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Abstract: Central in this paper is a puzzling innovation project involving the introduction of a new machine in an assembly plant in the aviation industry. The project drew our attention because it achieved remarkably high performance results despite being launched with a negative business case. The observed performance trend neither corresponds to uncertainty reduction nor results from a pure investment in the unknown: we demonstrate that this case is an anomaly with regards to investment decision-making logics and learning dynamics (Learning by Doing) which traditionally explain performance gains. We find that the dynamics at work were made possible by an original and rigorous managerial approach adopted to address the significant presence of unknown at project launch and during project deployment. Based on this case study, we identify three principles respectively aiming at guiding investment decisions, at (economically) managing projects and at organizing learning in the unknown. The first principle recommends to keep using the classical economic tools (e.g. business cases) which advise against the project, but in a "diverted" way, i.e. as a means to keep the losses under control in case of failure. The second one suggests to clearly set in the team's mission the objective to discover new performance variables. The third one proposes to deploy a learning strategy related to the newly-discovered variables that is based on the very objective to build profitability and turn the project into a profitable one.

1. Introduction

This paper focuses on a puzzling innovation project observed in a plant in the aviation industry. Firstly, this project was launched in spite of a negative business case. However, this feature is not the most disconcerting of the case since at their outset, such improvement projects are often marked by uncertainties. Further information and evidence must be acquired in order to reduce and eliminate the uncertainties. During project deployment, *Learning by Doing* mechanisms enable to collect such uncertainty-reducing information and evidence. Consequently, *Learning by Doing* represents the opportunity for the plant to achieve in the long run performance improvements (e.g. cost reduction, productivity growth…) which are higher than those that would be obtained without having invested in the project at all (Terwiesch and Bohn, 2001). Therefore, the perspective of *Learning by Doing* represents the possibility to justify the launch of

initially costly innovation projects (Mody, 1989 ; Terwiesch and Bohn, 2001). But in our case, uncertainty reduction during project deployment did not lead to performance improvements: quite the contrary, it oriented the project toward a less favourable conjuncture than forecasted in its business case. However, surprisingly, the overall performance of the project did turn out to be remarkably higher than estimated in the business case. Therefore, this case appears not to have followed traditional *Learning by Doing* dynamics. This leaves us with a couple of options to explain the rationale driving the decision to invest in this project and to explain the dramatic performance trend that it experienced. Either this project brings to light a new form of uncertainty reduction, in a form other than *Learning by Doing*. Either the literature suggests that not only uncertainties (related to previously identified states of the world) but also unknown-unknowns (related to non-initially identifiable states of the world) could have played in role in this project which would be the result of an investment decision in the unknown (Pich et al., 2002 ; Sommer et Loch, 2004 ; Sommer et al., 2008 ; Feduzi et Runde, 2014). This "investment in the unknown" scenario, implies managers paying in order to gather further information and evidence, but without initially knowing the nature of the information to be collected nor their related states of the world. In this second scenario, unknown-unknowns are expected to uncover additional information. In other words, this second explanation would imply that the plant, counting on serendipity, deployed a "gambling" strategy and accepted to pay in order to see what would happen.
In this paper, we demonstrate that our case does not fall within the scope of any of these two explanations. And we describe and attempt to characterize the original managerial response to unknown-unknowns that positively impacted performance. In other words, we observed an investment in the unknown framed by a rigorous managerial approach, which neither consisted in reducing uncertainties nor in awaiting unknown-unknowns to emerge, but which consisted in an organized approach structured around three principles respectively aiming at guiding investment decisions, at (economically) managing projects and at organizing learning in the unknown.

Consequently, we seek to provide answers to the two following research question. To what extent is the performance trend achieved in this case anomalous with respect to performance gains traditionally achieved by reducing uncertainty? How can we characterize the managerial approach (and its associated principles in terms of investment decision, economic steering and learning strategy) which resulted in the observed dramatic performance gains?

The plan of this paper is as follows. In Section 2, we review the literature related to investment decisions, *Learning by Doing* and uncertainty management. Section 3 explains the research method. Section 4 is dedicated to our case study: we demonstrate that our case is indeed an anomaly and we attempt to characterize the managerial logic and principles enabling to explore the unknown and to build such significant performance gains. We call 'Learning by Designing' this approach. Finally, research implications and practical implications are respectively given in Sections 5 and 6.

2. Review of the literature: *Learning by Doing*, investment decisions and uncertainty management

2.1 Learning by Doing as a lever to justify (costly) investments in innovation, engineering… efforts

Learning by repeating fixed tasks is the most obvious form of learning: by repeating tasks in a fixed-facility environment, individual workers accumulate experience and learn, which results in a reduction in the time needed to fulfil the tasks, and as a consequence allows costs reductions. This form of autonomous, free of charge and non-intentional learning has often been associated with both Wright's (1936) curves which describe labour-hours (and thus production costs) decreasing with cumulative production volumes in aircraft assembly plants and with Arrow's (1962) seminal notion of *Learning by Doing*. However, Wright (1936) notes the diminishing returns of the phenomenon described by his curves and he is less interested in learning at the level of individual workers than in levers which could reduce production costs, such as scaling effects, investment in new equipment... (Bell et Scott-Kemmis, 2010). Similarly, whereas many studies claiming to represent the 'Learning by Doing' frame focus on the relationship between cumulative production volumes (cumulative outputs) and firm's productivity, Arrow's original work studies the relationship between cumulative investments (cumulative inputs) and productivity (Bell et Scott-Kemmis, 2010). By focusing on cumulative inputs (which record investments in new equipment, triggering "new situations" in the production environment) rather than on cumulative outputs, Arrow is more interested in productivity gains resulting from "changed situations" than in productivity gains resulting from repetition:

> *"Learning associated with repetition of essentially the same problem is subject to diminishing returns. There is an equilibrium response pattern for any given stimulus, toward which the behaviour of the learner tends with repetition. To have steadily increasing performance, then, implies that the stimulus situations must themselves be steadily evolving rather than merely repeating." (Arrow, 1962)*

Thus, Wright's (1936) approach and Arrow's (1962) definition of *Learning by Doing* represent a lever to justify (costly) investments in projects involving new situations (e.g. new equipment, new processes…). In particular, they already indirectly represent a lever to justify investments marked by a part of uncertainty (triggered by the new situation).
Arrow's (1962) work introducing the concept of 'Learning by Doing' is theoretical. But more or less recent cases show that investments in *new* equipment and technical improvement turn out to explain dramatic productivity gains that could not be attributed to "Learning by repeating" mechanisms. This is namely the case for impressive productivity gains in aircraft and ship production during WWII which occurred in spite of important turnover and / or scarce labour force (Mishina, 1999 for the case of the Boeing B-17 ; Budrass et al., 2010 for several German manufacturers, and Thompson, 2001 for the Liberty ship producers). A study carried out in a more contemporary firm producing specialty chemicals (Sinclair et al., 2000) also finds cost reductions which seem to be more attributable to process R&D aiming at introducing technological innovations than to learning at the level of individual workers.

