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Sustainability Risk in Supply Bases: The Role of Complexity and Coupling

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Abstract

Health, safety, and environmental (HSE) issues are an emerging concern in sustainable supply chain management. Global brands sourcing from high-risk suppliers in emerging markets affect not only brand reputation but also production schedules and product quality. Based on 198 safety and 458 environmental incidents among 318 manufacturing firms in China, we found that incident firms have higher abnormal unsystematic and systematic risk than matched sustainable suppliers without HSE incidents. Reducing operational complexity and coupling can mitigate both likelihood and abnormal risks. The findings have implications for global supply chain managers assessing supplier risk from an HSE perspective.

Keywords: health and safety, operational disruption, risk, sustainable supply chain

1. Introduction

Sourcing from emerging markets is a common practice for global brands to save on labor costs. Recently, supply chain management scholars have begun to understand decisive factors in sourcing locations, besides cost, such as innovation and market (Ketokivi, 2017). When a global supply chain becomes increasingly dynamic and complex, cost-saving might not outweigh risk associated with suppliers that cause supply chain disruptions. Hendricks and Singhal (2008) found that disruption from a supplier can reduce a firm's stock price by around 11% on the day that the disruption is made public. The stock price of that firm can then fall by up to 40% over the subsequent three years. The impacts are more significant for smaller firms (Baghersad & Zobel, 2020). Firms with insufficient or no risk management strategies to cope with these disruptions exhibit relatively poor supply chain performance (Thun & Hoenig, 2011). These studies demonstrated that risk events could be spillover in supply chains. Thus, operations management (OM) scholars have increasingly focused on supply chain risk management in the last decade (e.g., Choi et al., 2019; Tang 2006; Tang & Musa, 2011).

The focus of firm performance has expanded from profit to include planet and people (known as the triple bottom line, or the goals of sustainable operations) (Kleindorfer et al., 2005). The concept of sustainable operations is increasingly understood by consumers, managers, and scholars; hence the risk associated with sustainability warrant more attention. Firms that engage in unsustainable practices are at risk of being held liable for jeopardizing workers' health and safety, and damaging the environment (Kleindorfer et al., 2005; Wolf, 2001). For example, workplace accidents can significantly reduce the available manufacturing workforce (Pagell et al., 2019). Environmental incidents (e.g., release of pollutants) may cause government agencies to close factories pending rectification (Lo et al., 2018). These adverse health, safety, and environmental (HSE) events can disrupt manufacturing operations, lead to costly legal action (Carter & Jennings, 2004), and reduce firm value (Klassen & McLaughlin, 1996; Lo et al., 2018), operating performance, and profitability (Pagell et al., 2019). These negative impacts may also spill over to the supply chain (Hendricks & Singhal, 2005; Lo et al., 2018).

Sustainability issues have become a source of supply chain risk that requires attention from both supply chain scholars and managers (Shrivastava, 1995). However, investment is required to cope with these adverse HSE events, which might increase operational costs for manufacturers (Esfahbodi et al., 2016). Such costs may be reflected in product prices. Thus, when making purchasing decisions, buyers face the dilemma of “is the risk of adverse HSE events significant enough when evaluating a manufacturer?” (Roehrich et al., 2014).

Recently, scholars have begun to investigate the topic of sustainable supply chains to understand the impact of adverse risk events in the global supply chain (Gouda & Saranga, 2018). However, the extent to which adverse HSE events increase risk in the supply base is not quantified in the literature. Thus literature is providing little help for buyers making sourcing decisions, including manufacturers evaluating the sourcing cost–sustainability risk trade-off. If evidence were available to demonstrate that adverse HSE events can severely increase risk in a supply base, buyers might be encouraged to rethink the potential long-term risk of sourcing from manufacturers that operate unsustainably. Thus, operations managers must minimize the risk of HSE incidents in their supply chain (Kleindorfer et al., 2005). The literature gap identified above motivated us to investigate manufacturers’ adverse HSE events from a risk perspective by addressing the following research questions: *(1) Do adverse HSE events increase risk in the supply bases?* and *(2) What kinds of manufacturer have a lower likelihood of adverse HSE events and the capability to reduce their impact?*

To develop a sustainable supply chain, both buyer and supplier firms are necessary to understand the consequences of adverse risk events that harm sustainability. Answering our research questions will enable a link to be constructed between risk management and sustainable operations (Carter & Rogers, 2008). Specifically, this study aims to advance the literature by exploring the impact of HSE impacts and disruptions on firm risk (both unsystematic and systematic), and how operational factors moderate this relationship. We also identify implications of our findings that will help manufacturers and buyers to understand (1) how to reduce the probability of HSE incidents when sourcing products from emerging markets and (2) how to mitigate the negative effects of such incidents when they occur. The basic theory premise of normal accident theory (NAT) is that accidents more likely happen when the operational system is more complex and tightly coupled (Perrow, 2011). We draw on this theory premise to explore the role of production complexity and coupling in HSE incidents.

The remainder of this article is organized as follows. Section 2 reviews sustainable operations issues in emerging markets and introduces our research context. Section 3 discusses the theoretical framework and develops the study hypotheses. Section 4 describes the propensity score matching research design and data analysis used to examine the hypotheses. Section 5 discusses the contributions and implications of our research.

2. Sustainable Operations in Emerging Markets

HSE incidents are conceptualized as supply chain risk in the OM literature (Kleindorfer et al., 2005). OM scholars have thoroughly investigated environmental management topics considering a firm's operations, such as carbon-efficient scheduling (Ding et al., 2016), capacity planning (Song et al., 2017), product configuration (Li et al., 2018), supply chain design (Daryanto et al., 2019; Park et al., 2015), technology choice (Drake, 2018), corporate social responsibility (CSR) investment (Modak & Kelle, 2019), and other operational decisions (see review in Zhou & Wen, 2020). However, social impacts, as another dimension of the concept of sustainable operations, receive relatively less attention in the OM literature, especially in the context of emerging markets (Fan et al., 2014). Unlike environmental incidents, socially related incidents such as workplace safety incidents often directly affect operational workers, which can severely disrupt a firm's operations, leading to lower product quality, slower delivery speeds, and damage to the firm's reputation (Fernández-Muñiz et al., 2009). Thus, this research includes both environmental and safety incidents and offers a more holistic perspective to understand the antecedents and consequences of these incidents.

The context of emerging markets represents fertile ground for OM scholars to investigate sustainable operations issues because their institutional environment (Lo et al., 2018), capital market (Oztekin et al., 2016), interest rate pattern (Ahi et al., 2018), and tax policies (Choi & Luo, 2019; Niu et al., 2019) differ from those in Western countries. Understanding of these differences is vital for overseas buyers to formulate better strategies for offshore outsourcing, beyond simple product-related issues such as design and development (Jonnalagedda & Saranga, 2019; Wang et al., 2016), and quality (Steven & Britto, 2016). Nowadays, these concerns go beyond workplace safety (Pagell et al., 2019) and environmental incident risk (Lo et al., 2018): when a consumer brand or its sourcing offices source suppliers from emerging markets, such as China, Southeast Asian and Eastern European countries, the brand must be careful to minimize the risk of HSE incidents, which can delay shipments and damage the brand's reputation among its clients (Lo et al., 2018). Understanding the antecedents of HSE incidents and their association with firm risk might enable sourcing agents to source from less risky suppliers in emerging markets and implement strategic plans for supplier development to prevent further unexpected adverse risk disruptions.

2.1. Research context: Chinese manufacturing sectors

The Chinese manufacturing sector is the most critical supply base in the global supply chain. It exports 2.4 trillion goods annually, ranking it first in the world (World Bank, 2020). Although Chinese manufacturers export goods worldwide for many brands, they are often criticized for engaging in unethical production practices, such as forcing employees to work overtime, employing underage laborers, and polluting the environment. In the past, China has been labeled the country with the largest number of sweatshops worldwide (Greider, 2001; Sung, 2007) and the world's primary pollution center (Kahn & Yardley, 2007). End consumers who care about the sustainability of upstream supply chains were increasingly wary of "Made in China" labels on products because of their connection to sweatshops and environmental problems. Annually, 0.0055% of China's workforce die in production-related accidents (China's State Administration of Work Safety, 2017). The figure is considerably higher than corresponding figures in developed countries; for example, 0.0034% in the United States (US Department of Labor, 2017) and 0.0005% in the United Kingdom (Health & Safety Executive, 2017). In addition, there have been numerous cases of illegal chemical discharge by manufacturing firms listed on the Shenzhen and Shanghai stock exchanges (Institute of Public and Environmental Affairs, 2018). Chinese government has realized the significance of HSE issues and highlighted "sustainable development" in the national policy of "Made in China 2025". Chinese manufacturers are therefore under both domestic and overseas pressure to clean up their "sweatshop" image to meet global demand for more sustainable supply chains, making the sector an ideal context in which to answer the research questions posed in this study.

