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Citation for published version:
Giardili, S, Ramdas, K & Williams, JW 2023, 'Leadership and Productivity: A study of US automobile assembly plants', *Management Science*, vol. 69, no. 3, pp. 1500-1517. https://doi.org/10.1287/mnsc.2022.4427

Digital Object Identifier (DOI):
10.1287/mnsc.2022.4427

forthcoming in *Management Science*

Leadership and Productivity: A Study of US Automobile Assembly Plants*

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April 8, 2022

Abstract

We examine the effect of plant managers on productivity using unique matched manager-plant panel data on US auto assembly plants during 1993-2007. Our econometric approach is two-pronged. Our first approach relies on using the panel nature of our data to measure variation in productivity due to managerial influence. We estimate the interquartile range of the effect of individual plant managers on average hours-per-vehicle to be about 30%. Further, we find that plant managers' experience with the models that are in production ameliorates the negative impact of new model introductions on productivity. We also observe evidence that managers' plant-specific tenure has a positive impact on productivity. In our second approach, we use high-frequency time-series data, along with structural-break tests and machine-learning methodologies, to predict variation in production using plant manager switches. We find that a plant manager's identity is predictive of changes in both the mean and variance of production, further highlighting their channels of managerial influence. These findings are robust to narrowing the sample to focus on retirements as an exogenous source of managerial switches.

Keywords: productivity, leadership, shop floor, managerial experience, managerial traits

*We are grateful to Jacob Malone, Madhu Madhusudhan, Elizaveta Nikolaeva, Vaidheeshwaran Venkatram and Kayla Wilding for research assistance.

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1 Introduction

Leadership and productivity are widely regarded as important determinants of organizational outcomes including profits, stock returns and ultimately, survival. Researchers across disciplines as diverse as business history, organizational behavior, strategy and economics have studied leadership. There is also a long established and still flourishing literature in economics and business on the drivers of productivity. Yet, there remains substantial unexplained variation in productivity across plants even within narrowly defined industries, and limited study of the role of leadership in explaining this variation. Syverson (2011) highlights this gap, noting that "perhaps no potential driver of productivity differences has seen a higher ratio of speculation to actual empirical study" than the role of individual managers and managerial practices.

This paper contributes to filling this gap by empirically studying the role of plant managers in determining plant-level productivity in the US auto industry. At the heart of our analysis is a unique manager-plant matched panel dataset covering 66 US auto assembly plants in the period 1993-2007, tracking the management spells of 115 different plant managers (whom we henceforth refer to as 'managers'). To our knowledge, ours is the first data of its kind, documenting operational leadership at a level lower than the C-suite. We analyze these data using a two-pronged empirical approach that applies panel data and machine-learning methods to relate plant-level measures of productivity and production to managerial identities. The complementary approaches reveal the proportion of variation in productivity differences across plants attributable to plant managers' identities, and provide insight into some channels through which plant managers can influence productivity.

From an econometric standpoint, a critical feature of our dataset is that we observe plant managers who have led more than one plant in our sample period. By virtue of having such "switchers" across plants, we can apply the approach introduced by Abowd et al. (1999) to examine wage differentials, to explain residual variation in productivity. In essence, switchers allow us to separately identify the fixed effects associated with both individual managers and specific plants. Absent switchers, one cannot say to what extent a highly productive plant owes its success to inherent aspects of the plant itself – like technology or worker demographics – or instead to inherent aspects of its manager. The panel data approach also permits the introduction of a time-varying measure of a manager's experience, distinct from measures of a plant's experience used in prior research (e.g., Levitt et al. 2013, Gopal et al. 2013). Controlling for the identity of plant managers also removes bias due to unobservable manager characteristics which are likely to be correlated with the explanatory variables commonly studied in the productivity literature.

We find that controlling for the identity of individual plant managers substantially increases explanatory power, over and above that of established drivers of productivity. Across a variety of specifications, controlling for individual plant managers explains about 7% of the overall variation in productivity. From our estimates, the difference in the contribution to productivity of the plant manager at the 25th percentile of the distribution of individual manager effects and the plant manager at the 75th percentile of this distribution is a 30% reduction in

hours-per-vehicle.[1] This substantial role for plant managers in determining the unexplained productivity across plants is consistent with the findings of Syverson (2004), who estimates a two-to-one ratio for the interquartile range of plant productivity within a 4-digit SIC industry classification.[2]

Through our panel data analysis we also seek to identify some channels through which plant managers influence productivity. The substantial negative impact of new model launch on productivity has been documented in recent prior research (Gopal et al. 2013, Levitt et al. 2013). Like these studies, we find that a new model reduces a plant's productivity (i.e., increases hours-per-vehicle) by 22%. We build on these studies to examine the role that the plant manager's experience has in mitigating such productivity disruptions. Previous research has shown that individual workers' experience improves their productivity in the specific production or service tasks they perform (Kellogg 2011, Maranto and Rodgers 1984, Atkinson et al. 2016). We find that a plant manager's experience leading plants that produced the specific models currently in production in his/her plant significantly improves productivity. This measure is distinct from a plant's experience with its current models, which we find also reduces productivity disruptions when a new model is introduced.

Managerial experience is a valuable asset in times of change. In the early 2000s, in reaction to oil shocks, US automakers switched from making large gas guzzlers to smaller, more fuel-efficient vehicles. For example, in 2003, Ford's Avon Lake plant in Ohio switched from making the larger Nissan Quest van to the hybrid Ford Escape SUV, which the plant's manager had no experience in producing. Hours-per-vehicle (*hpv*) at Avon Lake increased by 58% in 2003. Our estimates suggest that had the manager with the maximum experience making the Ford Escape SUV managed its launch at Avon Lake, the Escape's *hpv* would have been 24 minutes lower, implying a saving of $3.5 million at the plant over its first two years of production.

Finally, we see some evidence that an increase in the time since the last managerial switch event at a plant can have a significant and economically meaningful impact on productivity. For each extra year a manager spends at a given plant since the last manager switch, there is an increase in productivity of about 1.6%. These results remain even when controlling for the systematic influence of individual plant managers on productivity with manager fixed effects.

Next, we perform a series of complementary analyses using high frequency data, to provide additional evidence on managers' influence on productivity and further our insights into the channels through which managers exert this influence. Using weekly time series data on production at each plant over the period 1991 to 2005, we employ structural break tests (Ploberger and Krämer 1992) to determine whether a change in the plant manager significantly impacts production levels at a plant. We also perform a model-selection analysis using LASSO regression to determine whether managerial switches can predict ("out of sample") variation in production levels. In both cases, we find that individual plant managers systematically influence production levels. Importantly, these results are robust to restricting the sample to plants with a retiring manager, which is (presumably) a more exogenous source of variation in managerial

[1] Hours-per-vehicle is an auto industry productivity measure and equals total working hours divided by total number of vehicles produced.

[2] Firms within a 4-digit SIC code are very similar; e.g., within vehicle assembly "motor vehicles and passenger car body assembly" has a different 4-digit SIC code from "truck and bus body assembly."

switches.

Reducing variability is central to operations management. Lower variability in production can be indicative of smoother operations that are less subject to quality glitches, supply shortages or worker absences, which can hurt productivity. Also, while production levels need to be adjusted in response to shifting demand, matching supply with demand while keeping production variability low can reduce costs. Plant managers affect production levels using a number of levers including overtime, adding shifts, changing line speed and shutdowns (Bresnahan and Ramey 1994). Using tests for grouped heteroskedasticity, we find that individual plant managers differentially affect variance in production levels. Taken together, these analyses using high-frequency production data further reinforce our findings that the plant manager's identity has an important role in determining the mean and variance of production at a plant.

Our findings add to the extant literature on productivity in operations and economics. Researchers have identified capital usage, quality of the workforce, overall and model-related experience, new product launch, product variety, plant flexibility, extent of outsourcing, scale of operations and even weather as drivers of productivity (Lieberman and Lau 1990, Lieberman and Demeester 1999, Fisher and Ittner 1999, Van Biesebroeck 2003, Van Biesebroeck 2007; Syverson 2004, Syverson 2011; Cachon et al. 2012, Gopal et al. 2013, Lee et al. 2014). More recent research examines spillovers from buyer to supplier firms (Serpa and Krishnan 2018). Specific to the auto industry, there remains a great deal of unexplained variation in productivity in auto assembly plants (e.g., Van Biesebroeck 2007, Cachon et al. 2012, Gopal et al. 2013). Narrowing this productivity gap in the auto industry is important in itself. Indeed, this is a major area of focus for many large industry research institutes.[3] We provide evidence that plant-level leadership can explain a significant portion of the variation in productivity across plants.

While the role of plant-level leadership in improving productivity seems to have fallen between the cracks, leadership itself has attracted tremendous research attention. There is much conceptual, survey-based and experimental research on leadership in organizational behavior and strategy. This work focuses on the defining characteristics of leaders and how they exert influence (e.g., see Judge et al. 2002, Knippenberg et al. 2004), at both the top executive and middle manager levels (e.g., Burgelman 1985; Wooldridge and Floyd 1990). While some of this work has examined the leadership role of plant managers (e.g., Manz and Sims 1987, Mayer and Gavin 2005, Smith et al. 2009), this research stream does not delve into estimating the impact of plant-level leadership on productivity or other plant-level outcomes. Our interviews with several auto assembly plant managers confirmed that their key responsibilities include managing personnel, production, quality, safety and environmental impact. Better trained personnel, better production scheduling, reduced rework, reduced downtime due to safety glitches, and finding ways to meet environmental targets without compromising production levels can all improve productivity. Our interviews also revealed the importance of leadership attributes – including the ability to set clear goals, communicate, manage conflict and motivate their staff of

[3]For example, the International Motor Vehicle Program, The University of Michigan Transportation Research Institute, the Center for Automotive Research and Auto Alliance, among others.

several hundred or more employees – in carrying out their responsibilities. While plant managers are selected at the corporate level, we learned that plant managers typically select other plant personnel – e.g., line workers, quality control staff or engineers – who impact productivity. They also work with corporate to select key senior management hires at a plant, e.g., assistant plant manager.

Our work complements recent research in strategy and economics on how managerial practices impact productivity, e.g., via incentives and compensation, problem-solving teams, on-the-job training, information sharing and job rotation (Huselid 1995, Ichniowski and Shaw 1999, Bandiera et al. 2007, Bloom and Van Reenen 2007, Syverson 2011, Bloom et al. 2012). We highlight the importance of the model-specific experience and plant-specific tenure of managers, as opposed to that of managerial practices implemented in an organization, in explaining productivity. Finally, by showing that a plant manager's experience matters, above and beyond traditional measures of manufacturing experience (e.g., see Argote et al. 1990, Levitt et al. 2013), we also contribute to the literature on learning.

