Deployment of manufacturing flexibility: an empirical analysis of the North American automotive industry

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Abstract

The ability to manufacture several products on the same production line and switch seamlessly among them allows a firm to both hedge against demand uncertainty and respond to competition. In this paper, we empirically analyze the deployment of manufacturing flexibility in the North American automotive industry. In particular, we track demonstrated ability to manufacture automobiles with different platforms at 75 assembly plants over a period of eight years. We find that, consistent with extant theory, flexible capacity is used to manufacture products with high demand uncertainty and low demand correlation. We find evidence of product life-cycle effects: flexible capacity is used to manufacture models that are early in their life-cycle as well as aging models. Moreover, we find strong evidence that automotive manufacturers use flexibility as a "competitive weapon"; flexibility is deployed in market segments in which there are a larger number of flexible competitors. However, this use of flexibility as a competitive weapon may not be optimal, as suggested by lower plant productivity.

1 Introduction

In 2004, Nissan manufactured 260,066 vehicles in its Canton, Mississippi, plant, including 91,296 Titan pickup trucks, 68,684 Altima sedans, 43,958 Quest minivans, 40,437 Armada SUVs and 15,691 Infinity QXC56 SUVs (Zachary 2005) without shutting down the plant for changeovers for significant amounts of time. Such product flexibility (i.e., the ability to seamlessly switch from manufacturing one product to another) was unthinkable in the North American automotive industry a short time ago. However, over the last two decades, manufacturing flexibility has emerged as an important basis for competitive advantage along with price, quality and dependability, as Hayes and Wheelwright (1984) argued.

Historically, US automotive manufacturers relied on high-volume and inflexible plants with two, or even three, assembly lines making the same vehicle. This situation changed with the entry of Japanese manufacturers and continuing product proliferation. There are very few models now whose demand is large enough to justify dedicating an entire plant to their production, and the importance of flexibility in a hypercompetitive automotive industry is at an all-time high (Chappell 2005). There is plenty of evidence that all automotive manufacturers are striving for more and more flexibility. Ford already builds eight different truck models on two platforms at its Norfolk, Virginia plant and plans to adopt flexibility in 75% of its 21 North American assembly plants (McMurray 2004). General Motors pioneered the concept of chaining whereby each plant is made flexible enough to manufacture at least two models (Jordan and Graves 1995). DaimlerChrysler lags behind the "flexibility bandwagon" due to financial constraints, but is now heavily investing in flexibility; for instance, it is spending $0.5B to modernize its Belvidere plant to build vehicles on two different platforms (Priddle 2005). Nevertheless, Japanese companies are still considered more flexible than US manufacturers, an advantage that is at least partially responsible for the increasing market share of the Japanese carmakers (Mackintosh 2003, Holweg and Pil 2004a, Boudette 2006).

In this paper, our goal is to empirically examine the deployment of manufacturing flexibility in North American automotive assembly plants. We define manufacturing flexibility (flexibility in short) as the *demonstrated* or *observed* ability to manufacture vehicles from multiple platforms on the same assembly line, and we study its deployment in 75 manufacturing facilities in North America belonging to the "Big Three" US manufacturers (GM, Ford and DaimlerChrysler) from 1996 to 2003. We attempt to link flexibility deployment to environmental variables such as demand uncertainty, competition etc., as suggested by the findings from the analytical literature (Fine 1993, Roller and Tombak 1993, Goyal and Netessine 2006). We find empirical support for the hypotheses that flexible plants manufacture products with higher demand uncertainty, lower demand correlation and lower mean demand. We also discover that flexible capacity is often used to manufacture new car models as well as aging models. In line with our prediction, flexibility is deployed more often in segments with higher proportion of flexible competitors. The association between flexibility and competition is particularly strong lending credence to the theory that the automotive manufacturers use flexibility as a competitive weapon (Fine 1993). However, when measuring the impact of flexibility deployment on productivity, we find that flexible plants with a high number of flexible competitors have lower productivity. Hence, though it seems that companies respond to flexible competition with more flexibility, such a strategy may not be optimal (as also suggested by the analytical findings of Goyal and Netessine 2006). Finally, we do not find any significant time trends in flexibility deployment.

The rest of the paper is organized as follows. We survey related literature in Section 2 and develop our hypotheses in Section 3. In Section 4 we outline data sources and variables. Results are presented in Section 5, and we conclude with the summary and implications of our findings in Section 6.

2 Literature survey

Hayes and Wheelwright (1984) first advocated the importance of manufacturing flexibility as a competitive weapon. In their seminal book, Womack et al. (1990) raised awareness on the importance of flexibility and of the pioneering role Japanese companies played in its adoption in the automotive industry. Gerwin (1993) and Parker and Wirth (1999) provide comprehensive taxonomies of various aspects of manufacturing flexibility. Flexibility is a multi-dimensional concept (Parker and Wirth 1999) and different considerations affect decisions to invest into different dimensions of flexibility. For the purposes of this study, we only focus on product flexibility because extant literature provides a set of testable hypotheses while other flexibility types have received less attention from researchers. Furthermore, product flexibility is widely cited as one of the most (if not the most) strategically important flexibility types (Goyal and Netessine 2006, Jordan and Graves 1995), and we believe that it is paramount in the automotive industry. Finally, data required to measure other flexibility types is not available to us (e.g., assessing volume flexibility would require cost data at different levels of production).

Modeling papers study flexibility in two streams: as a hedge against demand uncertainty and as a strategic weapon under competition. Papers in the first stream consider investment in flexible vs. dedicated capacity in the absence of competition and analyze the trade-off between the higher cost of flexibility and its ability to hedge against demand uncertainty by manufacturing multiple products.

They demonstrate that the benefits of flexibility increase with higher demand uncertainty and lower demand correlation: see Fine and Freund (1990), Van Mieghem (1998) and Chod and Rudi (2005) for representative publications. Motivated by a real-life problem at General Motors, Jordan and Graves (1995) find that adding limited flexibility in the right place can achieve nearly all the benefits of total flexibility in terms of hedging against demand uncertainty. The second stream of papers analyzes the strategic value of flexibility. Fine and Pappu (1990) and Roller and Tombak (1990, 1993) show that flexibility intensifies competition and depresses prices. Goyal and Netessine (2006) model flexibility adoption under both competition and demand uncertainty and find that the use of flexibility should be higher under high demand uncertainty, low mean demand, low demand differential and low demand correlation, whereas the impact of competition is also contingent upon competitors' use of flexibility.

There are numerous empirical studies on manufacturing flexibility, and we refer the reader to Vokurka and O'Leary-Kelly (2000) for a comprehensive survey and critique. Many of these studies examine the role of organizational attributes in the adoption of flexibility, whereas our focus is on environmental factors associated with flexibility deployment. Another difference is that we study demonstrated flexibility as opposed to potential (or inherent) flexibility which is typically measured through surveys. One advantage of our approach is that our focus on demonstrated flexibility allows us to link flexibility and performance which is problematic in studies of potential flexibility (e.g., it is not clear whether potential flexibility should have a direct impact on productivity). Another advantage of our study is that it is both cross-sectional (at the plant level), spanning several companies within the entire industry, and intertemporal, spanning the time period between 1996 and 2003, whereas most studies cited in Vokurka and O'Leary-Kelly are limited to a single plant or a business unit and are done at a single point of time. Swamidass and Newell (1987) appear to be the earliest empirical study of manufacturing flexibility. They find that perceived environmental uncertainty increases the adoption of manufacturing flexibility. To the best of our knowledge, Mansfield (1993) is the only study that tracks the diffusion of flexible manufacturing systems over time until 1990. We track flexible manufacturing systems from 1996 onwards, and hence, our study succeeds Mansfield's in this respect. Roller and Tombak (1993) are the only other study we are aware of that analyzes the interrelationship between competition and flexibility adoption in the Japanese metalworking industry. Other representative studies are Suarez et al. (1996, printed circuit boards), Upton (1997, paper industry) and Anand and Ward (2004, manufacturing).

The automotive industry has attracted significant attention from empirical researchers due to both its significance in the world economy and data availability. Much of the research we cite is a result of MIT's International Motor Vehicles Program. These studies examine the effect of operational strategies on productivity. A further contribution of our paper is to link the use of manufacturing flexibility to productivity. Krafcik (1988) is one of the earlier works assessing productivity in the automotive industry. Lieberman et al. (1990) demonstrate that productivity improvements at the world's six major manufacturers have been achieved primarily through more efficient labor utilization, and Lieberman and Demeester (1999) find a strong association between higher productivity and inventory reduction. MacDuffie et al. (1996) find that parts complexity has a persistent negative impact on productivity. This study is related to ours because, as we do, it considers fundamental product variety (i.e., platform-level and body style-level varieties) produced in the same plant. Fisher and Ittner (1999) find that greater day-to-day variability in option content has a significant adverse effect on productivity and quality. Holweg and Pil (2004a, 2004b) link automotive product variety with order-fulfillment strategies (i.e., production to stock vs. production to order). Cachon and Olivares (2005) explain what drives inventories in the automotive industry using flexibility, demand uncertainty and other variables that we use.