It is worth noting that our research implications are not limited to the Chinese context because sustainability is not a problem affecting only Chinese manufacturers. Most developing countries that leverage cheap labor and only loosely enforce environmental and workplace safety laws neglect their employees and the environment in favor of marginal price skimming for economic benefit (Huq et al., 2016). For example, the Rana Plaza incident in Bangladesh revealed that the government of that country had been working with multinational enterprises and nongovernmental organizations to minimize their degree of liability for victims of the incident (Chowdhury, 2017). Such behavior results in the relatively high frequency of HSE incidents in China and other emerging markets.

3. Hypothesis Development

OM studies have explored how a firm's financial status affects its safety and environmental performance (Flammer, 2015; Luo et al., 2015). Researchers have found that the availability of slack resources significantly affects the likelihood of firm misconduct and improves overall safety and environmental performance (Gualandris et al., 2015). Adding to this line of thought with empirical evidence, Lo et al. (2014) drew on NAT and high-reliability organization theory (HRT) to propose that the characteristics of production processes (i.e., production complexity and production coupling) directly influence the effectiveness of OHSAS (Occupational Health and Safety Assessment Series) 18001, the most prevalent occupational health and safety management system. We believe that these production characteristics may also influence the likelihood of HSE incidents and moderate long-term risk in firms.

HSE incidents are often attributed to human error or system failures (Reason, 2000; Shrivastava et al., 2009). Modern supply chain and logistics management (e.g., zero inventory) emphasizes removing unnecessary slack (e.g., inventory) that puts operations managers under high pressure to not prioritize prevention of HSE problems in production. A synthesized view between NAT and HRT suggests that operational incidents are controllable if the employee is *mindful* of all safety rules and practices (LaPorte & Consolini, 1991; Weick & Roberts, 1993; Weick et al., 2008). According to Weick et al. (2008), a mindful employee exhibits the characteristics of preoccupation with failure, sensitivity to operations, deference to experience, reluctance to simplify interpretation, and commitment to resilience. When all employees maintain such mindfulness (known as collective mindfulness), a firm's operations are highly capable of detecting potential hazards and managing unexpected HSE incidents, leading to less risky operations in the future (Weick et al., 2008). A high level of mindfulness among employees regarding HSE problems can prevent operational accidents (Rijpma, 1997).

Lo et al. (2014) found that in complex and tightly coupled production processes, worker mindfulness can *drift* away more frequently, and this can lead to occasional unexpected incidents caused by workers not reacting quickly. Maintaining high reliability is extremely difficult because drift is virtually unavoidable. In particular, when a firm's production capacity approaches its limits, managers and workers focus on production efficiency, rather than appropriate control of HSE problems. Workers under pressure from productivity demands may become less mindful and take shortcuts to meet production quotas (Brown et al., 2000; de Koster et al., 2011). In many adverse risk incidents, worker safety and environmental pollution occur together because of mindfulness drift, especially in highly polluting firms such as chemical and petroleum refineries (Wolf, 2001). An accident leading to chemical leakage or illegal discharge of polluted air/water to the neighborhood would harm both workers and the environment. Thus, it is essential to explore how to minimize the risk of both environmental and workplace safety incidents, together with a better management system (Marais et al., 2004). Shrivastava et al. (2009) argued that the potential for *drift* increases in operations with high complexity and tight coupling, which increases the likelihood of HSE incidents, and thus also increases the necessity for control. Through the lens of NAT and HRT, we investigated both types of incidents under the same research model. Thus, the present paper proposes two key constructs that may lead to a higher likelihood of HSE incidents: production complexity and coupling.

3.1. Antecedents of HSE incidents

Based on NAT, we developed the hypotheses of the antecedents of HSE incidents. Labor intensity can proxy for production complexity (Swink & Jacobs, 2012, Lo et al., 2014, Fan & Zhou, 2018) because production processes in labor-intensive firms are complex and automating them is a difficult task. In addition, managers in such firms have substantial difficulty identifying all potential hazards associated with production processes and developing contingency plans for adverse events. Moreover, in such complex working environments, workers face relatively great difficulty performing immediate corrective actions for near misses that could lead to actual damage, such as pollution or worker injury (Perrow, 2011). Therefore, labor-intensive operations have a high likelihood of human errors. The human error is a typical manifestation of both workplace accidents (Lo et al., 2014) and environmental pollutions (Miao et al., 2015; Duffy and Duffy, 2020). These HSE incidents are manifestations of operational system failures. Thus, this study developed the following hypothesis:

H1: A firm's level of production complexity is positively associated with its likelihood of HSE incidents.

Production coupling refers to the connections between each stage in an operational process. A more tightly coupled operation usually involves less idle time for workers to rest and prepare for the next production goal. Inventory buffering is a primary decoupling technique in a manufacturing setting because inventory can buffer unexpected demand (Minner, 2001). Thus, inventory level is widely used as an indicator of coupling (Fan & Zhou, 2018; Wiengarten et al., 2017; 2019); that is, low inventory levels are associated with high coupling levels (Wiengarten et al., 2017;2019). A higher inventory level gives workers more time to react to a productivity goal brought on by a sudden demand change or supply glitch; this, in turn, enables employees to follow standard operating procedures, thereby reducing the likelihood of drift. Thus, with a reasonable level of additional inventory buffering for uncertainty, workers can remain focused, thereby minimizing the risk of HSE incidents. This led to the second hypothesis:

H2: A firm's level of production coupling is positively associated with its likelihood of HSE incidents.

3.2. Consequence of HSE incidents for manufacturers' risk

We next developed theoretical linkages between HSE incidents and risk in the supply base in China. A prevailing definition of organizational risk is income stream uncertainty for firms (Palmer & Wiseman, 1999). OM scholars have used equity risk to measure overall firm risk (e.g., Hendricks & Singhal, 2005; 2014). The total equity risk can be further divided into a firm's unsystematic (idiosyncratic) risk and systematic risk (Hendricks & Singhal, 2014). Based on this risk taxonomy framework, we discuss how HSE incidents could increase both unsystematic and systematic risk.

Unsystematic risk stems from firm-specific factors. HSE incidents usually happen at the operational level (Lo et al., 2014). These incidents are signals of flaws in a firm's operational system. Such flaws reflect managerial myopia in terms of prioritizing short-term profit and putting operational reliability at risk (Pagell et al., 2019). Operational (un)reliability is tightly related to production productivity (Lo et al., 2014). For example, incidents can cause labor injuries and illnesses, and lead to increased absenteeism (Greiner et al., 1998). In addition, a firm may be required to shut down for a period to allow investigation and corrective actions after environmental or safety incidents (Lo et al., 2018). The consequent loss of productivity can directly affect the profitability of the firm and increase firm risk (Lo et al., 2014).

Second, HSE incidents can damage investors' trust in the long term (Brown & Dacin, 1997; Kramer & Porter, 2006). Managers of widespread institutional investments, such as government pension funds in many countries, prefer to incorporate firms with fewer HSE issues into their portfolios. For example, the Japan Government Pension Investment Fund (the largest pension fund in the world) has invested JP¥1 trillion (~US$9.04 billion) in firms that meet certain social, environmental, and corporate governance criteria; the percentage of this investment will continue to grow to 10% of the portfolio (Fujita & Umekawa, 2017; Kyodo, 2017). When investors are more alert and reactive to a firm's future HSE incidents, the volatility of future cash flow may increase, which affects firm resources that can be deployed for production.

