PRODUCTIVITY IMPROVEMENT IN A NETWORK OF LEARNING FACTORIES: A LEARNING CURVE ANALYSIS

by

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Abstract

In 1984, Dutton & Thomas introduced a categorization of factors for accelerating the learning curve. This paper is the first –to our knowledge– that explores all these factors in a total factor productivity learning curve analysis. It does so in a network of production lines in three factories deliberately set up to acquire and share knowledge. The results indicate that even in such a network, transfer of knowledge is non-obvious. First, we find limited evidence that explicit knowledge is easier to transfer than tacit knowledge. Second, productivity improvement hinges on stability in process conditions, particularly stable capacity utilization, continuity in raw material suppliers, and non-increasing reject rates. Third, successful learning by experimentation in dynamic production environments requires control over resources and process settings across production stages.

(Learning Curve, Total Factor Productivity, Learning by Experimentation, Knowledge Transfer)

1 Introduction

In 1932, Wright was the first to report the learning curve phenomenon. He observed that with a doubling of units manufactured, the direct labor hours necessary to produce a single unit decrease at a uniform rate – the learning rate. Since Wright's observation, the learning curve phenomenon has frequently been estimated by scholars and used for planning by managers

(Yelle 1979).

A disappointing managerial implication of the larger part of the learning curve literature, is that the only way to speed up cost improvement is to speed up either cumulative volume or calendar time, which may neither be desirable nor feasible. Yet, experts have emphasized the competitive potential of the learning rate. Some even argue that "the rate at which individuals and organizations learn may become the only sustainable competitive advantage" (Stata 1989). Consequently, we need to improve our understanding on how to manage the learning curve. In particular, scholars have urged to research the managerial levers that accelerate the learning curve (see e.g. Adler 1989, Hayes & Pisano 1996, Jaikumar & Bohn 1992).

Learning rates show considerable variation within industries, within firms, even within plants. Drawing on more than 200 learning curve studies, Dutton & Thomas (1984) conclude that the learning rate should no longer be treated as some exogenously given constant, but as a dependent variable influenced by a firm's behavior. They propose a framework for exploring factors that drive the learning rate.

Dutton & Thomas categorize factors that affect the learning rate according to type of learning (autonomous/induced) and origin of learning (endogenous/exogenous). *Autonomous learning* is the learning that occurs automatically with sustained production. *Induced learning*, on the other hand, requires additional efforts explicitly directed at learning about the production process. *Endogenous origin* refers to learning within the production unit, whereas *exogenous origin* refers to insights obtained outside the production unit. Depending on the level of analysis, a production unit could be a plant, a shift, a production cell, and so on. Examples of factors that affect the learning rate are given in table 1.

This paper is the first –to our knowledge– that estimates the impact of all four factors in a learning curve analysis. It does so in a manufacturing company that decided to proactively manage the creation and transfer of better technological knowledge. Once it had obtained sharp productivity improvements on a production line run as a learning laboratory in one

	autonomous	induced
exogenous	productivity improvements with periodic equipment replacement	copying process settings derived elsewhere (R&D, other plants)
endogenous	learning-by-doing in the plant ("practice makes perfect")	productivity/quality improvement projects in the plant

Table 1: The framework of Dutton & Thomas (1984) with some examples.

factory, called a *"model line"*, it decided to start similar model lines in other factories. Total factor productivity learning curve analyses show that even in a network of model lines deliberately set up to acquire and share knowledge, transfer of knowledge is non-obvious. We find some evidence that induced learning is easier to share than autonomous learning. The paper discusses how learning by experimentation in the factory is impeded if management does not provide (i) stable process conditions, like stable capacity utilization, continuity in raw material suppliers and non-increasing reject rates, and (ii) control over resources and process settings *across* production stages.

This paper is organized as follows. In section 2, we review the few empirical tests that have focused on parts of Dutton & Thomas's framework, and discuss the emerging picture. Section 3 describes the research site, section 4 the data collection. In section 5, we present the learning curve estimates and relate the findings to the context of our research sites. We discuss our findings in section 6, and questions for future research in section 7.

2 The Acquisition and Transfer of Knowledge

This section reviews the empirical learning curve studies that have addressed either the endogenous origin row in table 1 (autonomous vs. induced learning) or the autonomous learning column (endogenous vs. exogenous origin).

2.1 Autonomous vs. Induced Learning within one Production Unit

Levy (1965) is a rare exception in the learning curve literature who investigates the autonomous-induced learning dimension. In fact, Levy's work was at the basis of Dutton & Thomas's (1984) framework. He investigates the impact of prior training and prior experience to explain different learning rates across workers. His analysis is cross-sectional.

Adler & Clark (1991) provide the first longitudinal test of Dutton & Thomas's autonomous-induced learning dimension. Cumulative production volume (CVOL) measures autonomous learning. Two forms of induced learning are investigated: cumulative number of hours spent on engineering changes (CENG) and cumulative number of hours spent by workers on training (CTRN). Interestingly, they find that both forms of induced learning can enhance as well as disrupt productivity improvement. The learning process behind the learning curve, therefore, is internally complex. As the authors admit, CENG and CTRN are proxies for more explicit learning efforts. They acknowledge that future research on these induced learning variables is necessary.

Mukherjee et al. (in press) identify two dimensions of induced learning efforts: conceptual learning (creating know-why) and operational learning (creating know-how). Lapré et al. (1996) provide insight why induced learning can be enhancing as well as disruptive by linking these efforts to a plant-wide quality learning curve. They find that the cumulative number of projects (CPROJ) with both conceptual and operational learning enhances the learning rate, whereas projects characterized by conceptual learning without the corresponding operational learning disrupt the learning rate. Projects without conceptual learning did not affect the learning rate. The nature of knowledge acquired, they conclude, is a key determinant of successful induced learning. The authors also identify an organizational context, a production line run as a learning laboratory called "model line", that appeared to consistently produce the learning rate enhancing mix of high conceptual and operational learning. The current paper builds on this work by studying learning in a network of model lines.

