Paper to be presented at the DRUID Academy Conference 2017 at University of Southern Denmark, Odense, Denmark on January 18-20, 2017

Learning from failure across products

Johanna Glauber
Ludwig-Maximilians University Munich
Institute for Strategy, Technology and Organization
j.glauber@lmu.de

Abstract

Learning from failure across products Johanna Glauber Ludwig-Maximilians-University (LMU) Munich, Institute for Strategy Technology and Organization Year of enrolment: 2014 - Expected final date: December 2018 j.glauber@lmu.de State-of-the-art. Product failures are costly for firms and degrade their reputation and competitive position (Rhee & Haunschild 2006). Hence, learning from past failures to avoid them is important for firm performance. In recent years, scholars have increasingly been interested in understanding how organizations learn from failure experiences (e.g., Baum & Dahlin 2007, Haunschild & Sullivan 2002, Kim & Miner 2007). This literature has significantly contributed to our understanding how organizations learn from failures of a single product. Yet, most organizations are multiproduct firms and learning across products in a multiproduct setting is not well understood. While the product and management literature broadly agrees that product variety increases the likelihood of failure (Fisher & Ittner 1999, Shah et al. 2016), the organizational learning literature indicates potential learning benefits from producing multiple products that help to avoid failure (Desai 2015, Haunschild & Sullivan 2002). Research gap. Although most organizations are multiproduct firms, learning across products in a multiproduct setting is not well understood. Some recent studies started investigating the effect of product heterogeneity on learning-by-doing and productivity gains (Egelman et al. 2016, Levitt et al. 2013, Schilling et al. 2003, Wiersma 2007) but we know surprisingly little about how product variety affects organizations' learning from failure. Firms are found to learn more from failures with heterogeneous causes and dispersed origins (Desai 2015, Haunschild & Sullivan 2002) and product variety influences manufacturing firms' improvements of product reliability after recalls (Kalaignanam et al. 2013). Notably, none of the above studies investigates how firms' learning curves are influenced by the production of a variety of products across multiple plants. To our knowledge, we are the first to shed light on how the heterogeneity of products and their location of production affects organizational learning curves from product failures. Theoretical arguments. Learning from failure in a multiproduct setting is more effective the better the knowledge is transferred across products. First, knowledge transfer is more successful, the higher the technological similarity of products. The reasons are that for products that are more similar, failure experience is likely to be technologically easier to transfer. In addition, attention to avoid a certain failure in the future is likely to focus on similar products for which a similar failure is more likely. Second, knowledge transfer is more successful for products produced at the same production plant. Employees of a plant experiencing product failures gain experience in recognizing, repairing and avoiding failure and can transfer failure experience for one product to another product produced at the same plant. Our theoretical arguments that learning from failure is predominantly influenced by attention, the technological ease of knowledge transfer and experience is in line with previous findings on learning from failure (e.g., Baum & Dahlin 2007, Desai 2015, Haunschild & Sullivan 2002, Sitkin 1992). Method. We test our hypothesis using data from the automotive industry. We obtained data on manufacturers' product recalls from the NHTSA and have information about the location of production of each car model and vehicle specifications from WardsAuto from 2002 to 2015. In our empirical analysis, we use a learning model allowing cross-product and –plant knowledge transfer (Epple et al. 1991, 1996). Results. Our results largely support our predictions and reveal some interesting conditions for firms' learning from failure across products and different locations of production.

Jelcodes:Z00,M00

Learning from failure across products

Johanna Glauber
Ludwig-Maximilians-University (LMU) Munich, Institute for Strategy Technology and Organization
j.glauber@lmu.de

December 2016

Abstract

Ensuring product quality is central to firms' competitive advantage. Thus, it is important for organizations to learn from past product failures to improve product quality. Although the vast majority of firms produces multiple products on different plants, we know very little about firms' learning across products. This study extends what we know about how organizational learning from failure by investigating how firms' product portfolio and production structure influence organizations' learning and knowledge transfer across products.

We empirically investigate this question by examining how car manufacturers learn from product recalls across car models. Opposed to the operations management literature, we find that product and plant variety do not only decrease quality but allow for learning benefits from knowledge transfer across products that compensate for the quality decrease. Additionally, we identify conditions for stronger knowledge transfer across products.

Introduction

Organizations learn from experience and in case of failures try to understand what went wrong to avoid the failure next time. Scholars have been increasingly interested in understanding how organizations learn from unusual performance outcomes such as success or failure (Baum & Dahlin, 2007; Haunschild & Sullivan, 2002; Kim, Kim, & Miner, 2009; Sitkin, 1992). This literature has significantly contributed to our understanding about learning on the aggregated organizational level (Haunschild & Rhee, 2004; Haunschild & Sullivan, 2002; Lapré & Tsikriktsis, 2006) and how organizations learn to improve quality within one service or product based on prior failure experience (Baum & Dahlin, 2007; Desai, 2015).

Yet, many organizations are multiproduct firms that additionally produce in different locations. Learning from failures can occur within products as well as across products. Although most organizations are multiproduct firms, learning across products in a multiproduct and -plant setting is not well understood. Egelman, Epple, Argote, and Fuchs (2016) started to shed light on firms' learning in multiproduct settings by investigating efficiency improvements in a single plant that produces several products.

We are interested in understanding how firms with varying product heterogeneity and distribution of products across plants learn from unanticipated quality failures. We examine how product and plant heterogeneity influence learning within and across products and thus product quality.

This is interesting to investigate as product and plant variety have two countervailing effects on product quality. On the one hand, the operations management literature stresses that product variety and multiple production plants increase the complexity of a firm's production. This complexity increases the likelihood of failure (Fisher & Ittner, 1999; Shah, Ball, & Netessine, 2016).On the other hand, heterogeneity allows for heterogeneous experience and knowledge transfer across products. In line, the organizational learning finds benefits to learning from heterogeneity in products and experience (Egelman et al., 2016; Schilling, Vidal, Ployhart, & Marangoni, 2003). We investigate how learning across products can compensate for the increased risk of failure associated with high product and plant variety. From what we know about product variety and organizational learning so far, it is ambiguous when learning from failure occurs across products and what determines the strength of knowledge transfer.