A stream of literature in business and economics has used panel data econometrics and event studies to examine whether, and how, top executives, chief supply chain and operations management executives impact stock returns and other accounting measures of firm performance (e.g., see Chatterjee et al. 2001, Bertrand and Schoar 2003, Boyd et al. 2010, Hendricks et al. 2015). However, this literature is silent on the effect of leadership at the level of manufacturing plants and service shop floors on facility-level outcomes such as productivity. Syverson (2011) emphasizes data limitations as a key "stumbling block", noting that even detailed production micro-data available today rarely include any aspect of managerial inputs. Our hand-collected data on managerial spells at auto assembly plants, along with traditional auto industry data, helps bridge this gap.

The remainder of the paper is as follows. In Section 2 we discuss data sources, describe variables used in the analysis, and provide descriptive statistics. Section 3 contains our panel data analysis and results, while Section 4 provides the analysis and results for the high-frequency data. Section 5 concludes the paper.

2 Data, Variables and Descriptive Statistics

We obtained data from several sources. Automotive trade journals provide data on productivity, production, new model launches, and established plant-specific production factors. For data on individual plant managers, we searched news releases and new articles, interviewed automotive industry personnel and industry experts, and conducted extensive search of different news and information platforms. Fortunately, new managers at auto assembly plants are always publicly announced, unlike other plant-level hires. Weather data is collected from the National Oceanic and Atmospheric Administration (NOAA).

Our matched manager-plant data covers 66 US automotive assembly plants and 115 managers from 1993 to 2007, resulting in 677 plant-year observations. When constructing our dataset, we follow Bertrand and Schoar (2003) and impose that managers have to be observed for at least 3 years. This 3-year restriction helps towards ensuring that managers have enough

time to imprint their management style in any given plant. We refer to this sample as the *full* sample. We further restrict our sample to the subset of plants for which at least one specific manager can be observed in at least one other plant. Note that we keep all observations for each plant satisfying this requirement, meaning that we include years in which the plant has managers who are never observed in any other plant. The resulting sample has 440 observations from 40 plants and 80 managers. We refer to this sample as the *connected* sample. Given that nearly 65% of the observations are preserved (i.e., 440 plant-year observations versus 667), this *connected* sample is nearly identical to the *full* sample in terms of observable characteristics of the plants and managers.

2.1 Dependent Variable

Our main dependent variable of interest is plant productivity, measured as hours-per-vehicle. We obtained productivity data from the Harbour Reports, a well-respected industry data source used in prior automotive research (e.g., Gopal et al. 2013, Van Biesebroeck 2007), for the period 1993-2007. Harbour Consulting published the Harbour Reports using plant-level data provided voluntarily by automobile manufacturers to aid its industry productivity benchmarking analyses.[4] Harbour representatives also visited the plants of participating auto manufacturers regularly to supplement data collection and verify their analyses.

The variable *hours-per-vehicle* (*hpv*) is defined as the total number of working hours at a plant in a year (including paid lunches, breaks and overtime) divided by the total number of vehicles produced. Prior to 1998, Harbour Consulting used a slightly different productivity measure, *workers-per-vehicle* (*wpv*). We convert *wpv* to *hpv* using a plant-specific conversion factor.[5] We also use high-frequency data on production, the denominator of *hpv*. This plant-level data on weekly production for the period 1991-2005 comes from Ward's Automotive, another reliable industry data source that is widely used in prior research (e.g., MacDuffie et al. 1996, Cachon et al. 2012).

Figure 1 plots the US auto industry's productivity trends. The left panel shows that, as a whole, the industry has seen tremendous gains in productivity during our sample period, while the right panel indicates that there is quite a bit of variation in productivity trends across manufacturers. GM and Chrysler began with much worse productivity in 1993, and showed dramatic improvements over time. In contrast, Ford, NUMMI[6] and the Japanese manufacturers started out with much higher productivity and showed relatively stable performance throughout the period.

Figure 2 shows the tremendous variation in outcome measures across plants. The left panel shows that the distribution of average *hpv* (computed over time in each plant) has a long right tail, with the worst plants having an average *hpv* of nearly 60. This dispersion demonstrates the importance of controlling for persistent plant-specific factors that drive productivity differences across plants, and is consistent with the observation of Syverson (2004) that even within

[4] Harbour is now a subsidiary of Oliver Wyman.

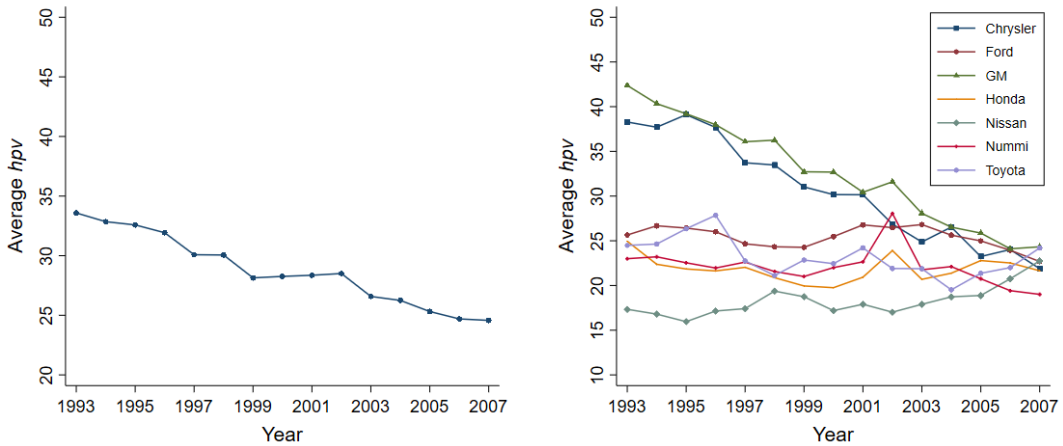
[5] For some years in our sample, we have data for both *hpv* and *wpv*, for each plant. We use the average within-plant ratio of *hpv* to *wpv* during such years as a plant-specific conversion factor.

[6] New United Motor Manufacturing, Inc. (NUMMI) was a GM-Toyota joint venture during 1984-2010.

narrowly defined industries there is substantial heterogeneity in productivity. As with *hpv*, the right panel shows that average *production* differs substantially across plants, with an average number of vehicles produced per week of 4,253 and a standard deviation of almost half that value.

Figure 1. Yearly Trends in *Hours-per-Vehicle*

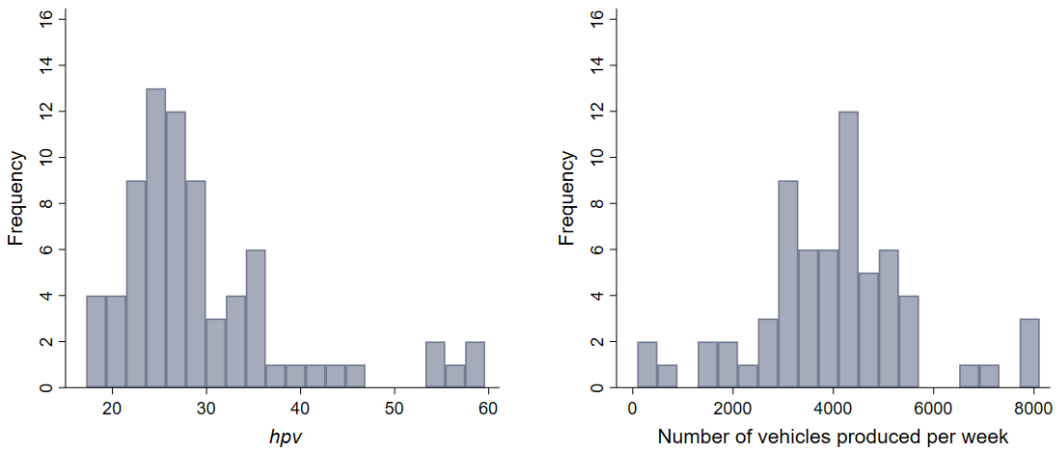
(a) Overall trend (b) Company-specific trends



Notes: Figure 1 displays auto industry productivity trends from 1993 to 2007. Figure 1(a) plots average *hours-per-vehicle* across plants in each year. Figure 1(b) plots average *hours-per-vehicle* across plants for each company in each year. The sample in the left panel comprises plants across all companies, while the sample in the right panel comprises plants for the seven companies with the longest time series in our data; other companies were excluded for clarity.

Figure 2. Between-Plant Variation in *Hours-per-Vehicle* and *Production*

(a) *Hours-per-vehicle* (b) *Production*



Notes: Figure 2 displays the between-plant variation in outcome measures. Figure 2(a) shows the distribution of average yearly *hours-per-vehicle* across plants during 1993-2007. Figure 2(b) shows the distribution of average weekly number of vehicles produced across plants during 1991-2005.

Figures 1 and 2 taken together hint that even within each plant there is likely to be high variation in productivity over time, particularly for those manufacturers that substantially improve over our sample period. We next discuss plant-specific factors that contribute to this within-plant variation in productivity.

2.2 Plant-Specific Explanatory Variables

While our primary interest is in how managers influence productivity, many plant-specific variables may be correlated with managerial changes and also impact productivity. We control for the most common variables identified in prior research and we also include plant fixed effects. A summary of these variables using the *connected* sample is presented in Table 1, while in the Online Appendix Table A.1 we provide the summary using the *full* sample.

New Model – The launch of a new model in a manufacturing plant can severely disrupt its productivity (Gopal et al. 2013, Levitt et al. 2013). Such productivity setbacks can delay market introduction. Prior research indicates that both announcements of new product introduction delays and actual delays significantly decrease market value and other accounting measures of firm performance (Hendricks and Singhal 2008).

We identified new model launches using production data from Ward's Automotive. $NewModel$ is an indicator for at least one new model being introduced in a plant in a year, where a new model has a different model name from any model that has been previously manufactured in a plant.[7]

Plant Experience with Current Models – It is well known that a plant's productivity improves with its experience in producing products (e.g., see Argote et al. 1990). We define $PlantModelExperience$ as the total number of vehicles produced in the past three years of the same models as those currently in production.[8]

If a plant has plenty of experience with the models it is currently making, introduction of a new model should be less disruptive than if the plant has little experience with these models. Experience enhances control and may provide the organizational slack needed to absorb unforeseen problems that naturally arise during a new model launch. For example, an auto plant manager whom we interviewed mentioned the need to migrate labor from other lines at short notice during launch, which could hurt the other lines more if they are less established. If there is little control over production, introducing a new model may have more severe consequences for productivity. To capture these effects, we introduce an interaction of $PlantModelExperience$ and $NewModel$.[9]

Other Plant-Specific Controls – Prior research has identified a number of additional plant-level factors that impact productivity. All else equal, higher product variety should hamper productivity, due to greater time spent in changeovers and reduced economies of scale in production (Fisher and Ittner 1999, Ramdas 2003, Van Biesebroeck 2007). Higher flexibility - i.e., ability to adjust and respond to new information (Van Mieghem 2008) - enables a plant to make multiple models (Moreno and Terwiesch 2015), albeit with a reduction in productivity (Van Biesebroeck 2007). Auto manufacturers often choose to outsource the production of components or subassemblies to suppliers. Outsourcing leads to an increase in productivity

[7]Our definition of a new model focuses on model changes that are substantial enough for the ensuing model to be given a new name. A minor model change on an existing model would not count as a new model.

