Measuring Expertise Learning Rates for Nonrepetitive Project Work

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Research on learning has largely centered around workers repeatedly performing a specific set of tasks. However, in service functions like management consulting, jobs are seldom repetitive. Nevertheless, expertise is acquired with practice. This paper proposes a model to quantify learning when a consistent methodology is applied to a wide variety of projects, and introduces an associated 'expertise learning rate'. The model is illustrated using panel data tracking 56 newly trained process improvement project leaders completing 233 projects over five years. Applications where trained personnel must work on nonrepetitive jobs or projects are common in services, e.g., insurance claims settlement, cost estimation in construction, and tax return preparation in accounting.

Keywords: learning rates, process improvement projects, management consulting

INTRODUCTION

In industrial process improvement programs at large companies, with possibly hundreds of projects underway, no two projects are alike; but they are all carried out by trained project leaders using a uniform approach (for example, using Lean Six Sigma methodology). These project leaders become experts from repeatedly working with the methodology on a variety of projects, and it is this learning that is quantified in this paper. Using panel data, performance is tracked for 56 newly trained Lean Six Sigma project leaders completing 233 projects over five years. The data show that project leaders became more proficient with experience, exhibiting an expertise learning rate of 86%. The proposed model allows for measuring the learning on such jobs.

Research into learning has a long and influential history. The observation that workers repeatedly performing a job tend to complete it faster led to the study of the learning curve phenomenon around the beginning of the twentieth century (e.g., Bryan & Harter, 1899; Thurstone, 1919; Graham & Gagne, 1940). Over the ensuing period, the subject has received sustained attention. Contemporary applications continue to arise in settings such as order-picking in fulfillment centers (Grosse et al., 2013), and online ordering in supply chains (Kull et al., 2007). However, while the tasks studied in research have ranged from assembly operations to large efforts like ship-building, the focus nevertheless has always been on the learning from repeatedly performing the same task. The research is much less extensive for situations where the tasks are likely to be different, like management consulting and other service sector jobs. The difficulty has been the varying nature of cases that a consultant is likely to encounter. Each case facing the consultant is likely different from the preceding case. However, consultants, as they gain expertise, are able to complete jobs faster. They learn by repeated application of the methodology, not by repeated practice on the same task. How might this learning be quantified? A model is proposed for such learning and a suitable metric is introduced which will be called the expertise learning rate. To the authors' knowledge, there has been little or no prior work on this topic.

The proposed model derives from the following insight. Consider a service application like management consulting and a newly trained consultant. The consultant faces a portfolio of different projects (cases) each with its own time-to-completion durations. The durations are typically log-normally distributed. With experience, by the time the consultant is ready to conduct their fourth project, for example, the projected durations are still log-normally distributed, but with a mean that is significantly lower, reflecting the fact that they can now complete each project in the population faster. Thus, with experience the consultant is able to complete projects faster, resulting in smaller population means. A Wright type power law applies to the reduction in the means.

To summarize, in applications like management consulting, projects are varied, the population of project duration is lognormally distributed and the distribution shifts to the left with means decreasing as the consultant gains experience. The reduction in means can be quantified and provides a way of assessing the learning that takes place. Thus, we focus on the population of tasks and not individual tasks, and show that learning is reflected in the decreasing population means.

The model will be illustrated using a study from process improvement. Many industrial organizations place significant importance on process improvement. Employees are often trained in successive cohort groups in techniques of process improvement, like 'Lean Six Sigma', and are encouraged to select and lead process improvement initiatives, often in addition to their normal responsibilities. While the projects may vary, they are all nevertheless addressed using the same methodology, the same software tools and management and documentation procedures. Project leaders learn from repeatedly utilizing the standard process, and it is proposed that learning is seen as a reduction in mean duration, as outlined above.

Panel data from a large oil and natural gas extraction company will be used to track the performance of 56 newly trained Lean Six Sigma project leaders as they progress, completing 233 projects over a course of five years. Project leaders become more proficient at the Lean Six Sigma methodology with experience. The learning rate for these projects is estimated to be about 86%.

