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Abstract
Researchers of industrial relations issues in manufacturing have long recognized that careful study of production has significant implications for laborproductivity. Recent theory and analysis has shown the large influence of organizational forgetting. The authors of this study demonstrate that forgetting by workers in an establishment or line of production as a substantive characteristic of actual production processes is overstated and that alternative, simpler theoretical and empirical explanations have at least as good explanatorypower. Using inside-the-firm analysis, they find that the omitted-variable bias in other studies due to data limitations has the potential for spurious estimatesof large forgetting rates by lines of work. Further, they find that forgetting, although important and interesting, is not as influential as previous work for labor productivity has suggested. Further analysis of the production function and the role of organizational forgetting needs to be fully specified in a model to include internal production and labor relations characteristics, like those in this study, to be a plausible model of the production process withinmanufacturing establishments.

Keywords
industrial relations, firm performance

ORGANIZATIONAL AND INDIVIDUAL LEARNING AND FORGETTING

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Researchers of industrial relations issues in manufacturing have long recognized that careful study of production has significant implications for labor productivity. Recent theory and analysis has shown the large influence of organizational forgetting. The authors of this study demonstrate that forgetting by workers in an establishment or line of production as a substantive characteristic of actual production processes is overstated and that alternative, simpler theoretical and empirical explanations have at least as good explanatory power. Using inside-the-firm analysis, they find that the omitted-variable bias in other studies due to data limitations has the potential for spurious estimates of large forgetting rates by lines of work. Further, they find that forgetting, although important and interesting, is not as influential as previous work for labor productivity has suggested. Further analysis of the production function and the role of organizational forgetting needs to be fully specified in a model to include internal production and labor relations characteristics, like those in this study, to be a plausible model of the production process within manufacturing establishments.

A central consideration in understanding changes in the organization of work in production is the learning curve. An important subset of the learning curve is forgetting, whose theory suggests that decreases in production rates after a product line has been operating will cause the organization to forget some of the process improvements it has learned, resulting in a decline in labor productivity. One area on which much of the fundamental research on learning and forgetting has been done is the production of aircraft (Arrow 1962; Benkard 2000). We explore similar issues using a more in-depth examination of the learning curve. This is of particular importance since approximately 20–25% of total learning in manufacturing could be lost due to organizational forgetting (Benkard *ibid.*). At the macro level, the aggregate cost of recessions with substantially higher unemployment is underestimated if forgetting is an additional cost of lost work time in the economy. For example, those individuals who lose jobs and take similar jobs after a medium to long period of

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unemployment are estimated to lose approximately 25% of their hourly earnings, part of which may be attributed to individual and organizational forgetting how to do tasks; thus, forgetting is an additional economic loss (Von Wachter, Handwerker, and Hildreth 2009). If these economic costs of changes in the production environment are universal in manufacturing or the economy, then researchers of labor and productivity should devote more attention to the issue of organizational and individual learning and forgetting.

In industrial relations, a key element of firm performance—productivity—may be reduced if workers are reallocated across jobs through either employee involvement or cross-training of workers, in addition to layoffs and recalls. Thompson (2001, 2003), however, has questioned some of the results of organizational forgetting in the context of Liberty ship production. In another context, estimates of the return to full productivity following a strike or work-to-rule slowdown tended to be small with little evidence of organizational forgetting following a three-month strike (Kleiner, Leonard, and Pilarski 2002). Our objective in this study is to provide additional evidence on these phenomena with better data within an aerospace manufacturing establishment and a more fully specified model.

The concept of organizational knowledge is a difficult one to observe empirically. Whether embedded in production by line workers, line management, or executives, organizational knowledge is idiosyncratic. The "shop floor knowledge" attributed to the organization is passed on between individuals as job responsibilities change but remains behind as part of the manufacturing process. Nevertheless, that which is individual learning or forgetting, and that which is intrinsic to the organizational entity, resides in the same individuals and are manifest in the same data as the overall productivity of labor. In the analysis of human capital, organizations may be subject to similar outcomes in which investments in learning can be accompanied by depreciation of skills when individuals are out of the workforce (Polachek 1975).

According to Cappelli's (2000) empirical analysis of the issue, when production ceases for any period of time, high levels of organizational forgetting occur, and memory loss actually increases exponentially as production slows down (Argote, Beckman, and Epple 1990; Darr, Argote, and Epple 1995; Benkard 2000). At the same time, we call into question previous outcomes of organizational forgetting analysis by more thoroughly modeling the production function when labor in production and industrial relations events are the key elements, and by adding more detailed data in the manufacturing of commercial aircraft.

Theory of the Learning Curve in Manufacturing

The learning curve in aircraft production has been observed and estimated over a long period of time beginning in the 1920s and 1930s (Wright 1936). In the post World War II period, a number of studies, including military ones, were published, and the learning curve analysis was extended to other types of manufacturing (Hirsch 1952; Asher 1956; Alchian 1963). Arrow's (1962) exposition entitled "Learning by Doing" set the standard behavioral model that has defined the starting point for research on the issue. Arrow's model postulated the important assumption that learning is a function of the experience level of the factory (worker) and can be written as follows:

$$L_i = \theta E_i^{\varphi}, \tag{1}$$

where L_i is the number of labor hours required to produce i units, θ and φ are constants, i is the ith unit produced, and E_i is the cumulative number of units produced through unit $i - 1$.

