FROM INTENT TO IMPACT: A PROACTIVE EVENT APPROACH FOR AMPLIFYING SUSTAINABILITY ACROSS TIME

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ABSTRACT

We extend Event System Theory (EST) to conceptualize proactive events and examine how event duration, timing, criticality, and disruption are related to two phases of change associated with an organizationally initiated event. Specifically, we explore the impact of a new sustainability monitoring system on energy consumption using longitudinal archival data from 87 manufacturing units of a Fortune 200 multinational firm. We use a variant of mixed-effects discontinuous growth modeling (DGM) to test EST propositions related to initial and longer-term changes associated with implementing the monitoring system. Results indicate that, while the new sustainability monitoring system is effective in reducing within-unit energy consumption on average, there are significant differences in change magnitude between units. The magnitude of change during the pre-post phase was related to between-unit differences in event duration, timing, criticality, and disruption. Longer-term change patterns were related to between-unit differences in managerial criticality behaviors. The results empirically validate several of EST's core propositions and provide an illustration of how DGM can be modified to study events that vary in onset and duration across entities.

***Keywords*:** event system theory; longitudinal; proactive event; event duration; event timing; event criticality

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There is growing concern from managers, policymakers, consumers, and other stakeholders (Atasu & van Wassenhove, 2012; Khuntia, Pattanayak, & Hiremath, 2018; Muthulingham, Corbett, Benartzi, & Oppenheim, 2013) about high levels of resource consumption in manufacturing (Bonini & Görner 2011; Joshi & Li 2016; Krass, Nedorezov, & Ovchinnikov, 2013; Sroufe, 2003). Indeed, ensuring sustainable production is one of the United Nations' development goals (UN DESA, 2022) as manufacturing plants can contribute to both global environmental sustainability efforts and their own economic interests by reducing resource consumption. Event System Theory (EST: Morgeson, Mitchell, & Liu, 2015) is an influential framework in management research that can provide a structure for examining how to optimize the implementation of sustainability-oriented initiatives. To date, EST research has primarily centered on understanding the impact of unplanned events (Liu, Morgeson, Zhu, & Fan, 2023), including external events such as Covid-19 (McFarland, Reeves, Porr, & Ployhart, 2020) and internal events such as a coding mistake in the development of a pharmaceutical compound (Morgen & DeRue, 2006). We expand EST research by examining how components of the theory apply to proactive events strategically initiated within a firm to "create a desired effect" (Morgeson et al., 2015: 533).

While the goal of management actions following an unplanned event is often to return to normal, the goal of a strategically initiated proactive event is to improve. Organizations initiate proactive events such as implementing new information technology systems, modifying human resource (HR) evaluation systems, adopting certifications (e.g., ISO 9000), and modifying manufacturing processes with the intent of achieving desired strategic top-down change. In many cases, these strategic initiatives are implemented by lower-level entities within the organization (e.g., regions, departments, plants, stores, etc.) that may have had little or no direct input into either the strategic decision or the specific implementation details. Using the EST framework, we model dynamic processes surrounding the implementation of a new firm-level sustainability initiative in manufacturing units. By so doing, we demonstrate how several EST propositions related to event duration, timing, disruption, and criticality can be tested to gain insights into improving the impact of planned events.

EST provides a compelling framework for examining the impact of proactive events in part because important aspects of event implementation typically vary across lower-level entities. For instance, for each manufacturing unit in our study, we can identify the point at which the technical aspects of the sustainability initiative began (onset of smart meter installation) and the point at which the technical aspects ended (final smart meter installation), but each unit differed in the specifics, such as duration, timing, and criticality. This and other types of unit variability provide an opportunity to understand how unit-level differences surrounding implementation are related to sustainability outcomes.

