

Operational resilience, disruption, and efficiency: Conceptual and empirical analyses

AUTHORS

Dominic Essuman

Department of Supply Chain and Information Systems, Kwame Nkrumah University of Science and Technology, Ghana; Gordon Institute of Business Science, University of Pretoria, 26 Melville Rd, Illovo, Johannesburg, 2196, South Africa.

Email: dessuman1@st.knust.edu.gh; kwasiipowel@gmail.com

Nathaniel Boso¹

Department of Marketing and Corporate Strategy, Kwame Nkrumah University of Science and Technology, Ghana; Gordon Institute of Business Science, University of Pretoria, 26 Melville Rd, Illovo, Johannesburg, 2196, South Africa; Strathmore University Business School, Strathmore University, Ole Sangale Road, Nairobi City, Kenya.

Email: nboso@knust.edu.gh; nboso@strathmore.edu

Jonathan Annan

Department of Supply Chain and Information Systems, Kwame Nkrumah University of Science and Technology, Ghana; Strathmore University Business School, Strathmore University, Ole Sangale Road, Nairobi City, Kenya.

Email: jothananan.ksb@knust.edu.gh

Highlights

- Operational resilience consists of disruption absorption and recoverability.
- Each of these capabilities is positively related to operational efficiency.
- The effect of disruption absorption is greater at a high disruption condition.
- The effect of recoverability is greater at a low disruption condition.

¹ Corresponding author: nboso@knust.edu.gh; nboso@strathmore.edu

Abstract

This research develops the notion of operational resilience and investigates its relationship with operational efficiency under differing conditions of operational disruption. Operational resilience is conceptualized as a multi-dimensional construct, consisting of two theoretically distinct components (i.e., disruption absorption and recoverability), which are argued to have unique effects on operational efficiency under varying operational disruption conditions. The study's hypotheses are empirically tested on primary data from a sample of 259 firms in a sub-Saharan African economy. Using structural equation modeling as an analytical tool, the study finds that both disruption absorption and recoverability have positive effects on operational efficiency. Additionally, the study finds that while the effect of disruption absorption on operational efficiency is stronger under conditions of high operational disruption, the effect of recoverability on operational efficiency is stronger under conditions of low operational disruption. A major implication of these findings is that the nature of operational resilience and the disruption circumstances under which it is deployed shape its efficiency value, thus advancing knowledge on the nuances associated with how and when operational resilience influences operational efficiency.

Keywords: Operational resilience; Operational efficiency; Operational disruption; Firm resources; Contingency perspective; Sub-Saharan Africa

1. Introduction

Disruption to operations (including supply chains) as a result of natural and man-made disasters is an unavoidable risk that confronts firms (Ivanov and Dolgui, 2019; Chowdhury et al., 2019), with efficacy to threaten survival of firms (Manhart et al., 2020; Haraguchi and Lall, 2015). Evidence shows that disruption to operations has direct and immediate negative consequences on operations systems and efficiency (Haraguchi and Lall, 2015). For example, Japanese automobile companies such as Honda, Toyota, and Nissan had their key operations systems shut down for several days as a result of the 2011 floods in Thailand, significantly raising the companies' operational costs (Haraguchi and Lall, 2015). Additionally, the 2019 fire outbreak in Australia disrupted major supply chains, operations and earnings, causing several million-dollar worth of losses to businesses and industries (Edwards, 2020). While Qantas Airways has its shares dropped to a two-month low due to several flight cancellations, retailers in Australia experienced a significant drop in shopping traffic. Furthermore, a New York Times report indicates that Hyundai suspended its production in South Korea, and Tesla, Ford, and Nissan shut down their factories in China in February 2020 following supply chain disruptions linked to the outbreak of the coronavirus disease in China (Victor et al., 2020). Apple's announcement of a drop in demand for Apple products within China as a result of the disruption caused by the coronavirus outbreak led to a 2.6% drop in the company's shares and wiping out US\$34 billion in its market value (Horowitz, 2020). Thus, the potency of disruptive events to cause deleterious impacts on operations systems makes resilience-building a top priority for business executives (Business Continuity Institute, 2019).

Research indicates that resilient firms have mechanisms for dealing with disruptions, enabling such firms to reap superior performance outcomes (Wong et al., 2019; Yu et al., 2019). While research interest in resilience is growing (e.g., Pettit et al., 2019; Ivanov et al.,

2017), knowledge of the operational resilience construct is limited in two important ways. First, besides the recognition that the resilience construct is not completely understood (Manhart et al., 2020; Pettit et al., 2019), previous research is limited to the study of the construct at supply chain network and firm levels. This leaves the field with limited knowledge of the nature of the resilience construct at the operations level of the firm. Yet, understanding the nature and consequences of resilience at the operations level is important in that operations is a unique subsystem of the firm and constitutes a primary value-creation function that generates earnings for firms and their supply chain partners. Besides, in the event of a disruption, operations is the system that is immediately impacted.

Second, despite the interrelations between operational resilience, disruption, and efficiency (Ivanov and Dolgui, 2019; Wong et al., 2019), empirical knowledge of their interplay remains underdeveloped. Whereas some authors express doubt about the efficiency value of resilience (e.g., van der Vegt et al., 2015), Ivanov and Dolgui (2019) propose the idea of low-certainty-need to suggest that resilience and efficiency can coexist when resilience-building behavior is less dependent on certainty of knowledge about the occurrence and impacts of disruptions. Subsequently, Wong et al. (2019) investigate the complexities associated with these variables by linking resilience to financial performance. Given the limited scholarly work on the resilience construct, therefore, calls for further research to establish its performance outcomes keep growing (Pettit et al., 2019; Wong et al., 2019).

Against this backdrop, this study examines the following research questions: *what is the conceptual domain of operational resilience?; how does operational resilience relate to operational efficiency?; and how does operational disruption condition the effect of operational resilience on operational efficiency?* This study addresses the first research question by following an output-base theoretical approach and insights from other relevant literature to propose the notion of operational resilience, which is defined as the ability of a

firm's operations to absorb and recover from disruptions (van der Vegt et al., 2015; Meyer, 1982). Thus, the study proposes a two-dimensional conceptualization of operational resilience, with components consisting of disruption absorption and recoverability.

Disruption absorption refers to the ability of a firm to maintain the structure and normal functioning of operations in the face of disruptions. Recoverability refers to the ability of a firm to restore operations to a prior normal level of performance after being disrupted.

Regarding the second and third research questions, the study extends resource-based theory to contingency perspective of the firm to generate new insights into how the components of operational resilience uniquely influence operational efficiency under low and high operational disruption conditions.