[8]We are able to compute plant experience in our starting year, 1993, as our production data from Wards Automotive goes back to 1985.

[9]Note that a plant's prior experience with new models is, by definition, zero.

by decreasing the work content per vehicle (Van Biesebroeck 2007).

Table 1. *Plant-Specific Variable Definitions and Descriptive Statistics*

Variable	Description	Source[a]	Mean	SD
Hours-per-Vehicle	Total working hours divided by total number of vehicles produced	HR	27.87	7.383
Production	Total number of vehicles produced	WA	4253	1836
NewModel	Indicator for at least one new model introduced	WA	0.166	0.372
PlantModelExperience	Total number of vehicles produced in the past three years of the same models as those currently in production	WA	116.2	106.9
Flexibility	Average number of platforms produced per production line	HR	1.065	0.327
Variety	Sum of the number of body styles and chassis configurations produced	HR	7.126	10.22
Outsourcing	Average of all task-specific outsourcing dummies	HR	0.194	0.101
Scale	Production capacity (in 10,000s)	HR	22.04	6.187
Size	Plant's square footage (in 10,000s)	HR	293.4	82.08
TechnologyLevel	Production capacity divided by plant's square footage	HR	0.081	0.031
SegmentTruck	Indicator for large truck manufactured	HR	0.011	0.106
SegmentLarge	Indicator for large/luxury car manufactured	HR	0.114	0.318
SegmentMidsize	Indicator for mid size car manufactured	HR	0.277	0.448
SegmentPickup	Indicator for pickup manufactured	HR	0.289	0.454
SegmentSmall	Indicator for small car manufactured	HR	0.064	0.244
SegmentSUV	Indicator for suv/crossover manufactured	HR	0.307	0.462
SegmentVan	Indicator for van manufactured	HR	0.120	0.326
Wind	Fraction of days with wind speed above 30 miles per hour	NOAA	0.045	0.026
Heat	Fraction of days with temperature below 15 degrees Fahrenheit	NOAA	0.057	0.056
Cold	Fraction of days with temperature above 90 degrees Fahrenheit	NOAA	0.051	0.040
Precipitation	Fraction of days with non-zero precipitation	NOAA	0.338	0.055

Notes: With the exception of the *production* variable that is observed at a weekly level, the unit of observation for all variables is plant-year. Descriptive statistics are calculated using the *connected* sample across 40 plants. Each of the data sources above is publicly available.

[a]HR stands for Harbour Reports; WA stands for Ward's Automotive; and NOAA stands for National Oceanic and Atmospheric Administration.

Similar to Van Biesebroeck (2007) we define *Variety* in an auto plant each year as the sum of the number of body styles and chassis configurations produced in the plant, *Flexibility* as the number of platforms produced per production line, *Outsourcing* as the average of all task-specific outsourcing dummies,[10] and *Scale* as a plant's yearly production capacity.[11]

[10]For a wide range of detailed tasks such as body stamping, frame welding, seat assembly, etc., the Harbour reports publish annual plant-specific data on whether or not the task is outsourced.

[11]Harbour reports compute production capacity using a constant line rate and the regular shift pattern used

Also as in Van Biesebroeck (2007) we include a vehicle segment fixed effect for each vehicle segment manufactured at a plant (e.g., small car, mid-size car, large car, van, SUV, etc.), to capture differences in *hpv* due to differences in the vehicle itself - e.g., subcompact cars requires less labor than minivans. In addition to these controls, we define $Size$ as a plant's square footage, and a plant's $TechnologyLevel$ as its capacity divided by its square footage, as more modern technology may result in higher capacity per square foot. Major technological changes are decided at corporate and could coincide with manager switches, so excluding them could introduce bias.

We also include measures capturing disruptions in production due to weather conditions. Lee et al. (2014) find that workers are more productive on bad weather days, possibly due to fewer cognitive distractions. In contrast, Cachon et al. (2012) report that automobile production is hurt by inclement weather, potentially due to causes such as interrupted supplies, employee absences and low morale. Naturally, similar causes can also reduce productivity. For example, workers who are present at work cannot assemble vehicles if components are missing due to a weather-related supply disruption. We control for the effect of weather on productivity using a procedure similar to that of Cachon et al. (2012). Using the exact latitude and longitude of each plant in our sample, we locate its closest weather station and use daily weather data from the NOAA's National Climatic Data Center at these weather stations over our sample period.[12] We convert daily weather data to yearly by aggregating each weather variable. $Wind$, $Heat$, $Cold$ and $Precipitation$ denote the fraction of days with wind speed over 30 MPH, temperature above 90 degrees Fahrenheit, temperature below 15 degrees Fahrenheit, and with non-zero precipitation, respectively.

Finally, we include plant fixed effects to control for all time invariant plant-level factors. Inclusion of this rich set of controls for time-varying and time invariant plant characteristics in our analysis is crucial to ensure that variation in productivity due to these factors is not mistakenly attributed to managerial changes.

2.3 Manager-Specific Explanatory Variables

Through a careful and thorough data collection process, we secure information on every individual who served as a plant manager at a plant in our sample. We searched Factiva and LexisNexis news archives for new plant manager announcements. These typically appear in company press releases or news articles in local newspapers or trade journals (e.g., Automotive News). We also spoke with managers and public relations officials at assembly plants and with automotive experts to get information on plant managers who had served at specific plants. We supplemented these searches with Google search using as keywords "plant manager" along with the specific company name, plant name and year. For more recent years LinkedIn profiles provided valuable information.[13] Unless otherwise specified, we use 'manager' and 'plant

during each year.

[12] We use data from weather stations at airports as the weather coverage at airports is more complete and accurate.

[13] We are confident that measurement error is not a concern. As we often have multiple sources of data for each manager, in cases of occasional discrepancy (e.g., two different start dates at a plant for a manager) we were able to dig deeper and determine which was the correct information.

manager' interchangeably.

For each plant manager identified, we collected data on their start date and end date as manager at each plant where they had served in our sample period. On average, a individual spent 5.1 years as a plant manager during our sample period.

Where available, we also collected additional biographic information on a number of manager-specific characteristics: education (type of undergraduate and graduate degree if earned), gender and an indicator for Japanese auto experience. Crucially, we're also able to collect information on retirements of plant managers, which serves as a source of plausibly exogenous changes in plant-level management. About 21% of managers retire during our sample. These variables, and others described in detail below, are defined and summarized in Table 2. In the Online Appendix Table A.2 we provide an analogous table to this one using the *full* sample.

Table 2. *Manager-Specific Variable Definitions and Descriptive Statistics*

Variable	Description	Mean	SD
TimeSinceSwitch	Number of years since the last manager switch	3.164	2.120
ManagerModelExperience	Number of vehicles produced of the same models as those currently in production, in plants that the plant manager led in the past three years (in 10,000s)	25.21	28.82
Female	Indicator for female manager	0.087	0.284
Retired	Indicator for whether a manager retired in our sample period	0.213	0.412
UndergraduateDegree	Indicators for Undergraduate Degrees		
Business		0.237	0.428
Industrial Engineering		0.125	0.333
Other		0.313	0.466
None		0.325	0.471
GraduateDegree	Indicators for Graduate Degrees		
Business		0.225	0.420
Industrial Engineering		0.075	0.265
Other		0.025	0.157
None		0.675	0.471
JapaneseExperience	Indicator for prior Japanese experience	0.112	0.318

Notes: Our manager data is from a variety of online sources including Linkedin, LexisNexis, and other sources like local newspapers that cover changes to a plant's management, supplemented with discussions with auto industry personnel and industry experts. Descriptive statistics are computed using the *connected* sample of a total of 80 managers across 40 plants.

Manager Experience – Just as a plant's experience with manufacturing the models currently in production may enhance productivity, a plant manager's experience in managing plants that have manufactured the models that are currently being produced in his/her plant[14] should similarly enhance productivity. By having managed the production of the same models in the past, the plant manager may have learned about particular model-specific problems to look out

[14]This experience could include both experience making continuing models at the focal plant and experience drawn from other plants in making new model(s).

for, as well as solutions to such problems, which should increase bandwidth to absorb a new model introduction.

We define $ManagerModelExperience$ as the total number of vehicles produced of the same models as those currently in production in his/her plant, in plants that the manager led in the past three years.[15] Note that $ManagerModelExperience$ can only be separately identified from $PlantModelExperience$ if there are cases in which the manager had some experience in a different plant, in the past three years.

Similar to the argument for why disruption due to a new model launch should be alleviated by a plant's experience with manufacturing the other models currently made at the plant, the manager's experience in overseeing the other models made at a plant should help reduce disruption due to a new model's launch. To capture this effect, we introduce an interaction of $ManagerModelExperience$ and $NewModel$. The coefficient of this interaction term can only be identified separately from that of the interaction of $PlantModelExperience$ and $NewModel$ if some managers have been transferred in from a different plant in the three years preceding a new model launch.

Time Since Last Manager Switch – We define $TimeSinceSwitch$ as the number of years since the last manager switch at a plant. This variable is identified separately from manager fixed effects and manager experience, and captures other systematic changes that might be occur at a plant when a new manager comes in.

Manager Fixed Effects – For each manager in our sample, we define a manager-specific fixed effect (μ_m) that captures the impact on productivity of the manager's innate ability, education obtained prior to our sample period, ethnicity, gender and a host of other time-invariant attributes, as well as the average effect of all time-varying attributes, including preferences and risk aversion. As part of his personal management style, a new plant manager may choose to make changes within a plant's management, e.g., hiring new reporting managers or altering their span of control. The impact of such changes would also be captured by individual manager fixed effects.