Last, HSE incidents are highly socially undesirable; they can damage a manufacturing firm's reputation and legitimacy because stakeholders may consider that the firm has failed to take proper CSR (Beddewela & Fairbrass, 2016). CSR can be viewed as a product feature that provides value to customers (Peloza & Shang, 2011). Socially responsible manufacturers can help buyers to reduce the overall environmental and social impact of products throughout their lifecycle. Therefore, HSE incidents undermine the capability of manufacturers to add value to the supply chain via CSR features (McWilliams & Siegel, 2000).

In summary, we argue that loss of productivity, investor trust and firm reputation can induce uncertainty in a manufacturer's future income stream. Thus, we hypothesize:

H3a: Firms with HSE incidents have higher abnormal systematic risk than firms without HSE incidents.

Unsystematic risk can be diversified as it is firm-specific, while systematic risk is not diversifiable. Systematic risk stems from the sensitivity that a firm's income was affected by the exogenous shocks (e.g., macro-economic factors). We argue that HSE incidents are signals of flaws in a firm's operational system; such flaws increase the ability of the firm to respond to adverse exogenous market environment changes.

First, HSE incidents can undermine firm productivity, reducing production capacity. The loss of production capacity reduces the capacity to meet a spike in demand (Fan et al., 2020). In addition, employees and insurance companies may ask for higher premiums to cover unsafe and polluted workplaces (Hendricks & Singhal, 2014). Compensations and penalties arising from HSE incidents also undermine a firm's financial health, which can be used to buffer against future economic downturns (Lo et al., 2014). These vulnerabilities, therefore, lead to income stream uncertainty for manufacturers.

In addition, HSE incidents undermine the capability of a manufacturer to utilize external resources to survive a recession. In economic downturns, firms may need to supplement working capital from outside sources such as investors and creditors. However, as discussed above, HSE incidents may undermine investor trust (Toms, 2002), making it difficult for manufacturers to access finance in stock markets. Regarding creditors, the banking industry has increasingly adopted socially responsible lending (Gutiérrez-Nieto et al., 2016). CSR performance has become a vital criterion for banks to consider when evaluating loan applications (Renneboog et al., 2008). Thus, HSE incidents may increase the difficulty for a firm to secure a bridging loan with ideal terms (e.g., interest rate).

In summary, we argue that HSE incidents limit a manufacturer's resources internally and externally, which makes the firm vulnerable in the face of macro-economic downturns. That is, the firm's income will be highly sensitive to decreased demand, which may be reflected in the firm's increased systematic risk. Thus we hypothesize that:

H3b: Firms with HSE incidents have higher abnormal unsystematic risk than firms without HSE incidents.

3.3. Moderating the (HSE) incident–risk relationship

The final objective of this study was to explore the factors that compel firms to minimize the negative effects of HSE incidents. As posited in H3a and H3b, investors are concerned with HSE incidents that lower the production capability and increase the chance of production disruptions. We argue that the effects of such disruptions are reduced in less complex and more loosely coupled operations (Lo et al., 2014; Wiengarten et al., 2017).

First, in a complex operation with high labor intensity, firms have relatively great difficulty identifying the root causes of HSE incidents (Fan & Zhou, 2018; Lo et al., 2014). Managers must consider not only technological factors but also complicated human factors associated with HSE incidents. Any corrective actions in response to an HSE incident are likely to be superficial; thus, the underlying hazards entrenched in operation may not be detected or removed, and the firm in question maintains the same or an even higher likelihood of experiencing similar incidents in future. Thus, linearizing complex production processes (reducing complexity) facilitates identification of potential hazards and mitigates firm-specific risk. In addition, linearizing complex production can mitigate the vulnerability of firms when encountering negative exogenous conditions. For example, HSE incidents may cause employee absence, but automated firms can cope with demand spikes during such absences more easily than can firms that rely heavily on manual works.

Second, tightly coupled operations usually involve little operational slack, and this is useful for firms in buffering against operation glitches (Wiengarten et al., 2017). An operation disrupted by an HSE incident has low capability to meet customer demand. However, a firm with additional safety inventory is more capable of buffering against demand spikes during disruptions, which helps prevent the losses in customer satisfaction, market share, and compensation that would arise from delivery schedules not being followed. Thus, future concerns over cash flow volatility would be lower.

Based on this discussion, we anticipated that production complexity and coupling would not only affect the likelihood of HSE incidents (as posited in H1 and H2), but would also moderate the effect of such incidents on a manufacturer's risk. This led to the fourth and fifth hypotheses:

H4: A firm's level of production complexity positively moderates the relationship between HSE incidents and abnormal risk.

H5: A firm's level of production coupling positively moderates the relationship between HSE incidents and abnormal risk.

4. Method and Results

This study focused on Chinese public firms in the industrial sector (Chinese industry classification codes B06–D46) because CSR problems prevail in this sector (Jenkins & Yakovleva, 2006; Lo et al., 2014, 2018). We designed a three-stage event study to examine the aforementioned hypotheses. In the first stage, we regressed HSE incidents against labor intensity (for complexity) and reversed inventory days (for coupling) to test H1 and H2 by running logistic regressions. In the second stage, we aimed to capture the abnormal changes in unsystematic and systematic risk in firms where HSE incidents occur, and created sample–control pairs based on the propensity score matching results obtained in Stage 1 to test H3a and H3b. In the third stage, we regressed abnormal unsystematic and systematic risk against labor intensity and reversed inventory days to test H4 and H5.

4.1. Stage 1: Logistic regression analysis of HSE incidents

We investigated the environmental and safety dimensions of HSE and focused on events that cause actual damage to the environment or employees. There is a methodological gap in the literature on supply chain risk management (Sodhi et al., 2012) because for a long time, data on catastrophic incidents were not easy to collect. However, in recent years, the Chinese government has enhanced the transparency of government information and developed various databases to publicize and record HSE incidents (Xu, 2017). Environmental incident data were collected from the IPE (Institute of Public and Environmental Affairs) —a nonprofit organization that collects and collates corporate environmental information in China. The IPE's database discloses environmental incident records, including each polluting firm's name, incident date, and facility location. Safety incident data were collected from the SAWS (State Administration of Work Safety) database kept by the central and provincial governments in China. SAWS is China's government agency that enforces safety regulations. Its safety incident database provides information regarding each incident's date, the firm involved, and numbers of injuries and fatalities.

4.1.1. Data collection

The data collection procedure started with a list of public firms in the industrial sector obtained from the China Stock Market and Accounting Research database. We then searched for each firm's name in the IPE and SAWS databases to view their HSE incidents. We found 458 environmental incidents and 198 safety incidents in 318 firms from 2004 to 2013. We collected financial information for these 318 firms and control firms (firms without incidents and within the same industries). Given that we used 1-year-lagged financial data for independent variables to dependent variable (HSE incidents covered from 2004 to 2013), financial data from 2003 to 2012 were covered. Data from the aforementioned three databases formed a panel dataset with 10,357 firm–year observations for examination of H1 and H2.

The dependent variable *HSE incident* was measured in terms of whether firm *i* had HSE incidents in year *t*. We defined the term HSE incidents based on the clause of ISO 14001 and OHSAS 18001. Specifically, an HSE incident is an adverse work-related event in which damage occurs to occupational health and safety, and the environment. These events could lead to operational disruptions and productivity loss. We collected environmental incident events from the IPE database. One example is an environmental incident in 2010 involving Shenzhen

Zhongjin Lingnan Co Ltd. The company discharged wastewater with excessive thallium in Shaoguan City, Guangdong Province. The title of this incident is “Zhongjin Lingnan’s river-polluting factory shutdown.” We collected safety incident events from the SAWS database. One example is a BYD incident that occurred in 2011. The incident description is “9/20, 17:40pm, BYD company in Dayawan, Huizhou City, Guangdong Province, a tower crane collapse causes 4 deaths.” Firms with one or more incident in year *t* were coded as “1” and those without were coded as “0.” This binary measure for HSE incidents is consistent with the approach in previous studies investigating other forms of corporate malfeasance (Harris & Bromiley, 2007; Yiu et al., 2014). A total of 473 observations had at least one incident in each year.