Examples where trained personnel undertake activities not necessarily identical, but falling within a domain expertise, occur frequently in the service sector (e.g., para-legal work, hazard remediation service, cost-estimation in construction, etc.). The proposed model should be useful to these jobs as a way of quantifying the learning that takes place.

LITERATURE REVIEW

As noted earlier, the origins of industrial learning research are in the performance of repeated operator tasks. It was soon observed that small groups of workers carrying out a job repeatedly exhibited learning much like individuals (e.g., Leavitt, 1951; Guetzkow & Simon, 1955; Baloff, 1967). Indeed, large organizations engaged in carrying out a task, like building a certain ship or aircraft repeatedly, are also found to exhibit learning. The study of organizational learning, in this sense, has a long history, beginning with Wright (1936), Rapping (1965), and Arrow (1971), and the topic has had sustained interest ever since (e.g., Argote, 1990; Argote et al., 1990; Argote & Hora, 2017; Yelle, 1979; Thompson, 2012).

Other streams of research have looked into the persistence and depreciation of learning (Argote, 1990), incorporating learning curves in decision support systems (Newman, 1994), in design activities (e.g., Dar-El, et al., 1995), and project and acquisition cost estimation and planning (e.g., Goldberg & Touw, 2003). Research has long been concerned with explaining the learning process. Fioretti (2007) examines how some observable organizational characteristics might map into the parameters of the random graph model of organizational learning proposed by Huberman (2001), toward the goal of making possible the prediction of learning rates. In this direction, it is also important to include the work of Levy (1965), Adler & Clark

(1991), and Lapré et al. (2000), who studied ways to uncover the influence of managerial actions on learning.

Learning research also has implications for work design and team management. To that end, research has looked into the effects on performance of team diversity (Huckman & Staats, 2011), of work variety and specialization (Staats & Gino, 2012), and goal-relatedness (Clark et al., 2018). Researchers have also looked into various alternative mathematical forms for the learning curve and under what circumstances they might apply (e.g., Baloff, 1971; Carlson, 1973; Plaza et al., 2010; Dar-El et al., 1995). Gross et al. (2015) provide a very comprehensive summary of models previously considered in the research literature.

Thus, all of the prior research pertains to learning on a central task or process. However, mastery of an expertise often occurs through practice on varied jobs. Examples abound, especially in service functions, as noted. We make a start toward a possible model to capture this type of learning. Clearly, the earlier work summarized above provides a road-map for further research in this new direction.

Specific to process improvement, while to our knowledge there has not been attempts at assessing learning predicated on experience, researchers have looked at the mechanism of knowledge acquisition and its relationship to project success (Savolainen & Haikonen, 2007; Anand et al., 2010; Mukherjee et al., 1998). Arumugam et al. (2013) investigated how learning occurs in Six Sigma projects and empirically showed that success appears to derive from both technical resources and social practices within the team. Easton & Rosenzweig (2012) examined the likelihood of Six Sigma project success as a function of four experience variables: individuals, the organization, the team leader, and team familiarity. The authors concluded that team leader experience had the strongest relationship with project success. Staats et al. (2011) found that Lean techniques do improve project outcomes in an empirical study of software projects carried out at an Indian software services firm.

The work by Lapré et al. (2000) cited earlier was based on data from 62 quality improvement projects at Bekaert, a steel-wire manufacturer. The projects, under a Total Quality Management (TQM) program, were all focused in support of wire production, a highly repetitive manufacturing process. The setting there is very different from our process improvement study, which is that of individual project leaders acquiring mastery of Lean Six Sigma skills through different projects of opportunity, no two of them alike.

THE MODEL

Project leaders develop expertise by carrying out tasks, which we will refer to as projects. We refer to tasks as projects, for often they are of significant duration and complexity and foster expertise development. In the tradition of learning rate research, we model the time required to complete a project as a function of experience. Project durations are long-tailed, spanning orders of magnitude, and several studies have reported that log-normal distributions fit duration data well (e.g. Little, 2006; Strum et al., 2000; May et al., 2000; Mohan et al., 2007). In our model, the random variable T_0 is the time required by a newly trained project leader to complete any of the set of projects available in the firm. We propose that $T_0 \sim Lognormal(\mu_0, \sigma^2)$.