If investments in new situations trigger learning effects, which enable to reduce uncertainty and reach performance improvement targets, one can seek to better understand how exactly such learning mechanisms operate (subsection 2.2) and which managerial principles "efficient learning" and efficient performance improvement rely on (subsection 2.3).

2.2 Reducing uncertainty by experimenting

Let us consider a process characterized by a set of *n* variables in a plant. The performance of the process is determined by the value of some of these *n* variables. In order to improve performance, a manager can decide to introduce new equipment. Such a deliberate decision to invest in new equipment can be seen as a decision to invest in a form of induced (deliberate) learning (Dutton and Thomas, 1984) which Terwiesch and Bohn (2001) call *experimentation*. This triggers a new situation (as described by the "Learning by Doing" theory) which destabilizes the knowledge that the manager has about some of the *n* variables characterizing the process (Bohn, 1994). For instance, instead of accurately knowing the value of a given variable, only a probability distribution indicating the mean and a standard deviation around this mean is known. In other words, the new equipment introduces uncertainty and the plant loses control of some of the *n* variables of the process (Bohn, 1994). The reason is that some information is missing (Tyre and von Hippel, 1995) (because of uncertainty), which therefore induces problems to solve. A classical approach enabling to acquire the missing information, in order to reduce uncertainty and regain control over the destabilized variables is to deploy an experimentation plan. Thomke (1998b, 2003) namely proposes an "experimentation model" relying on iterative experimentation cycles, and more specifically, on trial-and-error cycles involving the four following steps:

- Designing an experiment
- Building the necessary models or prototypes (the "apparatus") to deploy the experiment
- Running the experiment
- Analysing the results: the results provide new information (new knowledge). Armed with these new information (i.e. having learned), designers can deploy consecutive cycles which will enable to progressively converge toward a performance target (or an "*acceptable result*" (Thomke, 1998b)).

Efficiently reducing uncertainties, and therefore efficiently reaching the performance targets requires a well-designed experimentation plan: this implies deploying a relevant sampling strategy, by devoting experimentation efforts to topics marked by critical uncertainty.

Numerous research works have proposed to characterize and model what well-designed experimentation strategies are. For example, Thomke (1998) notes that the heterogeneity in terms of firm performance can be explained by the heterogeneity of their experimentation strategy, i.e. by the way in which they combine the possible forms of experimentation (simulation, prototyping…). Consequently, Thomke (1998) proposes a model aiming at enabling managers to identify the optimal "mix" of these different strategies: building this mix represents a lever to optimize both development costs and lead-time when developing a new product. More specifically, the model identifies an optimal point which informs managers of when it is time to switch from one form of experimentation to the other. Thomke (1998) insists on the fact that budgets (e.g. simulation budget, prototyping budget) should be allocated depending on this optimal point, instead of following an arbitrarily-decided budget distribution (such as switching from simulation to prototyping once all the ex-ante allocated simulation budget is exhausted).

Justifying investments in experimentations in a plant is not obligatorily straightforward, since in the short run, deploying improvement initiatives and associated experimentations as enablers to reach performance targets can appear costly, in comparison with focusing on ensuring that the production line is run at full-capacity (indeed, with such experimentations, problems are encountered, which slows down the production rate…) (Terwiesch and Bohn, 2001). However, Terwiesch and Bohn (2001) stress the idea a plant which accepts to bear experimentation costs earlier is likely to yield better performance in the long run, namely in terms of quality (which involves economic cost avoidance). In order to help guide decisions of investments in experimentation, they propose a model involving the costs and benefits of experimenting.

In sum, in this subpart, we described the mechanisms through which experimenting generates new insights and learning effects which enable to address uncertainty. However, in the two following subsections, we will see that 'Learning by experimenting' is applicable up to a certain degree of uncertainty only. In particular, when the degree of uncertainty is such that we are in the presence of unforeseeable uncertainties (i.e. in the presence of unknowns), experimentation as defined above is ill-adapted (Gillier et Lenfle, 2018). One major issue is managerial: Gillier and Lenfle (2018) demonstrate that the management principles proposed by Thomke (2003) to frame the above-mentioned experimentation cycles are not adapted when it comes to deal with the unknown, which calls for new principles (and they identify new managerial principles, as we will explain later).

The rest of this section is structured as follows. Since subsection (2.2) highlights that deploying experimentations to reduce uncertainty is all but automatic and that it calls for strategic decision-making and for a rigorous organization during deploying:

- subsection 2.3 is devoted to the existing approaches to manage experimentation in the presence of (basic) uncertainty (and thus reduce uncertainty)
- subsection 2.4 focuses on the issues faced in the presence of unknowns and on the possible management principles

2.3 Managing uncertainty reduction

In line with Arrow's conception of learning stemming from 'changed' situations, Mishina (1999) investigates the learning mechanisms responsible for dramatically increasing productivity in the plants producing the Boeing B-17 during WWII, and supports the idea of "learning" as the consequence of new situations, with the expression *"Learning from new experiences"*. However, the sole modifications of the production systems do not lead to productivity gains. Mishina (1999) stresses that learning at the level of core managers plays a significant role in the observed productivity gains (through an efficient work coordination, namely making it possible for operators to be tasked with operations in which their potential is optimally exploited: no waiting times…)

According to many research works (Adler et Clark, 1991 ; Sinclair et al., 2000 ; Carrillo et Gaimon, 2004 ; Budrass et al., 2010), the efficiency of learning mechanisms relies on managerial learning, with managers being empowered to make decisions on two dimensions:

(1) Investing in new equipment / in technical improvement / innovation process / in engineering activities (which boil down to experimentations which will trigger new situations)
(2) Investing in new knowledge, competences, expertise (through trainings, hiring new employees…)

Researchers have investigated the mechanisms through which the decisions on these dimensions enable to build learning, and performance eventually. A first issue is the very decision of investing. Carrillo and Gaimon (2004) seek to model how managers allocate their budgets on these two dimensions (investing in process change and investing in human capital). Modelling situations in which managers are motivated by the incentive to reach a given target, they study how uncertainty impacts the manager's choices: they demonstrate that the nature and the rules of the firm's managerial system (more or less severity toward failed projects for example…) have a strong impact on what is learned, and on firm's performance as a consequence.

Budrass et al. (2010) epitomize the importance of objectives and incentives managers are subject to: during WWII, the National Socialist regime imposed fixed-price contracts on German aircraft manufacturers: this represented the incentive to reduce costs for the industrials, all the more so as they could keep the benefit of the margin resulting from cost reduction). New contracts being based on the reached production costs at the expiration of the previous contract, managers were encouraged to think ahead of time about new technical solutions which could be deployed to reduce costs even more. For this reason, several successive waves of cost reduction are observed.

Therefore, a clear purpose (set at the level of managerial objectives) seems to be an important characteristic of economically-efficient learning.

The mechanisms through which 'Learning by doing' takes place and impacts firm's performance can be summarized as follows: firm's managerial system and objectives set at the managers' level influence managerial investment decisions in

(1) Technical capital (new equipment, new processes…)
(2) Knowledge capital

These investments trigger experimentation situations, which enable to collect further information and evidence (i.e. learning), which enables to reduce uncertainty and bring about economic improvements phenomena (productivity gains, cost reduction…). These very learning mechanisms are due to steered experimentations which are deployed in an attempt to solve problems raised by the perspective to introduce or raised by the introduction of new equipment or processes. As these problems are being solved by experimenting, the convergence toward an initially-set performance target is achieved.