H1 and H2 hypothesize that firms that implement operations with higher levels of production complexity and coupling are more likely to have HSE incidents. We followed Swink and Jacobs (2012) and Lo et al. (2014) to operationalize operational complexity based on *labor intensity* because labor-intensive processes are inherently more variable and difficult to automate than are non-labor-intensive processes (Swink & Jacobs, 2012). Thus, they increase the need for management efforts to cope with such complexity. For example, training and skills are required to ready workers for operations (Swink & Jacobs, 2012). Labor intensity was calculated based on the ratio of number of employees to total assets (in million US$) (Lo et al., 2014).

We followed Wiengarten et al. (2017) in operationalizing operational coupling by inventory. An essential reason for firms to maintain inventory is to decouple operations through buffering for demand and lead time uncertainty (Stevenson & Sum, 2014, p. 561). A firm with shorter inventory days has a lower inventory level and thus lacks the capacity to decouple operations. Thus, we measured operational coupling based on *reversed inventory days*. The number of inventory days in a firm was first calculated by dividing the average inventory by cost of goods sold (inventory turnover ratio). We then multiplied the inventory turnover ratio by 365.

We included several control variables to minimize concern over alternative explanations and improve the explanatory power of the models. First, we controlled for firm performance and size by including *return on sales* (*ROS*) and *total assets* because profitable and large manufacturers are more resourceful in tackling HSE problems. Second, we controlled for *firm age* because older firms are more likely to have inherited negligent HSE practices, and this could increase the risk of HSE incidents. Third, we included *quick ratio*[1] to control for the financial situation of manufacturers, as well as *cash* and *receivable days* because firms with higher liquidity are less likely to cut corners with respect to health, safety, and the environment. Fourth, we controlled for operational resources by employing *production capacity*[2] and *working capital per employee*. Firms with more operational resources are more capable of responding to uncertainty. In addition, we controlled for firm willingness to invest in employees by *wage expense per employee*. Firms with higher willingness to invest in employees are less likely to place employees at safety and environmental risk.

We incorporated several corporate governance factors, including each firm's *top management team (TMT) ownership* (percentage stock share held by the TMT). Managers with higher ownership are less likely to make opportunistic decisions that place their personal wealth at risk (Wiseman & Gomez-Mejia, 1998). Further, we included *board size* (number of directors) and *percentage of independent directors* on the board. A larger board with more independent directors may have more power to monitor and restrict opportunistic decisions being made by the TMT (Forbes & Milliken, 1999).

Finally, we included industry dummy variables and *firm year* to control for invariant factors related to time and industry. We performed natural logarithm transformations for total assets, cash, production capacity, board size, and TMT ownership to correct for skewness. The statistic model is expressed as follows:

$$HSE\ incident_{ijt} = F(labor\ intensity_{ijt-1}, Reversed\ inventory\ days_{ijt-1}, ROS_{ijt-1}, Total\ assets_{ijt-1}, Firm\ age_{ijt-1}, Quick\ ratio_{ijt-1}, Cash_{ijt-1}, Receivable\ days_{ijt-1}, Capacity_{ijt-1}, Working\ capital_{ijt-1}, Wage_{ijt-1}, TMT\ ownership_{ijt-1}, Board\ size_{ijt-1}, Independent\ director_{ijt-1}, Year_t, Industry_j, u)$$

where *F(.)* is the logit function, *i* represents the *i*th company in industry *j*, and *t* represents the year of observation.

Table 1 presents correlation relationships and descriptive statistics for the variables. The maximum variance inflation factor was 3.698; thus, multicollinearity was not severe. Table 2 presents Model 1—the logistic regression analysis—including all control variables. Our omnibus test confirmed that the variables created satisfactory control ($\chi^2 = 649.577$, $p < .01$). Model 2 examined H1 and H2 through inclusion of labor intensity and reversed inventory days.

[1] *Quick ratio* was calculated as (current assets − inventory) / current liability.
[2] Production capacity was calculated as the value of property, plant, and equipment scaled by annual sales.

The coefficient of labor intensity was significantly positive (0.1250; $p < .05$, odds ratio = 1.132). The marginal effect of labor intensity is presented in Fig. 1. When we held other factors constant by shifting labor intensity from 0 to 3 (i.e., one standard deviation above average labor intensity), the likelihood of HSE incidents increased by 1.56%. The coefficient of reversed inventory days was also significantly positive (0.1679; $p < .05$, odds ratio = 0.00168). The marginal effect of reversed inventory days is presented in Fig. 2. When we held other factors constant by decreasing the number of inventory days from 400 (i.e., one standard deviation above the average number of inventory days) to 0, the likelihood of HSE incidents increased by 2.51%. Given that the average likelihood of HSE incidents was low (4.60%), the practical effects of labor intensity and inventory days were substantial. The results revealed that the goodness of fit of Model 2 improved (incremental $\chi^2 = 29.318$, $p < .01$) by a significant margin. Therefore, H1 and H2 are supported.

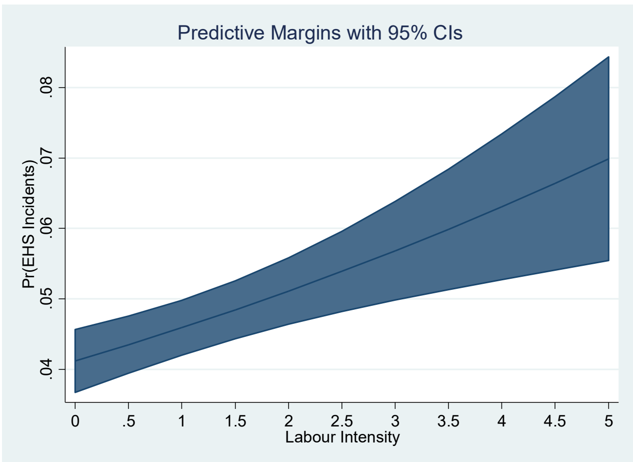

Fig. 1: Marginal effects of labor intensity

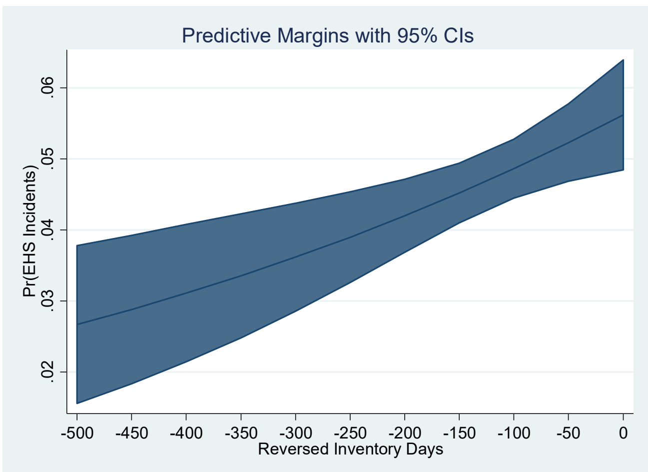

Fig. 2: Marginal effects of inventory days

Table 1: Descriptive statistics and correlations

	Mean	Std. deviation	HSE incidents	Labor intensity	Reversed inventory days	Production capacity	ROS	Total assets	Firm age
HSE incidents	0.046	0.209							
Labor intensity	1.317	1.842	.004						
Reversed inventory days ('00)	-1.515	2.874	.011	.013					
Production capacity (log)	-0.911	0.962	.026**	-.030**	-.078**				
ROS	-0.051	3.021	.007	-.110**	.107**	-.152**			
Total assets (log)	21.504	1.211	.154**	-.249**	.025*	.006	.077**		
Firm age	7.549	5.551	.061**	.007	-.023*	.060**	-.042**	.191**	
Quick ratio	1.895	4.436	-.044**	-.071**	.012	-.136**	.027**	-.126**	-.220**
Cash (log)	19.495	1.492	.100**	-.255**	.092**	-.274**	.165**	.763**	-.062**
Receivable days	95.691	507.050	-.018	.020*	-.118**	.147**	-.771**	-.079**	-.007
Working capital ('000)	153.492	5,782.563	.011	-.016	-.005	-.082**	.065**	.045**	-.057**
Salary ('000)	21.400	207.293	.008	-.047**	-.001	.013	-.001	.074**	.063**
Board size (log)	2.205	0.206	.043**	-.016	.015	.094**	.036**	.268**	-.002
TMT ownership (log)	9.050	6.702	-.034**	-.079**	.023*	-.082**	.032**	-.010	-.252**
Independent director %	0.358	0.053	.004	-.035**	.006	-.077**	-.002	.041**	.006
			Quick ratio	**Cash**	**Receivable days**	**Working capital**	**Salary**	**Board size**	**TMT ownership**
Cash (log)			.117**						
Receivable days			.001	-.148**					
Working capital ('000)			.069**	.122**	.000				
Salary ('000)			-.009	.063**	-.005	.150**			
Board size (log)			-.094**	.176**	-.038**	.001	.000		
TMT ownership (log)			.171**	.121**	-.004	.009	-.025**	-.093**	
Independent director %			.037**	.064**	-.010	.006	.010	-.333**	.057**

Note. ** and * indicate significance at 0.01 and 0.05 levels; N = 10,357; two-tailed test; Currency in CNY.

