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# Learning from Omission Errors

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| Abstract: | Within organizations, the ability to learn from mistakes is central to performance improvement and adaptation. Given that many types of decisions are made repeatedly – to approve a project, to allocate R&D resources, etc. – learning works through a continuous process of making decisions and observing feedback. But different types of errors importantly produce different levels of observable feedback – commission errors generally produce direct feedback, but omission errors often do not. Thus, in order for managers to learn from omissions they must have the ability to know the outcomes of choices not pursued. One key source of such information comes from observing competitors, but attending to competitors may in itself affect learning and adaptation. In a series of experiments, we study whether decision makers learn from feedback provided by observing competitors. We argue and find that decision makers' ability to learn from their decision errors depends on their position relative to the competitor. Specifically, leaders tend to learn from their omission errors because they actually pay attention to competitor decisions, but laggards tend to learn only from commission errors. This has implications for our understanding of learning from failure and organizations' attempts to learn from competitors. |
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**ABSTRACT**

Within organizations, the ability to learn from mistakes is central to performance improvement and adaptation. Given that many types of decisions are made repeatedly – to approve a project, to allocate R&D resources, etc. – learning works through a continuous process of making decisions and observing feedback. But different types of errors importantly produce different levels of observable feedback – commission errors generally produce direct feedback, but omission errors often do not. Thus, in order for managers to learn from omissions they must have the ability to know the outcomes of choices not pursued. One key source of such information comes from observing competitors, but attending to competitors may in itself affect learning and adaptation. In a series of experiments, we study whether decision makers learn from feedback provided by observing competitors. We argue and find that decision makers' ability to learn from their decision errors depends on their position relative to the competitor. Specifically, leaders tend to learn from their omission errors because they actually pay attention to competitor decisions, but laggards tend to learn only from commission errors. This has implications for our understanding of learning from failure and organizations' attempts to learn from competitors.

## INTRODUCTION

Adaptive learning is the core of the behavioral theory of the firm (Cyert and March 1963, March and Olsen 1976). Decision makers choose a solution to a specific problem, and then use performance feedback on that solution to affect the search for future solutions: if the performance feedback is positive, they are expected to choose the successful solution again; if the performance feedback is negative, they are expected to avoid the solution in the future (Glynn et al. 1991). While decision makers have been found to learn from their successful choices, it is much less clear that they learn from their errors (Bennett and Snyder 2017, Kc et al. 2013, Haunschild and Sullivan 2002). Behavioral changes spurred by errors in previous choices can lead to improved performance in some circumstances, but not in others (Eggers and Suh 2019) suggesting that learning from mistakes is not a simple process.

One complication in learning from errors is that judgment errors take two different forms - errors of commission, where the decision maker does something that produces a negative result, and errors of omission, where the decision maker declines to follow an action that would have improved performance (Green and Swets 1966, Sah and Stiglitz 1986). Commission errors lead to specific penalties for behavior, while omission errors lead to foregone rewards. For example, a manager of an automaker may decide to launch a car that turns out to sell poorly or she may decide against the launch of a car that would have been a success with customers. Such errors in decision-making occur regularly, making learning from prior errors feasible and necessary (Csaszar 2012). While inferring the correct action to take in response to an error is always a challenge, the opportunity to learn from commission errors is always present – experiential learning processes provide feedback that directly affect future choices (Eggers 2012, Maslach 2016). Learning from omission errors, meanwhile, is more complex and challenging. The primary difficulty is that information on errors of omission is not always available to decision makers. In most situations where information on errors is available, it comes from observing competitor choices on identical or similar projects (Maslach et al. 2018). Venture capital firms and record labels may be able to see the success of opportunities that they rejected, and pharmaceutical companies may be able to observe valuable drugs from competitors that represent paths they chose not to pursue. This suggests that observation of competitors may allow decision makers to learn from their omission errors.

A core challenge, however, is that attending to competitors affects not just the ability to learn from omission errors, but also affects social comparison processes that produce additional changes in behavior and challenges to learning that complicate the ability to learn and adapt to feedback (Kacperczyk et al. 2015). In this study, we seek to separate the effect of information on omission errors from the competitive effect of observing competitors through the use of an experiment (Di Stefano and Gutierrez 2019). This allows us to assess whether individuals learn from their commission and omission errors, as well as how learning differs across sources of performance feedback. We focus on a simple product approval task where participants repeatedly decide whether to accept or reject a product for development. Features of a product are repeated in multiple products over time, such that learning from rejecting a profitable product (*omission error*) or accepting an unprofitable product (*commission error*) is feasible. We manipulate what type of feedback participants receive: (a) just their own (historical) performance without information on their hypothetical performance in the case of product rejections, which should allow for learning from commissions but not omissions, (b) adding information on the hypothetical performance of product rejections, and (c) disclosing information about the value of omission errors through the behavior of a competitor. We theorize that the presence of a competitor introduces a reference point which alters learning depending on whether the decision maker is performing above or below the competitor.

Our results demonstrate multiple aspects of the complexity of learning from omission errors. As expected, we find no evidence of learning from omissions without information on the value of rejected products. While the inclusion of this information facilitates learning from omissions, we find that such learning tends to crowd out learning from commission errors – there are limits on how much information participants can process. When feedback on omissions is provided through information about hypothetical competitors, we find that learning effects diminish in general. While information overload appears to be partly responsible for this diminishment, the results intriguingly show that the lack of learning from omission errors through competitive performance stems from the introduction of an aspiration level. Specifically, participants focus on learning from their commission errors when trailing the competitor, while their focus shifts to using their competitor's experiences to learning from their omission errors when they are ahead of the competitor. These findings suggest that learning by observing competitors can be an effective way to improve the opportunity to learn from omission errors, but that the social comparison effects of such information clouds the ability to efficiently use all available data to learn from mistakes.

