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Fast Track to Learning: Explaining the Puzzle of Heterogeneity in Learning

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Abstract

Do some firms learn faster than others? Although traditional learning curve research has found that low-performing organizations are faster learners, some recent studies have demonstrated the opposite.

We explain these contradictory results by looking at learning from salient stimuli: train accidents. Using two measures of accident reduction as dependent variables we allow for variation across firms and across time in learning rates and use two experience predictors: recent events and whether the firm has been fast learner in the past, here defined as performing better than the industry average. We find that both factors have positive effects on learning rate and that their interaction term is negative, suggesting that they act as substitutes for one another. That is, having many accidents reduces accidents faster, but being a good learner also reduces accidents at a higher rate, meaning that both low and high performing firms can enjoy high learning rates.

Using a 25-year data window we also consider how the maturation of the industry impacts the distribution of learning rates across firms. Finally, we look at the impact of market focus on learning rate in the context of learning from failure.

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Introduction

Although a significant part of research on organizational learning has assumed identical learning rates across firms, numerous studies have proven the existence of heterogeneity in learning within industries (Lapré and Tsikriktsis, 2006; Haunschild and Sullivan, 2002). If heterogeneity in learning actually exists, why are some firms better learners? While some studies suggest that low-performers learn faster because they have greater room for improvement (Darr et al. 1993; Argote and Epple, 1990), recent investigations have shown that experienced organizations are faster learners (Boone et al., 2008, Balasubramanian, 2011). In this study, we unveil two potential explanations for these conflicting findings: first, experience measurement may affect the shape of the learning curve, and second, context-related moderators should be taken in account.

We will more particularly look at organizational learning from failure. Failures play a crucial role in learning because a failure is more salient than a success, especially as factors of operational successes often are purposefully obscured (Ingram and Baum, 1997). Moreover, looking at failures is particularly useful in the context of research on heterogeneity in learning rates: they provide uniformly negative feedback, which is consistent across firms, and are highly salient events. In the railroad industry, the factors of failures are more likely to be publicly exposed and interpretable: any accident that incurs a cost of more than $6,700 (in 2002) has to be reported to the Federal Railroad Administration, which compiles accident data and makes it publicly available. The number of freight train accidents in the US drastically fell by over 70% since the 70s. Seen over a longer time period the industry has developed from being the second deadliest industry in 1880, after mining, to a paragon of safety at the end of the 20^{th} century.

THEORY AND HYPOTHESES

Organizational learning is the process through which organizations evaluate their past performance and adapt their routines (Levitt and March, 1988). Some organizational learning scholars tend to conceptualize learning as a stimulus-response process (Weick, 1991). We consider failure as one type of stimulus and want to study subsequent adjustment and learning processes. Past research has suggested that failure - although being a rare event - is crucial to learning (Sitkin, 1992; Weick, 1991; Denrell, 2003; Baum and Dahlin, 2007). Since learning requires organizations to link its actions to relevant outcomes, including negative ones such as operational failure (here accidents) a main issue when organizations experience negative events, is that the causal processes might be harder to analyze: while everyone is happy to be part of a success, the threat of penalties makes it riskier and (especially in cases of fatalities) emotionally more difficult to accept own culpability, and hence correctly understand cause-effectto understand what lead to an accident.

Heterogeneity of learning rates

Although past research has looked at the heterogeneity of learning rates among individuals within a firm (March, 1991) and suggested that heterogeneity of learning had a positive impact on the average learning curve (Dodgson, 1993), very few studies have paid attention to heterogeneity in learning rates at the field level. Do some firms learn at a higher rate than others? Past studies have implied the existence of heterogeneity in learning across firms (Haunschild and Sullivan, 2002): learning rates show considerable variation within industries in both manufacturing and service sectors. If so, why are some firms better learners? To answer this question, we use data on rail accidents in the United States between 1975 and 2001.

