

Forgetting curves: a case study

Luis López

INCAE, Graduate School of Business
P. O. Box 960-4050, Alajuela, Costa Rica
Tel. (506) 437-2389, Fax. (506) 433-9101
Email: lopezl@mail.incae.ac.cr

ABSTRACT

In this paper we explore organizational forgetting, the notion that firms' knowledge can be lost through human capital decay. An in-depth case study research, which is guided by the conceptualization of a system dynamics model, is conducted. The evidence appears to support the presence of forgetting. This gives rise to the possibility of productivity falling in spite of continued output accumulation, due to changes in the characteristics of the resource where experience resides. Most prior research on learning curves, however, assumes that productivity will always increase with cumulative firm output.

INTRODUCTION

As organizations accumulate output, some measure of productivity increases. The theoretical details of this idea go back to the work of Wright (1936) who suggested a non linear relationship between the average direct labor man hour cost and the cumulative number of units produced in the manufacturing of airplanes. Thereafter, many empirical studies have documented this "learning by doing" phenomenon. The classic study of Rapping (1965), for instance, documented large gains in productivity improvement in the production of WWII Liberty vessels. In observing productivity gains, measured in man-hours required to produce a Liberty ship, with average annual increases of "about 40 per cent", Rapping tried to unravel variables which could influence the rate of output for given levels of other factor inputs and found that a very good explanatory variable was cumulative output. Thus, a link between output, in units, and productivity was established. More specifically (Rapping, 1965: 86):

Evidence showed that cumulated output, an ex-post volume measure, could account for productivity advance during the war. It was assumed that as cumulated output of a particular vessel type increases, labor and management learn from the accumulated experience, and consequently,

the secular improvement in output per man-hour during the war is attributable to learning or adaptation.

Since then, these “manufacturing progress functions” or “learning curves” have been found in many and different organizations including those that produce capital goods (e.g., rayon: Hollander, 1965; nuclear plants: Joskow et al., 1979; ships: Searle et al., 1945) and also service organizations (Darr et al., 1995).

Progress functions even turned into a tool of widespread acceptance. Dutton et al. (1984) describe the diffusion of this tool or, as they rightly call it, this managerial technology. The apparent simplicity and intuitive appeal of the manufacturing progress function made for a useful instrument for cost estimation and control (Dutton et. al., 1984: 206):

The progress function eventually led to economic and managerial theories recognizing that productivity tends to increase continuously due to a growing stock of embedded knowledge about production. Such knowledge accumulates in physical equipment, in materials used in production, and in the skills of producers. As accumulated knowledge came to be seen as a key element in economic progress, progress functions came to be used in business and government policy decisions that involved determining and controlling future costs.

Thus, learning curves, progress functions, and experience curves, have diffused and become a mainstay of academic and managerial business literature and practice.

A common feature of many early studies was the constant reference to learning. Such gains in productivity occur because people and organizations learn. Learning is a notion present in many disciplines, from economics to history. Its meaning, though, varies. Some, particularly the economists, tend to view the notion as measurable improvement in activities. What is measured here is the outcome of learning. Others, mostly organizational theorists, see it as changes in processes and organizational routines. Here, “...organizations are seen as learning by encoding inferences from history into routines that guide behavior” (Levitt and March, 1988: 320) or, more simply, through a process of detecting and correcting error (Argyris, 1982).

Whatever the discipline or the conceptual slant, it is clear that learning at the organizational level can hardly be dissociated from the resources of the firm, particularly its human capital, but also its stocks of plant and equipment, and the infrastructural knowledge represented in routines. In fact in the work (particularly the early work on progress functions, as in Rapping, 1965, quoted above) on learning, the observed productivity gains were ascribed to dynamic gains in experience that became embedded in the firms’ resources. Thus, learning can

simply be seen as an accumulation of human capital, and the firm's experience becomes necessarily embodied in its workers.

Yet, while recognizing this, most literature ends up looking at organizational-level learning, and at learning curves, in particular, through some output variable that is not necessarily and concretely related to firm resources. Most models establish a positive relationship between experience and productivity using cumulative production as a measure of experience. Because cumulative production can never decline, productivity can only rise over time (Sterman, 2000).