4.2. Stage 2: Propensity score matching event study

We adopted a long-term event study approach to conduct a quasi-experiment for the examination of H3. We defined year 0 as the event year when a firm had an HSE incident. Year –1 was the base year when the incident firm was free from the effects of the incident. We investigated each firm's unsystematic and systematic risk change over 3 consecutive years starting with the base year (i.e., years 0, 1, and 2).

HSE incidents can be considered a random treatment for the sample because stock market investors have no prior knowledge of an HSE incident before it is revealed. Thus, we needed to match each sample (with HSE incidents) with a control (without HSE incidents) to form a quasi-control group for control of counterfactual (or unobserved) outcomes (Caliendo & Kopeinig, 2008; Heckman et al., 1998). We adopted propensity score matching to match sample firms to control firms with similar probabilities of HSE incidents (Caliendo & Kopeinig, 2008). This helped us isolate the effects of HSE incidents from other firm- or industry-specific factors that affect firm risk.

We calculated the propensity score (i.e., probability) for HSE incidents for the samples and controls in every fiscal year, based on the significant predictors presented in Table 2. We then applied the nearest neighborhood matching method to create sample–control pairs. The sample–control pairs needed to meet the following criteria: (1) firms must be in the same industry; and (2) the control firm must have the closest probability to the sample firm of an HSE incident in the incident year (Levine & Toffel, 2010). We eliminated all matches with a probability difference larger than the 0.07 caliper (Levine & Toffel, 2010) and further discarded all matches with missing data regarding systematic risk during the research period. Finally, for the 473 incident observations in Stage 1, we generated 278 matches that met the matching criteria.

Although one-to-many matching has been used in previous studies (e.g., Lo et al., 2014), this matching strategy suffers from the disadvantage that some control firms that are not sufficiently adequate may be included, which leads to an increase in bias (Leite, 2016). The nearest neighborhood ensures that a matched untreated firm is the control firm that is most similar to its corresponding sample firm. To prove the quality of the sample–control pairs, paired *t* tests were carried out for independent variables (from Table 2) and results are presented in Table 3. We found that no differences among variables were significant ($p > .01$, two-tailed test), suggesting that no systematic differences existed among the samples and controls (Levine & Toffel, 2010).

Table 2: Logistic regression analysis of HSE incidents

DV: HSE incident at year *t* (1 = yes, 0 = no)				
	Model 1		**Model 2**	
Variable	**Coef.**	***p***	**Coef.**	***p***
Labor intensity			0.125	0.000
Reversed inventory days ('00)			0.168	0.001
Production capacity	0.089	0.235	0.138	0.082
ROS	0.024	0.808	0.395	0.024
Total assets	0.365	0.000	0.402	0.000
Firm age	0.039	0.000	0.043	0.000
Quick ratio	-0.069	0.102	-0.077	0.081
Cash	0.129	0.084	0.114	0.130
Receivable days	-0.001	0.225	0.000	0.831
Working capital	0.000	0.347	0.000	0.085
Salary	0.000	0.616	0.000	0.173
Board size	0.059	0.827	-0.014	0.958
TMT ownership	-0.012	0.158	-0.012	0.143
Independent director %	0.116	0.910	0.090	0.931
Industry	Included		Included	
Year	Included		Included	
Intercept	-32.51		-32.703	
Chi^2	649.577	0.000	678.895	0.000
Incremental chi^2			29.318	0.000

Note. $N = 10{,}357$; two-tailed tests; 0.000 indicates <.001.

Table 3: Matching quality examination

Variable	*p*-value from paired t-test
Labor intensity	0.119
Reversed inventory days	0.268
Production capacity	0.194
ROS	0.821
Total assets	0.283
Firm age	0.389
Quick ratio	0.176
Cash	0.511
Receivable days	0.663
Working capital	0.188
Salary	0.324
Board size	0.266
TMT ownership	0.587
Independent director %	0.339

H3a and H3b test abnormal unsystematic and systematic risk by comparing risk change in the sample (before and after HSE incidents) with that in the controls during the same period. The capital assets pricing model (CAPM) was used to calculate the risk values for firm *i* in year *t* (Singhal & Raturi, 1990).[3] Specifically, we used the following model to estimate unsystematic and systematic risk, for firm *i* in year *t*, the data in recent one calendar year to year *t* was used for the estimation of:

$$R_{it} - R_{ft} = \alpha_{it} + \beta_{it}(R_{mt} - R_{ft}) + e_{it}$$

where R_{ft} is the risk-free return, R_{it} is the firm stock return, and R_{mt} is the market return. Market return is the market capitalization weighted return of all listed firms on the

[3] The Fama–French (FF) model is an alternative method for this calculation. The CAPM (market) model assumes that a firm's stock price is associated with the market index, while the FF model assumes that the firm's stock price is also associated with small(capitalization)-minus-big (SMB) and high (book-to-market ratio)-minus-low (HML) portfolios. However, the literature shows that FF factors are good proxies for risk factors of portfolios, while only the market factor is appropriate for proxying risk factors for individual stocks (Lin et al., 2012). The market portfolio and HML factors are found to have no significant effect in the estimation (Hu et al., 2019). Thus, we adopted the market model for estimation in our study.

Shanghai and Shenzhen stock exchanges. Systematic risk is the square root of the difference between the total variance of the stock return and the variance of the residuals, while unsystematic risk is the standard deviation of $e_{it.}$ This operationalization is a conventional risk measure adopted in the finance (e.g., Bowman, 1979), strategic management (Miller & Bromiley, 1990; Miller & Reuer, 1996), information systems (Tian & Xu, 2015), and OM (Hendricks & Singhal, 2005; 2014; Singhal & Raturi, 1990) literature..

We adopted the difference-in-difference approach to estimate abnormal risk for comparison between the sample and control firms. Specifically, we subtracted the change in the unsystematic and systematic risk of the sample firm from the change in that of the control firm for each sample–control pair. Specifically, the calculation was:

$$\textit{Abnormal risk}_{(t\ to\ t+j)} = [\textit{Sample firm risk}_{(t+j)} - \textit{Sample firm risk}_{(t)}] - [\textit{Control firm risk}_{(t+j)} - \textit{Control firm risk}_{(t)}]$$

where t and j are the start and end year for the comparison, respectively. Given that abnormal risk may not be normally distributed, we used the nonparametric Wilcoxon signed-rank test to examine H3 and used parametric t-test as robustness checks. We followed previous studies in presenting the paired t test and signed-rank test results.

We examined H3a and H3b based on the results in Table 4. We observed an abnormal increase in both unsystematic and systematic risk 1 year after HSE incidents. Specifically, the median of unsystematic and systematic risk among the sample firms increased by 0.004 and 0.027 respectively compared with that of the control firms from year 0 to year 1 ($p < .10$). In addition, the cumulated abnormal unsystematic risk from year –1 to year 1 was positive (0.008, $p < .05$). The significant positive result is also reflected in the cumulative abnormal systematic risk from year –1 to year 1 (0.042, $p < .01$). These results provide support for H3a and H3b. We note that the significant effects on systematic risk can be captured in a longer period (year 2), while the result is inconclusive for unsystematic risk.

Table 4: Event analysis of HSE incidents

Table 4: Event analysis of HSE incidents, $N = 278$, two-tailed tests.