We shed light on this question by investigating firms' learning from product recalls in the automotive industry. We obtained data on car manufacturers' product recalls in the US from the NHTSA and examine product recalls for car models produced between 2002 and 2015. For these models, we have information about the location of production and vehicle specifications from Ward's Automotive.

Specifically, we examine how firms' learning from product recalls is influenced by the technological variety of their products, their variety of plants and the distribution of products across plants. To reduce technical complexity, car manufacturers typically try to use shared components for several car models and build product "families", which share the same technological "platform". We use information on firms' platform to measure the technological variety of a firm's products.

Our finding s suggest that firms are able to improve their current products' quality due to learning from past recalls of other products. Thus, learning from failure occurs across products. We find that learning across products even appears to be more important for firms' learning from recalls than learning from recalls within a certain product. Learning from failure across products is stronger for firms with high platform variety and a larger degree of platform and plant sharing. Platform and plant sharing describe the extent to which products are co-produced on the same technological platform and plant. Learning benefits from platform variety and plant sharing are sufficiently large to compensate for an increased likelihood of failure that arises from a complex product and production structure.

The study's results contribute to the literature on organizational learning and in particular, the emergent literature interested in organizations' learning from failure. Prior studies showed that organizations learn from failures and that past failure experience can improve the current product quality. These studies observed that organizations differ in their rate of learning.

Our findings add how organizations' product portfolio and production structure explain different learning rates as they affect organizations' potential to learn across products. Earlier work only investigated organizations' aggregated learning curve (Haunschild & Rhee, 2004; Haunschild & Sullivan, 2002) or learning within one single service or product (Baum & Dahlin, 2007; Desai, 2015). We shed light on when firms learn from failure across products and thus contribute to a theoretical understanding of multiproduct firms' learning. Moreover, our findings contribute to the production and operations management literature. This literature argues that product and plant variety decrease firms' product quality due to increased complexity. Our results indicate that learning benefits from knowledge transfer across products can compensate for the decreased quality.

Theory

Research setting and product recalls

Product recalls indicate a major quality issue of firms' products and typically are extremely expensive for firms. For instance, in the automotive industry each recall is on average associated with a potential economic consequence of $20 million or more.[1] Recalls can result in lower market share, lower stock prices and can lower sales for a firm's whole product portfolio (Liu & Shankar, 2015; Rhee & Haunschild, 2006; Yubo Chen, Shankar Ganesan, & Liu, 2009).

Hence, firms should strive to avoid recalls. Yet, the recall literature predominantly focused on studying potential consequences of recalls and paid little attention to drivers of recalls (Shah et al., 2016). Three exceptions are Haunschild and Rhee (2004), Thirumalai and Sinha (2011) and (Shah et al., 2016).

The automotive industry is an interesting context for shedding light on the drivers of recalls and specifically for investigating learning from recalls across products. First, quality is important for cars. It is crucial for saving lives. Additionally, cars are luxury products and a reputation for good quality is important for many manufacturers. Still, the automotive industry faces regular recalls that can create major public attention.[2]

Second, the automotive industry is characterized by large firms selling multiple car models that are produced on plants distributed all over the world. Firms vary in the number of models they produce, the technological similarity of models, their number and size of plants and the distribution of models across plants. This variety is interesting, as it is likely to influence firms'

[1] Jarrell and Peltzman (1985) calculate that on average the per car recall cost are $200 if repair, replacement, and lost sales are included. The average of cars involved in each auto recall from 1980 to 2013 is 100,000, resulting in $200 per recall (Shah et al., 2016).

[2] A famous case are the Toyota recalls in 2009 and 2010. Toyota had to recall several vehicles experiencing unintended acceleration, which caused serious accidents and loss of life. This case globally created public attention.

ability to transfer knowledge across products and plants and thus firms' ability to learn from prior product recalls across products. Learning across products produced at different plants may allow firms to (partly) compensate for an increased failure likelihood due to complexity. We are interested in understanding this compensation effect and the effect of firms' decisions on product and plant variety on their ability to learn from failures across products.

Organizational learning from failure

Organizational learning curves have been observed in many setting. They describe how organizational performance improves with experience (Lapré & Nembhard, 2011). Traditionally, researchers focused on efficiency improvements arising from learning-by-doing and investigated how manufacturing time or unit costs decrease with the cumulative number of units produced (Argote, McEvily, & Reagans, 2003; Wright, 1936). More recently, scholars started to investigate how organizations learn from prior experience beyond learning from the conventional operating experience (Kim et al., 2009; Lapré & Nembhard, 2011). A growing literature is interested in how organizations learn from unusual performance outcomes such as failure experiences (Baum & Dahlin, 2007; Haunschild & Sullivan, 2002; Sitkin, 1992). These studies suggest that firms can learn from past failures, yet indicate that organizations' learning rates vary considerably (Baum & Dahlin, 2007; Haunschild & Sullivan, 2002; Lapré & Tsikriktsis, 2006).

Specialist airline companies, for instance, are found to learn better from failures with heterogeneous causes than failures with homogeneous causes while generalist airlines do not benefit from heterogeneity (Haunschild & Sullivan, 2002). Desai (2015) observed that hospitals experiencing failures with concentrated sources learn slower than hospitals experiencing failures with distributed sources. Both studies argue that the difference in learning occur because firms pay more attention and invest more effort in understanding failures with heterogeneous causes and failures with distributed sources.

Organizations' learning rates further depend on the organizations' relative performance compared to their aspiration levels (Baum & Dahlin, 2007) and their level of other relevant, prior experience (Kim et al., 2009).

Two prior studies find that organizations can learn from product recalls, which are rather unanticipated quality failures of firms' products. Haunschild and Rhee (2004) found that firms learn more from voluntary than from mandated recalls for reducing future involuntary recalls. A firm's recalls in the prior year have been found to have a positive influence on product reliability in the following year (Kalaignanam, Kushwaha, & Eilert, 2013). This indicates that firms learn to improve their products' quality after experiencing recalls.