To summarize, our paper provides the following contributions relative to the extant literature. First, we provide evidence of the diffusion of manufacturing flexibility in the automotive industry over the last eight years for the Big Three US manufacturers. Second, we test empirically many of the drivers of manufacturing flexibility suggested by the modeling literature and find support for several of them. In particular, our paper is one of the first to find a strong association between flexibility and competition which, for the first time, provides empirical support for the widely held belief that flexibility is used as a competitive weapon. Our study is also the first to demonstrate empirically the relationship between flexibility and demand correlation and between flexibility and product life-cycle. Finally, we show that deployment of flexibility is linked to assembly line productivity, a connection that has not been formally established previously.

3 Hypotheses formulation

The decision to invest into manufacturing flexibility is complex and it is typically a part of the strategic planning process (see Fleischmann et al. 2006 for an extensive discussion). This decision is closely intertwined with capacity investment and product line decisions, and it is also affected by competition, life-cycles of current products and the overall demand for the industry. When investing into manufacturing flexibility, the automotive manufacturer balances a long-term strategic planning of demand with production capabilities. Often, a horizon of such plan spans up to 12 years (Fleischmann et al.

2006). First, the firm decides on the set of future products and estimates sales figures. Second, models get allocated to plants and required production capacity is determined. Model allocation is driven by, among other considerations, technical feasibility and skills available. At this stage the firm may decide to invest in flexibility to balance demand with supply and achieve high plant utilization. For example, a model nearing the end of its life cycle may have demand decreasing over time thus resulting in underutilized capacity. At this point a decision can be made to move another model to this plant or launch an entirely new model using spare capacity. In addition to these long-term considerations, there are short-term adjustments that are made each year based on observed demand. For example, a model might experience demand that surpasses expectations and therefore the decision might be made to move this model to a bigger plant or to split product among multiple locations. Naturally, allocation of several models to the same plant simplifies the task of balancing utilization, and similarly production of high-volume products in multiple plants offers flexibility in dealing with demand uncertainty (Fleschmann et al. 2006).

Consistent with these practical considerations, the literature in operations management suggests that manufacturers deploy flexibility to mitigate the impact of demand uncertainty and to respond to competition. In this paper, we study the demonstrated (rather than potential) flexibility level in the automotive assembly plants. This distinction is crucial since, from the data that we have, we can only discern demonstrated flexibility. For instance, a plant may be inherently capable of producing many different products (potentially flexible) but produces just one (no demonstrated flexibility); hence we would consider the plant inflexible in the data. The reason to focus on the demonstrated flexibility is that there is no easy way to measure potential flexibility of automotive plants. Theoretically speaking, any automotive plant can manufacture any car. The question is: At what cost? Typically, one to three years prior to production, the manufacturer has to invest in appropriate tooling, machines and training to enable production. If a newly introduced product is "similar" to the one currently produced, this investment might be small, whereas for very different products the investment might be quite large. Hence, to measure inherent flexibility, one needs to estimate the amount of investment required, which is often unknown in advance. For example, initially the Chrysler PT Cruiser was scheduled to be produced at a factory that manufactured the Dodge Neon, a model with the same platform as the PT Cruiser. As it turned out, the PT Cruiser needed a paint bath that was larger by just 2 inches (see Boudette 2006). Replacing the paint bath was prohibitively costly, and production was moved to another facility at the last moment. Hence, what was thought to be a production facility capable of manufacturing multiple products turned out not to be so. Given such problems in measuring potential flexibility, we rely on a more objective measure (demonstrated flexibility), and restrict the interpretations of our findings accordingly. We also acknowledge that some of the plants in our data set might be in the process of acquiring flexible technology but, since we are unable to observe this process, these plants would appear to be inflexible until they start producing multiple products.

In what follows, we propose six hypotheses that are based on previous analytical models and on discussions with automotive executives and consultants. These hypotheses concern the association between flexibility deployment and demand uncertainty, demand correlation, product substitutability, level of competition and mean demand for products. Our hypotheses do not suggest causality; instead, our goal is to evaluate the use of demonstrated flexibility against various environmental variables in order to understand whether it is consistent with the extant theory.

Our first hypothesis relates demand uncertainty and flexibility. In many different contexts, the operations literature suggests that higher demand uncertainty leads to a higher mismatch between demand and supply, and therefore higher costs (see Cachon and Terwiesch 2004). Starting with the seminal work of Fine and Freund (1990), it has been shown that flexibility mitigates the harmful impact of demand uncertainty by shifting production from goods with low demand to goods with high demand (Van Mieghem 1998, Chod and Rudi 2005, etc.). Empirical literature too suggests that flexibility should be used to respond to environmental uncertainty, which is typically represented by uncertainty in demand (see Swamidass and Newell 1987, Vokurka and O'Leary-Kelly 2000 and Anand and Ward 2004). In the context of the automotive industry, the assignment of a vehicle to a plant happens somewhere between one and three years before actual production begins, and the average difference between forecast and sales over this time period is about 40% (Jordan and Graves 1995). Thus, automotive manufacturers are highly susceptible to demand uncertainty.

Clearly, it is undesirable to manufacture products with highly uncertain demand in inflexible plants, as there are significant costs associated with scaling production up or down, necessitated by demand variability. Therefore, we hypothesize that products with predictable demand are allocated to inflexible plants and products with highly uncertain demand are allocated to flexible plants.

H1 The use of flexibility is associated with higher uncertainty in demand for individual products.

In addition to uncertainty in demand for individual products, it is important to consider the interdependency among products in the form of demand correlation. Eppen (1979) was the first to demonstrate that the lower the demand correlation among products the stronger the effect of risk pooling[1]. This

[1] Here and later, when referring to "lower demand correlation" we imply correlations closer to -1 when demands are

notion extends to manufacturing flexibility: Fine and Freund (1990), Van Mieghem (1998), Chod and Rudi (2005), Goyal and Netessine (2006) and many other papers demonstrate that flexibility is most useful under low demand correlation. When demand correlation is low, uncertainty in demands from different products tends to cancel each other: when demand for one product is high, demand for the other product is low, resulting in low aggregate uncertainty faced by a flexible plant. On the contrary, positively correlated demands rise and fall in tandem – either all products tend to have a high demand or all products tend to have a low demand. Consequently, it is difficult to shift production between products, and the value of flexibility is limited. Early literature (Fine and Freund 1990) even suggests that flexibility is useless under perfect positive correlation, but later papers (for example, Van Mieghem 1998) demonstrate that this is not always the case. Furthermore, in the context of the automotive industry, Jordan and Graves (1995) suggest that flexibility should be deployed in plants that manufacture products with lower correlation in demand. Although theoretical evidence on the connection between correlation and flexibility is overwhelming, we are not aware of any empirical studies testing this relationship.

H2 The use of flexibility is associated with lower demand correlation for individual products.

Products manufactured in all automotive plants, either flexible or inflexible, may end up competing within the same segment of the automotive market. Starting with Hayes and Wheelwright (1984), the literature on manufacturing flexibility has argued that flexibility is a competitive weapon (Fine 1993, Gerwin 1993, Upton 1997), which enables a company to respond to competition more effectively. This notion has been particularly well reflected in the automotive industry, because Japanese manufacturers historically possessed much higher levels of flexibility than their US counterparts. For example, back in the 1980s, Mazda's plant in Hiroshima already built the RX-7 (a rear-wheel-drive sports car in standard and convertible versions), the 929 (a rear-wheel-drive luxury car), the 121 (a front-wheel-drive mini car), and the 323 (a front-wheel-drive compact) on the same assembly line. All these cars were on different platforms and came with various trim levels, body styles and right- or left-hand drive options (see Krafcik 1988 for this and other similar examples). As Japanese companies started capturing a higher and higher share of the US market by entering into more segments, their ability to switch among different models was pronounced as one of their major competitive advantages. The following is a characteristic statement from the popular press: "Given all the benefits of flexibility, the surprise is that it has taken US manufacturers so long to start emulating their Japanese rivals" (Mackintosh 2003). In

negatively correlated and when demands are positively correlated we imply correlations closer to 0.

support of these observations, two theoretical studies that focused on flexible vs. inflexible technology choice under competition (Roller and Tombak 1993, Fine and Pappu 1990) found that, in equilibrium, all competitors should adopt flexibility.