Our findings contribute to a stream of literature examining learning from failure (Eggers 2012, Maslach 2016). Prior research has begun to outline conditions under which learning from failure may be impaired (Audia and Greve 2006, Eggers and Suh 2019, Gaba and Joseph 2013, Maslach 2016). For example, Eggers and Suh (2019) find that learning from decision errors is possible when decision makers have the capability to determine which part of the decision caused it. We suggest that learning may even be impaired under situations of simple decision tasks and with a single source of performance feedback (Haunschild and Beckman 1998) and that this is due to dynamics of social comparison. Specifically, the presence of a competitor induces a reference point above which learning differs from being below that reference point. While the presence of a competitor has been previously found to impact learning behavior (e.g. Baum and Dahlin 2007), we point to their differential effects on omission versus commission errors.

In addition, we contribute to social aspiration research (Cyert and March 1963, Greve 1998, Joseph and Gaba 2015) by extending our understanding of the behavioral consequences of social aspirations. Such aspirations may aid self-assessment (Audia et al. 2015), induce search for new solutions (Greve 1998, Baum et al. 2005), and increase effort and productivity (Blanes i Vidal and Nossol 2011). We point to another behavioral consequence – learning from omission errors may be suppressed, i.e. choosing a performance target to strive for based on competitor performance may lead decision makers to discard useful competitor information that would otherwise allow them to learn from their omissions. This may be particularly relevant when omission errors are costly, i.e. firms cannot miss too many opportunities to stay competitive (Csaszar 2012). Thus, ironically, focusing on a better performing competitor with the explicit goal of closing the performance gap to that competitor may lead to more omission errors and thus cement the position behind the leading competitor.

Lastly, we build on the literature of competition between individuals. Prior studies have found an effect of rivalry (Kilduff et al. 2010) as well as co-acting in a similar task on performance (Flynn and Amanatullah 2012). While prior work established performance effect, the mechanism remains unclear. Specifically, Flynn and Amanatullah (2012, p.412) have speculated that effects are "the result of learning rather than motivation". Our study confirms an effect of observing someone else's performance in the same task on learning. Specifically, our results suggest that co-acting in a similar task can inhibit either learning from commission or learning from commission errors depending on whether the focal actor is trailing or leading in task performance.

## THEORY AND HYPOTHESES

The ability to learn from mistakes and make improvements in behavior that improve future performance is a central aspect of both individual and organizational learning. From a behavioral perspective, learning typically emerges from a simple process of decision and feedback – a decision maker chooses a solution and then observes the performance feedback she receives from this choice (Cyert and March 1963). If the feedback is positive, she chooses this solution again in the future, if the feedback is negative, she will not choose this solution again (Glynn et al. 1991). Specifically, a solution that looks similar to a solution that worked in the past, will likely be implemented while a solution that looks similar to a solution that did not work in the past, will likely not be implemented again. This suggests that successes will lead to repetition, while failures will lead to changed behavior (Kacperczyk et al. 2015).

A central aspect of this simple learning dynamic is feedback, as it is feedback on performance that enables learning and adaptation (Greve 2003). The importance of feedback creates complications for learning from errors, as different types of errors produce different types of feedback (Sah and Stiglitz

1986, Klingebiel 2018). Errors of commission – engaging in behavior that produces undesirable results – typically produces clear feedback that can enable learning. Numerous studies have focused on learning from commission errors at the individual and organizational level, studying learning from unsuccessful new products launched by the firm (Eggers and Suh 2019), from accidents (Baum and Dahlin 2007, Madsen and Desai 2010), and failed R&D experimentation (Khanna et al. 2016). The overall finding is that learning from commission errors can take place (and exceed learning from successes) to the extent that decision makers can adequately interpret the feedback in terms of which aspect(s) of the initial decision produced negative feedback. Learning is further dependent on number, timing, and importance of failures (Khanna et al. 2016).

By contrast, omission errors – decisions not to engage in behavior that would have produced appealing results – are often more complex in terms of learning. Some omission decisions produce clear and actionable feedback. For example, a physician who errs by not prescribing a useful treatment may see a clear deterioration in the health of their patient (though health may deteriorate even with proper treatment). Likewise, a city mayor who does not declare an evacuation for a hurricane, but the hurricane makes a direct hit, will clearly understand the gravity of their mistake (Dye et al. 2013). But in many cases, feedback on omission errors is not readily available. When Csaszar (2012) looked at omission errors by mutual fund managers, it was difficult as a researcher to identify specific omission errors, and would be even more difficult for the mutual fund manager herself. The difficulty is to have information on every decision (including the decision not to pursue a project) as well as on the quality of the projects that a decision was made on. The manager would therefore need to be privy to all past decisions (of which there will often be no record when the project was not pursued) as well as project quality. In many cases, decision makers may get little or no direct feedback on their omission errors. In such a case, learning from omissions would likely be difficult or impossible. Thus, we expect that:

*Hypothesis 1. Decision makers will learn from their errors of commission but not their errors of omission in the absence of direct feedback on their hypothetical payoffs.*

It is also conceivable that feedback on omission errors is directly available. For example, when IBM shut down its Scientific Data Systems project, some of the engineers involved in the project went on to leave IBM to form the new company SAP. The fast success of this new company gave the IBM executives direct feedback on their error of omission. A venture capital partner, publishing house executive, or recording label producer who "passes" on a given potential deal to sign may be able to observe the eventual success or failure of the venture, writer, or musical act, respectively. Bessemer Venture Partners, for example, publishes a webpage with their "anti-portfolio" of missed investment opportunities, which they presumably try to learn from to improve future decision-making. In such cases, the availability of direct feedback on the missed performance of omission errors can help decision makers learn from their omission errors.



Information on omission errors being available, however, also may have an effect on learning from errors of commission. Generally, decision makers in most situations exhibit an omission bias, i.e. they put more weight on omissions than commissions in the evaluation of their errors (Baron and Ritov 2004). Beyond a greater emphasis on omissions when information on them is available, learning from omission errors also requires the opposite behavioral antecedent as learning from commission error – while one requires accepting more projects, the other requires an increase in rejections (Klingebiel 2018). Thus, we argue that:

*Hypothesis 2. If direct feedback on omission errors is available, decision makers will learn from their errors of omission but not their errors of commission.*

**Learning about omission errors by observing a competitor**

One of the most common sources of information about omission errors comes from competitors. To the extent that a decision maker's competitors face a similar set of decisions to make, the decision maker can learn about the performance of their omission errors by focusing attention on their competitor.