Low-performing firms may naturally learn faster than their peers when we assume a constant rate of production or failure. This is a well-documented feature of the learning curve (Darr et al. 1995): although organizations learn from experience they do it at a decreasing rate. Two factors may explain this situation. First, low-performing firms have more room for improvement. Second, low-performing firms have a bigger experience base, i.e. more accidents to learn from. Conversely, high-performing firms may learn slower: their experience base is smaller, and the marginal cost of additional accident reduction should increase (Sorenson, 2003). Thus, we may argue that the firms that are at the beginning of the learning curve will learn faster.

Hypothesis 1a: Low-performing railroads – firms that recently experienced more accidents – have a higher learning rate.

In contrast to the traditional learning-curve view, Boone et al. (2008) suggest that learning experience matters for learning rates. According to their study of facilities engineering projects, learning accelerates with experience – here the experience enabling railroads to actually avoid accidents - and the knowledge stock has a positive impact on the rate of learning. This effect increases in the industries with high learning intensity (Balasubramanian, 2011). Wiersma (2007) explains how a mature firm can still maintain a positive learning curve. In this context, the rate of learning depends upon past performance. Thus we could formulate an opposite hypothesis.

Hypothesis 1b: High-performing railroads – firms that recently experienced fewer accidents – have a higher learning rate.

We are confronted with two contrasting views that state that either low performers (many recent accidents) have a greater opportunity to reduce their accidents or that high performers (few recent accidents) are better at learning. How can we reconcile these antagonistic perspectives?

Organizational learning is commonly defined as an improvement in performance due to experience (Balasubramanian, 2011). There are nevertheless many different ways to measure performance and experience in the context of learning. We believe the way learning rates are measured makes a significant difference. Classic learning curve literature (the proponents of the hypothesis 1A) conceptualizes the learning rate as the decrease in the cost of production (Argote and Epple, 1990, e.g. Darr et al., 1995; Sorenson, 2003, Wiersma, 2007). Similarly, Boone et al. (2008) also look at the percentage decrease of labor input by unit, although they found opposite results. In their case however, the unit is an architecture engineering project, i.e. a non standardized output. Cumulative years of operating experience have also been used as a measure of learning (Ingram and Baum, 1997). We see how the definitions of performance and experience are interlaced. Operating experience differs from experience of success. Correspondingly, the operationalization of performance will be different. If experience is simply measured as operational track record, performance measurement will focus on process improvement leading to higher productivity and/or lower costs. By contrast, if experience is the success history of the organization, then future successes will be an appropriate measure of performance. From a success to another, different factors might be at stake, while operating experience is a monotonous and unidimensional construct.

If we consider size, a high performer can have more accidents than a low performer,. That is, another comparison in accident performance across firms is to analyze accident rates, or number of accidents per million operating miles. This variable plays a different role because of vast size differences between firms in operating miles, with the largest firms representing almost 25% of operating miles and the smallest just the fraction of one percent. The effect of size differences on learning is that while the overall industry accident rate in 2001 was 4.25 accidents per million miles (FRA, 2012). The firm with the second largest number of accidents (BNSF) experienced about 20% of all accidents, but was still a railroad with a lower-than average accident rate (3.8 accidents/million miles). This would suggest that the combination of a large experience pool to learn from and a high learning performance can explain why some well performing learners still can push down the learning curve faster than other firms. In other words, railroads that blend a high-number of accidents and a lower-than-average accident rate learn faster...

`Hypothesis 2`: Railroads that combine a high learning performance (low accident rate) with a large experience pool (high number of accidents) have a higher learning rate.

