Toward an Understanding of Learning by Doing: Evidence from an Automobile Assembly Plant*

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Abstract

We use highly detailed data from an assembly plant of a major auto producer to investigate the learning by doing process. We focus on the acquisition, aggregation, transmission, and embodiment of the knowledge stock built through learning. We find that most of the substantial learning by doing knowledge at the plant was not retained by the plant's workers, even though they were an important conduit for knowledge acquisition. This finding is consistent with the plant's institutionalized systems for productivity measurement and improvement. We further explore how overall learning is undergirded by what happens at the hundreds of individual processes along the production line, revealing aspects of the learning process in a complex production system rarely observed by researchers. These results shed light not only on how productivity gains accrue at the plant level, but also how firms might apply managerial inputs to expand production optimally. They also provide some empirical content suggesting how comparative advantage arises and what leads to specialization.

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I. Introduction

Learning by doing has occupied a central place within economics ever since Arrow (1962) used the concept as a workhorse in his theory of endogenous growth. Arrow conceptualized learning by doing within the actual activity of production, with cumulative gross investment as the catalyst for experience. Nearly two decades later, the role of experience in shaping and driving productivity growth was central in Lucas' (1988) explanations of increasing returns to human capital. Indeed, Lucas (1988, p. 27) argues "on-the-job-training or learning by doing appear to be at least as important as schooling in the formation of human capital." Yang and Borland (1991) furthered this line of thought by theoretically linking the division of labor and learning by doing, highlighting an important source of comparative advantage.

Empirical studies have confirmed the importance of learning by doing in practice. Scholars have frequently observed that improvements in the efficiency with which outputs are produced from existing technologies and inputs are an important source of total factor productivity (TFP) growth. One early example was described in Lundberg (1961), who describes the experience of the Horndal iron works plant in Sweden. Although the plant had no new investment over a period of 15 years, output per worker hour rose about 2 percent annually. Another stark early observation of such progress was in the aircraft industry. As Wright (1936) and Middleton (1945) note, labor inputs per airframe declined considerably as the total number of airframes produced increased. Progress of this sort has been found across scores of studies, often attributed to adaptation efforts by labor, and argued to occur independently of scale effects.

In this paper, we harness rich data from an assembly plant of a major automaker to address open questions about how the knowledge built through learning by doing is acquired, aggregated, diffused, and embodied. Our core data set covers in incredible detail the production of about 190,000 cars over the course of a production year. The year was full of potential learning opportunities, as the firm had both redesigned the cars made at the plant and introduced a new production process into the plant. We observe, for each vehicle the plant assembles, several hundred individual operations on the assembly line. We see the specific time at which each of these operations takes place and any problems that arise with the operation, allowing us to compute the rate at which production problems (defects) occur, either car-by-car or over aggregated time periods.

Our analysis reveals a number of interesting findings. Consonant with previous learning by doing studies, we find that the auto assembly plant quickly realized large efficiency gains in both the quality and quantity dimensions. Both assembly defects per vehicle and the average number of hours required to assemble a car dropped by about 70 percent during the first eight weeks of production. These quality gains in particular, which typically have not been measured in the literature, are further verified in two additional data sets: quality audits performed on randomly selected vehicles and initial warranty claims by buyers of the cars made at the plant.

When we track the transmission and embodiment of learning by doing knowledge, we find that, interestingly, despite the substantial learning these early productivity improvements represent, the plant's second shift was able to come on line in the eighth week of production and immediately operate at the first shift's contemporaneous quality performance. Further tying the performance of the shifts together, we document that the hundreds of processes involved in assembling a car had highly correlated defect rates across shifts within the same time period. In other words, most defect-prone processes on one shift tended to be the most defect-prone processes on the other, even though the workers completing these tasks were different.

These across-shift patterns stand in contrast with what we observe when production of a new *model variant* ramped up at the plant, as happened twice later in the year. In those cases, the learning process started again; production of the new variant initially exhibited much higher defect rates than the variant(s) already being produced. We also test whether worker absenteeism was related to defect rates, we find that it was, but that the impact was economically small. These results in combination indicate that, in terms of knowledge transition and embodiment, most of the substantial learning by doing at the plant was not retained by the plant's workers, even though they were an important conduit for knowledge acquisition. This is consistent with the plant's institutionalized systems for productivity measurement and improvement.

In exploring additional features of the learning mechanism, we document that the distribution of process-specific defect rates across the hundreds of assembly processes done at the plant is both highly skewed and persistent. Quality improvements arise from changes that drop all process defect rates proportionately; they are not driven by relatively large gains among initially defect-prone processes and few changes elsewhere. We also show that defects on one car spill over to cars following on the assembly line; an additional defect on a given car is tied to statistically significant increases in defect rates for the next 15 cars. However, these spillovers do not become smaller as the year goes along, indicating that the productivity gains we measure do not reflect improvements in the automaker's ability to prevent spatially correlated production problems.

In sum, we find considerable evidence of learning by doing in quality and quantity productivity performance, particularly early in the production year. Yet the second set of results—the immediate performance of the new shift, the correlation in contemporaneous defect rates across shifts, the contrast of these across-shift patterns with the re-learning that occurs when production of a new model variant begins, and the small effect of absenteeism—indicate that most of the knowledge stock built by learning does not stay with the plant's line workers. Instead, it quickly becomes embodied in the physical or broader organizational capital of the plant. While this at first may seem surprising, it is consistent with the key institutionalized learning mechanisms at the plant that we describe in more detail below. Finally, the third set of results—those regarding the skewness and persistence of process-level defect rates as well as the patterns in defect spillovers across agent cars on the assembly line—reveal aspects of the learning process in a complex production system that are rarely observable to researchers.

Our findings add new insights to a literature that has been attempting to move beyond a progress function that simply relates efficiency gains to cumulative production. Much of the economic research on learning by doing in specific production settings has focused on measuring the overall dynamics of the learning process—for example, how fast productivity gains accrue or whether measured learning rates imply that knowledge might be "forgotten" over time. More recent work, however, along with a separate operations management literature on learning by doing, has sought to go beyond characterizations of learning curves as mechanical processes driven by production experience. These studies have explored how producers' organizational structures and decisions interact with and affect the ways in which learning occurs.[1]

[1] The relevant literature is too large to cite fully. Some examples of more recent work include Malerba (1992); Jarmin (1994); Darr, Argote, and Epple (1995); Jovanovic and Nyarko (1995); von Hippel and Tyre (1995); Epple, Argote, and Murphy (1996); Hatch and Mowery (1998); Benkard (2000); Sinclair, Klepper, and Cohen (2000); Thompson (2001); Thornton and Thompson (2001); Schilling et al. (2003); Thompson (2007); and Hendel and Spiegel (2012). Argote and Epple (1990) and Thompson (2010, 2012) offer surveys. A related yet distinct line of economic research has used detailed production data to do "insider econometrics" (Ichniowski and Shaw (2012)) and explore how various factors like incentive pay, human resources policies, and management practices affect a firm's productivity. Examples include Lazear (2000), Hamilton et al. (2003), Krueger and Mas (2004), Bandiera et al. (2007, 2009), Hossain and List (2009), Bloom et al. (2011), and Das et al. (2013).

This work, however, has revealed less—largely because of data limitations—about the nature of the knowledge stock that is built through learning by doing. In particular, there remain many open questions about the specifics of how production knowledge is acquired, aggregated, and transmitted throughout complex production operations, and where and how this knowledge stock is eventually embodied in inputs. By fleshing out several details of the learning by doing process in an important industry, we learn more about the nature of the production knowledge stock itself. In this broader, more full-fledged view of learning by doing, a producer's experience gains do not so much cause efficiency enhancements themselves as they provide opportunities for management to exploit (Dutton and Thomas (1984)). Knowing more about such opportunities starts us on a path to better understand how specific productivity gains accrue at the plant level and how firms might optimally expand production. In addition, it provides some empirical content suggesting how comparative advantage arises, and what leads to specialization.

The remainder of the paper is structured as follows. Section II describes the production setting from which our data are drawn. Section III overviews the data. Sections IV, V, and VI present empirical results that, respectively, document the basic learning by doing patterns at the plant, explore the transmission and embodiment of the learning knowledge stock, and study additional detailed aspects of the learning process. A final section discusses implications of our empirical results.

II. The Production Setting

Our production data are from an assembly plant of a major automaker. Assembly plants are factories that piece together the thousands of parts that make up an automobile for delivery to final customers, either directly to fleet buyers such as car rental companies or indirectly through retail dealerships.[2] Non-assembly operations in the plant mostly involve conducting an assortment of quality-control tests of finished vehicles.

A. Plant Operations during the Sample Model Year

[2] The extent to which assembly plants are vertically integrated backward into making the parts they assemble varies somewhat across the industry, though there has been a general trend to move more parts fabrication offsite. Our particular plant reflects that movement; engines are brought into the plant ready to install from a separate factory, for example. Body panels are also struck at a separate though geographically close stamping plant.

Our sample is from the first year of operations following a substantial reorganization of the plant's production. This involved major redesigns in the vehicles assembled at the plant, changes in the assembly line's physical layout, and a shift into team-based production.[3] Team production dispenses with the traditional assembly line practice of having individual workers hold responsibility for a particular task on the line. Instead, a team of typically 5-6 workers is jointly responsible for a set of related tasks. Team members rotate through these tasks during the day and help their teammates when needed. One worker (a line worker not considered as management within the plant's hierarchy) is designated as a team leader. This worker is paid a small wage premium and has particular responsibilities involving oversight, training, and information aggregation.

These changes mean that, in many ways, the plant and its workers were starting over, or what the literature refers to as entering the 'ramping up' process: they were making new products in a new way. This provides us with a unique glimpse of the learning by doing process, since as has typically been found in other studies, learning is nonlinear: large gains are realized quickly, but the speed of progress slows over time. Therefore we are likely to observe considerably larger changes in defect rates than if we were to follow production of a product the plant had already been making for some time.[4] The high learning rate over our sample permits us to observe details of the learning process with greater resolution than would be possible later in the product design cycle, improving our ability to study the details of the learning by doing process. Another distinct advantage of examining data during the ramp up stage relates to shrinking product life cycles. As the lifespan of manufactured goods has decreased, especially among high-tech products, ramp up events have become more common. Understanding the factors influencing the time it takes to reach full production are valuable not only for plant-level profits, but economy-wide efficiency.

Production for the model year ran from August to July. We leave the specific calendar years unspecified for proprietary reasons, but it was during the 2000s. We refer to the August-December period as occurring in Year 1 and the January-July period as being in Year 2. A small

[3] While new capital and tooling were put in place before the start of the production year, the quantity of the plant's physical capital inputs was essentially fixed over the production year, reducing concerns that the addition of unobserved inputs creates spurious learning by doing productivity patterns (Thompson (2001)).

[4] This is confirmed in our case. Defect rates were much lower at the end of the model year previous to our sample, and had changed only slightly over the prior year. These earlier models had been produced for over six years at the plant, and as such most of the production kinks had already been worked out.

number of prototype vehicles, on the order of a few dozen per week, were produced in late July and early August of Year 1. These were built to determine whether major difficulties in the production process existed, and to train line workers in their new tasks and orient them to the plant's new team production process. As one might expect, defect rates during these first few weeks were extremely high. While no doubt part of the learning process, the fact that there were so few vehicles involved and average defect counts so varied between them led us to leave these first weeks out of the sample. We begin our sample in the first week in which over 100 cars were produced (when running at capacity, the plant can produce 3500-4000 cars per week.) This 100-car threshold was met in mid-August.[5]

The plant began the year with one shift producing a single model variant. During the model year, however, a second shift and two additional model variants were brought online (these additional ramp-ups were scheduled at the beginning of the year and were not responses to observed demand conditions). The second shift began production seven weeks after the first shift started. The three model variants assembled at the plant were built around a common platform. They have similar body frames and powertrains, but their exterior and interior styles are different enough that it may not be obvious to the untrained eye that the vehicles are such close cousins.[6] Each of these variants had just undergone its first major redesign in six model years. The redesigns involved both mechanical and stylistic changes. The automaker even renamed one of the variants to further signal the platform's novelty. Without going into proprietary detail, we can say that these car types are distinct enough that each requires variant-specific parts and assembly procedures. Production initially focused exclusively on Model 1. Model 2 was introduced 17 weeks later while production of Model 1 continued, albeit at a lower volume. Assembly of Model 3 began another 13 weeks after the start of Model 2. From that point on, all three model variants were simultaneously assembled at the plant.[7] Production within a day is not bunched by variant; consecutive cars on the assembly line can be and often are of different variants.

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[5] In specifications using daily production data below, we require that the plant produces at least 20 cars per day.

[6] Two of the variants are sedans with differing makes and model names. The third is a specialized style of car sold under the same model name as one of the sedans, though its specialization makes it obvious that it is a different variant.

[7] For the sake of consistency, when describing the introduction dates of Models 2 and 3 we impose a threshold of 100 cars per week being produced of the particular variant for the cars' production data to be included in the sample.

In total, the plant assembled about 190,000 vehicles during the model year. Figure A1 shows the total number of cars assembled in each workweek over the course of the year. The production ramp up during August and September is evident. Much of the week-to-week variation in output after the ramp up comes from differences in the length of the workweek due to scheduled holidays. Figure A2 reports weekly production by shift, and Figure A3 shows similar numbers by model variant.

B. Institutional Learning Mechanisms at the Plant

As we are exploring the nature of the learning by doing process at the assembly plant, it is worth discussing the organizational and institutional features of the mechanisms set up at the plant to measure and improve productivity.

Quality Measurement and Control. The plant's quality control system had several components. There were three primary sources of contemporaneous information about productivity at the plant: the Factory Information System (FIS) from which our core data set is obtained, random quality control audits on finished vehicles, and a whiteboard system that allowed line workers to communicate production issues to plant management.[8]

The Factory Information System (FIS) is proprietary software that interfaced with production through multiple modes to track production speed and quality (we describe the FIS data in greater detail below). The system automatically sent to the plant's quality control engineers daily summary reports on production defects, aggregated by area on the line (clusters of several dozen assembly processes). Our conversations with these engineers indicate that they used these reports to form a general sense as to which parts of the line were having an unusual amount of problems. When an anomaly became consistent they would begin a process to identify and address the difficulty.

The quality audits were conducted on roughly 15-20 randomly selected cars per day. These very thorough audits, done on finished cars just after they come off the end of the assembly line, examined hundreds of details ranging for example from measuring the gap

[8] Warranty claims by customers who have purchased cars produced at that plant are another source of information about production quality, and we use claims information in our empirical tests below. However, because of the average lag between the production date and the time a customer purchases a car and notices a problem, claims data are a relatively minor part of quality feedback during the a model's first production year, as is the case in our setting.

between the hood and the front fender along the hood's length to verifying that the headlights come on when the proper switch is actuated. Problems that were found were scored into one of four categories by severity: 1-point defects (the most minor), 5-point defects, 10-point defects, and 20-point defects (the most serious). By way of example, a small irregularity in the hood-fender gap would be a 1-point defect, while a failure of the headlights to turn on when the switch is actuated would be a 20-point defect. The summed scores for a car were indicative of the severity-weighted defect rates on the car. The plant's quality control engineers monitored audit results and addressed revealed problems, while reporting more severe defects to higher levels of management within the company.

The whiteboards system gathered information directly from line workers in and conveyed it to plant management. The system was simple. Each team of 5-6 line workers had a whiteboard near their stations that workers could use to note problems they encountered in the production process. Plant management and quality control engineers visited every team periodically (on the order of once every two weeks) to discuss issues on its board. Management would form and implement plans to address problems that they felt could be dealt with cost-effectively.

Line Worker Experience and Training. As will become evident below, the background and training of the plant's workforce, especially those working the assembly line directly, will inform the interpretation of some of our key findings. This is especially true with regard to any contrasts between first and second shift workers.

While our sample production year was the first after a major redesign of the production system at the plant, the vast majority of the plant's line workers had already been working at the plant for several years. Thus the basics of car assembly were familiar to them, though working in teams was not.