Contrary to this popular belief that higher (flexible) competition drives firms to invest in more flexibility, analytic findings in Goyal and Netessine (2006) suggest otherwise. Goyal and Netessine (2006) consider a single-period model in which two competitors face uncertainty in demand curves in two markets and decide on, consecutively, the type of technology to invest into (either product-flexible or product-dedicated), the capacity size (with flexible capacity being more expensive), and finally they observe true demand curves and produce to capacity. This model incorporates competition, demand uncertainty, demand correlation and product interdependence through substitutability (closely related models of Fine and Pappu 1990 and Roller and Tombak 1993 do not model demand uncertainty). Goyal and Netessine (2006) find that, when competition invests in flexibility, the advantages of being flexible often diminish. Hence, a firm facing flexible (inflexible) competitors is less (more) likely to invest in flexibility. This finding is consistent with observations in some industries where flexible and inflexible plants coexist in equilibrium. For example, Upton (1995) found that in the fiercely competitive paper industry, different competitors employ different technologies while manufacturing essentially similar products.

This conflicting view on the impact of competition on flexibility adoption is best resolved empirically, which is the focus of this work. In this spirit, Hypothesis 3 postulates the relationship between competition and flexibility adoption by taking the view of the majority of extant literature that praises benefits of flexibility under competition.

*H*3 *The use of flexibility is associated with larger proportion of competitors employing flexibility.*

Back at the beginning of the last century, Ford was building a single Model T, and hence did not need any flexibility. However, increasing product proliferation and competition resulted in market fragmentation with a steadily decreasing demand per vehicle. Most sources cite a number of 200,000 to 250,000 vehicles per year (see Lieberman and Dhawan 2005) as the minimum feasible capacity of an automotive plant that can be profitably sustained. Lower volumes are not economical because fixed costs of plant operation must be covered. As a result, fewer and fewer vehicles remain that can justify allocating an entire plant to their production. It might, however, be desirable to manufacture these few high-volume vehicles in inflexible plants. For example, the Ford F-series has seen a relatively steady demand of between 700,000 and 800,000 units per year over the last few years. Clearly, there is little benefit in manufacturing other products on the same production line with the Ford F-series, and consequently an entire (inflexible) plant can be dedicated to their production. The same prediction comes out of analytical models in Goyal and Netessine (2006), Chod and Rudi (2005) and others: flexible technology is best used to manufacture products with lower mean demand.

*H*4 *The use of flexibility is associated with lower mean demand for products.*

Flexibility is most useful when a plant has a lot of freedom to shift capacity from manufacturing one product to another. Intuitively, if two products manufactured in the same plant are very different in terms of their mean demand, the advantages of flexible manufacturing capacity are diminished, because the plant is likely to dedicate a major part of capacity to the product with the larger demand, which does not leave much "free" capacity to move around. At the extreme, if one product has a much larger demand than the other, a flexible plant becomes very similar to an inflexible plant with one product. On the other hand, if two products have approximately equal mean demand, the benefits of flexibility are maximized. Goyal and Netessine (2006) formalize this intuition and demonstrate this result analytically. The association between flexibility and demand differential forms the basis for this hypothesis.

*H*5 *The use of flexibility is associated with a lower difference in mean demand (demand differential) for products.*

Demand correlation measures the extent of statistical interdependency between any pair of products. Another interdependency arises through customers' perception of products, and is measured by the extent to which products are substitutable or complementary. In the automotive industry, all products are substitutable in the eyes of the customers: that is, increasing the price of one product stimulates demand for other similar products, and vice versa. This intuitive statement has been demonstrated empirically by Berry et al. (1995), who measured cross-elasticity of demand using data from the automotive industry. As Goyal and Netessine (2006) show, the deployment of flexibility should depend on the strength of this substitutability. Namely, if demand uncertainty is high and the products are more substitutable, higher demand for one product reduces demand for another product, and hence manufacturing them in a flexible plant becomes more useful than when products are essentially independent.

*H*6*a* *The effect of demand uncertainty on the adoption of flexibility increases in the degree of substitutability in the marketplace.*

Another interaction in Goyal and Netessine (2006) occurs between substitution and demand differential. As we see above, when the demand differential is high, flexibility is less beneficial. This effect is amplified by high substitutability: if products are substitutable, it is easier to manufacture just one of them (with higher demand) for multiple markets, making flexibility undesirable. This insight provides grounds for the second interaction hypothesis with respect to the substitutability effect.

H6b The effect of demand differential on the adoption of flexibility decreases in the degree of substitutability in the marketplace.

4 Research design, data sources and variables

4.1 Research design and data sources

We test our hypotheses using data that has both cross-sectional and time-series components. Cross-sectionally, we cover most of the North American automotive assembly plants in Canada, Mexico and the US. The advantage of a cross-sectional data is that we have information on plants belonging to all three major US automotive companies: GM, Ford and DCX (DaimlerChrysler). Although we also have data on plants in North America that belong to other companies (Honda, Toyota and several smaller firms), we exclude them from the analysis because data that we have on these plants is spotty, with many missing values. We focus on assembly plants (as opposed to stamping or powertrain plants) because assembly is the largest contributor to the final product. We focus on plants in North America because of data availability. In addition, it is well documented (see Krafcik 1988) that Japanese automotive manufacturers in Japan are highly flexible, but less is known about US manufacturers in this respect.

The data itself comes from two primary sources: The Harbour Reports (Harbour Consulting 1996-2004) and Ward's Automotive (WardsAuto.com). The Harbour Reports are annual surveys of all automotive manufacturing plants in North America published by Harbour Associates. The company became well-known after publishing two groundbreaking reports in 1980 which, for the first time, demonstrated that Japanese companies enjoyed a twofold advantage in terms of productivity. Currently, most automotive manufacturers voluntarily provide data to the company. Harbour Associates then audits the data through plant visits and publishes annual reports that compare productivity across plants and manufacturers. From time to time certain plants and sometimes entire manufacturers (notably Honda) refuse to participate in Harbour reports. In these cases Harbour reports might contain estimates of plant's productivity or it might just exclude some plants. The data in the Harbour Reports includes plant capacity, annual production, the number of platforms manufactured in the plant, the model types for each plant, the number of paint, assembly and body lines, etc. We use this data to calculate the plant level measures such as flexibility, utilization and productivity. The advantage of this data set is that it is independently collected and audited. For product-level data, we rely on Ward's Automotive. This data includes monthly sales, prices and vehicle descriptions at the model level. We restrict our analysis to the period from 1996 until 2003 because the data in the Harbour Reports before 1996 comes in a different format, and several fields that are necessary for our analysis are missing (e.g., data on the number of production lines).

The unit of our analysis is one plant in one year. We focus on individual plants, because there are too few automotive manufacturers in the world, so there is little hope of achieving statistical power at this higher level (even at the division level we face the same problem). On the time dimension, we focus on a given year, although monthly and even weekly demand and production data is available. However, demonstrated flexibility does not change that often over time: a typical car model is manufactured for about five to seven years and is rarely moved from plant to plant. We do, however, utilize monthly demand data to calculate mean demand, demand uncertainty and correlation to achieve better precision. We carry our final analysis on 478 plant-year observations.

4.2 Variables

In this section we define and detail the variables used in the analysis. Table 1 lists descriptive statistics for all independent variables. We begin with the dependent variable – flexibility.

Flexibility. Our goal is to measure demonstrated (or observed) product flexibility, which is the demonstrated ability to manufacture multiple *products* in the same *manufacturing facility*. There are two key terms in this definition that need to be elaborated: "products" and "manufacturing facility."

There are many ways to define a *product* in the automotive industry. MacDuffie et al. (1996) cite distinct platforms (i.e., each having a unique underbody and floor pan and serving as the foundation design for multiple models), models (i.e., variants on a common platform with more than 50% different exterior body panels), body styles (i.e., 3-door, 4-door), drivetrain or chassis configurations (i.e., front-wheel vs. rear-wheel drive), and export variations (i.e., right-hand vs. left-hand steering) as possible fundamental ways of defining a product. In Table 1 we list the number of platforms, models, body styles and chassis per plant (as obtained from Harbour reports). However, both Krafcik (1988) and MacDuffie et al. (1996) give maximum weight to platforms. Consistent with this view, we define a product at the fundamental level of a platform. The importance of using platforms in measuring flexibility was also borne out of our discussions with various automotive experts. We do not take into account the "parts complexity" or the "option content" in measuring flexibility (MacDuffie et al. 1996, Fisher and Ittner 1999) because our focus is on the strategic dimensions of flexibility, hence we require a more macroscopic definition for a product.

