Turnover-induced Forgetting

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ABSTRACT

A firm's productivity may fall despite continued accumulation of output. We show such productivity decline by means of an in-depth case study with detailed longitudinal data. Hiring of inexperienced labor disrupts the firm's knowledge stock by bringing in workers with less than average experience. Thus, the firm's knowledge becomes diluted through labor-turnover induced organizational forgetting.

Introduction

Empirical research on knowledge depreciation through organizational forgetting has been carried out in different settings. Yet, extant studies have not established a significant relationship between forgetting caused by personnel turnover and its effects on productivity. Argote and Epple (1990), for instance, demonstrated empirically the existence of forgetting, but they were not able to establish a relationship between personnel turnover and productivity.

Other research about the antecedents of forgetting in manufacturing firms attempted, again, to show a relationship between knowledge depreciation and personnel turnover. Argote, Beckman, and Epple (1990), modeled WWII Navy Liberty ship production output as a function of knowledge variables controlling for personnel hiring and firing. The authors concluded that hiring and firing did not contribute significantly to productivity changes.

Theoretically, knowledge could depreciate because individuals forget how to perform their tasks, or because people leave and are replaced by others with less experience. While there is no evidence that turnover contributed to knowledge depreciation in the Liberty Ship environment, it might matter in other organizational contexts (Argote et al., 1990: 151):

> Empirical research in service organizations has not been able to compellingly conclude that turnover-induced knowledge depreciation is related to reductions in productivity.

Darr et al. (1995) studied acquisition, transfer, and loss of knowledge in 36 pizza stores belonging to 10 franchise chains. Again, hypotheses related to productivity decay associated to forgetting due to personnel turnover could not be accepted. Notwithstanding this, Darr et al. (1995) suggested high personnel turnover as one possible cause of knowledge depreciation:

Though empirical research is inconclusive, a compelling argument can be made, from a theoretical standpoint, of a strong relationship between knowledge depreciation, personnel turnover, and productivity (decline). Organizational learning becomes embedded in firms' resources, routines, activities, and people (Dogson, 1993). Olivera (2000) has posited that firms' social networks are repositories of organizational knowledge. These networks of individuals serve to store, and retrieve, the knowledge an organization has gained through experience (Olivera, 2000). Because much organizational knowledge resides in these social networks (Olivera, 2000), organizational knowledge could be lost when such networks are disrupted, due to personnel turnover. When knowledge, embedded in firm resources, is lost, the organization forgets.

Although such arguments make clear the possibility of productivity declining when firm's resources are disrupted, extant empirical support to these theoretical arguments is weak at best. This might happen because of two reasons. The first one is that empirical datasets available make it difficult to uncover such forgetting effects. The second reason might be that forgetting and learning mechanisms are not clearly articulated. Most literature looks at organizational-level learning through some output variable that is not necessarily and concretely related to firm's resources where knowledge resides. Thus, when modeling learning effects, most formulations establish a positive relationship between experience and productivity, using cumulative production as a measure of experience. This is not adequate because, as Sterman (2000) points out, given that cumulative production can never decline, such formulations only permit productivity to rise over time.

With traditional learning curve formulations, firms find it hard to determine, ex ante, what the possible effects on productivity might knowledge disruptions have, whether such disruptions are due to changes in labor force composition, changes in available production technology, or simply due to knowledge decay.

Prompted by these questions, we collected empirical data for one production line and attempted to estimate firm-specific parameters which, thereupon, could be used for modeling forgetting effects using a generic System Dynamics model.

Research design and setting

The weak or ambivalent results obtained when testing hypotheses related to forgetting due to personnel turnover and productivity might be related to the choice of research methods used in previous research.

Almost all extant studies are cross sectional, and, thus, it becomes very hard to find in such data the manifestations of a phenomenon which is longitudinal in nature. All studies reviewed which used longitudinal data have very large time frames, with much time elapsing between succesive observations. It is plausible that effects on productivity induced by changes in firm-specific knowledge could wane during such long periods, thus becoming undistinguishable in the data. To the best of our knowledge, there is no detailed study in which personnel experience (tenure and turnover) has been observed on a permanent basis for an extended period of time.