One of the more relevant differences between first and second shift workers regards the workers' past experience at the plant. Seniority was the overriding factor in determining the shift to which a worker was assigned. Because more senior employees had first choice of slots and most employees prefer working days to evenings, workers on the first shift were systematically more experienced than those on the second.

The second shift started operations seven weeks after the first shift. Training of workers on this later shift was modest: they observed first shift workers operate at their stations for the week prior to the ramp up of their own shift (i.e., the seventh week of the first shift's operations). Some engineering and management staff was assigned to span both shifts during ramp-up of the second shift, and this may have facilitated some indirect transfer of knowledge in addition to what the line workers obtained directly during their observational training week. In contrast, the vast majority of line workers, somewhere on the order of 95 percent, were employed on only one shift (we obtain this estimate from our absenteeism data, which records the absent employee's name and the shift they were scheduled to work that day). This allows little scope knowledge transfer through this channel.

III. Data

Our primary data set is taken from the assembly plant's Factory Information System. This software records information about the production process using several input channels. These include direct links to the tools themselves. For example, the FIS can read and record the torque applied by a particular wrench to bolts.[9] The system also interfaces with line workers directly, either prompting them to respond to a query about a particular operation or alerting them to a defect that needs attention. Throughout the production process the FIS tracks information about the many distinct assembly operations that occur in the plant; most records are not defects. For instance, for operations done on safety-critical parts, FIS is used to document that the task was done successfully. When defects do occur, the system marks them with particular identifiers. Therefore we can track production defects with a high degree of accuracy.

Car-level defect data is straightforward to extract from the FIS. We simply follow the car through the production process, counting any defects that it experiences along the way. We can track a single car through production because its vehicle information number (VIN)—a unique ID number given to every car assembled—is assigned to its critical component parts before production begins. FIS starts tracking these parts as soon as they enter the production process, and continues to follow the VIN through various stages of assembly until it leaves the factory.[10]

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[9] This sort of information is of obvious use to the automaker regarding the quality and speed with which production operations take place. But it is also used to conform to regulations requiring verification of certain production operations deemed critical for safety reasons, such as tightening the lug nuts that hold the wheels on the vehicle.

[10] We observe a total of about 194,500 VINs at the plant over the course of the year. We remove 5,600 VINs that have unusual time stamps (stations are out of sequence, or occurs overnight or on the weekend when the plant is shut down), leaving a total of slightly under 189,000 cars in our data set.

More aggregate measures of defect rates, such as average defect rates per car per week, take an extra step to compute. The numerator of this rate is the total number of defective production operations over the course of a time period. Measurement of the denominator, the number of cars produced during a period, is complicated by the fact that cars do not always start and end their time on the production line in the same period. For example, some cars begin production on a Friday and are completed on a Monday. Our approach is to break up the production process into segments that are divided by benchmark operations that FIS records for every car. This divides every car's production run into a consistent set of segments (though the segments are not exactly equally spaced). We then apportion the car to a production week by segment. For example, if the first two of six segment-ending benchmarks occur on Friday and the final four on Monday, we assign one-third of the car to Friday and two-thirds of it to Monday. The sum of complete and partial cars produced within a period gives us the dominator of our defects-per-car measure.

We also have a separate data set containing the results of quality audits that were performed on randomly selected cars as they come off the end of the production line. We have this for all audits conducted through Week 15 of Year 1—essentially, the first two-thirds of the production year. This data gives us an independent measure of average defect levels at the plant.

We obtain data on worker absenteeism from an administrative database that the plant uses to track employee attendance. The record level is at the individual absence, stating the date of absence and the employee's ID number. It also contains the employee's shift as well as which one of the plant's seven broad operations departments (e.g., body, paint, chassis, trim) to which the employee is assigned. We use these data to construct time series of absenteeism rates at the plant, shift, and department levels.

Our third data set contains car-level warranty claims. These have been entered by technicians at retail dealerships when buyers have brought in cars needing covered repairs. This information includes each car's VIN, the date, a description of the problem, a diagnosis, and two types of costs: customer and warranty. Customer costs are the responsibility of the car buyer and as such are not out-of-pocket costs for the auto manufacturer. (Of course, they could involve loss of goodwill, but we do not attempt to measure that here.) The latter is a direct cost to the manufacturer of the warranty claim. We test whether this cost is tied to the frequency of manufacturing defects as recorded in our FIS data by linking vehicles by VIN.

IV. Documenting Learning by Doing at the Plant

We first document the basic learning by doing dynamics of the plant and show that they are qualitatively similar to those patterns found throughout the broader literature.

A. Overall Patterns

Figure 1 plots the average number of defects per car by week.[11] When production begins in mid-August, average defect rates were on the order of 75 per car. Eight weeks later, they had fallen by two-thirds, to roughly 25 defects per car. These strong initial learning effects are consistent with findings in the broader literature on learning by doing. The absolute pace of defect reductions noticeably declined after that, with the remainder of the model year seeing a downward drift in defect rates to a final level of around 10 per car.

This slowing of the absolute rate of productivity growth is consistent with literature-standard power law specifications of the relationship between productivity and production experience. These specifications assume $S_t = AE_t^{\beta}$, where S_t is productivity at time t (average quality per unit in our case), E_t is production experience up to that point (cumulative production), and A and β are parameters. Because we use a measure of inverse average quality (average defective operations per car) in our analysis, learning by doing implies β is negative; defect rates fall with production experience. Taking logs gives us an empirical description of the learning process:

(1) $\ln(S_t) = a + \beta\ln(E_t) + \varepsilon_t$,

where $a \equiv \ln(A)$ is a constant and ε_t is a period-specific error term.

Table 1 shows the results of estimating this specification with our sample. Panel A contains the results from specifications using weekly data (average defect rates over the week and production experience at the week's outset); panel B shows results obtained using daily observations.

Column 1 in both panels shows the estimated value of the learning rate β from (1). In this most basic specification, production experience is simply the cumulative number of cars produced in periods prior to t: $E_t = \sum_{\tau=1}^{t-1} q_{t-\tau}$, where q_t is the number of cars made in period t.

[11] As discussed above, the data shown in Figure 1 are subject to the condition that the plant produces at least 100 cars during the week.

Estimates of the learning rate β are similar in both the sampling frequencies, -0.289 in the weekly data and -0.306 in the daily data. The simple empirical model fits the data very well at both frequencies, with the R^2 of the weekly and daily specifications at 0.961 and 0.931, respectively. This fit can also be seen in Figure 2, which plots the logged average defect rate against cumulative production in the daily data. Given the power-law form of the learning by doing function, a learning rate of β = -0.3 implies that average defects will be roughly halved for every ten-fold increase in cumulative production.[12] Thus defect reductions are particularly notable early in the production process. In our sample, cumulative production increases by a factor of 100 by mid-October.

To distinguish whether the quality improvement is tied directly to production experience or more simply reflects progress that accrues with the passage of time, we add a time trend to (1). Results are in column 2 of both panels of Table 1. The time trends are actually positive rather than negative, though small in magnitude, and the estimated learning rates are slightly higher. Quality improvement therefore appears to be related to production activity per se, not the passage of time since production began. Indeed, conditioning on production experience, the passage of time may even slightly decrease quality.

This last fact suggests, perhaps, that an organization's knowledge capital depreciates over time—there is "forgetting" (e.g., Benkard (2000), Thompson (2007)). To allow more explicitly for potential forgetting, we estimate a specification that allows for knowledge depreciation over time. Specifically, we assume experience is accumulated according to a perpetual-inventory process: $E_t = \delta(E_{t-1} + q_{t-1})$. Experience at the beginning of period t is a fraction δ of the sum of two components: the experience at the start of the prior period and production in the prior period, q_{t-1}. Thus δ parameterizes forgetting, or more precisely, retention.[13]

[12] The multiple to production k that drops error rates to one-half of any initial level is $k = 2^{(1/-\beta)}$. Thus with β = -0.3, $k = 2^{(1/0.3)} = 10.1$. Another measure of learning speed common in the literature is the progress ratio, the productivity gain—in standard settings, percentage drop in unit costs—obtained from each doubling of cumulative output. Here, a doubling of cumulative output leads defect rates to fall by 18.8 percent ($2^{-0.3} = 0.812$), which would be defined as a (quality) progress ratio of 0.812.

[13] We could have alternatively specified $E_t = \delta E_{t-1} + q_{t-1}$, so that the full amount of the prior period's production is added to the experience stock. We use our approach because it is more intuitively appealing for the specifications below where the retention rate is a function of worker absenteeism.

Nonlinear least squares estimates of the "forgetting" model are in column 3 of both panels.[14] Not surprisingly, the estimated retention rate in the weekly data of 0.965 is smaller than the 0.985 rate seen in the daily data, but when the latter is compounded over five-day production week, the implied retention rate is 0.927. Thus the models imply that about 3 to 7 percent of the plant's effective production experience stock is lost every week. This compounds quickly; over the course of a 45-week model year, only about 3 to 20 percent of the initial experience stock would remain if not replenished by production activity. Nevertheless, the R^2 values indicate that explicitly modeling the forgetting process does not substantially improve the ability of the power-law specification to fit the data, particularly relative to simply controlling for a time trend.[15]

We focus on quality-based productivity measures in this paper because we have an unusual opportunity to measure it well. However, it is also useful to compare the quality productivity patterns we just documented to the unit cost productivity measures more typically used in the learning by doing literature. Previous work has measured learning by doing rates by looking at changes in, for example, worker-hours per unit. Here, we use hours per car, which are very tightly linked to (the inverse of) worker-hours per unit because the number of line workers per shift is essentially constant in our setting. We measure the time it takes to assemble a car by adding up the time that passes between the cars' appearances at the aforementioned checkpoints on the production line.

Figure 3 shows how the average number of hours to assemble a car evolves over the production year. The figure is qualitatively, and to a large degree quantitatively, similar to the quality productivity patterns in Figure 1. During the first few weeks of the production year,

[14] We set the starting values for the intercept and the learning rate equal to those estimated from the no-forgetting model in column 1, and the starting value for δ of 0.9. The results are not sensitive to these starting values.

[15] Interpreting the estimates of β in these specifications as causal requires that across-period differences in production experience are exogenous to shocks in defect rates. In the basic specification, differences in production experience equal the number of cars produced over the interval between periods; in the "forgetting" specification below, experience differences are a more complex function of production in all previous periods, where production that occurred further in the past has less weight. As Thompson (2012) notes, if productivity shocks are highly correlated over time, and the producer responds by making more output when productivity is high, then past production levels (i.e., variation in experience) can be correlated with current productivity. This yields biased estimates of β. Further, simply controlling for a time trend may not be enough to eliminate this bias. We treat the possibility that production levels are exogenous more explicitly below by using the production rate in one of the plant's shifts to instrument for the production rate of the other shift. In that specification we also find no evidence that management systematically shifted the volume of production (across shifts, in that case) in anticipation of changes in defect rates.

assembling a car takes about 350 hours. By Week 43 of Year 1, however, only about two months after the start of production, average hours per car fell to about 100. This 70 percent drop is similar to the change in defect rates over the same period. The drift downward in average hours after this point in the year is weaker than in the defect rate series, and week-to-week fluctuations in hours are noisier. Nevertheless, the estimated learning rates in this unit cost productivity measure are remarkably close to those for quality productivity. Estimating specification (1) using logged average hours per car as the dependent variable yields an estimated learning rate β of -0.286 (s.e. = 0.020) in weekly data and -0.331 (s.e. = 0.014) in daily data. Both the rate at which cars are assembled at the plant and their quality levels rise at roughly the same rates over the production year.[16]

B. Supplementary Evidence from Quality Audits

FIS data are the only source of information on the number of production defects for every car made in the plant. As mentioned above, however, the automaker conducts detailed quality audits on about 15-20 randomly selected cars throughout the production day. This offers an independent source with which to verify the results above.

We have data on all quality audits conducted through Week 15 of Year 1, the first two-thirds of the production year. Figure 4 plots the weekly average audit score per car over this period.[17] A car's audit score sums the points associated with each defect found during the audit, with the most minor defects counting as 1 point, and defects of increasing severity counting as 5, 10, or 20 points, as appropriate.

[16] It is worth noting that this production speed ramp-up pattern, which is common in many production settings (and we will see below is also present when the plant starts a new shift or when it begins producing new model variants), is consistent with a model where a firm allocates its time between a) producing output with a production function fixed by the current "knowledge" level, where greater knowledge implies higher productivity, and b) engaging in learning that raises knowledge (and productivity) in future periods (see Lucas and Moll (2011) for an example of a model with this tradeoff). When faced with this resource allocation issue, it is optimal under many conditions for the firm to allocate a relatively large amount of time to learning rather than producing when starting to make a new product, and hence operate at a low output rate, and then to steadily allocate greater shares of time to producing—i.e., run at a greater line speed—in later periods. This structure would explain the observed coincident patterns of increasing rates of production and decreasing defect rates. It also implies the relationship between productivity and cumulative production in standard use in the literature is incidental to a deeper causal mechanism tying a firm's productivity to its actively accumulated knowledge stock.

[17] A relatively small number of cars were audited during the production ramp-up in Weeks 34-36 of Year 1, so we aggregated audit data from those weeks together, labeling the aggregate in the figure as Week 36 of Year 1.

The quality improvement we document in the FIS data is reflected in the audit scores. Scores start at a high level and quickly decline in the first several weeks of the production year. Eight to ten weeks into the production year, average audit scores have fallen by about 70 percent from their initial levels. Scores gradually and noisily fall by perhaps another 10 to 15 percent of their initial level after this point until the end of the available data.

The similarity between this independent production defect measure and our core FIS data is reassuring in several ways. First, it eliminates the possibility that the drop in defects in the FIS data is simply an artifact of workers being less likely to log in and report production problems as the year goes along. Second, it indicates that the production defects we measure in the FIS data, even if they were sometimes corrected later in the assembly process, were correlated with defects that would nevertheless leave the factory with the car. The quality audits are conducted after all assembly processes are done; if not for the audits, the audited cars would have certainly been shipped to dealers with the defects found in the audits. Thus our FIS defects matter, or are correlated with other problems that matter, to the car's end consumer. This is further supported by the fact that, as we discuss shortly, initial warranty claims on the cars are correlated with our FIS defect levels.

Third, if we look at where the improvement in the audit scores comes from—that is, look at the changes in the relative frequencies of defects by severity score—the fastest drop in relative frequency is seen among the most severe 20-point defects, and the slowest drop occurs in the much more minor 1-point defects (the frequencies of each severity level of defect relative to their levels at the beginning of the production year are shown in Figure A4 in the appendix). This is a sign that quality improvement at the plant is a directed process; defects with the larger expected impact on the customer are addressed faster.

C. Supplementary Evidence from Warranty Payments

As yet another check on the ability of our FIS defect measure to capture consequential quality problems with cars, we exploit the fact that we observe car-level warranty payments for all vehicles produced at the plant. While the data has a limited time horizon—we can only follow claims for cars produced during our sample year for nine months after their production date, limiting our investigation to quality problems that arise quickly after purchase—we are able to explore if reductions in defect rates affect one bottom-line profit component.

To measure the quantitative relationship between defect rates and warranty costs, we estimate the following regression:

(2) $claimpayments_{it} = \alpha_0 + \beta \cdot defects_{it} + \lambda_t + \varepsilon_t$,

where $claimpayments_{it}$ are the warranty payments paid on car i which was made in week t, $defects_{it}$ is the production defect count for that same car, and ε_t an error term. We include week-of-production fixed effects λ_t to compare cars that were produced contemporaneously. Our sample consists of all cars in our FIS data. The car-level match of these warranty and production data sets is done using the cars' VINs.

We find a positive relationship between production defects on a car and the amount of warranty payments that the automaker pays on it. The regression of payments on defects yields a slope of 40.8 cents per production defect (s.e. = 7.1 cents). To benchmark the warranty savings due to learning by doing effects, if we apply this slope to the roughly 65 defect-per-car drop in average defect rates over the production year (see Figure 1), this is a savings of about $26.50 per car. Applied to the 190,000 cars made the year of our sample, this is just over $5 million in warranty claims savings. This is, of course, a very loose lower bound for the profit gain due to reductions in defect rates, as it does not include reduced future warranty claims later in the cars' service lives nor any increases in consumers' willingness to pay for higher quality cars.