The behavioral assumptions in this model are that individuals—and perhaps, through them, the organization—learn by the repetitive performance of essentially the same tasks. If one assumes that all workers are homogeneous in their capacity to learn, then the two parameters characterize the learning environment and fix the learning curve in the (E_i, L_i) space. For example, an increase in φ (smaller negative) would represent a flatter learning curve of an environment or process that lent itself to a slower absorption of knowledge with the production, E. The parameter θ is a positional parameter representing the location of the learning curve in the (E_i, L_i) space and essentially generates the cost of the particular process given the amount of cumulative production. Two processes with identical characteristics with respect to the potential rate of learning might differ greatly in cost if one of the processes were to present obstacles to learning while the other did not.

The Arrow model assumes the production rate to be constant so that the E_is are spaced out evenly in time and further that the good being produced is homogeneous through the production process. These two assumptions were not far from correct in the early manufacturing of aircraft, particularly the wartime production of military aircraft, in which the production rates tended to be dictated by capacity and each plane was the same. These assumptions are not valid in the production of commercial aircraft, however, in which there is much customization for each individual buyer and fluctuations in the demand for aircraft are significant. Additionally, in earlier work productivity was presumed to be isolated from and not due to economies of scale. Again, with production at capacity throughout the data set, the issue of economies of scale was not a factor.

Earlier studies of the learning curve found it to be a robust concept; thus little change was made to the basic model. These studies found a wide variety of theoretical and empirical functions in developing the learning curve for labor (Rapping 1965; Black, Krivelyova, and Lynch 2004). The point here is not to provide a complete survey of the literature, but to demonstrate that over time, researchers have found a myriad of effects, each of which shifts the learning curve's location and shape (θ and φ) and each of which has some empirical validity.

A large part of the learning curve literature has focused on both individual and organizational learning and forgetting (Globerson and Levin 1987). These models suggested both that one should incorporate forgetting into the learning curve model and that turnover rates and time between repetitions (individual forgetting) and communication and documentation (organizational forgetting) were factors to be considered.

A Model of Organizational Forgetting

We extend a model developed by Benkard (2000), whose study has been instrumental in generating new research on organizational forgetting and can be used to provide a contrasting approach to our model. Benkard presented a modification of the traditional production learning curve to account for the impermanence of knowledge. The microeconomic theory in our study is based upon classic production functions and assumes, as do previous studies, parametric learning curves such as those derived under constant production levels. The analysis modifies Benkard's model by the introduction of a shift variable (S) for line speed to account for changes in production rates. He expanded and modified the basic model by embedding the experience variable in a theoretical production function (i.e., a Leontief class of production functions) and incorporating the concept of depreciation of knowledge in the experience variable E according to the following:

(2) $$E_t = \lambda E_{t-1} + q_{t-1},$$

(3) $$E_1 = 1.0,$$

(4) $$E_i = E_t \text{ all } i \text{ produced at } t,$$

$$\log(L_i) = A\log(K_{i,t}) + \theta\log(E_i) + \gamma_0\log(S_i) + \varepsilon_i, \tag{5}$$

where E is a measure of the standard labor unit cost of production (e.g., this would include the hours used to produce the plane), q_t is the production level in time t, and λ is the depreciation coefficient. $1 - \lambda$ represents organizational forgetting, L is labor hours, K is capital, and S is the line speed.

The increases or shifts to the learning parameters (deviations of θ_t from a fixed coefficient θ) in Equation (1) found in the Benkard study are explained by the organizational forgetting parameter λ rather than a more general change to our θ above, because Benkard's analysis focuses on knowledge that is lost or depreciates over time as workers move to different tasks or is lost due to turnover layoffs or the passage of time.

Econometric Application of the Model

For estimating the econometric model, there are two dimensions changing at the same time—production and time—but they are not synchronized. This causes a problem for studies at this level of detail. Benkard (2000) correctly recognized that the experience variable is related to actual past production. The assumption that line speed is also related to past production is, however, open to question. His correction for this problem is sensible within the model, yet even when the $\{\varepsilon\}$ are orthogonal to the instruments, the two-dimensional problem remains. For each aircraft produced, the shock to that aircraft is

$$\varepsilon_{it} = \omega_i + \eta_t, \tag{6}$$

where ω represents the specific shock to aircraft i, and η is a shock to the entire factory floor at time t. These variables are assumed to not be interchangeable. For example, if on the one hand, aircraft i is being moved into its new production slot and a strut breaks, this may cause the assemblers at that location to wait for an hour until it is fixed. If after the delay they perform their jobs with as much efficiency as before and work one hour of overtime to make up for the delay, then only aircraft i will be affected $\{\omega\}$. If, on the other hand, there is a minor earthquake resulting in a one-hour power outage for the entire factory, then all aircraft being produced at time t will be affected $\{\eta\}$. For variable production rates, this is not a trivial distinction. It means that sequential εs may or may not be correlated with one another, depending on the production rates. Therefore, the covariance matrix of the $\{\varepsilon\}$ is not identified. Benkard's approach attributed the decline in productivity to organizational forgetting.