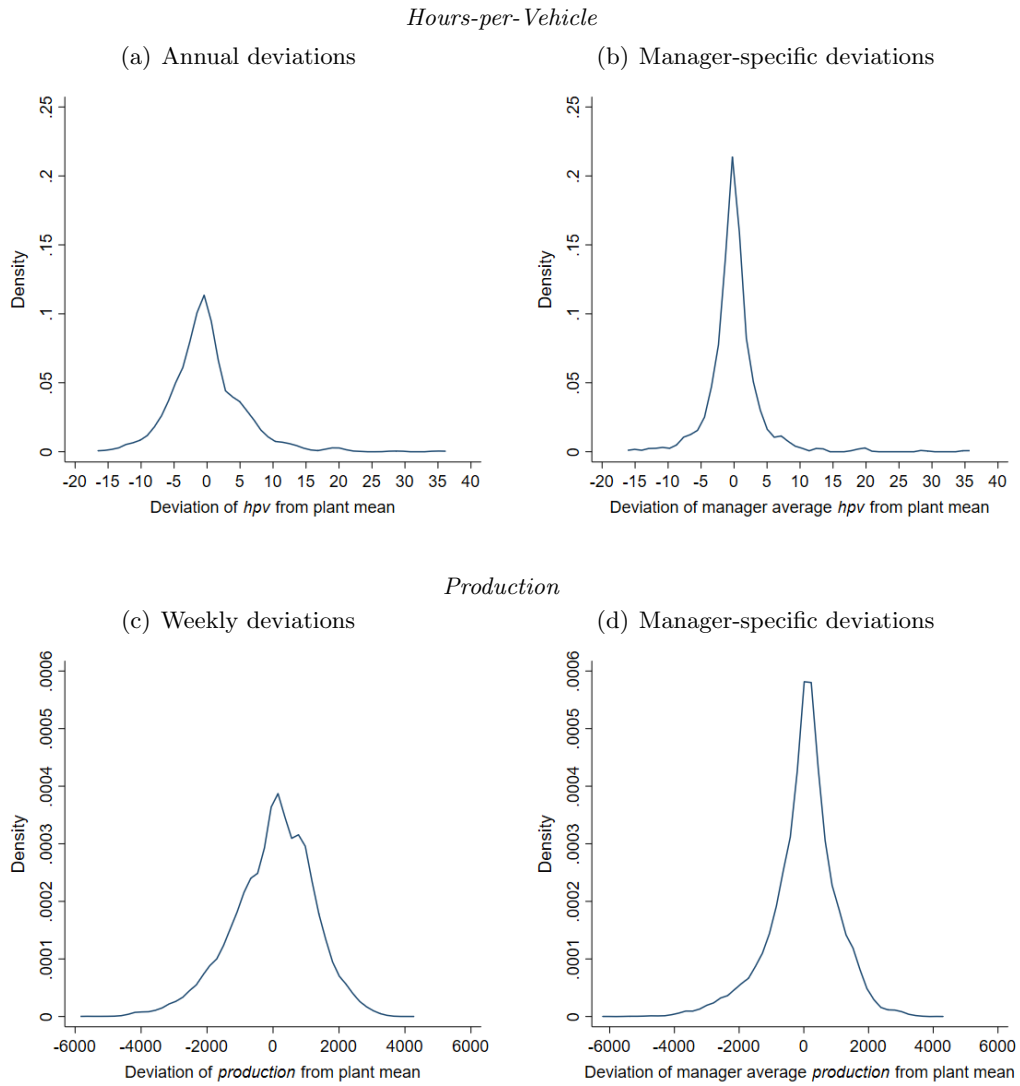
To avoid confounding due to plant-specific factors, we focus on estimating the effect of individual plant managers on within-plant variation in productivity (enabled in our regression analyses by using plant fixed effects). Figure 3 shows the extent of within-plant variation in plant outcomes in the form of density functions. Specifically, Figure 3(a) presents the pdf of the deviations of *hpv* from the average *hpv* in the plant at hand, i.e., within-plant deviations in productivity. The dispersion of this pdf demonstrates the tremendous amount of variation in productivity within plants. Figure 3(b) presents the difference between the average *hpv* during each manager's spell in a plant and the plant's average *hpv*. Although the distribution is substantially less variable, there is still a tremendous amount of variation in the productivity of different managers within a plant.

We see fairly similar results if we instead examine weekly production, as seen in Figures 3(c) and 3(d). Our regression analysis will seek to identify the portion of this variation that is due

[15] As with plant experience, we are able to calculate manager experience in 1993, as our production data from Wards Automotive goes back to 1985.

to managerial influence as opposed to other within-plant sources of variation in productivity.

Figure 3. Within-Plant Variation in *Hours-Per-Vehicle* and *Production*



Notes: Figure 3 displays the within-plant variation in outcome measures. The unit of observation for the distributions shown in the left panel is plant-year, while the unit of observation in the right panel is a manager-plant spell. Figure 3(a) presents the pdf of the deviations of *hpv* from the average *hpv* in the plant at hand. Figure 3(b) presents the difference between the average *hpv* during each manager's spell in a plant and the plant's average *hpv*. Figure 3(c) presents the pdf of the deviations of weekly *production* from the average *production* in the plant at hand. Figure 3(d) presents the difference between the average *production* during each manager's spell in a plant and the plant's average *production*. The sample in figures 3(a) and 3(b) covers the period 1993-2007. The sample in figures 3(c) and 3(d) covers the period 1991-2005.

Managerial Switches – A critical feature of our econometric approach relies on tracking managerial switches across plants. Table 3 reports that of the 80 plant managers observed in the *connected* sample, 32 (40%) led more than one plant. These 32 "switchers" produced 37 switches, because some of them led more than two plants. Around half of the switches involve managers switching to a bigger or a more technologically advanced plant. Managerial switches to a different company are rare.

Table 3. *Manager Switching Information*

	Obs.	Percentage
Managers	80	100.0%
Plant manager position leavers[a]	64	80.0%
Managers that served in more than 1 plant	32	40.0%
Total managerial switches	37	100.0%
Switches to a bigger plant	20	54.1%
Switches to a more technologically advanced plant	19	51.4%
Switches to a different company	3	8.1%

Notes: Our sample includes the subset of plants for which at least one specific manager can be observed in at least one other plant (the *connected* sample). This includes 80 plant managers, each with at least three years in our sample, who served 40 plants between 1993-2007. [a]Plant manager position leavers is an indicator for whether a plant manager was no longer in our sample in 2007, the last year in our study period.

3 Panel Data Analysis

In our panel data analysis, we use the *connected* sample described above to identify the impact of managerial influence on productivity. To this end, we first employ a way to separately identify the role of managers from that of plant-specific factors. Next, we examine channels through which managers impact productivity, specifically, their plant and model-related experience.

3.1 Fixed-Effects Framework and Identification of Managerial Influence

There are multiple difficulties that must be overcome to identify the impact of plant-level leadership on productivity. These identification problems arise because leadership at automotive plants is often invariant for long periods of time, and when managerial changes occur, these may coincide temporally with other changes made by the manufacturer, at either the firm (e.g., C-suite executive change) or plant (e.g., production of a new model) level.

To formalize some of these issues, consider a simple approach to identifying the role of managerial influence on productivity that estimates the following regression:

$$y_{pt} = X_{pt}^{'}\beta + \mu_m + \delta_t + \epsilon_{pt}, \tag{1}$$

where y_{pt} is a measure of productivity (i.e., log *hpv* in our analysis) in plant p in year t, X_{pt} represents a vector of time-varying plant-specific characteristics, μ_m are manager fixed effects, δ_t represents year fixed effects, and ϵ_{pt} a residual error term. Such an approach simply adds manager fixed effects to the regression framework of previous studies of automotive productivity. Despite the appeal of such an approach, it is not adequate for identifying the unique role of managerial influence on productivity.

Specifically, consider two plants, one with consistently excellent productivity (plant A) and another that is less productive (plant B). Further, (realistically) assume that this productivity gap is not completely explained by X_{pt}, such that there are unobservable determinants that

influence productivity that are specific to the plants. In such a case, the estimates of managerial effects would be biased because the greater productivity at plant A would mistakenly be attributed to the managers at that plant rather than to the unobserved factors specific to each plant. That is, managers at plant A (be it one or many managers) would receive false credit for the productivity gap between the two plants. An obvious, yet potentially inadequate, way to resolve this issue would be to simply augment Equation (1) as:

$$y_{pt} = X_{pt}^{'}\beta + \lambda_p + \mu_m + \delta_t + \epsilon_{pt}, \tag{2}$$

where λ_p denotes plant fixed effects. The reason that doing this does not adequately resolve the identification problem, separating plant- and manager-specific influence on productivity, is now more subtle.

In this setting, all time-invariant plant and manager factors are clearly controlled for, however, they are not technically separately identified for all data-generating processes. Thus, this approach of including λ_p is adequate to control for time-invariant omitted (unobserved) factors that may bias estimates of β but it is inadequate for identifying the influence of managers (μ_m). Or, if the manager fixed effects are themselves of interest, as they are in our analysis, this fixed-effects approach may still incorrectly attribute variation in productivity to managerial influence. Consider again the example above. Suppose that no managers at plant A or B switch plants during our sample period, that plants A and B have the same underlying productivity (i.e., $\lambda_A = \lambda_B$), and that all managers at plant A improve productivity (i.e., lower *hpv*) and all managers at plant B decrease productivity (i.e., raise *hpv*). This data-generating process yields estimates of the plant fixed effects such that $\hat{\lambda}_A < \hat{\lambda}_B$, which is incorrect. The plant fixed effects pick up average manager quality in the two plants, and this results in misattribution of the gap in manager quality between the two plants to plant-specific factors other than the managers.

Fortunately, this issue is a well-studied problem in the economics literature across many different applications, often in the context of wage differentials to separately identify firm- and employee-specific factors that explain variation in wages across industries, firms, and employees. Like our problem, which seeks to separate plant and manager influence on productivity, Abowd et al. (1999) show in the context of wages that separate identification of firm and employee effects is possible only when certain restrictions on the data-generating process are satisfied. In the application of Abowd et al. (1999), the *mobility* of employees across firms is crucial for identification. Consider the importance of mobility in our example by instead letting a single manager serve at both plants A and B during our sample. In this case, the *switcher* provides a common relative reference point between the plants and managers to separately identify the contribution of each in determining productivity.

Abowd et al. (1999) provide general results as to the restrictions on the data-generating process that provide identification in settings likes ours.[16] For our purposes, the manager fixed effects are separately identified for all managers that serve in a plant for which at least one manager in that plant was employed in at least one other plant. Thus, if we restrict our attention to the *connected* subset of our sample, i.e., those plants that had at least one manager

[16] Applications that apply variations of the Abowd et al. (1999) approach to study leadership include Bertrand and Schoar (2003) and Graham et al. (2012).

that served in two or more plants, then manager fixed effects are identified. Thus, the degree of *connectedness* of the sample relies on the mobility of managers.

In Table 4, we provide the joint distribution of the number of years a manager is in our sample and the number of plants in which he or she served. Around 40% of the managers in our sample served in more than one plant creating a high degree of *group connectedness* among the managers and providing a strong source of identification. In addition to the technical difficulties in identification of managerial influence on productivity, there are also additional issues to consider. For example, as discussed in Section 2, there are a variety of factors that vary temporally within a plant, such as new model launches, model variety and vehicle segment, which may be correlated with both managerial switches and productivity. Thus, it is crucial to control for these factors or else variation in productivity may be falsely attributed to managerial influence. To overcome this concern we collect the most common variables from previous studies of auto manufacturing and include them in X_{pt}. See Table 1 for additional details on plant-specific controls.

Further, as Figure 1(b) shows, there are company-specific trends that may introduce correlation across plants owned by the same company. To control for these trends, we replace δ_t with company-year indicators θ_{ct} that remove any common fluctuations within each company over time, that affects all plants that belong to the same company. Note that these fixed effects subsume year fixed effects which control for general macroeconomic trends such as labor market conditions or consumers' propensity to buy.

Table 4. Joint Distribution of Years as a Manager and Number of Plants

Number of Years as Manager	Number of Plants		
	1	2	3
3	14	3	0
4	16	6	0
5	10	6	0
6	4	7	2
7	1	2	0
8	0	2	0
9	1	1	1
10	1	0	0
11	1	0	0
12	0	1	0
14	0	0	1
Total	60.0%	35.0%	5.0%

Notes: This table presents data for 80 plant managers, each with at least three years in our sample. The managers represented in the last two columns contribute to managerial switches.