We sought a research setting in which a clear change in a firm's resource knowledge occurred, so that its effects could be inferred from comparing measures of performance taken at many intervals before an intervention with measures taken afterwards such intervention. We therefore chose a research setting that would allow us to accurately measure worker experience over long periods of time. Time intervals considered in the time series did not exceed one work shift, and for each time period we recorded a very detailed assessment of who was working and how many hours the employee had worked in the same job.

Our interest was to observe, longitudinally, the effects of turnover on learning and forgetting. This, evidently, called for a setting in which turnover could be accurately assessed over a sufficiently long period of time. We, thus, sought labor-constrained production environments, that is, settings in which capacity was primarily regulated by additions (and subtractions) of labor into the production environment. A second and equally important requirement was to avoid settings which allowed inventory build-up. Third, we wanted all other factors that might also affect the variable of interest (learning) to remain as constant as possible. Finally, it was important that, at least within an ample range, the addition of workers did not incur diseconomies of scale.

In following these general guidelines, our empirical data comes from an in-depth study of one production setting in a food processing industry. In our investigation we observed and carefully recorded very detailed information regarding the behavior and performance of this production line. We did so for a period of 12 months, shift by shift. The case we analyzed had particular characteristics that made it appropriate for isolating the phenomenon under scrutiny. First, the food products were perishable. It was, therefore, infeasible to stock them for periods over two months. Second, demand for these products was sharply seasonal. These two features made it impractical for the firm to produce on a level basis and made it necessary to follow demand by sharp increases in production capacity during peaks. As a result, the firm would hire temporary workers to comply with demand peaks. Thus, the firm had a fairly stable payroll during most of the year, punctuated by relatively large increases in personnel during short periods of time.

By carefully choosing our research setting we were able to isolate periods of high personnel turnover and compare them to periods when no turnover took place.

We collected detailed information for the period from April of 2005 to May 2006. No data were collected either when the plant was not working for other reasons, primarily during holydays. We ascertained that the process structural characteristics remained unaltered during this period. Interviews with supervisors and engineering personnel permitted to determine that the process under observation remained unchanged in the following:

There were no investments in new equipment. During the whole period the line had the same equipment.

The production line remained with the same physical configuration throughout. No change in production layouts or information flows took place.

Supervisory personnel were on the permanent payroll and no significant changes in its composition occurred throughout the period under analysis.

No improvement effort or initiative took place during this time. In fact, the firm under investigation had no formal procedure for fostering improvement, let alone actually carrying on improvement efforts.

Product line-up did not change in any meaningful way.

From our observations and from the extensive interviews carried on with supervisory and administrative personnel it can be safely said that the main changes underwent by this production line were the hiring and firing of temporary workers. We were confident, then, that changes in productivity could be related to these changes in personnel.

This production line was a manual operation. Though there was a modest degree of automation in some workstations, the machines in this line had very low utilization, on account of their excessive capacity, and in no case were they bottlenecks (except during few days of highest demand). Thus, hiring of temporary workers was necessary to increase line capacity.

Model

Traditional learning curve formulations establish a relationship between an output measure and cumulative production output. The inverse relationship is traditionally interpreted as learning that occurs with cumulative production which allows for increased output productivity. The measure of cumulative production is, thus, just a proxy for the implicitly learning (by doing) assumed in such productivity gains. More accurately, though, the relationship should be established between the stock of knowledge available at the firm and the given output. This stock of knowledge can increase (by, among other things, learning) or decrease (by, for instance, forgetting).

To allow for the possibility of organizational forgetting, it was 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 needed 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 function was also defined by the firm's experience (Figure 1). For simplicity we deal only with the experience associated to labor, though it was clear, as already stated, that such experience was also rooted in plant, equipment, and routines.

A simple model structure, inspired by Sterman (2000) was used to generate relationships between variables involved. The model constitutes a theoretical base to analyze empirical data related to knowledge stocks and flows under study.

Modeling relationships between productivity and stocks of knowledge (as shown in Figure 1) requires two state variables: one to track the resource and another to track its associated attribute. In our case we are interested in tracking the stock of labor and its experience.