Benkard's (2006) analysis began with traditional learning curve models for labor in production and found results similar to those of most of the previous researchers, which is a robust decline in labor productivity that he attributed to organizational forgetting. He also incorporated into his analysis the change in production models as well as adjustment costs and economies of scale. These innovations are important but will not be considered here.[1] Given the previous critique of the simplifications in the model, we look instead at a data set for another aircraft program from a similar time period and find that an alternative model without the issues linked to forgetting does at least as well. We also replicate the model proposed by Benkard for the L-1011 with data from another large commercial aircraft line, but the way the data we examined were collected by the McDonnell Douglas Corporation is different from Lockheed's method. For example, in his analysis, Benkard explained that data on materials and plant disruptions would have been important, but that he was unable to obtain them. We were able to obtain such data, which has allowed us to do more meaningful

[1] Benkard (2000) investigated the effect of the change in aircraft models from the less complex L-1011 model 1 and the L-1011 model 5. This innovation in his econometric model is important in capturing some of the more complex interactions in the production process.

analysis on the production of aircraft. Further, we have data on deviations from planned to actual production, whereas Benkard's data are for the cost of production with the use of instrumental variables.

MD-80 Aircraft Production

The starting point for our analysis of MD-80 production is the prediction of a standard learning curve model by production engineers. Fortunately, Douglas Aircraft, having used and developed this model extensively, made use of it in MD-80 production planning. Specifically, Douglas Planning used a historical learning curve, or "engineering production cost" calculations, frequently used in U.S. Department of Defense procurement.

The engineering and planning staff calibrated the learning curve to fit the MD-80 production program in developing what is called the "should cost" function, a relationship that embodies the standard learning curve assumptions and engineering-base estimates of the expected costs of production. In Figure 1, the "should cost function" is shown as a smoothly exponentially declining curve for the period 1983–1987; it remained basically fixed throughout the period. (The data plotted in Figure 1 are monthly average per unit aircraft labor hour assembly costs.) As the figure illustrates, at no time were the actual costs close to the "should costs," although the former were declining during the early part of the production period. Since the MD-80 was an extension of the DC-9, the engineering functions were calibrated to attempt to correctly take into account the differences that the production workers faced in assembly.

Although we use different measures, the pattern observed in the actual cost data is surprisingly similar in pattern to the L-1011 costs used in the Benkard (2006) study.[2] The figure shows that actual production costs have large upward deviations from the planned production costs. More importantly, the steep declining actual costs in the early years of the production of the MD-80 are followed by a plateau and then a somewhat gradual upward trend. At the plant we examined, the spike in costs in winter/spring 1983 were a result of a strike and the replacement of line workers with supervisory and management personnel.

Before turning to our formal model, we can use the MD-80 data along with the L-1011 data to examine the impact of strikes on organizational forgetting. According to "forgetting theory," decreases in production rates after a product line has been operating for a while will cause the organization to forget some of the process improvements it has learned, and productivity will decline. A strike is a period of time during which such a slowdown in production takes place. Workers are out of the plant and production is done by management or not at all. When the workers return, they will have forgotten—clearly because of inactivity—some of what they have learned (individual forgetting). The question now arises, has management also become involved in the process of forgetting? Management is still active in the production process during a strike, so to what extent is forgetting driven by workers and to what extent is it driven by managers? If management has knowledge of production, then forgetting is diminished.

Figure 2 shows there is some small degradation in the cost immediately before and after a strike for each of the aircraft programs—the MD-80 and the L-1011. After a strike, productivity returns rapidly to levels close to that obtained just prior to the strike in each event, which would be expected from a ramp-up in production rates. In neither of the plane production lines is there evidence of organizational forgetting. Recent evidence provided by Kleiner, Leonard, and Pilarski (2002) for aircraft manufacturing, Krueger and Mas (2004) for tires, and Mas (2007) for heavy equipment shows that labor unrest affects quality in

[2] See the work of Benkard (2000: 1039). The graph for Lockheed's production shows a decrease in unit costs through the production of unit 120, followed by a build-up as production rates dropped and then increased.

Figure 1. MD-80 Actual and Learning Curve Costs (1983–1987, 000 hours)