2.2 Endogenous vs. Exogenous origins: the Acquisition and Transfer of Learning by Doing

In the early 1980s, two cross-sectional studies addressed knowledge transfer across plants. Does experience gained by different firms in building power plants transfer across plants (i) within the firm, and (ii) throughout the industry? Zimmerman (1982) investigated these questions in the construction of 41 nuclear power plants. The cumulative number of plants completed within a firm and in the entire industry affected the unit cost of building a nuclear power plant. Yet, firm experience was more significant than industry experience. Joskow & Rose (1985) found no significant transfer of industry experience in a study of 411 coal-burning generating units. However, they did find significant transfer of architect-engineer experience and firm experience. In a cross-sectional study of 41 kitchens in a commercial food firm, Chew et al. (1990) found large differences in productivity, even after controlling for structural and other characteristics. From this persistence of variation they concluded that local know-how was not shared within the firm. In fact, existing incentive systems led to the widespread belief in the firm that plants and managers are unique, thus inhibiting transfer of knowledge in this multiplant network. These cross-sectional studies suggest that transfer of experience can be an important factor for the learning curve, but its occurrence should not be taken for granted.

A recent stream of research by Argote, Epple and co-authors constitutes all longitudinal tests –to our knowledge– of transfer of learning by doing along Dutton & Thomas's (1984) endogenous-exogenous dimension. Endogenous autonomous learning is measured by cumulative production volume (CVOL), the typical measure for learning by doing. Cumulative production volume summed across all production units ($\sum$CVOL) captures exogenous autonomous learning. In a study of 16 shipyards, Argote et al. (1990) identified transfer of learning at the start-up of a yard. However, they did not find ongoing sharing of learning measured by $\sum$CVOL once a yard started production. Comparing intercepts and slopes of simple learning curves, Adler (1990) found similar results in a multi-plant electronics firm.

	autonomous	induced
exogenous	$\sum$CVOL (+, 0)	
endogenous	CVOL (+, 0)	CENG, CTRN (+, −) CPROJ (+, 0, −)

Table 2: Empirical tests of Dutton & Thomas's framework. Argote et al. (1990s): autonomous column. Adler & Clark (1991), Lapré et al. (1996): endogenous row. (+) enhances learning, (0) no significant impact on learning, (−) disrupts learning.

Epple et al. (1991) found partial transfer of learning between two shifts in a truck plant. After adding a night shift in another automotive assembly plant, the day shift continued to learn. Transfer of this experience was the sole source of learning for the night shift (Epple et al. 1996). Darr et al. (1995) studied 36 pizza stores belonging to 10 franchisees. Transfer of learning occurred across stores from the same franchisee, but not across stores from different franchisees. This stream of work typically identifies no or partial sharing of knowledge between organizational units, thus strongly suggesting that knowledge typically does not become fully embedded in the technology. As a result, knowledge sharing is problematic.

2.3 An Emerging Picture

The existing longitudinal empirical tests of Dutton & Thomas's framework are summarized in table 2. It shows that (i) induced learning can be enhancing as well as disruptive, (ii) there is at best only partial evidence of transfer of learning by doing, and (iii) transfer of induced learning has –to our knowledge– never been studied in a learning curve analysis. This picture raises several questions. Why can induced learning be enhancing as well as disruptive? Why is transfer of knowledge problematic? What would be the impact on a learning curve of the yet unexplored factor of exogenous induced learning? Should managers attempt to rely on all four factors to accelerate their learning curves?

These questions become increasingly important as industries rely more on electronics, ceramics, biochemical and other similar technologies rather than the bending, cutting and assembling of sheet metal. Pisano (1994) shows that in traditional chemical based pharmaceuticals, where existing scientific knowledge is strong, learning-before-doing in a laboratory can be very effective. However, in new biotechnology based pharmaceuticals, where technology is more an art than a science, the best place to learn is in the full scale manufacturing environment.

Jaikumar & Bohn (1992) observe that many production environments are inherently *dynamic*, because contingencies –unexpected events which disrupt production– occur routinely. Causes for contingencies include heterogenous inputs, constantly changing environmental variables, and *incomplete technological knowledge* which is defined as incomplete understanding of the effects of the input variables of a process on the output. Contingencies define problems. Hence, in a dynamic production environment problem solving is a key task. Factory personnel continually have to create technological knowledge to adapt to changes in the production environment. They deliberately try to enhance improvement rates, i.e. they proactively manage their learning curves.

We still know very little about the effective management of learning by doing. Von Hippel & Tyre (1995) did discuss why problems in novel process equipment are not identified before doing and reason that it would be difficult to eliminate doing from learning by doing, but much work remains to be done.

On knowledge sharing, the literature on knowledge management provides some insight. Scholars have suggested that the more knowledge can be articulated, i.e. the more it is explicit instead of tacit, the easier it is to disseminate (Nonaka & Takeuchi 1995). Failure to convert tacit knowledge into codified (explicit) knowledge makes it rather difficult to replicate (Teece & Pisano 1994). Szulanski (1996, p.28) notes that "impediments to transfer capabilities within firms have received little attention." He studied the influence of a set of factors on effective transfer of knowledge in 122 best-practice transfers in 8 firms. Interestingly, he

found that instead of motivational factors, like the "not-invented-here" syndrome, the most important impediments to knowledge transfer deal with characteristics of (i) the knowledge transferred, (ii) the recipient of knowledge, and (iii) the context.

The nature of knowledge and the existence of transfer barriers could well have caused the empirical findings summarized in table 2. However, the role of the nature of knowledge and of transfer barriers have hardly been studied in learning curve analyses. Following Adler & Clark (1991), we prefer single firm research and gladly trade generalizability for the richness of interviews with knowledge workers and the richness of discussing quantitative findings with managers. This paper explores all four factors of learning in table 2 in a network of production units deliberately set up to (i) create deep process understanding–i.e. explicit knowledge, and (ii) to transfer that knowledge. This context is described in the next section.

3 The Context

3.1 Bekaert and Its Production Process

The research site for this study is N.V. Bekaert, S.A., a Belgian multinational corporation. Bekaert is the world's largest independent producer of steel wire. In particular, its Steel Cord Division, which hosted this research, produces about one-third of the world's output of the steel wire (called "tire cord") used in the production of steel belted radial tires. By European standards the firm was among the first to embark on a Total Quality Management program, for which it earned two major European Quality Awards in the early 1990s. This research project received the enthusiastic backing of CEO Rafaël Decaluwé, providing us with unlimited access to people and management information systems.