This paper makes three contributions to the resilience literature. First, we theoretically specify the operational resilience construct from an output-base perspective and shed light on how such an approach to resilience conceptualization help clarify the ambiguity in the existing resilience literature. The proposed conceptualization of operational resilience in this study is useful for research and practice in that it detaches the conceptual drivers of the construct from its core components (Hosseini et al., 2019; Scholten et al., 2019), affording a fine-grained theorization and appraisal of the performance consequences of operational resilience at its component level (Manhart et al., 2020). Second, this study extends previous research on resilience-efficiency linkage (e.g., Wong et al., 2019; Yu et al., 2019) by explicitly linking each component of operational resilience to operational efficiency to uncover their unique performance values. Third, in further advancing the work of Wong et al. (2019), we examine and test the unique effects of the components of operational resilience on operational efficiency at varying conditions of operational disruption. To this end, the study shows how changing disruption intensity situations shapes conclusions about the relationship between resilience and efficiency.

In the ensuing section, we discuss the literature and the direction of the present research. In the subsequent section, we develop the operational resilience construct and hypotheses linking its components to operational efficiency. Next, the empirical research design is presented after which study results and implications alongside limitations and avenues for future research are discussed.

2. Literature review

While supply chain and operations researchers continue to debate the nature of resilience construct (Manhart et al., 2020; Pettit et al., 2019), it is important to clarify aspects of this body of research. An assessment of the literature shows evidence of potential confusion on the conceptualization of resilience, which largely results from authors focusing on (1) different resilience elements and (2) different levels of analysis of resilience elements. While “resilience elements” refer to conceptual components of resilience, “level of analysis” refers to the type of system within which resilience is applied.

From the disruption profile (e.g., Li et al., 2019; Tukamuhabwa et al., 2015) and the proactive/reactive resilience literature (e.g., Ivanov et al., 2017; Chowdhury and Quaddus, 2017; Tukamuhabwa et al., 2015), it is evident that scholars, consciously or unconsciously, follow either an input-base approach (e.g., Chowdhury et al., 2019), out-base approach (e.g., Wong et al., 2019), or both approaches (e.g., Chowdhury and Quaddus, 2017) to conceptualize resilience in terms of its conceptual components. For the purposes of our discussion, we label the input-base approach as *input-base resilience* (IBR) and output-base approach as *output-base resilience* (OBR) perspectives.

The IBR perspective captures antecedents to OBR elements as essential manifestations of resilient firms or supply chains. This perspective assumes that a system’s ability to effectively respond to disruptions, in terms of absorbing and recovering from

impacts and repositioning itself in the face of disruptions, is determined by the system's score on IBR scales. Key IBR elements used to capture the resilience construct include firm flexibility, buffers, visibility, disruption preparedness, agility, collaboration, integration, and information sharing (see e.g., Chowdhury et al., 2019; Brusset and Teller, 2017; Birkie et al., 2017; Liu et al., 2018; Li et al., 2017).

On the other hand, the OBR perspective argues that a system's resilience level cannot be ascertained in the absence of a disruption (Vogus and Sutcliffe, 2007). Within this stream of research, concepts such as disruption absorption², recoverability, adaptability, and transformability have been identified as core OBR elements (Scholten et al., 2019; Pettit et al., 2019; Davidson et al., 2016). Following the OBR perspective, several empirical studies (e.g., Yu et al., 2019; Buyl et al., 2017; Brandon-Jones et al., 2014) argue that IBR elements do not capture the notion of resilience in that they cannot fully account for the variances in OBR elements. That said, it is argued that IBR elements do not in themselves reflect the core conceptual domain of resilience (Davidson et al., 2016): at best, they are indicative of "formative resilience elements" (Scholten et al., 2019), "resilience-enhancers" (Blackhurst et al., 2011) or "drivers of resilience" (Hosseini et al., 2019).

In terms of level of analysis, supply chain scholars have analyzed resilience at the supply chain level, with few studies (e.g., Ambulkar et al., 2015) limiting their analysis to the focal firm. Relative to firms, supply chains are more complex-adaptive systems and thus, the nature of resilience at the supply chain level may be different (Tukamuhabwa et al., 2015). From a system standpoint, it is reasonable to argue that an operations is a subsystem at the firm level (Slack and Lewis, 2017), which suggests that the nature of resilience at this level of analysis may take a unique form. Additionally, while some scholars have conceptualized and

² The label "disruption absorption" (Chowdhury and Quaddus, 2017; Davidson et al., 2016) is used in this study instead of "robustness" to minimize confusion. Some scholars (e.g., Brandon-Jones et al., 2014) who limit their view of resilience to the original dictionary meaning of the concept (i.e., recoverability) perceive robustness and resilience as different concepts.

operationalized supply chain resilience as a unidimensional construct (see e.g., Kwak et al., 2018; Brandon-Jones et al., 2014), others, guided by the idea of scope of supply chain network, have captured supply chain resilience as a multifaceted construct that entails upstream (supply) resilience, internal (focal firm) resilience, and downstream (customer) resilience components (Pettit et al., 2019; Gu and Hu, 2017). This latter category of research contends that internal and external (customer and supply) resilience are interdependent, to the extent that external supply chain actors' ability to manage disruptions effectively increases the focal firm's resilience level (Pettit et al., 2019). Similarly, the focal firm's ability to absorb and recover from disruptions minimizes rippling effects that increase external supply chain actors' resilience levels (Ivanov and Dolgui, 2019; Ivanov, 2018). In line with this reasoning, Sáenz and Revilla (2014) find that Cisco System's resilience-building effort was critical in enhancing the resilience of its supply chain network.

In focusing on the operations of the firm as a unit of analysis, this study extends the operations system view of resilience, which has by far remains underdeveloped despite its primacy in aiding firms and supply chains to create market value (Dormady et al., 2019; Slack and Lewis, 2017). In conceptualizing our operational resilience construct, we view the focal organization as a subsystem within a supply chain network, which itself has multiple subsystems (Flynn et al., 2016). We argue that operations systems is a critical subsystem of the focal firm as far as supply chain disruption is concerned (Dormady et al., 2019). This study contends that disruption absorption and recoverability capture the conceptual domain of the operational resilience construct.

3. Conceptualization and hypotheses development

3.1. Conceptualization of operational resilience

Two reasons are provided to justify our conceptualization of the operational resilience construct from an OBR perspective. First, while we agree that IBR elements are essential drivers of OBR elements, it is challenging to assume that variation in IBR elements necessarily implies variability in resilience. The formative nature of IBR elements suggests that for any given OBR element, a non-exhaustive list of IBR elements is required; something that appears practically impossible (Cadogan and Lee, 2016). Second, IBR elements may have to be bundled, configured, and leveraged to fully explain their viability to vary OBR elements (Jain et al., 2017; Brandon-Jones et al., 2014). These arguments highlight the problem of using IBR elements to make conclusions about the nature of resilience. Unlike IBR elements, OBR elements are defined and measured with respect to disruptions (see e.g., Wong et al., 2019; Yu et al., 2019; Buyl et al., 2017), allowing for effective appraisal of the strategic and operational value of resilience. Taken together, the OBR perspective allows analysis of resilience as a distinct concept that is separate from its antecedents and consequences.