The learning environment

It can also be argued that contextual elements explain this apparent inconsistency. In particular, the maturity of an industry (Wiersma, 2007) impacts learning opportunities and learning rate. Balasubramanian (2011) suggests that the importance of learning-by-doing in an industry evolves over time: technological evolution is a crucial factor. The more mature technologies and the processes are, the greater the chance that they will be equally spread among organizations (Abrahamson and Rosenkopf, 1993). In a similar fashion, the stability of the environment plays an important role, because volatility disrupts the link between experience and performance (Sorenson, 2003). Indeed, if the factors of success change from one period to another, these factors are harder to identify and replicate (Lave and March, 1975). Industry maturity is definitely a factor of stability: innovations are less common, technologies tend to be more widely spread, and the differences across organizations in terms of access to these technologies are slighter (Peltoniemi, 2011). In other words, industry maturity makes the learning environment more predictable.

We argue that industry maturity impacts the distribution of learning rates across firms. In a mature industry, the impact of your position on the learning curve on your learning rate matters less. As technologies and processes get well established and widely available, the heterogeneity in learning opportunities across firms is limited. Therefore, we suggest that industry maturity has a negative moderating effect on the relationship between experience and learning rate. While the railroad industry in the US is a highly mature industry both at the beginning and the end of our observation period, the regulatory context that traditionally varied greatly did during this period stabilize and, hence the learning environment matured.

`Hypothesis 3`: Industry maturity has a negative effect on the relationship between past experience and learning rate.

Firm focus and learning rate

In addition, a consistent stream of research has shown that focus had a positive impact on organizational learning (Lapré and Tsikriktsis, 2006). Ingram and Baum (1997) showed that firms with a specific geographic focus were better learners than geographic generalist: when hotel chains cover several areas, they aggregate specialized expertise, but fail to connect these clusters of knowledge. The U.S. airline industry shows similar patterns: Lapré and Tsikriktsis (2006) suggest that market (geographical specialization) and operating (flying only a few planes types) focus result in a higher learning rate. By repeating the same actions, employees learn faster, both individually and as teams. They can also deal with uncertainty more easily. More generally, learning from experience is hampered in complex organizations, because they are more hierarchical and compartmentalized. Similarly, we argue that focused railroad tend to learn faster.

`Hypothesis 4`: Focused railroads are more able to reduce their number of accidents.

EMPIRICAL SETTING AND METHOD

Our sample includes the major freight railroad (representing 97 % of the rail volume) in the US from 1975 to 2001, representing a total of 936 firm-year observations, documenting 121 740 accidents.

Dependent variable: We use two dependent variables, (1) the percentage change in accident rate (a firm's total number of accidents divided by million operating miles) from [t to t+1] and (2) the percentage change in accident count (a firm's total number of accidents) to test our hypotheses. Both dependent variables are skewed, that's why we log transformed them. Since the changes in both accident count and accident rate are first differences, we do not need to use fixed-effects models. Given the nature of the dependent variable, there is a potential problem with autocorrelation over time periods so we use Stata's xtregar function, which will not only handle the panel-data nature of the data but also the biases introduced due to autoregression. The Durbin-Watson statistic for all models is greater than 2, confirming our model choice.

Independent variables: To determine if a firm was a *fast learner*, we compared the firm's accident rate to that of the industry average in each year. If the firm's accident rate was lower, we consider it a fast learner and we give the variable value 1, otherwise a zero. To capture a railroad's own experience we used the logged count of last year's accidents.

We measure industry maturity, or predictability of the learning environment, as the cumulative number of safety legislations, *cumulative legislations*. The regulatory environment changed in 1966 with the Department of Transportation act, which lead to the creation of the FRA, Federal Railroad Administration. The mandate for the FRA is, among other things, to: "promulgate and enforce rail safety regulations; administer railroad assistance programs; conduct research and development in support of improved railroad safety and national rail transportation policy" (FRA, 2012). Early during the study period, there were about one legislation appearing every two years, but the rate of new legislation was lower during the 1990s. The cumulative number of legislations provides a measure of external control. In this context, external control is aimed at forcing railroads into reducing their accident rate. The more government organizations legislate, the narrower is the scope for heterogeneity in learning, and the more predictable is the learning environment.