This is contradictory. Intuitively, it is akin to accepting that organizations can only learn. Yet, organizations' knowledge resides in the company's human capital. Such knowledge is not limited to the individually acquired and accumulated dexterity. It spills over to routines and procedures, which can be, to a large extent, tacit. Losing resources, therefore, could result in reductions of productivity. For instance, a sudden migration of workers from a production line means losing knowledge that is firm-specific. Workers might well be part of routines deeply embedded into the firm. The consequences of this migration, unless compensated with an influx of equivalent or better experience, would be a decline in productivity. Firms, thus, would lose, or forget, what was previously learned.

Incipient empirical evidence has shown that organizations, like individuals, can forget too. Forgetting has been documented in intermittent production settings when, due to run changeovers and other interruptions, there is loss of learning. In these environments, where there are short production runs and frequent interruptions, learning is followed by forgetting followed by learning. Losses due to such learning-relearning dynamics are not negligible (Carlson and Rowe, 1976).

Benkard (2000) shows, for aircraft production data, that productivity, understood as the marginal costs of producing aircraft, is not necessarily ever decreasing smoothly, as it would be the case if only learning were present. More specifically, knowledge is lost through the depletion of resources. This gives rise to the possibility of productivity falling, in spite of continued output accumulation, due to changes in the characteristics of the resource where experience resides. If workers, for instance, should suddenly leave or were laid off, experience would diminish and productivity would fall. Simon (1991:128), for instance, posits that individuals within organizations are the repositories of organizational memory:

Since much of the memory of organizations is stored in human heads, and only a little of it in procedures put down on paper (or held in computer memories), turnover of personnel is a great enemy of long-term organizational memory.

According to this view, then, individuals store organizational knowledge. Moreover, these “human heads” form a collective entity, a social network which is a repository of organizational knowledge, its memory. As Olivera (2000) indicates, these networks of individuals serve to store, and retrieve, the knowledge an organization has gained through experience. Carley (1992) posits, using simulation, that turnover has an effect on organizational performance because knowledge is lost as personnel leave. Such lost knowledge is what we term here organizational forgetting. Following Martin and Phillips (2004:1606), organizational forgetting is defined as: “...the loss, voluntary or otherwise, of organizational knowledge”. Because much organizational knowledge resides in these social networks (Olivera, 2000), knowledge will be lost when such networks are disrupted, thus forgetting will occur.

Such possibility is not allowed in traditional learning models, and allowing for it is necessary. Literature that deals empirically with organizational forgetting is scarce and the implications of this phenomenon have not been studied. The goal of this paper is to explore salient aspects of this issue within a production setting. At this stage this research is still in progress and only preliminary results are presented here.

METHODS

To explore these ideas, particularly the idea of diminishing productivity over time, we use what we could term a generic system dynamics model to guide us in our research and data collection process. Thus, at this stage of this preliminary research, a very simple model structure, following Sterman (2000) is used to generate dynamic hypotheses regarding experience curves as related to the rise and depletion of a company’s stock of labor. Since at this stage we are trying only to gain insight into this rarely explored issue of forgetting at the organizational level, the intention is not, yet, to precisely calibrate a model to the observed data or use a model for policy testing. Rather we use a very basic model to develop fundamental, broad if you will, insights which are then measured up to empirical data.

MODEL

To allow for the possibility of organizational forgetting, it is necessary to establish a relationship between resources, experience and productivity. Instead of establishing a relationship between a firm’s output measure, like cumulative units produced, and some measure of productivity, we need to explore the evolution over time of the firm’s stocks of resources. The firm’s output, in terms of units produced, becomes then a function of the inputs, labor, materials, and capital,

but the production function¹ is also defined by the firm's experience. For simplicity we will deal only with the experience associated to labor, though it is clear, as already stated, that such experience is also rooted in plant, equipment, and routines. In what follows we closely follow Sterman (2000) and Benkard (2000).