We use the disruption profile framework to propose a two-dimensional conceptualization of operational resilience (Li et al., 2019; Sheffi and Rice, 2005). The disruption profile framework suggests that resilience of operations to disruptions can be ascertained by knowing the normal operating performance level prior to occurrence of a disruption. Subsequent to this prior information on the occurrence of a disruption, operational resilience can be determined by 1) calculating the magnitude of the drop in normal operating performance level immediately after the occurrence of a disruptive event and just before a recovery action is initiated, and 2) calculating the time it takes for a firm to restore operations

to normal performance level after recovery action is initiated (Li et al., 2019; DesJardine et al., 2017; Buyl et al., 2017). A greater drop in normal performance level suggests that the operations lacks disruption absorption capability, and a smaller drop in normal operations implies the operations possess a disruption absorption capability (Blackhurst et al., 2011; Sheffi and Rice, 2005). Operations with high disruption absorption can accommodate disruptions or persist in the face of disruptions (Buyl et al., 2017; DesJardine et al., 2017). The Li and Fung company's ability to continue serving its customers when its competitors halted their operations during the 1997 Indonesian currency crisis provides a case study to demonstrate this aspect of operational resilience (Tang, 2006).

On the other hand, longer recovery time suggests that an operations lacks recoverability, and the opposite is true (Li et al., 2019; Sheffi and Rice, 2005). Toyota's ability to resume production in twenty-nine plants just three to four days after the 1995 Kobe earthquake provides an exemplary case to explain the recoverability element of operational resilience (Fujimoto, 2011). Accordingly, we formally define operational resilience as the extent to which a firm's operations is able to absorb and recover from disruptions (van der Vegt et al., 2015; Meyer, 1982). The disruption absorption dimension is defined as the ability of a firm to maintain the structure and normal functioning of operations in the face of disruptions. The recoverability dimension is defined as the ability of a firm to restore operations to a prior normal level of performance after being disrupted.

This study argues that it is possible for a firm to possess both components of operational resilience and that each component plays unique and important role in disruption management (Li et al., 2019; Behzadi et al., 2017; Brandon-Jones et al., 2014). In line with the disruption profile framework, we contend that it may be difficult for a firm to activate both components of operational resilience simultaneously in that disruption absorption would logically and practically precede disruption recovery actions. After all, occurrence of

disruption events would justify the need for recovery action to be activated. High disruption absorption coupled with low impact disruptions may not cause normal operating performance levels to fall below specified critical threshold level that may necessitate activation of recoverability. In essence, possession of disruption absorption does not prevent a firm from possessing recoverability, and vice versa. Additionally, the fact that a firm has disruption absorption does not necessarily imply that the firm has recoverability (Behzadi et al., 2017). As Holling (1973) asserts, a system can be ‘resilient’ (i.e., persist in the face of disruptions) and yet lack ‘stability’ (i.e. the ability to return to an equilibrium state after being exposed to a disruption), and vice versa.

We describe operational resilience using disruption absorption and recoverability OBR elements as their intended purpose is to preserve the current domain of operations in the face of disruptions. This ‘static’ view of operational resilience seems appropriate, as in the short-run, it may be impractical and costly for organizations to redefine or change the domain of operations anytime disruptions surface. Naturally, when disruptions to operations systems occur, organizations would show a preference for first-order response actions to preserve the current domain of operations and restore output rates to normal levels (Sheffi and Rice, 2005; Meyer, 1982). Such actions aim at (1) maintaining the structure of the system and output rates within minimum critical bounds during disruptions, and (2) restoring output rates to normal levels after a disruption.

It may be argued that over time, as organizations adapt or transform their operations, they require dynamic capabilities to perform this task (Helfat and Winter, 2011). However, such modifications to the domain of operations may not necessarily be triggered by disruption or external forces of change: they can also result from a mere change in the strategic aspiration of top management. For these reasons, this research excludes adaptive and transformative resilience OBR elements from its conceptualization of operational resilience.

Therefore, operational resilience as presented in this research does not epitomize the dynamic/adaptive capability view of resilience as applied in prior research (e.g., Scholten et al., 2019; Tukamuhabwa et al., 2015).

3.2. The effect of operational resilience on operational efficiency

Researchers have made several attempts to examine the performance outcomes of resilience. While some studies have investigated the performance effects of resilience using IBR elements (e.g., Chowdhury et al., 2019; Liu et al., 2018; Li et al., 2017; Birkie et al., 2017), others have examined the performance outcomes of OBR elements (see e.g., Wong et al., 2019; Yu et al., 2019; Kwak et al., 2018). Despite the valuable insights these studies offer, several scholars (Dormady et al., 2019; Pettit et al., 2019; Wong et al., 2019) have called for further investigation into the resilience-performance relationship. In response to these growing calls, Wong et al. (2019) and Yu et al. (2019) draw on the organizational information processing perspective and the dynamic capabilities theory, respectively, to examine the effect of OBR elements on financial performance. Similarly, Kwak et al. (2018) complement the logic of competitive heterogeneity with insight from the dynamic capabilities theory to demonstrate that OBR elements positively influence firms' competitive advantage. Furthermore, from the resource-based view and contingency perspective of the firm, Chowdhury et al. (2019) shed light on how relational practice interacts with network complexity to condition the relationship IBR elements and performance.

In extending knowledge on these prior studies, this study uses the resource-based theory with complementary insights from the contingency perspective of the firm to explain the relationship between operational resilience and operational efficiency and the moderating role of operational disruption. To this end, we make a significant extension to the resource-based perspective of resilience by explicating the valuable, rare, inimitable, and non-

substitutable (VRIN) resource nature of OBR elements. Disruption absorption and recoverability qualify as VRIN resources and thus may generate sustained competitive advantage and performance. Both capabilities are valuable as they allow firms to neutralize the negative impacts of disruptions (e.g., inefficiencies, poor delivery performance, lost sales, and bad reputation). In addition, the two capabilities are rare in that they are path-dependent, idiosyncratic in nature (DesJardine et al., 2017), and are not readily available on the market for purchase. That is, complex IBR antecedent elements may drive the disruption absorption and recoverability capabilities (Brandon-Jones et al., 2014; Blackhurst et al., 2011), making them idiosyncratic, difficult to imitate, trade, and transferred (Barney, 1991). Furthermore, their unique intended purposes and roles in disruption management make them non-substitutable (Behzadi et al., 2017). Accordingly, all things being equal, we expect firms with high disruption absorption and recoverability to be more effective in managing disruptions (Kwak et al., 2018; Brandon-Jones et al., 2014).

Effective disruption management is a major determinant of operational efficiency (Ivanov et al., 2014). For example, unexpected power cuts, machine and technology breakdowns, supplier failure, raw material shortage, or restriction to movement of people and goods due to an outbreak of a pandemic (such as the coronavirus) can lead to delays in processes, increase in idle time, and underutilization of other resources. Additional overheads may accrue for fixing breakdowns in operations. For instance, in order not to disappoint and lose customers, some firms may go to the extent of incurring back-order costs, which may negatively impact on firms' operational efficiency levels. In events of disruptions, firms with high disruption absorption capability are better able to maintain the structure and functioning of operations within critical thresholds (Brandon-Jones et al., 2014), allowing them to preserve normal operating performance levels, and accordingly avoiding inefficiency associated with disruptions. Alternatively, firms with high recoverability are more effective at

restoring operations quickly following disruptions (Brandon-Jones et al., 2014), which helps minimize the chances of recording escalated levels of inefficiency.

