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Subverting Process-Based Controls: Oscillation in Automotive Recalls and a Simulation on Opportunism within a Network

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ABSTRACT

The increase in the frequency and impact of automotive recalls has had broad reaching economic and social consequences. Recent examples of automotive recalls suggest that some are due to deliberate actions of firms to subvert processes designed to ensure quality. Such controls are dependent on partners acting in good faith in the relationship and abiding by relational norms and so do not recognize the risks of firms lying, falsifying data, or intentionally circumventing process-based controls. Data on automotive recalls shows that recalls exhibit a statistically significant oscillatory pattern with an estimated period of around 3.6 years. We argue that the cyclical pattern in automotive recalls is due, in part, to opportunistic behavior within a network, which is likely to spread and be reciprocated. To test whether opportunism can lead to similar network effects, we develop an agent-based simulation to model opportunism within a network of connected firms. The simulation is based on an extension of the prisoner's dilemma where the cooperate/defect decision is based on a dyadic relational model driven by trust, knowledge, and dependence levels within each relationship. The results from the simulation suggest that cyclical patterns, similar to those in automotive recalls, emerge as well as "behavioral clustering" within the network, where connected firms exhibit highly similar behaviors that tend to cycle within small clusters. Therefore, opportunistic behavior in supply networks might be an important, relational determinant of product recalls. Our dynamic modeling approach differs from current perspectives on understanding product recalls, contributing to the current literature. [Submitted: October 16, 2019. Revised: May 21, 2020. Accepted: May 27, 2020.]

Subject Areas: Agent-Based Simulation, Fraud Triangle, Networks, Opportunism, Product Recalls, Risk, and Supply Chain Fraud.

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INTRODUCTION

Recently, the increasing frequency and impact of product recalls have received considerable attention from researchers. Much of the research, while exploring the negative performance impacts of a recall, has not adequately explored the causes of product recalls (Shah, Ball, & Netessine, 2016). Research has emphasized that "process-based controls" influence the likelihood of a recall, for example, operational practices (Shah et al., 2016), the characteristics of the firm (Thirumalai & Sinha, 2011), or the ability of a firm to prevent future recalls through learning (Haunschild & Rhee, 2004). Although this stream of research has yielded valuable insights, process-based approaches are ineffective in preventing recalls when the responsible party deliberately circumvents established processes. Lending support to this conclusion, Ball, Shah, and Wowak (2018, p. 59) find that competition "may encourage companies to relax quality standards during the manufacturing process, which may result in lower quality product." Product competition is shown to increase severe recalls where managers have limited discretion, but decreases recalls when managers have discretion to not issue a recall. This suggests that when facing competition, managers might prefer concealing information or choose to look the other way when minor quality failures arise. Agrawal and Muthulingam (2015, p. 350) provide several examples of recalls wherein "specific measures were undertaken by the firms to avoid such issues," leading to their assertion that "efforts to improve quality performance of vendors may not be effective" in preventing recalls. Supporting the inefficacy of traditional process-based controls for limiting opportunism, Babich and Tang (2012) find that inspections can only partially deter product adulteration, whereas deferred payment can eliminate the problem. We conjecture that opportunistic actions made by firms intentionally to circumvent process controls might underlie product recalls.

Several recalls in the automotive industry have been caused by opportunistic behavior done intentionally to circumvent quality and process-based controls. Takata's opportunistic behavior was responsible for causing the largest automotive recall in history, impacting over 34 million vehicles (Ivory & Tabuchi, 2015). Prior to the recall, Takata "routinely manipulated results of air-bag inflator tests" (Trudell & Fisk, 2016). Takata deleted test data to cover up higher risks associated with the substitution of ammonium nitrate for tetrazole in the manufacturing of airbags (Trudell, Hagiwara, & Jie, 2014; Trudell & Fisk, 2016), transferring the risks of using a less stable chemical compound to buyers and consumers. Volkswagen engaged in deceptive behavior by manipulating emissions testing software to achieve higher performance (Contag et al., 2017). Aston Martin recalled approximately 75% of the cars produced between 2007 and 2012 because a tier three supplier provided counterfeit DuPont plastic for the accelerator pedals despite the specifications requiring the use of a specific plastic from Dupont (Klayman, 2014). These counterfeit parts did not meet standards and could break in use, prompting the recall. Each of these examples is notable not only because of the scope of the recall, but also for the following reasons:

(1) The recalls were caused by deliberate actions to defraud members of the supply chain to advance the interests of the perpetrating party at the expense of the customer.

(2) Process-based controls such as information sharing of safety tests, regulatory tests, and approved suppliers that were put in place specifically to prevent these issues were intentionally circumvented by the perpetrating firms.

(3) The opportunistic behaviors occurred at multiple tiers in the supplier chain (including an OEM, a tier one supplier, and a tier three supplier), demonstrating that opportunistic behavior leading to recalls can span multiple tiers in the supply chain.

These examples suggest that there is a need to better understand the role of opportunism in supply networks in product recalls. This article addresses calls in the literature for research that explores the causes of automotive recalls (Shah et al., 2016), particularly research with an emphasis on nontraditional causes of recalls (Wowak & Boone, 2015). Interfirm relationships and supplier relationships have been identified as key areas for future research in studying recalls (Lyles, Flynn, & Frohlich, 2008; Marucheck, Greis, Mena, & Cai, 2011).

We address this research need through two separate approaches: analysis of the number of automotive recalls per year, followed by a network simulation modeling opportunistic behavior between firms. First, data on automotive recalls from the National Highway Traffic Safety Administration (NHTSA) are analyzed for the years 1966–2018. The data show that there are cyclical patterns in recalls over time with an estimated cycle time of 3.62 years with a 95% confidence interval from 3.45 to 3.78 years. Second, a network simulation on opportunism is developed using an agent-based simulation model. The model is based on a cellular automata (CA) network that nests dyadic relationships within a larger network of firms. The simulation uses an iterated prisoner's dilemma game model where the choice between cooperation and defection (referred to as cooperation and opportunism to avoid confusion with quality defects) is based on the relational dynamics of *trust, knowledge, and dependence* in dyadic relationships. The dyadic relationships in the network evolve over time in the CA model. The network-level behaviors—clustering and opportunism—in the model are consistent with the temporal behavior identified in the secondary data on automotive recalls. Specifically, the average opportunism at the network level in the model exhibits a pattern similar to the pattern observed in the secondary data on automotive recalls. Our research suggests that relational (governance) approaches that impact trust, knowledge, and dependence might effectively complement process-based controls to mitigate product recalls.

OSCILLATORY BEHAVIOR IN AUTOMOTIVE RECALLS

In analyzing automotive recalls from 2000 to 2006, Shah et al. (2016) note that recalls demonstrate "clustering" effects for specific years with relative peaks in the years 2000 and 2005 (see Figure 1). The discussion of clustering is relatively short, with the authors noting the existence of possible clustering effects in the data

Figure 1: Selected automotive recalls by vehicle year (source: 2016).

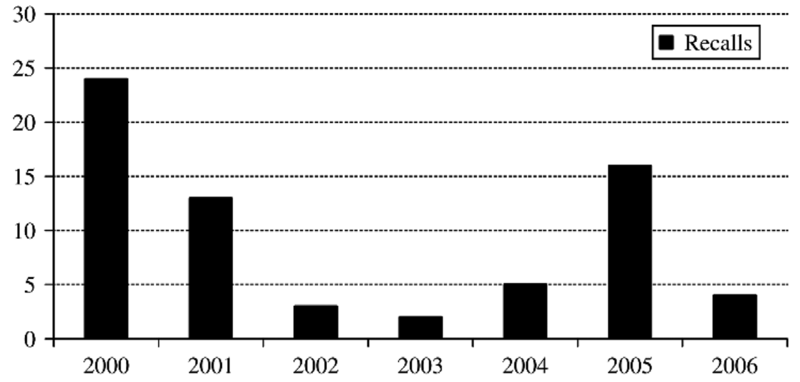
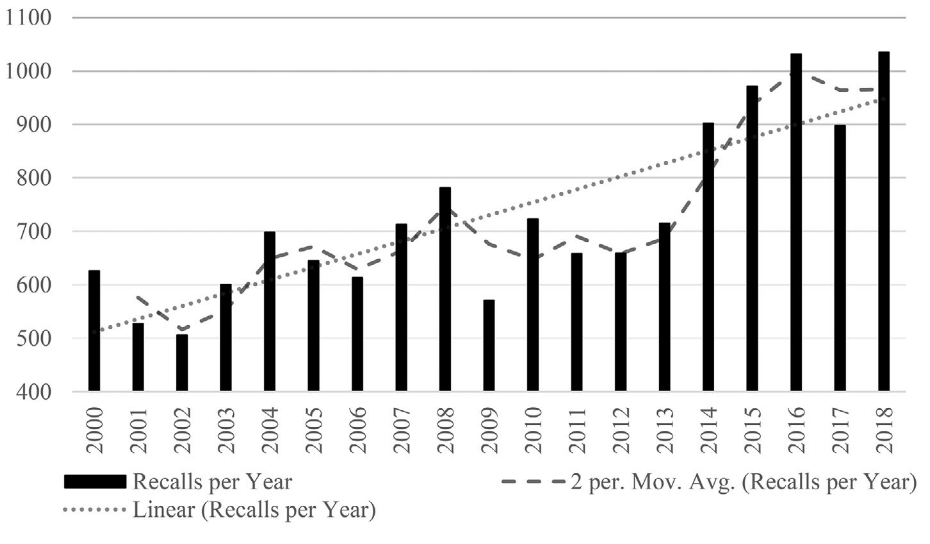


Figure 2: NHTSA automotive recall data by year.



and then selecting a method that allows for clustered dependent variables and other unmeasured dependencies between outcomes. To the best of our knowledge, the temporal fluctuations suggestive of clustering in automotive recalls have not yet been statistically evaluated or explained.