Equation (2) assumes that managerial influence is constant over time, as μ_m is not indexed by t. However, the effects of tenure and learning are well documented in both the economics and the operations management literature. To relax this assumption, we further augment our

regression specification as

$$y_{pt} = X_{pt}^{'}\beta + Z_{mt}^{'}\gamma + \lambda_p + \mu_m + \theta_{ct} + \epsilon_{pt}, \tag{3}$$

where Z_{mt} includes our measures of managerial experience with manufacturing models currently produced in the plant and time since the last managerial switch. We also interact elements of X_{pt} and Z_{mt} to explore whether managerial experience alters the impact of certain plant-specific factors, like new model launch.

Equation (3) can be estimated using ordinary least squares (OLS), and the collective influence of plant managers can be tested using a Wald statistic calculated based on the null hypothesis that the manager dummies are jointly insignificant, $\mu_m = 0, \forall m$. While the Wald statistic is of interest for statistical significance, the change in the proportion of variation explained is perhaps a better measure of economic importance. So, as in Bertrand and Schoar (2003), the change in the adjusted R-squared measure of fit when manager fixed effects are added will be of interest as well. When estimating (3), we account for serial correlation of errors by clustering the standard errors at the plant level.

3.2 Main Results

To demonstrate the variance in productivity that is attributable to different factors, we present our results in three steps. Specifically, we first estimate different versions of Equation (3) in which we include various fixed effects but none of the time-varying characteristics of plants or managers. Next, we include time-varying characteristics of plants and then of managers to demonstrate how the results change when managerial influence is cleanly identified.

The first two columns of Table 5 provide a decomposition of productivity via regressions of log *hpv* on various fixed effects. The check marks in each row indicate the included set of fixed effects. Column 1a shows that about 73% of the variation in productivity can be explained by plant-specific indicators and company-year fixed effects, which is consistent with the time trend visible in Figure 1 and the substantial between-plant variation in *hpv* in Figure 2. If manager fixed effects are added (column 1b), the adjusted R-squared increases to 0.794, an increase of 6.4 percentage points. Note that here, as well as in the other two specifications with the manager fixed effects (column 2b and 3b), we find the set of individual manager indicators to be jointly significant, as indicated by the Wald statistics p-value.

Note that without additional controls, the large jumps in our measure of fit are likely due to misattribution of other sources of variation in productivity that have little to do with managerial switches. In other words, the results of the fixed-effects specification do not control for a variety of factors that fluctuate temporally within a plant. These omitted factors may bias our estimates of managerial influence if correlated with changes in plant management. In columns 2a and 2b of Table 5 we introduce plant-specific characteristics. Specifically, we include plant-specific controls for new model launches, plant experience with the models currently being produced, an interaction of these two variables and various other factors commonly used in the literature: model variety, flexibility, outsourcing, technology level, vehicle-type dummies and weather. Again, we find a sizeable jump in fit with inclusion of manager fixed effects. In the last

two columns, we explore whether this large jump in our measure of fit remains after including time-varying manager-specific characteristics. Specifically, we introduce managerial experience with the models currently being produced in a plant, the interaction of manager's experience with the indicator for whether a new model was introduced, and time since the last manager switch.

The last two columns show that, after controlling for plant fixed effects and plant and manager time-varying characteristics, the manager fixed effects still explain a little over 7% of variation in productivity (adjusted R^2 increases from 0.791 to 0.849). This percentage is higher than the magnitude of the variation in firm-level outcomes in prior research (e.g., Bertrand and Schoar 2003). This is not surprising as in those studies the focus was on how top executives influence firm outcomes, whereas we focus on how frontline managers impact a plant outcome, productivity. Naturally, we expect the actions of plant managers to be closely tied to the pulse of operations and so to have a more visible and direct influence on outcomes at the plant-level, than would a C-suite executive on firm outcomes.

Table 5. Managerial Influence on Productivity

	1a	1b	2a	2b	3a	3b
NewModel			0.158***	0.185***	0.177***	0.200***
			(0.037)	(0.041)	(0.036)	(0.043)
PlantModelExperience			-0.000	-0.000	-0.000	-0.000
			(0.000)	(0.001)	(0.000)	(0.001)
NewModel×*PlantModelExperience*			-0.001**	-0.001*	-0.000	-0.000
			(0.000)	(0.000)	(0.000)	(0.000)
TechnologyLevel			-2.648***	-1.270*	-2.575***	-1.231*
			(0.829)	(0.747)	(0.820)	(0.714)
ManagerModelExperience					0.000	0.000
					(0.000)	(0.001)
NewModel×*ManagerModelExperience*					-0.002***	-0.002**
					(0.001)	(0.001)
TimeSinceSwitch					-0.000	-0.016*
					(0.005)	(0.008)
R-squared	0.796	0.877	0.851	0.921	0.857	0.924
Adjusted R-squared	0.730	0.794	0.784	0.844	0.791	0.849
Wald stat p-value ($\mu_m = 0, \forall m$)	-	0.000	-	0.000	-	0.000
Observations	440	440	374	374	374	374
Plant FEs	✓	✓	✓	✓	✓	✓
Company-Year FEs	✓	✓	✓	✓	✓	✓
Plant-Specific Controls			✓	✓	✓	✓
Manager-Specific Controls					✓	✓
Manager FEs		✓		✓		✓

Notes: This table presents fixed-effects regression results of equation (3) using the *connected* sample. All included managers have been observed for at least 3 years. Other plant-specific controls such as variety, extent of outsourcing, flexibility, vehicle-segment dummies and weather controls are included but not reported. Standard errors, shown in parentheses, are clustered at the plant level. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

To demonstrate the importance of managerial influence, we follow Graham et al. (2012)

and calculate the interquartile range of the estimated manager fixed effects. Our estimates imply that replacing the 75th percentile plant manager with the 25th percentile plant manager decreases average hours-per-vehicle by 30%.[17]

To formally demonstrate the bias resulting from exclusion of manager fixed effects, we conduct a Hausman test comparing the estimates from column 3a and 3b in Table 5. Specifically, we test whether the non-managerial coefficient estimates are biased when manager fixed effects are excluded from the regression. We find a p-value of 0.004 on the chi-squared test statistic, which suggests that substantial biases are introduced if indicators for the identity of managers are not included in the regression. This demonstrates the importance of controlling for the effects of individual managers even when this is not the focus of the analysis.

We consistently find that new model launches reduce productivity (i.e., increase *hpv*, as found by Gopal et al. (2013) and Levitt et al. (2013). Specifically, we find that launching a new model increases a plant's hours-per-vehicle by 22% and that both plant and manager experience help reduce this productivity disruption. To get a sense of the marginal effect of manager experience during launch, consider Ford's Avon Lake plant in Ohio, which made the Nissan Quest van until 2002. In response to oil shocks in the early 2000s, this plant shut down, revamped, and switched to making the Ford Escape SUV in 2003, which is a hybrid with higher miles per gallon. With the introduction of the new model, hours per vehicle (HPV) at Avon Lake increased by 58%, from 32.2 to 50.8 hours per vehicle. In 2003, the plant manager at Avon Lake had no experience making SUVs. From the distribution of manager model experience for managers heading plants producing the Ford Escape SUV, the manager with the maximum experience making such vehicles had 1.775 million units of experience.[18] Had this manager been assigned to the Chicago plant for the Ford Escape introduction, the change in HPV would have been 18.2 hours (18.6- 0.002*177.5) instead of 18.6 hours, a saving of 0.4 hours (24 minutes) in HPV. Avon Lake produced a total 62,530 vehicles over 2003 and 2004. At a labor cost of about $70/hour, this HPV reduction implies an saving of 62530*0.4*70= $3.5 million at the plant over these two years.

We also see some evidence that an increase in the time since the last managerial switch event has a significant and economically meaningful impact on productivity. For each extra year a manager spends at a given plant, there is an increase in productivity of about 1.6%.[19,20]

To further assess the validity of our main results, we explore whether managers' effects persist over time and across different plants, as in Bertrand and Schoar (2003). We construct

[17] We use the largest connected set in our *connected* sample to compute the interquartile range, which has 275 observations. For this largest set the jump in the adjusted R-squared is also about 7 percent.

[18] In our data, in new model launch plant-years, no manager had prior experience with the new model. Thus the coefficient of *ManagerModelExperience* is identified based on variation in managers' experience with making continuing models. Our underlying assumption is that a unit of prior experience with a continuing or a new model contributes in the same way to productivity in a launch plant-year.

[19] Note that, when describing the results, we refer to hpv and not to the log of hpv (which is our dependent variable) because we exponentiate the coefficients to get effect size on productivity level.

[20] In Table A.4 of the Online Appendix we include a set of regression results based on different samples and specifications analogous to the last two columns of Table 5. In particular, we first repeat our analysis based on the *full* sample. We then do small variations based on the *connected* sample: (i) we provide estimation results when using the outcome variable *hours-per-vehicle* in level (original) form instead of log-linearised, (ii) we exclude the *TechnologyLevel* variable (iii) we replace the *TechnologyLevel* variable for the *Scale* variable, (iv) we add a dummy variable capturing the time previous to a managerial switch, and (v) we exclude weather variables.

manager-plant residuals by regressing *hpv* on plant, company-year fixed effects and all time-varying controls and then collapsing these residuals by manager-plant spell. Then, we regress the manager's average residual in the second plant he/she is observed at on the average residual at his/her first plant. We see a positive and marginally significant relationship between the manager's residual across plants, indicating some sort of persistence of unobservable managerial traits (such as leadership style) on plant productivity. In other words, the positive and significant manager fixed effects that we estimate for plants experiencing a period of increase productivity do persist over time in the future plants these managers lead. We then conducted a falsification test by creating a fake residual for the second plant that a manager is observed at by using the average residual of the manager(s) who worked in that plant during the two-year period before the "switchers" manager's arrival. In this case we find that the coefficient is not statistically different from zero and that the R^2 is almost half of the size of the original. See Table A.5 of the Online Appendix.

Last, we follow the minimum-distance procedure proposed by Chamberlain (1982) and applied by Nevo (2001) to tease apart the effects of all the time-invariant manager characteristics (education, gender and experience in a Japanese plant) that are subsumed into the manager fixed effects. The results of this exercise show that none of these variables is statistically significant. This analysis is reported in Table A.6 of the Online Appendix.

4 High-Frequency Data Analysis

Our high-frequency data offers an opportunity to analyze each plant in greater detail as an individual time series. This in turn can clarify identification of managerial influence and highlight some channels through which plant managers impact productivity. Specifically, we can exploit the particular circumstances of a managerial switch (e.g., a retirement versus a change for an unknown reason) to identify the causal impact of managerial switches. This increases confidence that the change was for an exogenous reason (i.e., age) and is therefore unlikely to be correlated with other temporal changes in the plant. Further, the high-frequency data offers an opportunity to look at higher-order moments of outcome variables, in particular variance in production, that a manager may be able to influence. As discussed in Section 1, lower production variability may be indicative of fewer production disruptions, and may thus enable higher productivity.