The approaches so far described consist in 'Learning by reducing uncertainty on *n* known variables' (by deploying well-designed experimentation plans). They apply when the states of the world involved in the project are exhaustively known and when managers have the possibility to estimate how the different variables will be impacted by their decisions (knowing at least the mean and the standard deviation of the variables). In this case, when it comes to decide whether to launch a project or not, managers have the possibility to compute expected values to inform and guide their investment decision. All the states of the world being known, the topics (e.g. the performance variables) most affected by critical uncertainty are identifiable. Therefore, managers and their teams can establish clear objectives, deploy a sampling strategy and design experimentations which will efficiently address these critical topics, by generating the necessary knowledge. In sum, when all the states of the world are known, managers can knowingly make their investment decisions. And they can design experimentation plans likely to effectively reduce uncertainty and optimize the convergence of the project toward an initially-set performance target. In some, a rather straightforward and clear process (implying the identification of the critical topics affected by uncertainty, the definition of a sampling strategy, the definition of hypotheses and associated experiments, the deployment of tests and the collection of the new information) appears when it comes to manage uncertainty reduction.

However, 'Learning by reducing uncertainty on known variables' is unsuitable when it comes to deal with *unforeseeable uncertainties* or *unknown unknowns.* In particular, the perspective of 'Learning by reducing uncertainty on known variables' does not offer the possibility to justify costly investments in the presence of unknowns, nor to efficiently manage project deployment in the unknown.

2.4 Investment decisions and project management in the unknown

When dealing with uncertainty, all the *(n)* variables affecting performance are known beforehand, although for some of them, only the mean and the standard deviation (instead of a precise value) are identified. In contrast, when dealing with the unknown, initially unforeseen events are likely to arise and to uncover new performance variables (related to new states of the world) whose standard deviation cannot even be estimated.

- *Investment decisions in the unknown*

Unknown unknowns can be defined as the inability to identify beforehand "all relevant variables affecting performance", i.e. as the inability to identify beforehand all states of the world (Sommer et al., 2009) or as "events which could not be imagined as a possibility prior to their occurrence" (Feduzi et Runde, 2014). The unknown makes it difficult to justify investment decisions: managers have an incomplete view of all possible the states of the world which are likely to be involved and impacted in the course of the project (Pich et al., 2002 ; Sommer et Loch, 2004 ; Feduzi et Runde, 2014). The calculation of investment costs and benefits being based on incomplete information, it is imperfect, if not impossible. For this reason, economic tools, such as the Net Present Value and Business Cases often predict non-profitability for promising innovation projects. Therefore, managers face a dilemma. Either they do not invest in the project at all, which represents the risk for the firm to miss opportunities, or to be unprepared to face market or competitive shocks... Either they invest, i.e. they pay to see what happens. The firm's level of risks and error acceptance, more or less openness regarding 'Learning from errors'… play a role in deciding on the dilemma. However, these considerations do not involve elements related to the economic performance of the project. What makes the economic decision tricky is that some information are missing (e.g. non identifiable states of the world). Feduzi and Runde's (2014) propose an algorithm enabling to generate beforehand "alternative hypotheses" (which enrich the initial decision space with new states of the world): the rationale is to proactively eliminate unknown-unknowns, in order to avoid encountering them during project deployment. But the problem related to guiding the economic decision remains open: traditional managerial techniques do not indicate when generating alternative hypotheses and testing them with experiments (in order to create new knowledge) stops being economically-efficient (Feduzi et Runde, 2014).

If managers decide to invest, the rationale of the investment decision is to gather further knowledge and information during project deployment. Experimentation is again a key approach to collect initially-missing information (Feduzi et Runde, 2014 ; Gillier et Lenfle, 2018). But in this case, managers are in charge of experimentations in the unknown, which cannot be steered in the same way as described in subsection 2.3.

- *Project management in the unknown*

One can note that Thomke's (1998b, 2003) trial-and-error model is resilient to unknown-unknowns. With its successive experimentation cycles, the approach is flexible enough so that managers can integrate in the subsequent experimentation cycles the unknown-unknowns discovered during a previous experiment. Indeed, trial-and-error learning offers the possibility to actively search for new information, and to progressively adjust, refine and even redefine the objectives depending on what is learnt when collecting further information and knowledge (Sommer et al., 2009). However, the decision to invest in experiments and the design of these experiments (especially the definition step) are based on the initially-known states of the world only. If unknown unknowns are to be unveiled, they will only be taken into consideration from the next experimentation cycles onwards. Managers patiently wait for unknown-unknowns to emerge and are ready to adapt the project accordingly (Snowden et Boone, 2007). Trial-and-error learning consists in a *reactive* approach to unknown unknowns. Accompanied with Thomke's (2003) management principles (cf. table 1 below), this approach works as long as managers and their team own the necessary knowledge to generate hypotheses and define experiments to test these hypotheses. But in the absence of prior knowledge, i.e. when uncertainty reaches a degree that can be designated as "extreme", Thomke's (2003) principles do not apply (Gillier et Lenfle, 2018). Gillier and Lenfle (2018) explain that "completeness" (in the sense of Garud et al., (2008)), represents the "boundary" for the applicability of Thomke's principle: under the completeness condition, managers and their teams own sufficient knowledge to fairly specify the problem they need to address and thus, to design experiments accordingly. From the case of the Manhattan project, they also define key features which characterize an experimentation in the unknown (1- lack of theoretical knowledge, 2- lack of theoretical instruments, 3- absence of a pre-established organization) and which render Thomke's principles inapplicable. Consequently, based on the Manhattan Project, Gillier and Lenfle (2018) propose principles to manage experimentation in the unknown, in the absence of prior knowledge (cf. table 1 below).

Thomke's principles	**Gillier and Lenfle's principles**
Anticipate and exploit early information	Identify what cannot be predicted by current theory & focus on the most challenging aspect
Experiment frequently but do not overload your organization	Create new divisions and recruit new expertise
Combine new and traditional technologies	Observe and measure unknown phenomena with new instruments
Organize for rapid experimentation	Conduct overlapping experiments
Fail early and often, but avoid mistakes	Do not expect perfect tests & learn from imperfect tests

Table 1: comparison between Thomke's (2003) experimentation principle & Gillier and Lenfle's (2018) experimentation principles

Contrarily to the knowledge developed in Thomke's (2003) approach, which draws on already known information, the knowledge generated when applying Gillier and Lenfle's (2018) principles is related to new states of the world since they draw on a diagnosis on the unknown (completed by identifying what cannot be predicted by current theory).
Regarding the deployment of a learning strategy, the extended principles proposed by Gillier and Lenfle (2018) highlight that the processes that govern experimentation in the unknown are far less straightforward and sequential than the process that appears for uncertainty reduction (that is: identification of the critical topics affected by uncertainty, definition of a sampling strategy, definition of hypotheses and associated experiments, deployment of tests and collection of the new information). In the unknown, as outlined in the fourth principle, experiments overlap: one given experiment does not match one clear set of hypotheses to be tested and associated tests results. Thomke and Gillier's (2018) principles imply carrying out "crude experiments" in order to "see what happens" and start building basic knowledge and theory. In this approach, close interactions between theory-building and practical experimentations enable to progressively structure the exploration of the unknown.