In our study we attempt to establish a causal relationship between the stock of available knowledge in an organization and its associated productivity. We establish a longitudinal baseline productivity measure and an associated baseline organizational knowledge measure. This knowledge is altered at some point in time by the addition of new employees that change the knowledge stock. Our study allows us to observe the effect of removing the treatment variable. In other words, after some period all new employees added to the payroll are fired, and the organization returns to its initial state. We, thus, are able to track longitudinally the effects hiring and firing have upon the stock of knowledge and, in turn, the effect changes in the stock of knowledge have upon productivity.

We first define the main constructs and the measures used. The relationship of interest is that between the knowledge stock and productivity, and how productivity changes when the knowledge stock is altered because of personnel turnover.

Constructs and variables:

Productivity: The construct productivity is defined as the quantity of output produced divided by the amount of resources used to obtain it. In this case we analyze human productivity using total kilograms of output per shift divided by the number of total person-hours available during that shift (kg/h).

In previous studies (Smunt, 1987; Argote et al., 1990; Darr et al., 1995) productivity, specifically accumulated output, is directly associated to the knowledge stock (i.e. it is taken as a proxy for the accumulated knowledge stock). In this study we are not establishing such operationalization.

For confidentiality's sake, and by request of the companies studied, productivity variables in this study are not reported in absolute values (i.e. in kg/h), but relative to the company’s benchmark standard productivity which was estimated using established production standard times. This conversion does not change the final conclusions, but productivity observed is compared to what the management would expect according to its standards. We have termed this relative variable *efficiency*.

Knowledge stock: We have operationalized the firm's collective knowledge stock as the aggregate tenure of all the employees working in one turn. Tenure was measured as the number of accumulated shifts each individual had working in the same post.

Given this, the stock of knowledge may stay constant in varied situations. For instance, the stock of knowledge could amount to 100 if 2 employees with an accumulated number of 50 shifts each are working the shift, or due to 10 employees each accumulating 10 shifts each. Because the number of employees may vary between periods, to be able to compare the stock of knowledge when the number of employees is different, we use average experience. This average experience is defined as the mean knowledge each individual contributes to the total stock of knowledge and it is obtained dividing the total accumulated knowledge (in shifts) by the number of individuals.

Organizational learning and organizational forgetting: We assert that the organization learns when there are positive increments of mean experience, and the organization forgets when there are negative increments of mean experience.

According to this definition, learning can occur because of three reasons: 1. The addition of individuals who bring a knowledge stock which is larger than the average knowledge stock of the individuals in the line. 2. Learning by doing due to individuals staying in the same post (thus increasing their tenures), and 3. Individuals with a knowledge stock which is less than the line personnel's average knowledge stock abandoning the system (Although in absolute terms knowledge is lost, in relative terms the remaining personnel would be more expert on average, and, hence, we consider this a learning process).

Forgetting, accordingly, happens because of three possible reasons: 1. The addition of individuals who bring a stock of knowledge which is smaller than the average stock of knowledge of the group. 2. Knowledge depreciating as time passes, and 3. Individuals with a knowledge stock which is larger than the group's average knowledge stock abandoning the system.

Personnel turnover: We define turnover as the inverse of mean tenure time. Turnover is affected by the date of hiring and the date of firing. Tenure time is the number of days elapsed between both dates. If such figure is large (i.e., employees are fairly stable), turnover is small. If the figure is small (i.e., tenures are small), turnover becomes large. An increase in hiring of temporary employees increases turnover. Hiring and firing will influence knowledge stock variables because temporary employees enter the group with a knowledge stock equal to zero and will eventually abandon the group with knowledge stock proportional to the acquired tenure. Moreover, an increase in the number of employees will directly affect total available hours, but not necessarily productivity.

To follow these constructs longitudinally, several variables are then defined as follows:

L_{ib}: Longitudinal assessment of the labor force (L) per shift (i). This is measured in number of people, with a breakdown by type of employee (b=0: permanent or b=1: temporary).

h_{ib}: number of people hired at the beginning of the shift (i) (b=0: permanent workers, b=1: temporary workers)

a_{ib}: number of people fired at the end of workshift (i) (b=0: permanent workers, b=1: temporary workers)

C_i: Personnel capacity available per shift (in hours per shift). This is equivalent to the number of people working multiplied by the number of hours available in the same job during the shift (usually 8 per shift). This gives a good idea of line production capacity.

p_{ij}: Output per shift (in kg of each sku). Kilograms of sku (j) produced in shift (i).