The annual recall data from 2000 to 2018 are shown in Figure 2, with a linear trend line and a two-period moving average of annual recalls superimposed, which shows a cyclical pattern. Examination of Figure 2 suggests that there is an upward trend in product recalls and an oscillatory pattern to the recall data.

In order to statistically verify whether automotive recalls demonstrate cyclical behavior, data on automotive recalls from the NHTSA (NHTSA, 2015, 2019)

Table 1: Summary statistics on automotive recalls.

Total number of recalls	22,592
Date range	1966–2018
Mean recalls per year	426.26
SD of recalls per year	256.33
Range of recalls per year	[58, 1,035]

are examined. The data include the total number of automotive recalls every year from 1966 to 2018. Summary statistics on the data are presented in Table 1.

An Unobserved Components Model (UCM) was used on the time series to test whether the data exhibit a statistically significant cycle. UCM decomposes a time series into multiple subcomponents and provides both an estimate of cycle time and a statistical test of the significance of the cycle component (Harvey & Jaeger, 1993). The univariate time series model specification was adapted from Koopman and Ooms (2011), based on the original work of Harvey (1989). The specified model is a time series model that includes a random walk trend component (μ_t), a cyclical component (ψ_t), and irregular components (ε_t) and is given by

$$y_t = \mu_t + \psi_t + \varepsilon_t,\ \varepsilon_t \sim NID\left(0,\ \sigma_\varepsilon^2\right),\ t = 1,\ \ldots,\ n.$$

The random walk trend (μ_t) component is specified as

$$\mu_{t+1} = \mu_t + \eta_t,\ \ \eta_t \sim NID\left(0,\ \sigma_\eta^2\right),$$

where η_t is serially and mutually independent of all other disturbance terms and is a normal variable, independently distributed with a mean of zero and a variance of σ_η^2. The cycle component (ψ_t) is specified as a stochastic cycle model which performs similarly to that of the autoregressive moving average process (Harvey, 1989) and is given by

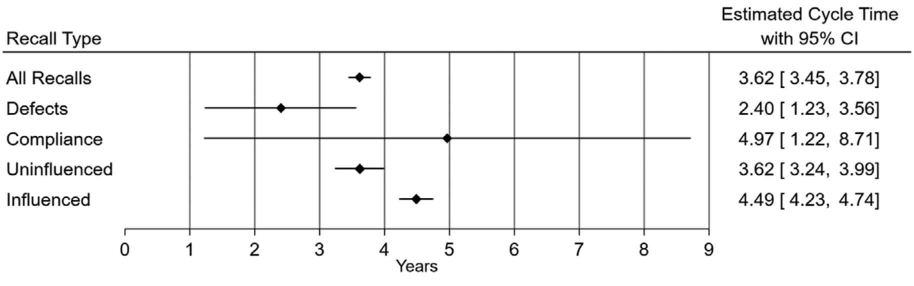
$$\begin{bmatrix} \psi_{t+1} \\ \psi_{t+1}^* \end{bmatrix} = \phi_\psi \begin{bmatrix} \cos\lambda_c \sin\lambda_c \\ -\sin\lambda_c \cos\lambda_c \end{bmatrix} \begin{bmatrix} \psi_t \\ \psi_t^* \end{bmatrix} + \begin{bmatrix} \kappa_t \\ \kappa_t^* \end{bmatrix},$$

$$\begin{pmatrix} \kappa_t \\ \kappa_t^* \end{pmatrix} \sim NID\left(0,\ \sigma_\kappa^2 I_2\right),\ \begin{pmatrix} \psi_t \\ \psi_t^* \end{pmatrix} \sim NID\left(0,\ \frac{\sigma_\kappa^2}{1-\phi_\psi^2} I_2\right),$$

where λ_t is the frequency in radians bounded as $0 \le \lambda_t \le \pi$, κ_t and κ_t^* are two mutually uncorrelated white noise disturbances with a mean of zero and a common variance, and ϕ_ψ is a damping factor bounded as $0 \le \phi_\psi \le 1$. For additional explanation regarding the development of the models, we refer the reader to Harvey (1989) and Harvey, Koopman, and Penzer (1998).

The data from the NHTSA are categorized according to two groupings: influenced/uninfluenced recalls and recalls due to defect/compliance. Uninfluenced recalls represent 80.0% of the total recalls and are initiated by the firm. Influenced recalls represent 20.0% of the total recalls and are initiated by the NHTSA. Recalls due to defects represent 81.4% of the recalls, and recalls due to compliance represent 18.6% of the recalls.

Figure 3: Estimated cycle times by recall type.



The model was tested in Stata using the *ucm* command. The results indicate a statistically significant cycle ($p < .01$) with an estimated period of 3.62 years and a 95% confidence interval of 3.45–3.78 years for the total number of annual recalls. This analysis was repeated for specifications of uninfluenced recalls or influenced recalls, as well as for defect or compliance related recalls. The estimated cycle times for each of the types of recalls are presented in Figure 3. They demonstrate that the overall estimate of around 3.62 years is a reasonable approximation of the cycle time and that a statistically significant cycle emerges for each type of recall. There was some difference in the estimated cycle times by recall type, with influenced recalls having a longer estimated cycle than unfluenced.

These results provide statistical support for an oscillatory pattern in automotive recalls, a phenomenon which has not yet been addressed by research on recalls. Because the cyclical pattern emerges with data aggregated across all firms in the industry, it is reasonable to conjecture that there is some degree of interdependence of automotive recalls within a network of firms. In the absence of such interdependence, fluctuations in recalls of individual firms would likely cancel each other out when aggregated. These arguments motivate our study that examines clustering and opportunism in the network as an explanation for cyclical behavior observed in the aggregate automotive recalls data.

We hypothesize that relational dynamics in networks, in particular, opportunistic behavior, might explain the oscillatory pattern in recalls over time. Research exploring opportunism shows that "trading partners match their behaviors [opportunistic behavior]; one party tends to treat the other party in a way that is similar to how it is treated" (Caniëls & Gelderman, 2010, p. 249). This suggests that opportunistic behavior can instigate additional opportunistic behavior through the dynamics of dyadic relationships and network interactions. Accordingly, we model the supply network as a dynamic system to capture opportunistic behaviors within a network and emergence of "clustering" at the network level. Previous research has used networks of coupled dynamic systems to model biological oscillators (Watts & Strogatz, 1998).

In the following sections, we develop opportunism as one possible explanation of automotive recalls and establish a theoretical foundation for the factors which lead to opportunistic behavior.

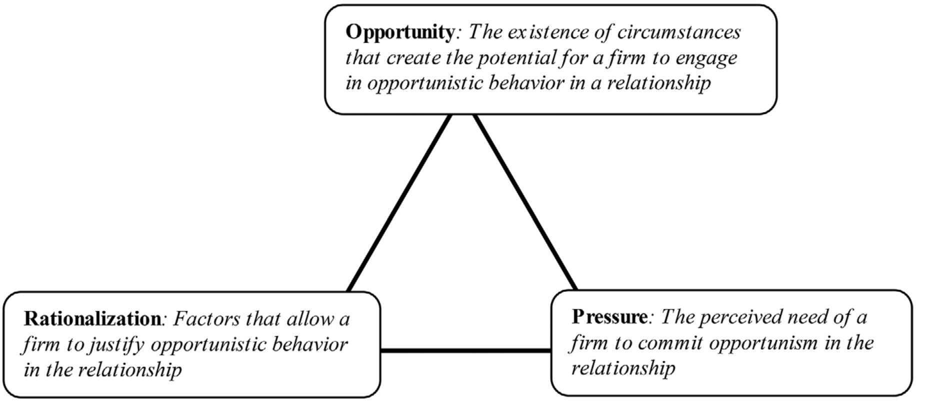
Opportunism as a Driver of Automotive Recalls

There are several examples of opportunistic behavior, or "self-interest seeking with guile" (Williamson, 1985), leading to an automotive recall, including Takata deleting test data (Trudell & Fisk, 2016), Volkswagen cheating on emissions tests (Barrett et al., 2015), and a supplier of Aston Martin using counterfeit plastic materials (Klayman, 2014). In each of these cases, a firm intentionally deceived their supply chain partners. Although process-based controls might help alleviate quality concerns, opportunistic behavior can lead to deliberate efforts to circumvent such controls. Because processes can be circumvented by intentional behavior, process-based controls might fail completely to address recalls caused by opportunistic behavior in a network. Research has suggested that intentional disruptions due to opportunism require a relationship-based approach (DuHadway, Carnovale, & Hazen, 2019). Relational risk necessitates different mechanisms for understanding and limiting product recalls associated with actors who are willing to intentionally subvert traditional controls. The examples given to motivate this study demonstrate the need for a better understanding of the role relational risk plays in supply chain dynamics and recalls.

In the Volkswagen emissions scandal, the opportunistic behavior appears to have extended beyond Volkswagen. Research has identified many other automotive manufacturers with significantly higher pollution levels in realistic driving conditions compared to the test conditions, including Citroen, Fiat Chrysler, Hyundai, Nissan, Renault, and Volvo (Carrington, 2015). It was also found that the opportunistic behavior spread through the supply chain network: "we find strong evidence that both defeat devices were created by Bosch and then enabled by Volkswagen and Fiat for their respective vehicles" (Contag et al., 2017, p. 232). Based on these real-world examples that suggest that opportunistic behavior can spread through a network of connected firms, we explore the role of opportunistic behavior in dyads and as a network phenomenon.

