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TIME DELAYS, COMPETITIVE INTERDEPENDENCE, AND FIRM PERFORMANCE

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Research summary: *Competitors' experiences of prior interactions shape patterns of rivalry over time. However, mechanisms that influence learning from competitive experience remain largely unexamined. We develop a computational model of dyadic rivalry to examine how time delays in competitors' feedback influence their learning. Time delays are inevitable because the process of executing competitive moves takes time, and the market's responses unfold gradually. We analyze how these lags impact learning and, subsequently, firms' competitive behavior, industry profits, and performance heterogeneity. In line with the extant learning literature, our findings reveal that time delays hinder learning from experience. However, this counterintuitively increases rivals' profits by reducing their investments in costly head-to-head competition. Time delays also engender performance heterogeneity by causing rivals' paths of competitive behavior to diverge.*

Managerial summary: *While competitive actions such as new product launches, geographical expansion, and marketing campaigns require up-front resource commitments, the potential lift in profits takes time to materialize. This time delay, combined with uncertainty surrounding the outcomes of competitive actions, makes it difficult for managers to learn reliably from previous investment decisions. This results in systematic underinvestment in competitive actions. The severity of the underinvestment grows as the time delay between an investment and its positive results increases. Counterintuitively, however, competitors' collective underinvestment increases profit-making opportunities. In industries with large time delays, companies that do invest in competitive actions are likely to enjoy high returns on investment. It is also likely that rivals' paths of competitive behavior bifurcate. Together, these mechanisms generate large differences in competitors' profits.* Copyright © 2016 John Wiley & Sons, Ltd.

INTRODUCTION

Competitive dynamics researchers often adopt a behavioral perspective (e.g., Chen *et al.*, 2010a; Hsieh, Tsai, and Chen, 2014; Kilduff, Elfenbein, and Staw, 2010; Marcel, Barr, and Duhaime, 2010), recognizing that managers must make decisions concerning rivalry in the absence of a clear understanding of how their firm's competitive actions translate into performance outcomes. This lack of clarity prohibits treating competition as a mere optimization problem and motivates managers to base their decisions on the outcomes of earlier choices (Cyert and March, 1992; Lamberg *et al.*, 2009). As learning from prior experiences can influence managers' decisions, identifying factors that affect the

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process of learning from experience can help understand how competitive interaction patterns form over time (Chen and Miller, 2012). This can, in turn, facilitate addressing fundamental questions in strategy such as how and why performance differences emerge among firms.

Building on this insight, we examine time delays in interfirm rivalry as an antecedent of differences in industry profitability and performance heterogeneity among competitors. Time delays have interested competitive dynamics scholars for the entirety of the field's existence (e.g., MacMillan, McCaffery, and Van Wijk, 1985), and such delays are a natural focus of inquiry for studying the factors that affect learning in rivalry. Scholars recognize that time is needed to execute competitive actions (Chen and Hambrick, 1995; Miller and Chen, 1994) and to realize the results of these actions (Bridoux, Smith, and Grimm, 2013). Such time delays can affect firm performance. For example, research has demonstrated that slow competitors are usually at a disadvantage in capturing contested opportunities (e.g., Boyd and Bresser, 2008; Chen and Hambrick, 1995; Ferrier, 2001; Hawk, Pacheco-De-Almeida, and Yeung, 2013; Miller and Chen, 1994). However, to date, research has focused on the immediate economic consequences of time delays. The effects of time delays on longitudinal patterns of competitive interaction have not been systematically studied.

We employ computational modeling to uncover how time delays shape rivalry beyond the short term by influencing managers' learning from previous competitive interactions. Our findings are consistent with the existing literature on learning in showing that time delays hinder learning from experience (Rahmandad, Repenning, and Sterman, 2009; Sterman *et al.*, 2007). In particular, time delays reduce the perceived reward of investing in competitive actions, causing companies to underuse them. However, this effect may counterintuitively enhance competitors' performance because, at a collective level, time delays cause firms to invest less in costly head-to-head competition. The positive performance effect of time delays has gone unnoticed to date because prior research on time delays in learning has not considered the impact of competitors' decisions on a focal firm's performance (e.g., Rahmandad, 2008; cf., Katila and Chen, 2008). We also show how the impact of time delays on learning fosters performance heterogeneity by causing rivals' behavioral trajectories to diverge. Overall, our study establishes time delays firmly alongside other explanations of industry profits and performance heterogeneity (e.g., Lenox, Rockart, and Lewin, 2010). The paper also advances our understanding of how micro-level behavioral mechanisms shape macro-level patterns of competitive interaction over time (e.g., Chen and Miller, 2012).

THEORETICAL BACKGROUND

Our study investigates the phenomenon of interfirm rivalry, which is a fundamental issue in strategic management. In line with the literature on competitive dynamics (Chen and Miller, 2012: 137), we conceptualize interfirm rivalry as a series of competitive actions and interactions. In this study, competitive actions are defined as product market moves that aim to increase the attractiveness of a firm's offerings in the eyes of customers relative to competitors' products and services (Miller and Chen, 1994). Such actions might include product introductions that provide new benefits to customers, geographical expansion initiatives that bring a firm closer to customers, or marketing campaigns that build a favorable brand image.

The competitive moves that rivals make today hinge on their history of previous competitive encounters (e.g., Kilduff *et al.*, 2010), as firms' previous competitive experiences of past success shape their current decision making (Lamberg *et al.*, 2009). Any factor that influences firms' learning from experience may have indirect but cumulatively significant implications for how and what competitive interaction patterns emerge. We propose that time delays are one such factor with the potential to shape rivalry over repeated competitive interactions by affecting managers' learning from experience.

The strategic significance of time is well established in the competitive dynamics literature (Ferrier, 2001). Scholars have investigated, for example, how lags in competitive responses (Boyd and Bresser, 2008), in the speed of decision making (Eisenhardt, 1989), and in the temporal spacing of actions (Laamanen and Keil, 2008), as well as inertia in "altering [a] competitive stand" (Miller and Chen, 1994: 2), affect the performance of competing firms. Scholars also recognize that the full performance consequences of competitive actions do not materialize immediately and that there can be differences in the speed at which different competitive moves affect firm performance (Bridoux *et al.*, 2013).

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We consider the role of time in interfirm rivalry (Ancona *et al.*, 2001) from the perspective of learning. In particular, we examine how rivalry-related time delays influence competition by delaying the feedback that a firm receives about its decisions concerning competitive actions. In general, the significance of delayed feedback from the perspective of learning is well established. For example, the cognitive "myopia" of managers can constrain learning from temporally distant outcomes (Diehl and Sterman, 1995; Levinthal and March, 1993). Moreover, stakeholders often pressure executives to take actions based on short-term outcomes, which may be counterproductive if success presupposes patience (Aspara *et al.*, 2014). Organizational learning may also be compromised when time delays between decisions and outcomes span beyond the tenures of key decision makers (Paich and Sterman, 1993).

Our analysis focuses on two rivalry-related time delays. First, *market reaction lag* refers to the time distance between the launch of a competitive action and observable changes in customer behavior in response to shifts in the relative attractiveness of rivals' offerings. A related term in marketing is "wear-in time" or "the lag before the peak impact on sales is reached" following a marketing action (Srinivasan, Vanhuele, and Pauwels, 2010: 680). Market reaction lags are positively associated with the "time to positive performance impact" (Bridoux *et al.*, 2013: 931). Various factors can contribute to market reaction lags. For example, customers do not immediately change their purchasing behavior when new products and services become available because they may be either unaware of the new product or service or uncertain of its benefits (Horsky, 1990). This is the case especially if product and price comparisons are difficult or if switching costs are high (Chatain and Zemsky, 2011). Low decision-making frequency might also contribute to delayed sales responses to competitive actions; for example, potential customers who reconsider their service subscriptions once a year will respond to a change in price levels more slowly than customers who revisit their decisions bimonthly. Finally, customers may choose to delay responses to new products or price cuts in the hope of seeing even better products launched and further price cuts (Horsky, 1990). Because these lags largely reflect buyer characteristics and behaviors, market reaction lags are generally *industry-wide*; that is, competitors experience similar delays in how quickly the market responds to their actions.