P_i: Aggregated production (in standard hours per shift). $P_i=\Sigma_j (p_{ij}*ST_j)$ where ST_j is the standard time of sku (j). To be able to aggregate production we use standard time as the common unit. P_i is the sum of times required to obtain the quantities of each sku produced in shift (i). Standard times for each sku were obtained directly from the firm.

η_i: Line efficiency per shift, $\eta_i = (P_i/C_i)*100$. If, for instance, the standard production is close to the available hours, we know the line operated close to its theoretical maximum capacity. If, on the contrary, more time was used for production than the theoretical standard hours warranted, the line would have efficiency below 100%. Of course, when enough experience is accumulated, a good line can outstrip the theoretically determined standard (i.e., perform the operations faster than the standard, or, in other words, operate with efficiencies higher than 100%). In settings where compensation is based on output, such occurrence is not uncommon.

e_{ij}: Individual experience of person (j) at the end of shift (i), as the number of shifts worked in the same job. The experience of each person is recorded shift by shift. This variable encompasses the effects of learning by doing, and also the effects of knowledge decay. For convenience, we used a linear scale of 100 shifts as an upper limit for experience, indicating that the maximum possible individual experience was attained after working 100 shifts. Permanent workers were assigned a value of 100 directly. After 100 turns, learning is marginal. We calibrate a model using our data in order to estimate initial experience of permanent workers.

E_i: Average experience of the stock of people working in the line during shift (i). The experience of each person, measured in number of shifts (e_{ij}), is averaged. It is calculated for each production shift recorded.

The aforementioned are depicted in Figure 1.

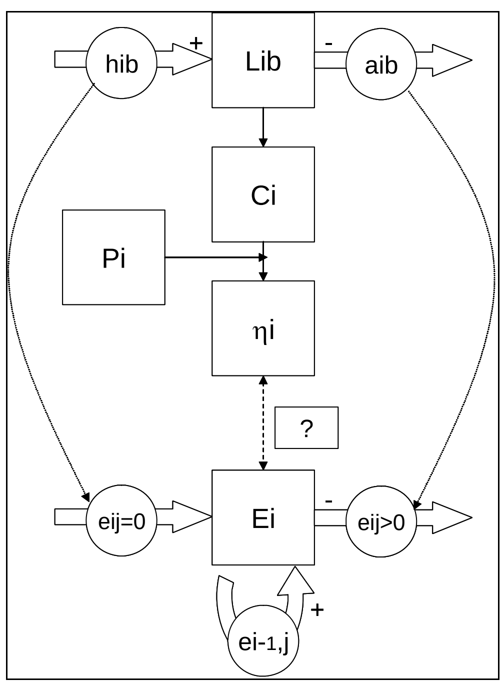

Figure 1: Stylized structure of model (Sterman, 2000)

Case study: Salted codfish processing line

The company imported codfish from the Faroe Islands (Denmark) for processing and distribution in its home country. Its main customers were retail distributors, delicatessens, supermarkets, and hypermarkets. Company operations included codfish reception (the product came in bulk, normally in pallets), product cutting (in different formats), product desalting (or not, depending on the format), and repackaging with the company's own brand.

The unit of analysis in this case is the cutting operation. This manual operation was at the beginning of the production process, and, to avoid stoppage of downstream work stations, it required to be permanently staffed with at least one worker.

The cutting operation was composed of 10 identical manual stations in parallel. The basic operation consisted of taking a piece of the salted codfish and cutting it into several pieces with a mechanical saw. Once cut, the product was placed on a conveyor belt which moved the product to a second operation where the cut pieces were classified and similar ones grouped into appropriate containers. The cutting operation required little technical knowledge, but acquiring a good level of dexterity required practice. Because this operation implied working manually in close proximity to a sharp high-speed moving blade, inexperienced operators proceeded with extreme caution. Despite security equipment being worn at all times, fear of injury reduced worker productivity until sufficient experience was attained. The line could function with any number of workers, from 1 to 10. Staffing levels varied according to output volumes required. Production data was gathered by shift for the whole workstation. Unfortunately no individual productivity data were available, but for the whole line.