In its simplest form, modeling experience as influenced by labor requires two state variables: one to track the state of the labor force and another for the experience of the production unit. The labor force is measured in units of people while the experience is measured in units of time, like accumulated hours, weeks or shifts. In system dynamics terms, a coflow structure is necessary to track the experience of the labor force. Thus, Labor force, L , is a state variable that rises with hiring, h , and is reduced by attrition, a , both measured in people per unit of time. Hence,

$$(d/dt)L = h - a$$

We assume that attrition and hiring are a function of the hiring growth rate and the fractional attrition rate. Both are assumed exogenous at this point.

The experience of the labor force is tracked in a stock of experience, E . This stock can change for several reasons. It may increase because of experience acquired on the job. In this case experience is gained in terms of on the job tenure. This stock may also increase with the experience new hires bring. The stock decreases for two possible reasons: because people forget relevant knowledge or because employees leave and their experience leaves with them. Thus, if l_h is the experience accrued from hiring, l_j the experience gained on the job, f_f the experience lost due to natural decay, and f_a the experience lost from attrition,

$$(d/dt) E = l_h + l_j - f_f - f_a$$

We use a learning curve specification of the following form (Benkard, 2000; Sterman, 2000):

$$L_i = A E_i^\phi$$

where L_i is labor input per unit, A is a constant, E_i is experience, and ϕ is a coefficient that describes learning. The equation is specified in terms of a productivity measure by substituting labor input, a measure of cost, for P , a measure of productivity. Thus, the specification is as given in Sterman (2000)²:

¹ i.e. the output rate of the product that can be achieved from the specified set of labor, materials, capital, and experience inputs.

² As in Sterman, $\Phi = \ln(1+f_p)/\ln 2$. In other words f_p , the fractional change in productivity per doubling of effective experience would be equal to $1+2^\Phi$. If a measure of cost were used, the expression would be $1-2^\Phi$

In general, we can see that new hires cause, initially, a steep decline in productivity followed by an increase essentially governed by the strength of the learning curve. If attrition remains at a higher rate than before, productivity settles at a lower level. Evidently this result could not be allowed by traditional learning models. Because traditional models found in the literature do not track experience, productivity can only rise. The sharp decline observed when the rate of hiring is changed would be essentially irrelevant. Experience increases with the new hires, though average experience declines also. This is so because we set the new hires with an experience smaller than the experience of the model in equilibrium. At this point we are only interested in exploring whether these basic dynamics can occur in practice, and our premise is to simply investigate whether it could be possible to identify at least to some extent, the dynamics observed in Figure 2. The model permits, nonetheless, to establish as a very general hypothesis, that if attrition increases, productivity will fall, and if attrition remains constant at this new level, productivity will reach a steady state at a new (lower) equilibrium level.

DATA

A CASE STUDY IN A PRODUCTION LINE

To investigate the effects of forgetting on firm performance, we gathered data at a production plant that makes items for human consumption. Because the company requested anonymity, our description of the products and its manufacturing process omits some detail. The plant has 9 production lines, 7 of which are used on a day to day basis. We concentrated our attention on one production line. On this line the company makes a total of 45 items. Ten items are produced at a rated line speed of 2520 items per hour, while the rest is produced at 3,000 items per hour. Lines are staffed with 8 to 12 people. Most products are made with 11 people working on the line.

Figure 3 shows a simplified schematic process flow of the production line under study.

keep the temporary worker policy for all future hiring. This meant keeping the same amount of line workers and hiring temporary workers as needed. This temporary help would be contracted with an outsourcing company which we will call TempPower (TP).

Description of main variables.

We will use Figure 1 to organize information regarding the most important system variables.

h: hiring in the plant is done, as described, on an as-needed basis. As the number of shifts increases, the plant supervisor spreads permanent workers as evenly as possible on all 7 production lines. This means that the line under study could be operated by as little as two in-house workers and up to 10 TP workers. The supervisor avoids placing TP operators in the most critical stations (black circles in Figure 3). To get an idea of how much *h*, the hiring rate in people per unit of time, changes, we gathered data on personnel assignments for a total of 471 shifts between 2003 and 2004. These 471 shifts were staffed in all by 80 people. This would mean that, on average, each operative only worked 5.9 shifts during this period. This was not necessarily so. Figure 4 shows that there were TP workers who were hired on a regular basis while others would leave after working only a few shifts. Over half of the workers sampled had less than 12 shifts accumulated during the period.