Product and plant variety and learning across products

While we know that firms can learn from failures such as product recalls, the effect of product and plant variety on learning from failure is not well understood. The operations management literature investigated the direct effect of variety on internal quality performance and recalls (Fisher & Ittner, 1999; Shah et al., 2016).These studies argue that the number of products and the number of variants per product produced on a plant increase the likelihood of mistakes and quality issues. Greater variety increases the number of changeovers on an assembly line and require task switches for workers. Changeovers and switches can create confusion and increase the cognitive load for workers due to multitasking (Adler, Goldoftas, & Levine, 1999; KC, 2014). Both can contribute to mistakes. Additionally, variety increases the operational and managerial complexity of a firm's production and therefore can make products more prone to mistakes (Shah et al., 2016). Several studies investigated the effect of variety on firms' internal quality performance, yet the effect of variety on firms' external quality performance such as recalls only very recently caught scholars' attention.Shah et al. (2016) find that the number of variants per product produced at a plant indeed increase the likelihood of recalls. Interestingly, the number of models produced at a plant only increase the likelihood of recalls in case of high plant utilization. A potential explanation for this finding is that learning benefits due to knowledge transfer across models occur in case of model variety on a plant. Yet, learning benefits from knowledge transfer across products have not been taken into account by operations management researchers so far. The organizational learning literature gives some insights into how variety in tasks affects learning and investigated how knowledge transfer across organizations and shifts. In a lab experiment, Schilling et al. (2003) observed that related task variation can increase the rate of learning suggesting that learning in one task can be transferred to another task. In line, Bernard, Redding, and Schott (2010) overserved that product switching can lead to a more efficient allocation and use of resources and the learning rate of the Royal Dutch Mail benefited from heterogeneity in related products (Wiersma, 2007).

Moreover, studies investigated how knowledge transfer across organizations and shifts influence learning. Knowledge gained in learning-by-doing processes can transfer to other organizations. Organizations beginning production later are observed to be more productive than those with early start dates (Argote, Beckman, & Epple, 1990). Additionally, firms learn from other firms' failures. Baum and Dahlin (2007) present empirical evidence that when a railroad's accident rate deviates from aspiration levels, the railroad learns more from the accident experience of other firms than from its own experience. Kim et al. (2009) observed that banks learn more from failure experience of geographically close and more similar firms.

Within single organizations, several studies investigated knowledge transfer across a plant's shifts. They suggest that organizations can transfer a substantial part of the operating experience accumulated in one shift to another shift (Epple, Argote, & Devadas, 1991; Epple, Argote, & Murphy, 1996; Levitt, List, & Syverson, 2013).

Knowledge on defect avoidance gained in one shift can be completely transferred to a second shift (Levitt et al., 2013). Levitt et al. (2013) indirectly observed hints of potential knowledge transfer across product. If new models are ramped up in the plant, defect rates for the new model are initially higher suggesting that a new learning process starts. Yet, later models never reach the defect rates of the first model in the beginning of production pointing to knowledge spillovers across models. In line, Gopal, Goyal, Netessine, and Reindorp (2013) present empirical evidence that plants with experience in product launches and in manufacturing similar products show a smaller productivity loss in case of a new product launch. This suggest that the plant was able to transfer knowledge about other products to the manufacturing of the current product.

Although, these studies provide indications that knowledge transfer across products can occur there is, to our knowledge, only one study directly investigating learning benefits and the strength of knowledge transfer across products in a multiproduct production setting. Egelman et al. (2016) investigated productivity and leaning-by-doing of a single plant that produces several generations of a focal product and some other products. Productivity improved when several generations were produced simultaneously due to knowledge transfer from older to newer product generations. Yet, no transfer occurred between the focal product and other minor products. Egelman et al. (2016) studied one plant of a single firm. Automobile manufacturers and firms in other industries operate several plants and sell more than one focal product.

Hence, we are interested in how the specifications of firms' product portfolio and the distribution of their products across production plants influence learning and knowledge transfer across products. In contrast to Egelman et al. (2016) who investigate productivity and transfer of operation experience, we are interested whether firms can learn from quality failures across products. More specifically, we are interested in learning from product recalls, which represent external failure costs for firms. In contrast to production costs or internal failure costs, substantial time can pass by between the production and recall of a product.

We examine how firms' learning from product recalls is influenced by the technological variety of their products, their variety of plants and the distribution of products across plants. To reduce technical complexity car manufacturers typically try to use shared components for several car models and build product "families", which share the same technological platform.

To grasp the importance of technological variety for failure learning across products, we investigate how the variety of platforms on firm- and product-level and the number of products that share the same platform influence learning across products. To understand the effect of products' location of production on failure learning across products, we examine how the variety of production locations and the number of products produced at the same location influence learning from recalls across products.

Method

Data and Sample

We study learning from product recalls across products in the automotive industry. In the US, the National Traffic and Motor Vehicle Safety Act specifies safety standards that any vehicle or equipment sold in the US must adhere to. These safety standards set minimum performance levels for all vehicle parts that affect drivers' safety. If vehicles are considered noncompliant with the standards, the National Highway and Traffic Safety Administration (NHTSA) enforces a recall of the vehicle by the respective automaker (http://www-odi.nhtsa.dot.gov/recalls/recallprocess.cfm). In addition, automakers may voluntarily recall a vehicle if they discover safety defects in their own tests and inspection procedures.

The NHTSA tracks data on all motor vehicle and equipment recalls in the US since 1966. We collected this data in August 2016 from the NHTSA's website. For any recall, the data reports the vehicle make, the model name, model-year, recall date and type, the approximate number of cars affected, the recall originator (firm or NHTSA) and a defect description.

To obtain information on models' location of production, their technological platform and further vehicle specifications, we use data from Ward's Automotive (www.wardsauto.com). We have information on all car models produced globally between January 2002 and December 2015. We focus our investigation on large, established car manufacturers that have at least one plant in Northern America, Western Europe or Japan and produce more than 1000 units in at least one month between January 2002 and December 2015. We do not include manufacturers that only produce electrical cars in the sample.

We merge the two datasets by taking into account firms' ownership structures as well as different names and spellings for manufacturers, makes and models. We exclude car models that were launched before 2002. For these models learning processes started before our period of observation which can distort our results. The final dataset includes all recalls for 309 models produced in the model years 2002 to 2015. These models are produced by 15 manufacturers and are sold under 42 makes.