Firm focus is an indicator set with three possible positions: Class I railroads (operating revenues of more than 250 MUSD/year, on average about 350 MUSD) that tend to have other activities under their corporate umbrellas; regional railroads, that are usually class II railroads (1988 freight operating revenues between 20.5 MUSD and 277.7 MUSD over at least three consecutive years), and short-line, or class III railroads (<20MUSD operating revenues). Our data represents all Class I, about 70% of the Class II and a smaller fraction of class III and railroads. At the same time the sample represents well over 95% of the industry operating revenue and accidents.

The most focused firms are the smallest actors, however, regional railroads are the most recent organizational form that is specializing in rail operations and using more systematic approaches to management and operations (some firms are active in freight rail across continents). We therefore consider regional operators the most specialized actors, with class III railroads coming in second, and Class I firms, that usually own the track and land rights for vast areas and have diversified into transportation insurance, other transportation modes and historically they have owned hotels at major junctions. Canadian Pacific, a Class I railroad describes its diversification moves (Canadian Pacific, 2012):

> "Through its history, CPR got into numerous other ventures including abattoirs, animal husbandry, bus transportation, china and crockery, containers and pallets, forestry, foundries, immigration and colonization, insurance, irrigation, manufacturing, milling and foodstuff, mines and minerals, newsreels, oil, pulp and paper, radio broadcasts, stockyards, supply farms, trucking, waste management, even bottled spring water. In 1942, CPR even took to the skies, amalgamating 10 northern bush plane companies into Canadian Pacific Airlines."

Control variables (all lagged a year): Firm level control variables are severity of accidents measured as total direct accident cost; firm size (in logged million employee hours); the firm's logged operating miles for the last five years, discounted by the square root of the time lag; firm age; accident heterogeneity (calculated using Blau's index for five different accident causes) and the logged number of passenger miles the railroad operated in a year.

Industry-level control variables are industry accident experience computed as the annual industry-level (lagged) accident count, subtracting the focal railroad's accidents and divided by the number of operating miles of all firms except the focal one; the firm's 5-year logged, lagged and discounted operating experience; industry accident heterogeneity; a production index, which denotes the productivity in the industry (from the US DOT), and year fixed-effects. All independent variables and control variables are lagged.

Results

Table 1 contains summary statistics and correlations. Table 2 presents the panel-data random effect estimation for change in accident rate (model 1, 2 and 3) and for change in accident count (model 4, 5 and 6). Year fixed effects are included but not reported in all models.

Insert Table 1 here

Insert Table 2 here

We formulated two contradictory hypotheses: on one side, we suggested that the more accidents a railroad has experienced the more room it has for improvement (Hypothesis 1A), and on the other side, we argued that the more skilled a railroad has been at avoiding accidents the faster they would keep reducing its accidents (Hypothesis 1B).

Our models 3 and 6 confirm the second proposition: the positive coefficient for the railroads' own accident experience is significant ($p<.01$). In other words a higher level of recent accident stock leads to a higher rate of learning, or inversely a lower level of accident stock leads to a lower rate of learning. Fast learners continue to do better, that is, having had a lower accident rate than the industry average in the past, leads to faster learning in the present. The interaction between being a Fast learner and having a high recent accident stock is negative (the joint significance for the amin effect and the interaction term is z=14.46*** in Model 3 and z=8.04*** in Model 6), which indicates that there is a limit to the advantage of having had many recent accidents. The joint significance of the interaction signals a substitutability between having many accidents and being a fast learner: the fast learner has less of an advantage of the large experience pool than the slow learner. This would explain some of the contradicting findings in the literature.

While the cumulative legislation is significant in Model 2, in Models 3 and 6 we see that tests for the interaction of a railroad's own experience and legislation on change in accident rate are not significant (joint significance test of the main and interaction terms are also n.s.), why we reject Hypothesis 3.