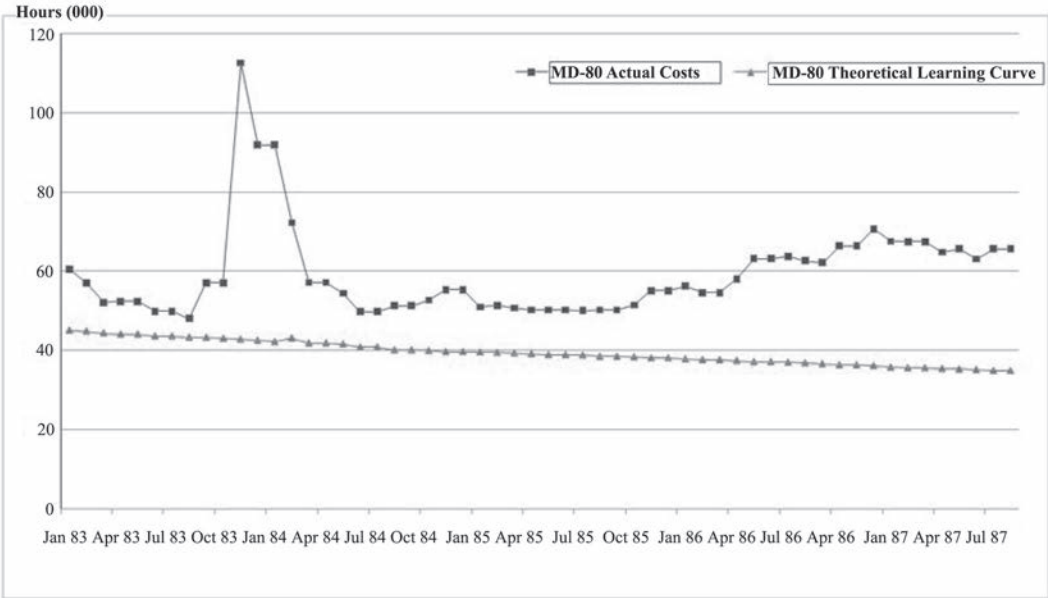
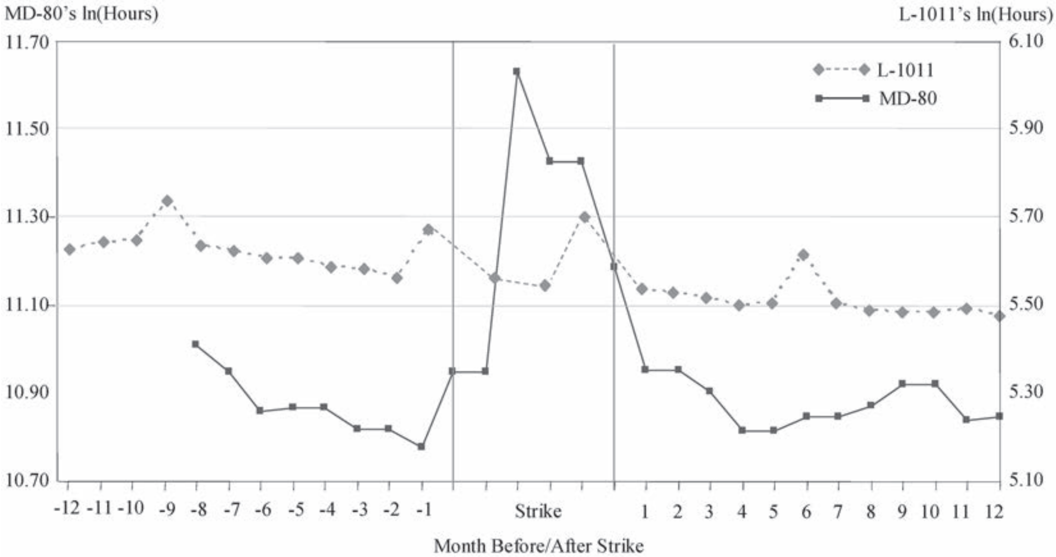


Figure 2. Production Costs of MD-80 and L-1011: 12 Months Before and After the Strike



Source: Data provided by Lanier Benkard on the L-1011 and on the MD-80 from the McDonnell Douglas Company.

manufacturing. Unlike tires and tractors, however, in aircraft production quality is tightly regulated by the Federal Aviation Administration (FAA), and each step of the assembly process must be signed off by an independent Quality Assessment inspector in which the FAA controls each step. Therefore, a decline in quality results in increased rework and increased costs rather than direct consumer losses in quality. The small amount of increased costs associated with the previous three strikes is consistent with individual forgetting on the part of the striking assembly workers and quality degradation found by others, leaving little room for the large organizational forgetting found by Argote, Beckman, and Epple (1990) and Benkard (2000).

MD-80 Labor Learning Curve Model

We use an alternative approach to forgetting theory by taking the learning curve for each product not to be fixed in the (cost, units) plane with a fixed θ in Equation (1) or $A\log(K)$ in Equation (5). Instead, we assume that deviations will be explained by shocks to the production process that move up and down the learning curve, and by θ being a variable of the production process that itself is moving the entire estimated curve of the plane's production. By this we mean that the original assumption of a static learning environment is relaxed to admit factors that affect the learning process. Among these factors may be the absence of parts causing out-of-sequence assembly, continual interruptions to the production process of disturbing the repetitive nature of the process, and the bumping process, which means giving a position on the line to the most senior worker covered by the collective bargaining agreement due to increases and decreases in rates as they manifest themselves through union work rules. For the employees in the plant that we study, workers who were moved off the production of these planes were moved to the assembly of military planes or were laid off but were not given the option of further training in Kaizen or quality circle programs.

To understand the high and non-intuitive patterns in learning in the MD-80 data, we model learning by doing on the McDonnell Douglas MD-80 assembly line by the following:

$$C_{it} = B(\cdot(t),\cdot(\mathrm{t}))^{*}g(i) + e_i, \tag{7}$$

where i represents the line position of the aircraft, C_i is the cost in standard labor units of the assembly of the ith unit, $B{*}g(i)$ is the learning curve function (similar in form to Benkard's function F in (1) above), $B(.(t),..(t))$ is a function of the internal environmental factors affecting the learning process, g is the standard engineering learning curve function, and the e_i are the i.i.d. random shocks to the production of the ith aircraft.