Our unit of analysis is a model-model-year. Our dataset includes all model years of a model in which the car was produced, irrespectively if the model experienced a recall in the specific year. Thus, our final sample includes 2,350 observations. Changes during a model year are not common and difficult to implement in the automotive industry. It thus seems suitable to measure firm learning on a yearly basis.

To take into account the recall history of manufacturers before 2002, we additionally add information on recall since 1998 for the manufacturers in our sample. This is 15 years before our period of observation starts. Prior findings on firm learning suggest that knowledge depreciates over time and suggest that a window of 15 years is enough to capture all relevant effects of the recall history (Epple et al., 1996).

Car models are often produced in different generations. While smaller makeovers and changes can be implemented for any model-year, a new generation of a model often represents an almost completely new product. An insider from BMW explained to us that due to cost pressures and technological advancements, automanufacturers are typically forced to do major changeover for any new generation. Typically, new generations are introduced any 5 to 7 years. It is likely that major changeovers may affect firm learning. Therefore, we collected information on the generations of all models in our sample. We manually collected this information by browsing information on car models published by manufacturers, auto magazines and blogs.

Variables

Dependent Variable

Our dependent variable is the total number of recalls of a car model in a given model year. The variable includes all recalls filed for the respective model in the US before August 2016.

Independent Variables

Cumulative recalls of the focal model. We measure the recall experience for the focal model in the respective model-year by the cumulative number of recalls for the model that occurred before the production of the respective model-year. We only consider recalls for the same generation of the model, as the difference between model generations can be considerable and even larger than between two different model of the same manufacturer.

Cumulative recalls of the other model. The cumulative experience that a manufacturer gained form recalling other models than the focal model is measured by the number of recalls of a manufacturer's models excluding the focal model that occurred before the production of the focal model model-year. To capture all relevant effects of the recall history of a manufacturer even before our period of investigation, we take into account recalls since 1998.

Variables describing firms' product and production structure

Platform variety. A measure for the technological variety of a car manufacturer's product portfolio is the number of platforms that the manufacturer's products are based on. All large car manufacturers nowadays pursue a platform strategy. A platform can be described as "a relatively large set of a product components that are physically connected as a stable sub-assembly and are common to different final models" (Muffatto, 1999, p. 145). A manufacturer that uses a higher number of platforms for a given set of models has a higher technological variety than a manufacturer using less platforms for the same number of models. We use the number of platforms of a manufacturer to describe a manufacturer's platform variety.

Model variety. To grasp the technological variety on product level, we take the number of different platforms used for a car model as a proxy. For some models, car manufacturers offer different variants on the market. Sometimes these variants differ only in minor characteristics such as a roof-light and are built on the same platform. Yet, for some models, variants are more distinct and are built on different platforms. We use the number of different platforms used for a car model as a proxy for model variety.

Platform sharing. A number of different models can be built on the same platform. These models are technologically more similar than models on a different platform, which may ease the transfer of recall experience. For each platform of the focal model, we estimate the number of other models using the same platform. We then use the average of this numbers across all platforms of the focal model as proxy for a model's degree of platform sharing.

Plant variety. The number of plants producing the focal model describes the variety in location of production for the respective model. We use the number of plants producing the focal model in the respective model year as measure for plant variety.

Plant sharing. Knowledge transfer may be easier for models produced on the same plant. To estimate the extent of a model's plant sharing we compute the number of other models produced at each plant of the focal model. We then use the average of this numbers across all plants of a model as estimate for the extent of a model's plant sharing.

Plant distance. The number of countries covered by a model's plants describe the geographical distribution of a model's locations of production. We use the number of covered countries as proxy for plant distance.

Control Variables

Years Since Launch. In the first years after the launch, products are likely to experience more recalls. To control for this, we collected information on the first model year of each model and include the number of years between the launch year and the current year in our analysis.

Number of previous generations. Although firms typically implement major changes for any new generation, firms may still have gathered more knowledge about models that are produced since several generations. This may affect the quality of the current model. Therefore, we control for the number of previous generations of the current model version.

Recalls of previous generation. We control for the quality of the previous generation of a model by using the number of recalls of the proceeding product generation as proxy.

Number of models. To avoid that any effects of the platform or plant variables are pure effects of a manufacturer's number of products, we control for a manufacturer's total number of car models in our analysis.

Production experience. The number of units produced of a product was found to affect its quality (Levitt et al., 2013) and is likely to influence the recall likelihood. Hence, we include the number of units produced of the respective model in the analysis to control for a firms model specific production experience.

Year. To take into account any heterogeneity that may occur over time, we use indicator variables for each model year in our regressions.

Manufacturer and Model. Depending on whether we are interested in within-model or between-model effects, we include model- or manufacturer-fixed effects in form of indicator variables in our analysis. This allow us to control for the general quality of the focal model or the general quality of a manufacturer's models.

Method of Analysis

The literature conventionally assumes a power law specification for the relationship between productivity and production experience (Egelman et al., 2016; Epple et al., 1991; Levitt et al., 2013). Accordingly, learning curves are conventionally written as:

$$\frac{l}{q} = CQ^{-\gamma} \qquad (1)$$

Where l/q refers to the hours l worked for output q at each date. Q is the cumulative output and C and γ are constants. The larger γ, the faster an organization learns. The rate of learning is typically expressed in terms of the progress ratio related to γ, which is: $p = 2^{-\gamma}$.

The ratio represents the percentage by which the dependent variable improves with a doubling of cumulative experience. As most prior studies, we use the logged inverse of equation (1) to empirically describe learning:

$$Ln(q_t/l_t) = a + \gamma\ LnQ_{t-1} + \varepsilon_t \qquad (2)$$

In our case, q_t/l_t refers to the number of recalls for a certain car model in the model year t, Q_{t-1} denotes the cumulative number of recalls at the end of the last model year, γ describes the degree of learning, a=Ln(1/C) is a constant and ε_t the year-specific error term.

Our main empirical approach is based on equation (2). We estimate ordinary-least-square regressions and add additional independent variables of interest and control variables to equation (2). In the only study that investigated firms' learning from recalls so far, Haunschild and Rhee (2004) argue that on firm-level a different model than the one above provides the better fit. They use yearly firm recalls as a count, dependent variable and as independent variable only consider recalls that a firm accumulated in a window of three years prior to the focal year. To take into account the count-characteristics of their dependent variable, they estimate negative binomial regressions. We check if the estimation strategy used by Haunschild and Rhee (2004) changes our results.