Despite the likely efficiency performance outcomes of operational resilience capabilities, it is important to acknowledge that building stronger resilience capabilities may come with greater investment in inefficiency-producing initiatives such as redundancies. In particular, one can argue that investment in resilience-building practices may generate sunk-costs, which cannot easily be recovered and re-channeled into other efficiency-enhancing projects (Pettit et al., 2019; Wong et al., 2019). Therefore, it is likely that efficiency gains associated with increasing operational resilience may be canceled by associated costs.

Notwithstanding these alternative arguments, empirical evidence shows that greater levels of disruption absorption and recoverability generate an enhanced competitive advantage (Kwak et al., 2018) and financial performance (Wong et al., 2019; Yu et al., 2019). Accordingly, we test the following hypotheses:

H1a: *Disruption absorption is positively related to operational efficiency.*

H1b: *Disruption absorption is positively related to operational efficiency.*

While we expect both disruptive absorption and recoverability capabilities to be positively associated with operational efficiency, it could be argue that, compared to disruption absorption, recoverability may have a stronger positive association with operational efficiency. The basis for this expectation is that recoverability is largely driven by flexibility strategies (DesJardine et al., 2017), which may be less associated with inefficiency (Sheffi and Rice, 2005). Relative to recoverability, disruption absorption may be associated with investment in redundancies and buffer capacities at a pre-disruption stage which are major sources of inefficiencies (Ivanov and Dolgui, 2019; Puchkova et al., 2020), and may,

therefore, lower the efficiency benefit of disruption absorption. Therefore, we hypothesize that:

***H2.** Relative to disruption absorption, recoverability has a stronger positive association with operational efficiency.*

3.3. The moderating role of operational disruption

Previous research indicates that important environment contingencies may condition the extent to which operational resilience influences operational performance outcomes (e.g., Chowdhury et al., 2019; Wong et al., 2019). An argument is that disruption to operations is a fundamental issue to the resilience-efficiency nexus to the extent that variability in disruption conditions may shed additional light on operational efficiency benefits of operational resilience. Thus, we follow Wong et al. (2019), and integrate the resource-based theory and the contingency view (Donaldson, 2006) to investigate the moderating effects of operational disruption on the operational resilience-operational efficiency relationship. Operational disruption is defined as the frequency at which a firm experiences unexpected events that interrupt a smooth flow of operations (Blackhurst et al., 2011).

Research suggests that resilience elements are a function of disruption intensity: frequency of occurrence and intensity of impact (Brusset and Teller, 2017; Ambulkar et al., 2015; Bode et al., 2011). Besides, Wong et al. (2019) find that while supply chain resilience has stronger positive associations with both risk performance and market performance at high levels of supply-side, infrastructure, and catastrophic disruptions, its effect on financial performance is not contingent upon these forms of disruptions. For Pettit et al. (2019), resilience-building should be a balancing act involving matching investment in resilience-enhancing capabilities relative to exposure to disruption impacts. When the risk of disruption is low, increasing resilience can erode profit (Pettit et al., 2010). On the contrary, high levels

of risk of disruption coupled with low investment in resilience increase a firm's level of vulnerability. While these insights suggest that it may be justifiable for firms experiencing greater levels of operational disruption to increase operational resilience, knowledge of whether under such a situation, the operational efficiency benefits of disruption absorption and recoverability amplify or weaken is underexplored.

We argue that uncertainty and information processing needs increase under conditions of high operational disruption. Under such a condition, the need for certainty and operational stability may increase, resulting in a greater emphasis on resilience-building strategies (Ivanov and Dolgui, 2019; Bode et al., 2011), which can both increase and decrease operational efficiency level. In particular, greater emphasis on resilience as a result of high operational disruption may result in greater investment in resilience-building strategies, which can increase costs of managing disruptions (Ivanov and Dolgui, 2019). Alternatively, conditions of high operational disruption may suggest vulnerability and create heightened situational awareness of disruption, which can induce firms to become more effective in detecting and avoiding disruptions, helping minimize disruption impacts and costs. The potential efficiency-value of operational resilience is realized when firms face disruptions. Therefore, in a low operational disruption situation, it can be counterproductive, efficiency wise, to increase operational resilience. Inefficiencies associated with maintaining high levels of operational resilience in a low operational disruption condition can, therefore, erode the associated efficiency benefits of resilience (Wong et al. 2019; Pettit et al., 2010).

Accordingly, we hypothesize that:

H3a. *The positive relationship between disruption absorption and operational efficiency is stronger under high operational disruption condition.*

H3b. The positive relationship between recoverability and operational efficiency is stronger under high operational disruption condition.

4. Methodology

4.1. Design and sample

Consistent with prior studies (Kwak et al., 2018; Chowdhury and Quaddus, 2017), cross-sectional survey data is used to assess the research hypotheses. We obtained data from firms in a major Sub-Saharan African economy – Ghana. The precarious economic, institutional, and market conditions in sub-Saharan African economies, coupled with the region's underdeveloped financial/capital markets and supply chain infrastructure, renders supply chains and companies in the region extremely vulnerable. Specifically, transportation network disruption, technology and communication failure, energy shortage, outsourcer failure, loss of talent/skills, and currency exchange rate volatility are key sources of disruptions to business operations in the region (Business Continuity Institute, 2018), making a study of operational resilience of firms in this region crucially important and timely.

A total of 750 questionnaires were administered to manufacturing and service firms having employee size of between 5 and 500 employees, have existed for at least 3 years (Boso et al., 2013), and operate in the two most industrialized/commercialized cities in Ghana (i.e., Accra and Kumasi) (Ghana Statistical Service, 2016). Information about the firms was extracted from Ghana Yellow online directory. Quota sampling, followed by purposive sampling, was adopted in the study as the researchers needed to obtain a sufficient number of samples from the various firm groups (i.e., industry type and size) and had to consider the location of the firms. This sampling approach compares favorably with those used in prior resilience research (e.g., Chowdhury et al., 2019). A delivery-and-collection approach was

used to administer the questionnaire using a team of credible field agents who were trained and worked the researchers' supervision.

A total of 284 of the 750 questionnaires were retrieved. Out of this total, 259 were considered usable, representing an effective response rate of 34.53%. Seventy-three percent of the data came from service firms while the remaining came from manufacturing firms. The average firm employed 42 employees approx. (SD = 61 approx.). An average firm had operated for 6.60 years (SD = 3.89 years). These profile information of the effective sample generally reflect those of the study's population (Ghana Statistical Service, 2016). Moreover, a test of difference in the characteristics of the firms (age, size, and industry) and their scores on the variables of interest between early and late responses revealed no statistical difference, indicating that non-response bias is not a major concern in the study.