V. The Embodiment of Learning by Doing

The results discussed thus far indicate that learning by doing is an important factor in this production process. This holds not just for unit input requirements, the focus of most of the empirical work on the subject, but for quality-based productivity measures as well. In this section we use multiple features of our data to investigate the acquisition, aggregation, diffusion, and embodiment of the production knowledge stock built through learning by doing.

A. Introduction of a Second Shift

We begin by comparing defect rates across the plant's two shifts. Figure 5 shows average defect rates (again on a per car basis, averaged over the week) separately by shift.[18]

[18] Cars are not produced start-to-finish within a single shift. We apportion cars to shifts using the same procedure described above for apportioning them across time periods. The fraction of a car produced on a shift equals the share of the benchmark production stations that we observe occurring during each shift.

Recall that the second shift begins operating in Week 41 of Year 1, seven weeks after the first shift began. Notably, the figure shows that the second shift does not start with the high initial defect rates experienced by the first shift. Indeed, they are in fact *lower* than the first shift's contemporaneous defect rates. Furthermore, this pattern holds throughout the production year. Second-shift defect rates were on average about 10-15 percent lower than first-shift rates, a difference that is statistically significant at conventional levels in both the weekly (mean difference t-statistic = 3.2) and daily (mean difference t-statistic = 3.4) data. The average difference declines over time as the two series converge, however.

For comparison purposes, we estimate shift-specific learning by doing rates by estimating regression specification (1) separate for each shift. The results are in panel A of Table 2. The first shift's estimated learning rates in both the weekly and daily samples are similar to those found above in the overall sample. However, the estimated rates for the second shift are considerably smaller. This is largely a result of the flat defect rates observed during the first several weeks of the second shift's operations. Because cumulative second shift production is rising at a fast rate during this period while error rates remain flat, the estimated learning rate is pushed toward zero.

As discussed above, estimates of the learning rate β could be biased if plant management adjusts the production rate based on expected productivity. We further explore the potential endogeneity of production rates in the shift-specific specifications here. Specifically, if plant management steers production toward a shift that is expected to (and in realization does) have lower defect rates, estimates of β in the specifications above will be negatively biased. We address this possibility by re-estimating the shift-specific versions of (1) while instrumenting for each shift's cumulative production with the cumulative production of the other shift. This identifies learning rates by in effect comparing defect rates on a given shift to the systematic component of production rates across both shifts rather than shift-specific idiosyncracies (the shifts' cumulative production levels easily clear the first-stage relevance test, with t-stats in the double digits). The results are presented in Table 2, panel B. In all specifications—using both first- and second-shift defect rates as dependant variables and in both weekly and daily data—the results of these IV estimates are qualitatively and quantitatively similar to those presented in panel A, suggesting that endogenous production rates do not play a substantial role.

We conduct complementary tests to further explore potential connections in defect rates between the two shifts. To begin, we examine whether first-shift defect rates were higher during the period in which the second shift was ramping up production. We define ramp up as the first five weeks of second-shift production, the time it took second-shift output to rise to 95 percent of the level of the first. We do so by adding an indicator for the second-shift ramp-up period to the first-shift-specific learning regression in panel A of Table 2. Results are contained in panel C of the table. Estimated coefficients on the ramp-up period indicator are positive but statistically insignificant and economically modest, at 1.7 and 4.1 percent.

The two shifts' defect rates behave similarly over the course of the production year. Their levels have a correlation coefficient of 0.94 in weekly data, and their differences have a coefficient of 0.45. Further, as we will see below, defect rates at specific stations on the production line are correlated across shifts within a given week. Nevertheless, we find little direct evidence of other experience spillovers across the two shifts after the initial ramp up.

We also investigate shift-specific trajectories of unit costs (hours per car). Figure 6 plots weekly averages of hours per car for each shift over the production year. The second shift came online at basically the same production rate that the first shift was running at. The low initial defect rate of the second shift cannot be explained by appealing to it operating at a slower pace.[19]

These shift-specific defect patterns indicate that whatever was learned in the early production period did not become embodied solely in the workers on the line at that time. The quality gains seem instead to be fully incorporated into second shift production almost immediately even though new workers are on the job. As Epple, Argote, and Murphy (1996) note in their own study with a similar finding of rapid across-shift learning transfer (though slightly slower than the immediate transfer we observe), this points toward the productivity gains from learning being embodied in the broader organization rather than being retained within the human capital of line workers.[20]

[19] The lower initial quantity of cars produced by the second shift, as seen in Figure A2, reflects the fact that the shift did not immediately run a full day. When the line was running, however, cars were being produced at a similar pace as during the first shift. In fact, the second shift ran at a slightly faster pace than the first shift throughout the production year.

[20] Of course, we cannot completely rule out a worker-embodiment hypothesis if the first-shift workers are able to fully convey their information to the second-shift workers during the week that the second-shifters observe the first-shifters in operation. However, the transfer of this knowledge, which took several weeks of production to build, would have to occur within one week. Further, even complete transfer would imply that the second shift would

B. Introduction of Additional Product Variants

While the start of a second shift did not necessitate an intense new learning period, outcomes were different during the other type of production ramp up in our data: the introduction of the new model variants. This is apparent in Figure 7, which plots weekly average defect rates per car by model variant.

Overall defect patterns are qualitatively similar for the three model variants. Each starts at a high defect rate that quickly falls as production continues. For Model 1, the high initial learning rate discussed above resulted in an 85 percent drop in average defect rates by the time production of Model 2 began in December of Year 1. Despite these quality gains for Model 1, initial average defect rates on the new variant were much higher for Model 2, though they were not as high as Model 1's defect rates at inception. Model 2's defect rates subsequently declined quickly, dropping to meet the level of Model 1 after four weeks. When production of Model 3 began in March of Year 2, again initial defect rates were high and dropped quickly after production began. In this case, though, they did not fall to the level of the other models' defect rates before the end of the production year. Over the last 12 weeks of the model year, Model 3 averaged about 15 defects per car while Models 1 and 2 averaged roughly half that. Thus, unlike the introduction of the second shift, introduction of a new variant involved a considerable amount of learning.

We estimate model-specific learning by doing rates analogous to the shift-specific regressions discussed above, where experience is measured as cumulative production of the specific model variant. Empirical results are contained in panel A of Table 3. Model 1's estimated learning rates are similar to those found in the overall sample above. The estimated rates for Models 2 and 3 are somewhat smaller, on the order of -0.2. We also test for spillovers across model variants; the results are shown in panel B of the table. Because of the timing of the model variant production, the Model 1 defect rate regressions include indicators for ramp-up periods of Models 2 and 3, while the Model 2 defect rate regressions include only a Model 3 ramp-up dichotomous variable indicator.[21]

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achieve defect rates equivalent to the first shift; yet as we discussed, observed second-shift defect rates are on average significantly below those of the first shift.

[21] Analogously to the second-shift ramp up, we define ramp-up periods as beginning when production of the model variant reaches 100 cars per week and ending when production first exceeds 95 percent of the production level of at least one of the models whose production began earlier. This was a five-week period for Model 2 and a three-week period for Model 3.

The estimates in the first two columns of panel B of Table 3 indicate that ramp ups of Model 2 and, especially, Model 3 coincided with increased defects in Model 1. Ramp-up coefficients are positive and, with the exception of the Model 2 ramp up estimate in the weekly data, are statistically significant. The Model 3 ramp up period corresponded to a nearly 30 percent increase in Model 1 defects, notably larger than the 7 percent bump tied to Model 2's ramp up period. In contrast, similar spillovers from Model 3 ramp up into Model 2 defect rates are not apparent. Here, the ramp-up indicator coefficients are actually negative, small (on the order of four percent), and insignificant. These results across variants are particularly interesting in light of and perhaps explained by the fact that Model 3 is a specialized version of Model 1. Problems that arose as Model 3 began production detracted more resources from production of its closer cousin, Model 1, than from the more distant Model 2.

Comparing the results in Figures 5 and 7 as well as Tables 2 and 3 emphasizes that learning by doing knowledge stocks in the plant were not accumulated simply by the plant's workers producing *any* type of car. Workers who had already acquired experience producing one product variety could not fully transfer this knowledge to the production of new varieties. This is inconsistent with the most general of organizational learning models where workers simply need to become acclimated to operating together. It also suggests, as the shift-specific results above, that learning by doing knowledge is not simply contained in the individuals employed at the plant. Rather, it is likely embodied in the physical capital (e.g., tools are adjusted or workstations redesigned) or organizational capital of the plant. We discuss this further below.

C. Station-Level Patterns across Shifts

In addition to being able to observe the product quality that emerges from the overall production process—that is, the number of production errors per car—we observe outcomes for each of the hundreds of individual stations on the production line. We use this unusually detailed information to further investigate the tight across-shift relationship in defect rates documented above. In particular, we measure the correlation of station-level error rates across shifts.

To measure this correlation, we first construct the distribution of station-level weekly defect rates for each shift. We group stations within each distribution by quintile and compare a given station's quintiles across the first and second shifts in that week. Table 4 reports the results. Each cell reports the fraction of stations in each quintile-by-quintile grouping (the cells sum to 100 percent). Rows correspond to a station's first-shift quintile; columns correspond to its second-shift quintile. For example, 15.2 percent of stations were in the first (lowest) defect rate quintile in both the first and second shifts in a given week. Another 5.4 percent were in the lowest quintile in the first-shift defect rate distribution but the second quintile of the second-shift distribution.

Defect rates are correlated across shifts within a week. The table's largest elements tend to be along the diagonals, and the correlation is greatest for stations at the distributions' tails. In other words, stations that are error-prone during the day shift tend to be error-prone during the second shift as well. Because the personnel working at the station have changed between shifts, the correlation in defect rates implies that the main explanation for a station's defect rates is something about the process itself, not the workers operating the process.

D. Absences and the Role of Worker-Embodied Learning by Doing

Our findings to this point imply that a considerable amount of the production experience stock is embodied in either physical or organizational capital rather than within individual workers. We investigate worker-embodied knowledge one further way, by exploiting our worker absenteeism data. If individual workers retain production knowledge, we should see slower learning or even productivity regression when more workers are absent.

Figure 8 plots the plant's average weekly absentee rates over the production year. Absenteeism was volatile, with particularly low rates occurring when the second shift trained and began production (weeks 40 and 41 of Year 1) and in January of Year 2. Spikes occurred in mid-November of Year 1 (a combination of Veteran's Day weekend and the beginning of the state's firearm deer hunting season) and the week of Presidents' Day. Average absenteeism rates trended upward over the production year.

The divergence in the absenteeism and defect rate trends over the production year indicates that learning by doing productivity growth occurred in spite of trends in worker attendance rather than because of them. If there are any effects of absenteeism on productivity and learning, they must be from a more subtle source. We follow two empirical approaches to further our inquiry. In the first, we again take advantage of the detail in our data. Namely, we test if absenteeism and defect rates are correlated at finer levels of operations within the plant while controlling for overall trends. In the second, we revisit our "forgetting" versions of specification

(1) and allow the rate at which knowledge stock depreciates in a given period to vary with the fraction of workers who are absent. The notion is that worker absences prevent any knowledge embodied within them from being applied to the production process in their absence, and limits the accumulation of new knowledge.

To test if absenteeism and defect rates are correlated at finer levels of operation, we compute defect and absences by department-shift-day cells, where department denotes a major portion of the line's operations.[22] Combining these data, we have a panel of 3292 observations. We then estimate the following regression:

(3) $\ln(S_{it}) = \alpha_0 + \rho\ln(abs_{it}) + \delta_i + \theta_t + \varepsilon_{it}$,

where S_{it} and abs_{it} are respectively the defect rate and number of absences in department-shift i on day t, δ_i is a department-shift fixed effect, and θ_t is a day fixed effect. This specification shows whether department-shifts at the plant (e.g., Chassis operations taking place during the second shifts) that are experiencing unusually high absenteeism relative to other department-shifts on a particular day have, in expectation, systematically greater (or perhaps lower) defect rates on that day. Consistent estimation of ρ requires these relative absenteeism differences to be exogenous to other factors that influence within-day differences in department-shift defect rate changes; essentially, workers cannot be choosing whether to show up based on their expectations of defect rates on their area of the production line that day relative to other areas.

The estimate of ρ is 0.153 (s.e. = 0.031), indicating that at this level of aggregation worker absences were in fact related to higher defect rates. The economic size of this relationship is modest, however: the estimated elasticity of 0.153 implies a one-standard deviation increase in a department-shift's absences raises defect rates by about 1/5th of a standard deviation.

The absenteeism-augmented forgetting specification allows the retention rate δ for a period to vary with plant-level absentee rate in that period. Specifically, we let $\delta_t = \frac{1}{1+\gamma \cdot abs_t}$, where abs_t is the plant's overall absenteeism rate on period t, and γ is a parameter we estimate. Note that with this functional form, if $abs_t = 0$, then $\delta_t = 1$. As absences grow, the retention rate falls at a rate that depends on γ. Table 5 shows the results of this specification for weekly and

[22] There are seven departments. In the order in which they occur on the line, they are Body-in-White (the assembly of the car's metal frame and major body pieces such as fenders and the hood), Paint, Trim (parts of the car that are not part of the powertrain and steering systems, including seats, handles, and dashboard), Chassis (engine, transmission, and other major mechanical systems), Final (finishing details and parts), Reprocessing (addressing any stages not fully completed or needing further attention) and Quality Control (operational and aesthetic inspection and testing).

daily data. We estimate the specification using nonlinear least squares, with the same starting values for intercept and slope as in the constant-retention-rate specification in Table 1, and the starting value for γ chosen so that at the average value of abs_t in the sample, the implied value of δ_t equals the estimated coefficient from the earlier specification.

In both the weekly and daily data, γ is positive and statistically significant; periods when more workers are absent have lower retention rates. However, the magnitude of the variation in δ_t is economically small. The average δ_t implied in the weekly data is 0.968; the standard deviation across weeks is only 0.007, however, and the range spans 0.955 to 0.980. Similarly, the average implied daily δ_t is 0.992, with a standard deviation of 0.002 and a range from 0.976 to 0.996. We simulated what these estimates imply average defect rates would be if absences were held to the level of their 25th percentile in the sample. Consistent with the small variation in the estimated δ_t, this reduction in absences would lower average defect rates by only 0.7 percent in the weekly specification and 1.1 percent in the daily specification.

Therefore absenteeism did have statistically significant effects on defect rates, suggesting there was some role for worker-embodied production knowledge in explaining learning by doing patterns at the plant. However, the estimates also indicate any such effects had a relatively small economic magnitude.

E. Discussion of Embodied Learning

The results above indicate that the substantial knowledge obtained through learning by doing at the plant is, to a large extent, not retained by the plant's workers. First, while considerable learning occurs during the first two months of the first shift's operations (average defect rates and the hours required to produce a car both fell by about 70 percent), the plant's second shift—which is staffed by less experienced workers with minimal training—was able to immediately begin operating at the productivity levels of the first shift, whether measured in quality or unit labor costs. At the same time, the fact that substantial relearning did occur when a new model variant was introduced means that it was not simply that everything at the plant was "dialed in" by the time the second shift started, or that organizational learning is simply a matter of employees becoming acclimated to working with one another. Additionally, the defect rates of the several hundred individual processes along the assembly line were highly correlated across shifts. That is, the most (and least) defect-prone processes on the day shift were likely to be the most (and least) defect-prone processes on the evening shift, despite there being different workers completing these tasks. Third, while worker absenteeism is tied to higher defect rates, indicating some degree of worker-embodied learning, the impact is economically small.