We posit that one possible driver of oscillations in the automotive recalls is the changing relational dynamics in a network of firms over time. Previous research on opportunism emphasizes two key elements for opportunism that motivate this possibility: time and network behavior. Unlike traditional process control approaches that might remain relatively stable over time, relationships in a supply network are dynamic. Relationships can change constantly based on new information, success of the interaction, and the relational conditions (Borgatti & Cross, 2003). Nooteboom (1996) emphasizes three key factors behind the incentive for opportunism, the opportunity toward opportunism driven by contractual control and monitoring, propensity toward opportunism driven by trust over time, and asymmetric dependence depending on switching costs and partner values. These factors can change over time, shifting the pressures to engage in opportunistic behaviors or cooperate. Caniëls and Gelderman (2010, p. 249) note a pattern of reciprocation within a network regarding opportunism: "Finally, we found a strong and positive association between buyer's and supplier's opportunistic behaviour. This finding indicates that trading partners match their behaviours; one party tends to treat the other party in a way that is similar to how he is treated himself ('tit-for-tat')." Based on changing relational dynamics and the network influences on

Figure 4: Components of the fraud triangle for opportunistic behavior.



opportunism, we seek to understand whether relational dynamics over time nested within a larger network can lead to similar cyclical behaviors as observed in the automotive recalls.

We seek to demonstrate that relational risk, that is, opportunism, which cannot be managed through specifications and process controls, constitutes an independent cause of product recalls. The following section identifies the conditions under which opportunism risks are expected to be their highest, based on the theory of the Fraud Triangle.

The Fraud Triangle and Opportunistic Behavior

The "Fraud Triangle," introduced by Cressey (1950) to explain criminal behavior in firms, identifies three elements as prerequisites for fraudulent behavior to occur. The fraud triangle in Figure 4 consists of the three elements: *opportunity, pressure, and rationalization*. Opportunity represents the circumstances that enable the perpetrator to engage in fraudulent behavior. Pressure represents the perceived need to engage in this behavior. Rationalization represents the ability to justify the act of fraud. The fraud triangle has been used extensively to identify motivations to engage in fraudulent behavior (Trompeter, Carpenter, Desai, Jones, & Riley, 2013) and has been so successful for predicting fraud that it has been formalized into recommendations for auditors investigating fraud in the Statement on Auditing Standards (SAS) No. 99/AU where §316.31 includes the dimensions of the fraud triangle as fraud risk factors (DuHadway, Talluri, Ho, & Buckhoff, 2020). One empirical investigation exploring the value of the fraud triangle on predicting fraud found a model using proxies for the fraud triangle was able to correctly predict a firm's fraud/no-fraud status 73% of the time, providing support of the use of the fraud triangle factors for detecting fraud (Skousen, Smith, & Wright, 2009). Subsequent work has found further value in using fraud triangle proxies as predictors for fraud (Roden, Cox, & Kim, 2016). The fraud triangle has also been used in supply chain research to measure corruption (Arnold, Neubauer, & Schoenherr, 2012) and levels of supply chain fraud (DuHadway et al., 2020).

We incorporate the relational constructs of trust, knowledge, dependence, and their interrelationships under the rubric of the fraud triangle to investigate the *emergence* of opportunistic behavior in networks. It is possible that opportunistic behavior by a firm within the network impacts the motivation of other firms to engage in opportunistic behavior, suggesting that a network perspective of behavior over time is necessary.

To explore the relationship between opportunism and network-level behaviors, we develop a network simulation model that explores opportunistic behavior over time. The model simulates a network of dyadic relationships among 400 firms. In each time period, each firm decides to either cooperate or behave opportunistically for every transaction it has with its partners. Applying the concept of the fraud triangle, the decision to cooperate or behave opportunistically by a firm in each time period is based on the degree of opportunity, pressure, and rationalization that it experiences.

NETWORK SIMULATION OF DYNAMIC RELATIONAL BEHAVIOR

The simulation model bridges the dyadic and network-level behaviors of a tightly connected network of firms. The decision to engage in opportunistic behavior or cooperative behavior is made in each dyadic relationship based on a Dynamic Relational Model (DRM), which is based on three key drivers of relational behavior: trust, knowledge, and dependence. These aspects have been identified as critical concerns for operational and relational performance in the automotive industry (Corsten, Gruen, & Peyinghaus, 2011). These three aspects of relational behavior, along with the dimensions of the fraud triangle, were modeled relying on established relationships from prior research (DuHadway, 2016). The studies from which the mathematical relationships in the simulation model are derived are shown in Table 2 with supporting arguments from the literature. The simulation model uses the concepts associated with the fraud triangle to determine whether firms will engage in cooperative or opportunistic behavior in dyadic relationships. This forms the basis for the DRM.

Each firm's decision to cooperate or be opportunistic is made at a dyadic level, but these decisions are then nested within a network of firms using a CA model. CA is a modeling technique that uses a two dimensional network structure to establish relationships among a set of agents to explore network-level behaviors based on simple rules that guide each local relationship (Wolfram, 1984, 1994). At the network level, the simulation models the decision to engage in either opportunistic or cooperative behavior for each firm for each of their eight dyadic relationships. The DRM and CA models allow us to observe network-level opportunistic behavior based on dynamically evolving dyadic relationships throughout the simulated network. The overall structure of the simulation is presented in Figure 5. The DRM is developed in "Dynamic Relational Model" section and the CA in "Cellular Automata Model" section.

Table 2: Dynamic relationship model variables.

Var Type	Variable Name	Variable Definition	Symbol	Var Characteristics
	Focal firm	Firm currently making decision	Subscript j	$\{0,\ 1,\ 2,\ \ldots N\}$
	Partner firm	Partner of focal firm for decision	Subscript k	$\{0,\ 1,\ 2,\ \ldots 8\}$
DV	Cooperation	$\{\begin{matrix} -1\ if\ OS^t_{jk}\ k\ is > OL \\ 1\ if\ OS^t_{jk} is \leq OL \end{matrix}$	C^t_{jk}	-1 or 1
DV	Partner cooperation	$= \{\begin{matrix} -1\ if\ OS^t_{kj}\ k\ is > OL \\ 1\ if\ OS^t_{kj} is \leq OL \end{matrix}$	PC^t_{jk}	-1 or 1
P	Divestment rate	The % rate that firms divest in a relationship toward the desired investment level based on trust levels	DR	$[0,\ 1]$ $\mu = .1$ $\sigma = 0$
P	Firm pressure	The amount of pressure within firm j to succeed	P_j	$[0,\ 1]$ $\mu = .5$ $\sigma = .2$
P	Investment rate	The % rate that firms invest in a relationship toward the desired investment level based on trust levels	IR	$[0,\ 1]$ $\mu = .2 \sigma = 0$
P	Knowledge gain	The rate of knowledge gain for firm j. This is bounded by KOR in order to keep K^t_j bounded to [0,1]	KG_j	$[0,\ KOR]$ $\mu = .05$ $\sigma = .025$
P	Knowledge obsolescence rate	The % based loss in total knowledge for every firm in each time period	KOR	$[0,\ 1]$ $\mu = .1$ $\sigma = 0$
P	Knowledge transfer rate	The % of knowledge that is transferred from firms with higher knowledge toward firms with lower knowledge	KTR	$[0,\ 1]$ $\mu = .1$ $\sigma = 0$
P	Opportunism limit	The limit at which firm will engage in opportunism	OL	$[0,\ 8]$ $\mu = 2.0$ $\sigma = 0$

Continued

Table 2: Continued.

Var Type	Variable Name	Variable Definition	Symbol	Var Characteristics
P	Trust elasticity	The rate at which firm *j* adjusts trust based on partner behavior	TE_j	[0, 1] $\mu = .05$ $\sigma = .025$
P	Trust reciprocity	The rate at which firm *j* adjusts trust based on asymmetric trust levels	TR_j	[0, 1] $\mu = .025 \sigma = .0125$
SV	Dependence	The dependence of the focal firm on partner firm *k* in time period *t*	D^t_{jk}	[0, 1]
SV	Dependence asymmetry	$D^t_{kj} - D^t_{jk}$	DA^t_{jk}	[−1, 1]
SV	Divestment	The decrease to investment by focal firm j with regard to the relationship with partner *k* in time period *t*	D^t_{jk}	[0, 2]
SV	Dyadic performance	$(\frac{FG^t_{jk}}{FG^t_{kj} + FG^t_{jk}})$	DP^t_{jk}	[0, 1]
SV	Firm gain	Score from prisoner's dilemma table based on cooperation or defection of focal firm *j* and partner *k*	FG^t_{jk}	[0, 2]
SV	Firm pressure	Pressure faced by firm *j* to perform	FP_j	[0, 1]
SV	Incoming trust	The trust signal that focal firm *j* receives from partner *k*	IT^t_{jk}	[−1, 1]
SV	Independent performance	$\frac{\sum_{k=1}^{8} FG^t_{jk}}{8}$	IP^t_{jk}	[0, 2]
SV	Investment	The increase to investment by focal firm *j* with regard to the relationship with partner *k* in time period *t*	I^t_{jk}	[0, 2]
SV	Knowledge Advantage	The knowledge that focal firm *j* has above that of their partner firm *k*	KA^t_{jk}	[0, 1]