In terms of *manufacturing facility,* the automotive assembly plant has three areas: the paint shop, the body shop and the general assembly area[2]. The paint shop is typically quite flexible: as long as vehicles can fit in the paint bath, any vehicle type can be painted. Since the paint shop is either completely flexible or not at all, we do not measure flexibility in the paint shop. On the other hand, both the body shop and the general assembly areas are typically limited in their flexibility, which limits the entire plant. Hence, we focus on the general assembly and the body shop to develop our measure of flexibility.

The next issue that deserves attention is the number of production lines in the general assembly area and the body shop. Often factories produce more than one platform but on separate production lines, which is not, in our view, a manifestation of flexibility. Likewise, the 1995 Harbour Report notes on page 20 that "A plant that has only one [production] line but handles several different platforms would be very flexible." In this spirit, a measure of flexibility ought to account for the number of production lines within the plant, as in MacDuffie et al. (1996). For instance, a plant manufacturing two platforms on one production line ought to be flexible, whereas a plant manufacturing two platforms on two separate production lines ought not to be.

The question now is whether to account for production lines in the body shop or the general assembly area, and how to obtain a measure of flexibility for the entire plant. For instance, if a plant manufactures two platforms and has two production lines in the body shop but only one production line in general assembly, is the plant flexible? To answer this question, we need to understand the sources of flexibility in general assembly and the body shop. The body shop brings different parts of the car together (doors, underbody etc.). This process is typically highly automated so that body line flexibility is often driven by the level of automation and manufacturing practices. In contrast, general assembly is the most labor-intensive area, typically involving a chain of 150-250 workstations with a line rate of about 60 vehicles/hour. Sequencing of operations (through a common bill of process) is one of the more important drivers of flexibility here (see also MacDuffie and Pil 1997). Since the sources of flexibility in the body shop and general assembly are very different, it is problematic to obtain one unifying measure that incorporates flexibility of both the body shop and the general assembly area. Hence, we need to consider each separately. Moreover, from our discussions with automotive experts, we learned that measuring flexibility in the body shop is problematic, because often a factory will have more than one

[2]Sometimes assembly plants also include a stamping area, but since many plants do not have in-house stamping, we omit it from consideration.

body line just to keep up with the production rate of the general assembly line, though each production line may be able to manufacture more than one platform. Hence, we propose a proxy for flexibility at the plant level that is based on the demonstrated ability of the general assembly line to manufacture different car platforms.

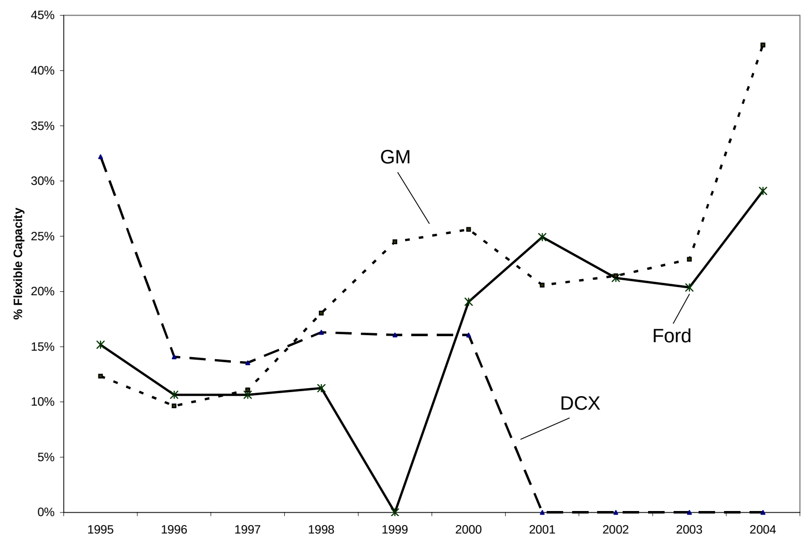

Figure 1. Flexibility deployment over time.

Assembly Line Flexibility (ALF). 1 if the number of platforms manufactured in the plant is greater than the number of assembly lines and 0 otherwise.

We also tried an alternative measure of flexibility: body-line flexibility or BLF (with a value of 1 if the number of platforms manufactured in the plant is greater than the number of body lines and 0 otherwise) but this measure is highly correlated with assembly-line flexibility. We report the relationship between assembly- and body-line flexibility in Table 2 and focus on ALF in the reminder of this paper. Tables 1 and 2 indicate that approximately 15% of plant-year observations in our study are assembly-line-flexible, and Figure 1 illustrates changes in flexible capacity over time for all of the Big three manufacturers. The graph seems to indicate that, while GM and Ford have steadily increased their deployment of flexibility, DCX has steadily decreased it. This observation is consistent with Priddle (2005) who cites the lack of capital to make major investment as a reason not to adopt flexibility at DCX but notes that this decision might have been justified ex-post because cost of flexible technology decreased over time.

We could also measure flexibility as a continuous variable (for instance, with a flexibility measure of 1.5 if there are three platforms manufactured on two lines). However, given the relatively small percentage of flexible plants in our sample, this approach would further dilute our dependent variable.

Moreover, such representation would be inconsistent with the analytical literature that we rely on in our hypotheses which treats flexibility as a 0-1 variable.

We acknowledge that our measure of flexibility is not perfect, and probably no other measure is. For example, it is possible that a plant with two assembly lines manufacturing two platforms might still be flexible because it produces two platform on the same assembly line. However, our discussions with automotive executives indicate that such situations, if they exist, are highly unusual. There are certainly other ways of defining (and measuring) flexibility. For instance, one could measure flexibility as the ease of shifting production from one product to another. Such measure highlights the *degree* of flexibility, which is driven by a different set of variables, and hence presents a different set of testable hypotheses. Given our focus on more strategic dimensions of flexibility (especially as a hedge against demand uncertainty and as a competitive weapon), one could also measure flexibility at the company level by looking at the number of plants that can manufacture a given model and the number of models manufactured by a given plant (similar to the *chaining* argument of Jordan and Graves 1995). However, this definition necessitates measuring potential flexibility which is problematic. We verified that the number of models that are manufactured in more than one plant are rather few (about 15%), and a majority of them are manufactured in multiple plants simply to cope with high demand (e.g., the Ford F-series trucks). These alternative measures of flexibility present interesting avenues for future research and merit a separate study.

We next detail the six independent variables: demand uncertainty, correlation, mean demand, competition, demand differential and substitutability. The descriptive statistics and correlations among these variables are provided in Tables 1 and 3. We compute significance of Pearson (2-tailed) correlations among independent variables in Table 3 using "pwcorr" command in STATA with the option "sig." We report no significant collinearity problems.

Demand Uncertainty. All underlying theoretical models that we use to formulate our hypotheses utilize single-period frameworks with exogenously specified demand distribution. Ideally, we would like to measure demand uncertainty as uncertainty in demand forecast. Unfortunately, forecast data has only become available from WARDS Automotive in recent years and moreover, even this demand forecast includes a single figure (point forecast) with no indication of uncertainty. We therefore utilize a proxy by measuring uncertainty in demand for a plant with a total standard deviation of sales for all models produced at this plant. Clearly, this approach is not exact since uncertainty that the plant faces may differ from uncertainty in sales. However, we believe that our proxy for demand variability at the plant level is acceptable because in practice factory orders are triggered by consumer demand occurring at the dealerships, and higher (lower) demand for any of the models produced at a given plant translates into higher (lower) demand for the factory output. We first calculate the variance in demand for each model using de-trended (first-differenced) monthly sales data. The plant-level variance is estimated by adding the individual variances for all models produced in the plant. The standard deviation is further obtained by taking the square root of this total variance. Monthly demand data is obtained from Wards Automotive. Average standard deviation of monthly demand in our sample is 4,785. We performed robustness checks using 19 different ways to estimate demand uncertainty and most of them resulted in qualitatively similar estimates. We attempted to use both raw (not de-trended) data as well as data that is both first-differenced and 12-differenced. Our results were qualitatively unchanged although usage of raw data sometimes (understandably) weakened results related to demand uncertainty. In the base model we retain estimation using first-differenced data for we believe that it is important to control for trends that persist in the automotive industry but it is not necessary to control for seasonality (e.g., by 12-differencing the data) because flexibility can be used to mitigate variability due to seasonality (e.g., it is beneficial to manufacture two models that have different seasonality in the same plant). We also attempted to estimate uncertainty using the coefficient of variation in demand (standard deviation divided by the mean), sum of coefficients of variations for individual models as well as the demand-weighted sum of coefficients of variation. With the exception of the weighted sum of coefficients of variation, these measures of demand uncertainty yielded qualitatively similar results. However, measuring demand uncertainty using the coefficient of variation is inconsistent with the theoretical models we rely upon (Goyal and Netessine 2006) and moreover, this measure of uncertainty is strongly correlated with mean demand. Thus, we retain the measure of demand uncertainty using standard deviation. Note that we do not incorporate demand correlation into the measure of demand uncertainty because we control for correlation separately to test Hypothesis 2.