Decision makers frequently attempt to learn from better-performing competitors by imitating their practices (Haunschild and Miner 1997). Specifically, they imitate what they can observe and what they believe to be generalizable (Baum and Dahlin 2007). There are, however, a number of problems with attempting to learn in this way. First, since imitated practices are not selected based on their effectiveness but on the overall performance of the competitor using them, those practices may be ineffective in the focal firm (Abrahamson 1991, DiMaggio and Powell 1983, Haunschild and Miner 1997). Secondly, very successful peers may employ riskier practices and just have gotten lucky to make it to the top by chance in which case imitating their practices would likely be detrimental to the imitator (Denrell 2003). Lastly, the focus on few successful peers' practices may lead to a narrow set of practices in the field (Porac et al. 1989) and thus hinder adaptability in the long run.

The potential challenges of focusing on competitors in order to obtain useful information are especially relevant because competitors are typically the most important source of information about omission errors available to decision makers (Haunschild and Miner 1997). For example, an automobile manufacturer may decide to cancel an R&D project at a developmental stage but later observe a similar project being pursued to completion by a competitor and, subsequently, observe the sales numbers of the competitor model. The publishing executives that failed to sign J.K. Rowling, for example, could observe her success with Bloomsbury publishing.

Social comparisons, however, may affect the behavior of decision makers and organizations in ways beyond learning and imitation. We particularly focus on the idea of competitors offering a social comparison reference point for performance (Bromiley and Harris 2014). Given that extensive research has explored how learning behavior is different when decision makers are above or below social comparison reference points (Baum and Dahlin 2007), we identify below how focusing attention on the behavior of competitors to learn from the decision maker's own omission errors may affect the learning process.

When faced with the choice between accepting and rejecting potential investments, the decision to accept is inherently risky to performance. Rejection always leads to status quo, while acceptance either increases or decreases performance. Thus, taking action is inherently risk seeking, while avoiding commitment is risk averse[1]. When decision makers are performing below their competitive reference point, we expect that they will become increasingly risk-tolerant in an effort to catch up with the competitor (Bromiley et al. 2001, March and Shapira 1987, 1992). This means that decision makers will be more likely to make commission errors when performing below the reference point. This will affect learning in two ways. First, making more commission errors leads to more data that can improve the opportunity to learn. If decision makers do not make commission errors, it will be difficult to learn from their commission errors, by default. Small sample learning is exceptionally difficult (Lampel et al. 2009, March et al. 1991), so an increased sample of commission errors will provide more opportunity. Second, while decision makers below aspirations may become more aggressive in order to try and catch up, they will want to avoid potentially large mistakes that could impair this effort. Any opportunity they see as "on the margin" will likely be pursued, so the real challenge is avoiding significant commission errors. As a result, the decision maker will focus their own limited attention on trying to diagnose their own commission mistakes in the past, and will pay less attention to the competitor's specific decision history. This will manifest as a laggard decision maker focusing on "getting their own house in order" first, before paying any significant attention to the decisions of the competitor. Such a focus on the decision maker's own history will inherently limit their ability to learn from anything other than commission errors. As a result, we hypothesize that:

*Hypothesis 3. Decision makers will learn from their errors of commission when performing below their reference point but not from their errors of omission.*

Above the reference point, we expect decision makers to show the opposite behavior. First, they will be less willing to take risks, which translates to approving fewer projects. Consequently, they will commit errors of omission more often, which analogously provides additional data on omission errors from which to learn (using information from the competitor to understand their omission). Second, successful decision makers will have the opportunity to engage in more explorative learning. The

[1] This, of course, is only true in an environment in which performance rewards are stable, whereas in an environment with changing rewards, omissions may well be riskier (see Klingebiel 2018, Silcoff et al. 2013)

success of being above a reference point makes decision makers more confident, leading to an increase in exploring new approaches (Cyert and March 1963, Levinthal and March 1981). Scholars have identified two different types of learning – explorative and exploitative. While performing below the reference point may cause both explorative and exploitative learning, performing above the reference point causes explorative learning (March 1991). Explorative learning implies seeking new types of data from which to learn, which will increase the salience of competitive performance data. For this reason, explorative learning is linked to learning from the experience of others (Baum and Dahlin 2007). The resulting behavior will be that higher performing decision makers who have limited reasons to study their own previous commission errors will instead focus on the opportunity to learn from their own omissions by focusing attention on the behavior of the competitor. This leads to our final hypothesis:

> *Hypothesis 4. Decision makers will learn from their errors of omission when performing above their reference point but not from their errors of commission.*



## METHOD & DATA

This study explores how different available performance feedback mechanisms affect learning from both omission and commission errors. We do so by using an online experiment that allows for causal identification of the effect of performance feedback on learning in the absence of confounding elements like the simultaneous arrival of performance feedback from multiple sources (Busemeyer et al. 1986, Cook and Campbell 1979, Sterman 1987). This empirical approach also allows for easy replication to verify our findings (Bettis et al. 2016).

### Experimental task

Our experimental task mirrors the approach used in many modeling papers on learning (e.g., Csaszar 2013), where a decision maker is asked to assess projects that arrive in sequence, where each project must be either approved or rejected before considering the next project. Each project is an aggregation of multiple characteristics, which affect project performance. The sequencing of projects allows for the potential for learning from previous choices. Each project has a true, but hidden, project performance value which is only revealed after a decision is made. As a result, each round the participant will experience one of four potential outcomes drawn from signal detection theory (Dye et al. 2014) – a true positive, a false positive (commission error), a true negative, or a false negative (omission error). This provides a simple opportunity to test our broader theory about learning from omission errors based on the availability of feedback.