In their recent review of event-based research, Liu et al. (2023) note that “fine-grained, event-centric analyses are needed to discover which strength, temporal, and spatial cues can lead to important outcomes and how they can do so” (Liu et al., 2023: 2178). Accordingly, we illustrate how a novel variant of discontinuous growth modeling – DGM (Bliese & Lang, 2016; Singer & Willett, 2003) – can be used to examine events where the duration of the event differs across entities. Using this analytic framework, we also test the impact of other EST event attributes and predict how these event attributes are related to the impact of the sustainability initiative for specific units. A key aspect of our approach is that it differentiates two forms of change (see Bliese, Adler & Flynn, 2017). The first form represents change that occurs during the event by contrasting pre-event outcomes with outcomes immediately following implementation. The second form captures longer-term change in outcome trajectories after the implementation phase has been completed by comparing post-event outcome trajectories to an expected trajectory generated during the baseline period prior to the event. Using these two forms of change, we can distinguish between *initial* and ongoing *longer-term* changes in outcomes. As we show, between-unit characteristics differentially explain one or both change parameters in ways that inform theory and practice. We identify between-unit characteristics that allow direct tests of the role of event duration, timing, and criticality. In exploratory analyses, we also examine an index of disruption. We note here, and elaborate elsewhere, that we assume the EST attribute of novelty to be roughly equivalent across entities in our context; consequently, we offer no tests of novelty.

Our paper makes four main contributions. First, we extend EST to conceptualize proactive strategically initiated events. This conceptualization builds on calls to expand event research beyond unplanned events (Liu et al., 2023; Morgeson et al., 2015) and to consider the cross-level nature of events initiated with a desired change in mind. Second, we provide a way to analytically examine events that vary in timing and duration across units. Third, we illustrate how focusing on unit differences in outcome trajectories can help refine theory about event impact with respect to both initial change and longer-term change. Fourth, we show how EST can provide insights into optimizing the potential benefits of sustainable production, helping to address one of the United Nations' sustainable development goals and opening the door to future research at the intersection of theory and practice (Markman, 2022).

We used a longitudinal field study involving manufacturing units of a large multinational organization. The organization initiated a sustainability program through the rollout of smart meters and a managerial system to track energy consumption. The program was staggered across manufacturing units. We used 2,079 monthly observations nested within the 87 manufacturing units to compare temporal patterns of energy consumption before and after the event.

A PROACTIVE EVENT DEFINITION

While much of the event-based research has focused on unplanned events, seminal event system research focused on a variety of events, including those that were proactive such as beginning a series of new studies, changing strategy, creating a strategic sourcing initiative, and adding new team members (Morgeson, 2005; Morgeson & DeRue, 2006). Accordingly, we integrate perspectives on planned events and build from EST's discussion of proactive events (Morgeson et al., 2015) to provide the following definition:

> *Proactive events are planned, deliberate events that are strategically oriented with a desired improvement in mind.*

Our definition of proactive events has four important elements. First, proactive events are planned, deliberate, and strategically initiated. Second, proactive events are typically cross-level where the event is initiated or created at one level and the effects can be top-down or bottom-up (Liu et al., 2023) although in our example we focus on top-down processes. Third, proactive events are fundamentally endogenous at the higher-level (e.g., firm) but become more exogeneous in nature for lower-level entities implementing the change. That is, given the nature of how proactive events are implemented within organizations, many of the principles of EST can be applied to understand lower-level entities' responses to an event where the event did *not* originate because of specific pre-existing attributes of the lower-level entity. As we note, there are also limitations to the inferences that can be drawn from a cross-level examination of proactive events; nonetheless, we show that applying EST principles in this context yields important insights. Fourth, proactive events are initiated by an entity, which we refer to as the agent of proactivity. We focus our theory and analyses on understanding how lower-level entities react and respond to a proactive event.

We briefly detail two examples. First, a common example of a strategically initiated event involves using enterprise resource planning (ERP) systems to implement data-driven HR management systems such as Workday, Oracle, SAP, Sage, or Kronos to facilitate the management of human capital resources (Hoch & Dulebohn, 2013). In this case, the agent of proactivity is the chief human resource officer and/or other leaders who decide to implement the ERP and the top-down effects require lower-level entities (e.g., business units, stores, plants) to change work design and HR tracking and reporting systems. The second example involves implementing electronic record-keeping systems to reduce costs and improve the quality of health care under legal requirements of the Affordable Care Act (Fontenot, 2013), where the government is the agent of proactivity and hospitals are the lower-level entities responding to the event by enacting significant changes in technology and patient tracking systems.