Bekaert's basic process flow is deceptively simple: Thick wire ("wire rod") are pulled ("drawn") through dies which progressively reduce their diameter. Very thin wire ("filaments") are wrapped around each other to form tire cord. The simplest cord has two filaments; the most complex, hundreds. At intermediate points the wire is heat treated to

make it ductile, and a chemical process coats the wires with brass. See figure 1.

Figure 1 about here.

Of course, reality is much more intricate. No supplier for steel cord plants could guarantee homogeneity of properties for the raw materials. As a result, microscopic flaws in the wire can cause fractures (Bekaert's major productivity problem) at any process stage. Different tire manufacturers demand customized product properties. Despite the use of sophisticated controls, wires which are heat treated and coated together do not necessarily have identical properties. There is no complete technological knowledge concerning the effects of upstream process settings on downstream quality. In other words, steel cord plants readily fit Jaikumar & Bohn's (1992) definition of dynamic production environments.

3.2 Model Lines

In the late 1980s, Bekaert realized that central R&D laboratories lacked the characteristics of the dynamic production environment encountered in the factory. It therefore re-located process optimization to the factory. In 1988, Bekaert established a "model line" at its Belgian flagship plant A (MLA) for an important, representative product, and it gave a senior R&D manager the responsibility to create fundamental process control knowledge as well as to produce saleable wire.

The MLA was a fundamentally new organizational structure at Bekaert. Typically, Bekaert steel cord factories organize personnel and machines by functional departments corresponding to the stages in the production process depicted in figure 1. The MLA, on the contrary, is an integrated line corresponding to a product *cutting across all functions.* People and machines are *dedicated to a product*, and managed by a team led by a senior R&D manager.

Mukherjee & Jaikumar (1993) show with two case studies at Bekaert, that an organizational structure like the MLA is essential for creating better technological knowledge if the impact of upstream actions on downstream product properties is ill-understood. To do so,

the MLA team sets goals for productivity and quality improvement based on both R&D and production experience. It collects data on any product/process variable deemed relevant. The MLA team typically solves problems by building scientific models from which it derives testable hypotheses. These hypotheses are tested with natural and controlled experiments (Bohn 1987). The resulting regression output is then used to modify limits for Statistical Process Control (Wadsworth et al. 1986). The MLA is essentially a plant-within-a-plant run as a learning laboratory (Leonard-Barton 1992).

After two years, the MLA was perceived to be very successful. By 1991, impressed with the productivity and quality improvements achieved on the MLA, Bekaert started model lines for similar, important, representative products at two other major European steel cord plants B and C, which we will refer to as MLB and MLC1 respectively. The first manager of the MLA was appointed as the corporate model line manager with the responsibility to coordinate these model line efforts at central R&D. In 1993, a second model line was added in plant C (MLC2).

Given that Bekaert's model lines were deliberately set up to meet the challenge of creating better technological knowledge in a dynamic production environment, they make for a particularly interesting test bed to explore the different factors of learning in Dutton & Thomas's framework. As Epple et al. (1991, p.69) note, it is a challenge in field research on learning "...to find quasi-experiments in the field that make it possible to control for some factors while varying others." As we will discuss below, Bekaert's model lines were managed in different ways. Consequently, we can explore different ways of managing learning controlling for firm, product type, resource market, and production technology factors.

4 Data

4.1 Total Factor Productivity

Following Hayes & Clark (1985), Adler (1990), Adler & Clark (1991), and Ittner (1994), we study monthly total factor productivity (TFP) learning curves. TFP is output divided by the sum of four inputs (direct and indirect labor, capital, and raw materials)[1]:

$$\mathrm{TFP}_t = \frac{p_{93} y_t}{\sum_i w_{i,93} x_{it}}$$

where p_{93} is the 1993 unit cost per ton, y_t the output produced in month t, $w_{i,93}$ the 1993 unit cost for input i, and x_{it} the quantity of input i used in month t. We chose 1993 as the base period for fixing prices and costs, as it was the only year during which all four model lines were operating. The data to compute TFP was primarily collected from the management information systems used by model line personnel. They report productivity data for each process step on a monthly basis. For the MLA, data was available from start-up for the complete line (Sep 1989) till transfer of the product to a US plant (Aug 1993). For the other lines data was available from start-up (between July 1991 and Feb 1993) till April 1995. For each line, we aggregated the data available for the different process steps to derive TFP for the entire model line. We defined output and input quantities as follows:

- **Output.** For plants A and B, output was directly available as good tonnage produced at the final step. For plant C it had to be estimated by multiplying the amount of raw material released to the process with the product of the yields at every step. Yields were easily derived from the available reject rates per step. The corporate model line manager estimated the 1993 unit costs for the different lines. These estimates were verified in the plants.

[1]There are two other inputs: energy and consumables. Data on these two inputs, however, were not consistently recorded. For one model line the energy data available showed a perfectly constant amount of energy consumption per ton. Excluding energy therefore has little impact on the variation in TFP. Consumables make up less than 5% of the unit cost, so again exclusion does not have a big impact on TFP.

- **Direct labor.** Direct labor hours per ton were directly available for each step. Multiplying with the tonnage processed on the corresponding steps, then summing across all steps, gave the total direct labor hours. These total direct labor hours were multiplied with the 1993 average direct labor cost per hour (including benefits).
- **Indirect labor.** A model line is essentially a plant-within-a-plant, run by a model line team. So, the indirect labor is simply the head count of process engineers, technicians, and indirect workers assigned to the model line team. Evolutions of these headcounts obtained from the model line managers were confirmed by model line personnel and documents. Headcounts were weighed by annual 1993 labor costs (including benefits) for each category divided by 11. (Bekaert produces 11 months per year.)
- **Capital.** Machine hours per ton for each step, directly available, were multiplied by the output produced at the corresponding step, yielding total machine hours per step. For each machine type, 1993 machine prices (including installation costs) were obtained from R&D documents. Using steel cord plant linear depreciation schemes, these machine prices were transformed to an hourly basis. Following Hayes & Clark (1985), Adler (1990) and Adler & Clark (1991), we operationalized total cost of capital as the return *of* capital (depreciation) plus the return *on* capital (opportunity cost). For the former we obtained the linear depreciation schemes from the plants' accounting departments. For the latter we followed recent TFP studies (Adler 1990, Adler & Clark 1991, Ittner 1994) by estimating the return on capital at 7%, reflecting the long run average inflation corrected cost of a typical mix of debt and equity (Kaplan 1986). Multiplying the resulting machine cost per hour for each machine type with the total machine hours at the corresponding process step, then summing across all steps, we obtained total capital costs.
- **Raw materials.** At plant C wire rod tonnage released to the process was directly available. For plants A and B, it was derived using final output and intermediate reject rates. On model lines A, C1 and C2 there were repeated shifts from expensive,

high quality wire rod to cheaper, lower quality wire rod. Monthly percentages of the different wire rods used were also collected. For each wire rod quality, 1993 prices were obtained from the plants' purchasing departments.