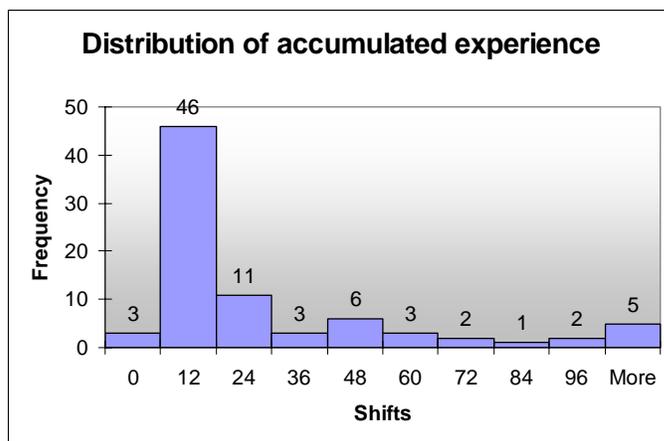


Figure 4: Distribution of experience.

a: attrition reflected the above hiring policy. TP only sent those workers required to fulfill programmed production. Thus, this rate would be the complement of hiring. Figure 5 shows, for a longitudinal series of consecutive work shifts, the number of temporary workers used in the line under study. The line was, as the figure shows, staffed, at some points, with up to 10 TP workers. On average, between 3 and 4 workers were hired per shift (3.7).

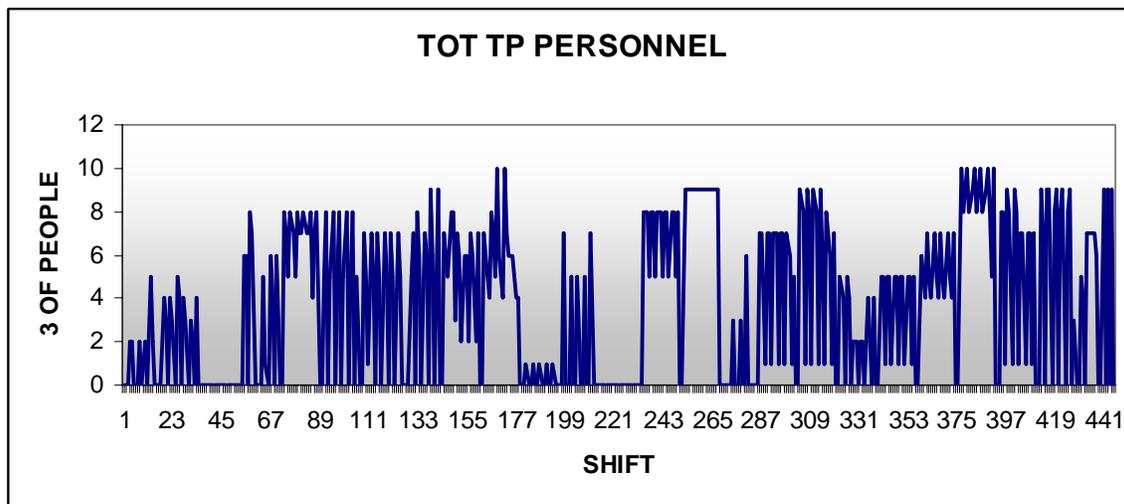


Figure 5: Staffing by temporary workers for 440 consecutive work shifts. Plant close-downs for vacation excluded.

I_n: From Figures 4 and 5 it can be seen that the average experience of new hires was generally small. In fact, for the series of work shifts analyzed, 70 people who had never worked in the plant before came to work here during that period.