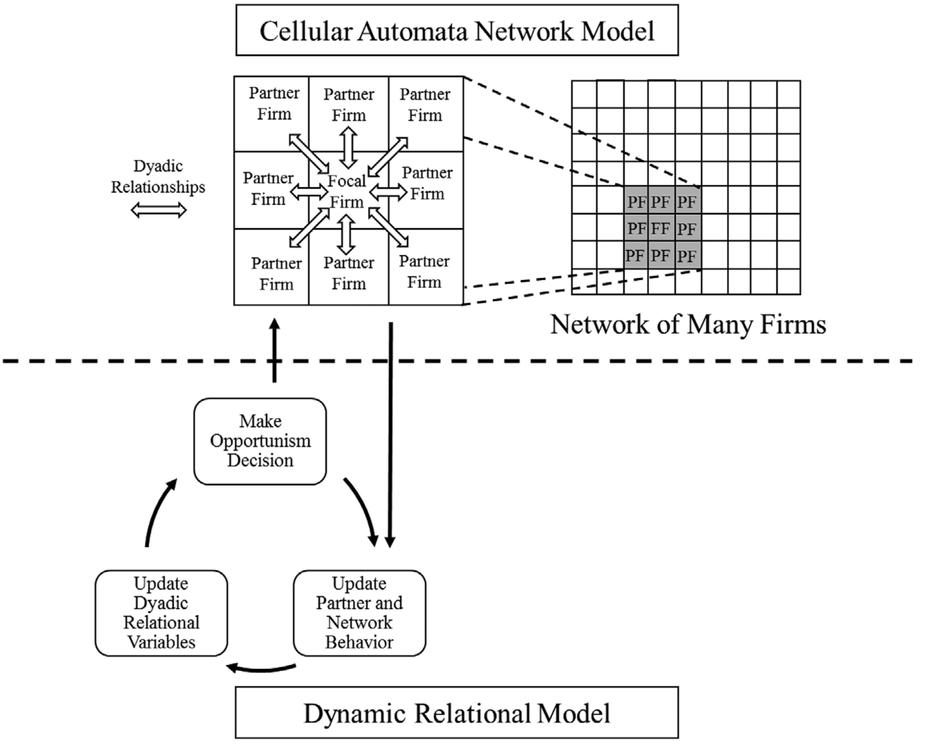
Continued

Table 2: Continued.

Var Type	Variable Name	Variable Definition	Symbol	Var Characteristics
SV	Knowledge deficit	The shortage of knowledge that focal firm *j* has below partner firm *k*	KD^t_{jk}	[0, 1]
SV	Knowledge	The level of knowledge for firm *j* in time period *t*	K^t_j	[0, 1]
SV	Partner cooperative behavior	The degree of cooperative behavior observed by focal firm *j* in time period *t* with respect to partner *k*'s behavior	PCB^t_{jk}	[−1, 1]
SV	Network opportunistic behavior	The degree of opportunistic behavior observed by focal firm *j* in time period *t* in their local network	NOB^t_j	[0, 2]
SV	Network performance	$\left(\frac{\sum_{k=1}^{8} FG^t_{jk}}{\sum_{k=1}^{8} RS^t_{kj} + \sum_{k=1}^{8} RS^t_{jk}}\right)$	NP^t_j	[0, 1]
SV	Opportunism score	Utility value for opportunistic behavior based on the fraud triangle	FTS^t_{jk}	[0, 8]
SV	Opportunity	The degree of opportunity to engage in opportunistic behaviors	O^t_{jk}	[0, 2]
SV	Outgoing trust	The trust that focal firm *j* has in firm *k*	OT^t_{jk}	[−1, 1]
SV	Pressure	The degree of pressure to commit opportunistic behaviors	P^t_{jk}	[0, 2]
SV	Rationalization	The degree of rationalization to justify opportunistic behaviors	R^t_{jk}	[0, 2]
SV	Relational investment	The current investment level of focal firm *j* in the relationship with partner *k*	RI^t_{jk}	[0, 2]

DV, decision variable; P, parameter; SV, state variable; μ, mean; σ, standard deviation.

Figure 5: Simulation model.



Dynamic Relational Model

The DRM drives the decision in each time period for a firm to act opportunistically or cooperate. The DRM is based on system dynamics and models the *temporal interactions among the relational variables*—trust, dependence, and knowledge—along with the fraud triangle dimensions of opportunity, pressure, and rationalization. The equations comprising the DRM were developed based on previous research. The DRM is characterized by a set of seven key equations for the primary variables in the relational model. The values for these variables are calculated for each of the eight relationships a firm has (one for each connected firm) in each time period of the simulation. Table 2 lists the variable names and characteristics.

A firm's decision to engage in opportunism is based on *opportunism score*, calculated as a combination of opportunity, rationalization, and pressure based on the theory of the fraud triangle, which argues that opportunity, pressure, and rationalization are all tightly connected to the decision to engage in opportunistic behavior (Nooteboom, 1996; Das & Rahman, 2010). Opportunism score is determined by the degree of opportunity combined with pressure and rationalization. The evidence supporting the link between opportunism and the factors of opportunity (see e.g., Klein, Crawford, & Alchian, 1978; Provan & Skinner, 1989; Griesinger, 1990; Ghoshal & Moran, 1996; Nooteboom, 1996; Kim, 1998; Singh & Sirdeshmukh, 2000; Wathne & Heide, 2000; Luo, 2007; Caniëls & Gelderman, 2010; Das & Rahman, 2010), rationalization (see e.g., John, 1984; Ghoshal & Moran, 1996; Doney & Cannon, 1997; Singh & Sirdeshmukh, 2000; Luo, 2007; Caniëls & Gelderman, 2010), and pressure (see e.g., Klein et al., 1978; Kim, 1998; Luo, 2007; Das & Rahman, 2010) is compelling. Table 3 presents a review of relevant statements from the literature that are used to justify the equations below. Additional references for specific equations are provided in Table 3, as well as for each of the equations below (see e.g., Griliches, 1979; Conner & Prahalad, 1996; Sako & Helper, 1998; Argote & Ingram, 2000; Morgan, Kaleka, & Gooner, 2007; Hillman, Withers, & Collins, 2009; Mysen, Svensson, & Payan, 2011; Ozkan-Tektas, 2014).

The decision to engage in opportunism or cooperate is based on the relationships established by the fraud triangle, which suggests that fraud occurs in the presence of opportunity, pressure, and rationalization. These relationships are established in Equation (1). For opportunistic behavior to emerge, we argue that opportunity serves as the critical pathway for opportunism. That is, some level of opportunity must be present in conjunction with either pressure or rationalization in the relationship for a firm to decide to engage in opportunistic behavior.

$$Opportunism\ Score^t_{jk} = f\left(O^t_{jk},\ P^t_{jk},\ R^t_{jk}\right) = \zeta_1 * \left(O^t_{jk}\right) * \left(\zeta_2 * R^t_{jk} + \zeta_3 * P^t_{jk}\right), \tag{1}$$

where $\zeta_n = \begin{bmatrix} .33 \\ .33 \\ .33 \end{bmatrix}$.

Equations (2)–(7) determine the drivers of opportunity (2), rationalization (3), pressure (4), trust (5), knowledge (6), and dependence (7) and are used to calculate the level, changes, and interactions associated with each of these variables. Opportunity, rationalization, and pressure (Equations (2), (3), and (4), respectively) are updated for every relationship for each time period based on the factors that have been identified as critical influences in prior research and referenced in Table 2. *Opportunity* is calculated by an equally weighted score of the degree of dependence asymmetry, knowledge asymmetry, and incoming trust, which we define as the partner's level of trust.

$$Opportunity^t_{jk} = f\left(DA^t_{jk}, KA^t_{jk},\ IT^t_{jk}\right) = \sum_{n=0}^{N} \alpha_n Y_n, \tag{2}$$

where α is a vector of weights associated with the vector of input variables Y.

$$Y = \begin{bmatrix} DA^t_{jk} + 1 \\ KA^t_{jk} + 1 \\ IT^t_{jk} + 1 \end{bmatrix},\quad \alpha_n = \begin{bmatrix} .33 \\ .33 \\ .33 \end{bmatrix}.$$

Rationalization is calculated for every relationship from dependence asymmetry, trust levels, the previous opportunistic behavior exhibited by a firm's local network, and the previous opportunistic behavior of a firm's partner. Firms with an advantage in dependence asymmetry have lower levels of trust, experience more

Table 3: Empirical, analytical, and conceptual foundations for simulation model relationships.

Equations Supported[a]	Supported Relationships (Terminology Used in Source Material)	Representative Statement(s)	Method	Source
(1) O→OS (1) R→OS (2) IT→O	Trust (contractual control and monitoring) → Opportunity toward opportunism → Opportunism	[Three key factors drive the incentives for opportunism: opportunity toward opportunism (driven by contractual control and monitoring), propensity toward opportunism (driven by trust over time), and asymmetric dependence (switching costs and partner value)]	Analytical	Nooteboom (1996)
(1) O→OS (3) IT→R (3) OT→R	Trust → Rationalization (propensity toward opportunism) → Opportunism	"the partner's propensity towards opportunism … is dependent on the growth of trust in time" (p. 1002)		
(1) O→OS (2) DA→O (7) RI→DA	Asymmetric dependence → Opportunities for opportunism (captivity) → Opportunism	"Y's incentives towards opportunism also depend on the extent to which Y perceives himself to be dependent on X: if Y is more dependent on X than vice versa, it is in Y's interest to be careful about opportunism." (p. 998)		
(1) O→OS (2) DA→O (7) RI→DA	Asymmetric dependence (asymmetric alliance-specific investments) → Opportunism	"We propose an extended definition of partner opportunism and three categories of the determinants of partner opportunism based on a review of the literature. These categories comprise economic factors (equity involvement, asymmetric alliance-specific investments, mutual hostages, and payoff inequity), relational factors (cultural diversity and goal incompatibilities), and temporal factors (alliance horizon and pressures for quick results)." (p. 55)	Literature Review	Das and Rahman (2010)

Continued

Table 3: Continued.