Second, we consider *execution delays* that stem from the process of carrying out competitive actions. Several barriers to competitive actions exist that contribute to execution delays. For example, managers and specialists often require time to amass various customer, competitor, and technology-related knowledge to help determine the specifics of their competitive actions (e.g., product design, advertising media) (cf., Ferrier, 2001). Moreover, the launch of complex products involves time-consuming coordination across departments (MacMillan *et al.*, 1985). Finally, the execution of competitive actions may require dealing with public authorities or renegotiating with suppliers, which further delays the launch of competitive actions. Firms possess differential levels of ability to address these barriers to action (e.g., Hambrick, Cho, and Chen, 1996; Hawk *et al.*, 2013). For example, some firms may have better information-processing systems that help them more quickly resolve uncertainty (Eisenhardt, 1989); some companies have developed organizational routines that facilitate intra-organizational coordination (Becker, 2004); and some organizations have more established relationships with external parties, reducing inter-organizational negotiation and coordination. This leads us to assume that execution delays are generally *firm specific*.

The existing competitive dynamics literature has not extensively discussed the performance implications of market reaction lags (see, however, Bridoux *et al.*, 2013). But when regressing firm performance variables on lagged product market actions, scholars *assume* that market reaction lags exist (e.g., Young, Smith, and Grimm, 1996: 250). With regard to execution delays, the existing literature considers them typically problematic. In intensive rivalry where opportunities are contested and therefore short-lived (Chen *et al.*, 2010a; Hambrick *et al.*, 1996; Hawk *et al.*, 2013; Smith *et al.*, 1991), execution delays increase the risk of preemption by faster competitors (Hawk *et al.*, 2013). Furthermore, the sluggish execution of competitive actions can hamper the release of committed organizational resources to other uses, thus reducing strategic flexibility.

Although existing research acknowledges the existence of time delays in rivalry and recognizes their potential impact on rivals' performance (e.g.,

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Boyd and Bresser, 2008), scholars to date have focused on the immediate or near-term economic consequences of time delays. To extend this line of inquiry, we employ computational modeling—in particular, system dynamics (Sterman, 2001)—to uncover how time delays shape patterns of rivalry and associated performance outcomes over time by affecting firms' learning from previous competitive interactions.

Our model builds upon the literature on reinforcement learning in psychology and management (e.g., Atkins, Wood, and Rutgers, 2002; Diehl and Sterman, 1995; Lam *et al.*, 2011; Lurie and Swaminathan, 2009; Rahmandad, 2008; Rahmandad *et al.*, 2009), which emphasizes actors' tendency to move in the action space in directions that increase the perceived reward. Causal ambiguity impedes but does not completely inhibit managers' ability to attribute changes in performance to their decisions (Lippman and Rumelt, 1982; Mosakowski, 1997). Building on research concerning the psychology of learning (Shanks, Pearson, and Dickinson, 1989; Wasserman and Miller, 1997), we assume that managers use the temporal proximity of their decisions to changes in performance in discerning which decisions are responsible for particular performance outcomes.

The influence of time delays in performance feedback on the lessons that managers derive from their previous decisions has received the attention of numerous management scholars over the past few decades (King, 2007; Moxnes, 1998; Rahmandad, 2008; Rahmandad *et al.*, 2009; Sterman, 1989; Sterman *et al.*, 2007). For example, resource-based scholars have argued that the temporal distance between an investment in capabilities and the associated performance outcomes hinders firms' ability to discern which capabilities underlie the success of high-performing firms. Whereas experience generally reduces causal ambiguity about the drivers of performance (Mosakowski, 1997), time delays can limit the utility of learning from experience. King (2007: 170) proposes that time delays have the potential to foster performance heterogeneity by obstructing managers' capacity to understand what drives the performance of their rivals or of their own firms.

The existing management literature has focused on explaining how time delays in decision-making feedback produce various decision-making pathologies. Empirical and computational evidence suggests that time delays obstruct managers' ability to connect strategic decisions with performance outcomes, potentially leading to behavioral oscillation and suboptimal courses of action (Denrell, Fang, and Levinthal, 2004; Rahmandad, 2008; Rahmandad *et al.*, 2009). In normative terms, these results suggest that managers seeking to enhance their ability to learn from feedback should minimize the temporal distance between their decisions and observed performance outcomes.[1] This could be achieved, for example, by creating appropriate information systems (Eisenhardt, 1989) or by designing organizational structures that ensure rapid information flows (Smith *et al.*, 1991).

We build on these insights to explore how rivalry-specific time delays shape competitive interaction patterns by making it more difficult for managers to identify productive courses of competitive behavior based on performance feedback. We thus extend the competitive dynamics literature, which has not systematically examined the learning implications of time delays in rivalry, as well as the learning literature, which has not considered the implications of delayed feedback in competitive settings.

MODEL DEVELOPMENT

Conceptual overview

Our model (see Figure 1) focuses on dyadic rivalry, which unfolds over time as a series of inter-temporally connected decisions about competitive actions (Ferrier, 2001). Each decision requires a rival to anticipate trade-offs between the expected expenses and sales associated with performing competitive actions. Competitive actions, which are costly to execute, may generate sales by tapping into poorly catered market needs, by targeting current customers to prevent them from switching to competitors' offerings or by targeting rivals' customers. However, managers cannot reliably estimate the performance outcomes of their competitive actions *ex ante*. Competitive actions introduce something novel to the market, which always triggers an element of unpredictability in terms of both customers' responses and the actual

[1] This generalization is not entirely without boundary conditions. Noisy feedback (Lurie and Swaminathan, 2009) and cognitive capacity constraints (Lam *et al.*, 2011) limit the benefits of frequent performance feedback.

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costs required to carry out the action. Thus, the uncertainty surrounding the performance outcomes of a firm's competitive actions is Knightian rather than probabilistic in nature (see, e.g., Mosakowski, 1997: 438).

Consequently, we assume that competitors' learning processes are backward looking, as rivals cannot know "the value of a strategy not yet chosen" (Greve, 2002: 5). Feedback shapes decisions about the future through the mechanism of reinforcement learning. The temporal proximity between a decision and an observable change in performance is used as a cue for causality (Shanks *et al.*, 1989; Sloman, 1996; Wasserman and Miller, 1997). In each decision-making event, which occurs at specific time intervals (Gersick, 1994), a firm evaluates its previous decision and then adjusts its competitive behavior until the next decision-making opportunity occurs. The firm's decision variable is the number of competitive actions to be undertaken over a given time period. This is referred to as *firm-level competitive activity.* For a dyad over a given time period, the *intensity of dyad-level rivalry* refers to the sum of firm-level competitive activity of both rivals (Young *et al.*, 1996).

The effects of competitive actions on performance

We model competition as an ongoing struggle to maintain attractiveness in the eyes of customers rather than as a one-shot positioning game (Hotelling, 1929). Unless a firm continues to invest in costly competitive moves, its attractiveness in the eyes of customers, relative to competitive alternatives, will erode. We build an attraction model to capture these dynamics. This family of models has long been used to model competing firms' market shares (Farris *et al.*, 1998; Nakanishi and Cooper, 1974). In our model, customers are willing to pay for a firm's products or services to the extent that the firm takes actions that maintain or increase the attractiveness of those offerings. The firm's competitive behavior is modeled as a continuous, potentially varying stream of competitive actions, x_i. Customer choice is modeled as a probability that is a function of a firm's decisions to take competitive actions. The more competitive actions a firm takes, the higher the likelihood that customers are attracted to that firm instead of to its competitors. Specifically,

$$P_i = \left(x_i/x_0\right)^{\alpha} / \left[\Sigma_{\mathrm{j}} \left(x_j/x_0\right)^{\alpha} + \left(x_\phi/x_0\right)^{\alpha}\right] \quad (1)$$

Parameter x_ϕ reflects the attractiveness of the none-of-the-above alternative, including the option of saving the money for later use (Lenox, Rockart, and Lewin, 2006), and x_0 is the reference value of attractiveness. Customers' sensitivity to the competitive actions of firms is reflected in α. Equation 1 implies that customers generally prefer to transact with firms that take competitive actions to increase their attractiveness relative to competitors. However, for reasons detailed earlier, customers' responses to changes in the attractiveness of available products and service are delayed. To operationalize these *market reaction lags*, denoted by τ_{m}, we define the firm's market share, MS_i, using a differential equation:

$$\mathrm{d}MS_i/\mathrm{dt} = \left(P_i - MS_i\right)/\tau_{\mathrm{m}} \quad (2)$$

Equation 2 states that a firm's market share approaches a level determined by its level of competitive activity, but this occurs gradually as customers become aware of the attractiveness of the firm's offering and accordingly change their behavior.