It can often be challenging to evaluate the impact of proactive events for at least two reasons. First, specific action(s) enacted during the event may or may not achieve desired goals. For example, implementing new technology alone rarely guarantees desired outcome changes (Fontenot, 2013; Marler & Fisher, 2013). Rather, implementation is most effective when characteristics of the new technology and human behaviors are aligned (Ngwenyame & Nielsen, 2014; Venkatesh & Davis, 2000). Second, the impact often unfolds over time as managerial processes adapt to the event, suggesting the need for careful attention to temporal dynamics as part of any evaluation.

Overall, proactive events have the potential to vary in strength, duration, and timing and are likely to have four key attributes. First, proactive events are bounded in time, with a discrete beginning and an identifiable ending point. Second, proactive events may have different starting points in time, durations, and even ending points for lower-level units within the organization. Third, changes are dynamic, with some outcomes only becoming apparent over time. Finally, specific characteristics associated with how the event unfolds for each lower-level entity can serve to mitigate or amplify outcome impact.

The current study is focused on a top-down proactive event involving the implementation of real-time monitoring technology that provides a stream of energy consumption data (Ainin, Naqshbandie, & Dezden, 2016; Zampou, Plitsos, Karageannaki, & Mourtos, 2014) with a goal of reducing overall energy consumption. The agent of proactivity was the top management team who created this strategic initiative. Using similar technology, Walt Disney World reduced its annual electricity consumption by 100 million kW hours by collecting and distributing consumption data to appropriate managers and maintenance staff (Allen, 2005). In this case, repair crews could be dispatched as soon as an aberration was detected, rather than waiting for a monthly utility bill to indicate a problem. In the next section, we build on our conceptualization of proactive event-based change for a real-time monitoring event by reviewing EST and further developing a framework for studying proactive events.

EVENT-BASED THEORY

EST (Morgeson et al., 2015) seeks to explain how events influence ongoing organizational processes and outcomes. Ongoing behaviors and automatic processes among entities are typically stable unless disrupted by events. According to EST, event strength (novelty, disruption, and criticality) determines event salience, which shapes reactions over time.

EST also specifies that events vary in duration between entities and events can occur at different lifecycle stages across entities. Thus, both the duration and timing of an event play a role in the event's impact. The lasting dynamic impact of an event is dependent upon the components of the event system such that highly salient events have larger (Morgeson, 2005; Morgeson & DeRue, 2006) and longer-lasting effects on outcomes over time than events with low salience.

As noted, many proactive events, like the one we examine, originate as a firm-level strategic initiative for units across the organization. Senior leaders within the firm are agents of proactivity who determine factors such as time of onset and event duration for subordinate entities. In part, this external influence occurs because firm-level initiatives are supported by firm-level resources allocated to lower-level entities. For instance, our firm used implementation teams that worked with a subordinate unit until implementation was complete before moving to another unit. The observation that onset and duration are external to the unit suggests that unit managers may have little or no influence over factors such as timing, duration, and disruption – an observation that is in line with EST's assertion that "events originating at higher levels will be more likely to (create) change" (Morgeson et al., 2015: 525). In contrast to factors such as timing, duration, and disruption, which vary across units due to higher firm-level factors, we expect criticality to vary due to lower-level managerial actions. Criticality represents the degree to which an event is seen as a priority and can be assessed by examining indices of management behaviors related to the event.

In the context of our proactive event, the only factor that we assume to be roughly similar across entities is novelty. We base this assumption on the fact that each unit is experiencing the same initiative (e.g., smart meter installation). That is, we believe novelty would best be studied if different entities experienced different events – for instance, if one set of units experienced smart meter installation and another set experienced a complete change in the product line.