Correlation. To calculate demand correlation, we divide plants in two disjoint sets: plants that manufacture more than one model and plants that manufacture exactly one model. For plants that manufacture more than one model, the pair-wise correlations are obtained from monthly de-trended (first-differenced) sales data to make it consistent with the way we estimate demand uncertainty. We then use the average of these pair-wise correlations (if there is more than one pair) to obtain a measure of the correlation faced by a plant. For plants manufacturing only one model there is no explicit way to calculate correlation. Instead of assigning zero correlation to these plants (which may introduce bias) we use *potential* correlation. To obtain it, we group these plants by companies – e.g., all GM plants together (call it set P_{GM}) and all Ford plants together (set P_F). We then ask the question: "Were the plant to manufacture another model within the same company, which model would it be?" For instance, to calculate the correlation in any given year for a plant (say, plant $p_x \in P_{GM}$), we take a model in the set P_{GM}/p_x that gives the minimum correlation for plant p_x, which can be interpreted as the potential correlation faced by a plant were the company to allocate two models with the lowest possible correlation to this plant (as the extant theory suggests). Note that since plants that manufacture a single model are inflexible plants, by considering the minimum correlation for these plants, we do not introduce any bias in favor of our Hypothesis 2. Average correlation for our sample is 0.50. To check robustness, we attempted 13 different ways to calculate demand correlation. Results using both raw and 12-differenced data to calculate correlation were qualitatively similar. Further, we attempted to take the minimum rather than the average of pair-wise correlations in multi-model plants to make it consistent with the way we estimate correlation for single-model plants. This approach strengthened results related to correlation. However, we believe that such approach might bias our results in favor of accepting Hypothesis 2 because the average number of model in flexible multi-model plants is higher than the average number of models in inflexible multi-model plants in our data. Finally, since the literature provides no guidance on how to best estimate demand correlation in single-model plants in empirical studies, we performed robustness checks by running regressions on multi-model plants only and results were qualitatively similar.

Mean Demand: This is the average demand per model manufactured in a plant. It is calculated as the sum of the mean demands for all models manufactured in the plant, divided by the number of these models. There is a mean demand per model of 16,989 units per month in our sample.

Competition. For each plant we measure competition using the proportion of flexible plants among all competing plants within the same market segment after excluding the plant itself. Segment definitions are taken from Ward's Automotive (e.g., Upper Middle, Lower Middle, Luxury Middle, etc.). We measure competition at the model level within an industry segment and aggregate it to the plant level by estimating the proportion of flexible plants in all market segments in which models manufactured in a plant compete. If more than one model is manufactured in the plant (and possibly each model belongs to a different segment), then we calculate the total competition for the plant as a proportion of flexible competing plants in all relevant segments taken together. Note that, in order to calculate this proxy, we include data for all manufacturers (e.g., Japanese, Korean etc.), not just the big three US manufacturers because the market share of non-US firm is quite significant. On average, there are 16% (ranging from 0% to 100%) flexible competitors at the plant level. To check robustness, we also measured competition as a raw number of flexible competitors within a segment but results were qualitatively similar. We acknowledge that it might be better to measure competition among companies and not plants. However, such measure of competition would not be very useful in our study since we only have three firms in the sample. We do believe that measuring competition at the plant level is a reasonable approach since the decision to implement flexibility at a given plant is more closely related to the actions of competitors directed towards models manufactured at this particular plant rather than to the actions directed towards the entire company.

Demand differential. The demand differential is a pair-wise measure estimated as the mean difference in demand faced by a plant. Demand differential is the sum of these pair-wise differences. As an alternative, we calculated demand differential as a variance, standard deviation and a coefficient of variation of mean demands and these alternative approaches did not affect our results. If there is only one model produced in a plant then we calculate demand differential using the same approach as in calculating demand correlation above. We also attempted excluding single-model plants and our results remained unchanged. Average monthly demand differential in our study is 27,073.

Substitutability. The substitutability variable measures the extent to which two products are similar. There are many ways to measure substitutability depending on the assumptions one makes about consumer preferences. If one believes that products are horizontally differentiated then, setting price aside, people disagree on which product is the best. This approach is taken in Berry et al. (1995) and it requires extensive data on differences among cars other than price (e.g., wheelbase, weight, mileage etc.). If, however, one believes that products are vertically differentiated then, price aside, everyone agrees on which product is the best. An example of this approach of estimating demand for cars is in Bresnahan (1987). We focus on the former approach for we believe that this is a more representative description of the automotive industry. This approach postulates that the level of utility that a consumer derives from a given product is a function of both a vector of individual characteristics as well as a vector of product characteristics. Consequently, as in Berry at al. (1995), we consider the problem of estimating the parameters of the demand system (including product substitutability parameters) from product level data. We use the following set of variables to estimate substitution coefficients: body style, wheel base, length, width, height, weight, net horse power, torque, automatic breaks system (optional or standard), traction control (optional or standard), cylinders and type, engine size, valves per cylinder, fuel system, fuel intake, cylinder bore and strokes, compression ratio, transmission type, miles per gallon, retail price. All this information is obtained from Ward's Automotive and it is also reported by vehicle manufacturers. We refer to Berry et al. (1995) for details on the estimation procedure. If there is only one model produced in a plant then we calculate demand substitution using the same approach as in calculating demand correlation above. Average level of product substitution in our model is 0.15. We do not have sufficient data to estimate product substitution for all models and therefore we only obtain substitution measure for 429 out of 478 observations. As a robustness check, we also performed estimation on just these 429 observations but our results did not change. We also attempted an approach based purely on price differential but it did not yield any significant results.

In this study, we also use several control variables: plant capacity, model price, model age, product life-cycle dummies, manufacturer and yearly dummies.

Plant capacity. Extant literature (Lieberman and Dhawan 2005) suggests that plants that are able to accommodate different models should be larger. Hence, we include capacity as a control variable. Annual plant capacity is regularly included in the Harbour Reports and averages 208,501 vehicles per year in our study.

Price. Since more complex/higher quality cars might be more difficult to produce on the same assembly line, we control for complexity and quality using average model price. Price data (MSRP prices) is obtained from Ward's Automotive. Average price in our sample is $25,767.

Model Age and Model Life-Cycle Dummies. Since flexibility investment decisions are often intertwined with product life cycle-effects, we introduce three plant-level dummies to control for the Start of Life Cycle (if a plant manufactures a model which is within first two years after launch), End of Life Cycle (if a plant manufactures a model which is within last two years before being phased out) and finally a variable Start and End of Life Cycle which controls for plants that have both models that are at the end and at the beginning of the their respective life cycles. 27% of our observations were plants with models at the Start, 11% at the End, and 5% at both Start and End of the Life Cycle. Moreover, we also control for model age at the plant level estimated as an average age of all models produced. This variable is different from End of Life Cycle variable which is often not observed (e.g., if the model is phased out after our study ends). The average model age in our sample is 4.60 years. Alternatively, one could control for product life-cycle effects using plant utilization or lagged plant utilization. We used these variables in robustness checks but they were never significant. We therefore retained product life-cycle dummies because the utilization variable does not provide information on whether utilization is low due to the end or the beginning of product life-cycle.

Manufacturer dummies (GM, FORD, DCX). This control is introduced to ensure that our results are not driven by any one manufacturer. We always use DCX as a base-case and hence omit its control variable.

Yearly dummies (1996-2003). It is possible that some of variables in our study exhibit time trends (e.g., demand or competition). Thus, some of the variables can exhibit spurious correlation through time. Moreover, we would like to see if flexibility deployment has changed over time (when controlling for other effects) so we introduce time dummies.

5 Analysis

5.1 Hypotheses tests

We provide evidence supporting our hypotheses using a multivariate logistic regression analysis. An alternative to the logistic regression model is to use a hazard model but we believe that the logistic model approach is superior for at least two reasons. First, the hazard model is designed for longitudinal data on the occurrence of events. In our case, the event would need to be defined as changing from an inflexible to a flexible plant. In our data we observe 9 of 75 plants making a total of 11 changes: 9 changes are from inflexible to flexible but 2 of the changes are from flexible to inflexible. The fact that changes can go both ways makes the hazard model less appealing. Second, a hazard model assumes that, even though a plant is inflexible, through the entire time period it will eventually become flexible (right censoring). Furthermore, it assumes that plants observed to be flexible throughout the entire time series probably made the change before the observation window (left censoring). We do not believe that this inevitable occurrence of an event is an appropriate assumption for our problem. Through interviews and observations we believe that plants can be inherently flexible or inflexible and may never even plan to switch.