	Nonparametric test			Parametric test		
Abnormal unsystematic risk (H3a)	**Median**	**WSR-Z**	***p***	**Mean**	**Paired *t***	***p***
Year -1 to 0	0.002	0.996	0.319	0.005	1.225	0.222
Year 0 to 1	0.004	1.738	0.082	0.006	1.766	0.079
Year 1 to 2	-0.005	-1.483	0.138	-0.004	-1.108	0.269
Year -1 to 1	0.008	2.469	0.014	0.011	2.657	0.008
Year -1 to 2	0.002	1.057	0.290	0.007	1.689	0.092
Abnormal systematic risk (H3b)	**Median**	**WSR-Z**	***p***	**Mean**	**paired *t***	***p***
Year -1 to 0	0.004	0.876	0.381	0.022	1.15	0.251
Year 0 to 1	0.027	1.763	0.078	0.028	1.764	0.079
Year 1 to 2	-0.01	-0.67	0.503	-0.008	-0.533	0.594
Year -1 to 1	0.043	2.69	0.007	0.05	2.681	0.008
Year -1 to 2	0.024	1.746	0.081	0.041	2.167	0.031

4.3. Stage 3: Cross-sectional analysis of event study

The risk mitigation approaches have two major objectives: 1) to reduce the likelihood of risk event and 2) to reduce the negative consequences when the risk event happens. In the examination of H1 and H2, the dependent variables were the likelihood of HSE incidents, thus they were addressing the first objective. H4 and H5 postulate moderating effects of complexity and coupling on abnormal risk caused by HSE incidents, which addressing the second objective. Although variation in complexity and coupling was controlled between sample and control firms, variation in these two variables among sample firms enabled us to explore whether they could be used to predict variation in abnormal risk. We used abnormal unsystematic and systematic risk (Hendricks & Singhal, 2005; Singhal & Raturi, 1990) as the dependent variable throughout the research period (year –1 to year 2). Use of data regarding the entire research window as the dependent variable is consistent with previous long-horizon event studies (e.g., Lo et al., 2014; Swink & Jacobs, 2012). The independent variables for examining H4 and H5 were labor intensity (indicating complexity) and reversed inventory days (indicating coupling) in year –1. In addition, we included all the control variables used in Stage 1 alongside an additional control variable, multiple events, to control for the number of HSE incidents of a firm in the same year. The model specification for this cross-sectional analysis is expressed as follows:

$Abnormal\ unsystematic/systematic\ risk_{ij(t-1\ to\ t+2)} = F(labor\ intensity_{ijt-1},\ Reversed\ inventory\ days_{ijt-1},\ ROS_{ijt-1},\ Total\ assets_{ijt-1},\ Firm\ age_{ijt-1},\ Quick\ ratio_{ijt-1},\ Cash_{ijt-1},\ Receivable\ days_{ijt-1},\ Capacity_{ijt-1},\ Working\ capital_{ijt-1},\ Wage_{ijt-1},\ TMT\ ownership_{ijt-1},\ Board\ size_{ijt-1},\ Independent\ director_{ijt-1},\ Year_t,\ Industry_j,\ u)$

Table 5 presents Model 1 and Model 3 including all control variables for the dependent variables of systematic & unsystematic risk respectively. Model 2 and Model 4 examined H4 and H5 through inclusion of *labor intensity* and *reversed inventory days*. In Model 2, the coefficient of *labor intensity* was significantly positive in both Model 2 and 4 (Model 2: 0.0390, $p < .05$; Model 4: 0.0120, $p < .01$). If we held other factors constant by shifting labor intensity from 0 to the mean (1.316), the abnormal systematic risk increased by 0.051 while unsystematic risk increased by 0.016. The coefficient of *reversed inventory days* was significantly positive (0.020, $p < .10$) in Model 2 while nonsignificant in Model 4. If we held other factors constant by increasing the number of inventory days from 0 to the average (209.27), abnormal systematic risk increased by 0.042. The goodness of fit of Model 2 (incremental $\chi^2 = 5.127$, $p < .10$) and Model 4 (incremental $\chi^2 = 5.980$, $p < .05$) improved significantly. Thus, H4 is supported and H5 is partially supported. The result for H5 suggests that the inventory slack is more valuable for responding to disruption caused by exogenous shocks such as supply glitch and production shutdown. At the same time, additional inventory may increase the firm-specific risk in terms of firm opaque, inventory depreciation and dead stock (Stevenson and Sum, 2014).

Table 5: Cross-sectional analysis of abnormal systematic risk

	DV: Abnormal systematic risk (year -1 to year 2)				DV: Abnormal unsystematic risk (year -1 to year 2)			
	Model 1		Model 2		Model 3		Model 4	
	Coef.	*p*	Coef.	*p*	Coef.	*p*	Coef.	*p*
Labor intensity (H4)			0.039	0.038			0.012	0.006
Reversed inventory days (H5)			0.020	0.066			0.002	0.434
Production capacity	0.024	0.420	0.014	0.628	0.011	0.122	0.010	0.169
ROS	0.394	0.015	0.475	0.004	0.071	0.150	0.087	0.076
Total assets	0.024	0.611	0.026	0.584	0.005	0.616	0.007	0.498
Firm age	0.004	0.374	0.005	0.265	0.000	0.940	0.000	0.709
Quick ratio	-0.007	0.861	-0.011	0.790	0.013	0.165	0.013	0.171
Cash	0.000	0.295	0.000	0.641	-0.007	0.467	-0.007	0.503
Receivable days	0.000	0.654	0.00	0.608	0.000	0.058	0.000	0.112
Working capital	0.000	0.075	0.000	0.034	0.000	0.729	0.000	0.704
Salary	-0.021	0.624	-0.018	0.671	0.000	0.042	0.000	0.010
Board size	-0.145	0.175	-0.146	0.171	-0.025	0.289	-0.025	0.294
TMT ownership	0.004	0.287	0.004	0.232	0.000	0.599	0.001	0.482
Independent director %	-0.308	0.354	-0.181	0.579	-0.028	0.738	-0.014	0.861
Multiple incidents	-0.016	0.740	-0.030	0.499	-0.003	0.756	-0.006	0.438
Industry			Included				Included	
Year			Included				Included	
Chi^2	57.624	0.000	62.752	0.000	49.417	0.301	55.397	0.188
Incremental chi^2			5.127	0.077			5.980	0.050

Note. $N = 278$; 0.000 indicates <.001.

4.3.1. Robustness check

4.3.1.1. Alternative time lag for independent variables

We used 1-year-lagged independent variables to examine H1 and H2. However, the complex nature and coupling nature were relatively stable in each firm's operations, and thus may have long-lasting effects on firms' HSE performance. To address this concern, we used the independent variables at $t - 2$ to conduct an analysis; the results are presented in Table A.1. The coefficients of *labor intensity* (0.1675) and *reversed inventory days* (0.0014) were significantly positive ($p < .01$), consistent with the results in Table 2.

4.3.1.2. HSE incidents as rare events

Given that HSE incidents are rare, some may argue that our dependent variable contains a high proportion of "0," which may have caused bias in the testing of H1 and H2. However, Cramer et al. (1999) reported that parameter estimation is robust in samples involving large percentages of "0" observations. In addition, Bayus (2013) argued that gaining statistical support is more difficult with a higher number of "0" observations. This suggests that the high number of firms without HSE incidents rendered the hypothesis testing more conservative. To address concerns over the large percentage of "0" or no-incident observations, we used a rare-event logistic regression model to re-estimate the regression model in Table A.2. The coefficients of *labor intensity* (0.1262) and *reversed inventory days* (0.0012) were significantly positive ($p < .01$), consistent with the results in Table 2.

4.3.1.3. Separating health and safety, and environmental incidents

Our primary model integrated health and safety, and environmental incidents into one variable (HSE incident). In a robustness analysis for H1 and H2, we divided the dependent variable into environmental incident, and safety incident, respectively, and reran the analysis. The analysis results (Table A.3) show that both complexity (labor intensity) and coupling (low inventory level) contributed to the increased likelihood of environmental incidents ($p < .01$). However, we found that only complexity had an impact on safety incident ($p < .10$) while the impact of coupling was not significant ($p > .10$). This result provides additional support for H1. It also provides a boundary condition for our H2 by indicating that Chinese firms generally were not using inventory slack to cope with safety incidents.