The procedure was conducted through an online, 20 round experiment on Amazon's Mechanical Turk. In the experiment, participants are put in the shoes of a manager deciding repeatedly whether to introduce a new car to the market. A car in our task can be described by a unique combination of its three main features (engine, transmission, body style), each which in turn can hold 4 values (e.g. "V engine" or "convertible"; full list of features and values in Appendix 1). A mix of features could for example be a convertible with a V engine and manual transmission, and each affected profit in a simple and independent manner. Thus, a manual transmission might always be positive for car performance across all potential cars considered by the subject. While many car features may actually affect performance in an interdependent manner, such a task would make learning significantly more difficult. For each of the three car features, the best performing value increased performance by three points (see more details on points below), while the worst decreased performance by three points and the others performed in between. Thus, a given car's aggregate performance ranged from positive nine to negative nine. All cars which were launched by the participant affect profits (positively or negatively), while cars that are not launched do not affect profits. Thus, learning could take place about a mix of features by observing the performance feedback on other, similar cars. The performance feedback was immediate, unambiguous and non-stochastic. It was made clear to the participants that no knowledge of actual cars was required to perform well in the experiment.

**Experimental design**

**Incentives.** In providing monetary incentives to the participants, we applied the induced-value approach (Smith 1976): for the participants, more profitable product launches resulted in higher bonus payments. In line with prior experimental work, the participants were shown only correct information

(Ortmann and Hertwig 2002). For 10 minutes of their time, participants were paid 25 US cents as a base payment plus an additional payment of up to one US dollar depending on their performance in the task. The monetary reward at stake in the experiment is commensurate with prior experimental work (Harmon et al. 2015) as well as with reservation wages of workers on Amazon Mechanical Turk (Burbano 2016, Horton et al. 2010). What is more, previous studies on monetary stakes in experiments have shown that behavior is largely invariant to varying stakes for choice (as opposed to effort) tasks (Camerer and Hogarth 1999, Smith and Walker 1993). Throughout the task, participants could accumulate performance points (an experimental currency) that would then later be translated into US dollars. At the beginning of the task, all participants were given 75 performance points and each round, participants could lose or win up to 9 points. One performance point translated into one US cent ($0.01). We chose an experimental currency with an initial endowment rather than a bonus because accumulated profits during the task could otherwise plunge into the negative, thus taking away money from the participant. This format ensured that participants always achieved at least a small bonus, even if they got everything wrong. Participants knew of the experimental currency / US dollar exchange rate.

**Procedure.** Upon starting the survey, participants were informed of the estimated length, the performance incentives, and the number of rounds of the exercise. In each of the 20 rounds, participants were shown the same decision screen (see Figure 1 below). On that screen, the current round was displayed (A) and under it the question of whether to accept or reject the current proposed car (B). The bottom of the screen contained a table (C) with information on the current car features as well as information from past rounds on features, decisions and performance. The table also noted the participant's current point total (D).

----------------------------------- Insert Figure 1 about here -----------------------------------

After each decision, participants were shown their profits or losses, respectively, for last round's car. During the task, an attention test was shown between rounds eight and nine instructing participants to not click an accept or reject button to check they were engaging in the task mindfully. After task completion, participants were informed of their final score and presented a short questionnaire on demographic characteristics. Among the information polled in this questionnaire were a verbal account of the participants' strategy, their gender, age, motivation to participate, level of education, background in STEM subjects and average hourly wages on Amazon Mechanical Turk and offline. See Appendix 2 for screen shots of the entire survey.

**Treatments.** The central manipulation was the type of performance feedback that was shown to participants. All comparisons between treatments were done between subjects, i.e. each participant only participated in one treatment. In the control condition, only feedback on the participant's own product launches was displayed. Importantly, no information was given on how the car would have fared in the market if it was not chosen to be launched by the participant. In the first treatment condition, we introduced a competitor. Participants were instructed that they had a counterpart at their main competitor's company tasked with similar duties and that they would see the competitor's success in the market and their competitor's car features. This treatment added additional columns to Figure 1, noting the competitor's current performance level as well as the cars shown to the competitor. In the second treatment condition, there was no competitor information but direct feedback was provided (see Appendix 2) on how cars not chosen to launch would have performed in the market.

**Respondents.** All participants were recruited on the Amazon Mechanical Turk platform. We used only data on participants that finished the task, passed the attention check, and more than 3 seconds on reading the instructions. A total of 123 both finished and passed the attention check and spent more than 3 seconds reading the instructions. All statements about participants demographics refer to those 123 participants. We restricted the subject pool to residents of the United States to avoid difficulties with English as the language of instruction. Half (50%) of the participants were women, the average age was 37 years old, 49% had an academic background in a STEM subject, and 72% had at least a college degree. On average, participants earned 76 cents in bonus payment.

**Analysis**

To understand learning, we arranged our data with a single observation for each round of the experiment (20 rounds). Using fixed effects (at the individual level) allowed us to look within any given subject at their rate of learning, while controlling for any time-invariant factors that may affect performance. This fixed effect approach combined with randomization of the treatment assigned to any given participant allowed us to use a regression-based approach (since we have two independent variables), but we need employ no other control variables. As our dependent variable (see below) is binary, we used a fixed effects logit regression.

**Dependent variable**. The dependent variable captures success versus failure in a given round *i*. Success means making a correct choice, i.e. either rejecting a proposal that yields a negative reward or accepting a proposal that yields a positive reward. Thus, the dependent variable is a binary variable.

**Independent variables**. Given our focus on learning from omission and commission errors, we use the respondent's cumulative omission and commission errors as two independent variables. To avoid an induced slope effect in the cumulative errors, we focus only on errors committed in the previous four rounds (Bennett and Snyder 2017). Expanding the window of errors considered produces similar, and statistically stronger, results.

## RESULTS

We report findings of our baseline regression analysis in Table 1. For participants in the control condition (Model 1), we find a positive and highly significant effect for (0.360, $p < 0.001$) for the effect of prior commission errors on success. This coefficient (odds ratio = 1.43) suggests a 43% higher likelihood of making the right decision (i.e. not making a decision error) for each recent commission error. Meanwhile, there is no such effect for omission errors which is not surprising given that participants had no information on the hypothetical performance with cars they rejected. These findings are consistent with H1 and highlight how learning from mistakes is only feasible with adequate feedback on performance and potential outcomes of omitted decisions.