Two interpretations of the logistic regression analysis are possible. First, the observed binary variable (flexibility) might be an outcome of unobserved continuous latent variable which measures the propensity of a plant to adopt flexibility (see Long 1997, Chapter 3 for this interpretation of the logistic regression model). While we cannot observe this latent variable, at some point a large enough propensity to adopt flexibility results in adoption. Alternatively, we can interpret the logistic model as a non-linear function predicting the probability of adopting flexibility. Below we follow this latter interpretation.

Table 4 reports the results of logistic models used to predict the probability that a plant is assembly line flexible. Since we have multiple observations by plant, tests of significance for each coefficient are computed using robust standard errors clustered by plant. Tests without clustered standard errors tend to bias the hypotheses tests in favor of acceptance. We use "logit" command in STATA with the option "robust cluster(plant)." We note the overall significance of the model containing only control variables (column 1), as well as models containing the main effects (column 2) and the interactions model (column

3). The Pseudo R^2 values range form 0.04 in the control model to 0.12 in the interaction model. We note significantly increased explanatory power as we add hypothesized variables and later interaction effects to the model.

Among the control variables (column 1), Model Age is positive and significant indicating that relatively older models are manufactured in flexible plants. Moreover, the Start of Life Cycle dummy is also positive and significant. Thus, we confirm that the ability to launch and phase out products effectively is a useful feature of product flexibility. However, since new product launches are functions of many other considerations, more research is needed. It is surprising to find that there are no statistically significant differences across manufacturers even though, as Figure 1 suggests, DCX might be the least flexible among the Big three US manufacturers, which is consistent with the anecdotal evidence (Priddle 2005). It appears that, after controlling for other variables, there are no statistically significant differences among U.S. manufacturers in terms of their level of flexibility deployment. Likewise, there does not appear to be any statistically significant time trends in flexibility deployment. This is again somewhat surprising (given Figure 1). Although none of yearly dummies are statistically significant, they all have negative signs suggesting that, given the evolution of other explanatory variables over time, flexibility adoption might have a negative rather than positive time trend.

In the model with main effects (column 2), we find a significant association between Assembly Line Flexibility and Demand Uncertainty, the Correlation between models, Competitive Flexibility and the Mean Demand. These results support Hypotheses 1, 2, 3 and 4, and do not support Hypothesis 5. Higher demand uncertainty is associated with higher assembly line flexibility suggesting that firms do use flexibility as a hedge against demand uncertainty. Assembly line flexibility is negatively associated with the correlation between models indicating that in situations with highly positively correlated demand assembly line flexibility is less common. Plants in segments with higher level of competitive flexibility have higher propensity to deploy flexibility which is consistent with the popular view of flexibility as a competitive weapon. Finally, models with high mean demand tend to be manufactured in non-flexible plants.

In the model with interaction terms (Column 3), we note that the results associated with Start of Product Life Cycle dummy, Model Age variable, Competitive Flexibility, Demand Uncertainty and Correlation are still significant. However, the association between Mean Volume and Assembly Line Flexibility loses significance. To interpret the interaction effects, we follow a method prescribed by Norton et al. (2004) rather than using the output of STATA. Due to the non-linear nature of logit models, the interpretation of the coefficient as well as the significance of the interaction terms can differ through the range of data (Ai and Norton 2003). This requires computation of the effect and its significance at each point on the logit curve. The coefficient estimates presented in Table 4 are the logit coefficients for the main effects and the average coefficients for the interaction effects in the data with average Z values. However, the coefficients may be positive or negative and the significance of these effects may differ throughout the data. Using this method, we note no significant associations for both interaction effects for all of the data range.

As we stated earlier when defining variables, we performed a variety of robustness checks. In particular, we computed demand uncertainty and demand correlation using raw data and 12-differenced data in addition to first-differenced data, as well as by taking the residuals after fitting a linear demand trend. We took a minimum of pair-wise correlations in multi-model plants rather than the average. We tried excluding single-model plants because it is unclear how to calculate demand correlation, substitutability and demand differential for these plants. We measured demand uncertainty using the coefficient of variation computed in various ways. We used the variance, standard deviation and coefficient of variation of demand means as a proxy for demand differential. We also attempted to lag all explanatory variables by one year. Most of our results exhibited remarkable robustness across all these alternative specifications. The coefficient for Demand Uncertainty was positive across all specifications and it was significant in most of them. The coefficient for Demand Correlation was always negative and highly significant in most robustness checks. The estimate for Competitive Flexibility was always positive and significant. The results associated with Mean Demand were inconsistent: in some instances the coefficient changed sign and in others it was insignificant. The coefficient for Demand Differential was never significant and sometimes changed signs. We also observed that Model Age was always significant and the dummy variable for the Start of Life Cycle was typically significant. All other variables, interaction terms and dummies were either never significant, or were significant only marginally and in a small subset of robustness checks. Therefore, we conclude that the support for Hypothesis 3 is remarkably robust, and support for Hypotheses 1 and 2 is quite robust. We also note strong product life-cycle effects.

Since the U.S. automotive industry has been troubled by poor financial performance, an argument can be made that many plants adopt flexibility erroneously. Therefore, as an additional robustness check, we separate plants in our sample into the "best" and the "worst" performers and conduct estimation for these two groups separately. We use assembly line productivity to assess plant performance. Productivity is a complex measure that accounts for a variety of effects including downtime, vacations, work-relief, overhead, etc. Productivity measures are typically reported in the Harbour Reports, either in terms of hours per vehicle (HPV) or workers per vehicle (WPV). As detailed in the Harbour Reports, the WPV measure is calculated by dividing the total employment by the daily production. The total employment is the actual on-roll employment which includes hourly (both direct and indirect labor) and salaried employees, and takes into account normal daily total absenteeism. This measure fails to account for overtime and often overestimates the workers per vehicle, since it includes the total workers on the payroll and not necessarily the actual workers who report for work. HPV is calculated using the total actual hours paid divided by the actual units produced in the timeframe studied. As argued in the Harbour Reports, HPV is typically a better way to measure productivity in light of the problems associated with WPV. Moreover, the advantage of this measure is that it is relatively well-accepted in the industry and has been used in similar studies (MacDuffie et al. 1996). We do not have productivity data for 1996 in terms of HPV, and hence, after removing missing observations, we are left with 373 plant-year combinations. Figure 2 illustrates average productivity at the three US automotive manufacturers, suggesting that there is a sizable improvement over time for all of them. Note that higher HPV corresponds to lower productivity.

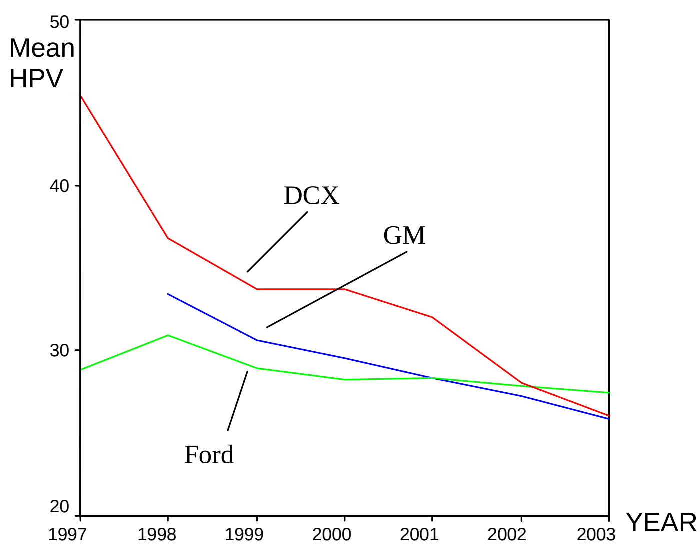

Figure 2. Productivity by manufacturer.

Based on HPV, we sort plants into upper and lower 50%. Since flexibility can be correlated with productivity, we conduct sorting separately for flexible and inflexible plants. Moreover, since productivity seems to improve over time (Figure 2), we sort plants separately in every year. Columns 4 and 5 in Table 4 show results of the logistic regression analysis for the two groups of plants. We observe that our results with respect to the life-cycle variables (Start of Life Cycle and Model Age), correlation and demand uncertainty are still significant and do not differ between two groups. However, only plants in the "worst" performing group support Hypothesis 3: the "best" performing plants do not seem to adopt flexibility when facing more flexible competing plants (the coefficient is negative but insignificant). This result hints that behavior of the "best" plants in the industry might be more consistent with the model of Goyal and Netessine (2006) than with the prevailing view of flexibility as a competitive weapon.