The parameter function B describes the learning environment. Factors that would improve learning are constant production rates, sufficient available tooling, and just-in-time parts, supplies, and subassemblies. Similarly, the absence of these factors would impede the learning process and cause the appearance of a move back up the learning curve. These factors are key to understanding the behavioral aspects of "organizational forgetting."

To estimate this function, we divide both sides of Equation (3) by the deterministic function $g(i)$. This scaling factor is exogenous to the behavioral variables in the model. The model now can be written as

$$C_i/g(i) = B(\cdot(t)),\cdot(t)) + e_i/g(i). \tag{8}$$

We can now write B as

$$B(\cdot(t),\cdot(t)) = \beta_0 + \Sigma\beta_j X_j(t) + \varepsilon(t), \tag{9}$$

where $\mathrm{Xj}(t)$ are such factors as changes in labor force, shortages of parts and assemblies, changes in the composition of the aircraft, changes in the production process, mandated interruptions in production, and labor stoppages. All of these establishment-specific variables were omitted in the study of the L-1011. The $\varepsilon(t)$ represent the time-dependent or more general plant-wide shocks to the production process.

Now combining (8) and (9), we have the scaled labor cost per aircraft assembly for the ith aircraft as

$$C_i/g(i) = \beta_0 + \Sigma\beta_j x_j(t) + \varepsilon(t) + e_i/g(i). \tag{10}$$

From the data on the production process, we find that aircraft delivered in the same month are in assembly simultaneously during the several-month period of the assembly process and are therefore subject to the same shocks ε. For example, aircraft k, $k+1$, and $k+2$ may be started in the month of September a few days or weeks apart and delivered in the month of December at approximately the same time. The reported costs for the aircraft would be at delivery. Then if the $k+3$ aircraft were started in October and delivered in January, we would have for the following error terms:

$$Var(C_k/g(k) - \beta_0 - \Sigma\beta_j X_j(t)) = \sigma_\varepsilon^2 + \sigma_e^2/g(k)^2, \text{ and} \tag{11}$$

$$\begin{aligned} Cov(C_k/g(k) - \beta_0 - \Sigma\beta_j X_j(t), C_{k+1}/g(k+1) - \beta_0 - \Sigma\beta_j X_j(s) &= \sigma_\varepsilon^2 \text{ for } s = t, \\ Cov(\varepsilon(t), \varepsilon(s)) &\text{ for } s \neq t. \end{aligned} \tag{12}$$

In the prior example, $s = t$ for $l = 0, 1, 2$ and $s \neq t$ for $l \geq 3$. The production process we consider here is one in which the rate of production is non-constant. Therefore, through the data set, the condition for $s = t$ changes and the variance-covariance matrix of the residuals is non-parsimonious through the time-series we specify. To solve this problem, we aggregate according to the month of production as

$$\begin{aligned} &\Sigma_k(C_i/g(i) \mid \text{all } k \text{ produced in time period } t)/K(t) = \\ &\quad \beta_0 + \Sigma\beta_j X_j(t) + \varepsilon(t) + (\Sigma e_i/g(i))K(t), \end{aligned} \tag{13}$$

where $K(t)$ is the total number of aircraft assembled in time period t. This yields an error structure:

$$\begin{aligned} &Cov(\Sigma_k(C_i/g(i) \mid \text{all } k \text{ produced in time period } t)/K(t) - \beta_0 + \Sigma\beta_j X_j(t), \\ &\Sigma_k(C_i/g(i) \mid \text{all } k \text{ produced in time period } s)/K(s) - \beta_0 + \Sigma\beta_j X_j(s)) \\ &\quad = Cov(\varepsilon(t), \varepsilon(s)), \end{aligned} \tag{14}$$

which is a standard time-series structure. If the theoretical scaling factor $g(i)$ is strictly accurate, as the null hypothesis of this study, then the $e_i/g(i)$ have identical variances for all i.

Empirical Results

We obtained monthly production data for the assembly of the MD-80 aircraft at the McDonnell Douglas factory in Long Beach, California, from the McDonnell Douglas Company.[3] The production process was begun in late 1979 simultaneously with the winding down

[3] Two of the authors were economists with McDonnell Douglas during part of the production run and worked on statistical cost analysis of the MD-80 program. This association allowed for the direct observation of labor in production and informs our analysis beyond the coefficients in the models.

of the earlier, similar model DC-9 aircraft.[4] The data begin to be useful in 1983, when the MD-80 line was produced in the plant without the confounding factor of the less sophisticated DC-9s on the assembly process. Thus, we use data only for the MD-80. The analysis of the data shown in Table 2 from 1984 through 1987 shows a sharp decline in unit costs over time, mirroring the "should cost" function, and the higher, parallel function is reasonably explained by the "should cost" function not incorporating two different aircraft being produced simultaneously.