In sum, the important point to bear in mind is that most of what has been so far theorized regarding how to manage experiments actually draws on uncertainty reduction dynamics. Gillier and Lenfle's (2018) paper on the Manhattan project is a notable exception. This is not very surprizing since, cases of management in the unknown are quite rare.

We did identify in a plant in the aviation industry a case which seems to have been driven by logics which have to do with management in the unknown, especially in terms of investment decision, economic steering and learning strategy. In this case, everything tended to support the hypothesis according to which the project was not profitable. No alternative information indicated that the project could turn out to be profitable. In spite of that, it was launched and proved far more economically-efficient than any hypothesis could suggest. Consequently, in the paper, we try to understand how an initially highly improbable hypothesis turned out to prove true during project deployment. We namely seek to characterize the managerial logics and principles which played a significant role in turning this highly improbable hypothesis into reality.

To this end, using the method described in Section 3, we draw on this case in an attempt to provide new insights regarding the management of investment decisions, economic performance and learning strategies in the unknown.

3. Method

Central in this paper is a puzzling innovation project which involved the introduction of a machine relying on a new drilling technology in an assembly plant in the aviation industry. This project drew our attention because it achieved remarkably high performance results despite being launched with a negative business case.

As mentioned in the introduction, we seek to address two research questions. To what extent is the performance trend achieved in this case anomalous with respect to performance gains traditionally achieved by reducing uncertainty? How can we characterize the managerial approach (and its associated principles in terms of investment decision, economic steering and learning strategy) which resulted in the observed dramatic performance gains?

In order to address the first research question (anomalous nature of our case), the method is the following. This case does not fall into the category of improvement projects experiencing uncertainty reduction, be it in the form of 'Learning by Doing' or in another form, nor into the category of investments in the unknown consisting in paying in order to collect further knowledge and "see what happens", in the absence of any structured economic steering approach. Consequently, this single-case study constitutes an anomaly (Siggelkow, 2007) which epitomizes the management of an investment in the unknown. We demonstrate this by applying a statistical method on data related to the costs and the savings generated by the project, with a particular interest in the trends and dynamics that followed these data. In order to understand the dynamics which affected the costs and the savings in our case, we broke these latter down and tried to understand how their nature evolved over time, as the project performance was evolving.

After having demonstrated the anomalous nature of our case, we attempt to characterize the managerial logic at work behind the observed performance trend (and thus answer the second research question) with an in-depth case study. As Thompson (2010) notes, studies at the level of individual plants offer the opportunity to gather rich data and precisely retrace dynamics followed by the firm, such as moving down its learning curve. Interviews with the managers carrying out the project provided us with narrative elements that we analysed, which offered us insights to better understand the mechanisms underlying the observed upward performance trend.

4. Case study: an innovation project demonstrating a highly remarkable performance evolution – from 'Learning by Doing' to 'Learning by Designing'

The case described below occurred in the assembly plant in the aviation industry. The project considered in this case consisted in launching automated-drilling robots on some stations of a given production line. The R&T department had been developing and testing the technology for four years when the plant started studying the opportunity of a pilot deployment in the production environment, as TRL 6 had just been reached. The project seemed very promising, with interesting benefits in terms of costs and lead-time reduction. However, it faced a classical hurdle for innovation projects: the business cases did not meet the profitability criterion (a less than two-year payback time) required to launch the project. In total, eleven business cases scenarii were studied. None was positive with respect to the two-year profitability criterion. In spite of that, because the plant managers supporting the project were confident in its potential, the project was launched (with a subsidy from the R&T department financing the part of the investment which made the business case negative). The selected scenario implied a step-by-step deployment of two robots on a given production line. After this step-by-step deployment project (project 1), another project (project 2) involving the deployment of 16 robots on another production line was launched.

We will describe and analyse the learning mechanisms, the economic trends and the managerial logics on both projects. To that end, we first demonstrate that project 1 is an anomaly since its performance trend is not governed by an uncertainty reduction dynamic, nor does it consist in a form of "investment in the unknown" theorized in the literature. Consequently, we will propose in subsection 4.4 the concept of 'Learning by Designing' to account for the observed mechanisms and managerial approach.

4.1 Project 1: Step-by-step deployment of two robots

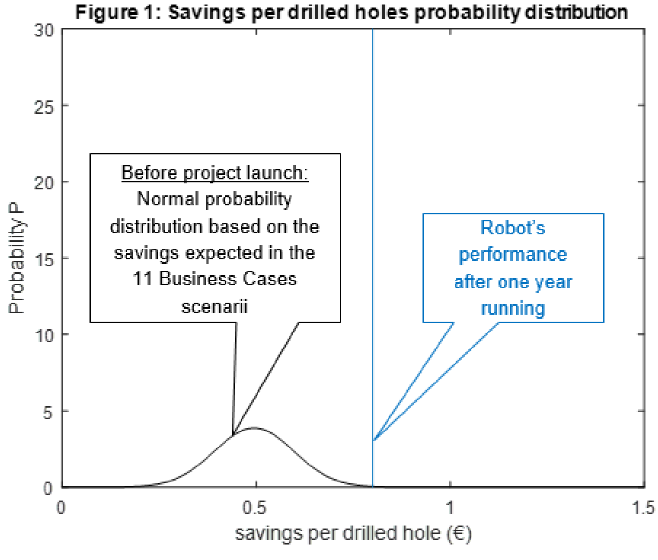
Given the uncertainties and the level of unknown surrounding the project (in spite of the fact that the managers responsible for the project were confident in its value), a first robot was deployed alone, as a pilot phase in Project 1, in order to validate some assumptions and get further knowledge before launching the second robot part of the project.

After one year running the first deployed robot, the results in terms of costs and benefits were stunning:

- Overcosts: +14% versus what was planned
- But also extra-savings per product: +31% versus what was expected

In the following subsection, we sought to understand better the nature of this upward trend in terms of savings. We namely attempted to understand what was contained in these extra 31%.