Our model assumes that a firm must make up-front investments prior to undertaking any competitive actions. Changes in the firm's level of investment take time to affect the level of competitive activity realized; this *execution delay* of the firm is denoted by τ_{e}. For example, although a decision to launch new products will quickly increase a firm's product development costs, the new products themselves will not be immediately available to customers. The execution delay reflects the time between when the decision is made and when the product is launched. Likewise, if a firm decides to reduce its investment in competitive actions, its up-front spending will decrease, but its competitive activity will not decline immediately; because previous investments in ongoing projects have already been committed, those projects will be completed. To capture these assumptions, the cost of competing depends on the desired (or intended) level of competitive activity, x_i^*. The cost of competitive actions, C_i, is assumed to be constant. Execution delay is modeled using a differential equation. The firm's level of competitive activity, x_i, approaches a level desired by management, x_i^*, where τ_{e} determines the speed of approach. In sum, the level of competitive activity and the consequent profit of firm i, π_i,

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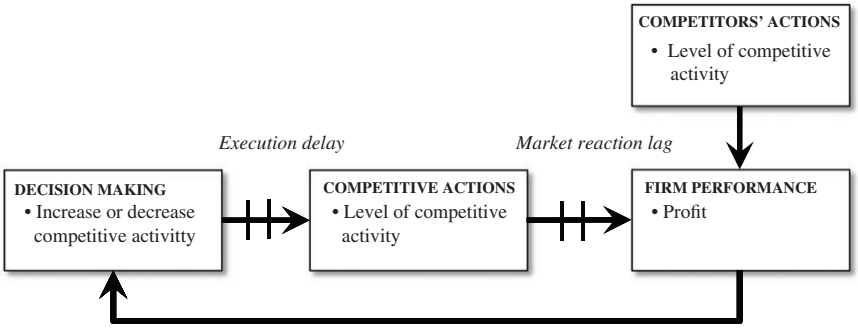

Figure 1. The firm's decision-making process

are given by the following:

$$\mathrm{d}x_i/\mathrm{dt} = \left(x_i^* - x_i\right)/\tau_{\mathrm{e}} \tag{3}$$

$$\pi_i = S \cdot \mathrm{MS_i} - \mathrm{C}_i \cdot x_i^* \tag{4}$$

where the largest possible market size is set at S.

An essential assumption in our model is that the information in Equations 1–4 is not transparent to managers. Instead, consistent with the notions of selective attention and causal ambiguity, managers have an imperfect understanding of what they have decided previously and how those decisions have been reflected in changes in performance. This limited understanding forms the basis for future decisions about competitive actions.

The decision process

The decision process that determines firm-level competitive activity is triggered at predefined time intervals, T. Because decisions take time to affect performance, it is better for a firm to evaluate its decisions after some time has passed rather than to evaluate them immediately. During each round of decision making, a firm performs a "search" to change its competitive behavior. Managers' decisions pertain to the direction of change in their firm's level of competitive activity. The firm may become competitively more active by exploring new opportunities or by capturing market share from rivals ($D_i(t) = 1$). Alternatively, the firm may reduce the use of competitive actions to lower costs ($D_i(t) = -1$). If a firm increases its activity and the firm's sales revenues increase more than the costs of increased competitive activity, then competitive activity is more likely to increase in the future. Similarly, if the firm decreases competitive activity and the cost savings exceed the lost revenues, then further reductions in competitive activity become more likely.

More formally, the propensity of a firm to increase (decrease) its competitive activity, $\mathrm{P}[D_i(t) = 1]$ $(=1 - \mathrm{P}[D_i(t) = -1])$ and the desired level of competitive activity are updated when $t = T$, $t = 2\,T$, *etc.,* in the following manner:[2]

$$\mathrm{P}\left[D_S^i(t) = 1\right] = w \cdot \mathrm{P}\left[D_i(t - T) = 1\right] + (1 - w) \cdot \left(FB_i + 1\right)/2 \tag{5a}$$

$$x_i^*(t + h) = x_i^*(t + h - T) + L_i(t) \cdot D_i(t) \tag{5b}$$

The magnitude of the change in competitive activity, $L_i(t)$, is drawn from a Poisson distribution with a mean of one. The stochastic component in the determination of the search step length accounts for idiosyncratic firm-specific situational factors that influence the scope of the search.[3] The shape of the Poisson distribution captures our assumption that small changes in competitive activity are more likely to occur than large changes. The extent of

[2] The precise sequence of events is that the firm first evaluates its previous decision (Equation 5a) and then changes its behavior in light of this information (Equation 5b). The time difference between these events is very small, h. (Simultaneous updating of beliefs $\mathrm{P}[D_i(t) = 1]$ (Equation 5a) and behavior $x_i^*(t)$ would cause a simultaneity problem.) We let $h = 0.5$, which is also the time step of our numerical integration algorithm.

[3] A fixed step size, the alternative assumption, would require a very strong assumption that firms' search behavior is entirely determined by external factors. The assumption of a fixed step size also leads to unrealistic model behavior. For example, when w is zero, a fixed step size induces firms to change their competitive behavior in perfect synchrony, which generates a "cooperation solution"; that is, an intensity of competition that maximizes the dyad's aggregate profits, which is an unlikely and unstable outcome in practice.

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a firm's reliance on historical vs. current feedback in determining the firm's search direction is captured by a weight parameter, w. We tested multiple values of the parameter between zero and one. These experiments did not alter our theoretical conclusions about how time delays influence learning. Thus, we report the results obtained with a representative value ($w = 0.75$). Feedback on the appropriate search direction, FB_i, is defined as follows:

$$FB_i = \text{sign}\left\{\left[\pi_i(t) - \pi_i(t-T)\right]\cdot\left[x_i^*(t) - x_i^*(t-T)\right]\right\} \quad (6)$$

The function sign $\{\cdot\}$ equals one (minus one) if the expression is greater (less) than zero. If the level of competitive activity or profit has not changed, the model assumes that a firm's propensity to increase its competitive activity will approach indifference (i.e., $FB_i = 0$).

Equilibrium analysis

We first calculate an analytical solution as a benchmark for our simulation analyses by assuming two rational profit-maximizing firms. Our assumptions about rationality are familiar to (neoclassical) economists: a firm perfectly understands demand and customer behavior, knows the costs of its own competitive actions and those of its rival firm, aims to maximize its profits, and assumes that its rival does the same. For simplicity, we also assume that there are no delays in the system, and we assume, as in the simulations that follow, that $\alpha = 1$. Under these assumptions, the profit of firm i is simply the following:

$$\pi_i = S\cdot x_i/\left(\Sigma_j x_j + x_\phi\right) - C_i\cdot x_i \quad (7)$$

The Nash equilibrium level of competitive activity is derived by finding the x_i in a system of equations where the partial derivatives of Equation 7 are set to zero, that is, $\partial\pi_i/\partial x_i = 0$ for $i = \{1,2\}$. We use *Mathematica* to perform the symbolic computation. The system of equations has two solutions, one of which is positive (competitive activity cannot be negative). Thus, the resulting equilibrium level of competitive activity for firm i is the following:

$$x_i^{NE} = \left\{-2C_i^2\cdot x_\phi + C_j\cdot\sqrt{S}\cdot\sqrt{\left[\left(4x_\phi\cdot\left(C_i + C_j\right) + S\right)\right]} - 2C_i\cdot C_j\cdot x_\phi + C_j\cdot S\right\} / 2\left(C_i + C_j\right)^2 \quad (8)$$

The equilibrium solution (Equation 8) is derived without time delays, but it is also the (Nash) equilibrium solution for the system with time delays. Consider that firms optimize their levels of competitive activity with respect to the profits obtained in a steady state. Steady-state profits are not affected by time delays (Equations 1–4). Hence, the optimal level of competitive activity does not change with the time delays in the model. We assume that rational actors can perfectly predict how current decisions affect future performance; because full information is already available, there is no learning over time. Thus, rational profit-maximizing firms will always choose x_i^{NE} (Equation 8), regardless of the time delays. We ensure that a firm's optimal policy does not change even when we manipulate the time delays in the model by holding all parameters in Equation 8 equal across simulations.

Design of simulation experiments

Our experimental design ensures that profitability differences both across and within simulated industries have purely "behavioral" origins. To achieve this goal, we assume that the industry is "objectively" the same in all simulations. The industry parameters are fixed across simulations; therefore, if competitors were rational, all simulations should produce identical levels of competitive intensity and industry profits. Similarly, we assume no resource heterogeneity between rivals by designating equal action costs across firms (i.e., $C_i = C_j$). In this situation, two rational rivals would choose the same level of competitive activity and obtain identical levels of performance.