5.2 Performance implications of flexibility deployment

In the preceding section, we characterize the differences in the levels of environmental variables that are associated with plants that are observed to be flexible and inflexible. Though we cannot claim causal relationships between these environmental variables and the deployment of flexibility, a natural issue to consider is the implication of deploying flexibility against the predictions of extant theories on plant performance. We utilize this approach in this section to study whether the deployment of flexibility that we observe in the 1996-2003 time period is "optimal" according to some criterion or benchmark.

We use seven environmental benchmarks, all based on our hypotheses, against which we assess the performance of plants. To measure the impact of flexibility deployment on plant productivity, we assign penalty points to plants that do not adhere to the seven suggested benchmarks. For instance, the inflexible plant manufacturing products with low mean demand would get a penalty point since it contradicts Hypothesis 4. This *penalty score* (which indicates the deviation from the appropriate benchmark) is regressed against the productivity measure to test whether higher penalty is associated with lower productivity. The penalty score requires a benchmark value for comparison. We report results based on a median cutoff. To continue with our example, the inflexible plant manufacturing a product with a mean demand below the median in the sample would receive a penalty point. Conversely, a flexible plant with mean demand above the median would receive a penalty point as well. A similar penalty score was calculated for each hypothesis as detailed below. We expect firms with higher penalty scores to have lower performance. A similar metric was also used by Randall and Ulrich (2001) to assess the financial impact of supply chain strategies.

Penalty scores are established for the seven benchmarks, which are based on Hypotheses 1 (we label this penalty scores Uncertainty Penalty), 2 (Model Correlation Penalty), 3 (Competitive Penalty), 4 (Mean Demand Penalty) and 5 (Demand Differential Penalty), 6*a* (Substitution/Uncertainty Penalty) and 6*b* (Substitution/Demand Differential Penalty). We also introduce the Total Penalty that combines all the above penalties.

We use assembly line productivity (HPV) to assess plant performance. We note that assembly line productivity is not an ideal performance measure. An alternative would be to use the financial performance of an assembly line because it is better aligned with the underlying theoretical models in extant literature which are all concerned with profit maximization. Unfortunately, most publicly available financial reports are at the company or at the division level and we do not believe that even manufacturers themselves estimate profitability of an assembly line separately. Another approach would be to obtain data on per-vehicle profitability but, again, this measure would take into account profitability of the entire manufacturing process (including material costs), not just the productivity of the assembly line. In this respect productivity is the performance measure that is most closely related to the assembly line. We argue that mismatches in each of the variable in our econometric model have direct influence on productivity. For instance, placing a product with low demand in an inflexible plant might result in shutting the plant down for extended periods of time and hence lower productivity. Likewise, not adopting flexibility when competitive situation favors it (i.e., when proportion of flexible competitors is high) might result in plants that are sitting idle due to fluctuations in demand for the product associated with actions of competitors that impact mean demand and demand uncertainty. Hence, overall performance measure would suggest low productivity for the inflexible plant, with the environmental variable (low mean demand or low competition from flexible plants) pointing towards the possible cause of this malady.

Table 5 shows robust regression estimates testing the notion that plant productivity measured by hours per vehicle is associated with a mismatch between the use of assembly line flexibility and environmental factors, which form the basis of the seven benchmarks. In this regression we additionally control for the number of chassis produced in each plant and plant utilization which is in line with earlier works (see Krafcik 1988). Chassis refers to all of the mechanical parts of a car attached to a structural frame and this variable is meant to control for complexity of assembly. Utilization has a direct bearing on productivity: we can expect less utilized plants to have lower productivity. Additionally, we control for product price as another proxy of product complexity. We use robust estimation with errors clustered by plant. In our case, robust estimation becomes necessary due to heteroskedasticity in the data detected by the Bruesch Pagan test (Greene 1997). We cluster errors by plant because observations by plant violate assumptions of independence typical of ordinary least squares regressions. We present three models: a base model (column 1), a model with the total penalty score (column 2) and a model with individual penalty scores (column 3). F statistics for all models are significant at the $p < .01$ level. The R^2 values range from 0.61 in the base model to 0.65 in the individual penalty score model.

We find consistent and significant results across control measures in each of our models. Hours per vehicle increase in the number of chassis configurations manufactured in each plant, in price, and in assembly line flexibility. At the same time, hours per vehicle decrease in capacity utilization and capacity controls. It appears that an increase in the number of chassis configurations adds complexity thus adversely effecting productivity. Higher price might be indicative of more complex vehicles so it is expected that these plants have lower productivity. It appears that flexibility has an adverse effect on productivity as well probably due to downtimes to switch from vehicle to vehicle. On the other hand, high utilization is reflective of a well-balanced plant with better productivity. Likewise, it appears that it is easier to achieve high productivity in larger plants. We observe the significance of dummy variables for General Motors and Ford indicating that these companies achieve significantly lower hours per vehicle (hence better productivity) than DaimlerChrysler, our base-line company (consistent with Figure 2). We observe a trend of decreasing hours per vehicle over the last two years when examining the dummy variables used to control for each year.

We anticipate that hours per vehicle will be positively associated with the mismatch between the use of assembly line flexibility and environmental factors, as measured by the penalty score. We do not find support for this notion in the second column of Table 5 where we observe that the total penalty does not have a statistically significant coefficient. To further investigate this result, we estimate a model using each individual penalty factor (third column of Table 5). Here we observe that the penalty based on competitive factors exhibits negative and statistically significant association with hours per vehicle while the penalties based on the Demand Differential and the interaction between Substitution/Uncertainty exhibit positive and statistically significant associations with hours per vehicle. Other penalty scores exhibit no significant relations with hours per vehicle. The observation with respect to competition is interesting – it suggests that firms facing a higher number of competitors that employ flexibility should *not* follow the same strategy. This observation also stands in contrast to the arguments provided by the industry and popular press (and supported by the results of the logistic regression earlier) that firms should invest in flexibility in response to higher flexible competition. At the same time, this result is more consistent with the theory developed in Goyal and Netessine (2006). The results regarding Demand Differential and Substitution/Uncertainty penalty are consistent with our expectations based on Hypotheses 5 and 6a.

We checked our results for robustness by calculating cutoffs at terciles. In models using terciles, we note that the total penalty score is significant. However, in the model with individual penalty scores, only the mismatch related to competition is negative and significant. We also attempted estimating mismatches for other measures of demand uncertainty and correlation and in some of these estimations the Total Penalty was positive and statistically significant.

6 Discussion and future work

Our study is the first to analyze empirically how flexibility is deployed in the automotive industry. We find strong support to the notion that deployment of flexibility by US automotive manufacturers is associated with higher number of flexible competitors. The design of our study does not allow us to distill the exact causes of this effect. It very well might be that flexibility adoption in the automotive industry follows the herding effect (see Chamley 2003): when faced with enormous market uncertainties, automotive firms decide to imitate technology adoption by their competitors in the hope to recoup this investment later. We do, however, find that only the "worst" performing plants follow the herd while the "best" performing plants do not. Moreover, consistent with the extant theory, we find that flexibility deployment is positively associated with demand uncertainty and negatively associated with demand correlation among different models. While empirical literature has long suggested that high environmental uncertainty should be associated with flexibility deployment (although evidence itself was mixed), our paper is the first to test the relationship between flexibility and demand correlation that has been suggested in numerous theoretical papers. Finally, we observe strong association between flexibility deployment and product life-cycle effects.

We test implications of flexibility deployment upon automotive assembly productivity. We find that the productivity of all three US manufacturers has steadily improved over the last two years and that DCX lags behind both GM and Ford in terms of productivity. Further, we find that flexibility adversely affects productivity. We find evidence that deploying flexibility when competition deploys it does not result in better performance, i.e., "following the herd" in terms of investment in flexibility may actually have an unfavorable impact on productivity. These findings suggest ways to improve productivity in practice through prudent deployment of flexibility.