Results

Table 1 shows the descriptive statistics for our variables. The correlations among the variables are included in Table 2. On average, a model experiences little more than 2 recalls per model year. We investigated the distribution of models' recalls over time. Most recalls occur in the years after a new generation's launch. Over the product lifetime of a generation, the number of recalls per model year decrease.

****
Insert Table 1 here
****

Most manufacturers produce two different models on the same technological platform. It is rare, that a model's variants are based on different platforms. The number of plants producing the same model varies between one and 16. On average, 2 models are co-produced at the same plant.

****
Insert Table 2 here
****

The number of years since a model's launch are highly correlated with the cumulative recalls of the model. In addition, the number of models and the number of platforms of a manufacturer show a high positive correlation. Both correlations are well explainable and unavoidable. The longer a model is on the market the more recalls it can experience and the more different products a manufacturer produces the more base technologies are likely to be necessary to realize the models. We checked if multicollinearity drives our results by including each of the variables alone and together in our regressions. Our results qualitatively do not change. We include all variables in our final regressions as they represent important control variables for establishing reasonable ceteris paribus conditions.

Table 3 presents our basic learning model and compares different specifications for the model. Model M1 shows our basic model that uses the most conventional specification for learning curves and predicts the logarithmic cumulative recalls on the logarithmic number of recalls.

Cumulative recalls of other models significantly reduce recalls of the current model, which suggests that firms learn from recalls across products. The learning rate is -1.18 and highly significant. Given the form of the model, a learning rate of $\beta = -1.18$ indicates that the number of recalls for a model in the focal model year is more than halved if the recall experience for other models doubles.[3] Many learning studies use the progress ratio to express the speed of learning, which is the percentage effect on the dependent variable resulting from a doubling of the cumulative experience. Using the progress ratio, a $\beta = -1.18$ implies that a doubling of cumulative experience reduces recalls of the focal model by about 56%.[4]

The cumulative number of recalls for the focal model itself has no significant effect on the current recalls of the focal model. This implies that no observable learning occurs from these recalls. We later discuss potential explanations for this result.

[3] The multiple to the cumulative experience k that decreases a model's recalls to one-half of any initial level is $k = 2^{(\frac{1}{-\beta})}$. When $\beta = -1.18$ then $k = 2^{(\frac{1}{1.18})} \approx 1.8$

[4] $2^{-1.256} \approx 0.44$. Hence, when recall experience doubles, recalls of the focal model fall by 56%.

****
Insert Table 3 here
****

In Model M2, we use manufacturer fixed-effects instead of model fixed-effects. While the effect of the recalls of other models stays almost the same, the effect of a model's own recalls increases and is significant. Many recalls of a model in the past make future recalls more likely. As this positive effect does not occur within models (cf. Model M1), but between models, it is likely to arise from general quality differences between models. A low quality model is likely to experience more recalls in the past and in the current year than a high quality model. This probably drives the large positive effect. In the following analysis, we are interested in investigating for which models manufacturers are more successful in learning across products. Hence, we are interested in between model effects rather than in changes within a single model over time that affect learning across products. Therefore, we use manufacturer and not model fixed-effects in the following regressions.

As described earlier, Haunschild and Rhee (2004) use a different model specification than the broader literature when they study learning from recalls. In Model M3 and M4 we follow their approach, use the count of recalls of a model in a model year as dependent variable and estimate negative binomial regression models. In Model M3 we use the same independent variables as in the previous models while we restrict our cumulative recalls to a three year window in Model M4. The findings in Model M3 are qualitatively the same as the previous results. A 100% increase that is a doubling of the cumulative recalls of other models, decreases recalls for the focal model in the current year by about 1.7. When we only take into account recalls that occurred in the last three year, the direction of the relationships remains the same, but the effect sizes get smaller.

We then are interested in how firms' product and production structure influence learning across products. In Table 4 we interact the recalls of other models with several variables related to the technological variety of a firms' products and products' location of production.

****
Insert Table 4 here
****

In Model M1, we are interested in the effect of the number of platforms, i.e. the overall technological variety of a firm. The main effect of platform variety is positive and significant in Model M1 and indicates that platform variety in general increases recalls for a firm's products. Yet, the significant negative interaction term suggests that in case of sufficient failure experience, firms are able to compensate the increased failure likelihood by transferring knowledge across models and platforms. For compensation, roughly 500 recalls in other models are needed, which is below the mean of firms' cumulative recall experience.[5]

The model variety, plant variety and the geographical dispersion of production do not significantly influence firms' learning from recalls across products. However, both platform and plant sharing strengthen knowledge transfer across products as indicated by Models M3 and M5. For both variables, the main effects are significant and positive. The higher the number of products using the same technological platform as the focal model and the higher the number of products produced at the same plants, the higher the likelihood of recalls. Yet, platform and plant sharing ease learning from failures across products, which can (partly) compensate for the increased failure likelihood. The benefits for learning from platform sharing is rather small compared to its negative effect on failure. More than 1800 recalls of other models are needed to see no effect of platform sharing on the recall likelihood of the focal model. However, benefits

[5] The compensating number of recalls R is $R = e^{\left(\frac{0.169}{0.027}\right)} \approx 522.$

from plant sharing are rather large and learning already allows to reduce the failure likelihood of the focal model in case of about 81 recall experiences for other models.

Discussion and Conclusion

This study examined how firms' product and production decisions influence their learning rate from failure by affecting knowledge transfer across products. This can be an explanation for the varying ability of firms to learn from past experience. Our findings indicate how firms' product and plant variety as well as the distribution of products across plants influence firms' learning across products and thereby their product quality.

We find that firms are able to improve their current products' quality due to learning from past recalls of other products. Thus, learning from failure and recalls occurs across products. Learning across products even seems to be more important for firms' learning from recalls than learning from recalls within a certain product. We do not find significant evidence that recalls for a product can help firms to avoid future recalls for the same product. Learning from failure across products is stronger for firms with high platform variety and a larger degree of platform and plant sharing. Platform variety as well as the degree of platform and plant sharing increase the complexity of a firm's product portfolio and production. This as such decreases the quality of products and increases the likelihood of recalls. Yet, especially for platform variety and plant sharing learning benefits are sufficiently large to overcompensate the increased likelihood of failure.