We perform two different types of analyses on each plant's weekly time series to measure managerial influence on the mean of production, using data from 1991 to 2005 on the 56 plants that had least two managers. First, following Ploberger and Krämer (1992), we perform a CUSUM test for parameter instability to identify whether managerial switches coincide with changes in production. Second, we perform a model-selection analysis using a LASSO regression to determine whether managerial switches can predict ("out of sample") variation in production. To ensure that our results reflect managerial influence, and not other possible factors that coincided temporally with the managerial switch, we compare the results for plants with and without a retiring plant manager.

To study the role of managerial influence on variability in output, we use the same

high-frequency production data to perform heteroskedasticity tests for manager-specific effects on variability. These tests measure whether the residuals from our time-series regressions used for the CUSUM tests exhibit a different variance by manager. Again, this analysis is performed for each plant to analyze whether the results for plants with and without retiring plant managers are similar.

4.1 Mean Production: Parameter Instability and LASSO Analysis

Tests for parameter instability seek to identify the presence and timing of instability in the values of parameters in a regression model. Identification of such breaks can provide insight into the source of the break if observable factors coincide temporally with the break. There are numerous alternative methods for testing for parameter instability, but some are preferable for our objective and application. Specifically, in our application there are many time-varying factors, observed and unobserved, that may impact production beyond just managerial switches. In addition, the length of our panel may make multiple breaks more likely. For these reasons, we apply the CUSUM test of Ploberger and Krämer (1992) that permits flexible testing for multiple breaks while controlling for an arbitrary number of other observable covariates.

Consider a simple time series model for production at time t, y_t, for a specific plant:

$$y_t = \beta X_t + \sum_{j=1}^{12} \gamma_j \mathbb{1}_j + \epsilon_t, \tag{4}$$

where X_t are time-varying covariates (such as a time trend), $\mathbb{1}_j$ are monthly dummies to capture seasonality that may impact production (e.g., weather-related delays for arrival of components), and ϵ_t is the error term.

To identify parameter instability or missing elements of the model, the CUSUM test looks for abnormal serial correlation in the residuals based on a test statistic that is the cumulative sum of the residuals. Under the null, each residual has zero expectation, and thus the expectation of any cumulative sum of the residuals at any point in the time series is also zero. On the contrary, if the time series is missing a time-varying factor, this can cause serial correlation in the residuals. This logic forms the basis for the CUSUM test statistic.

Consider a plant in which we observe two managers over our sample period, and assume that the first manager increases the plant's productivity while the second has a negative effect on productivity. Because the average of the residuals must be zero, we would expect the cumulative sum of residuals to increase with t up until the manager switch, and to then decrease. The CUSUM test formalizes this logic. Under the null that errors are uncorrelated, confidence bands are calculated for the test statistic, for each t, $1 <= t <= T$. Note that in fact T CUSUM subtests are performed, with the periods over which the sum of residuals is taken varying from the first period to the entire horizon T.

Next, we modify the parsimonious model in Equation (4) above by allowing the parameters

to vary with the identity of the plant manager.

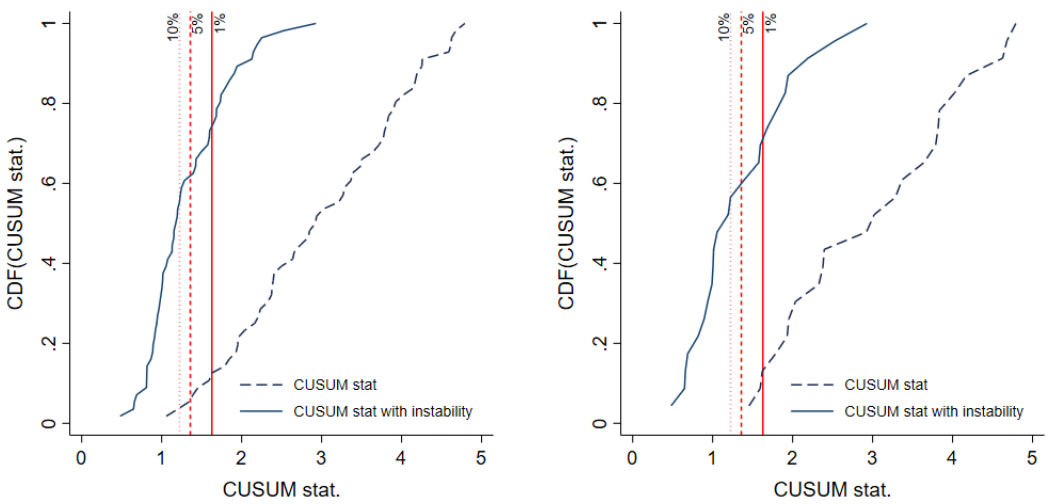
$$y_t = \beta_m X_{tm} + \sum_{j=1}^{12} \sum_{m=1}^{M} \gamma_{jm} \mathbb{1}_{jm} + \mu_m + \epsilon_t, \tag{5}$$

where β_m is a vector of manager-specific coefficients for time-varying covariates, γ_{jm} are manager-month dummies, and, as before, μ_m is a vector of manager fixed effects. Again, we can perform a CUSUM test using the residuals from the OLS estimate of Equation (5). If we reject the null of uncorrelated errors most of the time in the first case, but fail to reject the null most of the time in the second case, this would suggest that the timing of manager switches coincides with the timing of structural breaks in our data. Of course, it is possible that in fact the timing of manager switches coincides with some other changes that might also explain the structural breaks (e.g., new technology). However, because we are using high frequency data and know precisely when a managerial switch occurs, it is less likely that other changes may have occurred at exactly the same time.

We conduct plant-specific CUSUM tests for each plant using weekly production data. Figure 4a shows that managerial switches do coincide with structural breaks in production. When we allow the parameters to vary with the particular plant manager, we fail to reject the null of no structural break in most of the cases, while the opposite is true for estimation results without manager specific parameter instability.

Figure 4. CUSUM Tests of Managerial-Specific Production Instability

(a) All plants (b) Plants with retiring managers



Notes: Figure 4 displays the results of plant-specific CUSUM tests for parameter instability from OLS estimates of Equation (4) and Equation (5). The y-axis tracks the cumulative distribution of the CUSUM test statistic. The vertical lines represent critical values of the test for conventional significance levels, as indicated at the top of each line. The sample in 4(a) comprises 56 plants with at least two managers. The sample in 4(b) is a subsample comprised of 23 of these 56 plants, each of which had a retiring manager. The sample period ranges from 1991 to 2005.

We also repeat the analysis for the subsample of plants with retiring managers, for which managerial switches are plausibly exogenous. The results, shown in Figure 4b, are similar to those of the main sample and provide evidence on the coincident timing between structural

production breaks and managerial turnover.[21]

To reinforce and complement our findings from the parameter-instability tests, we use a LASSO model-selection framework to test whether variation in production can be *predicted* by manager switches. Specifically, we use an out-of-sample criterion for model selection to identify whether the identity of the manager is useful for predicting production.

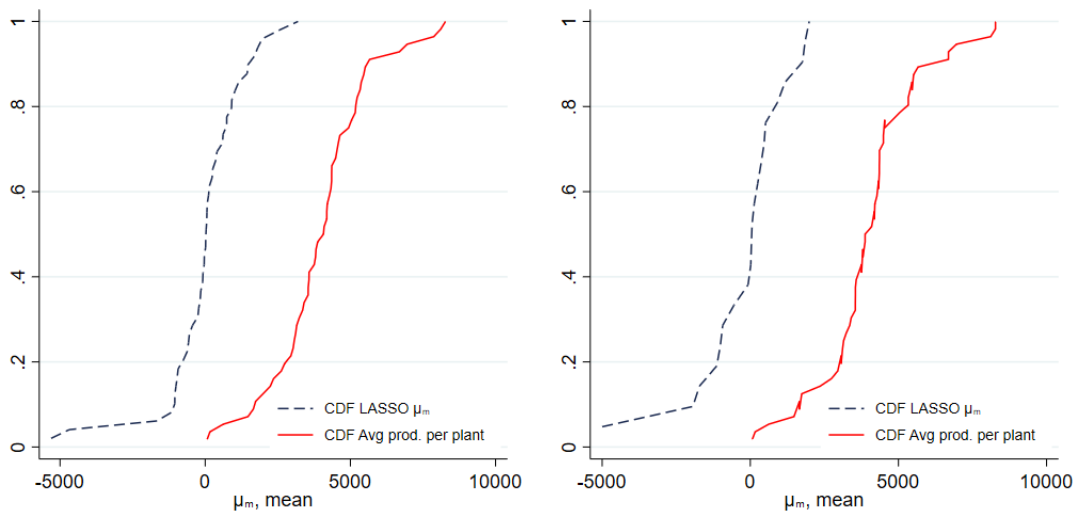
The model-selection feature of the LASSO, which is responsible for identifying useful predictors of output, is achieved through augmenting the ordinary least squares criterion with a shrinkage penalty. Specifically, if we consider the same baseline specification for a plant's output as in Equation (5), then the LASSO parameter estimates satisfy:

$$\min_{[\boldsymbol{\beta},\boldsymbol{\gamma},\boldsymbol{\mu}]} \frac{1}{T}\left[\sum_t y_t - \beta_m X_{tm} - \sum_{j=1}^{12}\sum_{m=1}^{M} \gamma_{jm}\mathbb{1}_{jm} - \mu_m - \epsilon_t\right] \tag{6}$$
$$\text{s.t. } \|[\boldsymbol{\beta},\boldsymbol{\gamma},\boldsymbol{\mu}]\|_1 \leq \lambda,$$

The shrinkage parameter, λ, is chosen through k-fold cross validation that minimizes an out-of-sample mean-squared error criterion from hold-out samples. This results in model estimates that are optimized to predict variation in production and identify those covariates that are successful in doing so. Thus, if managerial switches have a role in predicting variation in production, the model will identify their role and quantify their influence.

Figure 5. LASSO-Selected Plant Manager Effects and Weekly Production

(a) All plants (b) Plants with retiring managers



Notes: Figure 5 displays the results of a LASSO estimator. The dashed (blue) line shows the CDF of manager fixed effects coming from plant-specific LASSO regressions. We use k-fold cross-validation to select the shrinkage parameter. The solid (red) line shows the CDF of average weekly production per plant. The sample in 5(a) comprises 56 plants with at least two managers. The sample in 5(b) is a subsample comprised of 23 of these 56 plants, each of which had a retiring manager. The sample period ranges from 1991 to 2005.

Figure 5 displays the results of the plant-specific LASSO regressions using high-frequency

[21] This should reduce concerns about other factors that could have been temporally correlated with managerial switches.

production data for each plant time series. We plot the cumulative distribution function of the manager fixed effects selected by LASSO together with the cumulative distribution function of each plant's average production. We find that using all the plants in our study sample, or the subset of plants with retiring plant managers, the variance of the estimated μ_m closely matches the between-plant dispersion in production.