Next, we suggest that with experience μ_0 decreases, so that the random variable T_j, the duration of any project that a project leader might lead after they have completed $(j-1)$ prior projects is $Lognormal\left(\mu_j, \sigma^2\right)$ where $\mu_{j+1} < \mu_j < \mu_0$. In our model, we assume that the variance term σ^2 is constant, reflecting the spread in project durations inherent to project variety in the firm (or the market), but μ decreases with experience. We model $\mu_j = A + b \ln j\,, b < 0$.

Therefore, with Z representing the standard normal:

$$T_j = e^{\mu_j + \sigma Z} = e^{A + b \ln j + \sigma Z} \tag{1}$$

And the expected completion time for the *j*th project can be expressed as shown in equation 2:

$$E[T_j] = e^{A+b\ln j+\frac{\sigma^2}{2}} = Cj^b \left(with\ C\ set\ as\ e^{A+\frac{\sigma^2}{2}}\right) \tag{2}$$

The mean, $E[T_j]$, as shown in equation 2, has the functional form of the Wright learning curve. We then define the expertise learning rate as 2^b. The use of this model will be illustrated with a study from process improvement.

THE PROCESS IMPROVEMENT STUDY

Background

The authors have experience with providing management consulting on industrial Six Sigma projects. In our experience, rarely will a project leader do projects that are substantially similar. Indeed, expertise is the ability to tackle a variety of projects, often dictated by company priorities and needs. Nevertheless, project leaders learn by doing projects. It is this learning that we seek to understand. One of the authors has worked extensively with a large oil and natural gas extraction company. We were able to obtain from this company five years of panel data for this study. The data covers activities of 56 newly trained Lean Six Sigma project leaders. The data permitted us to tie projects to project leaders, extract project durations, and create panel data for each project leader. Other attributes, such as monetary value or scope, which may have helped in segmenting projects were not made available to us.

As mentioned, there is no uniformity in what projects a leader might undertake. In the data, there were project leaders who completed as many as six different projects in the five-year interval. Table 1 shows summary statistics. We see there were 56 projects that were the first for their project leaders. The mean duration for this group was 142.6 days. Next, there were 53 projects that were the second project for their project leaders; at this point we define the 'experience level' of the project leaders to be two. The mean duration of this group was 119 days. Overall, the mean duration of these groups is decreasing. We apply the model presented above to assess the learning exhibited.

The traditional Six Sigma system consists of project teams improving processes using a structured method for problem solving known as the DMAIC framework; Define-Measure-Analyze-Improve-Control (Pyzdek & Keller, 2003; Linderman et al., 2006; Schroeder et al., 2008). This DMAIC model was subsequently adopted by companies and integrated with Lean methods and has come to be known as the Lean Six Sigma method.

TABLE 1
STATISTICS ON PROJECT DURATIONS BY EXPERIENCE

Project Leader Experience Level	Sample Size	Mean (days)	Standard Deviation (days)
1	56	142.6	96.4
2	53	119.0	97.2
3	47	124.0	95.3
4	39	140.3	111.2
5	21	95.1	79.5
6	17	76.3	81.6

We will refer to the oil and gas extraction company as OGC hereafter. OGC is active in over 150 countries, employs in excess of 40,000 workers, and has annual sales exceeding $90B. Typical of many other companies, OGC chose to adopt the DMAIC framework as the basis for its Lean Six Sigma program, modifying and customizing this structure where it deemed necessary.

At the time of this writing, OGC had a corporate-wide Lean Six Sigma program in place for over 15 years (known within the company as Lean Sigma or simply LS). It ran numerous operating divisions around the world, and the level of commitment and progress towards LS varied within its divisions. Originally, the company rolled-out the LS program for key scientists, engineers, and other production personnel, beginning with two-weeks of intensive classroom training. OGC created a hierarchy of training levels typical of companies adopting Lean Six Sigma, and used project teams as the primary method for analyzing and improving a process. A hierarchical structure was established that consisted of trained “green belts” as project team leaders, with mentoring support provided by more extensively trained “black belts” and “master black belts”.