Following Hayes & Clark (1985), we graphed TFP and discussed the resulting patterns with the model line managers to understand the evolution of productivity (e.g. trends, peaks, plateaus). Although the model line managers were our key informants, we have discussed these patterns with managers at all levels within Bekaert, literally ranging from foremen on the factory floor to the CEO. Through these discussions we learnt that we had to re-calculate TFPs accounting for different raw material qualities and changes in the composition of the model line teams. Although Bekaert used many single dimensional quality and productivity measures like rejects and machine hours per ton at a particular step, its management completely lacked an overall measure for total model line productivity performance. Managers at all levels felt that the TFP measure was particularly well suited for this purpose as it gave them (i) a dynamic perspective, (ii) a measure not distorted by inflation effects, and (iii) a measure that aggregated the trade-offs between partial measures they typically focused on. The final TFP patterns confirmed the ideas managers intuitively had about productivity evolution, even though they lacked such a measure before. Again following Hayes & Clark (1985), we did not relate TFP estimates to the learning variables until Bekaert's management agreed on the computation of the measure and felt that the resulting pattern gave a good representation of the model lines' productivity evolution. See figure 2. To protect Bekaert's proprietary data, the scale is not reported. It is important to note that the evolution of the curves, i.e. the improvement rates, can be compared, but the absolute level cannot. The absolute TFP levels depend heavily on the 1993 unit prices negotiated with different customers. (The different model lines delivered to different customers.) The variations between the TFP curves, ranging from sharp improvements to no improvements at all, demonstrate that the different model line implementations gave different results. Explaining the factors that led to this variation is the focus of the remainder of the paper.

Figure 2 about here.

4.2 Learning Variables

Autonomous endogenous learning is typically operationalized by cumulative production volume (CVOL). Mishina's (1992) study of Boeing's production of B-17 heavy bombers shows that autonomous learning is more related to the scale-up of production as opposed to repeated production. His rationale is that learning occurs only if there is a challenge. Scale-up of production provides such a challenge. He used maximum proven capacity (maxVOL) to measure learning by new experiences. Findings by Epple et al. (1996) and von Hippel & Tyre (1995) are consistent with Mishina's results. The maxVOL measure is particularly appropriate in dynamic production environments like Bekaert's. Here scale-up can be achieved by adding new machines or increasing machine speeds. In both cases factory personnel need to acquire new technological knowledge on how to control their process in the changed production environment. We therefore also use Mishina's experience variable. For autonomous exogenous learning we sum output over the other model lines to compute $\sum$CVOL and max$\sum$VOL. Through interviews we learnt that a lot of learning on the model lines occurred by ongoing experimentation. Model line personnel continually try to create technological knowledge by running natural and controlled experiments to derive better statistical process control rules. Autonomous learning in this context of learning laboratories in the factory can therefore readily be characterized as learning by experimentation (Bohn 1987).

In addition to the ongoing experimentation, explicit projects were also defined and carried out by the model line teams. These projects typically dealt with specific quality/productivity problems. We use the cumulative number of projects completed (CPROJ) to measure induced endogenous learning within a model line. One of us extensively interviewed the model line managers to obtain the completion dates of all the model line projects. In his presence, they went through all their monthly activity reports from the start of the model line till 1996 to identify all projects and their completion dates. Summing over the other model

	autonomous	induced
exogenous	$\sum$CVOL max$\sum$VOL	$\sum$CPROJ
endogenous	CVOL maxVOL	CPROJ

Table 3: Measures to explore the framework of Dutton & Thomas in a network of model lines.

lines we compute $\sum$CPROJ to measure induced exogenous learning. Project knowledge was typically codified in monthly activity reports and shared with central R&D and other model line teams. Twice a year, model line teams met at central R&D to exchange such knowledge. Further, model line managers also communicated directly between them. Table 3 summarizes the learning variables for exploring the full framework of Dutton & Thomas.

4.3 Policy Variables

Our discussions with the model line managers revealed that various factors affected the TFP evolutions, thus suggesting different policy variables to control for in the respective learning curves.

- **Capacity utilization.** Due to the fixed indirect labor cost TFP can be sensitive to volume changes. We therefore define capacity utilization (CUT) as the ratio of actual output to estimated capacity. The latter was constructed by linearly interpolating between successive peaks of actual output during the scale-up phase (Hayes & Clark 1985). Once proven capacity reached its peak for the time horizon under study, we used this value. This approach is justified because capacity was never re-allocated to other production lines during the time horizons studied in figure 2. Compared to the other model lines, MLC2 showed little variation in capacity utilization.
- **Reject rates.** Hayes & Clark (1985) and Ittner (1994) found that rejects can have a profound effect on TFP. We used the intermediate reject rates to compute an aggregate

model line reject rate (REJECTS) to estimate this effect. Model line A improved its reject rate dramatically, whereas the others showed little to no improvement at all.[2]

- **Changes in raw material suppliers.** The previous two policy variables have been used before in TFP research at process companies. Discussions of the TFP patterns at Bekaert revealed another important one. In plant C, low TFP values turned out to be associated with changes in the wire rod composition. Changes to the expensive, high quality rod were made (i) if the regular supplier could not deliver, or (ii) to re-optimize the process if the customer modified specifications for product properties. To estimate the effect of changes in raw material, we introduce ΔRAWMAT specifying the share of wire rod for which a different quality is used compared to the previous month. Such changes typically require some re-adjustments in the production process and can therefore be disruptive.