The data were provided by senior managers (Ambulkar et al., 2015): CEO (12.4%), managing director/general manager (33.2%), operations manager (23.9%), and other middle managers (30.5%); with good educational and managerial experience. An average respondent had held his/her current position for 7.13 years (SD = 5.583), 76.8% of them had at least a bachelor's degree, and 34% are females. Three items were adapted from Boso et al. (2013) to assess the competence of the respondents. An average respondent scored 5.79 (SD = 1.032), 5.81 (SD = .961), and 5.99 (SD = .835) on the items relating to knowledge of the issues captured in the questionnaire, general confidence in the responses provided, and the accuracy of the responses provided in relation to their firm's situations respectively, suggesting that an average respondent was competent to provide data (Boso et al., 2013). Further analysis suggested that the variability in the respondent's competence level and their positions were not significantly correlated with scales tapping into the constructs of interest.

4.2. Measures

Disruption absorption and recoverability. Based on insights from Wieland and Wallenburg (2012) and Brandon-Jones et al. (2014), identified six items were used to capture disruption absorption³. The items were framed to reflect the consistency at which a firm has exercised this capability over the past 3 years when disruptions occurred. Five items were adapted from Brandon-Jones et al. (2014) to measure recoverability. The items were framed not just to reflect recovery speed but also recovery consistency/reliability over the past 3 years whenever operational breakdown due to a disruptive event occurred. The items for disruption absorption and recoverability were anchored on a 7-point scale that ranged from “strongly disagree (=1)” to “strongly agree (=7)”.

Operational efficiency reflects how well a firm minimizes costs associated with administering its business operations. “Costs” in this definition include actual monetary expenses (direct and indirect paid) incurred and volume of wastes in operations (e.g., waste of material and idle capacity) (Gligor et al., 2015; Ward and Duray, 2000). The study adapted five measures from Wong et al. (2011), Ward and Duray (2000), and Gligor et al. (2015) to capture operational efficiency. All items were measured using a 7-point scale that ranged from “very low (=1)” to “very high” (=7). Using this scale, the respondents were asked to indicate their firm’s efficiency performance with respect to each item statement over the past 3 years. This scale was reserved to help minimize common method bias. Higher scores (5-7) and lower scores (1-3) indicate operational inefficiency and operational efficiency respectively.

Operational disruption. We combined insights from prior research (e.g., Ambulkar et al., 2015) and interviews with managers to identify nine items to measure operational

³ See footnote 1.

disruption. The items, reflecting firm-specific unexpected and accidental events that can directly interrupt operations, were anchored on a 7-point scale that ranged from “strongly disagree (=1)” and “strongly agree (=7)”.

Control variables. Three key IBR elements: disruption orientation (Wong et al., 2019; Ambulkar et al., 2015), slack resource (Vogus and Sutcliffe, 2007), and collaborative resilience-building effort (Scholten and Schilder, 2015); and three firm demographic variables: firm size (log of number of employees), firm age (log of number of years in operation), and firm industry (service = 1, manufacturing = 0) (Pal et al., 2014; Pettit et al., 2019) were simultaneously included in the models of predictors (i.e., disruption absorption, recoverability) and outcome (operational efficiency) as covariates using structural equation modeling (SEM). Four items, adapted from Bode et al. (2011) and Ambulkar et al. (2015), were used to capture disruption orientation. Slack resource was measured with five items from Atuahene-Gima et al. (2005) while collaborative-resilience building effort was measured with a single item that reflects the degree to which the firm has in the last three years engaged business partners and industry experts to discuss and find solutions to events that threaten its business operations. The items in the slack resource, disruption orientation, and collaborative resilience-building effort scales were anchored on a 7-point scale that ranged from “strongly disagree (=1)” to “strongly agree (=7)”. The full list of multi-item scales used in the study is available in Table 1.

5. Analysis and findings

5.1. Measure assessment

Reflective measurement. Except for the scale for operational disruption, all other multi-item scales were had reflective items. Thus, confirmatory factor analysis (CFA) procedure in LISREL was used to validate them. A five-factor CFA model had a good fit to data: $\chi^2 =$

382.38, $DF = 265$, $\chi^2/DF = 1.44$, $RMSEA = .04$, $NNFI = .97$, $CFI = .98$, $SRMR = .04$ (Hair et al., 2014; Bagozzi and Yi, 2012). Table 2 shows the CFA results. The factor loadings were greater than .60 and significant at $p < .01$. The composite reliability values were greater than .60 while the average variance extracted (AVE) values were greater than .50. Together, these results indicate that each scale demonstrates convergent validity (Hair et al., 2014). The AVE value for each construct was greater than each pairwise correlations between the constructs while all correlations between constructs were less than .60 (see Table 1). These results provide evidence of discriminant validity (Hair et al., 2014).

Formative measurement. Operational disruption was measured with a formative scale. The items represent independent unexpected events that disrupt operations. Thus, changes in these indicators cause changes in the operational disruption construct (Jarvis et al., 2003). Following prior research (Bode et al., 2011), a formative index was created for this construct. Formative measurement raises concern of item multicollinearity but the correlations between the items were below .50 while all variance inflation factors were below 2.0. Accordingly, the formative index was created as the unweighted linear sum of the items (Bode et al., 2011).

Assessment of common method bias. To check whether common method bias (CMB) posed a problem, we compared our five-factor CFA model with two other competing models: method-only model and method and trait model (Boso et al., 2013; Bode et al., 2011). In the method-only model, all items were specified to load onto a single latent variable. This model fitted the data poorly: $\chi^2 = 7275.70$, $DF = 275$, $\chi^2/DF = 26.46$, $RMSEA = .31$, $NNFI = .21$, $CFI = .27$, $SRMR = .28$, suggesting that a single factor does not describe the data. The method and trait model, which included a single latent variable linking all the items in the CFA model, provided a marginal improvement in the model fit: $\chi^2 = 321.24$, $DF = 235$, $\chi^2/DF = 1.37$, $RMSEA = .04$, $NNFI = .98$, $CFI = .98$, $SRMR = .04$. These results generally suggest

that CMB was not likely to introduce substantial bias in our structural model analysis (Boso et al., 2013; Bode et al., 2011).