A Framework for Assessing Event-Based Change

Discontinuous growth modeling (DGM) and its variants (Bliese & Lang, 2016; Singer & Willett, 2003) are well-suited for inferring change in response to both exogenous and proactive events (Liu et al., 2023). Specifically, DGM provides a way to contrast trajectories of key focal outcomes before and after an event, and to model between-unit differences that account for variance in trajectory differences. Multiple characteristics of trajectories – direction, level, and rate – are testable, providing the ability to comprehensively examine the process of change surrounding an event. Using DGM, we propose a conceptual framework for studying event-based change processes within the context of our proactive sustainability event.

We conceptualize the process of change in terms of how outcome trajectories on energy consumption are altered by smart meter installation (the event). According to EST, events may stall, accelerate, or reverse the direction of an existing outcome trajectory (Morgeson et al., 2015). Formally examining outcome trajectories and trajectory change provides a dynamic view of process change that cannot be obtained from static or mean comparison approaches (Bliese et al., 2017; Liu et al., 2023). We use EST's dynamic view to examine event-based change in outcomes in two forms: initial (*Pre-Post*) change and longer-term (*Post-Event Trajectory*) change.

While not directly testing the concepts behind EST, illustrations of these two forms of event-based outcome change exist in multiple literature streams (Bliese et al., 2017). In one example, Hale, Ployhart, and Shepherd (2016) examined the initial and long-term effects of individual employee turnover on unit performance. Results showed that, on average, units had an initial decline following the turnover and subsequent performance improved over the post-event period, returning to near pre-event levels. The effect of the initial decline in performance was particularly pronounced for units with manager turnover, and the long-term performance growth was less pronounced for units with high interdependence. In another example, Li, Hausknecht, and Dragoni (2020) examined the impact of leader turnover on initial and long-term collective turnover trends. The authors found that initial levels of turnover were related to departing leader performance, while long-term turnover trends were related to both departing leader performance and the experience of the replacement leader.

Figure 1 illustrates how changes may unfold over time for energy consumption. This plot illustrates two hypothetical manufacturing units. *Paths a, b, and c* denote the within-unit changes that occur around an event, while contrasting the differences in patterns of change between units. *Path a* (Figure 1) denotes the baseline outcome trend prior to an event.

Insert Figure 1 Here

The initial *Pre-Post* phase is denoted as *Path b* and captures the degree to which post-event levels of energy consumption differ from pre-event levels. In many DGM examples, the event is discrete (e.g., the specific time the event occurred). In our case, the event is bounded by the specific month in which smart meter installation began and the final month of installation. We conceptualize this entire period over which *Pre-Post* change occurs, and capture duration as a key predictor. The *Post-Event Trajectory* phase is denoted as *Path c* and captures the rate of outcome change during the post-event period reflecting ongoing changes that follow the event.

Using the DGM framework, we first posit that average energy consumption post-event will significantly decline relative to pre-event baseline. Further, we anticipate units will continue learning to use information following the final implementation such that post-event energy consumption trajectories in the 12 months following the event will be more favorable than the 12-month pre-event baseline trajectories. We then test for significant between-unit differences in *Pre-Post* and *Post-Event Trajectories* of energy consumption. Central to using DGM as a framework to test EST propositions is formally testing whether outcome patterns among units differ (Schepker & Bliese, 2023). As Figure 1 illustrates with exemplar Units 1 and 2, between-unit differences in the pattern of within-unit changes around an event are apt to exist even when the overall sample displays a specific form of change.

Between-Unit Differences in Event Characteristics

Duration. Event duration describes an event's length of time from beginning to end (Morgeson et al., 2015). EST proposes that event duration has a conditional effect on event strength (Proposition 7); however, this aspect of EST tends to be somewhat underdeveloped. One of the challenges with expanding and testing theory related to event duration is that many events are brief, even though the effects of the events and/or the factors leading to the events vary in length. Examples of brief, albeit impactful, events include the April 11, 2011 earthquake and tsunami in Japan (Matsuo, 2015), the onset of the Great Recession (Kim & Ployhart, 2014), and changes in leadership (Li et al., 2020). Even brief events for individuals, such as heart attacks (Bonanno, 2004), job losses, or divorce (Lucas, 2007), are typically conceptualized and modeled as occurring at a single time point (e.g., the specific year, quarter, or day that the event occurred).