These patterns of production knowledge acquisition, transmission, and embodiment are consistent with the workings of the aforementioned productivity feedback and improvement systems at the plant. Two of the systems, daily FIS reports and the quality audit results, compile and send information straight to the plant's quality control engineers. The engineers use this information to identify the root sources of defects and, with management, implement process changes to rectify them. While the associated testing and adjustments can and often do involve line workers, the implemented solutions reside in the broader knowledge base of the plant as a whole. This means when a problem is fixed, its solution sits not just with any particular line worker, but also with the engineering department, among workers on nearby stations, workers at the same station on the other shift, and for particularly serious issues, among top management at the plant and even the corporate level. This broader knowledge stock can be thought of as organizational capital of the type described by, for example, Tomer (1987).[23]

The FIS and audit systems notwithstanding, large amounts of information about production still originated from the workers on the line. This is not surprising; hundreds of line workers interacted directly with the assembly process and experienced production difficulties firsthand. Aggregation and diffusion of this knowledge were the purposes of the whiteboard system. Workers were encouraged to note problems on the boards, and through the practice of regularly visiting a team's board and addressing those problems that could be addressed, management and engineering demonstrated to workers that their reports would be heeded. The system therefore quickly pulled information from individual line workers and allowed management to manipulate the production process in ways that benefited any worker at a similar

[23] To gain a sense of the types of fixes implemented as a result of these mechanisms, we present two typical examples given by quality control engineers at the plant. One involved an occasional misfit between two adjacent components of a car's outer body. First, a diagnosis of which two adjacent parts was the source of the problem was made by swapping the two parts across cars with good and poor fits. When the problem part was identified, a random sample of the part was closely inspected. Engineering discovered an unusually high variance in the part's finished shape coming out of the injection molder. This variance was reduced, and the overall fit problem solved, by slightly adjusting the chemical composition of the plastic used in the part. A second case involved an interior part that was not being adequately bolted down. This was fixed by reviewing and adjusting the bolting procedure with the relevant line workers. They were also required to verify and certify bolt torque for every car by placing a sticker on the part after assembly. This sticker was in turn checked by a worker later on the line who verified the presence of the sticker before removing it.

position (or even adjacent positions) on the line, not just the worker who first reported the problem. The system therefore acted as a conduit that gathered worker knowledge and, through the complementary efforts of management, transformed it into plant knowledge that became embodied in the plant's physical and organizational capital.[24]

VI. Digging Deeper into the Learning by Doing Mechanism

We have explored the nature of knowledge acquisition, transmission, and embodiment in the plant. In this section, we further leverage our data to deepen our understanding of the particular mechanisms through which learning takes place.

A. Distribution of Defects across Stations

As discussed above, we see outcomes for each of the several hundred processes that go into assembling a car. We use these data to answer questions about the composition of process-specific productivity gains that underlie the more aggregated productivity improvements analyzed above.

We first explore the process-level distribution of defect rates. Figure 9 shows the evolution over the sample of various quantiles of the process-specific defect rates. Each process's defect rate is computed as the number of defects recorded at that process (station on the line) in a given workweek divided by the total number of cars produced that week. The figure sorts these processes into quantiles based on that week's performance; i.e., a station will move from one quantile to another over time if its relative defect rate fluctuates.

Panel A of Figure 9 shows the 50^{th}, 75^{th}, and 95^{th} percentiles of the absolute levels of station-level defect rates (the skewness of the distribution relative to the scale of the figure makes it very difficult to visually distinguish quantiles below the median). Defect rates are highly skewed across stations, with a thick right tail. In the first full week of production, for

[24] This naturally raises questions as to the line workers' motivations for putting items on the whiteboard. Their pay did not directly depend, either positively or negatively, on productivity at the team or plant-wide level. On the other hand, continued poor performance by a worker or team can lead to unpleasant visits and complaints from management, or perhaps reassignment to other less appealing tasks at the plant. Fixing problems might also make a worker's job easier or more pleasant aside from any productivity effects. Finally, our conversations with workers suggested some felt an element of intrinsic motivation driven by *esprit de corps* and pride in their work. Indeed, management indicated to us that if there was any concern with the volume of reporting on the whiteboards, it was that workers placed too many problems on the board, including ones that were clearly impractical or intractable. It was not a case of workers underreporting what would be otherwise fixable items.

example, the defect rate at the 95th percentile station is 20 times the rate at the median station that week, and five times the 75th percentile rate. The tightening of the distribution early in the production year indicates that the large early-period productivity gains seen in the aggregate series come largely from defect reductions in the right tail of stations. Interestingly, though, the basic shape of the distribution stays the same throughout the production year. This can be seen in panel B of Figure 9, which shows the *ratio* of a quantile's defect rate in a particular week to that same quantile's defect rate during the first week of production. We add the 25th percentile series to this panel, as it can now be distinguished from the others. That is, the panel shows the percentage decline of the quantile's defect rate relative to itself. All quantiles follow essentially the same pattern, with considerable reductions in relative defect rates early in the production period that decelerate over time. Aggregate learning by doing at the plant therefore reflects a proportional tightening of the entire station-level defect rate distribution, with all quantiles experiencing similar percentage declines in defect rates.[25] It does not appear, therefore, that productivity gains reflect all-out efforts to address the most problematic assembly procedures while ignoring all the others. The relative defect rates of all processes fall essentially in tandem.

B. Persistence of Station-Level Defects

Figure 9 sheds no light on the question of whether the persistence of defect rates *for a given processes*. Specific processes could be relatively defect prone (or defect free) throughout the year, or they could jump from quantile to quantile, being major sources of defects at one point during the year while being nearly defect free at other times. To investigate persistence, we first split the model year production into three equal-length periods: beginning, middle, and end. We then calculate the station-level defect rate distribution within the first period, and assign a station to its quintile in the distribution during that period. We then count defects in each of the three periods by the first-period quintile of their process. The fewer changes we observe in the relative contribution of a particular quintile over time, the more persistence there is in process-level defect rates.

[25] The quantiles of the distribution are computed while including stations that report no defects, which number between 5-10 percent of stations in any given week. Qualitatively similar data patterns remain in both absolute and relative defect levels among the corresponding quantiles of the distribution conditional on stations reporting at least one production defect during the week.

We present the results of this exercise in Figure 10, which can be interpreted as follows. Panel A shows the results for the total number of production defects during the period. The bar labeled "1" breaks the total number of defects that occurred during the first production period, about one million, into quintile-specific components. The top portion of the bar is the portion of defects that occurred in the stations in the top quintile of the distribution. The skewness of the defect distribution analyzed previously is obvious in this figure as well; roughly 90 percent of all defects occurred at stations in the top quintile. Further, almost all of the remaining 10 percent of defects occurred at stations in the second quintile of the defect distribution, as indicated by the second color in the bar. Stations in the bottom three quintiles account for a miniscule portion of the total number of defects during the period.

The bar labeled "2" repeats the exercise for the second production period, but it holds the quintile assignments constant. Note first that the height of the overall bar is lower in period two because there are fewer total defects in this period is lower because of learning by doing. Because quintile assignments are held constant across time in Figure 10, the top color in the bar shows the number of defects in the second production period that are accounted for by stations that were in the top quintile of the distribution *in the first period*. If defect rates within stations have no persistence and are completely random over time, then we should expect each first-period quintile will account for 20 percent of all errors in the later two periods. This is clearly not the case. Stations at the right tail of the distribution in the first period still account for the vast majority of production defects in the second period.

The bottom three quintiles again account for only a tiny part of the total number of defects in the period. Defect rates at the station level are therefore quite persistent. There is some shift in stations' locations in the defect rate distribution, however, as the *share* of defects accounted for by top-quintile stations does shrink between the first and second periods. This can be seen more easily in the proportional results in panel B of Figure 10, shows values in terms of the share of defects in the period rather than the absolute number. These same patterns hold in the period 3 results. While total defect rates fall, the most error-prone stations early on the model year still account for a large fraction of the defects at the end of the year, again indicating a large degree of persistence in a process's propensity to lead to production defects.

C. Defect Spillovers across Cars

Our final investigation explores whether defect rates are correlated *across cars produced in sequence*. That is, we examine to what extent the probability of defects occurring spills over across adjacent cars on the production line. There are several mechanisms through which this could happen. If a defect occurs on one particular car, a worker may sometimes attempt to rectify the problem before the car moves to the next production process. This can lead to a longer time being spent on the operation than typical, reducing the time available for the operation on the following vehicle, which could in turn result in another defect on that car. Further, when a defect is not addressed at the location it occurs, a worker further down the line might sometimes attempt a fix. This could in turn result in a defect occurring in an adjacent car at that later station. More broadly, if a worker is distracted or otherwise performing poorly, then s/he is likely to be distracted on consecutive cars.

We are interested in spillovers in our context because one way learning-based productivity improvements can occur is if production experience reveals how to limit the extent of spillovers. To see how this might work, imagine a stylized world where a certain number of defects happen by random chance, and the nature of these defects is to adversely impact every car until someone catches and fixes the mistake. Learning-based productivity gains in this world could come from two sources: a reduction in the probability that defects arise in the first place, or more expedient identification and rectification of the defects that arise.

We investigate the issue by estimating a model that relates defects on one car to those on adjacent cars on the line. Specifically, we regress the defect count of a given car on the defect counts for each of the 40 cars that preceded it along the line:

(4) $$S_{ct} = \sum_{k=1}^{40} \alpha_k S_{c+k,t} + \theta_t + \varepsilon_{ct},$$

where S_{ct} is the defect count for car c produced on day t, $S_{c+1,t}$ through $S_{c+40,t}$ are the defect counts for the 40 cars preceding car c on the production line, θ_t is a day fixed effect, and ε_{ct} is an error term. The coefficients α_k give the marginal effect of a defect on car $c + k$ on the defect count of car c (this is analogous to an autoregressive model where a variable is regressed on its preceding values, and the coefficients reflect the marginal effect of a change in the value in k periods prior on the value in period c). Day fixed effects control for changes in average defect rates over the sample period. Thus the coefficients in this model reflect whether, relative to other cars produced on that day, defects on proximate cars lead the reference car to have more problems. If spillovers exist, higher defects on one car will lead to more defects on those that follow it in the production sequence. We estimate this specific separately for three different production periods: early in the model year, in the middle of the year, and toward year's end, to see if any spillover patterns change over the production year.

We show empirical results in Figure 11. Panels A through C show the estimated regression coefficients for each of the three production periods (early, middle, and final thirds of the year, defined as in our persistence analysis above), along with their 95-percent confidence intervals. We only plot the coefficients for the 25 cars prior to the reference car, as this is sufficient to see where spillover effects become statistically insignificant. Spillovers clearly exist. Production defects on one car raise the likelihood of defects on cars that come later in line. As one might expect, the magnitude of these spillovers falls as the distance between cars on the assembly line grows. Still, defects on one car have statistically significant spillovers on at least the next 15 cars on the line. In terms of magnitudes, a one-defect "shock" on a given car leads, on average, to about one-eighth of a defect on the next car in the line (or equivalently, an extra defect on the following car one-eighth of the time). The same shock leads to roughly 0.08 defects on the car that comes two positions later. The tenth car down the line experiences 0.02 more defects on average.

It does not appear, however, that a decrease in spillover effects during the production year explains the plant's learning by doing patterns. This can be seen in panel D of Figure 11, which overlays the coefficient estimates for the three time periods on a common set of axes. The three sets of coefficients have basically the same shape, with no noticeable decline in the size of defect spillovers across the production year.

VII. Discussion

A. Implications for TFP

One of the motivations of our study is the importance of understanding TFP growth. In this section, we use the results of our empirical analysis to compute an estimate of the TFP changes that occurred at the plant due to learning by doing. We stress that this calculation relies on several assumptions, so our numbers should be viewed as only suggestive.

The standard definition of TFP is as a Hicks-neutral shifter of a production function—that is, the value A in the value-added production function $Y = Af(K, L)$, where Y is value added, K is capital, L is labor, and $f(\cdot)$ is a function relating inputs to output. A value added production function essentially assumes gross output is a Leontief combination of value added and materials. In other words, intermediate materials are a fixed proportion of gross output. While this is not always a reasonable assumption, arguably it is here, given the relatively short horizon and the nature of the product and process.

One can show (see the discussion in Syverson 2011, for example) that the following is a first-order approximation to the logarithm of any general production function of the form above:

$$y = a + \alpha_K k + \alpha_L l,$$

where lower case letters denote natural logs of the corresponding uppercase variable, and α_K and α_L are respectively the shares of value added paid to capital and labor inputs. Rearranging and differencing across time gives an expression for TFP growth:

$$\Delta a = \Delta y - \alpha_K \Delta k - \alpha_L \Delta l.$$

The plant's quantity of capital is fixed over the production year, so $\Delta k = 0$. Therefore TFP growth depends on the difference between the growth rate of value added and the properly weighted contribution of the labor growth rate:

$$\Delta a = \Delta y - \alpha_L \Delta l.$$

To obtain a measure of TFP growth over the production year, then, we need to determine three numbers: the change in labor input, labor's share of value added, and the growth in value added.

The only change in average labor was the addition of the second shift. While the number of line workers doubled when the second shift was added, fewer nonproduction workers were necessary to cover the second shift than the first. Based on discussions with plant management, we know that adding a second shift raised employment at the plant by about 80 percent. This is an increase in natural logs of $\Delta l = 0.59$.

While we do not have information on labor's share of value added α_L at our particular plant, we can obtain an estimate from the NBER-CES Manufacturing Industry Database (we use an updated "beta" version of the data that extends to 2005). Over 2000-2005, payments to labor (measured as the total wage bill including benefits) averaged 21 percent of value added (revenues minus expenditures on intermediate materials) in the automobile manufacturing industry, NAICS 336111.

Value added growth has two components: the average quality of cars rose as defects fell over the year, and the quantity of cars produced per unit time—and therefore per worker-hour—increased. We cannot directly measure the value added implications of the quality improvements we observe, but our estimate of the relationship between defects and warranty payments above does offer some guidance. There, we found the roughly 65 defect-per-car drop in average defect rates over the production year resulted in about \$26.50 less in warranty payments over the first nine months of the warranty. If we assume—probably conservatively— that warranty payments are uniformly distributed across the typical 36-month warranty period, the drop in defects corresponds to a \$106 increase in profit per car. If we were to want to focus only on defect reductions during the initial seven week period in which only one shift was running, and therefore while the plant's labor inputs were held fixed, the roughly 50 defect-per-car drop in defects corresponds to an \$82 increase in profit per car (again, these are lower bound estimates, as they do not reflect the profit effects of what are likely substantial changes in consumers' willingness to pay due to quality differentials).

To benchmark these figures against average value added per car, we again work off the NBER-CES Manufacturing Industry Database. It indicates that industry value added as a share of revenue averaged 29 percent over 2000-2005. For the three model variants built at the plant in our year, the manufacturer averaged in the neighborhood of \$20,000 in revenue per car, implying an average value added of \$5800. Thus at the very least, quality improvements over the course of the first seven weeks of production raised value added per unit by about 1.4 percent (= \$82/\$5800) and by 1.8 percent (= \$106/\$5800) over the entire production year.

In quantity terms, the gains are enormous. Average daily production over the first three weeks of the year was roughly 53 cars. In the three weeks prior to the start of the second shift, this was 235 cars, a 4.5-fold increase. Average daily production was 820 cars in the last three weeks of the year, over 15 times its initial level.

Therefore in quality-equivalent value added units, production grew from 53 cars per day in the first three weeks to 238 per day (= 235*1.014, to reflect the increase in quality) just before the second shift started, and to 835 (= 820*1.018) per day at the end of the year. This implies changes in logged value added of 1.50 during the period Shift 1 was operating exclusively and 1.25 over the remainder of the production year, for a total change of 2.75.

Putting everything together, the implied change in logged TFP over the early seven week period in which only Shift 1 operated was $\Delta a = \Delta y - \alpha_L \Delta l = 1.50 - 0.21*0 = 1.50$. This corresponds to a 4.5-fold increase in value added per unit input ($e^{1.50} = 4.48$) in just a few weeks. The remainder of the year saw logged TFP growth of $\Delta a = 1.25 - 0.21*0.59 = 1.13$; value added per unit input was over 3 times its level when the second shift started. Total logged TFP growth for the production year was Δa = 2.75 – 0.21*0.59 = 2.63, an almost 14-fold increase in TFP.