While the firms' optimal policy, x_i^{NE}, is the same across simulations and firms, time lags affect the feedback that managers receive, which influences what managers *perceive to be* the reasonable course of action. For example, managers do not know how quickly additional R&D inputs will increase the output of marketable products (execution delay), nor can they be certain how quickly customers will react to an advertising campaign (market reaction lag). Prior literature suggests that firms have limited knowledge of time delays and short-termism prevails (Aspara *et al.*, 2014). To operationalize these assumptions, the delay parameter ranges are set to ensure that the upper values of delays are long relative to the decision-making frequency. Specifically, firms follow a decision-making cycle of five time periods, and time delays are assumed to vary

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between 0 and 10 periods. When feedback is immediate, the following modified equations apply:

$$\textit{Market reaction lag} = 0 \Rightarrow MS_i(t) = P_i(\mathrm{t}) \quad (2')$$

$$\textit{Execution delay} = 0 \Rightarrow x_i(\mathrm{t}) = x_i^*(\mathrm{t}) \quad (3')$$

Otherwise, the model is run according to Equations 1–6. To investigate whether the implications of time delays depend on the fact that we model dyadic rivalry in particular and not merely decision making in general, we compare the results for the dyadic simulations with simulation results obtained for an "independent firm." An independent firm performs a search in a competitive environment in which the rival firm does not change its behavior. Independent firm simulations represent the firm-centric assumption, commonly made in the behavioral strategy literature, that a focal firm's strategy and performance can be modeled in isolation from its rivals' strategies (e.g., Katila and Chen, 2008).[4]

The model's payoff structure resembles a Prisoner's Dilemma. Specifically, the Nash equilibrium is calibrated at 24 actions per firm per time period, with $S = 100$, $x_\phi = 12$, $C_i = 1$ and $\alpha = 1$. With this parameter configuration, the dyad's aggregated profits (Equations 1 and 4) would be maximized if both firms reduced their levels of competitive activity to 11.3 actions per firm per time period. Beyond this point, further reductions in the intensity of rivalry do not improve competing firms' performance because the outside-dyad competitive pressure ($x_\phi > 0$) causes rivals' sales to decrease if they employ competitive actions very infrequently. The model is run for 1,000 time periods. The model parameters and the values used in the reported simulations are summarized in Table 1. We measure the firms' behavior and performance at the end of each simulation run. Using end-of-simulation values (after a long simulation run) ensures that any transient dynamics caused by the initial conditions do not affect the results. Moreover, end-of-simulation values capture the full range of behavioral outcomes caused by the model, which would be suppressed if we calculated only within-simulation averages or sums.[5]

RESULTS

In the base case, we assume that (1) the firm is not affected by the decisions of a rival (*independent* firm) and that (2) there are no time delays in performance feedback. Under these simplified conditions, the assumed behavioral rules governing firms' decision making lead to behavior that resembles the behavior of an economically rational actor. We then relax the simplifying assumptions by allowing both competitive *interdependence* and time delays to influence learning from feedback. The ensuing simulations reveal systematic departures from what we would expect from a rational, profit-maximizing firm. We first show how the assumption of competitive interdependence affects firms' learning from feedback. Second, we examine how time delays affect the learning of an independent firm. Finally, we consider the interactive effects of these two mechanisms.

Learning dynamics

Competitive interdependence and learning

Figure 2 illustrates that competitive interdependence obstructs learning from feedback, which leads to performance heterogeneity. Two simulations are shown. A baseline model is first run with the independent firm assumption. This is operationalized by assuming the rival firm's competitive activity to be a constant at 24 actions per time period. When no rival obstructs the focal firm's learning from feedback, the focal firm's level of activity displays modest oscillation surrounding the optimal policy (i.e., 24 actions per time period), and the oscillation of performance is nearly indistinguishable from the performance obtained from the equilibrium analysis above. In other words, the independent firm's behavior and performance are reasonable approximations of the behavior and performance of a rational profit-maximizing firm. With this established, the model is then run with an assumption of dyadic rivalry. The rival firm

[4] This assumption may indeed be reasonable, for example, not only in monopolies but also in fragmented or emerging industries where the focal firm's performance is not substantially affected by any single rival's decision making. In contrast, dyadic simulations correspond to oligopolistic industries where the performance of one firm significantly depends on the competitive actions of rivals.

[5] Vensim DSS for Windows Version 6.1c Double Precision was used to run the model.

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Table 1. Summary of model parameters

Parameter	Default	Description
Rewards and costs of competitive actions		
x_ϕ	12	Attractiveness of the none-of-the-above option (action/period)
x_0	10	Reference value of attractiveness (action/period)
α	1	Sensitivity of customers to the firm's competitive actions
C_i	1	Unit cost of competitive actions (€/action)
S	100	Total market size (€/period)
$x_i^*(0)$	24	The firms' initial levels of competitive activity (action/period)
Decision making about competitive actions		
w	0.75	Weight parameter that determines the extent of a firm's reliance on historical vs. current feedback
$E[L_i(t)]$	1	Mean search step size (action/period)
$P[D_i(0) = 1]$	0.5	Propensity to increase competitive activity at the start of the simulation
T	5	Decision-making time interval (period)
Time delay		
τ_m	$\{0, 1, \ldots, 10\}$	Market reaction lag (period)
τ_e	$\{0, 1, \ldots, 10\}$	Execution delay (period)
Simulation control		
Final time	1,000	Length of the simulation (period)

is allowed to change its initial level of competitive activity (24) according to the same behavioral rules that govern the focal firm's decision making. In contrast to the independent firm simulation, the interaction between rivals' learning processes generates large and relatively enduring differences in firm-level competitive activity between firms, which result in significant performance differences.

There are two mechanisms by which interdependence between rivals affects their learning from feedback. First, a rival firm's level of competitive activity affects the focal firm's payoff landscape. The focal firm's optimal level of activity first increases and then decreases with the rival firm's level of activity. Initially, as the rival firm increases its competitive activity, the focal firm's optimal level of competitive activity increases. The intuition is that the focal firm must initially take more competitive actions to mitigate the erosion of profits as a result of lost sales revenues (Derfus *et al.*, 2008). As the rival firm further increases its competitive activity, maintaining sales becomes increasingly costly, which then deters the focal firm from investing in competitive actions (Ferrier, Smith, and Grimm, 1999).

Second, concurrent changes in rivals' levels of competitive activity confound efforts to learn from feedback. During any given decision event, an increase in a rival firm's competitive activity exerts downward pressure on the focal firm's performance. As a result, the focal firm is more likely to experience a performance decline, regardless of the focal firm's decision. For example, if the focal firm decides to increase activity, the advantages of its sales growth will be neutralized by the rival's concurrent increase in competitive activity and will therefore be unlikely to offset the costs incurred by additional investments in competitive actions. Alternatively, a rival's increased activity will exacerbate the diminishing sales that result from a focal firm's simultaneous decision to decrease activity, thus making revenue losses more likely to outstrip cost savings. Similar learning challenges arise when a rival firm decreases its competitive activity.

Time delays and learning

Time delays increase the difficulty of learning from feedback, leading to systematic departures from the optimal level of investment in competitive actions and to large differences between simulation runs. As shown in Figure 3, an independent firm's behavior is relatively close to the optimal policy (i.e., the Nash equilibrium) when feedback is prompt. However, if decisions about competitive actions and their observable performance outcomes are not close to one another in time, then the firm deviates systematically from the optimal policy. Specifically, time delays cause an independent firm's level of activity to be both (1) lower on average and (2) more varied