Although our findings appear suggestive, one must exercise caution with interpretations of their impact due to data limitations and imperfect proxies. Deployment of flexibility in the automotive industry is a complex decision associated with billions of dollars in capital investments and might be driven by the factors that we do not account for. Hence, as in any other empirical work, our study might have an omitted variables bias. In particular, we might have omitted correlated variables at the segment level which could potentially affect our results with respect to competition. Furthermore, at a higher strategic level the manufacturer has to select the portfolio of products that will be launched over the next 10 years as well as the set of plants that will be opened/closed. Often, assignment of models to plants is driven by these higher-level decisions that we are unable to account for. More work is needed in this direction. Another limitation is that our study focuses on US automotive manufacturers only. Arguably, Japanese companies (both in Japan and transplanted to the US) have been deploying flexibility over a much longer period of time and hence might be more experienced in this respect. Anecdotal evidence suggests that Japanese and European companies are, on average, more flexible, and thus it would be interesting to compare the deployment of flexibility across different countries if such data becomes available. Finally, although we commented on difficulties associated with measuring potential flexibility (as opposed to demonstrated flexibility in our study), one may attempt to assess theoretical capabilities of US automotive manufacturers. Although Upton (1995) finds a strong correlation between potential and demonstrated flexibility in the paper industry, the situation in the automotive industry may be different.

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Table 1: Descriptive Statistics (N = 483)

	Minimum	Maximum	Mean	Std. Dev.
Mean Demand	472	79837	16989	16186
Demand Uncertainty	101	19315	4785	3340
Correlation	-1.00	1.00	.5019	.3497
Competition	.00	1.00	.1619	.1602
Demand Differential	46	511365	27073	47529
Substitution	.0011	1.0095	.1549	.2173
Capacity	33088	327120	208501	61796
Price	8536	60597	25767	7517
Model Age	0	9	4.5971	2.1516
Start of Life Cycle	0	1	.2678	.4432
End of Life Cycle	0	1	.1109	.3143
Start and End of Life Cycle	0	1	.0523	.2229
Platforms per Plant	1	5	1.24	0.57
Models per Plant	1	5	2.31	1.08
Body Styles per Plant	1	16	3.29	2.62
Chassis per Plant	1	20	2.98	2.79

Table 2: Cross-tab of ALF and BLF

	BLF=0	BLF=1	Total
ALF=0	405	8	413
ALF=1	33	37	70
Total	438	45	483

Table 3: Correlations

	Competition	Correlation	Substitution	Demand Uncertainty	Demand Differ.	Mean Demand	Capacity	Price
Correlation	.07*							
Substitution	-.11**	.31***						
Demand Uncertainty	-.10**	.25***	.46***					
Demand Differential	-.07*	-0.01	.08*	.33***				
Mean Demand	-.15***	.00	.28***	.66***	.16***			
Capacity	.19***	.20***	-.18***	.09**	-.01	-.14***		
Price	.02	-.04	.07	-.01	.03	.03	-.22***	
Model Age	.07*	-.03	-.05	.13***	-.06	.09*	.03	.05

***, **, * denote correlations significant at the 0.01, 0.05 and 0.10 levels, respectively (2-tailed).

Table 4: Logit Models of Assembly Line Flexibility (75 plant clusters, z values in brackets)

	Base Model	Main Effects	Interactions	Best plants	Worst plants
Intercept	-15.00	-8.54	-16.62	-56.97	19.48
	[-0.57]	[-0.35]	[-0.56]	[-0.94]	[0.82]
GM	0.35	0.08	-0.10	-1.09	1.04
	[0.38]	[0.09]	[-0.11]	[-0.72]	[1.08]
FORD	0.21	-0.06	-0.30	-1.96	1.02
	[0.22]	[-0.06]	[-0.25]	[-1.00]	1.05
1997	-0.05	-0.14	-0.00		
	[-0.12]	[-0.32]	[-0.01]		
1998	-0.33	-0.42	-0.45	-2.26	0.19
	[-0.51]	[-0.75]	[-0.84]	[-1.34]	[0.16]
1999	-0.33	-0.48	-0.21	-3.26	0.20
	[-0.50]	[-0.68]	[-0.34]	[-1.48]	[0.15]
2000	-1.05	-1.12	-0.86	-5.06**	-0.70
	[-1.00]	[-1.17]	[-0.96]	[-1.96]	[-0.45]
2001	-1.39	-1.84	-1.56	-7.11**	-1.44
	[-1.11]	[-1.54]	[-1.44]	[-2.02]	[-0.92]
2002	-1.54	-1.96	-1.78	-8.21**	-1.60
	[-1.05]	[-1.43]	[-1.34]	[-2.06]	[-0.90]
2003	-1.41	-1.81	-1.42	-9.10**	-1.21
	[-0.87]	[-1.20]	[-1.03]	[-2.03]	[-0.78]
Start of Life Cycle	0.87**	0.87*	0.62*	2.09*	1.95*
	[1.97]	[1.86]	[1.78]	[1.87]	[1.65]
End of Life Cycle	0.55	0.21	0.07	0.12	0.058
	[0.83]	[0.33]	[0.12]	[0.93]	[0.05]
Start and End of Life Cycle	0.35	0.04	0.16		1.22
	[0.31]	[0.03]	[0.14]		[0.81]
Model Age	0.44**	0.47**	0.37*	1.41**	0.60**
	[1.99]	[2.10]	[1.92]	[2.29]	[2.36]
Ln(Capacity)	0.56	0.16	0.43	1.43	-0.40
	[0.61]	[0.18]	[0.34]	[0.32]	[-0.47]
Ln(Price)	0.44	0.29	0.71	3.64**	-2.05
	[0.27]	[0.20]	[0.46]	[2.43]	[-1.21]
Competitive Flexibility		2.31*	2.35*	-2.51	5.04***
		[1.82]	[1.82]	[-0.99]	[3.62]
Correlation		-0.89**	-0.81**	-2.50**	-1.27*
		[-2.15]	[-2.00]	[-2.43]	[-1.91]
Mean Demand		-0.000039*	-0.000062	-0.000066*	-0.00005
		[-1.86]	[-1.39]	[-1.91]	[-1.53]
Demand Uncertainty		0.00019**	0.00045**	0.00038**	0.00027**
		[2.44]	[2.45]	[2.45]	[2.05]
Difference in Volume		0.000000097	-0.0000016	0.0000019	0.0000035
		[-0.03]	[-0.42]	[-0.51]	[-0.43]
Substitution			2.28		
			[0.84]		
Substitution x Uncertainty			-0.000077#		
			[-0.83]		
Substitution x Difference in Volume			0.0000021#		
			[-0.42]		
Pseudo R-squared	0.04	0.09	0.12	0.25	0.21
Wald Chi-Square	47.00***	61.71***	69.20***	67.94***	68.87***
N	478	475	422	182	184

***,**,* significant at p<0.01, 0.05, 0.10 levels. # significance interpreted as per Norton et al. (2004)

Table 5: Robust Regression Estimates of Log(Hours per Vehicle)
(73 plant clusters, N=373, t-values in brackets)

	Base Model	Total Mismatch	Individual Mismatch
Intercept	7.35***	7.42***	8.18***
	[6.91]	[6.77]	[7.71]
# of Chassis Produced in a Plant	0.02**	0.02**	0.02**
	[2.45]	[2.46]	[2.43]
Assembly Line Flexibility	0.14***	0.14***	0.12***
	[2.78]	[2.82]	[2.84]
GM	-0.13***	-0.13***	-0.15**
	[-3.05]	[-3.12]	[-3.27]
FORD	-0.19***	-0.19***	-0.18***
	[-3.81]	[-3.85]	[-4.08]
Log(Capacity Utilization)	-0.23***	-0.23***	-0.22***
	[-4.16]	[-4.16]	[-3.91]
Log(Capacity)	-0.34***	-0.35***	-0.37***
	[-7.87]	[-7.83]	[-8.37]
Log(Price)	0.14**	0.14**	0.08
	[2.13]	[2.09]	[1.17]
1998	-0.03	-0.03	-0.04
	[-0.33]	[-0.29]	[-0.42]
1999	-0.09	-0.10	-0.08
	[-1.07]	[-1.06]	[-0.95]
2000	-0.11	-0.11	-0.10
	[-1.16]	[-1.14]	[-1.12]
2001	-0.16	-0.16	-0.16
	[-1.64]	[-1.59]	[-1.65]
2002	-0.22**	-0.22**	-0.21**
	[-2.23]	[-2.18]	[-2.14]
2003	-0.26***	-0.26***	-0.24**
	[-2.71]	[-2.65]	[-2.56]
Total Penalty		-0.005	
		[-0.43]	
Competitive Penalty			-0.08**
			[2.35]
Uncertainty Penalty			-0.02
			[-0.56]
Model Correlation Penalty			0.01
			[0.48]
Mean Demand Penalty			0.04
			[1.12]
Demand Differential Penalty			0.07*
			[1.95]
Substitution/Uncertainty Penalty			0.12***
			[3.14]
Substitution/ Demand Differential			-0.04
			[-1.20]
R-squared	0.61	0.62	0.65
F statistic	14.83***	13.80***	14.90***

***,**,* significant at p<0.01, 0.05, 0.10 levels respectively