Initially, green belt training and certification consisted of two, 5-day sessions, separated by several weeks (although, occasionally, they were held back-to-back). Over time, the company shortened its green belt training program to six days, creating two, 3-day classroom sessions, spaced a few weeks apart. At the conclusion of the training, attendees were considered green belt trained, but were not officially certified by the company until they had led at least two LS project teams through the first four phases of the DMAIC process. Specifically, green belt candidates were required to organize and lead at least two projects to the control phase within 18 months of training course completion. Furthermore, the projects were expected to meet a pre-determined minimum level of accrued financial benefit (AFB). The AFB was used as a reasonable estimate of the value created by a Lean Sigma project. These financial benefits could be measured in various ways, including revenue increases, savings in operating expenses, as well as soft non-AFB savings consisting of intangible benefits. Unfortunately, as noted earlier, financial impact information such as AFB was not made available to us.

In addition, a computerized project tracking system was created by the company, and all green belt candidates were required to enter relevant project information, beginning with the Define phase and its requisite problem statement and input-process-output (IPO) diagram. Since the Control phase was strictly an ex post verification period with a fixed length of 12 months, for purposes of this study, we only considered the elapsed time between project initiation and the beginning of the control phase (i.e., the time to progress through DMAI phases only). For all intents and purposes, projects are essentially finished within the DMAI period. Once the project moved into the Control phase, the project leader monitored and entered financial benefits into the project tracking system on a regular basis, over the course of 12 months.

Description of the Panel Data

For each project, we were provided the start and end dates for the various DMAIC phases, allowing us to compute the duration defined above (see Table 3). We deleted projects with duration less than 10 days. The dataset also listed mini-projects that followed an abbreviated DMAIC process (and thought to last less than 10 days), but our intent was to focus on the standard DMAIC projects. We also deleted projects with duration greater than 408 days (those flagged as outliers in data cleansing). Projects generally last about a year; indeed, teams were encouraged to reach the start of the Control phase in 3 to 6 months. Therefore, durations significantly longer than a year were suspect and were potentially caused by delays or mistakes in using the project tracking system. This pruning yielded data for 233 projects. These 233 projects were performed by 56 project leaders who had been trained on the DMAIC method of process improvement through one- or two-week training programs (flagged by a suitable indicator variable in the data). As noted, a leader might undertake projects of different sizes. Multiple leaders might work on a given project but the start and end dates of their involvement were separately logged. Furthermore, for each project leader, Lean Six Sigma training completion dates were provided by OGC. Additional information included details such as the facility identifier for each project. A copy of the data set in Excel format may be found on *GitHub* in the following location: https://github.com/venkav3/Expertise_learning_curve/blob/master/PI%20Study.xlsx

In the vast majority of cases, individual project leaders carried out projects of widely varying durations (See Figure 1). We were curious to see if project leaders self-selected longer projects as they gained more experience. Figure 2 shows box plots of project durations versus experience. There is no evidence that more experienced project leaders select longer duration projects. The Pearson correlation between duration and experience level was a small negative value of -0.139 (p-value 0.034).

TABLE 3
EXCERPT FROM THE DATA SET

Project leader ID	Training type	Training time-stamp	Project ID	Operating unit code	Project start	Project end	Project duration
1009	1	876	11323	2015	779	896	117
1009	1	876	11938	2015	824	929	105
1009	1	876	12926	2015	933	1062	129
1009	1	876	12908	2015	946	1294	384
1013	1	785	9458	2015	538	594	56
1013	1	785	10171	2015	664	882	218
1013	1	785	10170	2015	664	847	183
1013	1	785	13780	2015	1016	1112	96
1013	1	785	15674	2015	1184	1225	41