Using a simple linear structure of Equation (13), we estimated the following linear model

$$H(t) = \beta_0 + \beta_1 * \Delta AAUP_t + \beta_2 * \Delta AAUN_t + \beta_3 * LnPS_t + \beta_4 * STRK_t + \beta_5 * AOG_t + \varepsilon_t, \tag{15}$$

where

H:	Average Monthly Labor Assembly Cost Per Aircraft, Scaled
ΔAAU:	Percentage Change in Final Assembly Rate as measured by Douglas Aircraft Standard Units of Production (fractions of an aircraft assembled weighted by production engineering requirements)
ΔAAUP:	ΔAAU * Dummy(+), where Dummy(+) = 1 if $\Delta AAU \geq 0$, 0 otherwise
ΔAAUN:	ΔAAU * Dummy(−), where Dummy(−) = 1 if $\Delta AAU \leq 0$, 0 otherwise
PS:	Parts and Subassembly Shortages
STRK:	Strike Dummy Variable
AOG:	Airplane on Ground Reports to Customer Service.

When parts and subassemblies are present at the process-designated time and position, disruption of the assembly process caused by workers changing jobs should increase costs (a shift in the learning curve in our model). The presence of organizational knowledge as well as knowledgeable coworkers should quickly shift the new higher learning curve back to the original position. We model increases and decreases in production rate separately, since they represent different types of disruption to the production process. Increases correspond to a period of growth and usually represent a workforce with little uncertainty about continuity of their work, and the workforce being augmented by new employees. Decreases, such as times of contraction and layoffs, correspond to a workforce with greater uncertainty, with more senior employees moving into more junior positions or being laid off as output contracts.

The absence of parts and subassemblies causes rework to be done out of sequence and should, at the time they are absent, increase costs. This process is modeled by using the variable *Ln* (number of parts shortages per month). When an already in-service aircraft is grounded for maintenance (AOG), the airline may demand the replacement part from the manufacturer. McDonnell Douglas supported its in-service fleet of aircraft by agreeing to ship the first available part to the airline even if this meant taking a part already installed on an aircraft in production out of the aircraft. The strike dummy is included to represent the shift in production costs resulting from management replacing striking line workers during this period.

An explanation for the fit of the simple linear model (Table 1) is the non-linearity of the learning process. In particular, we would expect the absence of parts to interact in a non-linear way with the changes in rate since rate changes move workers into different and

[4] The MD-80 and DC-9 shared the same fuselage cross section, but the wing, electronics, and systems integration were different. The mixing of the two dissimilar models on the same production line dramatically increased the cost of the DC-9. Data for this mixed line are suspect.

Table 1: Estimates from a Linear Regression Model
MD-80 Aircraft Production (1984–1987)

	Simple Linear Model		*Linear Model with 1st Order Lagged Exogenous Variables*	
	Coefficient	*Standard Error*	*Coefficient*	*Standard Error*
Positive Rate of Change	–1.52	(1.06)	–1.13	(1.05)
Positive Rate of Change ($t-1$)			0.18	(0.23)
Negative Rate of Change	–3.15	(1.06)	–2.77	(1.10)
Negative Rate of Change ($t-1$)			–1.31	(0.49)
ln(Part Shortages)	0.06	(0.02)	0.06	(0.17)
ln(Part shortages) × Rate Change	0.33	(0.21)	0.28	(0.20)
Strike	0.32	(0.07)	0.26	(0.07)
AOG (× 100)	0.014	(0.005)	0.02	(0.001)
constant	–0.15	(0.08)	–0.19	(0.08)
N	55		54	
R^2	0.67		0.71	
DW(7,55)	0.87		1.12	

possibly new line positions. If the parts are available, line workers should be able to learn (individual learning) according to the theoretical learning curve. If they are not available, the learning environment will have changed. Organizational learning—the development of more efficient processes and procedures—is similarly slowed when the initial production process is interrupted by out-of-sequence rework.

The following model characterizes the learning process theoretically and empirically:

$$\begin{aligned} H(t) = {} & \beta_0 + \beta_{11}*\Delta AAUP_t + + \beta_{12}*\Delta AAUP_{t-1} + \beta_{13}*\Delta AAUP_{t-2} \\ & + \beta_{21}*\Delta AAUN_t + \beta_{22}*\Delta AAUN_{t-1} + \beta_3*LnPS_t \\ & + \beta_{41}*(LNPS_{t-1}*\Delta AAUN_{t-1}) + \beta_{42}*(LNPS_{t-2}*\Delta AAUN_{t-2}) + \\ & + \beta_5*(\Delta AAUN_t)^2 + \beta_7*(LNPS_t)^2 + \beta_8*STRK_t + \beta_9*AOG_t + \varepsilon_t. \end{aligned} \tag{16}$$