Where relevant, we expect TFP to have a positive correlation with capacity utilization, and a negative correlation with reject rates and changes in raw material suppliers. We now turn to the econometric analysis.

5 Empirical Results

5.1 TFP Learning Curve Estimates

The classic TFP learning curve controlled for capacity utilization is (Hayes & Clark 1985):

$$\ln \mathrm{TFP} = \beta_0 + \beta_1 \ln \mathrm{CVOL} + \beta_2 \ln \mathrm{CUT} + u \tag{1}$$

[2]Through any of the learning variables discussed in section 4.2, reject rates could improve. Later in the paper we return to this issue. For now it suffices to note that TFP captures a fundamental trade-off. On the one hand, changes to cheaper, low quality rod reduce cost thus enhancing TFP. On the other hand, changes to cheaper, low quality rod increase rejects thus disrupting TFP. TFP is therefore a better measure of the final objective on a model line, where reducing rejects is only one means of improving productivity.

Hayes & Clark (1985) extended equation (1) with managerial variables X_i in a multiplicative fashion to obtain

$$\ln \mathrm{TFP} = \beta_0 + \beta_1 \ln \mathrm{CVOL} + \beta_2 \ln \mathrm{CUT} + \textstyle\sum_i \beta_i X_i + u \tag{2}$$

We will use the same functional form to estimate TFP learning curves with the various learning variables discussed in the previous section:

$$\ln \mathrm{TFP} = \beta_0 + \beta_1 \ln \mathrm{CVOL} + \beta_2 \ln \textstyle\sum \mathrm{CVOL} + \beta_3 \mathrm{CPROJ} + \beta_4 \textstyle\sum \mathrm{CPROJ} + \textstyle\sum_i \beta_i X_i + u \tag{3}$$

$$\ln \mathrm{TFP} = \beta_0 + \beta_1 \ln \mathrm{maxVOL} + \beta_2 \ln \max \textstyle\sum \mathrm{VOL} + \beta_3 \mathrm{CPROJ} + \beta_4 \textstyle\sum \mathrm{CPROJ} + \textstyle\sum_i \beta_i X_i + u \tag{4}$$

where the X_i's are the policy variables lnCUT, REJECTS, and ΔRAWMAT.

For each model line, we estimated equations (3) and (4) with the AUTOREG procedure in the SAS package, specifying an AR(1) process for u (i.e. $u_t = \rho u_{t-1} + e_t$). The policy variables that were not significant were dropped, and equations (3) and (4) were estimated again. Tables 4 and 5 report the results. Intercepts are not reported to protect Bekaert's proprietary data.

None of the estimated autocorrelation coefficients were statistically significant, indicating that the TFP learning curve models (3) and (4) do not suffer from misspecification. Furthermore, except for the flat learning curve at MLB, the learning variables and the relevant policy variables explain the larger part of the variation in TFP evolution as witnessed by the R^2s ranging from 0.74 to 0.97.

If significant, all coefficients for the policy variables have the expected signs. It is easy to understand why some policy variables are not significant in the context of the specific model lines. Changes in raw material suppliers only played a role in factory C where discussions with model line personnel identified this variable. (On the MLA there was a gradual change to cheaper wire rod. On the MLB this shift occurred after the time horizon studied.) On the MLC2 capacity utilization varied much less compared to the other lines. For the others volume dropped several times to a third of maximum proven capacity. For the MLC2, however,

	MLA	MLB	MLC1	MLC2
lnCVOL	0.090***	0.048	0.065**	−0.032
	(0.013)	(0.040)	(0.029)	(0.030)
lnΣCVOL	−0.001	−0.035	−0.086	0.203
	(0.002)	(0.069)	(0.155)	(0.298)
CPROJ	−0.003	−0.010***	0.013*	−0.009
	(0.004)	(0.003)	(7.6E−3)	(0.007)
ΣCPROJ	1.7E−3	0.004	−9.1E−3*	7.6E−3*
	(1.5E−3)	(0.003)	(5.1E−3)	(4.2E−3)
lnCUT	0.130***	0.045***	0.129***	
	(0.012)	(0.011)	(0.031)	
REJECTS	−0.950***	−1.204***	−1.308***	−1.662**
	(0.174)	(0.351)	(0.299)	(0.591)
ΔRAWMAT			−0.059**	−0.075***
			(0.023)	(0.025)
ρ	−0.101	−0.185	0.094	−0.201
	(0.166)	(0.166)	(0.188)	(0.238)
R^2	0.973	0.506	0.785	0.741
R^2-LV	0.863	0.116	0.390	0.580
n	44	43	37	25

Dependent variable lnTFP. Standard errors in parentheses.

* signifies significant at 0.10 in a 2-tail test, ** at 0.05, *** at 0.01.

R^2-LV gives the R^2 of estimating equation (3) without the policy variables. As such, it is indicative of the part of the variation explained by the learning variables.

Table 4: TFP learning curve estimates with CVOL

	MLA	MLB	MLC1	MLC2
ln maxVOL	0.097***	0.093	0.171***	−0.072
	(0.027)	(0.085)	(0.034)	(0.112)
ln maxΣVOL	0.034	−0.000	−0.049	0.072
	(0.024)	(0.047)	(0.063)	(0.141)
CPROJ	0.005	−0.009***	0.015***	−0.009
	(0.004)	(0.003)	(0.005)	(0.006)
ΣCPROJ	0.002	4.0E−3*	−9.4E−3*	0.010***
	(0.002)	(2.0E−3)	(5.1E−3)	(0.003)
lnCUT	0.132***	0.042***	0.143***	
	(0.014)	(0.012)	(0.028)	
REJECTS	−1.076***	−1.109***	−1.298***	−1.531**
	(0.207)	(0.331)	(0.280)	(0.592)
ΔRAWMAT			−0.049**	−0.077***
			(0.022)	(0.026)
ρ	−0.114	−0.208	0.144	−0.167
	(0.166)	(0.165)	(0.187)	(0.239)
R^2	0.961	0.465	0.820	0.739
R^2-LV	0.819	0.094	0.411	0.574
n	44	43	37	25

Dependent variable lnTFP. Standard errors in parentheses.

* signifies significant at 0.10 in a 2-tail test, ** at 0.05, *** at 0.01.

R^2-LV gives the R^2 of estimating equation (4) without the policy variables. As such, it is indicative of the part of the variation explained by the learning variables.