We did not expect that learning from recalls does not occur within a single product. Yet, a possible explanation for this may be that we do not distinguish between different types of recalls. Recalls can occur for different reasons. They can either be a design or a manufacturing mistake. Additionally, they refer to errors in specific, different components or the whole product architecture. Learning may especially be possible within a certain type of recall that is a design mistake for the engine helps to avoid future recalls due to similar reasons. If the initial recalls of a product have very different reasons than current recalls, this can explain why firms do not significantly learn from recalls within a product.

The effects of firms' platform and plant decisions on knowledge transfer across products allow some conclusions about what theoretically drives learning in a multiproduct setting.

Many different technological platforms, that is many technological basis for a firm's products, ease failure learning across products. This is interesting, as many different technological basis make products less similar to each other. Prior research found that similarity of products can be a driver for knowledge transfer across products (Egelman et al., 2016). In line with Egelman et al. (2016), we observe that platform sharing, i.e. co-producing models on the same platform eases failure learning across products.

In combination, these two findings suggests that learning from failure is actually stronger across similar products that use the same platform. However, firms with a technologically diverse portfolio seem to be better in transferring knowledge across products irrespectively of their similarity. This may be the case because these firms learn to cope with a diverse structure, are more aware of the necessity to transfer knowledge across products and get better in transferring. An alternative explanation is that diverse technological solutions increase the diversity of failure experience. This diversity of past recalls for other products may allow firms to avoid more mistakes in current models, as the firm experienced more possible mistakes earlier and developed strategies to avoid them.

These findings provide an additional explanation why Haunschild and Rhee (2004) observed that generalist firms experience more mistakes, but learn faster from mistakes. Haunschild and Rhee (2004) argue that they observe this pattern because generalists experience more serious recalls in terms of press coverage and recalled units, which makes them learn faster from these mistakes. Our findings suggest that generalist firms, which are likely to have a larger platform variety, face more recalls due to the increased complexity, but learn faster due to stronger knowledge transfer across products.

We additionally find that knowledge transfer across products increases with the extent to which products share plants. The learning benefits from plant sharing are so strong that they typically compensate for the increased likelihood of failure due to the complexities arising from co-producing products on the same plant. This finding explains why Shah et al. (2016), as we in our study, observed that co-producing models on a plant decreases the number of recalls as a net effect. The finding also suggest that the location of production matters for the quality of a product and not all knowledge is completely embodied and codified in the technology used within the whole organization. Within a single plant, Levitt et al. (2013) observed that most of the knowledge is embodied in a plant's technology rather than in its employees. Our findings suggest that not all knowledge available at a plant is embodied in the technology of the broader organization. A certain part of the acquired knowledge is plant specific.

Our findings primarily contribute to the literature on organizational learning and especially to organizations' learning from failure. They additionally add to knowledge from the production and operations management literature.

Prior research found that organizations learn from product failures and that past failure experiences lead to improvement of the current quality. Organizations differ in their rate of learning.

We add to this by investigating how organizations' product portfolio and production structure explain different learning rates as they affect organizations' potential to learn across products.

Prior studies focused on how organizations learn to improve quality within one single service or product (Baum & Dahlin, 2007; Desai, 2015) or investigated organizations' aggregated learning curve for all products (Haunschild & Rhee, 2004; Haunschild & Sullivan, 2002; Lapré & Tsikriktsis, 2006).

Our findings shed light on how firms learn from failure across products and thus contribute to our understanding about how multiproduct firms with several production plants learn. Our study adds insights into how product and production heterogeneity influence learning curves by identifying driving conditions for knowledge transfer across products.

In addition, our findings contribute to the production and operations management literature, which argues that product and plant variety decrease firms' product quality due to increased complexity. The results of this study indicate that learning benefits from knowledge transfer across products can compensate for the decreased quality. Future studies should take into account these learning benefits in evaluating the effect of variety in production on firms' quality performance.

As with all work, this study faces some limitations. Yet, these limitations open opportunities for future research. We study the automotive industry, which is an established industry with few large firm. This may limit our results to the extent that they hold for industries with similar characteristics. They may be limited to complex technological products that are produced globally on different plants. We only observe vehicle recalls in the US. Our findings may therefore be influenced by the particular regulations in the US and the experience of firms on the US market. Future studies should investigate learning from recalls in a different industry and country. In addition, we cannot distinguish different types of recalls, such as recalls due to design vs. manufacturing mistakes or component vs. architectural mistakes. This limits our interpretation of results. Future studies should test the influence of a recall's type on learning.

In our study, we set out to shed light on when multiproduct firms with several production plants learn from failure across products. Our findings indicate that learning across products is highly important for these firms and is a stronger predictor of product quality than learning within one single product. Given the importance of learning across products, we consider it interesting to further examine this phenomenon. How do firms actually learn across products, that is which management practices drive learning across products? What are additional facilitating or inhibiting conditions for learning across products? We hope that this study inspires more research investigating these and similar questions.

References

Adler, P. S., Goldoftas, B., & Levine, D. I. (1999). Flexibility versus efficiency? A case study of model changeovers in the toyota production system. Organization Science, 10(1), 43-68. doi:10.1287/orsc.10.1.43

Argote, L., Beckman, S. L., & Epple, D. (1990). The persistence and transfer of learning in industrial settings. Management science, 36(2), 140-154.

Argote, L., McEvily, B., & Reagans, R. (2003). Introduction to the special issue on managing knowledge in organizations: Creating, retaining, and transferring knowledge. Management science, 49(4), v-viii.

Baum, J. A. C., & Dahlin, K. B. (2007). Aspiration performance and railroads' patterns of learning from train wrecks and crashes. Organization Science, 18(3), 368-385. doi:10.1287/orsc.1060.0239

Bernard, A. B., Redding, S. J., & Schott, P. K. (2010). Multiple-product firms and product switching. The American Economic Review, 100(1), 70-97.

Desai, V. (2015). Learning through the distribution of failures within an organization: Evidence from heart bypass surgery performance. Academy of Management Journal, 58(4), 1032-1050. doi:10.5465/amj.2013.0949

Egelman, C. D., Epple, D., Argote, L., & Fuchs, E. R. (2016). Learning by doing in multiproduct manufacturing: Variety, customizations, and overlapping product generations. Management science, 1-19.