A longitudinal assessment, shift by shift for a total 225 shifts, is shown in Figure 2. The graph shows the total number of employees that worked each shift, and, of those, the number of temporary ones.

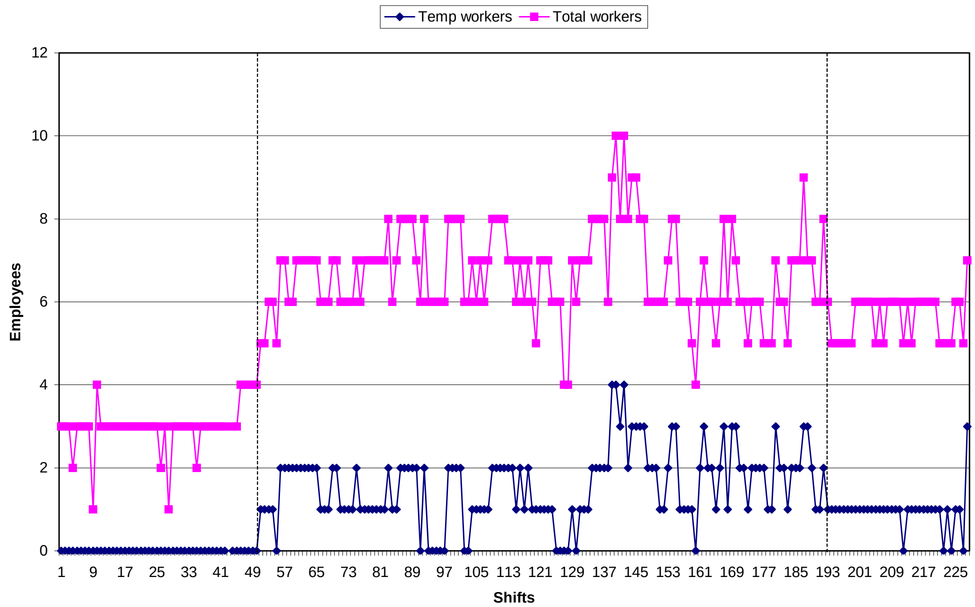

Figure 2.
Total number of employees and temporary employees in the line.

In Figure 2 we can see three periods (which we have separated with straight lines in the Figure). The first period did not have any temporary worker, and the task was performed by approximately three permanent employees. In the second period, the number of employees grew to between 6 and 10 people with the addition of both permanent (i.e. people who were on the permanent roster but working elsewhere before that point in time), and temporary workers. During this second period there were 9 temporary employees which alternated throughout the period (i.e., they would be come and go during the same period). In the third period, there were between 5 and 6 people working in the line and there was only one person who was pseudo-temporary, because, although he had a temporary contract (was not in the permanent roster), he had been hired during the second period and his tenure was greater than 60 shifts at the beginning of the third period.

Figure 3 tracks production capacity (C_i) for each shift (i) for the given labor force for that shift (L_i). Production capacity is calculated by multiplying the number of employees available for that shift by the number of hours in the shift. Figure 3 also shows actual production obtained in standard hours (P_i). This is obtained by multiplying the quantity, in units of product, obtained in each shift by the standard processing time required per unit of product.