Equations Supported[a]	Supported Relationships (Terminology Used in Source Material)	Representative Statement(s)	Method	Source
(1) R→OS (2) DP→R	Comparative dyadic performance (payoff inequity) → Rationalization (to regain equity) → Opportunism			
(1) P→OS	Pressure (alliance horizon and pressures for quick results) → Opportunism			
(1) O→OS (2) KA→O	Knowledge asymmetry (asymmetric information) → Opportunism	"The extent of the risk [of dishonesty] depends on the magnitude of the possible deception, the norms of disclosure surrounding the transaction, the possibility of detection, and the conscience of the potential offender. If the transaction is nonrecurrent, the information inherently asymmetric, and the parties strangers to each other (i.e., the moral character is not known), then the risk will be high and safeguards are warranted." (p. 486)	Conceptual	Griesinger (1990)
(1) R→OS	Rationalization (conscience) → Opportunism			
(3) T→R	Trust (norms of disclosure) → Opportunism			
(1) O→OS (2) DA→O	Dependence → Opportunism	"Dealer opportunism was found to be negatively related to dealer dependence on a primary supplier." (p. 209)	Empirical	Provan and Skinner (1989)

Continued

Table 3: Continued.

Equations Supported[a]	Supported Relationships (Terminology Used in Source Material)	Representative Statement(s)	Method	Source
(1) O→OS (2) KA→O	Knowledge asymmetry → Opportunity (inability to detect opportunism) → Opportunism	"In general, information asymmetry means that one party's ability to detect opportunism is limited … [which] gives the exchange partner the opportunity to pursue opportunistic actions without being caught." (p. 42)	Conceptual	Wathne and Heide (2000)
(1) O→OS (2) DA→O	Dependence asymmetry (lock-in) → Opportunity (vulnerability toward opportunism) → Opportunism	"Lock-in, in contrast, represents vulnerability because a party cannot leave a given relationship without incurring economic losses. As a consequence, a lock-in situation may require a party to tolerate opportunistic behavior." (p. 42)		
(2) DA→O	Dependence asymmetry → Opportunity to commit opportunism (opportunistic potential) → Opportunism	"If Y and Z each stand to gain the same amount from cooperation and each must make the same size idiosyncratic investment in order to make the cooperation work, then opportunistic potential is balanced between the parties. If opportunistic potential is balanced, the probability of opportunistic behavior is low, since the parties are in a 'stand-off' situation (Klein & Leffler, 1981, Williamson, 1983)." (p. 489)	Conceptual	Conner and Prahalad (1996)
(1) O→OS (2) KA→O	Knowledge asymmetry → Opportunism	"The more a supplier is asked to provide information to its customer without the customer reciprocating by giving information to the supplier, the greater the supplier's perception of customer opportunism." (p. 393)	Empirical	Sako and Helper (1998)

Continued

Table 3: Continued.

Equations Supported[a]	Supported Relationships (Terminology Used in Source Material)	Representative Statement(s)	Method	Source
(1) R→OS	Rationalization (relational norms) reduce opportunism	"Relational norms do have a mitigating effect on supplier opportunism." (p. 247)	Empirical	Caniëls and Gelderman (2010)
(2) DA→O	Dependence asymmetry (dominant power position) can lead to opportunism	"When the buyer has a dominant power position and puts this position into use, e.g. exerts buyer opportunism, then the effect is an increase in supplier opportunism. This suggests that dependent suppliers will be motivated to behave opportunistically against their buyers when the buyer actually puts its dominant position into use." (p. 247)		
(1) R→OS (3) NOB→R (3) PCB→R	Peer and network behavior (how one party is treated) → Rationalization → Opportunism	"Finally, we found a strong and positive association between buyer's and supplier's opportunistic behaviour. This finding indicates that trading partners match their behaviours; one party tends to treat the other party in a way that is similar to how he is treated himself ('tit-for-tat')." (p. 249)		
(1) R→OS (3) OT→R	Rationalization (attitudinal orientation between partners) → Opportunism	"Attitudinal orientation has a significant negative effect on opportunism." (p. 286)	Empirical	John (1984)
(1) R→OS (3) NOB→R (3) PCB→R	Rationalization (social contract) → Opportunism	"Taken together, our results provide evidence about the importance of the 'social contract' in maintaining efficient exchange in long-run relationships that are vulnerable to opportunism" (p. 287)		

Continued

Table 3: Continued.

Equations Supported[a]	Supported Relationships (Terminology Used in Source Material)	Representative Statement(s)	Method	Source
(1) R→OS (3) DA→R (3) NOB→R (3) PCB→R (3) IT→R	Rationalization (composed of reciprocity, fairness, cultural rules) → Opportunism	"Rather, market-mediated relational exchanges are socially embedded, and, consequently, the norms of social relationships (e.g., reciprocity, fairness) provide a countervailing force to constrain this inherent opportunism (Casson, 1997). In other words, the prevalent social and cultural rules for fair play press for behaviors that are perceived by exchange partners as trustworthy (Uzzi, 1997)." (p. 153)	Conceptual	Singh and Sirdeshmukh (2000)
(1) R→OS (3) IT→R	Incoming trust (moral consequence of opportunism) → Rationalization (expected change in trust) → Opportunism	"Thus, while the agents may like to act opportunistically, the moral consequences of being detected as blatantly opportunistic hold considerable sway on agents' behaviors." (p. 153)		
(1) R→OS (3) NOB→R (3) PCB→R	Peer and network observed behavior (sanctioning of self-serving behavior) → Rationalization → Opportunism	"To the extent that such self-serving behaviors are sanctioned, one might infer that targets in high power distance societies will act opportunistically and fail to associate high costs with opportunistic behavior." (p. 613)	Conceptual	Doney, Cannon, and Mullen (1998)

Continued

Table 3: Continued.

Equations Supported[a]	Supported Relationships (Terminology Used in Source Material)	Representative Statement(s)	Method	Source
(1) R→OS (3) OT→R (3) PCB→R	Attitudes about the relationship → Proclivity to opportunism → Opportunism	"Opportunism is influenced by three factors. The first is 'prior conditioning' (relationship 'i') that includes all the attitudes and values formed through exposure to conscious as well as subliminal stimuli … Second, opportunism is influenced by what we describe as the 'feeling for the entity,' which represents the individuals' favorable or unfavorable assessment of the specific transaction partner, the group or the organization… The third influencer of opportunism is opportunistic behavior." (p. 2)	Conceptual	Ghoshal and Moran (1996)
(1) R→OS (3) OT→R	Trust (assessment of the partner) → Proclivity to opportunism → Opportunism			
(1) R→OS	Opportunism → Proclivity to opportunism → Opportunism			
(1) R→OS (1) P→OS (3) DA→R (4) DP→P	Dyadic performance (captured as equitable reward sharing through distributive justice) → Opportunism	"Distributive justice is also important in curbing opportunism. With higher distributive justice, each party's incentive for interpartner exchange becomes stronger because of increased confidence regarding impartial gain-sharing… Improved distributive justice can also reduce the hazards of withholding information and shirking obligations, which are common examples of opportunistic behavior." (p. 864)	Empirical	Luo (2007)

Continued

Table 3: Continued.

Equations Supported[a]	Supported Relationships (Terminology Used in Source Material)	Representative Statement(s)	Method	Source
(1) P→OS (4) NP→P	Competitive pressure (competitive bidding) → Pressure (comparative advantage of short term gains) → Opportunism	"Since the long-term gain is decreasing in the number of competing bidders, excessive bidding competition may provoke the winning bidder's opportunism." (p. 907)	Analytical	Kim (1998)
(1) P→OS (4) DP→P	Profitability (premiums) → Pressure (gain from opportunism) → Opportunism	"One way in which this market mechanism of contract enforcement may operate is by offering to the potential cheater a future 'premium,' more precisely, a price sufficiently greater than average variable (that is, avoidable) cost to assure a quasi-rent stream that will exceed the potential gain from cheating." (p. 304)	Conceptual	Klein et al. (1978)
(5) O→T	Opportunism → Trust	"Results show that opportunist behavior of the suppliers have negative influences on both buyer trust and buyer-supplier relationship strength." (p. 22)	Empirical	Ozkan-Tektas (2014)
(5) O→T	Opportunism → Trust	"When a party believes that a partner engages in opportunistic behavior, such perceptions will lead to decreased trust." (p. 25)	Empirical	Morgan and Hunt (1994)
(5) O→T	Opportunism → Trust	"The results in the present study support the findings that opportunism is negatively associated with trust." (p. 446)	Empirical	Mysen et al. (2011)
(6) KD→K	Knowledge reservoirs exist and knowledge transfer occurs between firms	"In general terms, knowledge can be transferred by moving a knowledge reservoir from one unit to another or by modifying a knowledge reservoir at a recipient site." (p. 155)	Conceptual	Argote and Ingram (2000)

Continued

Table 3: Continued.

Equations Supported[a]	Supported Relationships (Terminology Used in Source Material)	Representative Statement(s)	Method	Source
(6) KG→K (6) KD→K (6) KOR→K	Firms accumulate knowledge, which depreciates and is transferred between firms	"There is also the issue of depreciation or obsolescence of this capital. If one distinguishes between the firm-specific knowledge capital and the general state of knowledge in the industry as a whole, then at least as far as the first is concerned, it is quite clear that its earning capacity erodes over time, both because better products and processes become available and because its own knowledge begins to lose its specificity (it leaks to other firms in the industry)." (p. 101)	Analytical	Griliches (1979)
(6) KD→K (7) KA→D	Knowledge transfer (knowledge spillover) occurs between firms Knowledge asymmetry (information asymmetry) leads to dependence	"Information exchange may cause knowledge spillover (Inkpen & Currall, 2004) and information asymmetry may create a power imbalance (Tsang, 1999)." (p. 1419)	Conceptual	Hillman et al. (2009)

[a]→ Should be read as "impacts."