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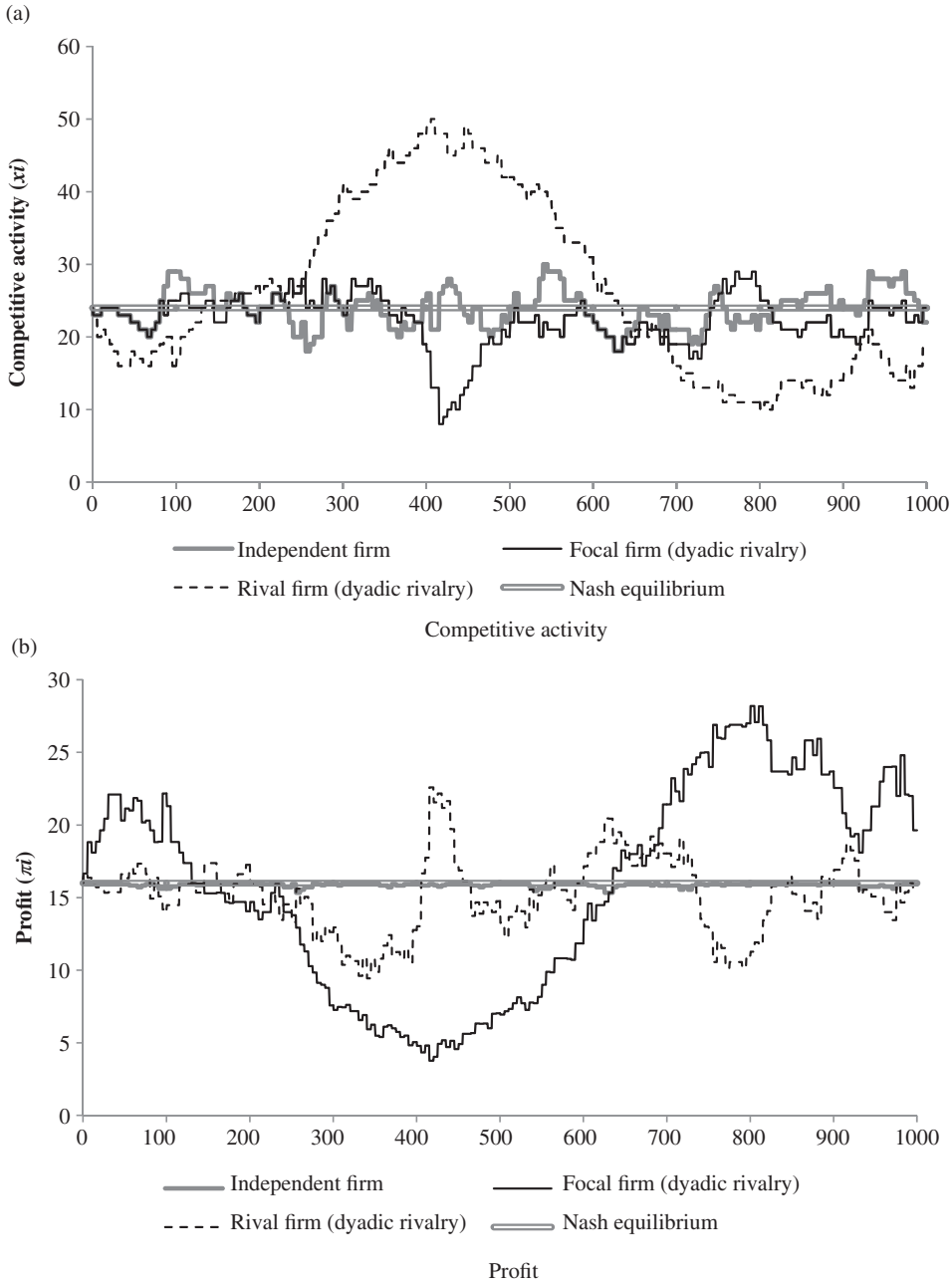

Figure 2. Independent firm vs. dyadic rivalry. (a) Competitive activity and (b) profit

over time. These patterns are consistent with earlier research and the intuition that time lags hinder the ability of a firm's managers to reliably make associations between decisions about competitive actions and performance outcomes, leading to oscillating and suboptimal behavior (e.g., Denrell *et al.*, 2004; Rahmandad *et al.*, 2009). Figure 3 demonstrates the consequences of time delays by showing the effect of selected time-delay configurations on an independent firm's behavior.

Time delays affect learning from feedback in two ways, both of which reduce an independent firm's average level of competitive activity. First, time delays can cause decision makers to make premature, erroneous conclusions that investments in competitive actions are mistakes. Because we assume that the costs of competitive actions generally materialize before the rewards do, a decision to increase competitive activity results in a transient decline in performance. Consequently, firms

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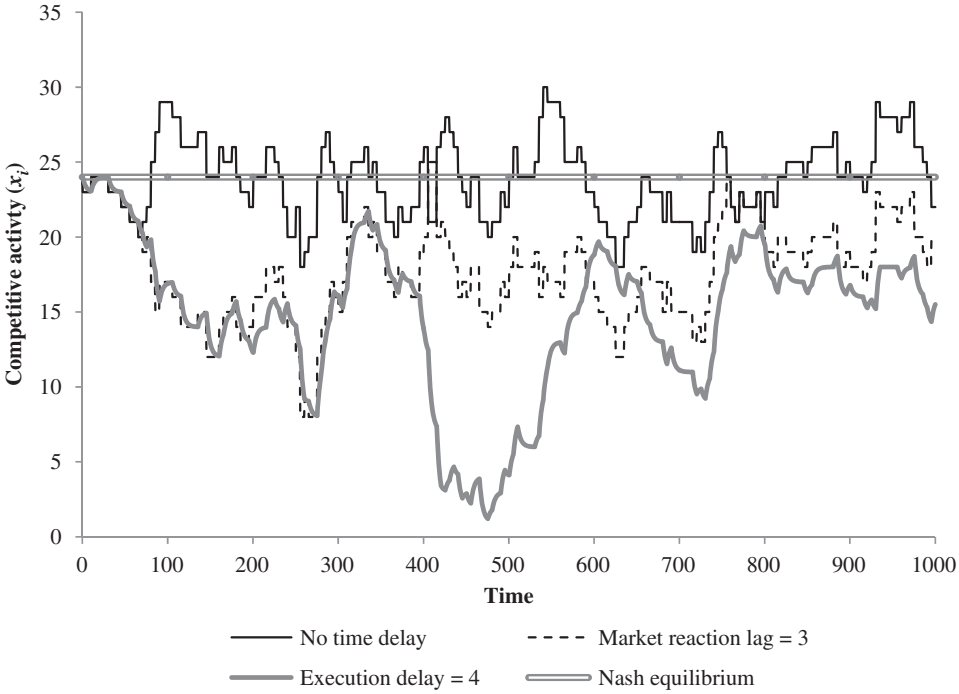

Figure 3. Independent firm's behavior with selected time-delay configurations

are more likely to reverse investment decisions that would in fact improve performance in the long term. Second, time delays increase a firm's tendency to repeat decisions to reduce spending on competitive actions. Reducing spending on competitive actions lowers costs immediately, whereas the decline in sales is not observed until after a delay. Consequently, with time delays, a firm is less likely to recognize that reduced spending on competitive actions is causing it to lose competitiveness.

In addition to the effects on a firm's average level of competitive activity, time delays lead to oscillation in competitive behavior because the effects of previous decisions carry over to influence feedback for subsequent decision-making rounds. This learning challenge has been called "temporal complexity" (Rahmandad, 2008). Because decisions to take action materialize after an execution delay and because the performance effects of actions are realized over multiple time periods, current levels of performance are the result of decisions made over multiple decision-making rounds. Thus, time delays introduce the challenge of discerning the effect of earlier decisions from the performance effects of the decisions made more recently, and this challenge increases the variation in firm-level competitive activity.

Time delays and performance

The competitive dynamics and learning streams of literature emphasize the negative effect of time delays on firm performance (e.g., Chen *et al.*, 2010a; Ferrier, 2001; Rahmandad, 2008; Rahmandad *et al.*, 2009; Sterman *et al.*, 2007). Although our model is capable of producing this result, the model also reveals additional, previously unnoted insights about how time delays influence firm performance. In particular, time delays can reduce the intensity of industry competition and thus have a positive effect on firm profits.

In general, when a firm's performance feedback is delayed, it tends to underinvest in competitive actions relative to the available profitable market opportunities. The implications for performance, however, depend critically on our assumptions regarding competition and time delays. Time delays always reduce firm performance in the independent firm condition, which assumes that firm performance is not affected by a competitor's decisions. However, in contrast to established wisdom about the detrimental effect of time delays on performance (e.g., Rahmandad *et al.*, 2009), industry-wide time delays *enhance* firm and industry performance in simulations with two interdependent rivals. Figure 4 illustrates these findings for

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both conditions by showing a focal firm's average level of competitive activity and profits calculated over 5,000 end-of-simulation values ($t = 1{,}000$).

The shape of the profit curve for interdependent rivalry is markedly different from the curve obtained by assuming an independent firm because time delays cause market opportunities to become less contested (cf., Lenox *et al.*, 2010: 123). Although firms explore fewer opportunities, as in the independent firm scenario, firms also engage less in head-to-head competition, which increases the profits that accrue in the industry. Therefore, as long as time delays are industry-wide, both competitors benefit. As delays grow very long, however, the positive performance effect eventually diminishes because customers have a none-of-the-above alternative (i.e., $x_\phi > 0$) that they can choose if industry players invest minimally in competitive actions.

An examination of firm-specific time delays further clarifies our main results for time delays and performance. Figure 5 depicts the impact of the focal firm's execution delays on the firm's performance relative to its interdependent rival (Figure 5(a)) and the dyad's aggregated profits (Figure 5(b)). Each line represents different levels of the rival firm's execution delay, ranging from 0 (light grey) to 10 (black) in increments of two. Consistent with prior literature, the results demonstrate that slow competitors perform worse than their fast counterparts (Chen *et al.*, 2010a). However, a previously unrecognized nuance also emerges. Firm-specific time delays have a positive effect on industry-level profits, up to a point, in line with the results concerning industry-wide time delays (see Figure 4). The turning point in profits is reached sooner if the rival firm's execution delay or the attractiveness of the none-of-the-above alternative, x_ϕ, is large.