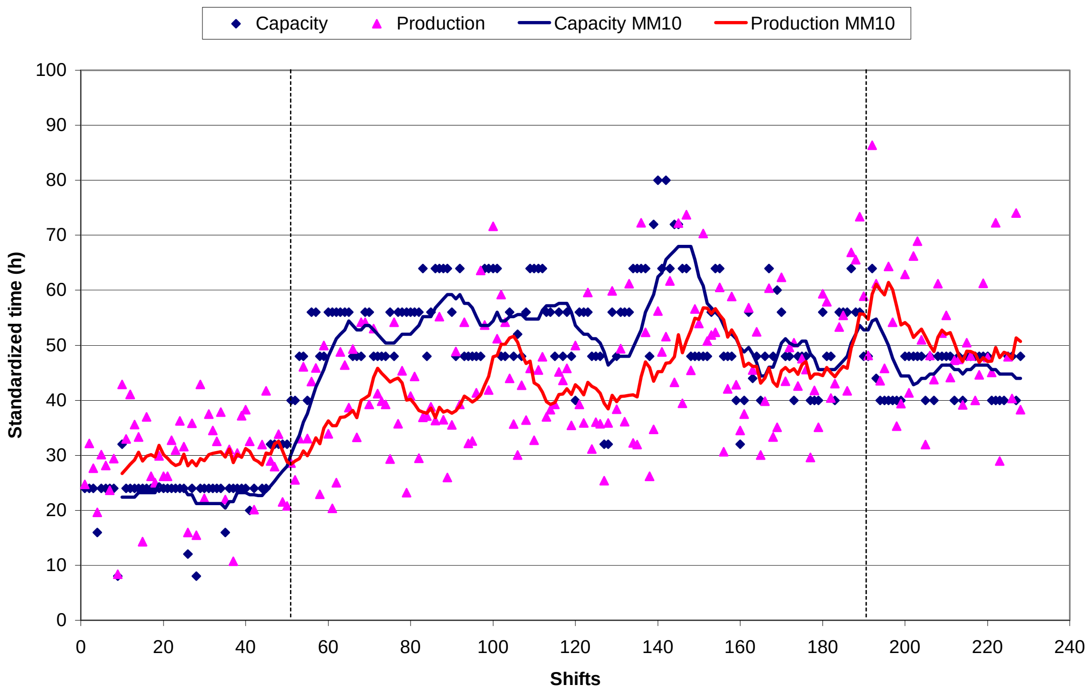

Figure 3.
Personnel capacity (C_i) and aggregate production (P_i).
Lines are smoothed averages of the time series.

The three aforementioned periods are also depicted in Figure 3. It is possible to observe that during periods when the line is staffed with permanent workers only, the plot of standard production hours is above the total available capacity in hours. This means that the quantity produced multiplied by the standard hours per quantity of product exceeded available hours. In other words, workers outpaced the standard. This is true at two different capacity levels, which rules out the possibility of diseconomies of scale in the production line. In the central period (treatment) depicted in Figure 3, when temporary worker employment was much more intensive, the standard production hours stayed clearly under theoretical production capacity. Workers' production rhythm was smaller than the standard, and production outputs did not increase proportionally to the increase in labor hours.

Figure 4 shows the mean group experience (E_i). Notice that during pre-treatment the line is staffed by permanent workers with a nominal experience of 100% each. As more temporary workers are added to the line, average experience diminishes. Turnover negatively affects mean group experience (i.e., turnover creates a negative increment of mean experience). We had defined this as a forgetting process because, as a result, mean tenure is smaller.

Figure 4 also shows the efficiency index of each shift. The efficiency index is the ratio between production (i.e., standard hours of output) and production capacity (available person hours). In this figure mean experience has been divided by a hundred to use the same scale as the efficiency indicator. Figure 4 shows that efficiency was greater than one, on average, only in those periods where mean experience was close to 100. This occurs when the line is staffed with permanent workers only (shown enclosed in dotted ovals). In the first period, efficiency was greater than 1.2. When hiring of inexperienced workers took place, efficiency fell to a value which was close to 0.8 throughout the treatment period: 0.4 below the initial, pre-treatment, situation with permanent employees only.