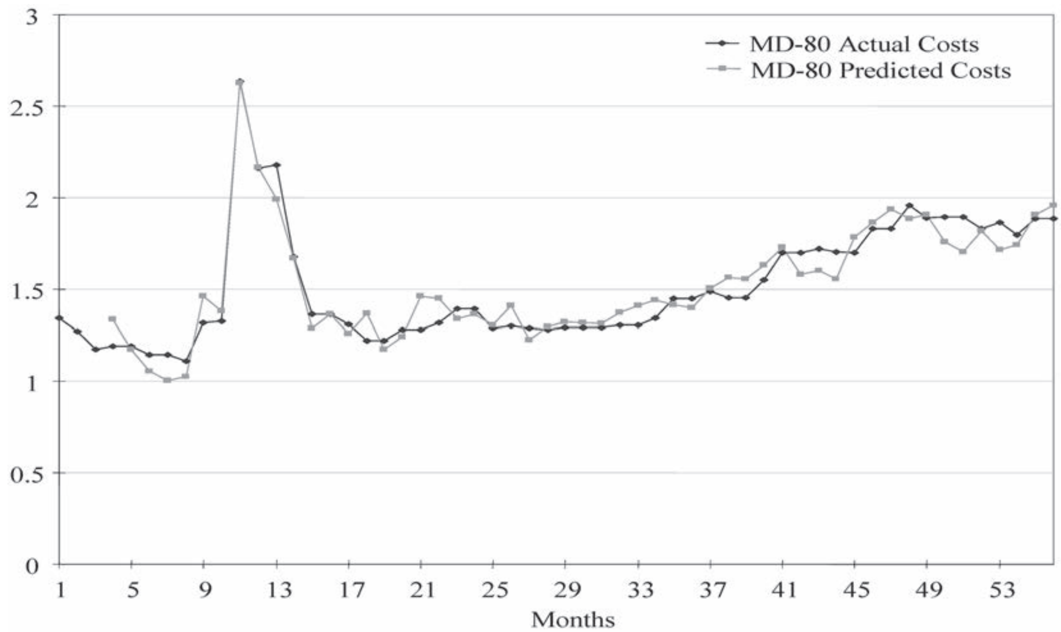
In Table 2 we present the coefficients and standard errors obtained in estimating Equation (16). We examined alternative specifications of the shift variables in establishing (16) and tested their statistical properties against each other. The full quadratic model with two periods of lags was found to be too non-parsimonious. Equation (16) provided the most robust estimation with respect to the addition of lags and shift variables. That is, the qualitative results did not differ significantly between model specifications. The model tracks the data well and provides an intuitive explanation of differences between actual assembly costs and expected costs.

In-sample fit is illustrated in Figure 3. The area of most interest is the increasing costs, shown after the labor-management action induced a spike. The steady upward movement in labor assembly costs tends to be tracked well by the model and corresponds to an increase in production rate as the economy and commercial aircraft orders improved. The model predicts that the learning environment, altered by the necessity of doing out-of-sequence manufacturing, would slow the learning of the work force and would therefore not admit a traditional downward-sloping learning curve analysis. The concept of "organizational forgetting" as the explanation of this cost increase is therefore not supported by the model. Rather, the constant rate repetitive process assumption of learning curves is violated by this rate change, and the explicit lack of parts associated with this rate change yields a new learning outcome.

Table 2. Estimates of Learning Curve Parameter Shifters

MD-80 Aircraft Production 1984–1987	*Coefficient*	*Standard Error*
Positive Rate of Change	0.18	(0.15)
Positive Rate of Change $(t-1)$	–1.06	(0.58)
Positive Rate of Change $(t-2)$	0.88	(0.32)
Negative Rate of Change	2.24	(0.74)
Negative Rate of Change $(t-1)$	–2.98	(0.65)
ln(Part Shortages)	–0.28	(0.05)
ln(Part shortages) × Rate Change $(t-1)$	0.30	(0.11)
ln(Part shortages) × Rate Change $(t-2)$	–0.12	(0.05)
Negative Rate of Change Squared	19.81	(3.38)
ln(Part Shortages) Squared	0.04	(0.00)
Strike	0.28	(0.04)
AOG (× 100)	0.004	(0.003)
Constant	0.57	(0.11)
N	53	
R^2	0.92	
DW(13,53)	1.47	

Figure 3. In-Sample Fit of Model to Actuals 1984–1987



We had the advantage of observing the production line, following workers, and seeing the changes in the manufacturing process (Helper 2000). To give an example, a control surface rigging was to be installed in position 5 prior to installation of the nose gear strut, but because the rigging was consistently not available until position 6, the order of assembly is different. It is not surprising that different assembly processes have different labor productivity outcomes.

The findings in Table 2 with respect to decreases in the rate of production in isolation of the learning environment shifts are through the parameter estimates of lower output, its lag, and the value-squared. These three parameters define the effect of reductions in the workforce on the labor cost of assembly. The initial impact, given by the quadratic in contemporaneous change in the work force, is a dramatic cost increase due to the disruption of workers being furloughed as well as the movement of more senior workers into more junior positions (seniority bumping). Interestingly, the impact is short-lived and the subsequent month shows a washing out of this effect. This strongly suggests that there was no organizational forgetting with rate decreases; rather, organizational disruption was taking place.

The impacts of increases in rate in isolation of the shifting learning environment are given by the parameters of increasing production, its lag, and the value-squared. As with decreases in rate, there is an impact due to the movement of workers between tasks, but it is short-lived. Interestingly, the current impact is minimal, possibly due to the overlap of new and existing workers or the colinearity of the three noted exogenous variables. This deserves further study.