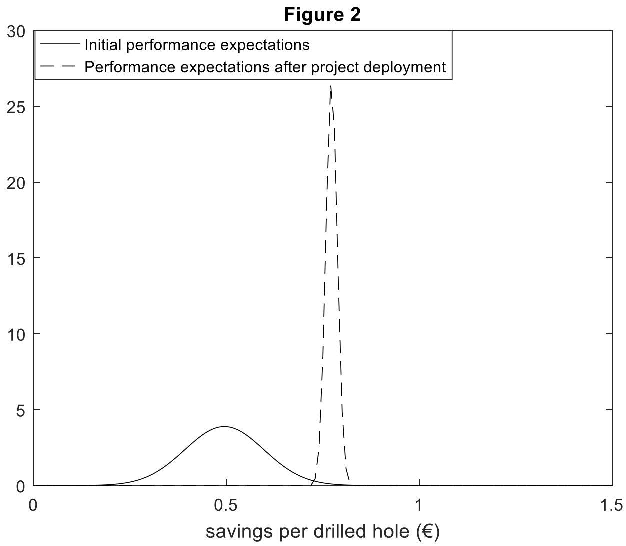
Figure 1: Savings per drilled holes probability distribution



4.1.1 Two first robots' performance evolution

Using the mean and the standard deviation of the 11 savings estimations in the 11 initial business cases, we were able to plot the probability distribution of the expected savings-per-drilled-hole (we used a normal distribution). After one year running the first deployed robot, the performance in terms of savings per drilled hole (represented by the vertical line in Figure 1) is far higher than expected and corresponds to a value which had a very low probability of occurrence in the initial distribution.

Before installing the second robot on the production line, savings estimations were re-adjusted, based on the savings generated by the first robot: eight new Business Case scenarii were realized. We represented the probability distribution of these adjusted savings with the dashed curve plotted in Figure 2. (The solid curve is the same as the curve plotted in Figure 1: it represents the initial saving estimations.) We observe a dramatic shift on the right, i.e. a dramatic performance gain with respect to the initial estimations before project launch.



Today, these two robots associated to initially non-profitable business cases are still running and generate profit. In other words, the performance gains were such that they enabled to turn Project 1 into a profitable project.

In the next subsection, we seek to explain this stunning robot's performance gain illustrated by the change from the solid curve to the dashed curve.

4.1.2 Narrative description of the events which arose during Project 1 deployment

As a link with the literature review in Section 2, we can consider that the drilling robot impacted a process characterized by *n* variables at the outset of the project. In particular, the savings estimations were distributed across two variables:

- Recurring Costs savings (induced by lead-time reduction: the robot installation-drilling-uninstallation time is supposed to be less than the time of the initial human-operated process ; and induced by a reduced number of blue-collars required to work on the line)
- Non-quality reduction

As described in the literature review, the introduction of the new robot destabilized some of the *n* variables, i.e. the managers and the operators lost full control of some of these variables.

If we look at the perspective of learning on the *2* known variables, by solving encountered problems, it did not help improve the performance in terms of savings per drilled holes. It even oriented the project toward a less favourable conjuncture because of some deficiencies in the initial assumptions. In particular, the specifications assumed that the robots would cover 100% of a certain kind of contingencies previously managed by human operators. However, they turned out to only be able to cover x% (x<100) of these contingencies. For instance, some perpendicularity conditions had to be met for the robots to be able to operate. The specifications implicitly assumed that these conditions would be met. But they were not always met: in this case, the robots were not able to autonomously restore perpendicularity, as human operators would do. Such events paralyzed the line and extra labour hours (implying extra Recurring Costs) were needed to restore perpendicularity (as a solution to the encountered problem). As a consequence, regarding the *2* known variables, the plant learnt that the robots operated on a restricted action field with respect to what was initially planned. So learning on these known variables impacted the performance negatively. In terms of probability distribution, this deterioration would correspond to the solid curve shifting on the left.

On the other hand, unforeseeable uncertainties (unknown unknowns) emerged during deployment, in the form of unanticipated events. Among these unknown unknowns was the interest that the robot, (as a co-worker of a new kind which was not working well and which was paralysing the production line), aroused among the operators. This unknown-unknown (the operator's interest) was strategically managed by the managers carrying out the project. They used it as an opportunity of "free trainings", to provide the operators with the opportunity to enhance their skills and become robots' programmators. Ultimately, the association between the robot operating on a restricted action field and the more-skilled operators turned out to be more efficient than the initial assumption of robots covering 100% of the contingencies. And a third variable emerged in the savings generated by the robot: *Rework Avoidance*, in addition to *Recurring Costs savings* and *Non Quality avoidance*.
In sum, managers turned the unknown-unknown which emerged (that was the operators' interests' in the robot) into an opportunity for the project. More specifically, they turned it into the opportunity to build a new variable / a new "dimension" (*Rework avoidance*) in the structure of the savings. This contributed to the robot's performance gains.

The narrative story of the deployment of the two first robots (project 1) suggests that "Learning in the Unknown" effects have played a significant role in the robot's dramatic performance gains. In other words, it suggests that the observed performance trend has nothing to do with "uncertainty reduction on known variables", i.e. with classical Learning by Doing and uncertainty reduction. In subsection 4.3, using the data concerning the savings per drilled hole, we test this hypothesis.

But before that, we describe the logics at work in project 2.

4.2 Project 2: Deployment of 16 new robots on the production line of another product

Following the first project, a second project involving the deployment of 16 new robots (identical to those deployed in Project 1) was launched. In this second project, not only was the affected product different from the one involved in the first project, but it also faced an important challenge in terms of ramp-up (contrarily to the product of the first project whose production rate was in a rather 'stable' dynamic). Aware that the two robots involved in Project 1 had become profitable and considering the strategic nature (due to the ramp-up challenge) of the affected production line, we expected the Business Cases of this second project to be positive. Interestingly, as we collected the data, we observed that they were negative, despite taking into account the learning effects induced by Project 1, namely by incorporating in the savings structure the *third* variable unveiled during Project 1, that was '*Rework Avoidance'*. Faced to this finding, we attempted to understand the learning effects and performance trends related to this project.

Project 2 clearly benefited from the learning effects that Project 1 yielded: the technology moved up from TRL6 to TRL9. Under the regime of cooperation between robots and programmators, the technology was now reliable. However, due to the ramp-up challenge, Project 2's managers imagined a more ambitious project aiming to efficiently *reduce the lead-time*. To that end, they imagined a more complex organization of the robots' work on the station (for instance implying concurrent tasks instead of sequential tasks in Project 1). How does Lead-Time Reduction impact the performance variables, namely, the *3* known savings variables?

- Firstly, lead-time reduction impacts the first variable of the savings structure that is *Recurring Costs Reduction* (since Recurring Costs directly result from the number of hours spent by blue collars on the process).
- Besides, the more reduced the lead-time, the more important the benefits over one period of time (one month, one year…), since more products are delivered: this aspect is not captured by our probability distribution which represents the savings per unit product per drilled holes (this view was interesting to illustrate the technical progress of the machine). However, in the firm's Business Cases evaluating the profitability of the projects, the estimated savings per unit product are multiplied by the expected production rate over a given year. As a consequence, the benefits resulting from the possibility to produce more units thanks to reduced lead-time was taken into account in the firms' prevision.
- However, in a context of ramp-up, lead-time reduction does not only impact the savings variable that is *Recurring Costs Reduction*. Indeed, behind each hour of delay lies the perspective for the firm of not meeting the ramp-up objective and facing severe penalties as a consequence. This aspect was not introduced into the Business Cases assumption, whereas the objective of using these robots as an enabler for a successful ramp-up (and *avoiding costs due to delays*) is the very managerial orientation which structured the deployment and the organization of Project 2. Consequently, *avoidance of costs which would be induced by unsuccessful ramp-up* is a new variable which joins the three other variables structuring the savings (that were *Recurring Costs reduction*, *Non Quality avoidance* and *Reword Avoidance*). This fourth variable was invisible in the Business Cases.