4.3.1.4. Endogeneity

In our primary models, we developed a panel dataset with the collected data for analysis. Panel data analysis has the advantage of being able to mitigate certain endogeneity risk (Ketokivi & McIntosh, 2017). First, a time lag exists between the independent and dependent variables to confirm a causality relationship (i.e., eliminating the possibility of reversed causality). Second, we controlled for *year* and *industry* for un-modeled time-invariant effects, such as regulation and seasonal factors related to industry and law enforcement variation in different years. However, time variation present in un-modeled variables may present endogeneity concerns during the evaluation of results. Such concerns could result from the possibility that unobserved factors affect independent and dependent variables simultaneously, leading to an alternative explanation(s) for our results. For example, a manager's risk propensity and adoption of advanced technology may affect their firm's operational complexity, coupling, and safety performance.

In light of the aforementioned discussion about employing approaches from previous studies using panel data to control for external factors, we used a generalized method of moments (GMM) analysis in our robustness check (e.g., Lam et al., 2016; Wiengarten et al., 2017) to further reduce the risk of endogeneity in our models. The GMM uses lagged values for endogenous factors as instrumental variables to reduce bias caused by endogeneity (Roodman, 2009).

We used the lagged values of *labor intensity* and *reversed inventory days* in our GMM models. Table A.4 presents the GMM analysis results alongside the results from Hansen (Hansen, 1982) and Arellano–Bond (Arellano & Bond, 1991) tests. The Hansen and Arellano–Bond tests indicated that the lagged variables were acceptable instruments for addressing endogeneity concerns in the GMM models. Thus, we concluded that the instruments were exogenous and did not correlate with the disturbance terms, and the GMM model mitigated the risk of endogeneity arising from un-modeled random variables. The coefficients of *labor intensity* (0.0037) and *reversed inventory days* (0.000014) were significantly positive ($p < .01$ and $p < .05$, respectively), which provides additional support for H1 and H2.

4.3.1.5. Robustness check for firm risk

The propensity score approach ensured that the sample–control paired firms were comparable. However, the abnormal increases in risk shown in Table 4 may have been caused by the continuing trend in risk change prior to HSE incidents. Following previous event studies (e.g., Lo et al., 2014), we further tested for abnormal change in the pre-event period (i.e., year –2 to year –1). The analysis did not capture a significant change in this period ($p > .10$); thus, the results in Table 4 were not caused by systematic bias. In addition, confounding events that occurred in the same years as HSE incidents may have influenced the effect on firm risk. Thus, we searched each sample firm's announcements to identify whether the firms had announced acquisitions or sales of assets or equity, or any corporate changes, including those involving major shareholders, senior management teams, members of boards of directors, auditing firms, corporate names, registration, or location. We eliminated 75 HSE incidents associated with these confounding events and reran the analysis. The analysis results are presented in Table A.5. Abnormal unsystematic and systematic risk change was positive and significant at the 0.1 level in the periods of year 0 to year 1 and year –1 to year 1. These findings suggest that the influence of confounding events was not strong and does not falsify H3a and H3b.

4.3.1.6. Alternative measure of coupling

We used reversed inventory days to measure operational coupling in the main analysis (Wiengarten et al., 2017). However, the assumption of inventory decoupling operations is that a firm should hold inventory that matches demand (Lo et al., 2014). Firms with large quantities of the wrong inventory require additional effort (e.g., more frequent setup, maintenance, and reproduction) to increase operational coupling (Fan & Zhou, 2018). Therefore, we replaced the independent variable of reversed inventory days in Tables 2 and 5 with inventory volatility to examine whether H2 and H5 had been falsified by the alternative measure. Inventory volatility was measured as the standard deviation of a firm's inventory by quarter, scaled by its mean quarterly inventory value in the year in question (Fan & Zhou, 2018; Lo et al., 2014). We transformed this variable to a natural logarithm to correct for skewness. The robustness check results are presented in Table A.6. Model 1 examined H2 and Model 2 examined H5. The coefficients of *inventory volatility* in both models were significantly positive ($p < .05$ and $p < .10$, respectively). The results from this analysis provide additional support for H2 and H5.

5. Conclusion and Discussion

This study was the first to resolve the empirical puzzle of how operational characteristics affect the likelihood, and moderate the effect, of HSE incidents in relation to risk in the world's most significant supply base: the Chinese manufacturing sector. Our quasi-experiment found that HSE incidents increase both unsystematic and systematic risk for Chinese manufacturers. In addition, regression analyses found that reducing labor intensity and increasing inventory slack of manufacturers can (1) reduce their likelihood of having HSE incidents and (2) mitigate the negative impacts of HSE incidents. Our findings have crucial implications for researchers by advancing knowledge of sustainable operations, supply chain risk, and NAT. This findings also have implications for supply chain managers aiming to reduce supply chain risk, particularly with respect to manufacturing stage and HSE issues. We discussed these implications in this section.

5.1. Theoretical contributions

The current study is the first to address the empirical puzzle of HSE incidents in relation to a manufacturer's risk; we find an essential link between sustainable OM and risk management. Related studies on HSE incidents have focused on short-term abnormal stock return (e.g., Klassen & McLaughlin, 1996; Lo et al., 2018) or long-term productivity, sales performance, and profitability (Lo et al., 2014). The findings of the present study regarding manufacturers' risk provide a valuable supplement to these studies. In addition to firms' abnormal returns and profitability, firm unsystematic and systematic risk are a key dimension in institutional investors' investment portfolios. Thus, the increased risk revealed here offers a fresh and vital angle to understand the consequence of HSE incidents. It is worth noting that we took the first step to investigate equity risk, although risk is a multi-dimensional construct that involves both internal and external uncertainties encountered by firms. Further research might expand the research scope to other aspects of risk such as market risk (Wiengarten et al., 2017) and policy risk (Darby et al., 2020).

This study also contributes to the supply chain risk management literature. Tang (2006) identified aspects of supply chain risk including supply, demand, product, and information management. Traditional supplier selection and governance criteria related to cost, quality, delivery, and flexibility, while scholars call for taking sustainability into account (Luthra et al., 2017). This study responds to this call by demonstrating that HSE incidents occurring during the manufacturing stage can increase instability (risk) in the supply base. We confirm that sourcing from socially responsible manufacturers reduces risk in the supply base caused by HSE incidents. Further research on supply chain risk should devote greater attention to the risk associated with HSE incidents.

Our findings also echo the proposition that "socially responsible suppliers are less risky" (McGuire et al., 1988) because such firms are usually more transparent and honest in their operations. The proposition was tested in a corporate bond market context, but those researchers found no significant evidence that more socially responsible firms than socially irresponsible firms risk premiums (Menz, 2010). In contrast, our findings support this proposition with significant results in a stock market context, possibly because institutional investors (unlike bond market investors) are more sensitive to HSE incidents, and transaction frequencies in the stock market are usually considerably higher than those in the bond market. Future research may investigate whether improving operational transparency to reduce supply chain risk would be worthwhile.

Our findings corroborate HRT's prediction regarding the likelihood of HSE incidents. Previous studies of NAT (e.g., Lo et al., 2014) have shown that coupling and complexity moderate the effects of OHSAS 18001 on financial and safety performance. The present research extends understanding of the applicability of these two factors in the context of environmental incidents. In addition, the research extends understanding of coupling and complexity in that these factors moderate both firm performance (i.e., financial and operational) and firm systematic risk. This is the first empirical study to verify the relationships between coupling and complexity, and firm risk.

In the OM studies about NAT, Lo et al., (2014) investigated whether complexity and coupling could affect the effectiveness of OHSAS 18001 adoption. Fan & Zhou (2018) investigate whether complexity and coupling could moderate the relation between supply-demand mismatch and safety violations. Wiengarten et al., (2017) study how coupling affects the likelihood of safety violations. Our study is differentiated in the following ways. First, these studies majorly investigate safety violations not accidents. Violation is an undesirable circumstance that could lead to accidents. If the corrected action can be done timely, the violations can be prevented from mushrooming to accidents. However, our research study accidents that have made actual harm to the labour or environment. Accidents are generally more serious. The characteristics of serious and minor incidents are inherently different (Norris et al., 2000). Serious ones cause more harm to workers, operations and communities by disrupting production and undermining productivity (Wright et al., 2002). Second, Lo et al., (2014) and Fan & Zhou (2018) investigate the indirect effects of coupling and complexity. Despite Wiengarten et al., (2017) focused on the direct effect, complexity is not considered in their research model. Thus, this study is differentiated by providing a more comprehensive view by investigating both direct (H1 & H2) and indirect effects (H4 & H5) of both complexity and coupling. We added these discussions in the theoretical contribution section to demonstrate our research uniqueness.