Note that execution delays are harmful—not because they decelerate cash flows or increase the hazard of preemption (Hawk *et al.*, 2013; Pacheco-de-Almeida, Hawk, and Yeung, 2015) but through the mechanism of reinforcement learning—as these delays lead to suboptimal levels of investment in competitive actions. Time delays in decision-making feedback can complicate learning in ways that make it more difficult for decision makers to ascertain how choices are related to outcomes (Moxnes, 1998; Sterman, 1989, 2001). In particular, because firms must make up-front commitments to competitive actions, execution delays cause managers to underestimate systematically the potential gains from investing in competitive actions, thereby decreasing managers' motivation to invest. As a result, a firm underutilizes available market opportunities. However, the same mechanism causes industry profits to increase. As a focal firm invests less in competitive actions that attract the rival's customers, competition deintensifies. The resulting increase in the rival firm's performance tends to be larger than the focal firm's performance loss, until the delays grow very large.

Time delays and performance heterogeneity

Because performance feedback does not unambiguously direct firms toward a decision, time delays in performance feedback may foster heterogeneity in managers' choices and in firms' performance (e.g., King, 2007; Rahmandad, 2008; Rahmandad *et al.*, 2009). We contextualize this general assertion in interfirm rivalry by specifying the mechanism through which rivalry-related time delays create heterogeneity (Harris, Johnson, and Souder, 2013).

Figure 6 illustrates how industry-wide changes in time delays (market reaction lag) affect the heterogeneity produced by the process of competitive interaction. For each value of the time delay parameter, we calculate the average difference between rivals in terms of competitive activity and profits over 5,000 end-of-simulation values. For benchmarking purposes, we also calculate these indices by randomly pairing 10,000 independent firm simulations (i.e., we analyze 5,000 pairs of independent firms). The results show that time delays contribute to heterogeneity in competitive activity, both across paired independent firms and between direct rivals. The effect of time delays on performance heterogeneity is even larger because time delays deintensify competition, which amplifies the performance difference produced by a given disparity between two firms' levels of activity.

Although the pattern of results is similar regardless of our assumption about competitive interdependence vs. independence, there is an important difference in the mechanism that produces the results. For independent firms, heterogeneity emerges simply because time delays increase firm-level oscillation in competitive activity and profits. A large firm-level oscillation implies that, at any given point in time, two randomly paired

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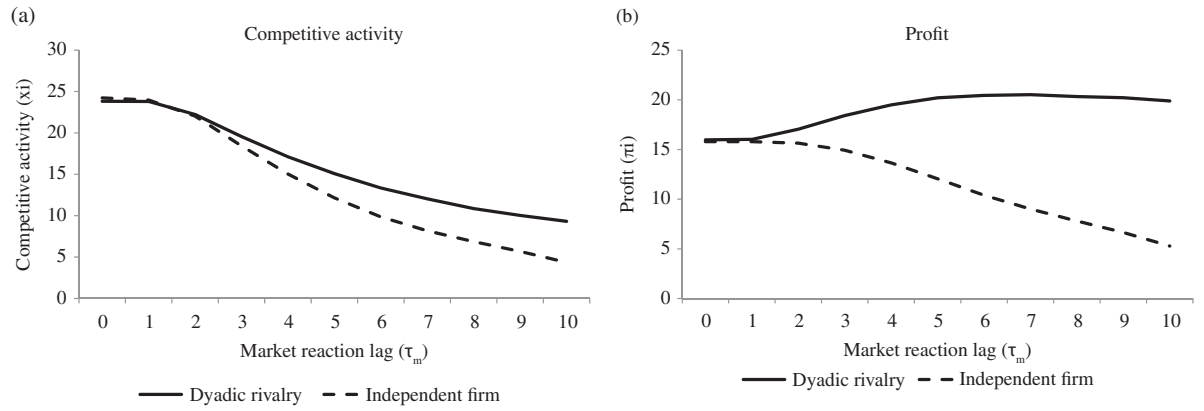

Figure 4. The effect of industry-wide time delays (market reaction lag) on the focal firm's (a) competitive activity and (b) profit

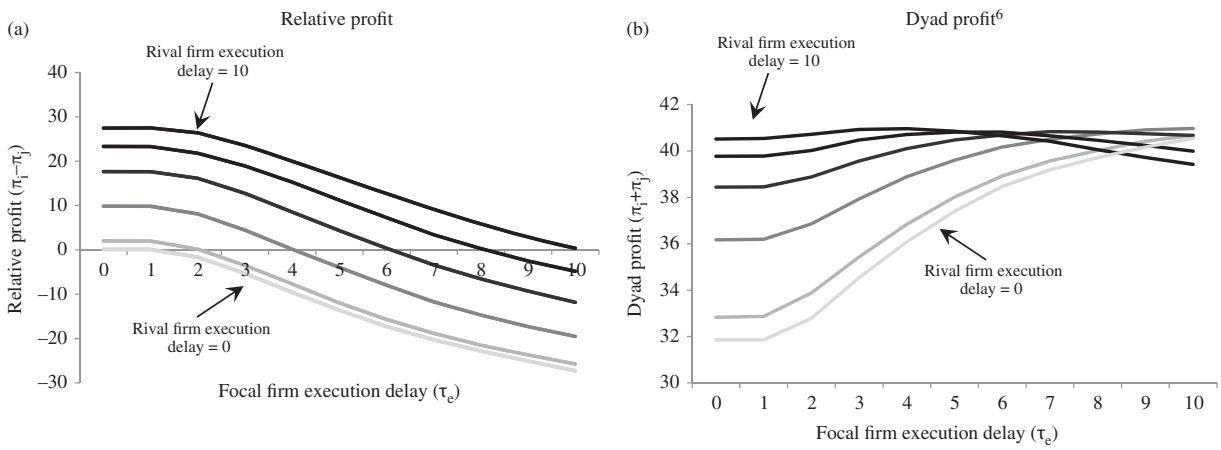

Figure 5. The effect of firm-specific time delays (execution delay) on (a) the focal firm's profit relative to its rival and (b) the dyad's total profit[a]

[a] Note that the x-axis crosses the y-axis at 30.

firms are unlikely to behave and perform similarly. This implication is consistent with how the existing literature has linked time delays to heterogeneity (e.g., Rahmandad, 2008; Rahmandad *et al.*, 2009). In contrast, the primary mechanism through which time delays foster heterogeneity in a rivalrous setting is that industry-wide time delays amplify small differences in rivals' decision making, causing interdependent rivals to follow divergent behavioral trajectories and consequently experience differential levels of performance.

This pattern is illustrated in Figure 7, which shows the correlation between (direct) rivals' levels of competitive activity and profits over 5,000 end-of-simulation values. The results show that increases in market reaction lags are associated with increasingly negative correlations between competitors' levels of competitive activity and profits. In other words, time delays cause rivals' behavioral and performance trajectories to diverge.

The following stylized scenario illustrates the logic underlying this pattern. Consider a decision point (A) for two equally active rivals. The focal firm increases competitive activity, and its rival decides to decrease its level of competitive activity. As a result, the focal firm will generally experience a performance increase, and the rival's performance will probably decline. This feedback encourages both firms to increase competitive activity in the subsequent decision-making round (B). However, time delays cause the performance effects of the firms' decisions to carry over to subsequent rounds (i.e., B, C). The focal firm's increased investment in round A will continue to increase that firm's

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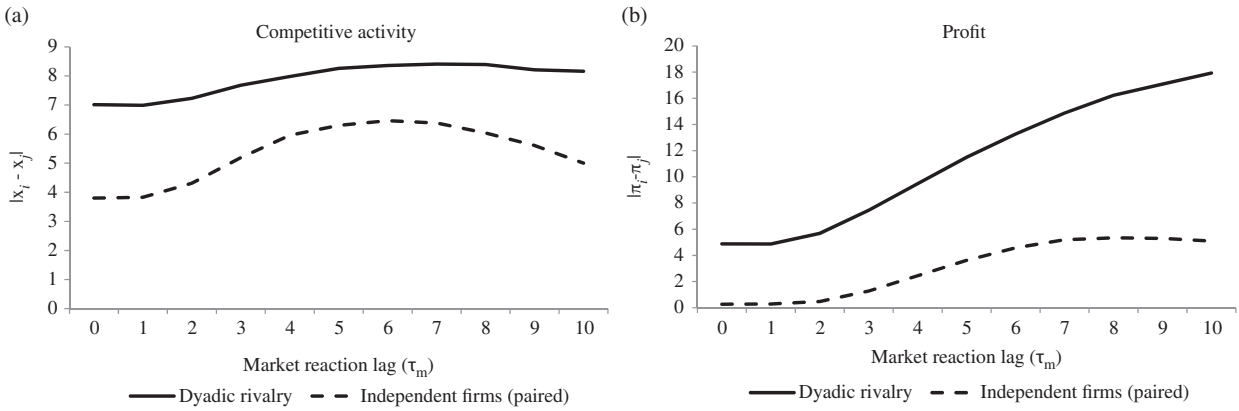