OS, opportunism score; O, opportunity; P, pressure; R, rationalization; T, trust; IT, incoming trust; DA, dependence asymmetry; K, knowledge; KA, knowledge advantage; KD, knowledge deficit; KG, knowledge growth; KOR, knowledge obsoletion rate; DP, dyadic performance; NP, network performance; NOB, network opportunistic behavior; PCB, partner cooperative behavior.

opportunism from partners, and are more likely to rationalize opportunistic behavior.

$$Rationalization_{jk}^{t} = f\left(DA_{jk}^{t},\ IT_{jk}^{t},\ OT_{jk}^{t},\ NOB_{j}^{t},\ PCB_{jk}^{t}\right) = \sum_{\mathrm{n}\,=\,0}^{\mathrm{N}} \beta_n V_n, \quad (3)$$

where β is a vector of weights associated with the vector of input variables V.

$$V = \begin{bmatrix} DA_{jk}^{t} + 1 \\ 1 - IT_{jk}^{t} \\ 1 - OT_{jk}^{t} \\ NOB_{j}^{t-1} \\ 1 - PCB_{jk}^{t-1} \end{bmatrix}, \quad \beta_n = \begin{bmatrix} .2 \\ .2 \\ .2 \\ .2 \\ .2 \end{bmatrix}.$$

Pressure is a function of a firm's performance compared to its network neighbors, a firm's performance compared to the partner in a relationship, and a stochastically assigned baseline level of pressure for every firm. Firms with less relative performance and higher firm pressures have more motivation to engage in opportunism.

$$Pressure_{jk}^{t} = f\left(NP_{j}^{t},\ DP_{jk}^{t},\ FP_{j}\right) = \sum_{n\,=\,0}^{N} \gamma_n * W_n, \quad (4)$$

where γ is a vector of weights associated with the vector of input variables W.

$$W = \begin{bmatrix} 2 * NP_{j}^{t} \\ 2 * DP_{jk}^{t} \\ 2 * FP_{j} \end{bmatrix}, \quad \gamma = \begin{bmatrix} .33 \\ .33 \\ .33 \end{bmatrix}.$$

Trust is calculated based on the previous level of trust adjusted for a partner's behavior and based on the reciprocated level of trust from partners. A firm's trust in its partner (outgoing trust) increases (decreases) in time periods in which a firm's partner cooperates (engages in opportunism) (Morgan & Hunt, 1994; Mysen et al., 2011; Ozkan-Tektas, 2014). The magnitude of the change in trust is based on the previous levels of trust such that a greater deviation from expected behavior has a larger influence on the change in trust. The negative adjustment to trust due to opportunistic behavior is greater when trust is high. This rate of adjustment is based on trust elasticity. Trust levels are also updated each time period by a reciprocity measure that adjusts a firm's outgoing trust toward the incoming trust levels of the partner firm to reflect the notion of reciprocal trust (Korsgaard, Brower, & Lester, 2014). Network Opportunism Behavior and Partner Cooperative Behavior scores are measured using an exponential smoothing adjustment in each time period from prior behavior updated in each time period.

$$OutgoingTrust_{jk}^{t} = OT_{jk}^{t-1} + TE_j\left(PC_{jk}^{t-1} - OT_{jk}^{t}\right) + TR_j\left(IT_{jk}^{t-1} - OT_{jk}^{t-1}\right), \quad (5)$$

$$IncomingTrust_{jk}^{t} = OT_{kj}^{t-1},$$

$$Network\ Opportunistic\ Behavior_{j}^{t} = NOB_{j}^{t-1} + BE_j\left(\sum_{k\,=\,1}^{8} \frac{-PCB_{jk}^{t} + 1}{8} - NOB_{j}^{t-1}\right),$$

$$Partner\ Cooperative\ Behavior^t_{jk} = PCB^{t-1}_{jk} + BE_j \left(PCB^t_{jk} - PCB^{t-1}_{jk}\right).$$

Knowledge levels are updated in each time period based on old knowledge becoming partially obsolete, firms developing new knowledge, and firms absorbing knowledge from partners with higher levels of knowledge (Griliches, 1979; Argote & Ingram, 2000; Hillman et al., 2009).

$$Knowledge^t_j = (1 - KOR) * K^{t-1}_j + AC_j * \left(KTR * \sum_{k=1}^{8} KD^{t-1}_{jk}\right) + KG_j, \quad (6)$$

$$Knowledge\ Advantage^t_{jk} = \begin{cases} K^t_j - K^t_k & if\ K^t_j > K^t_k \\ 0 & if\ K^t_j \le K^t_k \end{cases},$$

$$Knowledge\ Deficit^t_{jk} = \begin{cases} 0 & if\ K^t_j > K^t_k \\ K^t_k - K^t_j & if\ K^t_j \le K^t_k \end{cases}.$$

Dependence is a function of knowledge dependence (Hillman et al., 2009), relational investment (Emerson, 1962; Pfeffer & Salancik, 2003; Davis & Adam Cobb, 2010), and a stochastically assigned base level of dependence established for every relationship. Firms update their investments each time period by investing or divesting in the relationship according to trust levels.

$$Relational\ Dependence^t_{jk} = \tau_1 \left(D_{jk}\right) + \tau_2 \left(KD^t_{jk}\right) + \tau_3 RI^t_{jk}, \quad (7)$$

$$Dependence\ Asymmetry^t_{jk} = RD^t_{kj} - RD^t_{jk},$$

$$Relational\ Investment^t_{jk} = RI^{t-1}_{jk} + I^t_{jk} - D^t_{jk},$$

$$Round\ Investment^t_{jk} = \begin{cases} IR\left(\left(OT^t_{jk} + 1\right) - Inv^t_{jk}\right) & if\ OT^t_{jk} + 1 > Inv^t_{jk} \\ 0 & if\ OT^t_{jk} + 1 \le Inv^t_{jk} \end{cases},$$

$$Round\ Divestment^t_{jk} = \begin{cases} 0 & if\ OT^t_{jk} + 1 > Inv^t_{jk} \\ DR\left(\left(OT^t_{jk} + 1\right) - Inv^t_{jk}\right) & if\ OT^t_{jk} + 1 \le Inv^t_{jk} \end{cases}.$$

Cellular Automata Model

The DRM was nested in a CA model. CA models allow agents to interact in a localized network using a simple set of rules over a number of time periods to investigate self-organization within a network (Wolfram, 1984, 1994). This framework allows modeling the complexities of dyadic interactions as well as the complex adaptive nature of firm behaviors within a network. The simulation design follows the discussion on trust and opportunistic behavior by Nooteboom (1996, p. 987), who notes: "Transactions are to be seen as being embedded in relations that develop in time, while these relations in turn are socially embedded in their environment" (Granovetter, 1985). The simulation design reflects this structure by taking the dynamic dyadic relationship behavior that develops over time in each relationship (the DRM) and socially embedding those behaviors in their environment (the CA model). In other words, a firm makes a transactional-level decision in each time period to engage in opportunism or to cooperate based on each dyadic relationship.

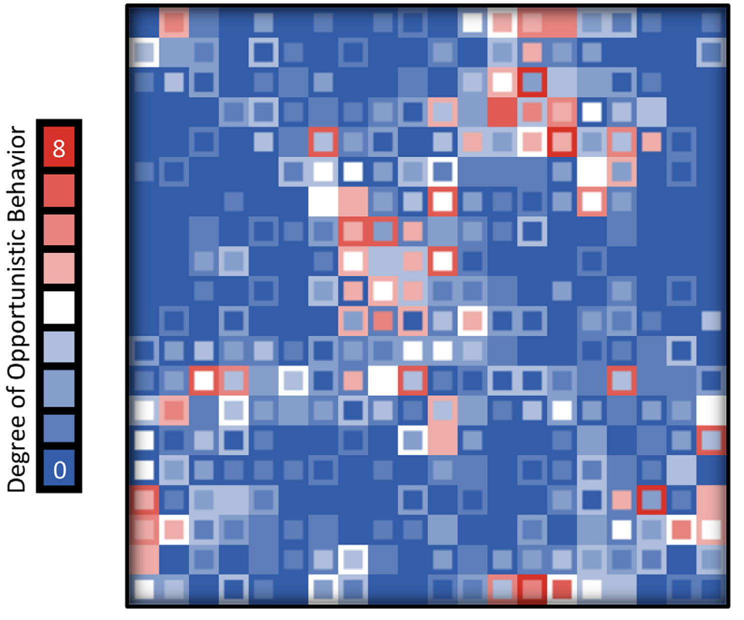
Each firm engages in eight decisions in each time period to cooperate or engage in opportunism and is also impacted by the decisions made by their eight partners to cooperate or engage in opportunism. Based on the decisions of a firm and those of the firm's local network of partners, the levels of trust, knowledge, and dependence are updated using the DRM. A firm engages in opportunistic behavior or cooperates according to the levels of opportunity, pressure, and rationalization that it experiences. These structural relationships between firms are modeled in the CA, which consists of 400 connected firms. Each firm has eight direct relationships, representing a total of 3,200 firm-level relationships comprising the network of firms.