----------------------------------- Insert Table 1 about here -----------------------------------

Participants in the full information treatment receive complete performance feedback on both proposals they have accepted and rejected, and the results are shown in Model 2. The results suggest that participants demonstrate positive learning from omission errors ($p < 0.01$), but now no longer demonstrate learning from commission errors. In terms of the effect size, this means that an additional error of omission is associated with a 39% higher likelihood of making the right decision subsequently. Meanwhile, participants in the third condition (Model 3) are aware of competitor choices and performance. These participants continue to show positive learning from omission errors (38% increase, $p < 0.1$), though the standard errors increase suggesting more variance. They do however demonstrate a small positive effect of learning from commission errors as well (22% increase, $p < 0.1$). Our second hypothesis (H2) had suggested that disclosing information about omission errors would help participants learn from omissions (supported in both Model 2 and Model 3), but doing so would crowd out learning from commission errors. The latter effect is supported in Model 2 (full information), but while the effects are weaker in Model 3 (competition), learning still manifests. This offers only limited support for H2, but the general pattern is broadly consistent with the idea that that learning from one type of error may crowd out the ability to learn from the other type of error.

To further explore the idea of "crowding out", we re-ran our experiment with a simpler task. Our supposition was that any impairment to learning that crowded out one type of learning could be driven by information overload. For example, rather than processing only own choices and feedback, participants in the competitor treatment also need to process the same information for the competitor. If information (or cognitive) overload is the reason for reduced learning, we would expect an increase in learning when the task becomes less complex. To simplify the task we reduced the number of features (e.g., engine) from three in the baseline condition to two in the reduced complexity condition. These results are reported in Table 2. In these results, we now find a consistent effect of learning from commission errors (35% in the control, 42% with full information, and 43% in competitor in Models 4-6, respectively), but we no longer find support for any learning from omission errors. Overall, we still observe a lack of learning in the competitor treatment even when the information load is reduced.

---------------------------------- Insert Table 2 about here -----------------------------------

Our third and fourth hypotheses focused on the idea that participants would be more able to learn from commission errors when they were performing worse than their competitor (H3), and more able to learn from omission errors when they were performing above their competitor (H4). In Table 3, we report the results split by reference point for the full complexity task (Models 7 and 8) and the reduced complexity task (Models 9 and 10). In line with H3, we find consistent and significant positive learning effects from commission errors when the participant is trailing the competitor (38% increase in full complexity, $p < 0.1$; 157% increase in reduced complexity, $p < 0.05$). When the participant is above aspirations, the effect is absent in the full complexity task and appears but is much smaller than the learning from omissions in the reduced complexity task (51% increase, $p < 0.1$). This generally supports H3.

------------------------------------ Insert Table 3 about here ------------------------------------

In line with H4, we find that learning from omissions only manifests significantly when the participant is ahead of the competitor, both in the full complexity task (97% increase, $p < 0.1$) and the reduced complexity task (163% increase, $p < 0.05$). While the coefficients on omission errors are not significant when the participant is below aspirations (in either complexity condition), it is worth noting that the coefficients are positive but the standard errors are quite large. This suggests that learning from omissions for participants below aspiration may be very uneven. It is important to note that participants above aspirations in the reduced complexity task seem to be able to learn from both commission and omission errors, though in line with H4 the effect of learning from omission errors is much stronger. This does provide limited support for the notion that task complexity may limit the ability to learn from both types of errors.

Our theory behind H3 and H4 suggested that only participants who were above aspirations would really pay attention to the competitor and try to learn from their omission errors. In this case, the core mechanism is attention to the competitor. We wanted to explore this mechanism directly, and subsequently created an additional experiment to test attention. Specifically, we displayed stars ("*") next to the features of the competitor cars. The number of stars displayed varied between two and six. After completing the task, we asked the participants to recall the minimum number of stars that appeared in any round. We then computed the distance of this measure from the true value. We normalized the measure between zero and one where zero meant a low focus on the competitor and one meant a high focus (i.e. an absolute accurate recollection of the minimum of stars). For the following analysis, the sample was split by those focused on the competitor (attention value above the median) and those not focused on the competitor (attention value below the median). This allows us to have a direct an unobtrusive measure of attention. We further asked participants directly how much attention they had paid to the competitor on a scale from zero (all attention focused on own performance feedback) to 100 (attention exclusively focused on the competitor).

We use this measure as an outcome variable in Model 11 in Table 4, where we check whether the number of periods the participant spent above social aspirations predicts the likelihood of paying attention to the competitor. As shown in the results, for each additional round above the reference point the participant was significantly more likely to pay attention to the competitor (4.5% increase, $p < 0.01$). This supports the core mechanism from our theory that the reason that participants above and below aspirations learn differently is because of attention to the competitor.

----------------------------------- Insert Table 4 about here -----------------------------------

To complete the test for the mechanism, we explored whether attention to the competitor affected the way in which participants learned. To do this, we split the sample based on those who paid attention to the competitor (i.e. those who remembered the minimum number of stars accurately) (Model 12) versus those that did not (Model 13) in Table 4. We find that participants only learn significantly from both types of errors when focused on the competitor. Specifically, an increase of one commission error is associated with a 33% higher likelihood of making the right decision ($p < 0.01$), while an increase of one omission error is associated with a 28% increase ($p < 0.05$). These results are somewhat surprising, suggesting that attention to the competitor is indeed the mechanism by which learning from omissions emerges, but it also seems to affect learning from commission errors, as well. This may be driven by the idea that participants need motivation to learn in order to engage in active learning, and this motivation may emerge from attending to competitor performance.

**DISCUSSION**

Previous research often does not differentiate between omission and commission errors when discussing learning from failure (e.g. Eggers 2012, Maslach 2016). But learning from omission errors is critical yet difficult as performance feedback on omissions is often absent. Decision makers may observe their competitors to learn from omissions, but we argue that such competitor focus may affect behavior and learning beyond simply providing insight into omission errors. This suggests that learning from decision errors is importantly influenced by context. Using a series of online experiments, we found no evidence for learning from omission errors unless feedback on the value of rejected projects was provided. When direct feedback on omissions was available, however, learning from omission errors crowded out learning from commission errors. When feedback was given by observing a competitor, we found overall diminished learning effects for both commission and omission errors. Specifically, we observed that learning effects were contingent on the position relative to the competitor – leaders were learning from their errors of omission but not their commission errors while laggards were learning from their errors of commission but not their omission errors. The core of our theory revolves around when and how leaders versus laggards will attend differently to competitors based on both their own incentives and availability of data. While laggards seem to learn mostly from commission errors, leaders focus on learning from their omissions. This is consistent with theories of performance feedback and risk taking (Bromiley et al. 2001, March and Shapira 1987, 1992) but has been ignored in previous studies on learning from decision errors.