Epple, D., Argote, L., & Devadas, R. (1991). Organizational learning curves: A method for investigating intra-plant transfer of knowledge acquired through learning by doing. Organization Science, 2(1), 58-70.

Epple, D., Argote, L., & Murphy, K. (1996). An empirical investigation of the microstructure of knowledge acquisition and transfer through learning by doing. Operations Research, 44(1), 77-86.

Fisher, M. L., & Ittner, C. D. (1999). The impact of product variety on automobile assembly operations: Empirical evidence and simulation analysis. Management science, 45(6), 771-786.

Gopal, A., Goyal, M., Netessine, S., & Reindorp, M. (2013). The impact of new product introduction on plant productivity in the north american automotive industry. Management science, 59(10), 2217-2236. doi:10.1287/mnsc.2013.1709

Haunschild, P. R., & Rhee, M. (2004). The role of volition in organizational learning: The case of automotive product recalls. Management science, 50(11), 1545-1560. doi:10.1287/mnsc.1040.0219

Haunschild, P. R., & Sullivan, B. N. (2002). Learning from complexity: Effects of prior accidents and incidents on airlines' learning. Administrative Science Quarterly, 47(4), 609-643. doi:10.2307/3094911

Jarrell, G., & Peltzman, S. (1985). The impact of product recalls on the wealth of sellers. Journal of Political Economy, 93(3), 512-536.

Kalaignanam, K., Kushwaha, T., & Eilert, M. (2013). The impact of product recalls on future product reliability and future accidents: Evidence from the automobile industry. Journal of Marketing, 77(2), 41-57. doi:10.1509/jm.11.0356

KC, D. S. (2014). Does multitasking improve performance? Evidence from the emergency department. Manufacturing & Service Operations Management, 16(2), 168-183. doi:10.1287/msom.2013.0464

Kim, J.-Y., Kim, J.-Y., & Miner, A. S. (2009). Organizational learning from extreme performance experience: The impact of success and recovery experience. Organization Science, 20(6), 958-978.

Lapré, M. A., & Nembhard, I. M. (2011). Inside the organizational learning curve: Understanding the organizational learning process (Vol. 10). MA, Hanover: Now Publishers Inc.

Lapré, M. A., & Tsikriktsis, N. (2006). Organizational learning curves for customer dissatisfaction: Heterogeneity across airlines. Management science, 52(3), 352-366.

Levitt, S. D., List, J. A., & Syverson, C. (2013). Toward an understanding of learning by doing: Evidence from an automobile assembly plant. Journal of Political Economy, 121(4), 643-681.

Liu, Y., & Shankar, V. (2015). The dynamic impact of product-harm crises on brand preference and advertising effectiveness: An empirical analysis of the automobile industry. Management science, 61(10), 2514-2535. doi:10.1287/mnsc.2014.2095

Muffatto, M. (1999). Introducing a platform strategy in product development. International Journal of Production Economics, 60–61, 145-153. doi:http://dx.doi.org/10.1016/S0925-5273(98)00173-X

Rhee, M., & Haunschild, P. R. (2006). The liability of good reputation: A study of product recalls in the u.S. Automobile industry. Organization Science, 17(1), 101-117. doi:10.1287/orsc.1050.0175

Schilling, M. A., Vidal, P., Ployhart, R. E., & Marangoni, A. (2003). Learning by doing something else: Variation, relatedness, and the learning curve. Management science, 49(1), 39-56. doi:10.1287/mnsc.49.1.39.12750

Shah, R., Ball, G. P., & Netessine, S. (2016). Plant operations and product recalls in the automotive industry: An empirical investigation. INSEAD Working Paper Series, 2016/01/TOM.

Sitkin, S. B. (1992). Learning through failure: The strategy of small losses. Research in organizational behavior, 14, 231-266.

Thirumalai, S., & Sinha, K. K. (2011). Product recalls in the medical device industry: An empirical exploration of the sources and financial consequences. Management science, 57(2), 376-392. doi:10.1287/mnsc.1100.1267

Wiersma, E. (2007). Conditions that shape the learning curve: Factors that increase the ability and opportunity to learn. Management science, 53(12), 1903-1915.

Wright, T. P. (1936). Factors affecting the cost of airplanes. Journal of the Aeronautical Sciences, 3(4), 122-128. doi:10.2514/8.155

Yubo Chen, Shankar Ganesan, & Liu, Y. (2009). Does a firm's product-recall strategy affect its financial value? An examination of strategic alternatives during product-harm crises. Journal of Marketing, 73(6), 214-226. doi:10.1509/jmkg.73.6.214

Tables

Table 1. Descriptive Statistics

Variables	Mean	SD	Median	Min	Max
Number of recalls	2.414	2.501	2.000	0.000	15.000
Cum. Recalls of other models	591.105	597.638	281.000	35.000	2,115.000
Cum. recalls of the focal model	2.259	3.127	1.000	0.000	23.000
Platform variety	11.424	5.057	12.000	1.000	20.000
Model variety	1.101	0.357	1.000	1.000	4.000
Platform sharing	2.057	1.223	2.000	1.000	6.000
Plant variety	1.707	1.588	1.000	1.000	16.000
Plant sharing	2.219	1.263	2.000	1.000	7.000
Years since launch	2.769	2.243	2.000	0.000	13.000
Nb. of previous generations	1.590	2.099	1.000	0.000	12.000
Nb. of models	21.784	10.267	20.000	1.000	49.000
Production experience	275.981	428.530	127.141	0.000	3,744.255

Notes. N=2350 observations. Abbreviations: max = maximum; min = minimum; SD= standard deviation.