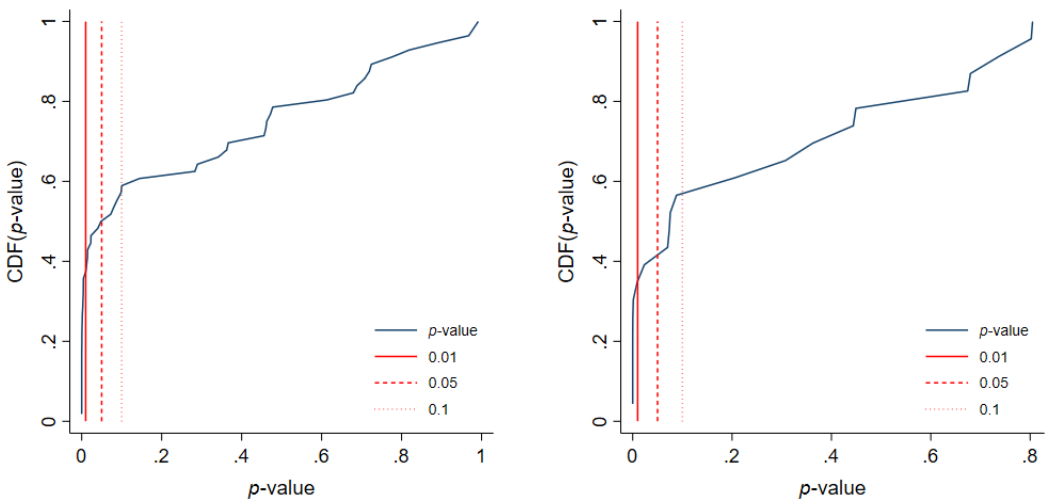
4.2 Variance of Production: Heteroskedasticity Analysis

It is also conceivable that individual plant managers may impact variance in production levels. A more competent manager may be able to smooth production, avoiding costly periods of disruption in production. To examine whether this is the case, we use the estimated residuals from Equation (5) to test for grouped heteroskedasticity. If managers do impact the variance of production, then error variance should differ by manager. The test assumes a null of equal variance of errors across all managers in a plant, so rejecting the null provides evidence that changes in the variance of production at a plant coincides with managerial switches.

Figure 6 plots the distribution of p-values corresponding to the plant-specific heteroskedasticity tests. The high over-representation of small p-values suggest that managers do have a differential effect on variance in production. More precisely, in about 50% (60%) of the estimates we reject the equal variance hypothesis at a 5% (10%) significance level.

Figure 6. Tests for Manager-Specific Heteroskedasticity

(a) All plants (b) Plants with retiring managers



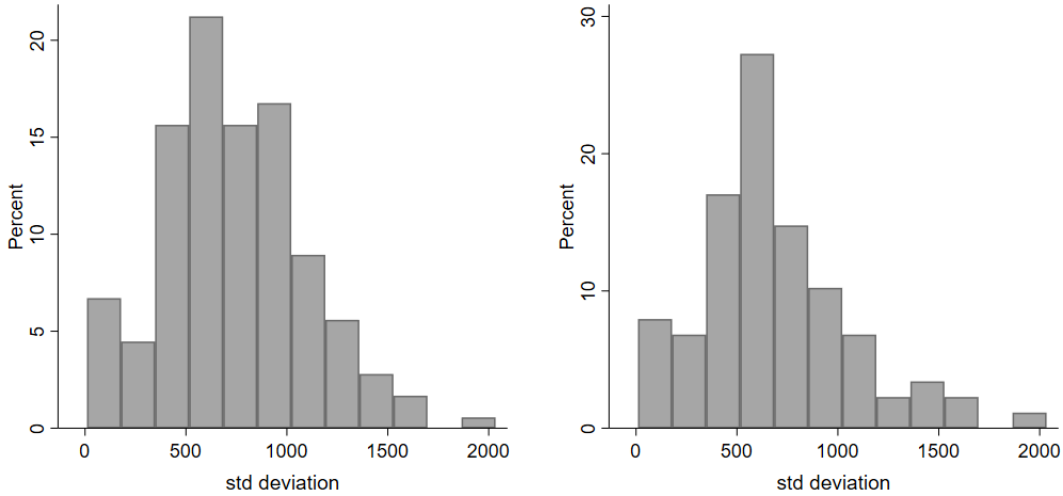
Notes: Figure 6 presents the results of the grouped heteroskedasticity test performed for each plant. The y-axis tracks the cumulative distribution of the Chi-squared statistic p-value. The vertical lines represent conventional cutoffs for statistical significance. The sample in 6(a) comprises 56 plants with at least two managers. The sample in 6(b) is a subsample comprised of 23 of these 56 plants, each of which had a retiring manager. The sample period ranges from 1991 to 2005.

Figure 7 presents the distribution of the manager-specific standard deviation of residuals in productivity. We find that the standard deviation of the residual of the manager at the 75th percentile of this distribution is almost twice that of the manager at the 25th percentile. The distributions when using all plants, or plants with retiring managers, are very similar. Using the two-sample Kolmogorov-Smirnov test, we can not reject the null of equal distribution (p-value

0.177).

Figure 7. Distribution of Standard Deviation of Production Residuals

(a) All plants (b) Plants with retiring managers



Notes: Figure 7 presents the distribution of the manager-specific standard deviation of residuals in productivity. The sample in 7(a) comprises 56 plants with at least two managers. The sample in 7(b) is a subsample comprised of 23 of these 56 plants, each of which had a retiring manager. The sample period ranges from 1991 to 2005.

5 Concluding Remarks

Cachon et al. (2020) highlight that it is difficult to establish how leadership may impact operational performance, noting that "It is unlikely that a precise answer can be given yet even imprecise answers could be very impactful." In our work, we have taken a first step towards highlighting the impact of facility-level leadership on a key operational metric, productivity.

We find that individual plant managers are a key determinant of auto assembly plant productivity. When managers have more experience with the models that are in production, new model introductions hurt productivity less. We also see evidence that managers' plant-specific tenure has a positive impact on productivity. Using high-frequency time-series data for each plant, we find that a manager's identity is predictive of changes in both the mean and variance of weekly production. This finding persists when the analysis is restricted to a subsample of plants with retirements, which provide an exogenous reason for managerial switches.

Our results, combined with the order-of-magnitude lower salaries of mid-level managers, suggest that firms should place much more emphasis on attracting talented mid-level managers to head up their plants or service shop floors. The econometric approach we use, a combination of panel-data techniques, structural-break tests, and machine-learning methodologies, can also be used to study how facility managers influence quality, safety, environmental footprint or other operational metrics. Such work could influence manager training, or guide data-driven methods to evaluate managers. The main limitation to date is data availability, as information on non-executive managers is rarely publicly available.

Aside from deserving examination in its own right, managerial influence, if not accounted for, can cause bias in many contexts of interest to researchers in operations. As real-time tracking of individual managers becomes more common – as is the case in retail and banking –

including this heretofore omitted variable can potentially become standard practice.

Future research should further examine the channels through which facility managers exert influence. While managerial experience in terms of total units overseen of the vehicles currently in production is important, with the availability of more data, more nuanced analyses could examine other facets of experience, such as the effect of varying levels of experience with multiple continuing models. Also, aside from how managers use operational levers, how they incentivize, inspire, and connect with their workforce may matter, to varying degrees. Our interviews with plant managers suggest that understanding workers' psychology is important. One plant manager noted that a disgruntled worker may exhibit 'malicious obedience' – by untraceably seeding future defects. Several noted that communication is critical. An auto plant manager often manages over 1,000 employees, and establishing direct lines of communication was viewed as key to mitigating the effects of unwelcome news. Given substantial unexplained variation in productivity and robust evidence that productivity is crucial to firm survival (Syverson 2011), such work is needed. New theory should incorporate managerial influence into standard operations management models for managing production or service facilities.

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A Online Appendix

A.1 Summary Statistics and Variation in Productivity – *Full* Sample

Table A.1. Plant-Specific Variable Definitions and Descriptive Statistics

Variable	Description	Source[a]	Mean	SD
Hours-per-Vehicle	Total working hours divided by total number of vehicles produced	HR	28.41	9.989
Production	Total number of vehicles produced	WA	4139	2110
NewModel	Indicator for at least one new model introduced	WA	0.160	0.366
PlantModelExperience	Total number of vehicles produced in the past three years of the same models as those currently in production	WA	100.8	98.69
Flexibility	Average number of platforms produced per production line	HR	1.063	0.335
Variety	Sum of the number of body styles and chassis configurations produced	HR	7.013	9.459
Outsourcing	Average of all task-specific outsourcing dummies	HR	0.204	0.139
Scale	Production capacity (in 10,000s)	HR	21.52	6.986
Size	Plant's square footage (in 10,000s)	HR	274.2	85.29
TechnologyLevel	Production capacity divided by plant's square footage	HR	0.085	0.034
SegmentTruck	Indicator for large truck manufactured	HR	0.022	0.148
SegmentLarge	Indicator for large/luxury car manufactured	HR	0.136	0.343
SegmentMidsize	Indicator for mid size car manufactured	HR	0.232	0.422
SegmentPickup	Indicator for pickup manufactured	HR	0.299	0.458
SegmentSmall	Indicator for small car manufactured	HR	0.118	0.323
SegmentSUV	Indicator for suv/crossover manufactured	HR	0.291	0.455
SegmentVan	Indicator for van manufactured	HR	0.121	0.326
Wind	Fraction of days with wind speed above 30 miles per hour	NOAA	0.041	0.027
Heat	Fraction of days with temperature below 15 degrees Fahrenheit	NOAA	0.067	0.065
Cold	Fraction of days with temperature above 90 degrees Fahrenheit	NOAA	0.048	0.043
Precipitation	Fraction of days with non-zero precipitation	NOAA	0.329	0.064

Notes: With the exception of the *production* variable that is observed at a weekly level, the unit of observation for all other variables is plant-year. Descriptive statistics are computed using the *full* sample across 66 plants. Each of the data sources above is publicly available.

[a]HR stands for Harbour Reports; WA stands for Ward's Automotive; and NOAA stands for National Oceanic and Atmospheric Administration.

Table A.2. Manager-Specific Variable Definitions and Descriptive Statistics

Variable	Description	Mean	SD
TimeSinceSwitch	Number of years since the last manager switch	3.431	2.358
ManagerModelExperience	Number of vehicles produced of the same models as those currently in production, in plants that the plant manager led in the past three years (in 10,000s)	24.50	27.39
Female	Indicator for female manager	0.078	0.270
Retired	Indicator for whether a manager retired in our sample period	0.200	0.402
UndergraduateDegree	Indicators for Undergraduate Degrees		
Business		0.191	0.395
Industrial Engineering		0.139	0.348
Other		0.313	0.466
None		0.357	0.481
GraduateDegree	Indicators for Graduate Degrees		
Business		0.217	0.414
Industrial Engineering		0.078	0.270
Other		0.061	0.240
None		0.643	0.481
JapaneseExperience	Indicator for prior Japanese experience	0.191	0.395

Notes: Our manager data is from a variety of online sources including Linkedin, LexisNexis, and other sources like local newspapers that cover changes to a plant's management, supplemented with discussions with auto industry personnel and industry experts. Descriptive statistics are computed using the *full* sample for a total of 115 managers across 66 plants.