We saw in Section V that line workers retain little of the learning by doing knowledge stock, though there is evidence from the effects of absenteeism that a small quantity of the productivity gains calculated here could still be attributed to knowledge embodied in the workers themselves. We estimated that defect rates would be about 1 percent lower if absenteeism were cut to its 25th percentile level. This value, extrapolated somewhat generously, suggests perhaps around 2 percent of the reductions in defects were attributable to worker-embodied learning. Given that value added TFP growth tied to defect reductions from any source was a bit under 2 percent, the knowledge that was retained by the workers accounted for a very small 0.04 percent of quality-based TFP growth. Quantity-based TFP growth was much larger, however. Perhaps worker-embodied knowledge played a bigger role through that channel.

To address this, we estimated a similar specification to the one above relating defect rates to absenteeism through forgetting. Now, however, we measure the influence on the average number of hours required to build a car. The results indicate that reducing absenteeism to its 25th percentile level would reduce build time by about 3 percent. Again extrapolating generously, maybe around 6 percent of the increase in number of cars per unit time is tied to worker-embodied learning. Since quantity increases dominate the calculated TFP growth numbers above, we approximate that about the same 6 percent of total TFP growth at the plant is due to knowledge retained exclusively by the workers. This is a small fraction, but given that TFP grew 14-fold over the year, the worker component accounts for about an 80 percent increase in TFP.

The massive TFP changes at the plant are much larger than typical year-to-year TFP growth among manufacturing plants (see, for example, Bartelsman and Doms (2000)). Those calculations typically use output and input values averaged over an entire year's operations. In contrast, the changes here all occurred within a single year, and indeed the fastest TFP growth occurred in a matter of a few weeks. This variation during the ramp up period would be averaged over in a TFP analysis using typical production microdata. Perhaps this aggregation is appropriate, as short-run gains during a plant's ramp up process, while large relative to a small base level, may be less consequential in terms of a firm's (or industry's, or economy's) overall performance. A similar argument might be made about the substantial increase in labor input associated with Shift 2 coming on line; again, this would be aggregated over in standard data. In any case, the analysis reveals that implied TFP growth at the beginning of a learning process can be enormous.

More enduring, however, are the TFP gains tied to the increase in quality. We know from discussions with plant engineers that most of the improvements in defect rates made during one production year are carried over to the next, as long as there are no major redesigns of the vehicles assembled at the plant. Hence the following year's production at the plant will start near quality levels that our sample year finishes at. Even in the absence of any differences in the average quantity of cars produced or employees at the plant in the following year, then, one will observe increases in quality-adjusted TFP from our sample year to the following year.

B. Implications and Directions for Future Research

We have used detailed data from an auto assembly plant to explore the nature of the learning by doing process and the knowledge stock that it builds. We find substantial learning in both quality-based and unit-cost-based productivity terms. The patterns look qualitatively similar to those seen in dozens of empirical studies documenting learning by doing in various production settings (though this work has tended to focus on unit-cost-based productivity measures). This broader literature has led learning by doing to become a trademark in theories explaining multiple features of modern economies like comparative advantage, industry life cycles, and sources of innovation and technical change.

What has often been missing from the literature, however, is specific information about the knowledge built through the learning process: how it is acquired, aggregated, transmitted and, eventually, embodied in a producer's inputs. Our detailed data allows us to offer new insights along these lines. We find several data patterns that indicate the knowledge obtained through learning by doing at the plant is by and large not retained by the plant's workers. These patterns are consistent with what we know about the operation of the plant's institutionalized systems for productivity improvement. Some of these systems bypass line workers altogether, while others are designed to quickly convey the knowledge obtained by line workers into the plant's physical and organizational capital. We also explore how the overall learning by doing productivity gains are undergirded by what happens at the hundreds of individual processes involved in a complex production operation. We find that process-specific defect rates are both highly skewed and persistent, and that the probability of a defect occurring at any given process drops at essentially the same rate regardless of how initially defect-prone the process was.

Beyond their theoretical and empirical relevance, our findings have managerial implications. In modern economies, shortening development times and fostering process improvements represent key drivers of success. Understanding the sources of learning by doing, rather than assuming that they are exogenous, provides managers with an important tool to achieve both high production rates and a high level of utilization earlier in the ramp up process. More research on the complementarities between the learning process and managerial practices, including both studies of existing behaviors among producers and through running experiments in the field, seem to us to have high expected returns.

We close by noting that our results reflect the learning process at one particular plant, in one particular industry (though an important one), and in one particular time. Thus our study shares the issue of generalizability with most of the rest of the learning by doing literature. Nevertheless, we believe the results here offer insights that can be cautiously extended directly to other production operations, particularly complex manufacturing processes. Better models of the microelements of the learning process could offer a theoretical guide to which particular aspects of production processes might offer the most general takeaways. Even when direct extension is not warranted, however, the results here can be used to direct future research on learning by doing.

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Figure 1. Average Defect Rates per Car

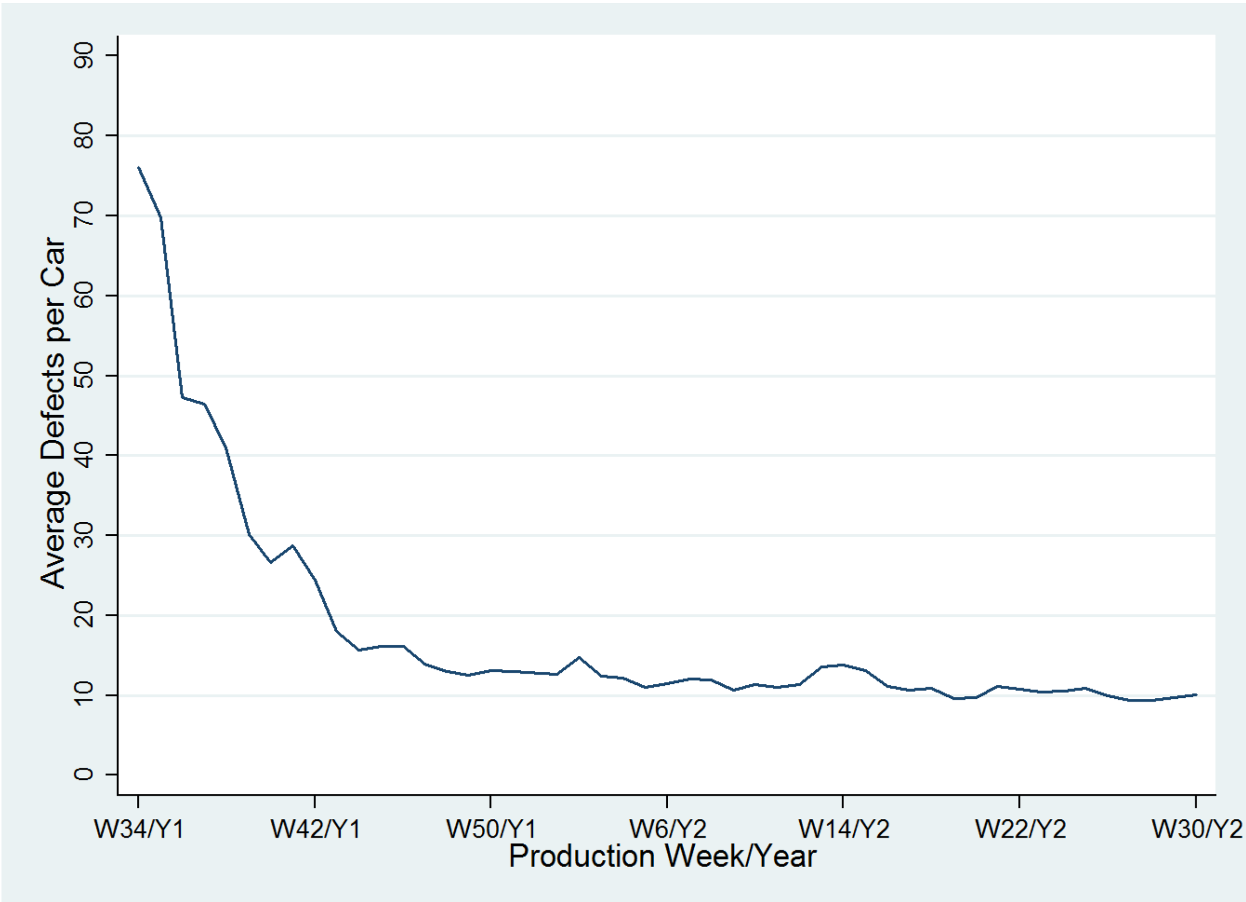


Table 1. Estimates of Learning by Doing Power Law Specification

A. Weekly Data

	[1]	[2]	[3]
Estimated learning rate (β)	-0.289*	-0.336*	-0.299*
	(0.007)	(0.017)	(0.024)
Time trend		0.007*	
		(0.002)	
Retention parameter (δ)			0.965*
			(0.021)
N	47	47	47
R^2	0.961	0.969	0.962

B. Daily Data

	[1]	[2]	[3]
Estimated learning rate (β)	-0.306*	-0.369*	-0.363*
	(0.006)	(0.014)	(0.013)
Time trend		0.001*	
		(0.0002)	
Retention parameter (δ)			0.985*
			(0.002)
N	224	224	224
R^2	0.931	0.943	0.944

Notes: These panels show the results of estimating power law learning by doing specifications of the type $S_t = AE_t^{\beta}$, where S is productivity at time t (average quality in our case), E_t is production experience up to that point, and A and β are parameters. In columns 1 and 2 of both panels, production experience is the cumulative number of cars produced before the current period. In column 3, the production experience stock is built up by a perpetual inventory process where experience at the beginning of the period is a fraction δ of experience at the start of the prior period plus production in the prior period. See text for details. Heteroskedasticity-robust standard errors in parentheses. An asterisk denotes significance at the five percent level.

Figure 2. Log Defects per Car vs. Log Production Experience (Cumulative Output), Daily Data