The most telling factors in the model are represented by the coefficients β_3 and β_6, and β_{41} and β_{42}. The coefficients of a quadratic in the natural log of parts and assembly shortages are β_3 and β_6. The combined impact is positive and exponential in the size of the shortages, suggesting a strong movement of the learning curve in response to the absence of repetitive tasks. β_{41} and β_{42} represent the temporal impact of the interaction between shortages in parts and the changes in the workforce. For increases in the workforce, the impact continues past the first month but then begins to abate. Although there are no data to confirm this, it may be a result of workers learning to better perform out-of-sequence tasks. The learning curve may have shifted, but learning by doing is still occurring. For the decreases in work force, these terms show a more rapid movement back to the original learning environment, due to the fact that in downturns, parts shortages are usually not a problem, and the fact that the more experienced and skilled workers, those with seniority rights, have experience in both in- and out-of-sequence assembly.

Using detailed production data, we find that non-transitory changes in costs are at least as likely to be related to changing learning environments as they are to be associated with running up the learning curve backward. Specifically, when there is an increased requirement for conducting out-of-sequence production and non-repetitive activity as a consequence of subcontractors not being able to keep up with the pace of production rate changes, the workers, new to their current positions, are not able to learn as quickly as historical predictions of the learning curve research would suggest. Changes in production rates responding to the cyclical nature of aircraft orders will generate observations such as those presented here.

As we noted earlier, the data available on production for the L-1011 and the MD-80 from the two firms are not the same, but we attempt to estimate how the omitted variables or unobservables in the estimates presented for L-1011 may have influenced the bias in the study that was then attributed to organizational forgetting (Benkard 2000; Altonji, Elder, and Taber 2005). In Panel A of Table 3, we show how parts shortages, the key variable within the MD-80 production lines, were influenced by the positive and negative percentage changes in the production schedule and its lag over time in the table. The estimates in this panel show that changes in the speed of the production line are somewhat related to parts shortages for the MD-80 with an F-value of 1.24 for all the lag variables in the models for the MD-80. In contrast, we estimate the speed of the production line as a function of production hours for the L-1011.[5] Consequently, these estimates of changes in production line are a plausible proxy variable for parts shortages, which is the key unobservable variable in the

[5] Since the production schedule is likely correlated with parts shortages, this could be a reasonable instrument for parts shortages in the L-1011 production line.

Table 3. Estimates of Proxy Variables on the Production of the MD-80 and the L-1011

	MD-80	*L-1011*
Panel A		
Positive Rate of Change	–0.829	1.141
	(3.011)	(1.221)
Negative Rate of Change	7.311	–3.275
	(5.546)	(1.169)
Positive Rate of Change ($t-1$)	–2.352	–0.917
	(2.742)	(1.144)
Negative Rate of Change ($t-1$)	0.958	0.470
	(6.042)	(1.221)
Positive Rate of Change($t-2$)	–2.009	–0.717
	(2.864)	(1.131)
Negative Rate of Change ($t-2$)	10.714+	–1.075
	(5.927)	(1.193)
Constant	6.396	–0.055
	(0.283)	(0.088)
R-squared	0.139	0.077
N	53	111
Panel B		
	MD-80	*L-1011*
Parts Shortages	–0.156	480.283
	(0.093)	(163.724)
Constant	1.327	350.2623
	(0.552)	(24.573)
N	53	111

Note: In Panel A, we used the change in the line speed as a proxy for parts and subassembly shortages and we used line speed_t-line speed_{t-1})/line speed_{t-1} in the L-1011 model. These variables captured the changes in production in both models. We used two-stage least squares to produce the estimates in Panel B.

L-1011 model. We now use changes in production as a proxy variable for parts shortages in the production function for the MD-80 and the L-1011 and present those results in Panel B of Table 3 using two-stage least squares. The estimates show that the proxy variable used is significant and of the hypothesized positive sign. In spite of differences in methods of measurement, the use of a potential omitted variable such as estimated changes in production speed as a proxy for parts shortages would potentially influence the role of organizational forgetting in the estimates presented by Benkard (2000). Moreover, having actual estimates of parts shortages would likely produce more robust estimates and further diminish the importance of the estimates for organizational forgetting.

Conclusions

An essential element to understanding changes in production and variations in the production function is the learning curve for labor, and an important subset of this curve is forgetting. We use the production of commercial aircraft as a venue to examine the issue of forgetting within the production process. Previous examinations of organizational forgetting have purported to find that a large part of lost output can be attributed to organizational forgetting. A more fully specified model that takes into account previously omitted variables finds a much smaller role of forgetting. That is, organizational forgetting is most likely not as influential as suggested by previous work.

We tested for how the disruption caused by changes in production rates, such as those resulting from a strike, affects production costs and whether skills once learned may be partially or fully forgotten, as is the case of the depreciation of human capital. Management, engineers, first-line supervisors, and skilled assemblers, who generally remain with the firm, often maintain any institutional memory and the optimal methods of production. Our analysis, including costs such as variations in production due to individual planes or day-to-day unexpected events, is consistent with learning theory and provides an alternative explanation within a more fully specified model. Moreover, our model shows the potential for omitted variable bias of not using these variables in estimates of production for the L-1011.

Consequently, the phenomenon of organizational forgetting based on rate of production is not supported by our analysis of the data. The theoretical and empirical analyses of the implications of organizational forgetting for industrial relations policy and strategy, while interesting, may be of more limited use than previously thought.

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