Further, this study confirms that these two factors affect firms' HSE performance in developing countries (China in this case), as well as developed countries such as the US (e.g., Fan & Zhou, 2018; Lo et al., 2014; Wiengarten et al., 2017; Wolf, 2001).

5.2. Management implications

The findings of this study expand understanding of the antecedents of HSE incidents in emerging markets—from financial slack and profit margin to production characteristics. Understanding of these relationships has management implications for factory operations managers, sourcing agents, and consumer brands that care about the sustainability of supply chains.

Regarding factory managers, because of growing pressure from international brands to ensure that supplier products are produced ethically and not only follow the host country's regulations, but also fulfill the home country's consumer expectations, the challenge of meeting sustainability expectations will likely only become increasingly difficult. For example, Foxconn—the supplier that produces iPhones for Apple—faced a problem regarding the use of sweatshops (Clarke & Boersma, 2017; Kates, 2015), with many workers committing suicide because of extremely high job pressure. As a result of rising labor costs in China, Foxconn must manage workers in a highly efficient manner to maintain its profit margin. Workers often lack adequate mental and physical care under tight production schedules, which increases the likelihood of HSE incidents. The labor problem becomes increasingly challenging as labor costs in China and other emerging markets continue to rise. In response to this problem, Foxconn converted their production process, mainly in its new factory in the US, from labor-intensive to fully automated Therefore, factory managers should identify processes that could automate and reduce the production complexity that requires a large number of labor workers for routine production tasks.

Another example of automation improving sustainability is provided by Esquel Group, a well-known vertical-integrated shirt manufacturer that produces over 100 million shirts annually. Esquel Group recently developed a fully automated yarn production facility in Xinjiang, China. With only 45 workers, they can manage fully automated spinning plants with 30,000 spindles that transform cotton fibers into high-quality yarn for premium shirt production. Esquel Group's customers are world-renowned brands such as Ralph Lauren and Brooks Brothers. Running a factory in such a manner can prevent serious workplace safety and pollution problems while minimizing production complexity through automation. Industry leaders have already seen the merits of automation and robotics technologies, which improve both production efficiency and overall sustainability. The results of this study support observations that, regardless of the nature of products (i.e., high tech or low tech), sourcing from more suppliers with high levels of automation helps reduce both the lead time and the likelihood of HSE incidents occurring in supply chains.

In addition to automation solving the production complexity issue, factory managers should be aware of production coupling, where the inventory level cannot be too low. Although the global trend is to aim for zero inventory to avoid waste, in the first quarter of 2018, H&M burned US$ 4.3 billion worth of unsold clothes (Paton, 2018), which constituted a huge waste of natural resources and resulted from unsuitable forecasting and sourcing decisions (Farmbrough, 2018). Zara, another fashion giant, manages production in a responsive manner to reduce the inventory for each style. Resolving production coupling problems does not mean producing more safety stocks—which could eventually turn into waste that could impact the environment—but rather acquiring the required inventory through effective communication with customers and more precise prediction of market needs and tastes.

For sourcing agents and consumer brands, their strategy of sourcing from sustainable suppliers should also cover suppliers' HSE records and production characteristics in relation to their likelihood of HSE disruption. Brands should source from suppliers that are more automated or have at least taken steps toward automation, as this measure would likely significantly lower the future likelihood of HSE incidents. In addition, brands should examine the average inventory level and inventory volatility of their suppliers over the preceding 3 years as these are a clear indication of how well customer demand is managed and how changing demand in a season can be responded to. Selecting suppliers with higher levels of production automation and more effective coupling management could significantly minimize future impacts caused by HSE issues.

5.3. Limitations

The findings of this study are subject to the following limitations. First, the measurement of the dimension of complexity could be improved. Second, time slack between production processes may also be a good indicator of coupling. However, we could not find such data in a readily available form. Future research might consider other dimensions of complexity and coupling. This study focused on HSE-related events; CSR-related events may also include product safety, social accountability, and equality. Future research can build on this research and investigate other CSR-related events. Last, a firm's CSR level may impact how stakeholders perceive HSE misconduct; for example, shareholders may not be surprised when a non-reputable firm engages in misconduct. Future research may include CSR level as a covariate in empirical models.

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Appendices

Table A.1: Logistic regression analysis of HSE incidents

DV: HSE incident in year t (1 = yes, 0 = no)		
	Model 1	
Variable	**Coef.**	***p***
Labor intensity (at $t-2$)	0.1675	.001
Reversed inventory days (at $t-2$)	0.0014	.003
Chi^2	420.02	.000

Note. N = 8,478; two-tailed tests; 0.000 indicates <.001; all control variables included but not shown.

Table A.2: Rare-event logistic regression analysis of HSE incidents

DV: HSE incident in year t (1 = yes, 0 = no)		
	Model 1	
Variable	**Coef.**	***p***
Labor intensity	0.1262	.000
Reversed inventory days	0.0012	.004

Note. N = 10,357; two-tailed tests; 0.000 indicates <.001; all control variables included but not shown.

Table A.3: Logistic regression analysis of environmental incidents and safety incidents

	DV: environmental incident in year t (1 = yes, 0 = no)		DV: Safety incident in year t (1 = yes, 0 = no)	
	Model 1		**Model 2**	
Variable	**Coef.**	***p***	**Coef.**	***p***
Labor intensity	0.153	0.000	0.033	.068
Reversed inventory days	0.002	0.000	0.000	.739

Note. N = 10,357; two-tailed tests; 0.000 indicates <.001; all control variables included but not shown.

Table A.4: GMM analysis of HSE incidents

DV: HSE incident in year *t* (1 = yes, 0 = no)		
	Model 1	
Variables	**Coef.**	***p***
Labor intensity	0.0037	.002
Reversed inventory days	0.0000014	.016
Chi^2	63.65	.000
AR1		.000
AR2		.774
Hansen test		.306

Note. N = 10,357; two-tailed tests; 0.000 indicates <.001; all control variables included but not shown.

Table A.5: Event analysis of HSE incidents (confounding event eliminated)

		Nonparametric test			Parametric test		
Abnormal unsystematic risk (H3a)	**N**	**Median**	**WSR-Z**	***p***	**Mean**	**Paired *t***	***p***
Year -1 to 0	203	0.002	-0.575	0.566	0.004	0.813	.418
Year 0 to 1	203	0.009	1.765	0.078	0.008	1.711	.089
Year 1 to 2	203	-0.007	-1.346	0.178	-0.004	-0.979	.329
Year -1 to 1	203	0.013	2.430	0.015	0.012	2.385	.018
Year -1 to 2	203	0.005	0.948	0.343	0.007	1.431	.154
Abnormal systematic risk (H3b)	**N**	**Median**	**WSR-Z**	***p***	**Mean**	**Paired *t***	***p***
Year -1 to 0	203	-0.003	-0.235	0.814	0.01	0.463	.644
Year 0 to 1	203	0.032	1.845	0.065	0.036	1.864	.064
Year 1 to 2	203	-0.013	-0.438	0.661	-0.005	-0.269	.788
Year -1 to 1	203	0.051	2.362	0.018	0.046	2.200	.029
Year -1 to 2	203	0.029	1.640	0.100	0.041	1.883	.061

Table A.6: Measuring operational coupling as inventory volatility

	Model 1 DV: HSE incident in year t (1 = yes, 0 = no) N = 10,053		Model 2 DV: Abnormal systematic risk (year -1 to year 2) N = 278	
	Coef.	***p***	**Coef.**	***p***
Labor intensity	0.125	0.000	0.038	.060
Inventory volatility	0.121	0.041	0.041	.094
Chi^2	437.21		41.5889	

Note. 0.000 indicates <.001.