Table A.3. Correlation Matrix

	New Model	Plant Model Experience	Flexibility	Variety	Outsourcing	Technology Level	Segment Truck	Segment Large	Segment Midsize	Segment Pickup	Segment Small	Segment SUV	Segment Van	Wind	Heat	Cold	Rain	Manager Model Experience	Time Since Switch
New Model	1.000																		
Plant Model Experience	-0.152	1.000																	
Flexibility	-0.006	-0.113	1.000																
Variety	-0.091	-0.004	0.098	1.000															
Outsourcing	-0.004	0.298	0.024	0.049	1.000														
Technology Level	-0.019	0.367	0.034	-0.086	0.127	1.000													
Segment Truck	-0.040	-0.071	-0.022	0.032	-0.044	-0.147	1.000												
Segment Large	0.150	0.054	0.108	-0.114	-0.091	0.166	-0.033	1.000											
Segment Midsize	0.020	0.051	-0.016	-0.308	-0.020	0.404	-0.057	0.026	1.000										
Segment Pickup	-0.105	0.115	0.058	0.547	0.128	-0.155	0.143	-0.230	-0.398	1.000									
Segment Small	0.011	0.067	-0.107	-0.073	0.112	0.224	-0.022	-0.091	-0.158	-0.157	1.000								
Segment SUV	0.126	-0.121	0.169	0.026	0.036	-0.137	-0.064	-0.136	-0.361	-0.093	0.040	1.000							
Segment Van	-0.024	-0.121	-0.125	-0.086	-0.016	-0.122	-0.029	-0.119	-0.207	-0.205	-0.082	-0.193	1.000						
Wind	0.118	-0.180	-0.072	-0.144	0.038	-0.235	0.096	-0.046	0.002	-0.045	-0.053	0.196	-0.139	1.000					
Heat	0.025	-0.102	-0.010	-0.040	-0.031	-0.211	0.023	-0.150	-0.007	-0.002	-0.093	0.198	-0.012	0.312	1.000				
Cold	0.049	0.033	-0.008	0.019	-0.010	0.126	-0.046	0.145	0.058	0.021	0.060	-0.120	-0.136	-0.116	-0.492	1.000			
Rain	-0.002	0.118	-0.089	0.045	0.017	0.275	0.010	0.195	-0.078	-0.014	0.178	-0.085	0.067	-0.278	-0.749	0.325	1.000		
Manager Model Experience	-0.130	0.407	-0.002	0.080	0.121	0.117	0.000	-0.117	-0.058	0.055	0.022	0.133	-0.103	-0.076	0.004	0.019	0.030	1.000	
Time Since Switch	0.011	-0.103	0.036	-0.015	-0.087	-0.054	0.156	-0.107	0.046	-0.065	-0.047	0.077	-0.032	0.066	-0.052	-0.002	0.011	0.548	1.000

Notes: Correlation coefficients for all possible combinations of variables used to estimate our main equation (3). These statistics are computed using the *connected* sample for a total of 80 managers across 40 plants.

Table A.4. Managerial Influence on Productivity

	Full sample		*hpv* in levels		No *TechnologyLevel*		Scale as control		Pre-switch dummy		No weather variables	
	1a	1b	2a	2b	3a	3b	4a	4b	5a	5b	6a	6b
NewModel	0.140***	0.153***	6.426***	6.976***	0.144***	0.154***	5.214***	5.924***	0.175***	0.198***	0.175***	0.195***
	(0.033)	(0.039)	(1.400)	(1.781)	(0.034)	(0.035)	(1.309)	(1.585)	(0.036)	(0.043)	(0.036)	(0.045)
PlantModelExperience	-0.000	-0.001	-0.007	-0.014	-0.000	-0.000	-0.009	-0.008	-0.000	-0.000	-0.000*	-0.000
	(0.000)	(0.000)	(0.007)	(0.016)	(0.000)	(0.001)	(0.006)	(0.017)	(0.000)	(0.001)	(0.000)	(0.001)
NewModel×*PlantModelExperience*	-0.000	-0.000	-0.016*	-0.018	-0.000	-0.000	-0.006	-0.012	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.009)	(0.012)	(0.000)	(0.000)	(0.008)	(0.011)	(0.000)	(0.000)	(0.000)	(0.000)
TechnologyLevel	-1.756**	-0.922*	-84.010**	-29.374					-2.606***	-1.331*	-2.487***	-1.178*
	(0.671)	(0.462)	(31.011)	(20.187)					(0.819)	(0.760)	(0.778)	(0.678)
ManagerModelExperience	0.000	0.001	0.005	0.012	-0.000	-0.000	-0.006	-0.012	0.000	0.000	0.000	0.000
	(0.000)	(0.001)	(0.012)	(0.020)	(0.001)	(0.001)	(0.012)	(0.023)	(0.000)	(0.001)	(0.000)	(0.001)
NewModel×*ManagerModelExperience*	-0.003***	-0.002**	-0.069***	-0.060**	-0.002***	-0.002**	-0.059***	-0.052**	-0.003***	-0.002**	-0.002***	-0.002**
	(0.001)	(0.001)	(0.018)	(0.024)	(0.001)	(0.001)	(0.017)	(0.023)	(0.001)	(0.001)	(0.001)	(0.001)
TimeSinceSwitch	-0.001	-0.012	0.005	-0.488*	0.001	-0.010	0.091	-0.200	-0.003	-0.019*	-0.000	-0.016**
	(0.004)	(0.009)	(0.120)	(0.252)	(0.006)	(0.009)	(0.124)	(0.287)	(0.005)	(0.009)	(0.005)	(0.008)
Scale							-0.392***	-0.163				
							(0.116)	(0.112)				
PreSwitch									0.031*	0.017		
									(0.016)	(0.025)		
R-squared	0.897	0.937	0.822	0.911	0.848	0.912	0.826	0.902	0.859	0.925	0.856	0.923
Adjusted R-squared	0.851	0.883	0.740	0.822	0.785	0.839	0.750	0.814	0.792	0.849	0.792	0.849
Wald stat p-value ($\mu_m = 0, \forall m$)	-	0.000	-	0.000	-	0.000	-	0.000	-	0.000	-	0.000
Observations	540	540	374	374	429	429	401	401	374	374	374	374
Plant FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Company-Year FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Plant-Specific Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Manager FEs		✓		✓		✓		✓		✓		✓

Notes: This table presents estimates of equation (3), as reported in columns 3a and 3b of Table 5, with slightly different specification as indicated in the columns header. With the exception of the first two columns, that reports estimates based on the *full* sample, all other specifications are based on the *connected* sample. All included managers have been observed for at least 3 years. Other plant-specific controls such as variety, extent of outsourcing, flexibility, and vehicle-segment dummies are included but not reported. With the exception of the last two columns, weather controls are also included but not reported. Standard errors, shown in parentheses, are clustered at the plant level. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.5. Persistence of Managerial Influence on Productivity

	Real Sample	Falsification Test
Manager's Residual 1st Plant	0.318*	-0.251
	(0.169)	(0.207)
Adjusted R-squared	0.083	0.021

Notes: Our manager data is from a variety of online sources including Linkedin, LexisNexis, and other sources like local newspapers that cover changes to a plant's management, supplemented with discussions with auto industry personnel and industry experts. For the first column, the dependent variable is the manager's residual on the second plant. For the second column, the dependent variable is the average residual on the manager's second plant 2 years before the manager arrival on that plant. Standard errors are shown in parentheses. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.2 Time-Invariant Characteristics and Managerial Influence

Estimates of Equation (3) provides insight into the importance of individual plant managers and the variation in managerial influence across managers. However, aside from the effects of managerial experience and auto industry tenure, it provides little insight into what makes a successful manager. The estimates of the manager fixed effects ($\hat{\mu}_m$) capture the collective effect of time-invariant observed and unobserved manager characteristics. To uncover the underlying manager characteristics that influence these manager-specific effects, we follow Nevo (2001) and apply the minimum-distance procedure proposed by Chamberlain (1982).

Let the matrix of observed (i.e., gender, education indicators) and unobserved manager-specific characteristics be denoted by W_m and ξ_m, respectively. We assume that the contribution of each of these factors in determining managerial influence on productivity takes a linear index form

$$\mu_m = W_m \alpha + \xi_m. \tag{7}$$

For this "second stage" regression, Chamberlain (1982) shows that estimates of α, the influence of observed manager characteristics (W_m) on managerial influence (μ_m), can be obtained as

$$\hat{\alpha} = (\mathbf{Z}'\mathbf{V}_{\widehat{\mu}_\mathbf{m}}^{-\mathbf{1}}\mathbf{Z})^{-1}\mathbf{Z}'\mathbf{V}_{\widehat{\mu}}^{-\mathbf{1}}\widehat{\mu}. \tag{8}$$

where the Mx1 vector, $\widehat{\mu}$, is the estimate of the manager fixed effects from Equation (3), and the MxM matrix $\mathbf{V}_{\widehat{\mu}}$ is the corresponding variance-covariance matrix of those estimates. Standard errors for $\hat{\alpha}$ are recovered through a bootstrap procedure of the asymptotic distribution of the manager fixed effects.

The results of this procedure are in Table A.6. Interestingly, we find that no observed manager characteristics are statistically significant in explaining variation in managerial influence. Thus, we find that observable characteristics are not particularly useful in explaining the success of managers.

Table A.6. Productivity and Time-Invariant Manager Characteristics

	Connected Sample	*Full* Sample
Female	-0.043	-0.065
	(0.197)	(0.157)
Japanese Experience	-0.047	-0.132
	(0.221)	(0.134)
Retired	0.035	0.053
	(0.156)	(0.120)
UndergraduateDegree		
Business	-0.118	-0.043
	(0.160)	(0.128)
Industrial Engineering	-0.274	-0.243
	(0.188)	(0.158)
Other	-0.036	0.012
	(0.160)	(0.125)
GraduateDegree		
Business	-0.026	0.031
	(0.149)	(0.124)
Industrial Engineering	-0.117	-0.087
	(0.208)	(0.173)
Other	-0.014	-0.051
	(0.375)	(0.230)
Observations	58	75
Adjusted R-squared	0.012	0.039
Controls included in First-Stage		
Plant FEs	✓	✓
Company-Year FEs	✓	✓
Plant-Specific Controls	✓	✓
Manager FEs	✓	✓

Notes: This table shows estimates of equation (7) using the manager fixed effects estimated using equation (3). The first column shows estimates using *connected* sample. The second column shows estimates using the *full* sample. Bootstrap standard errors, based on 200 bootstrap repetitions, are reported in parentheses. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.