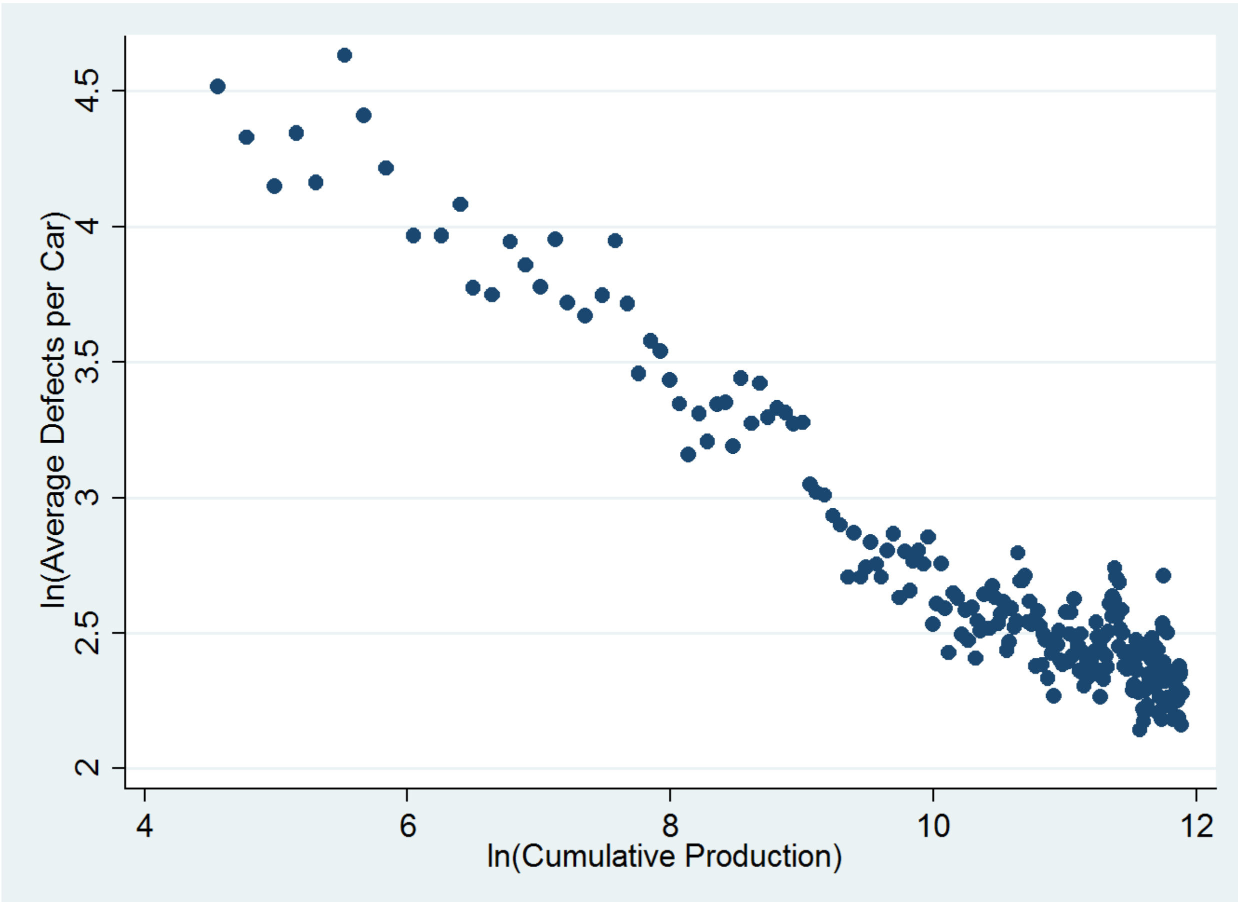


Figure 3. Average Hours Required to Assemble a Car

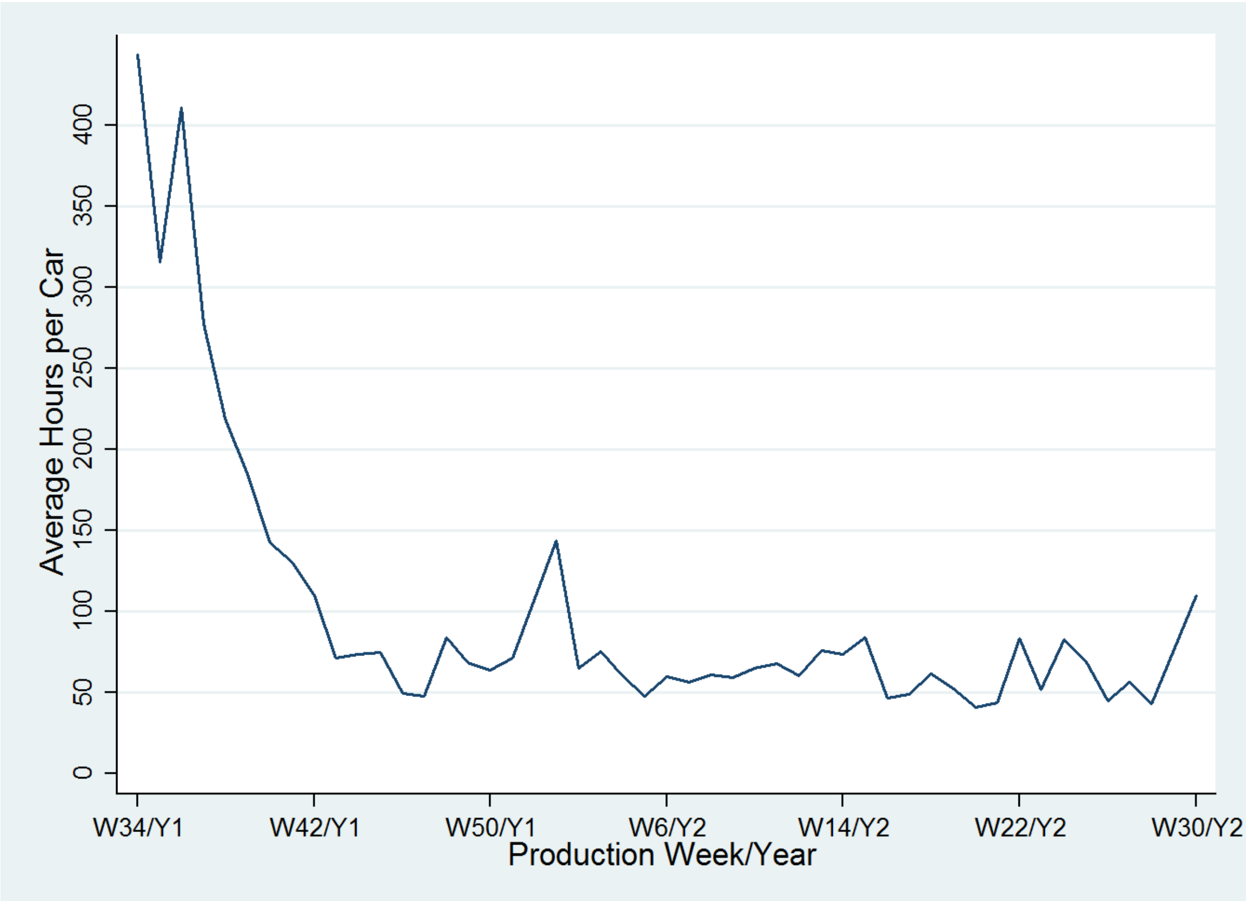


Figure 4. Average Quality Audit Scores per Car

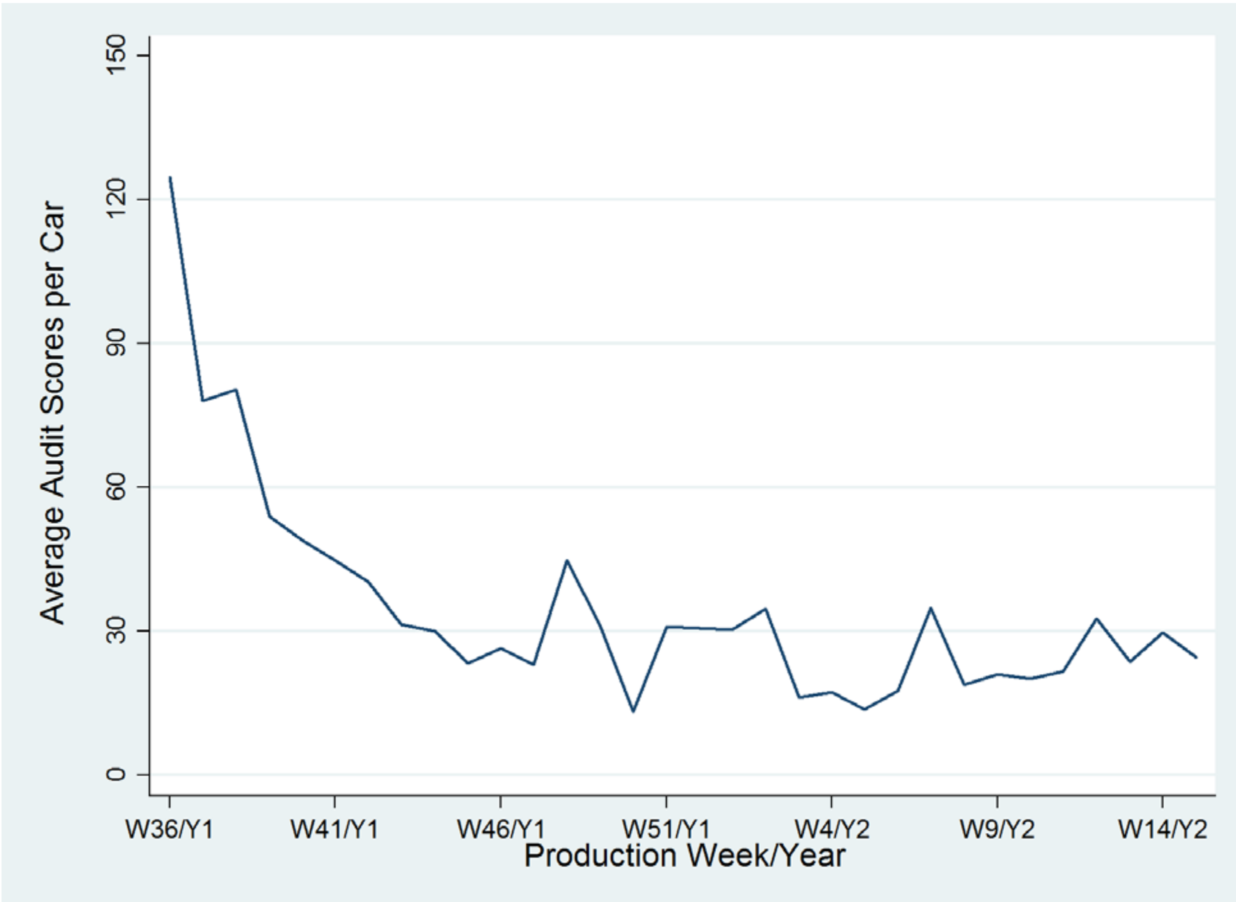


Figure 5. Average Defect Rates per Car, by Shift

Table 2. Shift-Specific Learning by Doing and Ramp-up Spillovers

A. Shift-Specific LBD

	Weekly First Shift	Daily First Shift	Weekly Second Shift	Daily Second Shift
Estimated learning rate (β)	-0.323*	-0.346*	-0.154*	-0.094*
	(0.010)	(0.008)	(0.011)	(0.021)
N	47	224	39	190
R^2	0.946	0.907	0.782	0.158

B. Shift-Specific LBD, IV Specifications

	Weekly First Shift	Daily First Shift	Weekly Second Shift	Daily Second Shift
Estimated learning rate (β)	-0.282*	-0.330*	-0.152*	-0.094*
	(0.042)	(0.024)	(0.011)	(0.021)
N	39	190	39	190

C. Ramp-Up Spillovers

	Weekly First Shift	Daily First Shift
Estimated learning rate (β)	-0.321*	-0.345*
	(0.010)	(0.008)
Second Shift Ramp-Up	0.041	0.017
	(0.076)	(0.041)
N	47	224
R^2	0.947	0.907

Notes: These panels show the results of estimating power law learning by doing specifications of the type $S_t = AE_t^{\beta}$ separately for each shift and where experience is shift-specific. Panel B instruments for a shift's production experience E_t with the production experience of the other shift. Panel C adds an indicator variable for the period in which second-shift production ramps up. See text for details. Heteroskedasticity-robust standard errors in parentheses. An asterisk denotes significance at the five percent level.

Figure 6. Average Hours Required to Assemble a Car, by Shift

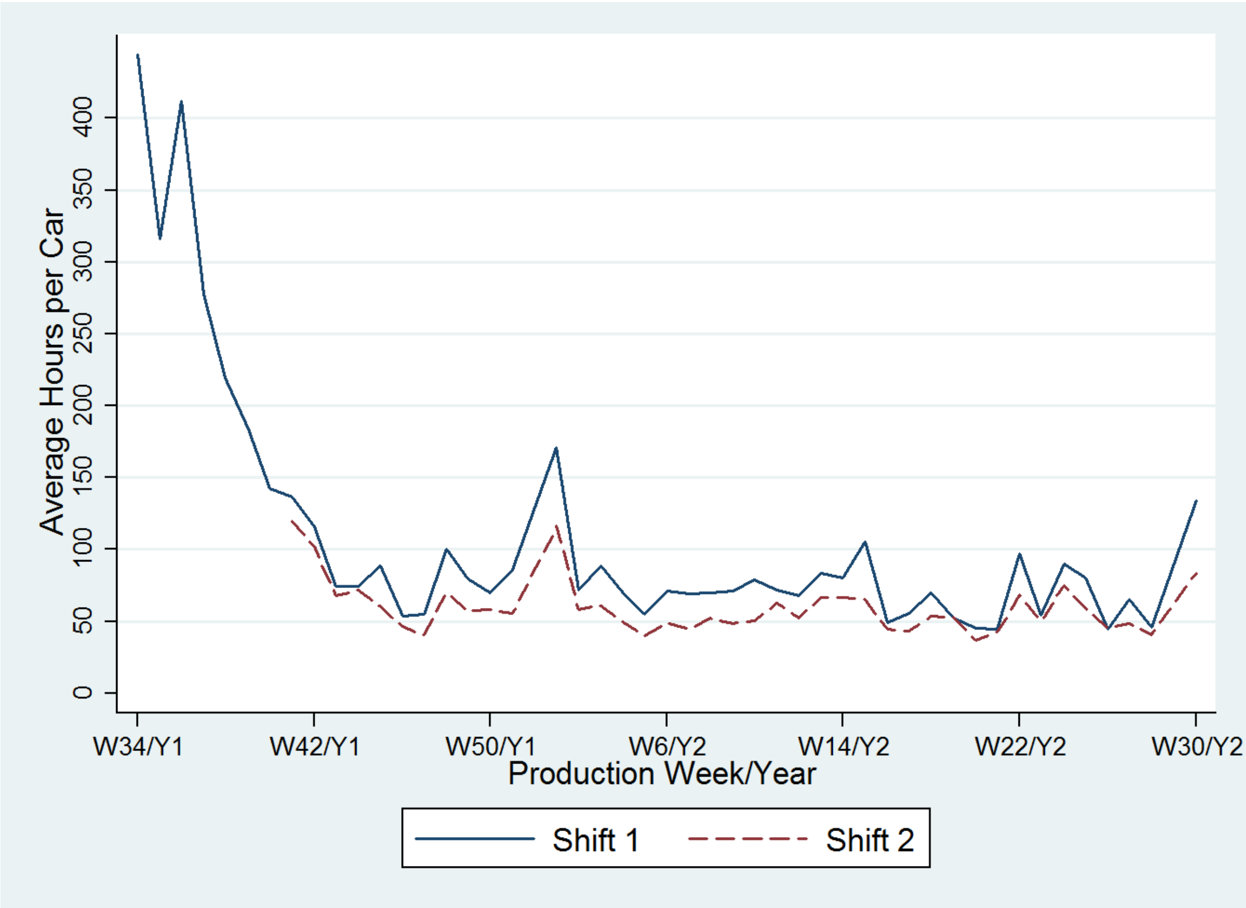


Figure 7. Average Defect Rates per Car, by Model Variant

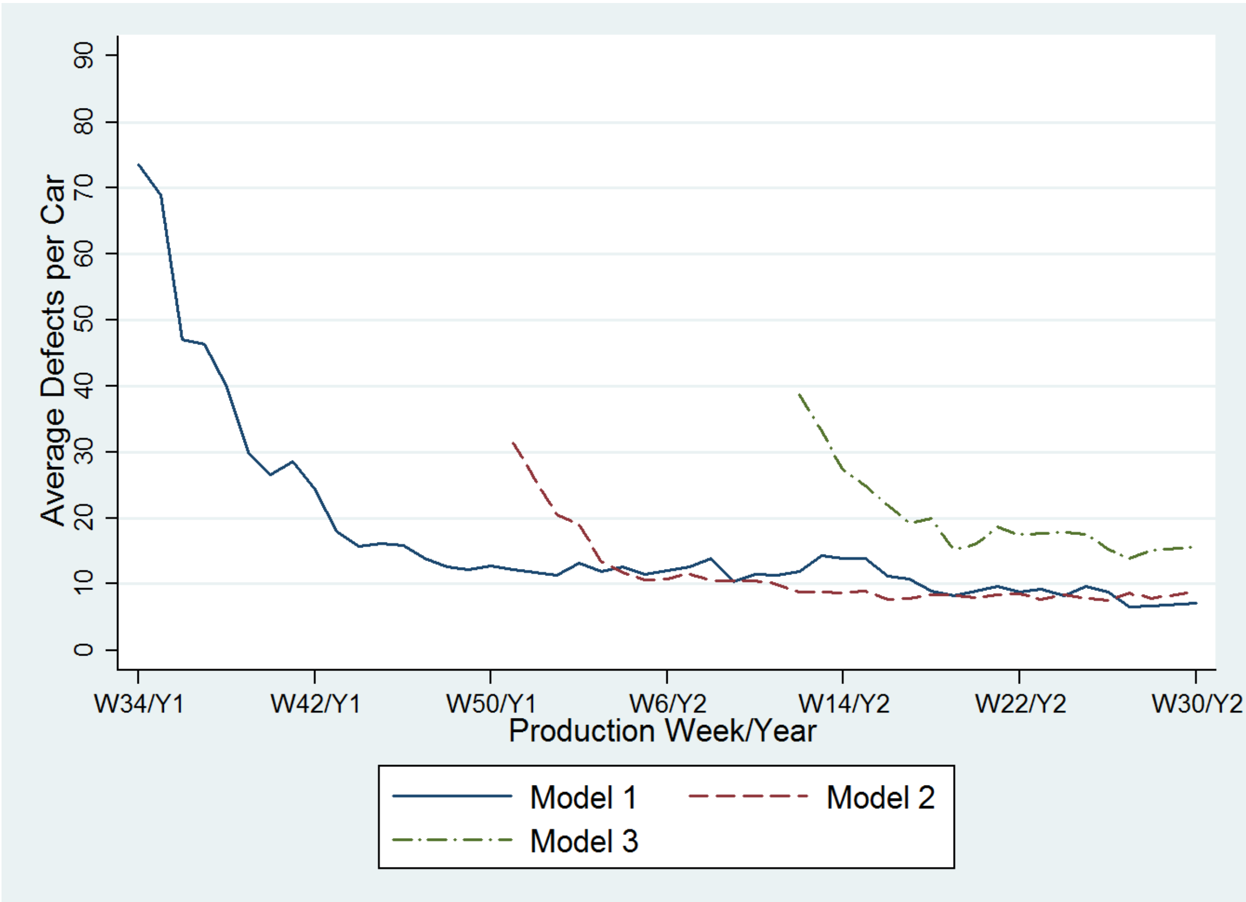


Table 3. Model-Specific Learning by Doing and Ramp-up Spillovers

A. Model-Specific LBD

	Weekly Model 1	Daily Model 1	Weekly Model 2	Daily Model 2	Weekly Model 3	Daily Model 3
Estimated learning rate (β)	-0.333*	-0.356*	-0.189*	-0.203*	-0.219*	-0.241*
	(0.014)	(0.009)	(0.014)	(0.014)	(0.010)	(0.012)
N	47	224	30	142	18	86
R^2	0.926	0.880	0.939	0.779	0.923	0.801

B. Ramp-Up Spillovers

	Weekly Model 1	Daily Model 1	Weekly Model 2	Daily Model 2
Estimated learning rate (β)	-0.342*	-0.365*	-0.188*	-0.202*
	(0.015)	(0.010)	(0.014)	(0.014)
Model 2 Ramp-Up	0.068	0.071*		
	(0.042)	(0.029)		
Model 3 Ramp-Up	0.289*	0.285*	-0.032	-0.040
	(0.060)	(0.046)	(0.018)	(0.024)
N	47	224	30	142
R^2	0.941	0.894	0.940	0.780

Notes: These panels show the results of estimating power law learning by doing specifications of the type $S_t = AE_t^{\beta}$ separately for each model variant and where experience is model-specific. Panel B adds indicator variables for periods in which production of later variants ramps up. There are no such regressions for Model 3 as no new variant is introduced after it. See text for details. Heteroskedasticity-robust standard errors in parentheses. An asterisk denotes significance at the five percent level.

Table 4. Across-Shift, Within-Week Station Defect Quintile Correlations

		Station's Second Shift Quintile in Week				
		1st	**2nd**	**3rd**	**4th**	**5th**
Station's First Shift Quintile in Week	**1st**	15.2	5.4	2.8	1.3	0.5
	2nd	7.2	3.1	2.5	1.4	0.5
	3rd	5.0	4.3	5.7	4.7	1.6
	4th	1.5	2.0	4.0	7.2	4.3
	5th	0.5	0.5	1.4	4.6	12.7

Notes: This table shows the percentage of production line stations in each quintile of the shift-week's defect rate distribution. For example, 15.2 percent of stations in the first quintile of the first shift's defect rate distribution during the week (i.e., those with the lowest defect rates) were also in the first quintile of the same week's distribution for the second shift. Another 5.4 percent were in the first quintile of the first shift but the second quintile of the second shift that week, and so on. (Row and column sums aren't always exactly 20 percent because of ties.)