Table 1: Details of measures and results of validity tests

Constructs and indicators	Loadings (t-values)
Slack resource^{1,†} (CR = .96; AVE = .81; CA = .95).	
Our company often has uncommitted resources that can quickly be used to fund new strategic initiatives	.87(20.99)
Our company usually has adequate resources available in the short run to fund its initiatives	.90(fixed)
We are often able to obtain resources at short notice to support new strategic initiatives	.91(23.44)
We often have substantial resources at the discretion of management for funding strategic initiatives	.92(24.34)
Our company usually has a reasonable amount of resources in reserve	.89(22.25)
Recoverability^{1,†} (CR = .96; AVE = .82; CA = .96). <i>Over the past 3 years, whenever our operations fail or breakdown due to a disruptive event,</i>	
it does not take long for us to restore normal operation	.89(fixed)
our company reliably recovers to its normal operating state	.88(20.82)
our company easily recovers to its normal operating state	.91(22.68)
our company effectively restores operations to normal quickly	.92(22.68)
we are able to resume operations within the shortest possible time	.92(22.86)
Disruption absorption^{1,†} (CR = .92; AVE = .66; CA = .92). <i>For the past 3 years, whenever disruptive events occur,</i>	
our company is able to carry out its regular functions	.83(fixed)
our company grants us much time to consider a reasonable response	.71(12.77)
our company is able to carry out its functions despite some damage done to it	.83(15.98)
without much deviation, we are able to meet normal operational and market needs	.87(16.97)
without adaptations being necessary, our company performs well over a wide variety of possible scenarios	.85(16.40)
our company's operations retain the same stable situation as it had before disruptions occur for a long time	.79(14.73)
Operational efficiency^{1,††, a} (CR = .90; AVE = .65; CA = .90). <i>Over the past 3 years,</i>	
the costs we incur in running our core operations has been...	.66(fixed)
the volume of waste in processes that we record has been...	.87(11.81)
the volume of material waste recorded in our company has been...	.88(11.95)
overhead costs incurred by our company has been...	.78(10.89)
the volume of idle capacity/ resources our company experiences has been...	.82(11.35)
Disruption orientation^{1,†} (CR = .85; AVE = .58; CA = .84).	
We always feel the need to be alert to possible disruptive events	.77(fixed)
Previous unplanned disruptions show us where we can help improve our company's operations	.83(12.63)
We think a lot about how threatening events could have been avoided	.74(11.45)
After an unplanned operational disruption has occurred, our management lead in analyzing it thoroughly	.69(10.67)
Operational disruption^{2,†}. <i>Unexpectedly,</i>	
some of our employees leave their posts (i.e., quit their job)	
some of our suppliers fail to make deliveries	
we experience vehicular breakdowns	
we experience service/product failure	
we run out of cash for running day-to-day operations	
we experience machine/technology downtime/ failure	
we experience a shortage of raw materials	
we experience power cuts	
some of our service providers fail to honor their promises	

Notes: ¹ = reflective scale, ² = formative scale, ^a = scale was reverse-coded. [†] = "strongly disagree (=1)" to "strongly agree (=7)". ^{††} = "very low (=1)" to "very high" (=7). CR = composite reliability, AVE = average variance extracted, CA = Cronbach's alpha.

5.2. Structural model estimation and evaluation of hypotheses

Table 3 presents descriptive statistics and correlations for the study variables. SEM (in LISREL 8.5) was used to test the research hypotheses. Maximum likelihood and covariance matrix were used as the estimation method and input variables respectively (Hair et al., 2014). SEM is generally considered an ideal causal modeling method as it allows researchers to simultaneously analyze complex casual relationships, control for measurement error, and provide information on the degree of fit of the tested model (Bagozzi and Yi, 2012).

A nested modeling procedure was used to test H1a, H1b, and H2. Consistent with arguments in Section 3.1, the components of operational resilience were allowed to covary freely. We tested H1a by estimating a model (Model 1) in which only the control paths and the path from disruption absorption to operational efficiency were allowed to be non-zero. Next, H1b was tested by estimating a second model (Model 2) in which only the control paths and the path from recoverability to operational efficiency were allowed to be non-zero. To test H2, we estimated a third model (Model 3) in which the control paths as well as the paths from both disruption absorption and recoverability to operational efficiency were allowed to be non-zero. The model fit indices and the path coefficients and t-values relating to Model 1, Model 2, and Model 3 are displayed in Table 3. Results support H1a and H1b which respectively argue that disruption absorption ($\gamma = .33, t = 4.44, p < .01$) and recoverability ($\gamma = .38, t = 5.23, p < .01$) are positively related to operational efficiency. Again, results from Model 3 indicate that relative to disruption absorption ($\gamma = .16, t = 1.85, p > .05$), recoverability ($\gamma = .29, t = 3.45, p < .01$) has stronger positive association with operational efficiency, in support of H2.

Table 2: Descriptive statistics and inter-construct correlations

Variable	Mean	SD	1	2	3	4	5	6	7	8	9	10
1. Operational efficiency	4.39	1.23	1									
2. Disruption absorption	5.30	1.09	.24**	1								
3. Recoverability	4.89	1.43	.29**	.57**	1							
4. Slack resource	4.47	1.43	-.00	.16*	.15*	1						
5. Disruption orientation	5.43	1.01	-.03	.16**	.20**	.16**	1					
6. Collaborative resilience-building effort	5.14	1.67	-.03	.30**	.21**	.31**	.27**	1				
7. Operational disruptions	27.27	9.33	-.12*	-.10	-.12	-.01	-.02	-.15*	1			
8. Firm size (log)	3.09	1.01	-.09	.23**	.27**	.26**	.14*	.29**	-.06	1		
9. Firm age (log)	2.55	.64	-.03	.09	.14*	.00	.02	.07	-.07	.55**	1	
10. Industry (service=1)	.73	.44	.11	-.01	-.07	-.09	-.02	-.07	-.06	-.11	-.06	1

Notes: *p < .05 (2-tailed); **p < .01 (2-tailed).

To test H3a and H3b, a multigroup analysis of structural invariance across low and high levels of the operational disruption scale was performed (Ambulkar et al., 2015). The median of the operational disruption index was calculated and the sample was split as close as possible to the median (Ambulkar et al., 2015), leading to the creation of two groups: low operational disruption condition (n = 140, mean = 20.27, SD = 4.552) and high operational disruption condition (n = 119, mean = 35.51, SD = 6.261). Given the relatively small size in each group and to avoid the risk of violating minimum sample size to parameter ratios, we used full measurement items to capture disruption absorption, recoverability, and operational efficiency and composite items to capture all other constructs. The paths from disruption absorption and recoverability to operational efficiency alongside all control paths were allowed to be free ($\chi^2 = 553.71$, DF = 411, χ^2 /DF = 1.35, RMSEA = .05, NNFI = .95, CFI = .96, SRMR = .06) and then constrained and set equal across the groups ($\chi^2 = 582.19$, DF = 432, χ^2 /DF = 1.35, RMSEA = .05, NNFI = .95, CFI = .95, SRMR = .09). There was no significant difference between the unconstrained model and the constrained model ($\Delta\chi^2 = 28.48[21]$, p > .05) as the nature of effects for both the substantive and control variables were different in both conditions (see Table 4). Consequently, we used the results from the unconstrained model to evaluate H3a and H3b.