I_i: Most jobs require manual dexterity. We had no data to estimate how much time was required for an operator to get up to speed. The line supervisor, however, estimated that 10 to 15 shifts were, as a minimum, required for an average person to be able to execute the simplest packing tasks, mostly manual repetitive motions. Cleaning and line changeovers would require an additional 10 and 5 shifts respectively (if specifically trained), and almost a year, about 75 shifts, would be required to master nuisances related to recognizing materials for each of the 45 items, recognizing equipment operating abnormally, and the like. According to the supervisor, when the line was staffed with experienced workers "it would break less." In her opinion, a fully experienced worker would require a full year of experience to know everything. Translated into work shifts, the supervisor estimated that learning would be marginal after a person had accumulated 100 continuous work shifts. Many mechanical failures, in fact, could be avoided if the worker would recognize situations in which his intervention would prevent a major interruption (such as spillovers, problems with the labeling machine, etc.). We monitored the only two product introductions the company made in the period under study. These two new products were made in two production runs in consecutive days by essentially the same people. The first product achieved 60% efficiency, measured as the ratio between rated (scheduled) production and actual production, after a first run of 6496 cumulative units, and 76% efficiency after 17892 cumulative units. The other product achieved a 61% efficiency after a first ever run with a cumulative output of 4408 units, and 65% efficiency in a second run after accumulating 28,136 units of output. This would indicate that learning curves are fairly steep for the

production line as a whole, although these runs were done with experienced company personnel.

f_f and f_a : Observation made it evident that there was forgetting due to interruptions in the production runs, but no data is available at this point to support this quantitatively.

Results

With our generic learning model we hypothesized that if attrition increased productivity would fall and, if attrition remained constant at this new level, productivity would reach a steady state at a new (lower) equilibrium level. In our case study, the hiring of temporary workers appears to be happening on a very frequent basis. Despite some, 10 exactly, temporary workers being hired on a regular basis, to the point that they are practically equivalent to in-house workers, the constant rotation of other workers has made average experience per shift to stabilize between 40% and 60% of the experience required to become completely knowledgeable. This can be observed in Figure 6. In this Figure we arbitrarily assigned the 100 shift figure to those temporary workers that were hired on a regular basis, and the actual experience to the others. The series is for approximately 300 shifts for which data were available starting in August of 2004. This was more than eight months after the TP policy had been implemented. Unfortunately there is no longitudinal data to contrast the graph in figure 6 to what the average experience was before the TP policy was implemented. Assuming that this was 100, the maximum possible, is not at all unwarranted, due to the low turnover in the firm. This would mean that average experience fell drastically, in some periods, since the beginning of this practice.