This variable has not been integrated in the Business Cases and has not formally been used as a lever to demonstrate the profitability of the project, because this new variable is 'being built / designed' by the project managers. This new performance variable has been 'imagined' ahead of time, very early in the project. The first months of the project consist by the way in a setup period aiming to accurately identify the number of lead-time hours that can be saved with the ambitious reorganization of the tasks carried out by the blue-collars and the robot (and to adjust and adapt the reorganization of the tasks so that lead-time savings are optimized). One can note a shift in the nature of the objective: whereas in Project 1, the purpose was to demonstrate the robot's capacity to reduce costs, in Project 2, the purpose is to optimize lead-time (for a successful ramp-up), even if this implies higher costs.

This addition of new performance variables can be seen as a generative / and expansive dynamic affecting the structure of the savings attributable to the robot. Managers play an important role in imagining and building these new variables. And building performance on these new variables seems to put learning mechanisms at work: by designing these new initially unknown variables, managers structure the unknown. We call 'Learning by Designing' this managerial logic, which we describe in more details in Subpart 4.4 to address our second research question.

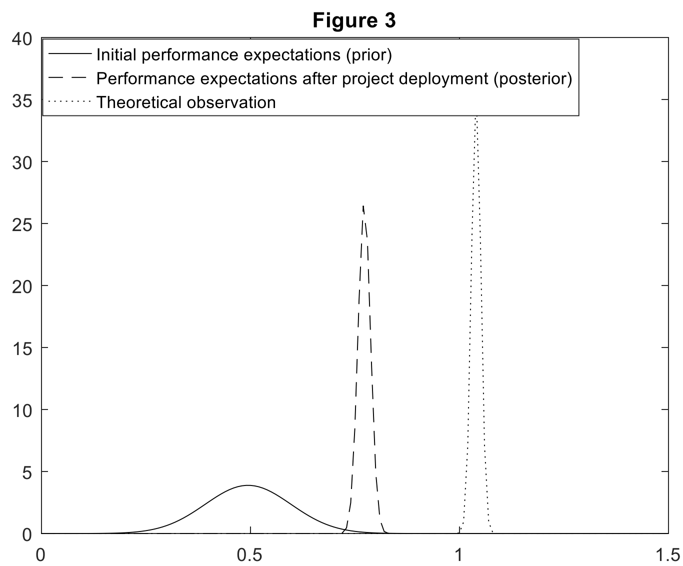
Before that, we address our first research question (to what extent is the performance trend achieved in this case anomalous with respect to performance gains traditionally achieved by reducing uncertainty ?) with a statistical method in subsection 4.3.

4.3 Testing the hypothesis according to which that the observed performance trend is not governed by "uncertainty reduction on known variables"

In the Bayesian statistics, reducing uncertainty consists in updating prior probability distributions on the basis of new information (gathered by making observations). The above-mentioned narrative elements show that 'Learning by Doing' mechanisms during project deployment are not responsible for the observed performance trend. Consequently, using the Bayesian statistics, we seek to verify whether another form of 'uncertainty reduction' played a significant role in this case. To that end, we test the hypothesis H_1 according to which the curve shift would result from "Learning by reducing uncertainty" on the n known variables of the process

Then, we test H_1 with Bayesian statistics. Indeed, if H_1 is true, the change from the solid curve to the dashed curve results from Baysian updating. This would mean that observations on initially known variables (estimated and summarized in the solid curve) have been made through probabilistic draws among these parameters. In other words, the savings estimations contained in the 11 initial business cases (solid curve) can be considered as corresponding to a prior probability θ ~ $\mathrm{N}(\mu_p, {\tau_p}^{-1})$ (where N is the normal probability distribution). If H_1 is true, the estimations contained in the 8 new business cases (dashed curve) adjusted on the basis of the performance of the first robot, can be considered as a posterior $\theta \mid$ y ~ $\mathrm{N}(\mu_{post}, {\tau_{post}}^{-1})$, where y is an observation of a known variable which would have yield the learning effects. In this case, since the prior and the posterior follow normal distributions, $y \mid \theta$ also follows a normal distribution $\mathrm{N}(\theta, {\tau_l}^{-1})$ whose parameters we can determine.

We find that the observation y=1.04 would have been made, with a precision τ_p = 90. We plotted the corresponding distribution with a dotted curve in Figure 3. If the change from the solid curve to the dashed curve resulted from regaining control on known variables by reducing the uncertainty affecting these variables, this would mean that the value 1.04 has been drawn when making observations. However, the value 1.04 was very improbable in the prior distribution (the associated p-value is less than 0.002%). Furthermore, 1.04 is far beyond the robot's performance reached after one year in operation.



Consequently, it is highly improbable that learning on the n initially known variables is responsible for the change from the solid curve to the dashed curve, which allows us to eliminate H_1.

This strengthens the hypothesis H_{unk} according to which "Learning in the unknown" effects have played a role in the dramatic robot's evolution. And this answers our first research question, confirming that our case is an anomaly with regards to economic performance gains traditionally achieved by reducing uncertainty.

Consequently, in what follows, we attempt to describe the managerial logic which accompanied the decision to invest in this project in the presence of unknown. Extending the "Learning by Doing" framework, we propose the notion of "Learning by Designing", as a frame for the managerial principles enabling these learning mechanisms to occur (Subpart 4.4). Doing so, we address our second research question, (How can we characterize the managerial approach (and its associated principles in terms of investment decision, economic steering and learning strategy) which resulted in the observed dramatic performance gains?)

4.4 'From Learning by Doing' to 'Learning by Designing'

In Section 2, we noted that the efficiency of 'Learning by Doing' mechanisms rely on managerial learning, with managers being empowered to make decisions on two dimensions (Adler et Clark, 1991 ; Sinclair et al., 2000 ; Carrillo et Gaimon, 2004 ; Budrass et al., 2010):

(1) Investing in new equipment / in technical improvement / innovation process / in engineering activities (which will trigger new situations)

(2) Investing in new knowledge, competences, expertise (through trainings, hiring new employees…)

Managerial decisions on these two dimensions induce "Learning by Doing" effects since the introduction of new equipment and process change triggers problems, which call for experimentation and new competences and knowledge acquisition in order to be solved, which trigger learning. An optimal mix in terms of (investment) efforts on these two dimensions yields optimal "Learning by Doing" effects, both "before doing" and "during doing". The decision of such a mix is the manager's responsibility. In a "Learning by Doing" frame, the manager's decision is influenced and determined by performance objectives: one of the plant's processes is characterized by *n* known variables, and the manager's decisions are oriented toward the objective to achieve a performance target on some of these variables. This performance is reached progressively, by experimenting on these known *n* variables.

"Learning in the unknown" is not covered by the (1) and (2) decisions dimensions. This raises the following question: what kinds of managerial decisions, objectives and principles are "Learning in the unknown effects" related to? The anomalous nature of case study seems to bring about some understanding to that question.