Table 3: SEM results (H1a, H1b, and H2)

	Model 1: Effect of disruption absorption (H1a)			Model 2: Effect of recoverability (H1b)			Model 3: Relative effects of disruption absorption and recoverability (H2)		
	Disruption absorption	Recoverability	Operational efficiency	Disruption absorption	Recoverability	Operational efficiency	Disruption absorption	Recoverability	Operational efficiency
<i>Control paths:</i>									
Slack resource	.04(.52)	.03(.52)	.03(.38)	.04(.53)	.03(.51)	.02(.37)	.04(.52)	.03(.51)	.02(.33)
Disruption orientation	.08(1.13)	.15(2.15) *	-.04(-.61)	.08(1.10)	.15(2.18) *	-.08(-1.14)	.08(1.13)	.15(2.17) *	-.08(-1.12)
Collaborative resilience-building effort	.23(3.37) ***	.10(1.42)	-.11(-1.50)	.23(3.38) ***	.10(1.42)	-.06(-.94)	.23(3.37) ***	.10(1.42)	-.09(-1.31)
Firm size	.19(2.45) *	.20(2.61) **	-.18(-2.14) *	.19(2.45) *	.20(2.61) **	-.19(-2.34) *	.19(2.45) *	.20(2.61) **	-.20(-2.49) *
Firm age	-.03(-.35)	.02(.31)	.03(.39)	-.03(-.35)	.02(.31)	.01(.17)	-.03(-.35)	.02(.31)	.02(.25)
Firm industry (services =1)	.03(.46)	-.03(-.46)	.10(1.57)	.03(.46)	-.03(-.46)	.12(1.93)	.03(.46)	-.03(0.46)	.11(1.83)
Operational disruption			-.12(-1.99) *			-.11(-1.81)			-.11(-1.79)
<i>Hypothesized paths:</i>									
Disruption absorption			.33(4.44) ***						.16(1.85)
Recoverability						.38(5.23) ***			.29(3.45) ***
<i>Model fit indices:</i>									
χ^2/DF	532.57/368 = 1.45			523.99/368 = 1.42			520.19/367 = 1.42		
RMSEA	.04			.04			.04		
NNFI	.96			.96			.96		
CFI	.96			.97			.97		
SRMR	.05			.04			.04		

Notes: Standardized coefficients (t-values) are reported in the table. *p < .05 (2-tailed), **p < .01 (2-tailed), ***p < .001 (2-tailed).

While, disruption absorption had stronger and significant positive association with operational efficiency under high operational disruption condition ($\gamma = .31, t = 2.12, p < .05$; in support of H3a), recoverability had stronger and significant positive relationship with operational efficiency under low operational disruption condition ($\gamma = .36, t = 3.35, p < .01$; lending no support for H3b).

Table 4: Multi-group SEM results (H3a and H3b).

Relationships	Standardized coefficients (t-values)	
	Low operational disruption condition	High operational disruption condition
<i>Hypothesized paths:</i>		
H3a: Disruption absorption → operational efficiency	.08(.75)	.31(2.12) *
H3b: Recoverability → operational efficiency	.36(3.35) ***	.20(1.42)
<i>Control paths:</i>		
Slack resource → operational efficiency	.00(.05)	.04(.46)
Disruption orientation → operational efficiency	-.05(-.57)	-.12(-1.25)
Collaborative resilience-building effort → operational efficiency	.00(.03)	-.20(-1.94)
Firm size → operational efficiency	-.23(-2.10) *	-.15(-1.31)
Firm age → operational efficiency	.03(.34)	.01(.05)
Firm industry (services =1) → operational efficiency	.12(1.38)	.11(1.20)
Slack resource → disruption absorption	.12(1.35)	-.08(-.81)
Disruption orientation → disruption absorption	-.04(-.47)	.30(3.30) ***
Collaborative resilience-building effort → disruption absorption	.16(1.80)	.29(3.00) **
Firm size → disruption absorption	.23(2.21) *	.18(1.58)
Firm age → disruption absorption	-.02(-.24)	-.06(-.59)
Firm industry (services =1) → disruption absorption	-.04(-.53)	.10(1.10)
Slack resource → recoverability	.10(1.21)	-.05(-.55)
Disruption orientation → recoverability	.03(.39)	.37(4.14) ***
Collaborative resilience-building effort → recoverability	.00(.03)	.19(2.00) *
Firm size → recoverability	.22(2.19) *	.20(1.77)
Firm age → recoverability	.03(.33)	-.02(-.15)
Firm industry (services =1) → recoverability	-.16(-1.98) *	.11(1.32)
Model fit indices: $\chi^2 = 553.71, df = 411, \chi^2/df = 1.35, RMSEA = .05, NNFI = .95, CFI = .96, SRMR = .06$		

Notes: * $p < .05$ (2-tailed), ** $p < .01$ (2-tailed), *** $p < .001$ (2-tailed).

6. Discussion and implications

6.1. Theoretical contributions and implications

In answering research question one, findings from this research helps advance the limited understanding of the resilience concept at the operations level of the firm. We draw on the

relevant resilience literature (e.g., Buyl et al., 2017; DesJardine et al., 2017) to use an OBR perspective to specify and empirically test a two-dimensional conceptualization of the operational resilience construct, comprising disruption absorption and recoverability capabilities. Our conceptualization of resilience from an OBR perspective offers important value for future empirical research on resilience. This perspective enables researchers to assess a system's resilience level following exposure to a disruptive event. This approach affords researchers opportunity to analyze the extent to which a system survives disruptions and the kind of response actions deployed to manage disruptions. This way, one can better theorize and gauge both the underlying drivers and performance consequences of a system's response capabilities (Manhart et al., 2020). We argue that since IBR elements may not guarantee the integrity and normal functioning of a system when a disruption occurs, analyzing the performance effects of resilience from the IBR perspective may mask important insights. In view of these, it can profit the progress of resilience research if future studies treat IBR elements as antecedents to OBR elements (Scholten et al., 2019; Brandon-Jones et al., 2014) and then link the latter to performance (Yu et al., 2019; Wong et al., 2019).

Furthermore, in line with the second and third research questions, we advance understanding of the interrelationships among operational resilience, disruption, and efficiency. Results from this study provide supports for the argument that disruption absorption and recoverability are important determinants of operational efficiency. These results lend credence to past research findings that OBR elements enhance business performance outcomes (Yu et al., 2019; Kwak et al., 2018). We contend that OBR elements meet the conditions of VRIN resources and thus, all things being equal, they can generate superior performance outcomes. However, additional insights from this study further show that the OBR elements impact performance in unique ways, necessitating the need for future research to avoid treating resilience as a unidimensional construct.

Additional results from the study indicate that the disruption absorption-operational efficiency link and the recoverability-operational efficiency link are stronger under high and low operational disruption conditions, respectively. These additional findings further enhance knowledge on performance benefits of resilience: while Wong et al. (2019) finds no support for the effect of resilience on financial performance under changing magnitudes of disruptions, findings from this study suggest that under a high operational disruption situation, the components of operational resilience do not yield the same efficiency gains. Disruption absorption, unlike recoverability, is largely built at the pre-disruption stage and involves more resource investment in buffers. Thus, when operational disruption is low, increasing levels of disruption absorption can generate lower efficiency gains. On the other hand, the efficiency benefit of recoverability can be greater in a low operational disruption condition as under such a situation, there may be little additional costs (e.g., overtime expenses) for restoring operations. Findings relating to H2 and H3a-b show that analyzing the effects of resilience at its disaggregated scale and considering varying conditions of operational disruption may shed important lights on when operational resilience is more or less beneficial for operational efficiency. This study shows that the efficiency benefit of operational resilience is contingent on its elements and under conditions of low and high operational disruption.