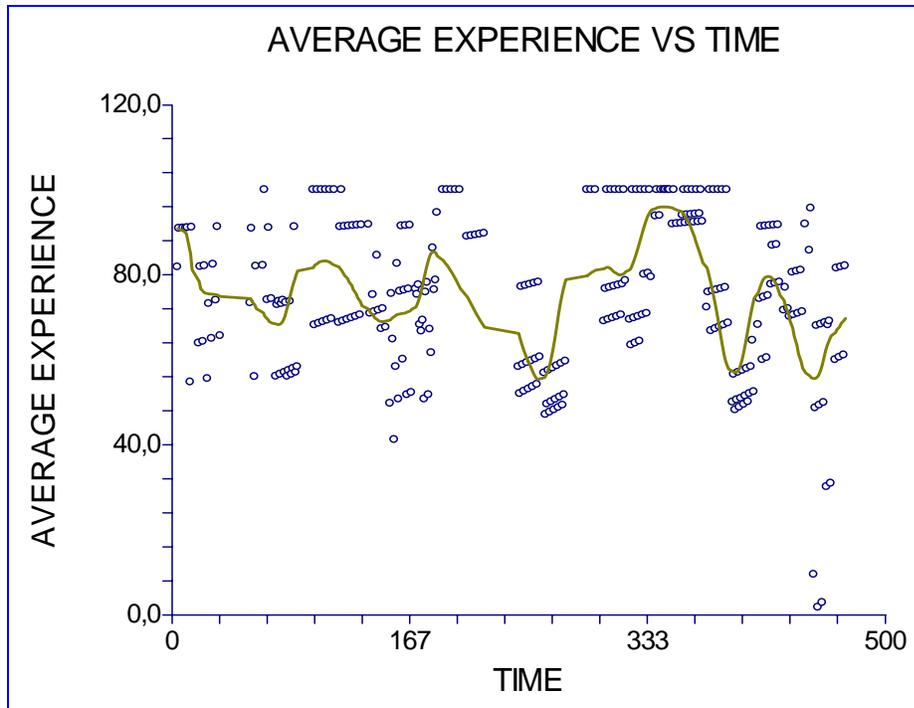


Figure 6: Average experience per shift using 100 shifts as the maximum effective experience. The line is smoothed.

Our hypothesis would point toward a productivity fall after the introduction of the temporary worker policy. On average, everyday between 3 and 4 temporary workers are assigned to the line, and the line operates with less than the experience required⁴. To look at this we collected data on productivity, measured as the ratio between rated line speed for a particular item and actual line speed, in percentage, for production runs before and after the implementation of the temp policy. A graph of this can be seen in Figure 7.

⁴ The fact that some workers might have more than 100 shifts of experience, thus increasing average experience, becomes somewhat irrelevant. The line actually operates as a unit, and much to the beat of its weakest link. If, for example, the feeder is slow, the whole line will suffer, no matter how much experience people have downstream. Output could increase more than proportionally if experienced workers were posted in certain stations in the line.

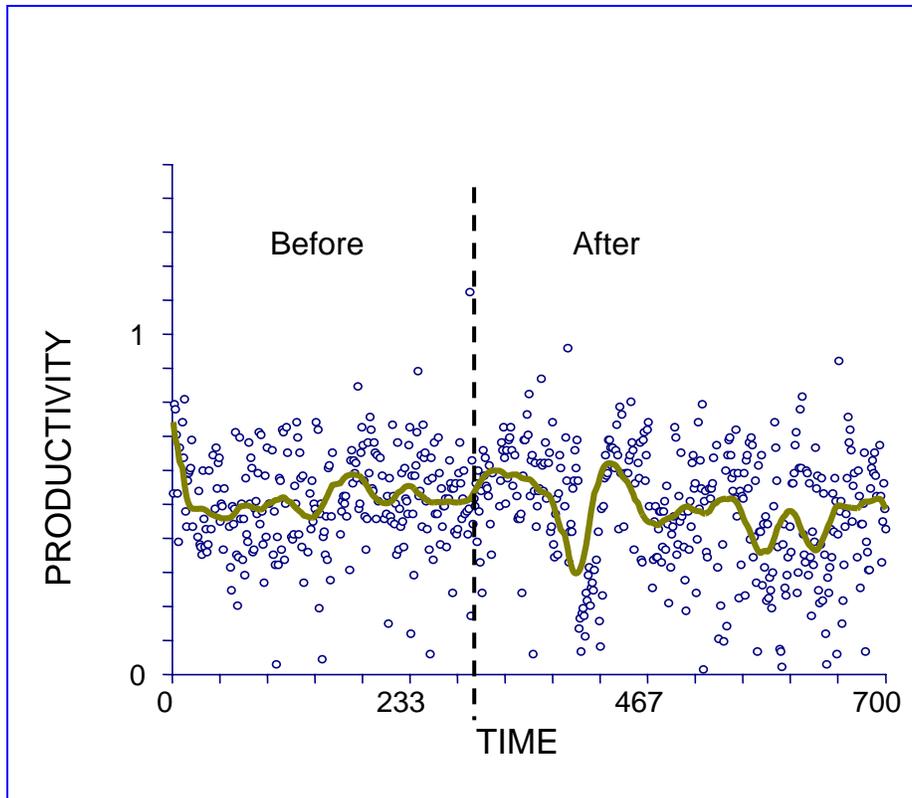


Figure 7: Productivity Before and after implementation of TP policy. Graph smoothed.