Figure 8. Average Weekly Absentee Rates

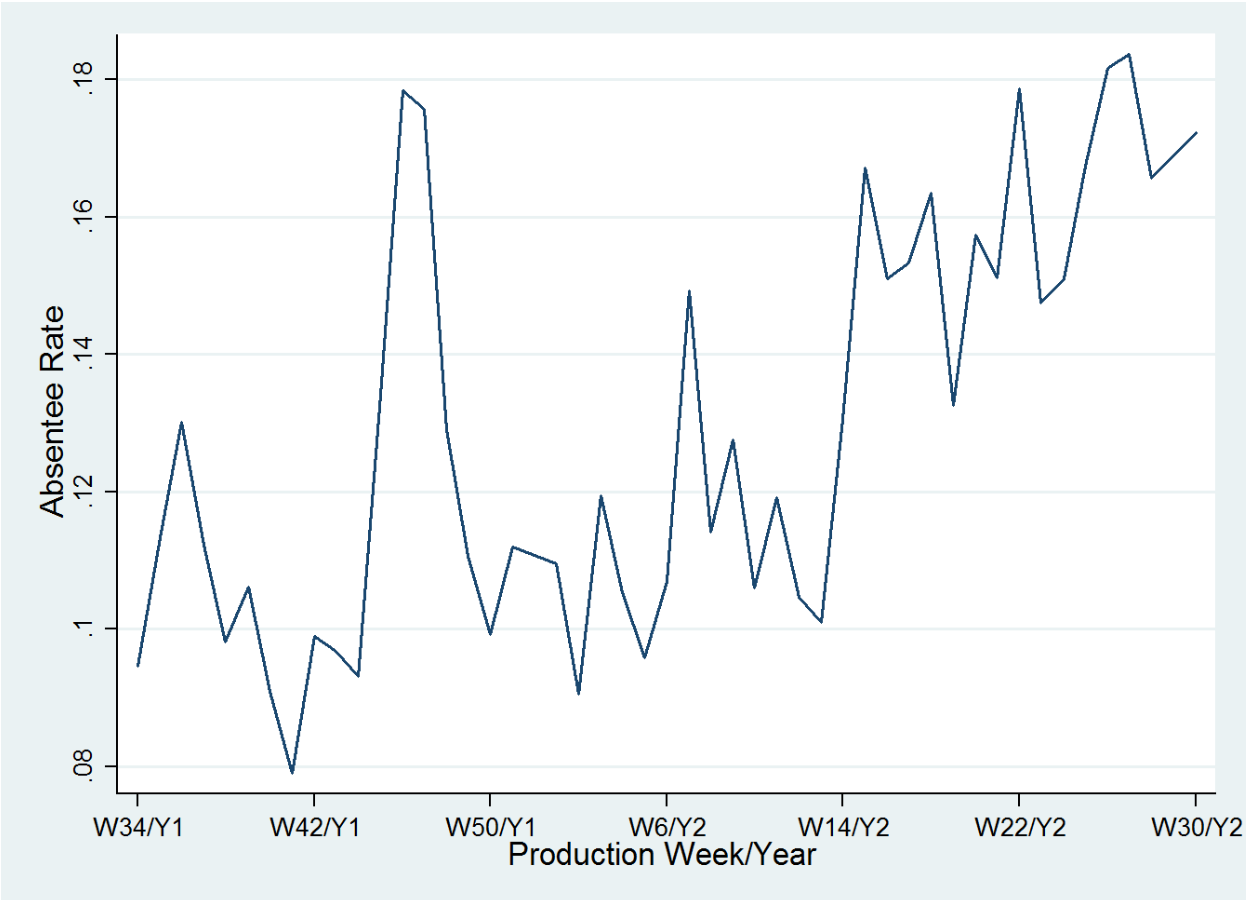


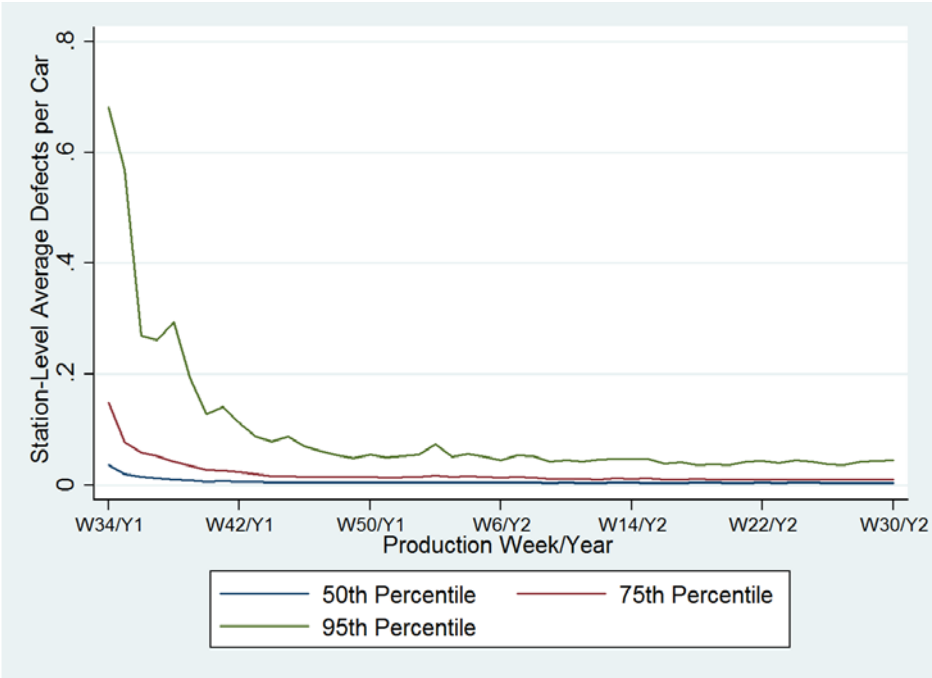
Table 5. Worker Absenteeism Rates and "Forgetting"

	Weekly Data	Daily Data
Estimated learning rate (β)	-0.297*	-0.338*
	(0.018)	(0.008)
Absences on retention (γ)	0.258*	0.070*
	(0.055)	(0.010)
N	47	224
R^2	0.961	0.941

Notes: This table shows the results of estimating power law learning by doing specifications of the type $S_t = AE_t^{\beta}$, where S is productivity at time t (average quality in our case), E_t is production experience up to that point, and A and β are parameters. Production experience stock is built up by a perpetual inventory process with a production experience retention rate of δ that is a decreasing function of the absenteeism rate during the production period. See text for details. Heteroskedasticity-robust standard errors in parentheses. An asterisk denotes significance at the five percent level.

Figure 9. Distribution of Station-Level Defect Rates

A. Absolute Levels



B. Levels Relative to Quantile's First-Week Level

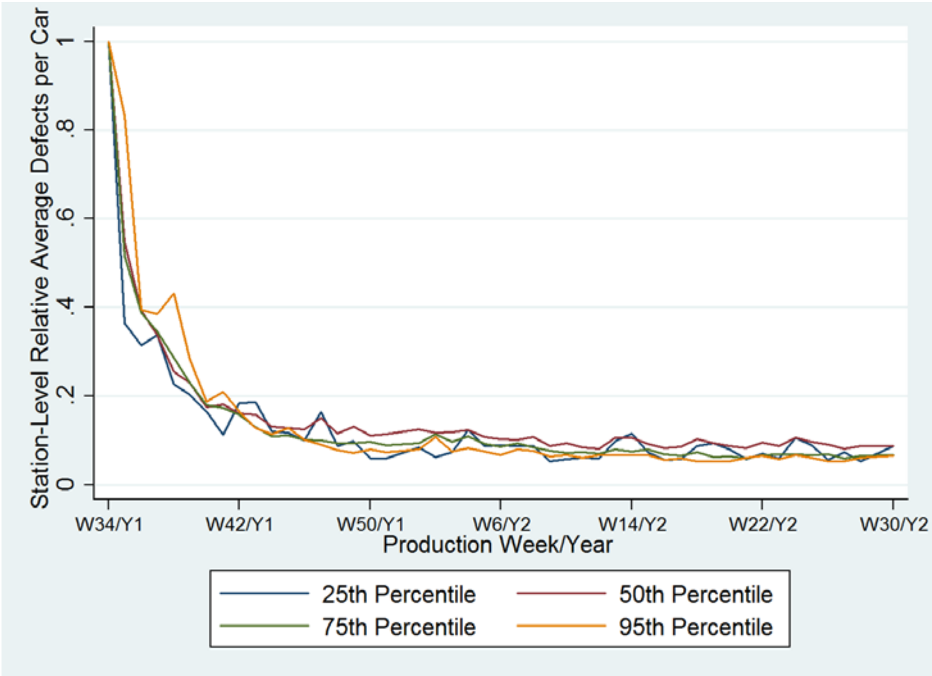
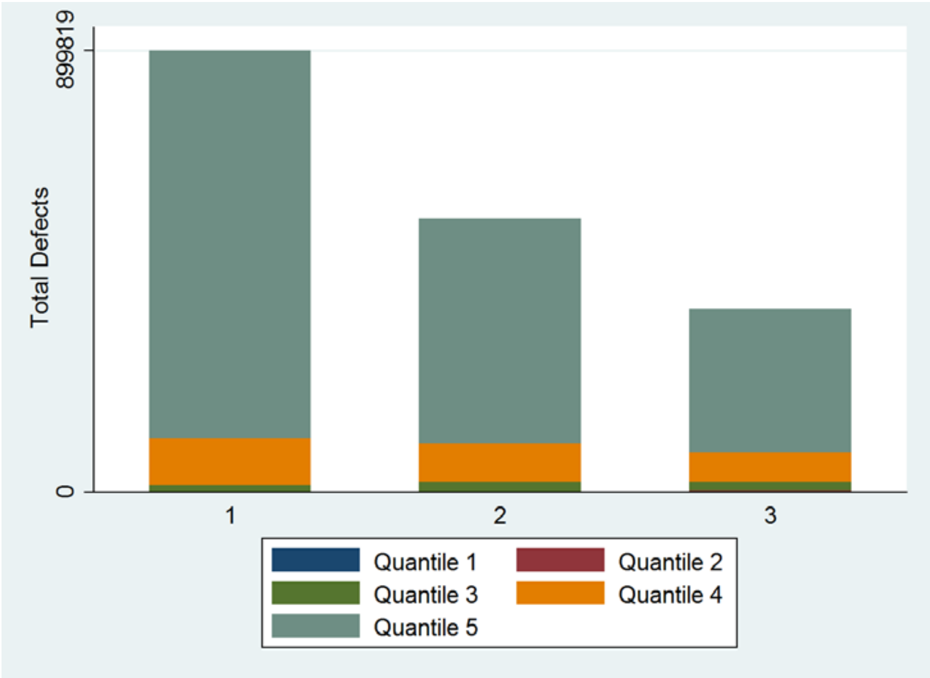


Figure 10. Defects by Station's Quintile in Defect Rate Distribution

A. Levels



B. Proportions

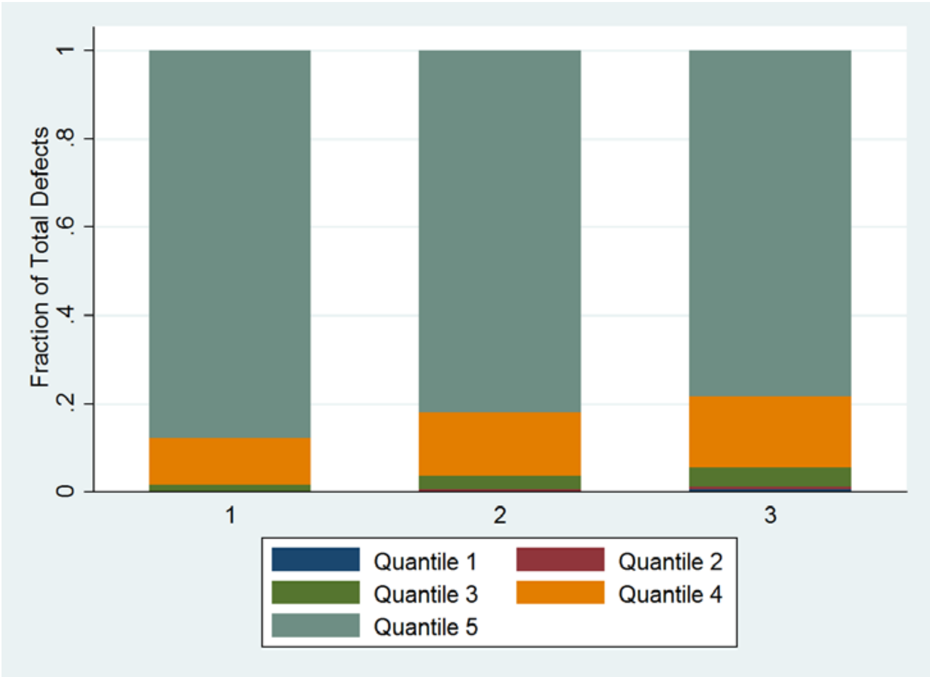
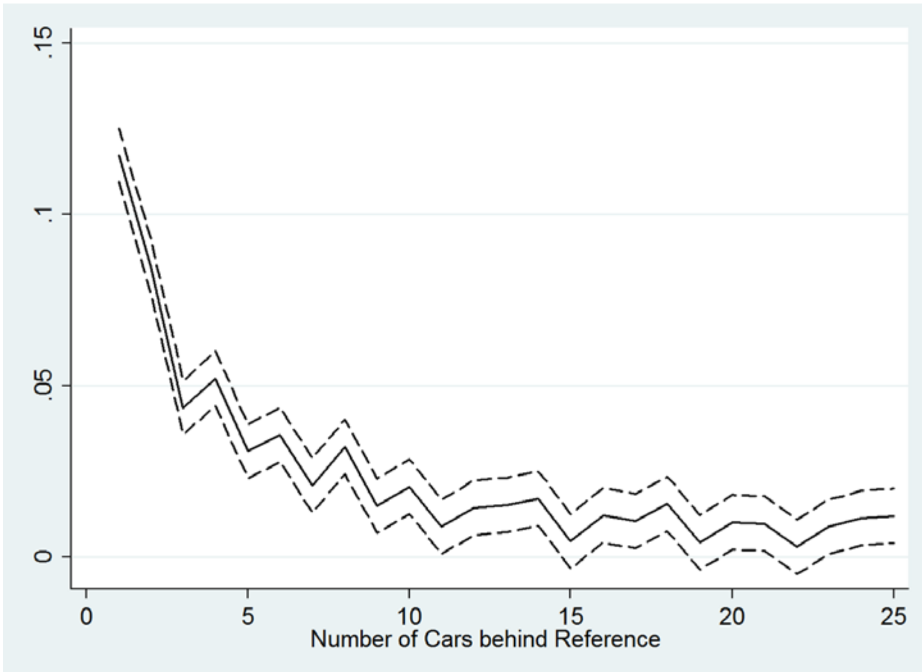