Our study provides three primary contributions. First, this study contributes to the literature of learning from failure (Eggers 2012, Maslach 2016). Previous studies have pointed out that learning may be impaired when it is unclear which part of the decision caused the error (Eggers and Suh 2019) or when performance feedback is coming from multiple sources (Haunschild and Beckman 1998). We identify an additional constraint to learning from failure. Concretely, we find that competitive dynamics may not only spur or suppress learning (Baum and Dahlin 2007) but also determine what errors are learned from. This suggests that research on learning from failure (or learning more broadly) needs to focus not only on the firm itself, but also the competitive context that may directly affect the ability to learn.

Second, our findings shed light on the behavioral consequences of social aspirations. Prior research has found that setting a performance target based on competitors' performance may aid self-assessment (Audia et al. 2015), induce search for new solutions (Greve 1998, Baum et al. 2005), and increase productivity and effort (Blanes i Vidal and Nossol 2011). Our results indicate that there may be another side effect of social aspirations. They may curb learning from omission errors. This may hurt organizational performance in particular when avoiding omission errors -i.e. not missing important opportunities- is crucial to gaining a competitive advantage (Csaszar 2012).

Third, this research adds to the literature of competition between individuals (Deutsch 1949, Deci et al. 1981, Beersma et al. 2003). The literature of interindividual competition spans mere co-acting (Flynn and Amanatullah 2012) to intense rivalry (Kilduff et al. 2010). Specific competition between individuals has been shown to have consequences for individuals' performance. For example, Kilduff et al. (2010) found a significant effect of rivalry on team performance in NCAA basketball competitions. Nonetheless, the mechanisms mediating such performance effects are not fully explained. While most studies point to motivation mediators (e.g. Kilduff et al. 2010), some (e.g. Flynn and Amanatullah 2012) have suspected that learning may explain part of the performance effects. Our findings suggest that observing a competitor may curb learning from commission errors when leading against the competitor and curb learning from omission errors when trailing the competitor.

More empirical work is needed to further explore how competitive dynamics influence learning from decision errors. Specifically, it is important to understand whether learning from omission errors above reference points and learning from commission errors below reference points replicates in an organizational context. In particular, do less profitable businesses focus too much on commissions but miss the next big opportunity when they are trailing their competitor(s)? This could be tested in the context of R&D activity in the Pharma industry. Omissions could be measured by patenting activity related to previously passed up projects and it would be easy to approximate historical and social reference points as done by previous studies (Lungeanu et al. 2016). Further, we focused on a single competitor's behavior as a source of learning about omission errors. It would be interesting to study the effect of observing groups of competitors. For example, firms increasingly have access to public repositories of other firms' failures, such as the MAUDE database for failures in medical devices (Maslach et al. 2018). This may constitute a boundary condition for our findings since the formation of reference points may be decoupled from the opportunity to learn about omission errors.

Importantly, out task represents a dramatically simplified version of actual organizational decision makers. For example, a real R&D manager deciding on which projects to invest in receives performance feedback on many dimensions and from multiple sources, think customer feedback, sales data etc. However, managers need to form a mental model in order to make any decision that is a simplification of reality, too (Gavetti and Levinthal 2000, Halford et al. 1994, Kelley 1973). Similarly, our experiments are different from many organizational decisions as the stakes involved are much lower. A failed car rollout may cost a manager his job, whereas in the experiment he is risking merely cents. Prior research has identified behavior to change in two ways for lower (monetary) stakes. First, individuals typically invest less effort (Smith and Walker 1993) and secondly, they take greater risks (Lefebvre et al. 2010, Weber and Chapman 2005). Our experiment, however, is not an effort task. Risk may play a role in the sense that approving a project always features a greater outcome variance than rejecting a project (outcome is always 0). This should affect all our treatment conditions in the same way and thus, is not expected to bias out results.

Another way in which the experimental task varies from a number of decision problems is that the likelihood of making an error of commission versus an error omission is balanced. For many managerial decision problems, on the contrary, the likelihood of making an omission error is much more likely than making a commission error (Klingebiel 2018). This is the case because the decision space is large and thus, many potentially beneficial projects are foregone at each point in time. Assuming a reality where omission errors are much more likely than commission errors, would make it even more difficult to learn about omission errors by gathering better data and all the more important to rely on similar competitors.

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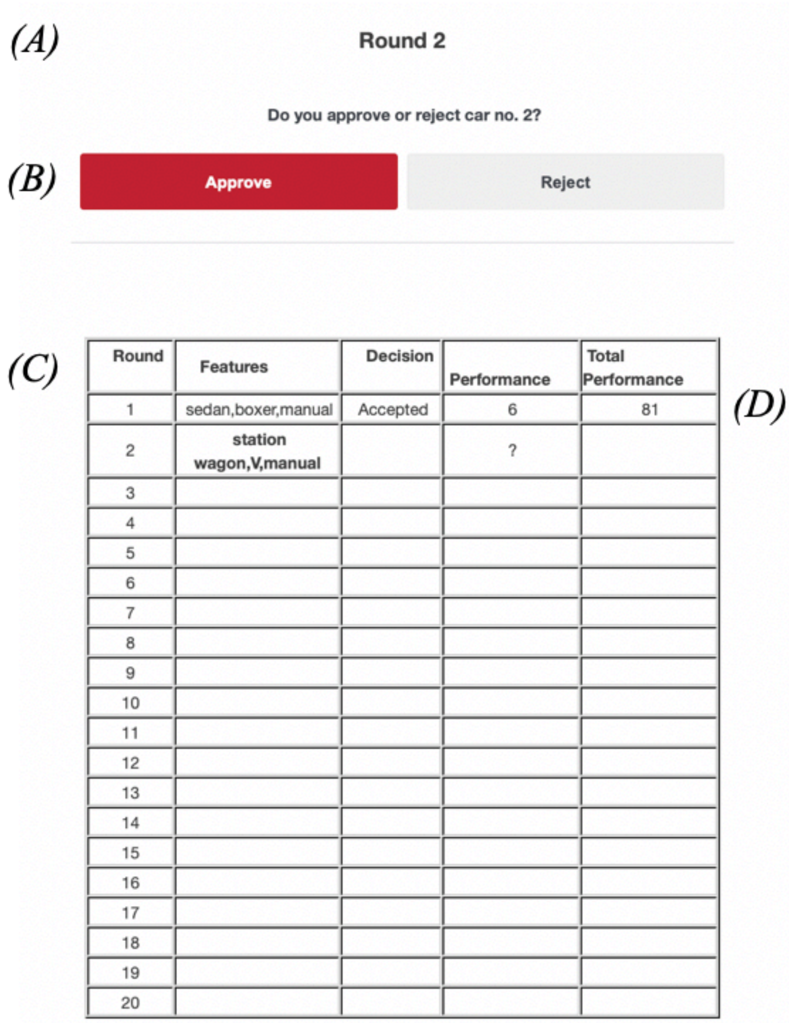
**FIGURE 1: Example Decision Screen**