Finally, we find that focused railroads are faster learners, supporting Hypothesis 4. Compared to the excluded Class I railroads, being a regional railroad (the most focused) has a positive impact on learning rate as does being a Class III railroad. The difference in coefficient values between Regional and Class III railroads are not significant (Chi^2=1 and Chi^2=0.51 for Models 3 and 6, both n.s.) so we cannot make a distinction between these two categories beyond that they are both doing better than the Class I roads.

DISCUSSION AND CONCLUSION

This paper explores the existing paradox in the organizational learning literature concerning heterogeneity in learning. While having a larger number of recent experiences to draw upon increases the learning rate, being a Fast learner in the past also speeds up current learning. The interaction between these two factors is, however, negative, indicating that there is a limit to the value of recent experiences. The substitution of one for the other suggests that there are, at least, two ways to enjoy a high learning rate.

We did not find that our measure of the learning environment, cumulative legislations, had an effect on learning rate. One possible explanation is that it is not the issuance of a law per se, but the way it is enforced that matters. A better way to measure the stability of the learning environment might be the number of enforcement actions, for instance.

Furthermore, we tested the relationship between market focus and learning rate. We found, in line with previous literature that more focused organizations learn more rapidly. In contrast, while it is often suggested that the best learner have an intermediate level of focus, we found no difference between the regional and the Class III firms in our sample.

At the organizational level, March (1991) has paradoxically argued that slow learners were crucial to organizational learning, because slow learners stay deviant from optimality long enough for the collectivity to learn from them. Could we infer a similar hypothesis at the industry level? Does the railroad industry learn faster because of some lame ducks?

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Table 1. Descriptive statistics.

		mean	st dev	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	ln(%change in acc rate)	-0.03	0.58	1																
2	ln(%change in accident count)	-0.03	0.56	0.84	1.00															
3	Fast learner	0.47	0.50	0.13	0.17	1.00														
4	Accident experience	2.60	2.14	0.07	0.06	0.07	1.00													
5	Cumulative legislations	3.34	2.61	0.06	0.05	0.06	-0.17	1.00												
6	Regional	0.38	0.48	0.04	0.01	-0.04	-0.37	0.21	1.00											
7	Class III	0.22	0.41	0.03	0.02	-0.04	-0.44	0.02	-0.37	1.00										
8	Firm accident cost (MUSD)	5.75	14.80	0.00	-0.01	0.16	0.72	-0.13	-0.29	-0.20	1.00									
9	Size (million employee hours)	11.00	25.20	-0.02	-0.02	0.25	0.64	-0.01	-0.31	-0.22	0.67	1.00								
10	Firm operating Experience (Miilion miles)	14.23	2.70	-0.06	0.01	0.24	0.92	-0.07	-0.33	-0.46	0.64	0.65	1.00							
11	Firm age	70.37	48.45	-0.04	-0.03	-0.05	0.09	0.02	-0.08	-0.20	-0.04	-0.19	0.14	1.00						
12	Accident heterogeneity	0.45	0.30	-0.19	-0.19	-0.16	-0.50	0.07	0.27	0.21	-0.25	-0.28	-0.52	-0.09	1.00					
13	Industry accident experience	2.25	0.36	-0.02	-0.03	0.01	0.20	-0.81	-0.20	-0.01	0.16	0.00	0.09	0.01	-0.07	1.00				
14	Industry operating experience	20.65	0.23	-0.08	-0.07	-0.14	-0.10	-0.65	-0.04	0.08	-0.14	-0.23	-0.18	0.00	0.04	0.54	1.00			
15	Production index	99.36	23.18	0.05	0.06	0.07	-0.16	0.95	0.21	0.02	-0.12	-0.01	-0.07	0.02	0.06	-0.79	-0.52	1.00		
16	Industry accident heterogeneity	0.26	0.02	-0.02	-0.02	0.00	0.18	-0.81	-0.19	-0.01	0.18	0.04	0.08	-0.05	-0.08	0.81	0.64	-0.74	1.00	
17	Number of firms	517.51	29.02	0.06	0.06	0.08	-0.18	0.97	0.22	0.02	-0.15	-0.01	-0.07	0.02	0.08	-0.87	-0.72	0.94	-0.85	1.00
18	Passenger miles (Millions)	29.90	127.00	-0.01	0.00	0.13	0.46	-0.01	-0.17	-0.14	0.68	0.55	0.43	0.10	-0.17	-0.02	-0.17	-0.01	-0.01	-0.01