Figure 6. The contribution of industry-wide time delays (market reaction lag) to heterogeneity in competitive behavior and performance. (a) Competitive activity and (b) profit

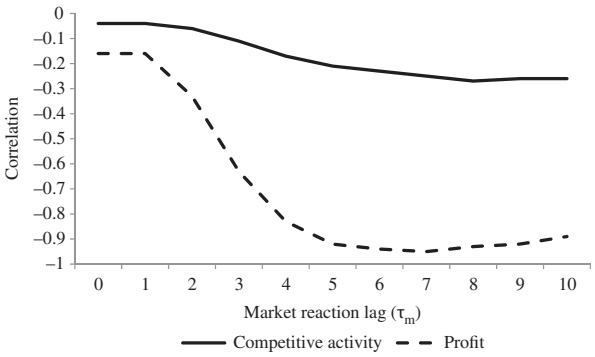

Figure 7. Effect of industry-wide time delays (market reaction lag) on the divergence of rivals' behavior and performance

performance, and the rival's performance will continue to decline. Similarly, the rival's decision to reduce costs in round A will continue to affect that firm's sales negatively while increasing the focal firm's performance. Therefore, while both firms increase their competitive activity in round B, they are likely to experience qualitatively different performance effects. The focal firm, encouraged by positive performance feedback, will be more likely to increase competitive activity in round C, whereas the rival firm, discouraged by negative performance feedback, will be more likely to reduce costs again. In this way, the behavioral trajectories of the rivals tend to diverge, resulting in performance heterogeneity between rivals.

The emerging differences in the firms' levels of competitive activity do not relate to *ex ante* differences in known, competitor-specific drivers of competitive aggressiveness (e.g., Chen *et al.*, 2010a; Ferrier, 2001). Heterogeneity emerges because the time delays amplify small differences in the earlier decisions of competitors. Essentially, heterogeneity emerges endogenously from the "history" of competition, as time delays amplify the amount of heterogeneity that history produces.

Robustness analysis

We performed extensive robustness tests to gauge the boundary conditions of our results, running the model 500 times per time delay parameter value (and more, if needed) for every alternative model specification (see Table 2). First, holding other parameters at their default values, we identified a theoretically meaningful lower and upper boundary for parameters affecting the costs and rewards of competitive actions, that is, S, x_ϕ, C_i and α (parameter x_0 was set at 10). For example, a natural lower boundary for the cost of competitive actions, C_i is zero. The upper boundary of C_i is such that the x_i^{NE} is zero actions per firm per time period. A similar procedure yielded the lower and upper bounds on α and x_ϕ. We reran the analyses at several points between the extreme values. For the market-size parameter S, we simply reran the analyses with a market size much larger than the default value.

We found the positive performance impact of industry-wide time delays to diminish with large values of C_i and x_ϕ and with small values of α and S. The logic here is that if circumstances encourage low levels of competitive activity relative to the attractiveness of the none-of-the-above alternative, then time delays cause customers—through firms' reduced competitive activity—to be attracted to that option, causing the decline in competing firms'

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Table 2. Summary of robustness analyses

Parameter or variable	Boundaries	Tested values	Robust range[a]	Observations
Rewards and costs of competitive actions[b]				
x_ϕ	Min = 0 Max = 100[c]	{0.001, 0.01, 1, 12, 24, 50, 90, 100}	{0.001, 0.01, 1, 12, 24, 50}	All results are robust for sufficiently low values. However, combinations of a large x_ϕ (e.g., 50) and a long rival firm execution delay (e.g., $\tau_e = 5$) causes increases in the focal firm's execution delays to affect industry-level profits negatively
α	Min = 0 Max = 1.937[d]	{0.1, 0.3, 0.5, 0.7, 1, 1.5, 1.7, 1.9}	{0.7, 1, 1.5, 1.7, 1.9}	All results are robust for sufficiently high values
C_i	Min = 0 Max = 8.33[c]	{0.05, 0.1, 0.25, 0.5, 1, 1.5, 2, 3, 4, 5, 6, 7, 8}	{0.05, 0.1, 0.25, 0.5, 1, 1.5}	All results are robust for sufficiently low values
S	Min = 12[c] Max = N/A	{12.5, 13, 15, 20, 30, 40, 50, 60, 70, 80, 90, 100, 1,000}	{60, 70, 80, 90, 100, 1,000}	All results are robust for sufficiently high values
Decision making about competitive actions				
w	Min = 0 Max = 1	{0.0, 0.1, … , 0.9}	{0.0, 0.1, … , 0.9}	All results are robust within the tested range of parameter values
$L(t)$	—	{Poisson(1), Poisson(3), Poisson(5), Beta(0.5,0.5), Beta(1,3), Beta(2,2), Beta(2,5), Beta(5,1), Unif(1), Unif(3)}	{Poisson(1), Beta(0.5,0.5), Beta(1,3), Beta(2,2), Beta(2,5), Unif(1)}	All results are robust within the tested range of distributions that are skewed to the left (including a uniform distribution) if the average step size is sufficiently small
Simulation control				
Final time		{1,000, 2,500, 5,000, 10,000}	{1,000, 2,500, 5,000, 10,000}	All results are robust within the tested range of parameter values

[a] Robust range refers to the set of model specifications where all of the paper's results remain qualitatively unaltered unless specified otherwise in the table. Besides changing the model parameters, we also tested alternative operationalizations of industry-wide and firm-specific time delays. Industry-wide time delays were modeled using market reaction lags as well as industry-wide symmetrical and asymmetrical execution delays. Firm-specific time delays were modeled using symmetrical and asymmetrical execution delays. In the robust range, all results hold using all tested operationalizations of the time delays. The robust range for individual results can be broader.
[b] The firms' initial levels of competitive activity, x_0, were set at the Nash equilibrium values in all robustness analyses.
[c] Calculated analytically using *Mathematica*: finding parameter values for which Nash equilibrium is 0.
[d] Calculated numerically. On each step, the firms take turns to maximize their profit with respect to the current position of the rival. Implemented using scipy/fminbound algorithm in *Python*. As α increases, firms' profits in the Nash equilibrium decrease, eventually reaching 0.

profits. Thus, our claims about the positive performance impact of industry-wide time delays are valid as long as competition occurs among incumbents rather than with entrants or substitutes (and as long as time delays are not extremely large relative to the decision-making interval, T). These assumptions hold especially in mature, oligopolistic industries. Similarly, the contribution of time delays to interfirm (performance) heterogeneity diminishes if the model parameters encourage low levels of competitive activity. Because zero actions per time period represent a lower boundary for firms' levels of competitive activity, there is no "room" for the firm-level variance of competitive activity to

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increase. This limits the amount of inter-rival (performance) heterogeneity produced by time delays.

Second, we tested different assumptions about firms' decision-making behavior. In particular, we changed the average magnitude of the changes in firms' levels of competitive activity as well as the shape of the distribution of L_i. The results were similar for all of the tested left-skewed distributions of L_i (i.e., when incremental changes in competitive activity are assumed to be more likely than drastic changes). More important, we found that the effect of time delays on inter-rival (performance) heterogeneity is diminished by large average values of L_i. The logic behind this result is similar to that identified in the context of parameters impacting the rewards and costs of competitive actions. If the magnitude of changes in firms' levels of competitive activity is large, there is little additional room for firm-level variance in competitive behavior and, consequently, little room for inter-rival (performance) heterogeneity to increase. Theoretically, the findings imply that the model predictions are most relevant in contexts where firms take numerous competitive actions in each time period and adjust their competitive behaviors incrementally in view of their experience. We also varied the firms' reliance on historical vs. recent performance feedback across the full theoretically meaningful range (i.e., $0 \leq w < 1$). We found that smaller (larger) values of w tend to increase (decrease) the amount of heterogeneity produced by time delays. Reliance on historical feedback reinforces path dependency, which increases the amount of heterogeneity created in the absence of time delays. This effect in turn reduces how much additional heterogeneity is produced by time delays. Finally, we examined an alternative, asymmetrical operationalization of the execution delay (Equation 3) in which decreases in competitive activity take effect instantaneously. Because asymmetrical execution delays cause only feedback about increases in competitive activity to be delayed, asymmetrical execution delays influence the model dynamics less than execution delays with a symmetrical form; however, the qualitative conclusions remain the same.