The TP policy was implemented at the end of 2003. During the first weeks they used mostly former company workers now employed by the temp company. This started changing when those workers were able to find steadier jobs in other companies and left TP. Visual inspection of Figure 7 indicates a fairly steady, somewhat upward, trend before the policy was implemented. Right after policy implementation there is a period of very low productivity followed by an apparent peak, but after that, it appears that productivity stabilizes at a lower level than it used to before temporary workers were used on a regular basis. Visually inspection appears to show that, on average, there is a downward trend after the policy was implemented. This trend only appears to stabilize at the end of the available series of data.

In the above data there is a statistically significant difference between the productivity before and after the policy was implemented. To avoid distortions that could be caused by the uneasy period that ensued the implementation of this policy, we compared productivity means well before the policy was implemented, to the means well after. In other words we took the leftmost 215 points in Figure 7 and compared them to the rightmost 211 points in the same graph. We rejected the null hypothesis that there was no difference in the means of both samples ($p < 0.0001$). A 95% confidence interval places the differences in means

between 5,0% and 13,0%⁵. The means of each sample were 60%, after, compared to 69% before the policy was implemented. This, indeed, is a large difference.

The policy appears to have other effects. As the number of TP workers in the line increases, so does the variance associated to productivity. In other words, output levels tend to vary much more when there are TP workers in the line. This can be seen in Figure 8, where productivity for particular shifts with different numbers of TP employees has been plotted⁶.

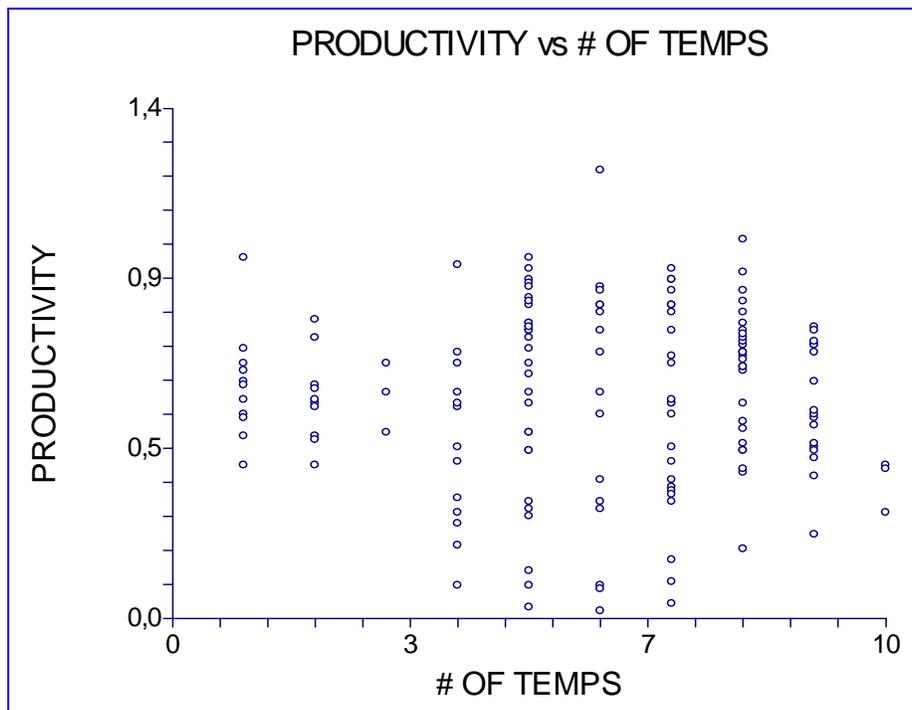


Figure 8. Productivity vs. Number of TP employees working in line.

This increase in output variability made production planning and scheduling very difficult. In doing the research it was noticed that frequent conflicts took place between line supervisors and upper management when the latter would inquire about discrepancies between actual TP personnel usage and planned usage. Planned usage was made according to an average target. Use of averages for planning, however, hid temporary needs for additional workers to get product out in second or third shifts, particularly product that had accumulated because of

⁵ The usual assumptions of normality and continuity were checked. The samples turned out to have unequal variances, therefore an unequal-variance test was used. The test remained strongly significant if all available datapoints were included.