FIGURE 1
PROJECT DURATIONS BY PROJECT LEADER

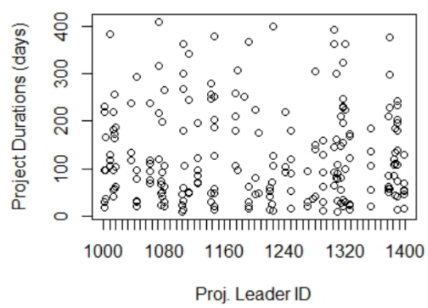
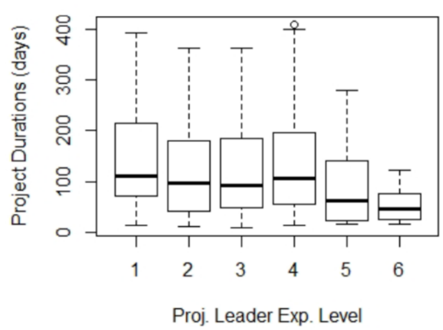


FIGURE 2
PROJECT DURATIONS BY PROJECT LEADER EXPERIENCE



A project leader would typically arrange a brain-storming session with their team to select a suitable project from a list of candidates. Projects were placed in four categories on the basis of benefit and difficulty. Projects judged easiest to complete, but with low payoff, were placed in the "Potential" category. Any projects with a predicted high payoff and low difficulty were placed in the "Implement" category. High payoff but difficult projects were positioned in the "Challenge" category, and projects with low payoff and high difficulty were placed in the "Kill" category. It was not uncommon for teams to start with a list of about six candidates, and most teams finished by selecting a project from the implement category. Thus, projects selected were almost always projects of opportunity.

Analysis

For ease of analysis, we introduce some terminology. If a project is the first project of its project leader we say that the project leader experience level was 1 when this project was carried out. Likewise, we say that the project was an experience level 1 project. In general, when a project is the *n*th project of its project leader, we say that the experience level of the project is n and likewise that the experience level of the project leader leading the project is n.

In our model we assumed that the distribution of project durations by experience level is log-normal with constant σ. To verify this assumption, we grouped projects by experience level and checked log-duration for normality (See Figure 3). The data show no departure from normality at $p = 0.05$. Furthermore, the sample standard deviations are approximately equal (See Table 2). We carried out Levine's Test and found no evidence to reject equality of variance at $p = 0.05$.

FIGURE 3
NORMALITY TEST FOR LOG-DURATIONS BY EXPERIENCE LEVEL

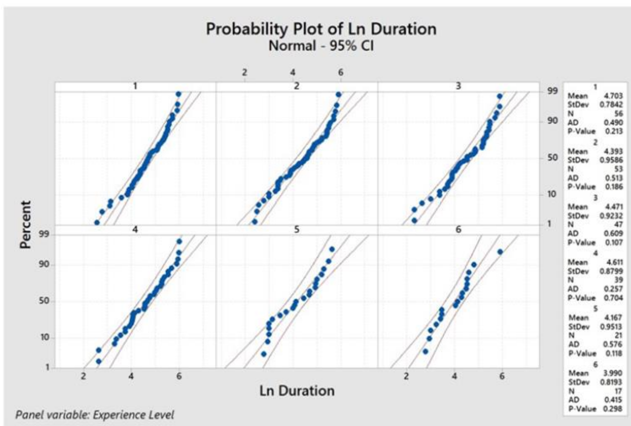


TABLE 2
STATISTICS ON LOG-DURATIONS BY EXPERIENCE LEVEL

Experience Level	Sample Size	Mean Log Duration	Log Duration Std. Deviation
1	56	4.703	0.784
2	53	4.393	0.959
3	47	4.471	0.923
4	39	4.611	0.880
5	21	4.167	0.951
6	17	3.990	0.819

Expertise Learning Rate

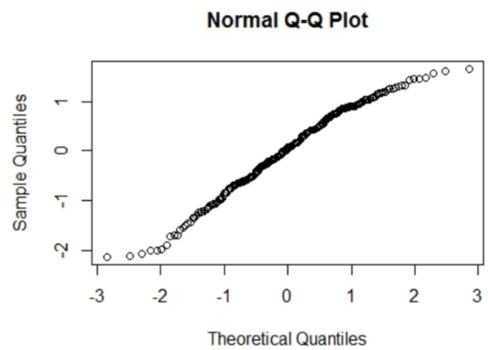
To assess the expertise learning rate, a Mixed Linear Model was fit to the data. Project leaders were considered a random factor; therefore, the data were grouped by project leaders. The groups were modeled as having random slopes but constant intercept. Recall that the intercept denotes the mean project duration of a newly trained project leader if they were to carry out all of the projects in the organization. Thus, the model allows for different learning rates for different project leaders, all starting from a common base denoted by the intercept.