As we noted already, Project 1 was launched, in spite of a negative business case, by managers who firmly believed in its potential for the plant. After having overcome the financial hurdles requiring a positive business case (with a subsidy from the R&T), the Project 1's managers had one major objective in mind: proving that the robot was effectively valuable for the plant and that it could yield valuable performance. Consequently, the managerial actions during project deployment were oriented toward this very objective. In addition, interviews the managers who carried out Project 1 revealed that at the outset of the project, they were aware that new dimensions would be discovered during the project. Indeed, introducing such a machine in the production environment was a real rupture and, to some extent, a leap in the unknown: the necessary competences were not available within the plant and were not even precisely identifiable at the beginning of the project. The plant had no referent Business Units nor experts regarding automation… Everything needed to be built. Project 1's managers were aware of this and they knew that beyond the initially identified risks, other unforeseen events were likely to arise. Consequently, they were expecting unknown unknowns to emerge. And they were ready to manage them and find a value-creating solution at the moment of their emergence. More specifically, finding value-creating solutions consisting in designing new variables in the unknown. In sum, managers had set themselves the objective to turn the new dimensions into opportunities at the moment they would emerge. This is what happened when they strategically managed the operators' interest in the robots, which triggered a valuable "cooperation" between more-skilled operators and the robots.

This example of the operators' interest in the robots, despite having been strategically managed, has perhaps a slight serendipitous connotation. However, in Project 2, the design of a new variable in terms of savings is all but accidental, since it constitutes the very purpose of the project: this new performance variable (that was *Avoiding costs which would result from an unsuccessful ramp-up*) was imagined at the outset of the project. And the perspective to design it and to turn it into a performance variable guides and structures the project (which is still ongoing today): it is a key element of the project since the outset.

Therefore, these findings lead us to add a third action dimension, including with three associated management principles (a., b. and c.), to the two existing dimensions ((1) and (2)) in the "Learning by Doing" theoretical frame. Whereas decisions (1) and (2) are oriented toward converging to a *performance target*, decision (3) is oriented toward the objective of meeting a *learning target* which implies adding new variables in a given action field by designing in the unknown.

(1) Investing in physical capital (new equipment, technical improvements…)
(2) Investing in new knowledge, competences, expertise (through trainings, hiring new employees…)
(3) Investing in the unknown, i.e. investing in the design of new variables which are "in the unknown" at the outset of the project.

Associated with this decision dimension, we propose the following management principles:

a. **Regarding the economic decision.** The economic calculation is imperfect, and often unfavourable, because of incomplete information, when it comes to estimate the profitability of an investment in the unknown. The Net Present Value (involved in business cases) is ill-adapted to fairly assess the value of innovation projects and is widely criticized for that. However, this classical economic tool can all the same have a usefulness in the economic steering of projects in the unknown (even if the nature of this usefulness is not the same as when NPV classically is classically applied). In the unknown, the "negative" or "positive" result of the NPV is not reliable. Consequently, this feature is not the one of the greatest importance for managers and some innovation or improvement projects are launched in spite of a negative NPV. In this case, the risk of not succeeding in turning the project into a profitable one exists. However, the computed NPV also provides managers with a kind of "railing", a kind of "protection" to ensure that the investment is capped and under control in case the project proves indeed non profitable. Thus the first managerial principle that we infer from our case is to <u>use classical (perhaps unfavourable) economic tools as a means to ensure that in case of failure, no investment other than the initial one will be lost</u>.

b. **Regarding managing project deployment in the unknown and especially regarding building economic profitability in the unknown.** Owning only incomplete information and evidence, managers who invest in the unknown, in spite of an unfavourable business case, seek to collect new knowledge. However, they do not know the nature nor the content of the information they are going to collect. Consequently, they cannot set precise objectives in terms of knowledge to be collected. However, one managerial objective can be clearly set and cascaded to the teams: the objective to discover new performance variables (new states of the world) which were initially unknown and to develop learning related to these new variables in order to find levers that will help either reduce the costs or increase the benefits (and thus make the project profitable). Thus, the second managerial principle that we infer is <u>to clearly set in the team's mission the objective to discover new performance variables</u>. One can note that these new variables can be imagined and contemplated as soon as the outset of the project, as in Project 2. Or, in cases when everything is to be built, such as in Project 1, they can be inspired by actively awaited unknown unknowns during project deployment.

c. **Regarding organizing learning in the unknown.** Once they are discovered, one needs to acquire further knowledge related to the new states of the world in an attempt to make them effectively contribute to the economic profitability. Acquiring this knowledge requires experimenting. As mentioned above, in the unknown, it is not possible to have clear expectations and to set clear objectives regarding the outcomes of these experimentations. However, the objective to reduce costs and / or increase benefits can be set, in order to turn the project into a profitable one. Thus, the third inferred managerial principle is <u>to deploy on the newly-discovered states of the world a learning strategy that is oriented toward the objective of turning the project into a profitable one</u>.

To summarize these three principles, the key purpose orienting the management of such investments in the unknown is to "design" and bring to life these contemplated variables, in order to structure the unknown and to benefit from new performance dimensions in this newly-structured world. The new variables being imagined (be it at the outset or later on in the project), the very objective of the project is to develop learning strategy enabling to take them out of the unknown and to generate knowledge that will make them turn the project into a profitable one. The project steering will be oriented to that end. Instead of being seen as a threat, initially missing information are seen as an opportunity which must be unveiled.

We call "Learning by designing" the learning process resulting from the managerial decisions and principles contained in (1), (2) and (3).

5. Research implications

Based on a single-case study, the 'Learning by Designing' framework extends the frame of "Learning by Doing", by outlining principles to guide investment decisions (a.), (economically) manage project deployment (b.) and organize learning (c.) in the unknown.

The first principle (a.) brings new insights into the problem of the economic evaluation and economic management of R&D projects. Indeed, similarly to the robot project we describe, many R&D projects find it difficult to prove that they are worth being launched when the classical financial tools, (e.g. Net Present Value (NPV)), are negative. Indeed, as highlighted in Hooge's (2010) literature review, the NPV is ill-adapted to fairly assess the profitability of a project in a context marked by uncertainty and incomplete information and has consequently been widely criticized for that (Barger, 1993 ; Phaal, 2005 ; Hartmann et al., 2006). Among other things, the NPV computation assumes that the project is financed up to completion, which introduces very little flexibility and makes the investment decision irreversible. Besides risks and uncertainties are summarized in one figure, the discount rate, ignoring the economic impact of more qualitative aspects. It namely ignores the impacts of learning effects and the potential spillovers that could be beneficial to subsequent projects. All these imperfections and approximations can lead the NPV to kill promising innovation projects. This is the reason why some research works propose new forms of NPV (stochastic NPV…) or even new tools (real options…) that value innovation projects more fairly.

Our case is also based on the observation that the NPV does not fairly assess promising projects. But instead of transforming the NPV into a better tool, our case suggests an original (and even diverted) use the very 'basic' NPV.