In contrast, strategically initiated proactive events frequently involve defining beginning and ending times that make questions about duration more salient. For example, when an organization purchases a new ERP system, this event is bounded by the length of the respective implementation period for each unit. Other examples include organizational restructuring and applying for a certification such as ISO 14000. In these cases, organizations may establish hard endpoints (e.g., ISO 14000 certification will be completed in the first quarter of 2024), but specific entities may follow different implementation schedules.

We anticipate that in many situations involving proactive events, a long unfolding timeframe will have a stronger influence on outcome change than a short unfolding timeframe (Morgeson & DeRue, 2006). In these contexts, longer event experiences are often more meaningful than shorter experiences because units spend more time and gain exposure to components of the change process. Specifically, Tushman, Neuman, and Romanelli (1981) contend that there is greater opportunity for learning, alignment, and modification of organizational elements during longer durations. These opportunities form a foundation for developing schemata to guide future action (Shipp & Jansen, 2011). For example, Jiang, Yin, and Liu (2019) found that the duration of discrete peak emotion during an entrepreneur's pitch was positively related to funding performance.

Within our conceptual framework, we can differentiate the effects of event duration on the changes associated with the *Pre-Post* energy consumption from *Post-Event Trajectory* effects. With respect to *Pre-Post* effects, we anticipate that when event duration is longer, the unit will experience greater change (Morgeson & DeRue, 2006) because of the longer opportunity to learn and develop new schemata. Contrary to abrupt events such as Black Friday in 1929 or a heart attack, events with lasting duration provide an opportunity to learn and react as the event unfolds. Research has shown that units reduce their costs as learning occurs (Arthur & Huntley, 2005) and that longer events enhance performance (Jiang et al., 2019). Extending this principle to the context of a proactive event, units that spend more time learning during the event phase should have more favorable outcomes. That is, units with longer events will learn over time and make greater changes aligned with the goal of the event. Thus, we hypothesize that:

Hypothesis 1a: Pre-Post declines in energy consumption will be greater for units with longer event duration than for units with short event durations.

With respect to *Post-Event Trajectories*, the impact of event duration is less clear as previous research on duration has examined static outcomes (i.e., venture funding, Jiang et al., 2019). On the one hand, a longer event duration may have a secondary effect of nurturing a learning culture where managers and employees continue to refine how they respond to information from new systems once all components are in place. In this case, we would anticipate that longer event durations would be associated with continued declines (benefits) in energy consumption after the implementation phase was completed. On the other hand, event duration by itself may not be sufficient for establishing a learning culture, in which case units would not experience continued declines in subsequent outcome trajectories. Consequently, we propose a non-directional Hypothesis 1b in the spirit of a true null-hypothesis significance test (i.e., a test where the null of no effect is the most plausible counterfactual because the expected effect is equivocal).

Hypothesis 1b: Post-deployment energy consumption trajectories will differ as a function of event duration.

Timing. EST discusses entrepreneurial cycles, team development models, and leader development to illustrate how entities change over time and the dynamic nature of contexts in which events occur (Morgeson et al., 2015). We broaden EST's conceptualization of event timing to describe the implications of event onset at different points in calendar time. Theory suggests that events are often more salient for those who experience the event earlier in calendar time (i.e., early adopters; Davis, 1989; Davis, Bagozzi, & Warshaw, 1989), which likely applies to both proactive and unexpected events. For example, the technology acceptance model contends that social pressures and mandates initially influence positive perceptions of a change but those effects wane quickly (Venkatesh & Davis, 2000). Similarly, with respect to unexpected events, individuals who caught Covid-19 in the early part of the pandemic had a significantly different experience in terms of personal impact than those who caught it later in the pandemic for a variety of reasons, even if the severity of the infection was the same.