The CA model is an adaptation of the N-person, the iterated prisoner's dilemma game model that has been used to explain complexities in "cooperate or defect" behavior of agents in a network (Nowak & Sigmund, 1993; Albin & Foley, 2001; Nair, Narasimhan, & Choi, 2009). The prisoner's dilemma model was adapted such that rather than using a simple strategy to cooperate or defect (such as "tit-for-tat" or predefined static strategies), the decision to cooperate or defect (in this case, engage in opportunistic behavior) in the simulation model was made based on the complex, dynamic interactions in each dyadic relationship in the DRM. The simulation was programmed using NetLogo, an agent-based simulation program for modeling complexity in a simple environment (Wilensky, 1999; Tisue & Wilensky, 2004). Firms were established within a 2-dimensional *toroidal lattice* and were assigned relationships with neighboring firms based on each firm's Moore Neighborhood, which comprises the eight neighboring firms surrounding a focal firm within a network lattice structure (see Figure 5). Edges of the 2-dimensional lattice connect to the opposite edge following a torus structure so that firms located at the edges form relationships with firms at the opposite edge of the lattice.

The combination of CA and DRM modeling creates a complex adaptive system that allows network-level behavior to emerge based on the interactions of individual dyads over time. This approach also has the advantage of combining "discrete modeling" and "continuous modeling" approaches (Borshchev & Filippov, 2004) and has been used in other simulation studies to bridge dynamic and discrete behaviors (Lauf, Haase, Hostert, Lakes, & Kleinschmit, 2012). This two-stage approach has the advantage of eliminating the possibility of tautological results by creating a distinction between the mathematical model of dyadic-level behavior and results at the network level (Lauf et al., 2012).

Firms decide to be opportunistic in their relationships when the incentive for opportunistic behavior exceeds an *opportunism threshold*, which is stochastically set for each relationship in each time period by adjusting the mean opportunism limits for the simulation. Figure 6 illustrates the decision to engage in opportunism or to cooperate for the entire network of firms in the right-most graphic. For each time period, firms decide to be opportunistic or cooperate in a transaction with every partner within their Moore Neighborhood. The total amount of opportunistic behavior in the range [0, 8] is graphically displayed for each time period based on the color scheme presented in Figure 5. Dark red indicates a high level of opportunistic behavior; dark blue represents a high level of cooperative behavior; and white represents an equal amount of opportunistic behavior and cooperative behavior in that time period. In the simulation, data are collected that relate to the

Figure 6: Simulation model output.



relational state for every dyad in the network as well as the decision to cooperate or be opportunistic in each time period. This was captured at a dyadic level and then aggregated at the network level to capture network-level behavior. The simulation displays a 20 × 20 matrix of firms (depicted as a square within a 2-dimensional matrix) with the opportunism rate of each of the 400 firms depicted based on the color of the square. An example is shown in Figure 6.

The simulation map shows the behavior of every firm within the network in the displayed time period. Colors at the center of a square represent opportunistic behavior exhibited by a firm toward its neighbors, whereas the border color of a cell represents opportunistic behavior experienced by a firm. An example of the simulation map is displayed in Figure 6 and a video of an example simulation run is available at https://youtu.be/hDlravqLMH8.

Figure 7 shows the rate of opportunism for both a single firm and the average rate for the entire network over an entire simulation run of 600 time periods where each time period represents a decision to cooperate or defect for every firm.

Figure 8 shows the fraud triangle factors from Equation (1) that drive opportunism or cooperation. Combined, the evidence suggests that individual firms experience shifts in factors that can lead to opportunism and that at a network level, such pressures exhibit oscillatory patterns that lead to network-level phenomena of both temporal and proximal clustering.

Simulation Verification and Limitations

In order to establish confidence in the simulation model, we followed suggestions from Senge and Forrester (1980) and Kleijnen (1995). Validation of the simulation

Figure 7: Opportunism levels from a sample simulation.

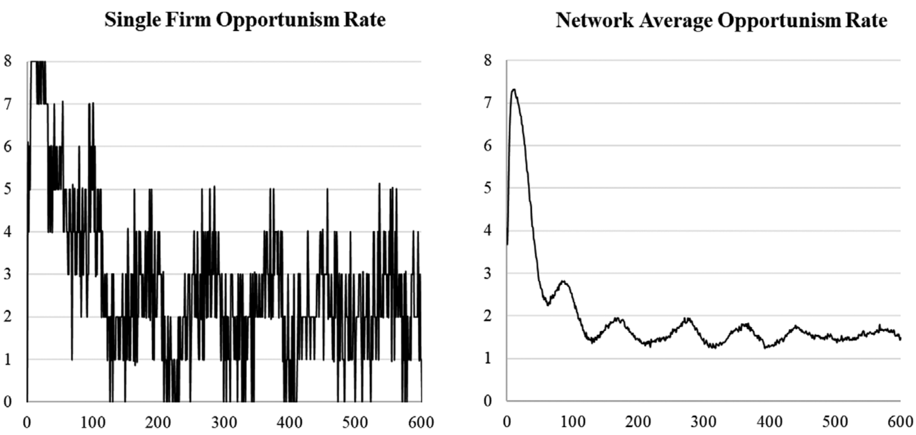
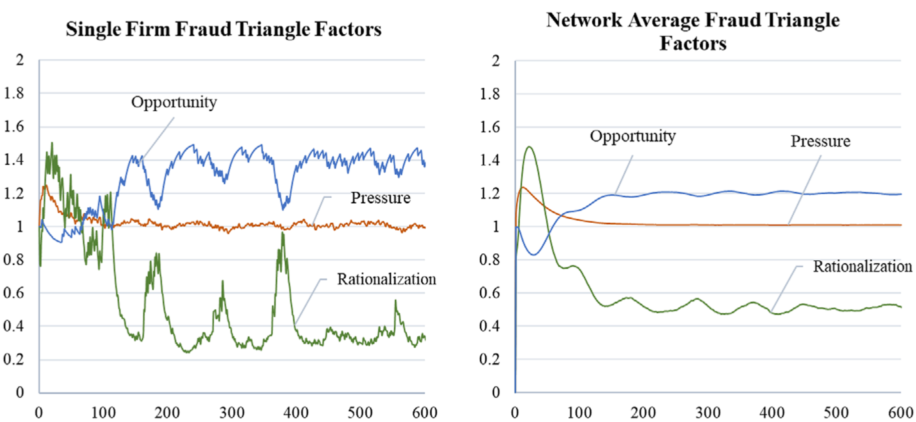


Figure 8: Fraud triangle factors from a sample simulation.



model was done in the development of the simulation model and through post hoc analyses. The DRM was tested by performing structure-verification, parameter-verification, extreme-conditions, and dimensional consistency tests (Senge & Forrester, 1980). Structure-verification was done using preestablished relationships between variables that were previously explored in the literature and mapping them to the theory of the fraud diamond. These relationships are presented in Table 2 and were developed after a series of testing to verify that each relationship used in the model was based on previously established literature findings. Parameter-verification was done by bounding the relationships within the model within meaningful ranges based on the structure-verification. For example, pressure, opportunity, and rationalization were bounded as [0, 2], meaning that each one independently could remove any motivation to be opportunistic, or could double the combined pressures of the other factors. The use of scaling parameters for the key relationships in the equation to be similar units further helped to ensure dimensional consistency. Extreme-conditions were tested by modifying each of the parameters to test the robustness of the findings to extreme conditions; for example, the rate of knowledge transfer, rate of trust change, competitive pressures, and thresholds for engaging in opportunism were all adjusted to verify that the simulation model results were consistent with the literature and expectations. In addition, the simulation model was developed in accordance with the suggestions by Kleijnen (1995): modular programming, verification of intermediate simulation output, comparison to real data, and animation to confirm that the simulation model was developed correctly.

To evaluate the robustness of the simulation model, additional simulation runs were made to verify that the findings were not sensitive to network structure and model specifications. These additional simulation tests included running the simulation using the von Neumann relational neighborhood (four relational pairings instead of eight), stochastic relationships in every time period instead of fixed relationships, and tests of networks that were very large or very small. In each of these additional models, the key findings of transitive opportunistic behavior and cyclical patterns emerged. With a sufficiently large network (2,500 firms), the cyclical patterns within the overall network did tend to cancel themselves out for opportunism levels across the entire network, despite subregions exhibiting cyclical opportunistic behavior. In very small networks (9–100 firms), the cyclical tendencies of opportunistic behavior at the network level were more pronounced. This suggests that the cyclical tendencies within an industry are likely related to overall size and density of a network, with very tightly connected networks such as that in the automotive industry exhibiting stronger cyclical patterns than a very large and disconnected network. Additional research should explore both the size of networks and the connectedness and density of networks to better understand opportunistic behavior in a network.

RESULTS

The CA-based simulation yielded two interesting network behaviors, which confirm that the relational perspective can be useful in explaining oscillations in automotive recalls. First, *distinct zones of opportunistic and cooperative behavior tended to emerge in the network over time*, supporting the notion of clustering in automotive recalls. This *clustering effect* emerged in the simulation based on the dyadic relational characteristics of firms in the larger network. These clustering effects are noticeable both in terms of regional clustering and temporal clustering for the network. Clustering is identifiable in Figure 6 as zones of similar color (dark blue or dark red), where many neighboring firms exhibit similar opportunistic or cooperative behavior. This suggests that opportunistic behavior is *transitive* and can lead to the emergence of locally connected networks that exhibit similar behaviors to each other. Firms in a “cooperation” dominant local network emulate cooperative behavior and those in “opportunism” dominant networks engage in higher levels of opportunistic behavior similar to their locally connected peers.