p<.01 for values >|.09|; p<.05 for values > |.07|; p<.10 for values > |.06|

Table 2. Regression results.

COEFFICIENT	(1)	(2) Ln(%change in accident rate)	(3)	(4)	(5) Ln(%change in accident count)	(6)
Fast learner (1/0)		0.736***	1.138***		0.579***	0.892***
		(0.068)	(0.12)		(0.080)	(0.14)
Accident Experience, AE		0.875***	0.847***		0.563***	0.583***
		(0.048)	(0.050)		(0.056)	(0.061)
Fast*AE			-0.146***			-0.112***
			(0.032)			(0.039)
Cumulative legislations		-2.295*	-1.200		3.353	1.639
		(1.26)	(1.26)		(3.43)	(3.44)
CumLeg*AE			0.010*			0.00858
			(0.006)			(0.0071)
Regional		0.279***	0.234**		0.218**	0.210**
		(0.10)	(0.091)		(0.11)	(0.10)
Class III		0.333***	0.299***		0.310**	0.307**
		(0.12)	(0.11)		(0.13)	(0.12)
Accident cost	.006*	-.008**	-.004	.004	-.005	-.002
	(.004)	(.004)	(.004)	(.037)	(-.005)	(.005)
Size	.004	-.004	-.003	-.005**	-.009***	-.008**
	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)
Operating experience	-0.0872***	-0.610***	-0.592***	-0.036*	-0.381***	-0.393***
	(0.019)	(0.036)	(0.034)	(0.020)	(0.043)	(0.043)
Firm age (1/100)	-0.528	1.47*	0.797	-0.953	0.370	0.045
	(0.60)	(0.80)	(0.73)	(0.63)	(0.79)	(0.76)
Accident heterogeneity	-0.793***	-0.517***	-0.443***	-0.662***	-0.552***	-0.486***
	(0.12)	(0.10)	(0.10)	(0.12)	(0.12)	(0.12)
Industry Accident	0.612	4.246***	4.944***	0.762	2.932***	3.706***
Experience	(0.91)	(0.98)	(0.95)	(0.95)	(1.11)	(1.14)
Industry Operating	-0.102	0.910	0.886	-0.639	-0.335	-0.254
Experience	(0.82)	(0.84)	(0.81)	(0.85)	(0.96)	(0.99)
production_index	0.0866*	0.0956**	0.0711*	0.109	0.135	0.0579
	(0.050)	(0.039)	(0.038)	(0.14)	(0.14)	(0.14)
Accident heterogeneity	-14.13	-6.019	7.792	0.593	2.075	14.22
	(13.0)	(11.8)	(11.7)	(13.6)	(14.2)	(14.5)
Number of firms	-0.012	-0.031	-0.046	-0.391	-0.460	-0.193
	(0.038)	(0.039)	(0.038)	(0.49)	(0.50)	(0.50)
Passenger miles	-.015	0.00	0.02	0.00	0.01	.03
	(.03)	(.028)	(.027)	(.03)	(.03)	(.03)
	(2.66)	(4.04)	(4.00)	(21.6)	(5.74)	(5.79)
Constant	0	0	0	214.2	217.8	85.83
	(0)	(0)	(0)	(247)	(229)	(230)
Observations	560	560	560	556	556	556
Number of id	36	36	36	36	36	36
R-squared	.15	.39	.42	.11	.21	.22

All models contain year fixed effect, not reported here
Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$