The economic management principle we identify does not rely on reaching (more or less artificially) a positive NPV to authorize project launch. If it is positive, it is of course better. However, in case the NPV is negative, the second and third management principles (b. and c.) of the 'Learning by Designing' frame recommend to imagine and design new performance variables and get new insights related to these latter, by experimenting, in order to make them contribute to the economic performance.

Secondly, our case study epitomizes the thesis according to which the unknown can be managed, namely economically. Be it in the presence of uncertainties or unknown-unknowns, the issue in both cases is that some information and evidence are missing. This calls for new knowledge to be developed (knowledge whose nature differs depending on if we manage basic uncertainties of unknown-unknowns). Yet, in the same way as uncertainty is managed in a philosophy of "reduction", most of the approaches that propose ways to manage the unknown aim at reducing and eliminating the unknown. For instance, as mentioned above Feduzi and Runde's (2014) algorithm which generates knowledge related to new states of the world, aims at eliminating unknown-unknowns before encountering them later on. In other words, the unknown is in general negatively perceived (Gillier et Lenfle, 2018).

However, Gillier and Lenfle (2018) detect in the case of the Manhattan project a paradigm which implies identifying what is unknown and designing initially unknown things. In other words, they identified an expansive approach which consists in designing in the unknown, instead of seeing the unknown as an undesirable threat. Our anomalous case turns out to be an additional example which fits into this expansionist paradigm. The managerial principles inferred from the case study encourage to adopt such an expansionist approach: the second principle (b.) encourages managers to clearly set the goal to develop new states of the world and the third one (c.) recommends to organize and deploy a learning strategy related the newly discovered states of the world, by centring this strategy on the very objective to build economic profitability.

Thus, our findings contribute to the research related to the Management of the Unknown, by bringing to light a case whose performance gains are attributable to learning in the unknown effects that were made possible by the deployment of three managerial principles. Falling within the research avenue pointed out by Gillier and Lenfle (2018) and as an additional proof to the fact that the unknown can be managed, this paper encourages to further explore the logics related to deploying projects in the unknown.

6. Practical implications

The managerial principles identified in the paper represent for firms the possibility to formally justify the launch of projects which, under classical tools and classical management rules, should not be launched. Our case illustrates that an initially unfavourable project can, if launched, represent the opportunity for a firm to allow the occurrence of initially impossible scenarii (dramatic performance gains and an eventually profitable project in our case).

The *Learning by designing* frame does not reject traditional economic tools, but diverts their use, by not paying so much attention to their binary "positive" versus "negative" predictions, but using them as a protection to control costs.

The financial sponsors of a project justified by the first identified principle (a.) are not asked to fund it in a "Let's see what happens" philosophy: the important idea is that they are asked to pay in order to make possible the steered discovery of new action variables which are likely to open new (extended) action fields, and make initially impossible scenarii become possible.

References

Adler, P., Clark K.B. (1991) A sketch of the Learning Process. *Management Science*, Vol. 37, No. 3, pp. 267-281

Arrow, K.J. (1962) The economic implications of learning by doing, *Review of Economic Studies* 29 155–173.

Barger, J. E. (1993). *Research and development project selection tools : probing wright laboratory's project selection methods and decision criteria using the lateral airfoil concept* (Thesis). US Air Force.

Bell, R. M., Scott-Kemis, D.. (2010). The mythology of learning-by-doing in World War II airframe and ship production. International Journal of Technological Learning Innovation and Development 3(1):1-35

Bohn, R.E. (1995) Measuring and Managing Technological Knowledge, Sloan management review 36(1):61 ·

Budrass, J. ; Scherner, J., Streb (2010), Fixed-price contracts, learning, and outsourcing: explaining the continuous growth of output and labour productivity in the German aircraft industry during the Second World War, *Economic History Review*, 63, 1, pp. 107–136

Carillo, J.E. ; Gaimon, C. (2004) Managing Knowledge-Based Resource Capabilities Under Uncertainty

Dutton, J. M., Thomas A. (1984) Treating Progress Functions as a Managerial Opportunity. *The Academy of Management Review.* Vol. 9, No. 2 (Apr., 1984), pp. 235-247

Feduzi A. & Runde J. (2014). Uncovering unknown unknowns: Towards a Baconian approach to management decision-making. *Organizational Behavior and Human Decision Processes*, 124(2): 268–283.

Gillier, T., Lenfle, S. (2018) Experimenting in the Unknown: Lessons from The Manhattan Project. *European Management Review*.

Hartmann, G., Myers, M., & Rosenbloom, R. (2006). Planning your firm's R&D investment. *Research technology management.*, 25-36.

Hooge, S. (2011). « Performance de la R&D en rupture et des stratégies d'innovation : organisation, pilotage et modèle d'adhésion. » (thèse), MINES ParisTech, Sciences de Gestion, Paris. P 108-110.

Loch C, Pich M, De Meyer A. (2002). On Uncertainty, Ambiguity and Complexity in Project Management. *Management Science* **48**(8): pp.1008-1023

Mishina, K. (1999) Learning by New Experiences: Revisiting the Flying Frtress Learning Curve, in *Learning by Doing in Markets, Firms and Countries* (Jan. 1999). pp. 145-184 University of Chicago Press

Mody, A. (1989) Firm strategies for costly engineering learning, Management Science 35 (4) (1989) 496 - 512.

Phaal, R. (2005, Avril 5). *Technology / Research Valuation Tools and Techniques*. Center for Technology Management- University of Cambridge présenté au Horizon - R&D : Managing New Trends.

Pisano, Gary P. (1996) "Learning-Before-Doing in the Development of New Process Technology." *Research Policy* 25, no. 7 (October 1996): 1097–1119.

Sinclair, G, Klepper, S., and Cohen, W. (2000) "What's experience got to do with it? Sources of cost reduction in a large specialty chemical's producer." *Management Science,* **46**(1):28-45.

Sommer, S.C; Loch, C.H. Dong, J. (2009) Managing Complexity and Unforeseeable Uncertainty in Startup Companies: An Empirical Study, *Organization Science* Vol. 20, No. 1 (Jan. - Feb., 2009), pp. 118-133

Snowden, D. J., & Boone, M. (2007). A leader's framework for decision making. Harvard Business Review, 85, 69–76.

Terwiesch, C., Bohn, R.. (**2001**) Learning and process improvement during production ramp up. J. *Production Economy*

Thomke S. (1998a). Managing Experimentation in the Design of New Products. Management Science/ Vol. 44, No. 6

Thomke S. (1998b). Simulation, learning and R&D performance: Evidence from automotive development. Research Policy 27 _1998. 55–74

Thomke S. (2003). Experimentation Matters. Harvard Business School. Press: Boston, MA

Thompson, P. (2001) How Much Did the Liberty Shipbuilders Learn? New Evidence for an Old Case Study, *Journal of Political Economy* 109:1, 103-137

Thompson, P (2010), "Learning by Doing". *Economics Research Working Paper Series*. 42.

von Hippel, E., Tyre, M., (1995). How 'learning by doing' is done: problem identification in novel process equipment. Res. Policy 19, 1–12.

Wright, T. (1936) "Factors affecting the cost of airplanes." *Journal of the Aeronautical Sciences,* **3**(4):122-128.