Note. Decision screen from the control treatment from round 2 including information on (A) current round, (B) question of whether to accept or reject the current proposed car (B), (C) information on the current car features as well as information from past rounds on features, decisions and performance, and (D) total points.

**TABLE 1: Main Results (Full Complexity)**

| | ***Model 1*** *Control* | ***Model 2*** *Full Info* | ***Model 3*** *Competitor* |
|---|---|---|---|
| *Commissions* | 0.360*** | 0.073 | 0.202* |
| | (0.095) | (0.086) | (0.119) |
| *Omissions* | -0.064 | 0.333** | 0.327* |
| | (0.129) | (0.145) | (0.192) |
| *Fixed Effects* | <included> | <included> | <included> |
| $R^2$ | 0.021 | 0.007 | 0.012 |
| N | 800 | 752 | 416 |

*Note: *p<0.10; **p<0.01; ***p<.001*
*Standard errors in parentheses*



**TABLE 2: Reduced Complexity Results**

| | ***Model 4*** *Control* | ***Model 5*** *Full Info* | ***Model 6*** *Competitor* |
|---|---|---|---|
| *Commissions* | 0.306** | 0.351*** | 0.363** |
| | (0.142) | (0.125) | (0.176) |
| *Omissions* | 0.191 | 0.119** | 0.174* |
| | (0.223) | (0.191) | (0.254) |
| *Fixed Effects* | <included> | <included> | <included> |
| $R^2$ | 0.012 | 0.014 | 0.017 |
| N | 400 | 576 | 288 |

*Note: *p<0.10; **p<0.01; ***p<.001*
*Standard errors in parentheses*

**TABLE 3: Split Samples Based on Social Aspirations**

| | *Full Complexity* | | *Reduced Complexity* | |
|---|---|---|---|---|
| | ***Model 7*** *Below* | ***Model 8*** *Above* | ***Model 9*** *Below* | ***Model 10*** *Above* |
| *Commissions* | 0.328* (0.171) | 0.263 (0.183) | 0.947** (0.417) | 0.419* (0.219) |
| *Omissions* | 0.385 (0.263) | 0.680* (0.350) | 0.560 (0.265) | 0.971** (0.424) |
| *Fixed Effects* | <included> | <included> | <included> | <included> |
| $R^2$ | 0.025 | 0.022 | 0.102 | 0.038 |
| N | 205 | 211 | 62 | 226 |

*Note: *p<0.10; **p<0.01; ***p<.001*
*Standard errors in parentheses*



**TABLE 4: Attention to Competitor**

| | *DV=Attention* | *DV=Performance* | |
|---|---|---|---|
| | ***Model 11*** | ***Model 12*** *Focus on Competitor* | ***Model 13*** *Not Focused on Competitor* |
| *Rounds Above Aspirations* | 0.767** (0.374) | | |
| *Commissions* | | 0.369*** (0.084) | 0.180 (0.112) |
| *Omissions* | | 0.289** (0.132) | 0.076 (0.161) |
| *Fixed Effects* | | <included> | <included> |
| *Constant* | <included> | | |
| $R^2$ | 0.046 | 0.022 | 0.006 |
| N | 90 | 972 | 463 |

*Note: *p<0.10; **p<0.01; ***p<.001*
*Standard errors in parentheses*

**Appendix 1**

| | *Car Features* | | |
|---|---|---|---|
| | *Engine* | *Transmission* | *Body* |
| ***Values of Features*** | V | Manual | Sedan |
| | Boxer | Semi-automatic | Convertible |
| | Inline | Automatic | Station wagon |
| | Wankel | Dual clutch | Hatchback |

## Appendix 2

### FIGURE A1: Instructions Experiment

Dear mTurk worker,

You are participating in an experiment on decision making.

It will take you about **10 minutes** to complete this experiment. Your base payment will be **25 cents** and you can earn a **bonus of up to 1 dollar**, depending on your decisions (and, to a lesser extent, on luck). At the end, we would like you to answer a few questions about yourself.

Everything that you need to know to perform well in this experiment is explained on the following screens. If you have any questions, please drop us an email at empiricist1740@gmail.com

→

In the following experiment, you will have the opportunity to accumulate **performance points**.

You start out with 75 performance points.

In each round, you can win or lose performance points.

At the end of the experiment, your performance points are translated into US dollars. Each performance point will become 1 cent.

→

**FIGURE A1: Instructions Experiment (continued)**

In this experiment, you will assume the role of a manager of a car manufacturer.

You play for 20 rounds.

In each round, your chief technology officer (CTO) will present you a new car.

You can then decide that it may be introduced to the market. In this case, between -9 and 9 performance points will be added to your account.

If you reject the engineers' proposal, you will earn no performance points and no score of what you would have earned if you had accepted the proposal will be shown to you.

→

A car has three different features that your company can modify: an **engine (V, inline, boxer, wankel)**, **transmission system (manual, semi-automatic, automatic, dual clutch)** and its **body style (sedan, station wagon, convertible, hatchback).**

Before you make a decision on a car, you will be informed about the composition of those features.
**Each feature contributes to its performance points.**
This means, one engine will be more profitable than another engine and one body style will be giving you more performance points than another one.