Table 5: TFP learning curve estimates with maxVOL

the largest drop was to 50% of maximum proven capacity, which was highly exceptional. So, it is not surprising that lnCUT did not affect TFP at MLC2. The results underline the importance of managing stable capacity utilization, continuity in raw material suppliers, and non-increasing reject rates.[3] We will discuss the importance of managing stability in these policy variables in section 6. First, we relate the estimates for the learning variables to the context of the four model lines.

5.2 Learning in the Different Model Lines

For each model line, equations (3) and (4) explain similar amounts of variation. In other words, based on the R^2s it is difficult to say whether autonomous learning is more associated with CVOL or maxVOL. There is a marked difference though between the estimates for equations (3) and (4). Some of the learning variables are more significant for equation (4) than for equation (3). There is both a statistical and a substantive explanation for this. First, by construction maxVOL is a smoother curve than CVOL, exhibiting less variation. As a result, maxVOL introduces less noise into the regression, thus decreasing the standard errors. Second, as described in section 4.2 there are substantive reasons why autonomous learning in Bekaert's context could be more associated with maxVOL than with CVOL. If this is the case, then introducing maxVOL instead of CVOL would reduce the amount of noise, thus decreasing the standard errors. Table 6 summarizes the learning factors that

[3]As noted in section 4.3, one could argue that the different learning variables also affected the reject rates. To study this, we estimated a system of two simultaneous equations where lnTFP and REJECTS are the endogenous variables; lnTFP is modeled as equation (3), REJECTS depends on the four learning variables and additional variables measuring wire fractures at different process steps–the main reasons for rejects. We estimated the resulting system with three stage least squares (3SLS) for the MLA and the MLC1. (For MLB there were no additional data on fractures; for MLC2 there were only few degrees of freedom.) 3SLS gave identical significance results for the lnTFP equation. The same learning variables driving TFP improvement also determined reject reductions. In the interest of parsimony, and given that no additional insights were obtained from the 3SLS estimates we focus on equations (3) and (4).

	autonomous	induced
exogenous	max$\sum$VOL:	$\sum$CPROJ: MLC2 (+)
endogenous	maxVOL: MLA (+), MLC1(+)	CPROJ: MLC1 (+), MLB (−)

Table 6: Sources for TFP learning in a network of model lines significant at 0.01 for model (4). (+) enhances, (−) disrupts productivity improvement

were found to be significant at 0.01 for model (4). These were also at least significant in model (3) at 0.1. We now relate the significant factors of learning to the context of each model line.

- **MLA.** The first model line at plant A started before the others and was stopped in 1993, because production was transferred to a US plant. Given its pioneering role, it is not surprising that it did not benefit from exogenous learning. The strong significance of autonomous endogenous learning confirms the effectiveness of learning by ongoing experimentation by the MLA team (Mukherjee & Jaikumar 1993). At first sight, it seems surprising that endogenous project learning was not significant. As the MLA team had full authority over production, it could implement changes straight away; it did not have to wait until projects were formally finished. More importantly, it did not have to seek plant management approval for implementing changes in production based on final project reports. The MLA had truly come to institutionalize continuous learning by experimentation.
- **MLB.** Investigation of the MLB data revealed that potential productivity gains in a particular process step were never capitalized on. The same amount of workers and machines were always allocated to the MLB product: if productivity gains were made in one particular step, personnel was simply re-allocated to another. The MLB team was given the responsibility to create technological knowledge, but not the authority to

implement changes in production. Furthermore, functional managers for the different process steps did not always coordinate actions with the MLB team, thus inhibiting the use of controlled experimentation. As a result, learning by experimentation like in the MLA case was impeded. Projects even had a disruptive effect on TFP. Due to the lack of authority over production, the MLB team could not validate project findings in full scale manufacturing. As Lapré et al. (1996) showed, such efforts can be disruptive to a factory's learning curve. Moreover, the MLB team was not always allowed to choose the projects to undertake. The MLB team's lack of authority in production also explains why no exogenous learning occurred. The barren organizational context at plant B did not support the transfer of project insights from other model lines (cf. Szulanski 1996).

- **MLC1.** The model line team at plant C realized productivity improvements on model line C1 through both types of endogenous learning: learning by experimentation and by projects. The team was given more authority to implement changes in full scale manufacturing compared to the MLB team, but not to the extent of the first model line team at plant A. As at plant B, the personnel working on the model line product were still reporting to traditional functional managers. Hence, some learning by experimentation got implemented immediately, while other projects first had to be signed off before they could be fully implemented. Although both endogenous factors of learning were effective in the MLC1, its TFP curve did not show the sharp improvements like the MLA did. Plant management was sufficiently supportive of the model line for it to have a significant impact on TFP, but paid little attention to the disruptive variations in capacity utilization, reject rates and raw material suppliers.
- **MLC2.** In 1993, the model line team at plant C, was given a second model line. However, it only invested 15% of its time and efforts to this MLC2, the other 85% remained focused on the MLC1. The MLC2 was mainly started to implement productivity improvements as opposed to creating new technological knowledge. Consequently, there

were few experiments and projects. Nevertheless, learning by projects at other model lines did enhance the productivity of the MLC2. Further investigation of $\sum$CPROJ reveals that during the period studied for MLC2, it was mainly the MLC1 that added projects to $\sum$CPROJ. As can be seen in figure 2 there was little overlap between the MLA and the MLC2. Further, there were few projects on MLB. So, the model line team at plant C essentially learnt by projects on MLC1 and transferred that knowledge to MLC2. This observation is similar to findings by Epple et al. (1996). They found that a truck plant learnt on one productive unit (the day shift), and transferred that knowledge to another unit in the same plant (the night shift). Similar to the MLC1 though, TFP did not grow as much as would have been possible, because of disruptive variations in raw material suppliers.

Although the MLA was perceived to be a success, the model line implementations at plants B and C did not yield similar improvements. Why did learning not have a bigger impact in plants B and C? Before we discuss the role of the policy variables, we have to rule out two alternative explanations. Factors that differed across the model lines concern the maturity in the product life cycle and the timing of the start of the model lines.