Table 2. Correlation Matrix

Variables	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.
1. Number of recalls												
2. Cum. Recalls of other models	0.065*											
3. Cum. recalls of the focal model	0.071*	0.177*										
4. Platform variety	0.015	0.690*	0.024									
5. Model variety	0.053*	-0.007	0.005	0.106*								
6. Platform sharing	0.065*	-0.247*	0.132*	-0.331*	-0.070*							
7. Plant variety	0.155*	-0.020	0.077*	0.011	0.349*	0.103*						
8. Plant sharing	-0.186*	-0.326*	-0.022	-0.219*	0.001	0.349*	0.009					
9. Years since launch	-0.235*	0.024	0.512*	-0.004	-0.031	0.048*	-0.052*	0.087*				
10. Nb. of previous generations	0.144*	0.006	0.093*	-0.016	0.300*	0.125*	0.477*	-0.029	-0.075*			
11. Recalls previous generation	0.192*	0.105*	0.145*	0.038	0.164*	0.193*	0.331*	-0.060*	-0.066*	0.531*		
12. Nb. of models	0.071*	0.772*	0.110*	0.826*	-0.007	-0.208*	-0.000	-0.238*	-0.016	-0.041*	0.031	
13. Production experience	0.068*	0.039	0.396*	0.034	0.234*	0.085*	0.510*	-0.031	0.378*	0.325*	0.259*	-0.006

Notes. N = 2350 observations. Table displays Pearson correlation coefficients. Significance level: * $p \leq 0.05$

Table 3. Basic Model and comparison of different model specifications

	M1 Ln(recalls+1)	M2 Ln(recalls+1)	M3 Recalls	M4 Recalls
Platform variety	-0.019*	-0.006	-0.009	-0.042**
	(0.009)	(0.009)	(0.013)	(0.015)
Model variety	0.120*	0.078*	0.157**	0.128*
	(0.051)	(0.039)	(0.055)	(0.056)
Platform sharing	0.025	0.053***	0.078***	0.068***
	(0.020)	(0.013)	(0.019)	(0.019)
Plant variety	0.061**	0.022*	0.030*	0.029+
	(0.022)	(0.011)	(0.015)	(0.015)
Plant sharing	-0.091***	-0.067***	-0.111***	-0.105***
	(0.020)	(0.012)	(0.020)	(0.021)
Years since launch	-0.085***	-0.104***	-0.185***	-0.156***
	(0.015)	(0.008)	(0.013)	(0.012)
Nb. of previous generations	-0.020	-0.014+	-0.027*	-0.017
	(0.082)	(0.008)	(0.011)	(0.011)
Recalls of previous generation	-0.023***	0.011***	0.011***	0.008*
	(0.004)	(0.002)	(0.003)	(0.003)
Nb. of models	0.010*	0.008+	0.010+	-0.003
	(0.004)	(0.004)	(0.006)	(0.007)
Production experience	0.000+	0.000*	0.000***	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Ln(Cum. recalls of other models +1)	-1.180***	-1.234***	-1.729***	
	(0.096)	(0.103)	(0.151)	
Ln(Cum. recalls of focal model +1)	0.021	0.207***	0.317***	
	(0.024)	(0.021)	(0.030)	
Cum. recalls of other models (3 year window)				-0.003***
				(0.001)
Cum. recalls of the focal model (3 year window)				0.100***
				(0.010)
Model fixed-effects	Yes			
Year fixed-effects	Yes	Yes	Yes	Yes
Firm fixed-effects		Yes	Yes	Yes
Constant	6.713***	5.225***	9.869***	-1.298***
	(0.516)	(0.445)	(0.777)	(0.082)
Observations	2,350	2,350	2,350	2,350
R-squared	0.580	0.296		

Notes. M1-M2 OLS regressions. M3-M4 negative binomial regressions. Standard errors in parentheses. Significance levels: *** p<0.001, ** p<0.01, * p<0.05, + p<0.1.

Table 5. Effect of technological and plant variety on learning across products

Dependent: Ln(recalls+1)	**M1**	**M2**	**M3**	**M4**	**M5**	**M6**
Platform variety	0.169**	-0.006	-0.005	-0.006	-0.006	-0.007
	(0.056)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Model variety	0.078*	-0.272	0.077*	0.084*	0.084*	0.086*
	(0.039)	(0.279)	(0.039)	(0.040)	(0.039)	(0.040)
Platform sharing	0.055***	0.053***	0.225**	0.053***	0.056***	0.053***
	(0.013)	(0.013)	(0.078)	(0.013)	(0.013)	(0.013)
Plant variety	0.022*	0.021+	0.022*	0.054	0.026*	0.132***
	(0.011)	(0.011)	(0.011)	(0.059)	(0.011)	(0.034)
Plant sharing	-0.069***	-0.068***	-0.066***	-0.066***	0.229*	-0.065***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.090)	(0.012)
Years since launch	-0.103***	-0.104***	-0.103***	-0.104***	-0.102***	-0.102***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Nb. of previous generations	-0.014+	-0.014+	-0.015+	-0.015+	-0.015+	-0.017*
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Recalls previous generation	0.011***	0.011***	0.011***	0.011***	0.010***	0.010***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Nb. of models	0.006	0.008+	0.007	0.008+	0.008+	0.007
	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)
Production experience	0.000*	0.000*	0.000*	0.000**	0.000*	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ln(Cum. recalls of focal model +1)	0.207***	0.209***	0.202***	0.206***	0.198***	0.205***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Ln(Cum. recalls of other models +1)	-0.875***	-1.293***	-1.173***	-1.223***	-1.143***	-1.217***
	(0.154)	(0.113)	(0.107)	(0.105)	(0.106)	(0.105)
Platform variety*Ln(Cum. recalls others)	-0.027**					
	(0.009)					
Model variety*Ln(Cum. recalls others)		0.059				
		(0.047)				
Platform sharing*Ln(Cum. recalls others)			-0.030*			
			(0.014)			
Plant variety*Ln(Cum. recalls others)				-0.006		
				(0.010)		
Plant sharing*Ln(Cum. recalls others)					-0.052***	
					(0.016)	
Plant distance						-0.063
						(0.079)
Plant distance*Ln(Cum. recalls others)						-0.012
						(0.012)
Firm fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	5.288***	7.930***	7.237***	7.495***	7.024***	7.472***
	(0.902)	(0.611)	(0.556)	(0.551)	(0.560)	(0.550)
Observations	2,350	2,350	2,350	2,350	2,350	2,350
R-squared	0.299	0.297	0.298	0.297	0.300	0.300

Notes. Standard errors in parentheses. Significance levels: *** p<0.001, ** p<0.01, * p<0.05, + p<0.1.