DISCUSSION

Our study examines time delays as an antecedent of industry profitability and performance heterogeneity among rivals. To this end, we develop a computational model that is built around the notion that rivalrous relationships evolve over time through repeated encounters (Kilduff *et al.*, 2010). Our computational experiments examine how time delays—in rivals' implementation of, or market responses to, competitive actions—influence learning and thereby patterns of rivalry and firm performance. Scholars in the field of competitive dynamics and learning usually assert that time delays diminish a firm's performance and that competitive speed and prompt feedback are desirable. Although our model is capable of reproducing these results, the model also highlights previously unrecognized implications and boundary conditions on these claims.

First, our study finds that a firm that is slow to implement competitive actions tends to be outperformed by its faster rival. Although this result is unlikely to surprise the reader, the mechanism is less known in the competitive dynamics literature. Our results emphasize that certain benefits of speed materialize over time through learning, which is distinct from more widely recognized benefits of speed such as minimizing the risk of preemption (Hawk *et al.*, 2013) and reducing the competitor's ability to build protective fences against attacks (Boyd and Bresser, 2008). We find that a firm's quicker competitive maneuvering may enhance its relative performance by enabling superior learning from more accurate performance feedback, leading to more optimal utilization of market opportunities.

Second, we consider the industry-wide performance implications of a focal firm's execution delays. According to our results, execution delays that are specific to one competitor can have a net positive effect on industry profits. An alternative reading of this result is that a focal firm's efforts to increase performance, through greater execution speed, triggers an even greater downfall in its rival firm's performance, resulting in a net negative effect on industry attractiveness. Prompt feedback, implied by brief execution delays, causes a firm to perceive greater profit in engaging in direct competition with its rival. This implies that competitors' parallel investments in competitive maneuvering capabilities are a negative-sum game, leading to increasing levels of competitive intensity and declining profits.

More generally, industry-wide time delays (i.e., time delays that concern *all rivals*) result in *higher* industry profits. Industry-wide time delays affect learning in ways that act as a barrier to escalating profit-destroying competition. This effect enhances

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the performance of competing firms as rivals compete less aggressively for the same market opportunities. This result stands in stark contrast to the existing literature on time delays in feedback-based learning, where the opposite performance effect is usually predicted (Denrell *et al.*, 2004). However, the results differ simply because previous studies have not incorporated competitive interdependence into their analyses of the performance effect of time delays. In essence, we conceptualize time delays as an impediment to direct competition among incumbents that may increase their profits and the industry's attractiveness.

Third, our paper offers insights into how time delays foster performance heterogeneity in rivalry among *ex ante* identical firms. Our findings are consistent with the existing learning literature indicating that time delays increase the difficulty of linking competitive actions to performance outcomes (Rahmandad, 2008). As a result, time delays lead to oscillation in an independent firm's level of competitive activity. In the context of two interdependent rivals, the mechanism producing heterogeneity is somewhat different. Time delays foster divergence in competitors' behavioral patterns. Time delays amplify small inter-rival differences in decision making about competitive actions, leading one firm to invest aggressively as its rival remains competitively inactive. Thus, we reveal previously unspecified complexity in how time delays may be related to performance heterogeneity. By doing so, we establish the construct more firmly alongside other behavioral explanations of heterogeneity (e.g., Camerer and Lovallo, 1999; Lenox *et al.*, 2006). These results also contribute to the competitive dynamics literature, as we demonstrate that the factors that influence competitors' learning from previous encounters (e.g., time delays) may shape the amount of interfirm heterogeneity that competition endogenously produces.

Beyond exploring the role of time in rivalry through a learning perspective, our study addresses a more general research gap noted by Chen and Miller (2012), as we explore how the interdependence of competitors' actions and responses gives rise to subsequent competitive behaviors (*ibid.*: 173). Specifically, the study explains how "longer-term patterns of interfirm rivalry" (Marcel *et al.*, 2010: 131) can emerge from inter-temporally connected decisions about competitive actions. This undertaking required an examination of how learning from previous decisions and their outcomes affect subsequent decisions about competitive actions. The interlinking of decisions over time renders competition a path-dependent phenomenon. The range of potential outcomes of such a process is difficult to predict using intuition and verbal reasoning (Sastry, 1997), which is why we employed computational modeling. In doing so, we point to a new methodological direction for competitive dynamics research, which has relied primarily on verbal reasoning and large competitive action datasets to develop and test theories (Chen and Miller, 2012).

Directions for future research

Our findings lead to several new directions for strategic management researchers to pursue. One fruitful direction for future research is to examine empirically the relationship among industry-wide time delays, the intensity of rivalry, and incumbents' profits. An obvious hypothesis emerging from our findings is that time delays could predict profitability differences across industries (cf., Lenox *et al.*, 2010). It should be noted, however, that competitive forces from outside the industry ultimately limit the positive performance impact of time delays (as is true of any mechanism that limits competition among incumbents). Moreover, because time delays simultaneously increase inter-rival performance differences, the profit increase is unlikely to be equal across competitors. More aggressive competitors will probably garner greater gains in profits if feedback is delayed. A multi-industry sample (King and Zeithaml, 2001) that captures significant industry differences in time delays (e.g., software firms or Internet publishing vs. pharmaceutical or aerospace) would facilitate deeper empirical insights into these kinds of performance implications of time delays.

Insights that time delays contribute to heterogeneity in competitive behavior and performance also merit further empirical research. Previous competitive dynamics research implies that differences between rivals' levels of competitive aggressiveness might emerge in a path-dependent manner, as past performance affects the future competitive aggressiveness of firms (e.g., Ferrier, 2001). Our results complement these findings by specifying the conditions that foster interfirm heterogeneity in competitive behavior. For example, we should observe greater heterogeneity among firms in their use of major product introductions

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but little variation between rivals in their use of price changes. Ultimately, industries with delayed feedback on central competitive actions are likely to display greater performance heterogeneity than industries with prompt feedback about the most important competitive moves. Our robustness analyses indicate that these predictions are likely to be most relevant in contexts where the volume of actions taken by competitors is large relative to the magnitude of changes in those volumes. Along with observational studies, experiments and experiential simulations are valuable research methods for investigating the effects of time delays and learning on rivals' development of competitive strategies (Chen, Lin, and Michel, 2010b).

In addition to testing empirical predictions that emerge from our model, an equally important path of inquiry involves expanding the use of computational modeling to study rivalry. For example, although our model assumes that firms are primarily concerned with improving their own performance, computational experiments could be designed to examine assumptions about retaliatory behavior (e.g., Chen, Su, and Tsai, 2007) and imitation (e.g., Hsieh *et al.*, 2014). Time delays are likely to influence both the probability of retaliatory behavior and managers' evaluations of the attractiveness of imitating a strategy employed by rivals. Researchers could also build more complex models of competitors' learning and reasoning about rival firms' competitive actions and specify the effect of time delays under different assumptions about rationality (Rahmandad *et al.*, 2009).

In addition to examining the effect of time delays on rivalry, computational modeling approaches could be used to address other questions of interest to competitive dynamics scholars. Possibilities include modeling the emergence and consequences of competitive asymmetry (e.g., Chen, 1996) and multimarket contact (e.g., Baum and Korn, 1999) as a result of firms' evaluation of feedback from repeated interactions. Likewise, following Lenox *et al.* (2006), interesting insights may emerge if future scholars introduce entry-exit dynamics and rivalry among incumbent firms in one model.

Other simulation techniques can be used to address important research questions pertaining to competitive dynamics. For example, system dynamics models treat variables such as competitive activity as continuous. However, in some situations, changes in competitive activity may occur in discrete "lumps" that may subsequently preempt a rival firm's competitive actions (Bromiley, Papenhausen, and Borchert, 2002). Discrete-event simulation models might be used to capture such dynamics. Agent-based models, in turn, could capture demand-side heterogeneity with greater granularity. For example, a history of competitive interaction might cause a firm to attract price-sensitive customers as its rival attracts customers that are drawn to prestigious brands. Such differences could have interesting implications for subsequent competitive decision making by generating heterogeneity in how customers respond to competitors' actions.

Finally, we hope this study motivates computational strategy scholars, who frequently assume firms to be unaffected by the actions of rivals, to examine systematically interactions between competition and their focal construct. As this paper demonstrates, the assumption of firm centricity can lead to very different conclusions about the behavioral dynamics of strategy compared with situations that involve two or more interdependent rivals.

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