The MLA product was relatively new, whereas the products on the other model lines had been in production for many years. Was there simply nothing left to learn for the latter products? The answer is no. On the MLB, the shift to cheaper raw material took place after the time horizon studied in figure 2, and gave a boost in TFP comparable to MLA improvements. On MLC1, the estimates for the learning variables in table 5 show that similar TFP improvements could have taken place were it not for the disruptive effect of the policy variables. These observations also rule out the timing of starting a model line as a possible explanation. Did the model lines at plants B and C incorporate all the learning from the MLA before productivity data was tracked? As observed above, both the MLB and the MLC1 still had a lot of "low hanging fruit" left. The next section discusses the management of policy and learning variables in explaining the differences in TFP learning

on the different model lines.

6 Discussion

6.1 Stability in Policy Variables

To appreciate the importance of the policy variables, look at their explanatory power. The variation in TFP explained by the policy variables ($R^2 - R^2$-LV in tables 4 and 5) is around 15% for model lines A and C2, whereas it is as high as around 40% for B and C1. On the MLA, stable capacity utilization, continuity in suppliers and reducing rejects were well managed. On the other model lines, however, variations in capacity utilization, changes in raw material suppliers, and increasing rejects had a significantly disruptive effect on TFP, thereby impeding the potential gains of the learning variables.

To illustrate the importance of stability, take the example of the MLC1. One additional project would improve TFP by roughly 1.5%. This effect, however, would be nullified by any of the following events: letting rejects slip 1.5%, reducing full capacity utilization by 15%, or changing to a different supplier for 30% of the raw materials. These events happened frequently.

Why can lack of stability disrupt TFP learning that much? The reason for learning in the full scale manufacturing environment of the factory as opposed to the R&D laboratory is high fidelity. This is particularly true if the existing scientific knowledge base is ill-developed as was the case for our site Bekaert. (See e.g. von Hippel & Tyre 1995, Pisano 1997, Iansiti 1998.) However, because of the "complex and sometimes chaotic environments" encountered in factories, "...slight, but unavoidable batch-to-batch differences in raw materials, equipment, workers, equipment settings, and other process parameters will reduce the signal-to-noise ratio of factory experiments" (Pisano 1997, p.46). Therefore, everything that can be controlled can prevent a reduction in the signal-to-noise ratio. This is the power of stable capacity utilization, continuity in raw material suppliers, and non-increasing rejects.

Loosely put, in a factory experiment, control what you can.

Capacity utilization is a function of demand. Close relationships with customers can reduce demand variation and thus enhance stable capacity utilization. Discontinuity in raw material suppliers at plant C was often a reaction to changing customer specifications or changes in the suppliers' production processes. If management would have been able to measure the economic impact of these reactions –with e.g. TFP– they might have been more careful in switching between suppliers. In any case, the potential benefit of communication in the supply chain is self evident. Not allowing reject rates to slip seems obvious, but reinforces the importance of quality control.

6.2 Endogenous Learning: Control over Resources for Experimentation and Implementation

It is useful to compare the different model line teams with different ways of organizing new product development teams. The MLA team fits the description of an "autonomous team", or *tiger team*, characterized by a project leader who is "a heavyweight in the organization and is given full control over the resources contributed by the different functional groups" (Wheelwright & Clark 1992, p.196). The model line team at plant C, on the other hand, resembles a "lightweight team", whose manager is "lightweight" as he/she is generally a middle- or junior level person faced with functional managers who remain in control of key resources. As Wheelwright & Clark (1992, p.194) note, "Lightweight project leaders find themselves tolerated at best, and often ignored and even preempted." In the MLB case, all control basically remained with functional managers.

The MLA team fully relied on autonomous endogenous learning. Even though it formulated formal projects, experiments run during these projects were implemented straight away like all other "autonomous" experimentation. For C1 both types of endogenous learning enhanced TFP growth. On the one hand, ongoing experimentation with relatively low cost solutions were implemented directly. For more expensive solutions, projects were formally

defined and on successful completion had to be approved by plant management in order to be implemented.

Depending on the amount of control over resources given to a model line team, the team can choose to rely on autonomous and/or induced learning. Both approaches can enhance TFP. However, if the team is not given the appropriate resources for experimentation and implementation neither form of endogenous learning might be effective, and as the MLB case shows this can even be disruptive.

For successful learning both knowledge and saleable products should be produced (Chew et al. 1991). For successful cross-functional experimentation in the factory this implies control over resources and process settings *across all production stages* (Mukherjee & Jaikumar 1993).

6.3 Exogenous Learning: Induced Learning May Be Easier to Share

We found little evidence of exogenous learning. No autonomous learning was shared; only model line C2 benefited from induced learning by other lines, mainly C1.

Prior learning curve studies did not find a lot of knowledge transfer either (see the literature review in section 2.2). Szulanski (1996) categorized barriers to transfer of best practice as characteristics of (i) the knowledge transferred, (ii) the source of knowledge, (iii) the recipient of knowledge, and (iv) the context. For the MLC2, the latter three were identical for autonomous and induced learning. The only transfer barrier that could have differed between autonomous and induced learning is the nature of knowledge transferred.

Projects (induced learning) are typically documented, i.e. they are encoded as explicit knowledge. Ongoing experimentation (autonomous learning), on the other hand, is often left undocumented; at best it remains in the organization as tacit knowledge. The MLC2 finding is –to our knowledge– the first (modest) evidence in a learning curve analysis that explicit knowledge is indeed easier to disseminate than tacit knowledge (e.g. Teece & Pisano

1994, Nonaka & Takeuchi 1995).

We found no evidence of exogenous learning for the other model lines, suggesting that even if knowledge is made explicit other barriers to knowledge transfer (Szulanski 1996) could be in effect.

7 Implications

This study is the first to our knowledge that explores the four different factors of learning proposed by Dutton & Thomas (1984). Their framework provides a good vehicle to study different factors that could accelerate the learning curve. This paper just started to scratch the surface by introducing the variable "cumulative number of productivity improvement projects summed across production units". The results give some limited support –in a learning curve analysis– for the oft cited notion that explicit knowledge is easier to transfer than tacit knowledge (e.g. Nonaka & Takeuchi 1995). Developing measures for exogenous induced learning and incorporating them in learning curve analyses could help advance our understanding of how knowledge gets shared in a network of organizational units.