Figure 11. Defect Spillovers across Cars

A. Early Period



B. Middle Period

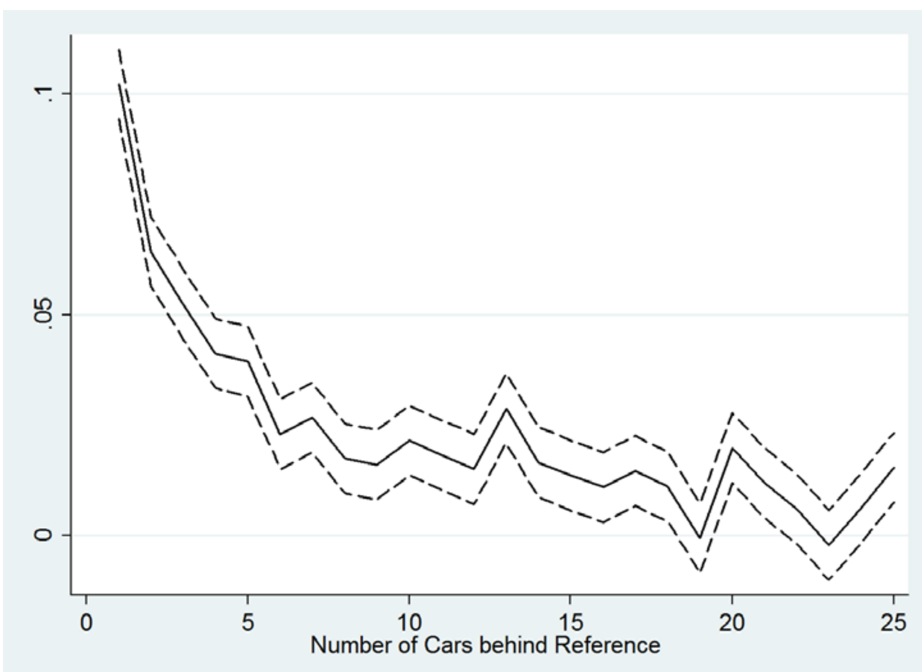
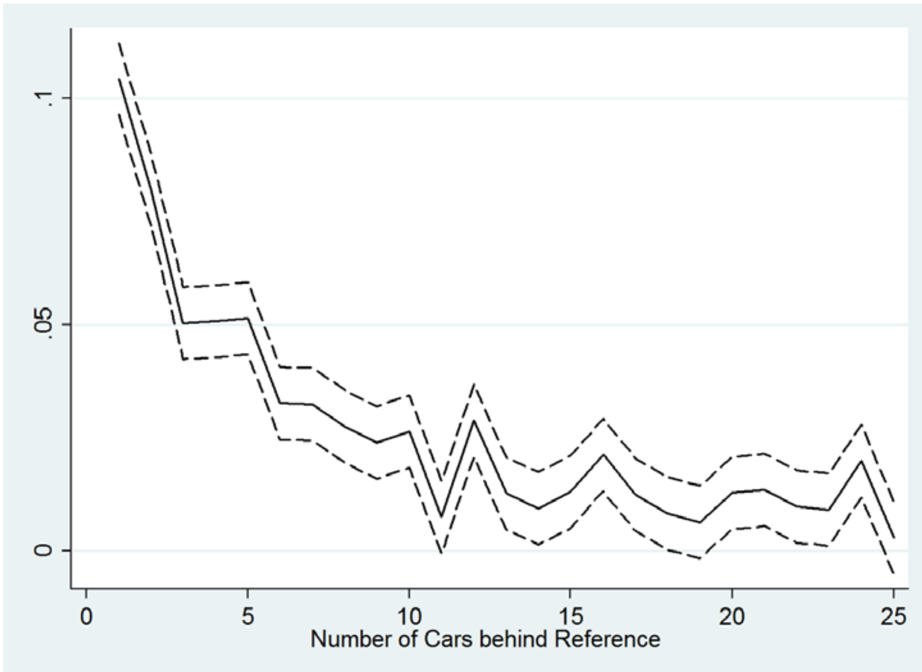


Figure 11 (cont.). Defect Spillovers across Cars

C. End Period



D. Comparison

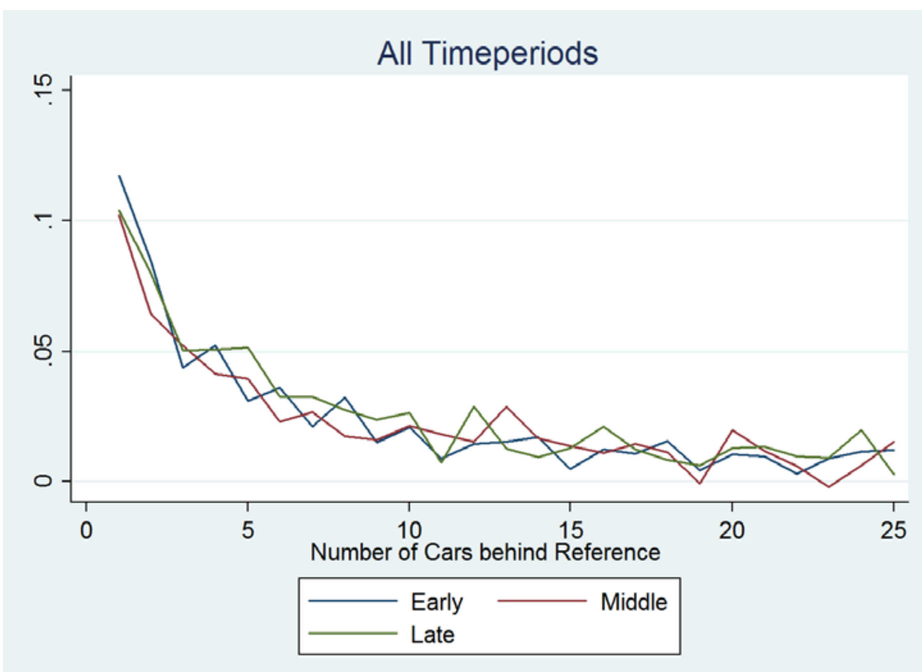


Figure A1. Weekly Production

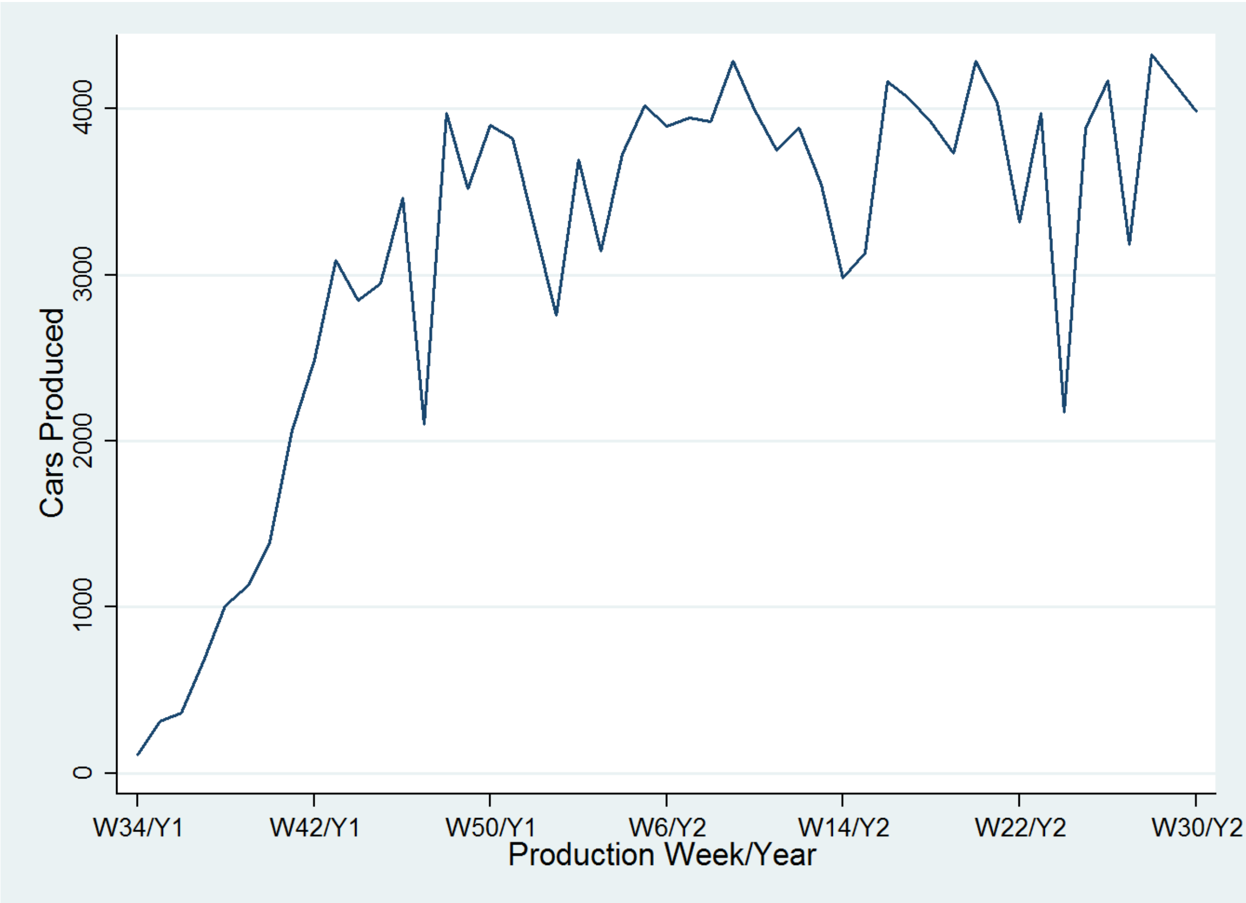


Figure A2. Weekly Production, by Shift

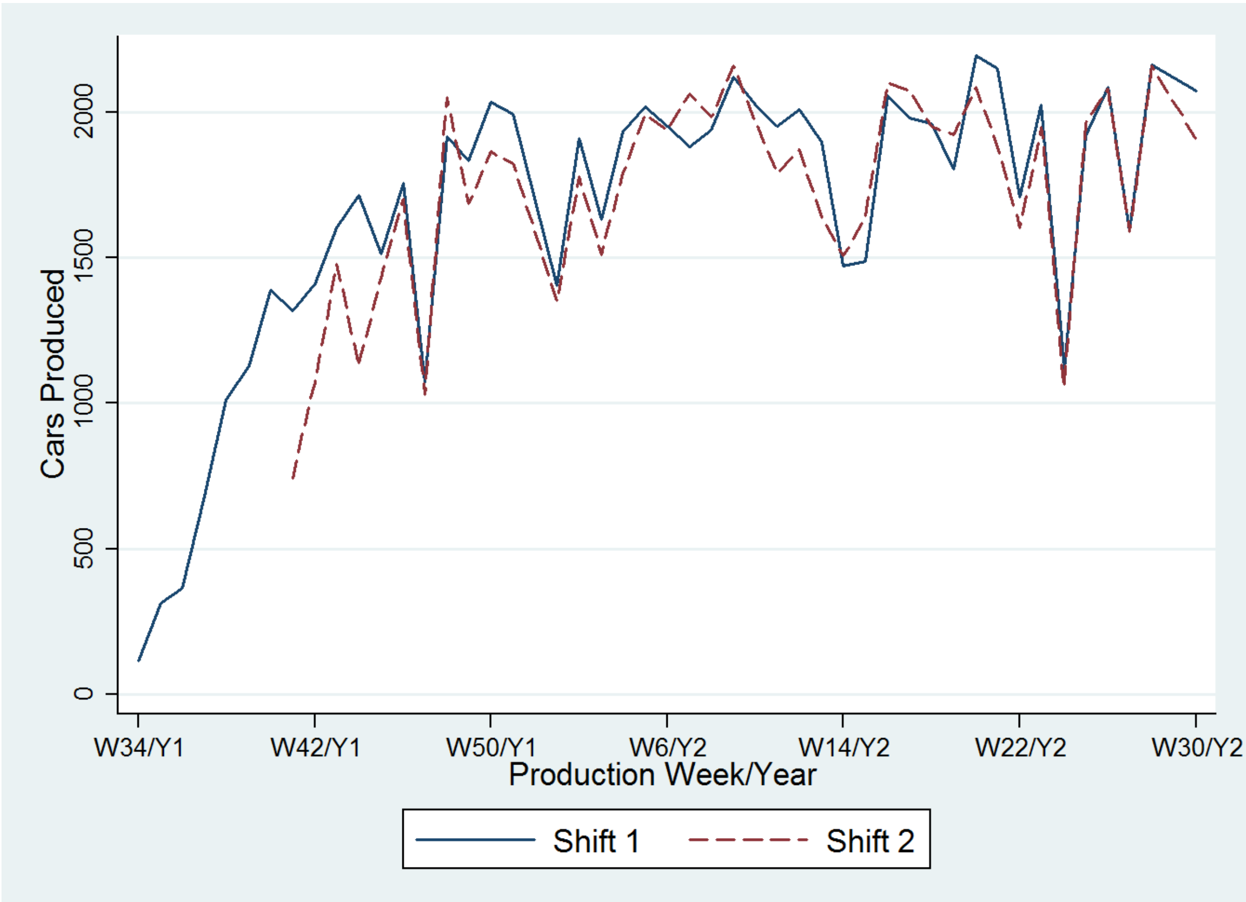


Figure A3. Weekly Production, by Model Variant

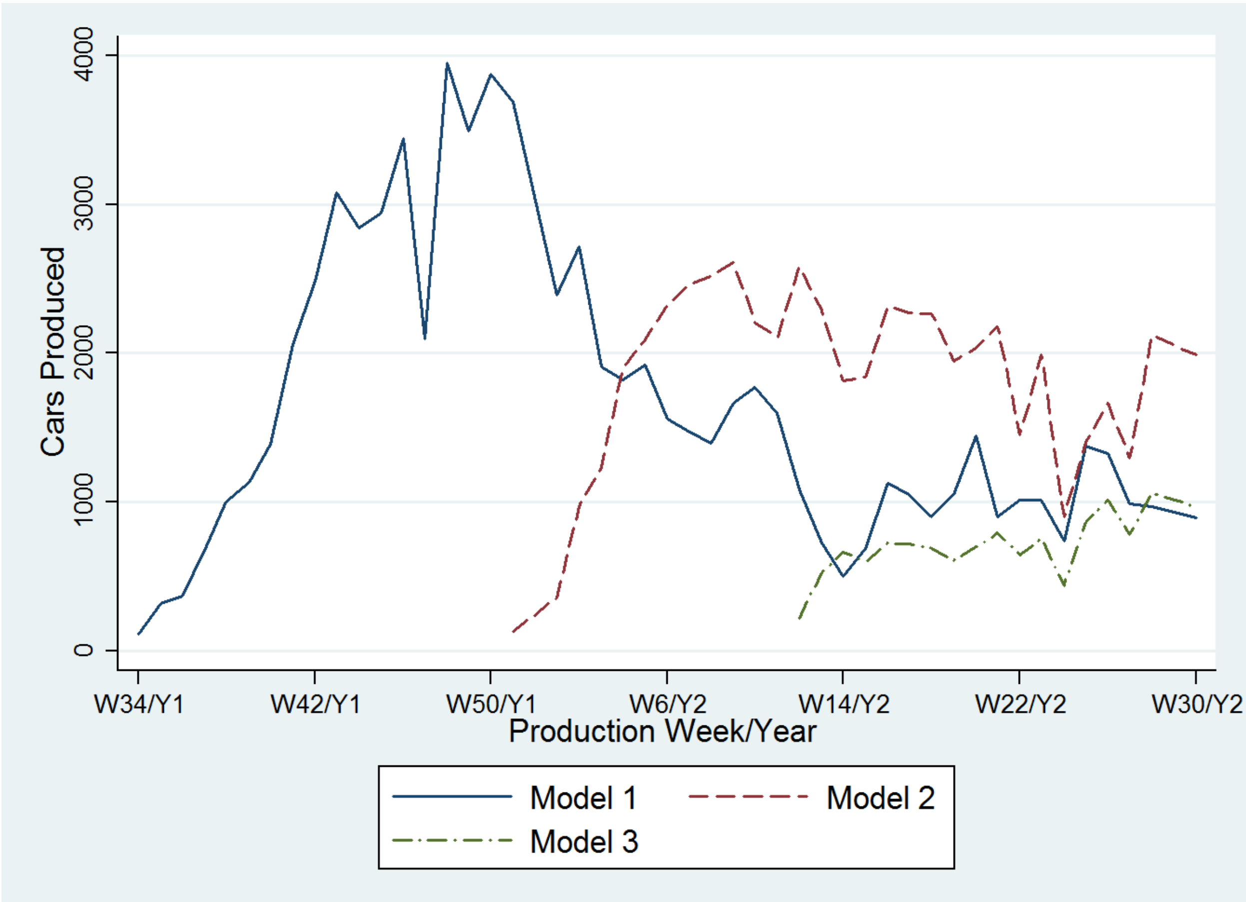


Figure A4. Audit Score Defects by Severity Level