**Please note, that these the value of he cars do in no way correspond to market prices of actual cars. Thus, you don't need any knowledge what so ever about cars to perform well in the following task.**

→

**FIGURE A2: Post-Experiment Screens**

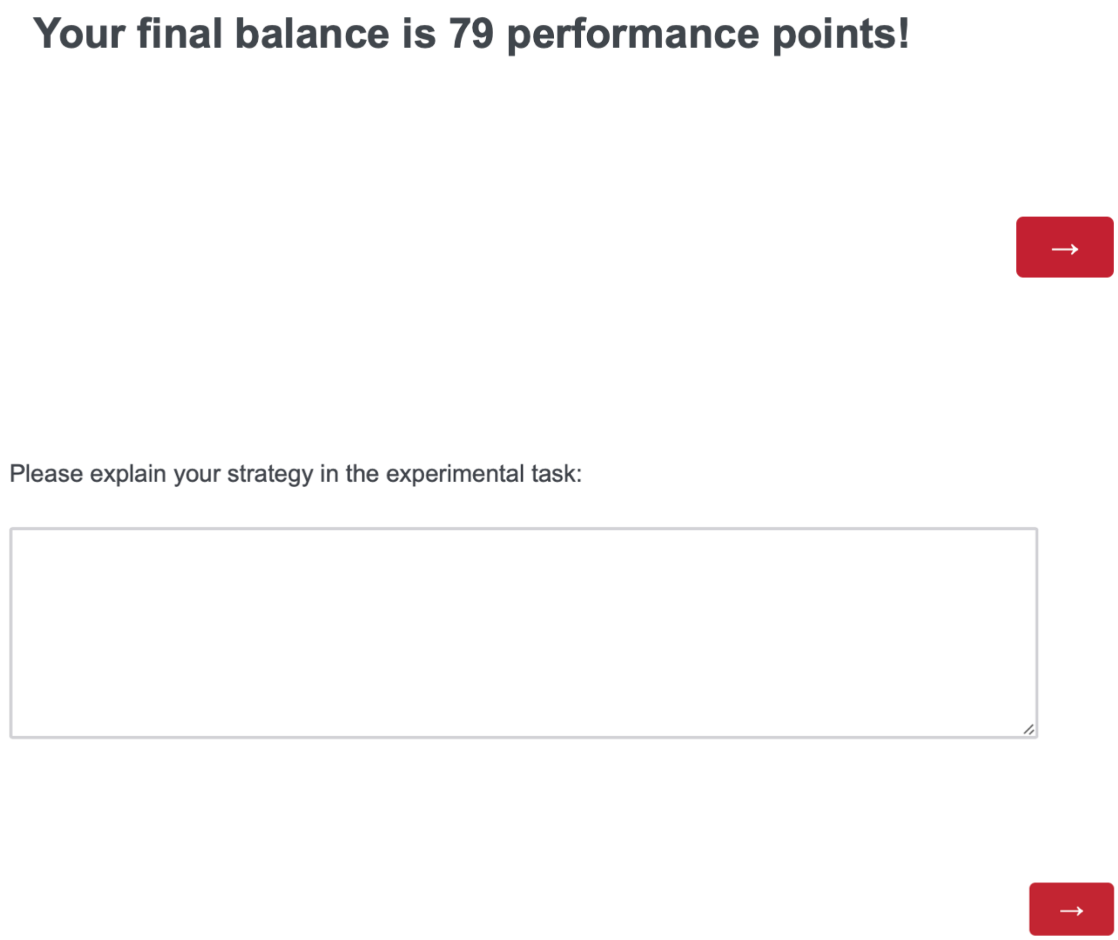


**FIGURE A3: Post-Experiment Questionnaire**

Gender
- Male
- Female

Age

Why are you participating in this study?
- MTurk experiments are my primary source of income.
- To earn some additional money.
- For entertainment.
- To kill time.
- Out of curiosity.
- I am a researcher and I like to spy on other projects.

What is your highest level of education?
- No formal degree
- High school
- Associate's
- Bachelor's
- Master's
- J.D.
- M.D
- Ph.D.

Do you have a background in one of these fields?
- Mathematics
- Natural Sciences
- Computer Science
- Economics or Finance
- Statistics
- Engineering
- No, I do not have a background in any of those fields.

What hourly wage did your last or current job pay?
- Less than $5.
- Between $5 and $10.
- Between $10 and $20.
- Between $20 and $30.
- Between $30 and $40.
- More than $40.
- Prefer not to say.

How much do you make, per day, as an mTurk worker on average?
- Less than $5.
- Between $5 and $10.

- Between \$10 and \$20.
- Between \$20 and \$30.
- Between \$30 and \$40.
- More than \$40.
- Prefer not to say.

**FIGURE A4: Treatment Information – Competitor Treatment**

Your main competitor company employs a decision maker who has the same duties as you.

She gets the same proposals featuring cars with the exact same elements as the ones you are confronted with.

In every round, you will see her performance as well as the proposals she received.

→

## Round 2

**Do you approve or reject car no. 2?**

**Approve** **Reject**

| | | | Own Performance | | Competitor Performance | | |
|---|---|---|---|---|---|---|---|
| Round No. | Features | Decision | Round | Total | Features | Round | Total |
| 1 | hatchback,wankel,manual | Accepted | 7 | 82 | hatchback,wankel,manual | 7 | 82 |
| 2 | station wagon,V,automatic | | ? | | | | |

## The car earned you 3 performance points in the market!

**FIGURE A5: Treatment Information – Full Information Treatment**

## Round 3

**Do you approve or reject car no. 3?**

**Approve** **Reject**

| Round | Features | Decision | Performance | Total Performance |
|---|---|---|---|---|
| 1 | hatchback,inline,automatic | Accepted | 1 | 76 |
| 2 | station wagon,boxer,dual clutch | Accepted | 5 | 81 |
| 3 | **hatchback,boxer,automatic** | | ? | |
| 4 | | | | |

**You rejected the proposed car and hence, earn no performance points in this round. If you would have accepted the proposal you would have earned -3 performance points.**