Results relating to the control variables in the study have important implications. Firstly, consistent with extant literature (Scholten and Schilder, 2015), results indicate that collaborative resilience-building effort plays a significant role in driving disruption absorption. Further result, however, indicates that collaborative resilience-building effort does not directly influence operational efficiency. Results further indicate that firm age, firm industry, and slack resource may play trivial roles in explaining disruption absorption, recoverability, and operational efficiency. The non-significant finding relating to the slack

resource-operational resilience link is quite intriguing. It must be noted that the slack resource scale in this study captures non-absorbed slack. Thus, one possible explanation for this finding is that non-absorbed slack resource may benefit disruption absorption and recoverability when it is deployed in the implementation of resilience-building strategies, something that this research does not capture. Thus, results from our research cannot be used to settle the debate on whether slack resource is a fundamental characteristic of resilient organizations (Vogus and Sutcliffe, 2007).

Again, this study's results show that firm size-advantage is critical for fostering disruption absorption and recoverability (Pal et al., 2014). Besides, results suggest that while size-advantage is negatively related to operational efficiency, this effect is mitigated by the role of size-advantage in increasing disruption absorption and recoverability. In addition, results suggest that disruption orientation may benefit recoverability more than disruption absorption and that its contribution to these capabilities become more salient in firms operating in high operational disruption setting. These findings crystalize Yu et al.'s (2019) findings and provide clarity on the argument that the disruption orientation-resilience link may be contingent upon operational disruption. Finally, consistent with Yu et al.'s (2019) findings, results indicate that disruption orientation is not directly related to operational efficiency.

6.2. Managerial implications

Developing knowledge of efficiency implication of operational resilience is of strategic importance in that resilience-building is characteristically a resource-consuming activity. However, such knowledge will be less useful and potentially mislead decision-makers if the operational resilience construct remains ambiguous. A sound appreciation of the conceptual domain of operational resilience is a crucial step towards enhancing and effectively managing

this capability and accurately evaluating its cost-benefit consequences (Manhart et al., 2020). Insights from this research encourage managers to assess operational resilience from the OBR perspective as the IBR elements are essential but insufficient for surviving disruptions. Assuming IBR elements (e.g., slack resource, visibility, agility, flexibility, collaboration, and information sharing) constitute the conceptual domain of resilience could lead to overconfidence, and accordingly obscure opportunities that can be exploited to rapidly absorb and recover from disruptive events.

This research suggests that operations and supply chain managers should evaluate operational resilience at two discrete levels: disruption absorption and recoverability. We show that disruption absorption and recoverability play unique roles in disruption management: not only do they have unique manifestation; they do also influence operational efficiency differentially. Thus, a key message for managers is that they should not view these capabilities as substitutes, but rather as complements. While disruption absorption permits operations to function normally during disruption events without major absorption changes to the constituents and configuration of operations system, recoverability ensures that operations output rates bounce back to prior normal levels following disruption; making both types of capabilities crucial in managing disruptive events.

Furthermore, managers can deploy bridging strategies including supply chain integration, information sharing, and collaboration alongside buffering strategies (e.g., keeping excess inventory and having multiple supply-base for each product line) to increase disruption absorption and recoverability capabilities (Manhart et al., 2020; Tukamuhabwa et al., 2015). However, the nature of disruption absorption suggests that increasing its threshold would require managers to focus greater attention on pre-disruption stage measures, particularly, buffering strategies, as these allow managers to hedge operations system from disruption impacts. On the other hand, swiftness in searching and seizing opportunities to

respond to disruptions would be an instrumental lever for boosting recoverability following disruptive events.

Moreover, while there is an economic benefit for building resilient operations, it is important to note that how and the conditions under which firms extract efficiency benefits of operational resilience can be complex. Findings from this study suggests that managers should take several factors into consideration. First, findings from this study reinforce prior research (e.g., Wong et al. 2019; Yu et al., 2019) to suggest that while resilience may be useful in enhancing firms' operational efficiency level, it is crucially vital that managers take into account disruption contexts to enhance efficiency benefit of resilience. Second, results suggest that there can be efficiency trade-off in developing different components of operational resilience and that the nature of this trade-off may depend on whether a firm operates under low versus high operational disruption conditions.

6.3. Limitations and direction for future research

This study can be extended in several ways and should therefore serve as a foundation for further thinking into the conceptual domain of operational resilience. A key question for discussion in a future research is whether an OBR perspective rather than an IBR perspective to operational resilience conceptualization is warranted; this way scholars would have a clearer understanding about what constitutes the nature and antecedents of resilience.

Additionally, debates about whether resilience is good or bad cannot be limited to its effects on efficiency (as it is the case of this study) or financial performance (as captured in previous studies). Survival and stability goals (Bode et al., 2011) rather than efficiency and profitability goals may be alternative motivation and justification for businesses to increase investments in resilience building. Besides, profitability (or the bottom-line question) is not

solely determined by efficiency. Accordingly, further research on operational resilience should consider other economic and non-economic performance outcomes.

Moreover, although this study accounts for relevant IBR elements as covariates in modeling operational resilience and operational efficiency, there are several other important IBR elements (e.g., flexibility, agility, and innovation) that should be controlled for in future studies. Additionally, this study only explored the moderating effect of operational disruption in the operational resilience-operational efficiency relationship as it is a prime organizational contingency to consider while analyzing the performance effects of resilience. Future studies can explore other relevant internal and external environment contingencies.

Empirically, our use of cross-sectional survey design, while consistent with prior research (Kwak et al., 2018; Chowdhury and Quaddus, 2017), limit the causal inferences of our results. Future research can address this limitation by utilizing either a longitudinal survey design (Manhart et al., 2020) and/or an experimental design (see Buyl et al., 2017). While this study relies on data from a unique and an under-studied empirical setting (i.e., SMEs in sub-Saharan African), future research may utilize data from other exotic settings to further investigate the operational resilience phenomenon.

7. Conclusion

In conclusion, this research demonstrates the benefits of conceptualizing and analyzing operational resilience as a multifaceted construct. The study shows that it may be problematic for researchers to conceptualize and operationalize operational resilience as a unidimensional construct as in doing so the construct's dimensional manifestations may be obscured, and thus making it difficult to determine how its dimensions uniquely influence performance. A major implication from this study is that it is necessary for scholars to recognize resilience as a multifaceted concept (Davidson et al., 2016) and incorporate relevant organizational

circumstances (Chowdhury et al., 2019; Wong et al., 2019) while analyzing its bright- and dark-sides. Insights from this study advances scholarly debate about whether resilience amounts to (in)efficiency and show how different aspects of resilience may relate differently to efficiency and the conditions that may reinforce or undermine the efficiency benefits of resilience elements.

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