These results, in conjunction with evidence of oscillatory behavior in the number of automotive recalls, suggest that opportunistic behavior in relationships has a transitive effect and might be used to explain larger systemwide outcomes. Such transitive firm behavior has been shown to exist in other contexts such as top-management hiring behaviors (Williamson & Cable, 2003). The apparent transitive nature of opportunistic behavior within a network is an interesting finding that merits further investigation. These regional behavioral clusters of opportunism or cooperation suggest that *opportunistic behavior should also be viewed as a network phenomenon* wherein firms are influenced by other firms in their ecosystem. These clusters of similar behaviors emerged in terms of both opportunistic behavior and cooperative behavior, suggesting that both positive and negative behaviors within a local network can lead to reciprocal effects from connected firms. The clustering effects tended to have a strong central point where the firms were entirely opportunistic or entirely cooperative, and then gradually decrease in intensity from the center (observable in Figure 5 by strong regions of dark blue or dark red which become lighter further away). Firms that are able to serve as these central points of cooperative behaviors within their network might be used to explain performance differences (in the long term) of firms from cooperation in their connected network. Firms able to create a region of positive behavior might be able to reap the benefits from a highly cooperative network, whereas firms that engage in opportunistic behavior, such as aggressive cost-cutting, might create a cascading effect through their network, which has long-term ramifications on connected firms (Henke, Yeniyurt, & Zhang, 2009; Henke & Zhang, 2010).

Network opportunism levels exhibited oscillatory behavior over time similar to the pattern observed in the automotive recall data (see Graph 4 in Figure 5). This result suggests that one possible explanation of the oscillation in automotive recalls is the transitive nature of opportunistic behavior and the impact of relationships within a closely connected network. This is a key insight from the dynamic model and simulation results. Analysis of the graphs from the simulation runs suggests that rationalization and opportunity play key roles in determining opportunistic behavior in the network, with shifting rationalization levels and opportunity leading to different levels of opportunistic behavior in the network. This can be understood by recognizing the influence that opportunistic behavior has on adjacent firms. In the absence of opportunistic behavior, high trust emerges in the relationship, combined with a high level of relationship specific investment. Although this can allow better performance in a cooperative scenario, it exposes a firm to the potential for opportunism. Previous research has found that the probability of a recall increases when an inspector inspects the same site multiple times (Ball, Siemsen, & Shah, 2017). This could be explained by the inspector reaching a level of trust or confidence in the inspected site, which leads to a higher level of opportunity for opportunistic behavior to take place, creating a potential starting point for this cycle. The higher levels of opportunity trigger the decision of a firm in the local network to behave opportunistically. This behavior then cascades through a local network as other connected firms reciprocate such behavior as they are facing additional pressures from being taken advantage of and rationalize additional opportunism within their own networks. The opportunistic behavior by a partner leads to a lower level of trust and lower asset-specificity, and thus decreases the opportunity for a partner to engage in opportunism until cooperative behavior can reemerge. These dynamic interactions in a network provide a possible and logical explanation for the oscillatory behavior in automotive recalls.

DISCUSSION AND CONCLUSION

This research presents two novel contributions focusing on automotive recalls and opportunistic behavior over time within a network. First, the evidence that automotive recalls exhibit a temporal cycle with an estimated time period of 3.6 years is a novel research contribution that has not been previously tested and confirmed with data on automotive recalls despite their significant impact. The length of the cycle is relatively short compared to many business cycles, which can range from a few years to many decades (Mass, 1975; Grinin, Korotayev, & Tausch, 2016), yet this is the first work to explore the dynamics of opportunistic behavior within a network. The cycle identified in our research is closely aligned in duration with the Kitchin cycle for fluctuating inventory levels, which is approximately 40 months (Kitchin, 1923) and is caused by inventory and work in process (Konečný, 2016). Similar to the Kitchin cycle, it is possible that informational delays connected to the production and sourcing process lead to the length of the cycle.

Second, we present a dynamic relational model and simulation which shows that opportunistic behavior and relational dynamics can be a cause of cyclical opportunistic behavior in networks of closely connected firms. System dynamics models present a powerful lens to view counterintuitive behavior of social systems because they formalize model assumptions and bring them into the open, making it possible to study complex models of social systems through clear models based on explicit assumptions and precise relationships (Forrester, 1971). We develop these relationships through a dynamic relational model established from prior literature. Individual relationships and their cascading influence in the network based on the behavior of "nearby firms" in the CA led to systematic shifts in the amount of opportunistic behavior that occurred at the network level. Similarly, zones of cooperative or opportunistic behaviors are apparent from the network model, suggesting that within a local area of networks, such behavior might be particularly prevalent. In our work, the primary emphasis on the decision to engage in opportunism was based on the dyadic relationship, yet norms of trust and dependence can be apparent to firms from the behaviors of others not in such a relationship as well. Such factors might increase the likelihood of network-level oscillation phenomena, as the interactions are not confined to trading relationships.

The *transitive nature of opportunistic behavior* in a network can be used to explain the previously unexplained evidence of oscillation in the number of recalls in the automotive sector, yet we expect that there might exist a number of other possible explanations as well. It is possible that such a pattern reflects a quality or risk vigilance cycle across the entire industry, leading to relatively rapid cycles of high and low quality and thus impacting the number of recalls that are issued. It is possible that a recall announcement sheds light on other related problems and so several related recalls might occur in the same time period. This could occur due to opportunistic behavior as developed in this manuscript, or simply due to structural relationships among supply networks. It is also possible that the cyclical behavior is due to external influences on the supply chain such as regulatory cycles, although because the evidence supports cycles emerging for influenced and noninfluenced recalls, we do not expect regulatory cycles to be the primary driver, as they would primarily be related to influenced recalls. Firms might also seek to "piggy-back" on other firm recalls by announcing their recalls following a competitor recall, timing their own recalls in order to minimize consumer and market reactions to recalls. There also might be other exogenous effects, for example, cycles of public concern or regulatory pressure. Further research to explore alternative causes of a cyclical pattern in automotive recalls should be investigated. Such approaches will likely require more detailed exploration looking at the cause of the problem, the motivations behind the announcement to recall, and detailed investigation of the temporal relationships between when the recalls were announced compared to the discovery of product failure.

In addition to exploring other exogenous factors, research investigating recalls at a more nuanced level is also necessary. Not all automotive recalls are identical; instead, they vary greatly in terms of scope, cause, and criticality. Many of the recalls are not due to opportunistic behaviors, but inadvertent causes. The number of cars and firms impacted by a specific recall varies substantially and these aspects should be considered by future research.

The novel contribution of this article is that opportunism can be a reason for recalls. Although literature has studied process-related factors such as quality management failures, we extend this to consider relational constructs through the fraud triangle to study the role of opportunism as an antecedent of recalls. To explore this dynamic phenomenon, we employ a dynamic modeling approach that captures network-level phenomena over time instead of relying on static data. Accordingly, it highlights the role of governance in avoiding recalls.

Theoretical Contribution

Previous research in automotive recalls has emphasized the operational precursors of a recall, with limited work that explores the nonoperational perspective (Wowak & Boone, 2015). We address this by exploring the role of relationships and opportunism as a precursor of automotive recalls. This research sets the stage for further exploration of automotive recalls and risk management in three key areas. First, we present statistical evidence that there is oscillatory behavior over time in the levels of automotive recalls. This is an important step to understanding a phenomenon which has not yet been explained, despite researchers having identified this interesting behavior in automotive recalls (Shah et al., 2016). We anticipate that future research on this topic can yield additional insights beyond that explored in this article.

Second, a perspective that emphasizes the relationship between opportunism and automotive recalls is established. The development of a CA model that exhibits oscillatory patterns similar to the data on automotive recalls for the simulated network contributes to the area of both risk management and explaining automotive recalls. This result suggests that recalls might be "emergent behavior" that arises from decisions made by firms in different tiers in a supply network. If validated, complex adaptive systems approach might prove to be a valuable avenue for investigating risk mitigation strategies in supply networks. By relating trust, knowledge, dependence, and their interrelationships to opportunistic behavior through opportunity, rationalization, and pressure, we demonstrate *emergent* behavior in a network of connected firms, an aspect of complex adaptive systems. The model yields both valuable methodological and theoretical contributions to understanding opportunism from a network perspective—that oscillatory patterns of opportunism in a network are an example of emergent behavior. Two interesting themes emerge from the simulation: clustering of behavior in closely connected firms and oscillation at a network level, which can lead to opportunism cycles. These results present multiple directions for future research to explore opportunism from a network perspective. Finally, we demonstrate that relationship-based analytical modeling can yield insights which might be difficult to identify in analysis of secondary data. A broader implication of our study is that by utilizing relationship-based approaches simultaneously with process-based approaches, firms will be better able to manage the different types of risk in supply chains. This combined approach of relationship and process-based risk management has been suggested as critical to balanced risk management (DuHadway et al., 2019).

Managerial Implication

A combined approach that recognizes both process-based and relationship-based methods for managing automotive recalls will be more effective than a singular approach. Firms need to strategically manage opportunity, pressure, and rationalization through the levels of trust, knowledge, and dependence that occur in relationships. Using the theory of the fraud triangle, a firm can identify overall levels of opportunism risk to which it is exposed. This perspective can help provide better understanding for managing relational risk to help protect a firm from opportunistic behavior. Emphasizing the role of managing trust, dependence, and knowledge levels to help limit opportunity, pressure, or rationalization can provide practical guidelines for managers to engage in effectively limiting opportunistic behavior. Furthermore, recognizing the role of relationships as a cyclical driver of behavior motivates long-term relationship perspectives, which engender positive relationships within a supply chain. Effective supplier relationship management has been argued as one of the key differentiating factors between the challenges of U.S. automakers compared to the success of Toyota and Honda in the early 2000s, suggesting significant potential from these types of strategies (Liker & Choi, 2004). Firms which are able to effectively address supplier relationship management strategies that account for trust, dependence, and knowledge levels between firms will likely face less of an impact from relational risk, which is inherent in a network of interconnected firms.

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