⁶ A modified Leven Equal Variance test permitted to reject the null hypothesis of equal variances between the before and after samples, with $p < 0,001$.

variability. Upper management would evaluate TP personnel needs based upon this average and ignoring the increased variability in output, hence erring.

In all, it appears, at least at this preliminary stage, that productivity, as our generic model suggested, fell significantly (in statistical terms) and has now reached a lower steady state. In all, the data for this production line appears to show evidence of firm behavior which is consistent to what we were able to hypothesize using our generic model.

There are other, more subtle, effects which will probably not show in the data in the short term. Because of the constant attention that getting production out requires for meeting short term production quotas, knowledge about the plant, in general, is decaying. Previous data-gathering routines and improvement initiatives are being abandoned. It was common for the supervisor to complain about this. For example, in an interview she said:

Today I have spent the whole morning explaining to the TP people how to pack. That is all I have been doing all day. But it is possible that those people who I taught today will not be here tomorrow, so what I taught today will be wasted.

Not only the supervisor, but the few experienced operators had to devote time for teaching. Moreover, certain improvement efforts were becoming stalled. As the supervisor indicated:

I have to stop doing what I am supposed to do so that I can teach these people, but my experienced workers also have to do so, and output diminishes even more. When we did not have this I used to control, check, and was constantly finding things to improve in the line. Now I just spend my time worrying about getting production out. For example, I was documenting cycle times, mean times to failure, and mean times to repair for the lines, but I am now unable to do so because I don't have time.

Thus, the fall in productivity appears to have effects elsewhere. Data on production interruptions was recorded for this line for about a year. The data approximates downtime by assigning buckets of 15 minutes and a cause for each line interruption. For the year after the implementation of the policy, interruptions that were recorded as caused by machine adjustments or machine failure increased from 22% to 25% of scheduled machine hours. Time required for finishing accumulated in-process inventory⁷ increased from 2% of scheduled machine-hours to 4%. Time used for training, in contrast, decreased, from 3% of scheduled-machine hours to 2%. This indicates that production pressures feedbacks into training, thus affecting long run productivity even more. Interestingly, line interruptions due to materials, which typically are incorrect or defective materials brought to the line from the warehouse, decreased from 6%

⁷ If packing personnel is too slow, compared to, particularly, the filler upstream, production is accumulated around the line. When accumulation becomes unfeasible, because there is no more room for more products, the line is stopped and the accumulated products are finished.

to 4% of scheduled line-hours. This is probably why complaints from distributors are on the rise. Workers are unable to classify, recognize, or, if necessary, reject, defective or incorrect materials. This is what the supervisor defined as the most difficult task to learn, indicating that a full year experience was probably required to master it.

Discussion

We wanted to explore, at least in a preliminary manner, forgetting effects at the firm level. To do so we guided a case study research with the help of a generic system dynamics model of learning and forgetting effects (Sterman, 2000). We used the model to make guiding hypotheses for gathering data. The empirical evidence collected appears to show some of the forgetting effects the conceptual model anticipated. It appears that by maintaining a steady state attrition and consequent rehiring of people with a low average experience, the firm has settled into an equilibrium that seems to be lower, in terms of productivity, than the one attained with full-time company employees.

The research shows, besides these learning and forgetting effects, additional and perhaps unintended feedbacks. Output per shift has a higher associated variance. Moreover, temporary employees appear not to have an effect solely on the velocity of the line, but also upon the frequency of unexpected interruptions. Subtle changes in the parameters of the production line, which would trigger compensatory operating adjustments in more experienced workers, do not register in those with less experience. The line, hence, stops more frequently. Moreover, because the line runs at a lower steady state productivity level, pressure to get production out cuts into training hours, thus resulting in even more degradation of line productivity. The line supervisor and the production manager have to constantly attend to line problems, neglecting activities that have impact on the long run productivity of the plant (improvement efforts, optimization of scheduling, external relations, etc.).

It appears, at least on the surface, that this case study shows evidence of forgetting at the firm level. Given this, it becomes necessary to calibrate a model for exploring this issue in much more depth. We are now taking steps in that direction.

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