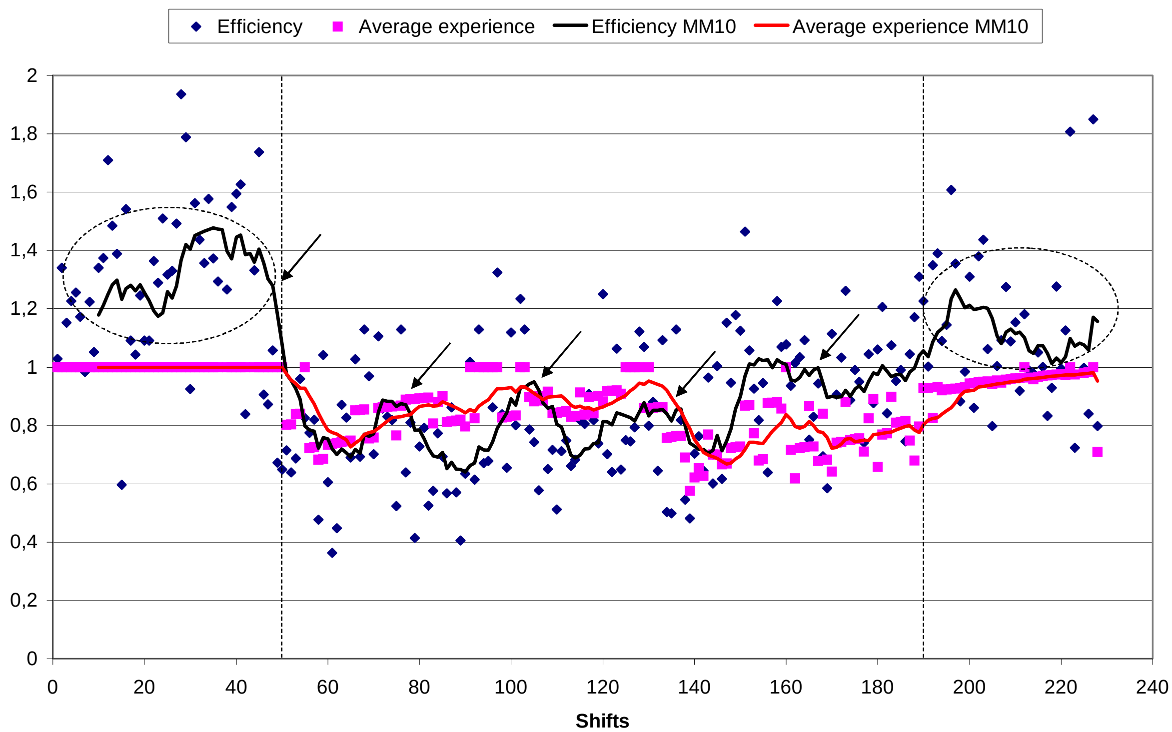

Figure 4.
Efficiency and average experience per shift.
Lines are smoothed averages of the time series.

In Figure 4 we have used arrows to indicate moments when forgetting occurred. These are moments when productivity decreased despite cumulative production rising. These are all within the period when a considerably large temporary labor force had started to work in the line (middle period). Going from left to right in the figure, we can see that the first arrow indicates where the mean experience went down because of the hiring of temporary workers. In this first instance of forgetting, reduction of mean experience happened because new people without experience joined the group. In successive occurrences, mean experience fell because of turnover within the temporary workers in the group. It is possible to observe that each time a new temporary worker joined the group, mean group experience became smaller and efficiency also fell.

Model

To assess model parameters we used the model depicted in Figure 1. We had detailed information on the stock of labor and its associated rates. In collecting data we assessed specifically who worked in the line and when. Throughout the period the line was staffed by workers drawn from a pool of 12 people in total, 6 permanent workers and 6 temporary workers. Since we knew exactly the days each of these people had been on the line, we drove hiring and firing rates exogenously. Thus, Labor Force is a state variable that rises with hiring, h, and is reduced by attrition, a, both measured in people per unit of time:

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

Attrition and hiring are assumed exogenous at this point.

The stock of experience was modified by flows of experience acquisition and decay. Experience could be acquired by on the job learning (time worked on the job) and by hiring people with more experience than the incumbent workers. The latter was never the case, as the 6 temporary workers had no experience whatsoever. Experience could be lost from people exiting the line or by experience possessed by the labor force simply becoming obsolete or forgotten.

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,

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

To estimate productivity we use a learning curve specification of the following form (Benkard, 2000; Sterman, 2000):

$$L_i = AE_i^{\Phi}$$

where Li 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 η, a measure of productivity. Thus, the specification is as given in Sterman (2000)[1]:

$$\eta = \eta_0\,(E/E_{\mu})^{\Phi}$$

[1] As inSterman, $\Phi = \ln(1+f_p)/\ln 2$. 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 $1-2^{\Phi}$.

where E is the average experience of the workforce, and η_0 is the productivity achieved at the reference experience, E_μ, level. In this case η is a proxy for productivity: a measure of efficiency with respect to the standard.

