squared	0.966	0.967	0.967

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

Table 4.3. Effect of Product Line Breadth on List Prices

VARIABLES	(1)	(2)	(3)	(4)
PLB	297.5***	270.8***	257.5***	286.5***
	(53.60)	(53.40)	(53.14)	(55.31)
PLATVOLUME				-0.000833***
				(0.000321)
LAUNCHED			389.4	290.4
			(319.4)	(313.8)
PHASEDOUT			-557.9**	-543.2**
			(255.9)	(251.0)
NEW_DESIGN			-287.4	-277.4
			(189.7)	(187.2)
AGE			131.8**	90.20
			(58.97)	(62.67)
SIZE		0.369*	0.385*	0.457**
		(0.209)	(0.210)	(0.215)
HPWT		41,286***	41,741**	38,942**
		(15,968)	(16,317)	(15,660)
MPG		-197.1***	-189.5***	-203.3***
		(71.48)	(71.44)	(70.93)
FIXED EFFECTS	Model	Model	Model	Model
TIME CONTROLS	Segment x Year	Segment x Year	Segment x Year	Segment x Year
Observations	997	968	968	968
R-squared	0.979	0.979	0.979	0.980

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

Table 4.4. Effect of Product Line Breadth on Estimated Production Costs

VARIABLES	(1)	(2)	(3)	(4)
PLB	204.8***	180.8***	156.4***	175.4***
	(52.35)	(51.96)	(52.43)	(54.38)
PLATVOLUME				-0.000547*
				(0.000297)
LAUNCHED			1,021***	956.5***
			(307.7)	(304.6)
PHASEDOUT			-887.4***	-877.7***
			(281.8)	(282.3)
NEW_DESIGN			49.00	55.55
			(174.0)	(172.2)
AGE			196.1***	168.8**
			(70.27)	(73.72)
SIZE		0.420*	0.339	0.387*
		(0.221)	(0.212)	(0.220)
HPWT		29,371**	30,073*	28,236*
		(14,586)	(16,062)	(15,707)
MPG		-133.1*	-137.8*	-146.8**
		(72.59)	(72.57)	(72.18)
FIXED EFFECTS	Model	Model	Model	Model
TIME CONTROLS	Segment x Year	Segment x Year	Segment x Year	Segment x Year
Observations	997	968	968	968
R-squared	0.976	0.975	0.975	0.976

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

Table 4.5. Effect of Product Line Breadth on Average Make Incentives

VARIABLES	(1)	(2)	(3)
PLB	57.72***	74.71***	74.81***
	(17.54)	(17.15)	(17.20)
GASPRICE		4.334	14.55
		(68.55)	(67.19)
MPGBREADTH		430.2***	409.6***
		(139.8)	(137.0)
MPGBREADTH X GAS		-2.973***	-2.748***
		(0.628)	(0.612)
MEDMPGMAKE			53.54**
			(25.69)
MEDMPGMAKE X GAS			-0.493***
			(0.0839)
FIXED EFFECTS	Make	Make	Make
TIME CONTROLS	Month-Year	Month-Year	Month-Year
Observations	2,988	2,956	2,956
R-squared	0.735	0.757	0.761

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

Table 4.6. Effect of Product Line Breadth on Average Model Incentives

VARIABLES	(1)	(2)	(3)
PLB	106.1***	122.6***	119.8***
	(10.30)	(10.63)	(10.60)
FLEX		-337.3***	-344.7***
		(42.87)	(42.65)
COMPINCENTIVE		0.316***	0.259***
		(0.0298)	(0.0302)
LAUNCHED		-376.0***	-347.0***
		(38.60)	(38.12)
PHASEDOUT		567.0***	580.9***
		(177.6)	(178.3)
AGE		-21.88*	32.10**
		(12.79)	(14.27)
MSRP		0.0972***	0.0876***
		(0.00685)	(0.00677)
NEW_DESIGN		-451.5***	-459.0***
		(23.34)	(22.93)
GASPRICE			9.787***
			(0.933)
MPGBREADTH			61.10
			(79.28)
MPGBREADTH X GAS			-1.687***
			(0.338)
MPG			76.44***
			(11.68)
MPG X GAS			-0.429***
			(0.0379)
FIXED EFFECTS	Model	Model	Model
OTHER CONTROLS	Time, Segment, Segment x Time	Time, Segment, Segment x Time	Time, Segment, Segment x Time
Observations	18,166	17,166	17,052
R-squared	0.686	0.708	0.714

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

Table 4.7. Effect of Product Line Breadth on Average Make Inventories

VARIABLES	(1)	(2)	(3)	(4)
PLB	3.116***	3.080***	3.079***	3.165***
	(0.448)	(0.454)	(0.454)	(0.452)
MAKEINCENTIVESPEND				-0.00133***
				(0.000493)
GASPRICE		5.596***	5.677***	6.479***
		(1.710)	(1.720)	(1.682)
MPGBREADTH		-5.063*	-5.159*	-4.718
		(3.012)	(3.001)	(3.018)
MPGBREADTH X GAS		0.0118	0.0133	0.0102
		(0.0124)	(0.0124)	(0.0126)
MEDMPGMAKE			0.491	0.600
			(0.616)	(0.613)
MEDMPGMAKE X GAS			-0.00408**	-0.00495**
			(0.00196)	(0.00196)
FIXED EFFECTS	Make	Make	Make	Make
TIME CONTROLS	Month-Year	Month-Year	Month-Year	Month-Year
Observations	2,962	2,930	2,930	2,925
R-squared	0.687	0.697	0.697	0.699

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

Table 4.A1. Demand Estimates

	(1)
VARIABLES	
MPRICEVY	-5.94e-05***
	(6.69e-06)
L_MKSHINSEGVY	0.291***
	(0.0920)
SIZE	0.000234***
	(2.24e-05)
HPWT	12.34***
	(2.837)
MPG	0.0263**
	(0.0105)
PLB	0.0550***
	(0.00812)
Constant	-8.185***
	(0.829)
Observations	1,403
R-squared	0.658

4.9. Figures

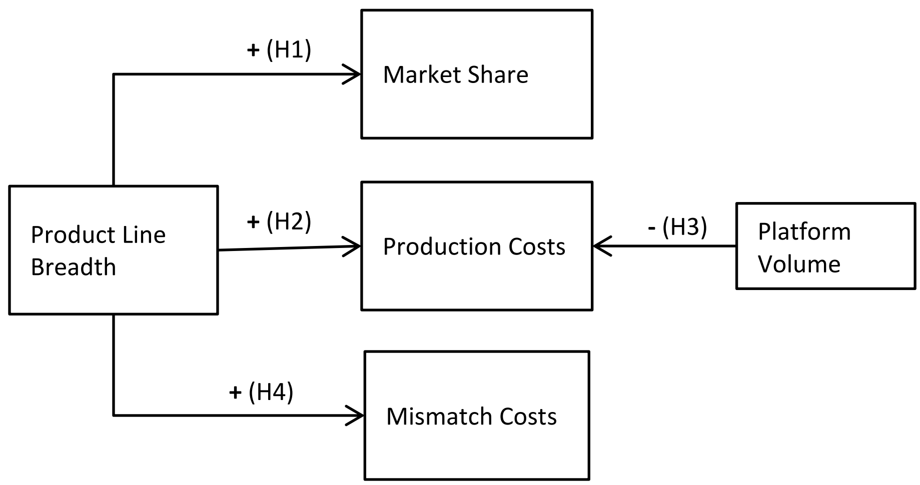

Figure 4.1. Hypotheses about the Effects of Product Line Breadth

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