Individual Learning Rates

The fixed effect deriving from the random slopes, b, may be interpreted as the mean learning rate of the population of project leaders. The results from the model fitting are as follows; $b = -0.22$ (p = 0.03), the standard deviation of the random slopes is 0.17, and that of the residuals is 0.87 (an estimate of σ).

An estimate of the intercept A is 4.68. The variation of the residuals reflects the inherent spread in duration of projects, and this is found to account for 97% of the stochastic variation in the data. As noted before, project durations span several scales of magnitude. A Likelihood Ratio Test and the KR test also confirmed significance of the model at p = 0.03. Residuals appear normally distributed (See Figure 4).

FIGURE 4
MIXED-EFFECTS MODEL – QQ PLOT OF RESIDUALS



The data show a mean learning rate of $2^{-0.22} = 86\%$. Individual $b_i s$ vary around $b = -0.22$ with a standard deviation of 0.17, resulting in varying individual learning rates. The constant C above is the mean of projects for experience level 1. Using the estimates A = 4.68 and $\sigma^2 = 0.76$ yields $C = e^{A+\frac{\sigma^2}{2}}$ = 157.6 days. The observed mean for this group was 142.6 days (See Table 1).

The decreased population means captures the learning of process improvement expertise. As they repeatedly complete projects, engineers become increasingly comfortable with the DMAIC sequence, utilizing the requisite statistical software, recording and documentation requirements, working as a team and so forth. Thus, a project leader carrying out their fourth project will take only 86% of the time it would have taken them had it been their second project.

DISCUSSION

The proposed approach could be used to measure expertise development in any application where trained professionals make use of a set methodology to carry out projects that are themselves quite varied. To illustrate the managerial significance of such analysis, consider the example of Lean Six Sigma process improvement.

Companies have long recognized the importance of continuous process improvement and have devoted significant resources to developing a culture of continuous improvement. The strategic benefits from improved operations are well studied (e.g., Bertsch & Williams, 2001; Anand et al., 2009; Shah & Ward, 2003; Zu et al., 2008). For instance, the United States Army reported that since the introduction of Lean Six Sigma in 2006, cumulatively 19.1B dollars have been saved through process improvement (OBT, 2011). In the 2011 fiscal year, 2,111 projects were under way, representing 3.6 B dollars in financial savings, and the Army had trained 5,700 Green Belts, 2,400 Black Belts and 175 Master Black Belts. Given the scale of resource and time committed to such endeavors, it becomes incumbent to understand the role of learning in skills development, how that might be fostered, and what is lost when trained Lean Six Sigma leaders leave the organization. Reporting on a study on Lean Six Sigma project failures in the *Wall Street*

Journal, Chakravorty (2010) cites the departure of experts from projects as one of the main causes of failures.

CONCLUSION

We focused on the learning of expertise which occurs through experience on varied assignments. For this situation, which is the case in many service functions like domain-specific management consulting, we present a model for quantifying the learning that accrues with experience. The model was illustrated with a study from process improvement, and showed that the expertise learning rate is appreciable, at around 86%. This might allow the organization to benchmark the impact, say, from losing a trained project leader who has carried out a significant number of process improvement projects. In addition, quantifiable learning rates allow the organization to assess the relative effectiveness of process improvement campaigns in different sub-units, with implication for training, resource allocation and prioritization. Future work will seek to quantify the expertise learning rate in other domain specific service functions such as cost estimation in construction, claims settlement in insurance and tax preparation in accounting.

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