Simulation shows that changing the composition of the labor force significantly alters production line productivity. Model calibration showed that for a reference experience of 100 shifts, $\eta_0 = 0.81$; $\Phi = 0.398$; and there is knowledge lost through decay driven by a fractional decay rate = 1%. Results are shown in Figure 5.

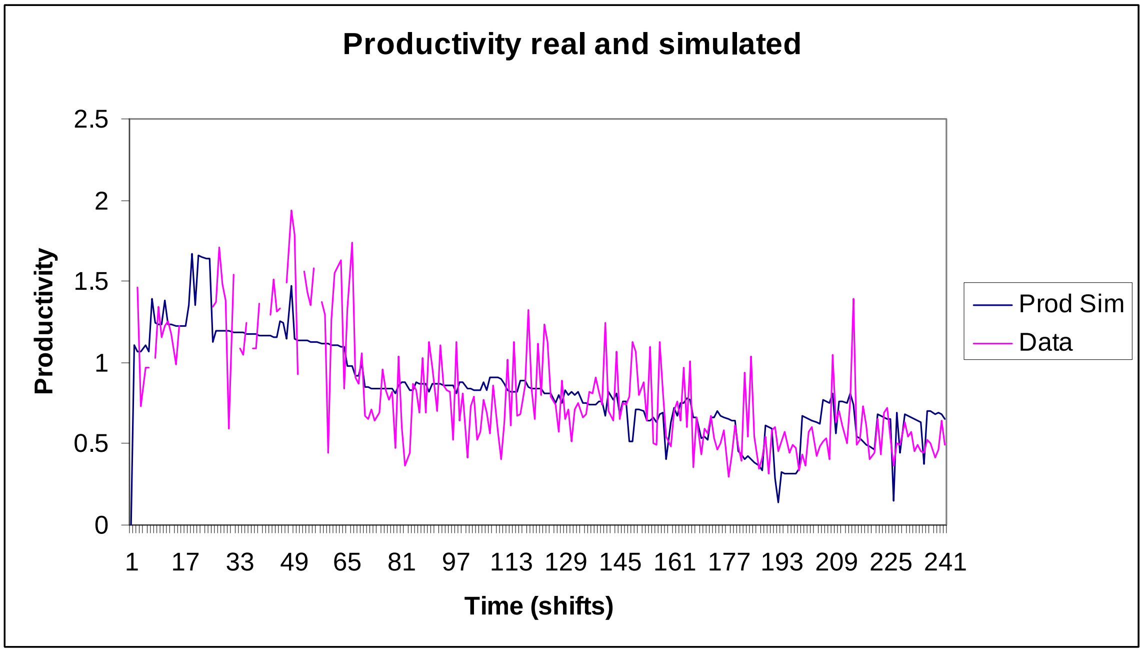

Figure 5. Actual and simulated productivity data.

Discussion

As shown in Figure 5, the productivity of this firm falls in spite of continued output accumulation throughout the period studied. The fall in productivity does not happen because of resources leaving the company (such as would be the case if knowledgeable employees suddenly left the firm taking with them accumulated tacit knowledge). The fall obeys to a more subtle disruption in the composition of the labor force due to turnover. By hiring workers with experience well below average, knowledge becomes diluted thus reducing the productivity of the line as a whole.

Our empirical evidence, along with model insights, shows that an increase in turnover during a controlled, limited, period, induces large efficiency losses. These losses were between 30% and 40% less than the efficiencies represented by the initial situation.

During this period the only variable that changed was the average experience of the group. i.e., this experience lost, or forgetting, was directly related to changes in production efficiency.

This research provides support to theoretical assertions that posit that employee substitution by other with less experience causes the organizational knowledge stock to decline.

In future studies we will expand the cases presented here with others of different nature and in which the effects of organizational forgetting could vary. The idea is to establish parameters for different line types.

From a practitioner's standpoint managers could benefit from this study in at least two ways. First, it shows the necessity of evaluating turnover-induced forgetting effects due to depreciation of the firm's knowledge stock, insofar as they imply productivity drops. Firms could determine a characteristic set of parameters for its production lines and estimate beforehand plausible efficiency losses due to the introduction of temporary workers.

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