Even though the different factors of learning explained an important part of the variation in TFP, a significant part –as large as 40%– was explained by policy variables. Drops in capacity utilization, increasing rejects and changes in raw material suppliers disrupted TFP. When low fidelity conditions in R&D laboratories dictate learning by experimentation in full scale manufacturing, management is well advised to create a stable production environment to reduce noise as much as possible. This paper made a first cut at introducing a supplier related variable in a learning curve analysis. Investigating the impact of supply chain management on factory learning curves warrants further research.

The results also pointed to the importance of providing control over resources for experimentation and implementation. Researching the organizational structures that facilitate the acquisition and transfer of knowledge would make for important work.

A single paper clearly does not resolve the issue of what triggers autonomous learning.

Both cumulative volume and maximum proven capacity explained the TFP learning curves quite well. Disaggregation down to process steps might shed some light on this issue. Repeated production, for example, may be more important in labor intensive technologies, whereas scale-up of production may be triggering learning in capital intensive technologies. Addressing these questions will help organizations to better measure and manage their learning curve processes.

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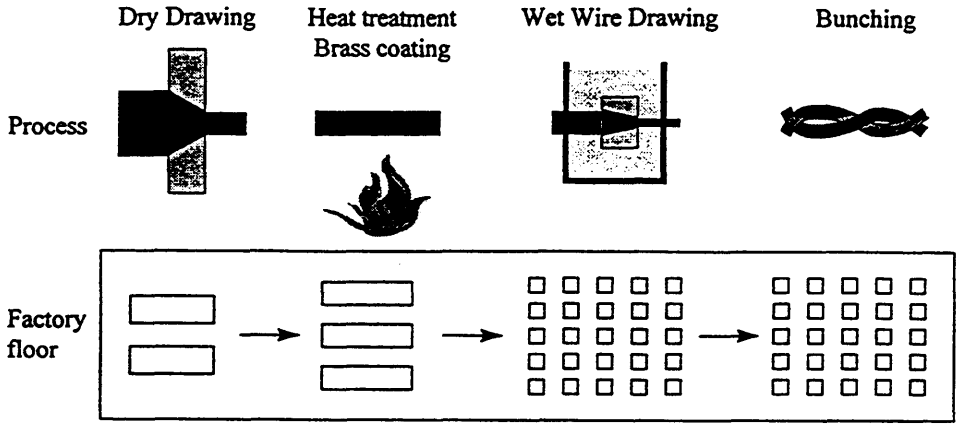

Figure 1: Simplified, schematic process flow of a Bekaert factory. In reality several steps are repeated. Causes for contingencies include heterogenous inputs, constantly changing environmental variables, and incomplete knowledge of the effects of upstream process settings on downstream quality. Typically, personnel and machines are organized by functional departments corresponding to the stages in the production process.

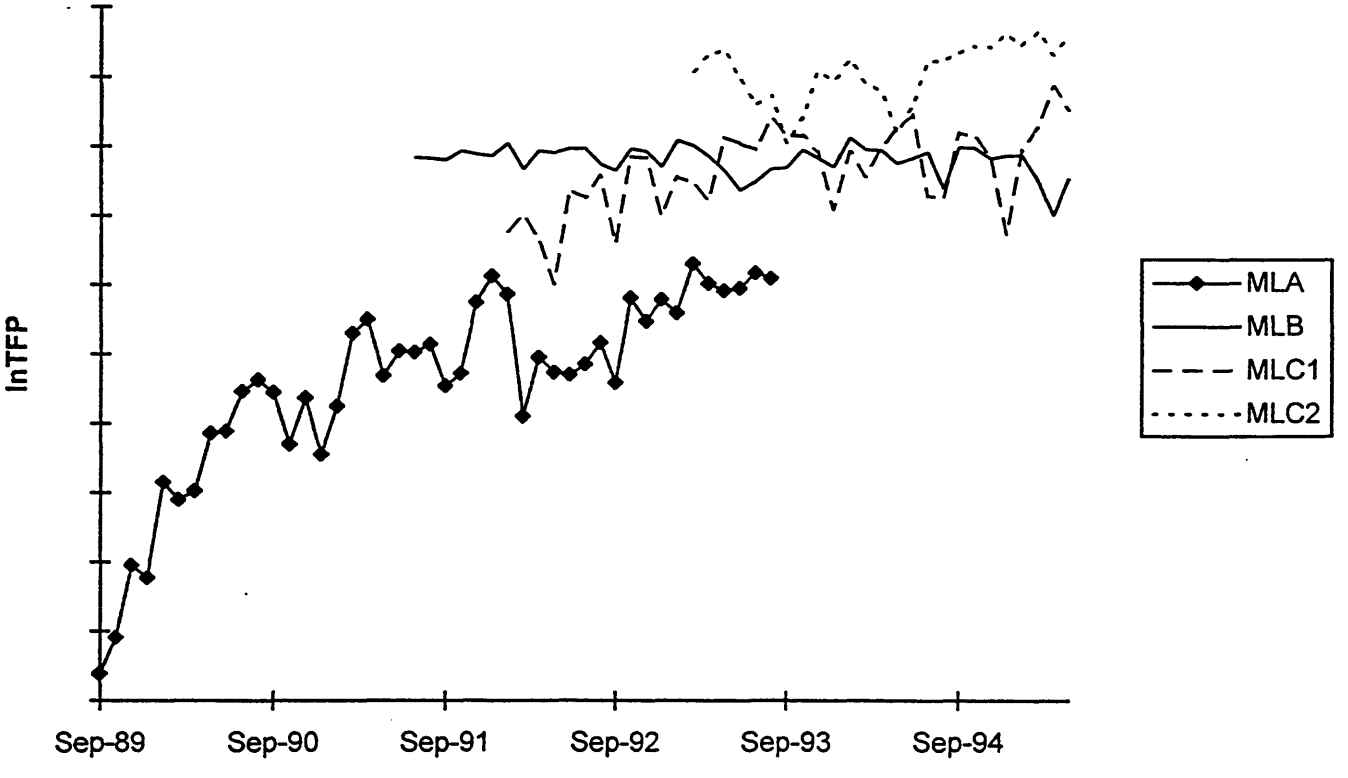

Figure 2: Logarithm of Total Factor Productivity for the four model lines.