For top-down proactive events, units selected earlier by leaders may be motivated to garner the presumed benefits whereas units selected later may be motivated by the legitimacy of the event within the organization (Westphal, Gulati, & Shortell, 1997). That is, DiMaggio and Powell (1983) observed that as “innovation spreads, a threshold is reached beyond which adoption provides legitimacy, rather than improves technical performance” (DiMaggio & Powell, 1983: 141). If later onset units are more focused on matching the successes of units selected earlier, they may superficially imitate implementation models (Abrahamson, 1991). Thus, practices of units selected later may be guided by a “logic of social appropriateness” rather than a logic of instrumentality (Campbell, 1997: 26). Because standard solutions may not meet the unique needs of a particular unit, the associated outcomes may be inferior.

Units selected early may also realize more change because they build practices that capitalize on their unique distinctive competencies and compensate for their relative weaknesses (Westphal et al., 1997). This has been shown for events including civil service reforms (Tolbert & Zucker, 1983), personnel programs (Baron, Dobbin, & Jennings, 1986), CEO incentive plans (Westphal & Zajac, 1994), administrative innovation in hospitals (Westphal et al., 1997), and logistics initiatives (Ni, Melnyk, Ritchie, & Flynn, 2016). In fact, evidence suggests that units with earlier proactive event onset are less concerned with direct economic benefits and more concerned with indirect initiative-related benefits for the public good associated with the proactive event (Ni et al., 2016). For instance, a study of hospitals found that earlier-onset units customized their response to a proactive event while later-onset units implemented more standardized responses (Westphal et al., 1997). That is, units with earlier event onset were more likely to experiment with developing strategies related to the event initiative. Together, these lines of research emphasize the potential for units selected early to undergo greater degrees of event-based change and improved event-based outcomes. Thus, we hypothesize:

Hypothesis 2a: Pre-Post declines in energy consumption will be greater for units selected earlier versus those selected later.

With respect to *Post-Event Trajectories*, the impact of event timing, like event duration, is less clear. On the one hand, the experimental iterations of earlier-onset units may nurture a culture of ongoing customization, where managers and employees continue to refine and improve how they utilize the new system. In this case, we would anticipate that earlier event onsets would be associated with continued declines (benefits) in energy consumption after the implementation phase was completed. On the other hand, being an earlier-onset unit may result in innovations that capture virtually all the potential gains during implementation, in which case units would not experience continued improvements. Consequently, we also propose Hypothesis 2b in the spirit of a true null hypothesis significance test.

Hypothesis 2b: Post-deployment energy consumption trajectories will differ as a function of whether the unit is selected earlier versus later.

Criticality. EST describes event criticality as the degree to which an event is seen as a priority, mainly within the context of unexpected events (Morgeson et al., 2015). Extending this notion to proactive events, we reason that managerial attention deriving from the degree to which a unit views the event as a priority will play a role in achieving desired effects. One proxy for whether an event is seen as a priority is the degree of effort and attention devoted to key aspects of the event. Theory suggests that attention is a scare resource and managers choose where to devote attention (Ocasio, 1997). For example, paying attention to safety concerns is an important element of team climate which facilitates better safety performance (Bradley, Postlethwaite, Klotz, Hamdani, & Brown, 2012; Hofmann & Stetzer, 1998). Event-based research has shown that criticality and attention are closely aligned where managers must devote more attention to critical events (Morgeson & DeRue, 2006) and, in some cases, critical events are inversely related to creativity (Chen, Liu, Tang, & Hogan, 2021). In both examples, the events studied were negative, so event criticality distracted attention from task performance. In contrast, proactive events are positive, so criticality should reflect attention paid to the strategic aims of the event. Thus, the more attention given to the event, the more aligned managers should be with the event's desired outcomes.

Managerial behaviors provide an index of event criticality by showing that managers are prioritizing the event and signaling the importance of the event to individuals within the unit (Ocascio, 1997). When managers devote attention aligned with the strategic aims, units are more likely to achieve the desired immediate outcomes (Pirola-Merlo, Härtel, Mann, & Hirst, 2002). As a clear example with important implications, work in medical research has found that devoting managerial attention to adverse events is a catalyst for understanding causes and developing failsafe processes to prevent such events from reoccurring. In this context, an adverse event is defined as an injury caused by treatment (Leape, 1994; Leape et al., 1995; Buerhaus, 1999). Adverse events include both unpreventable events, such as an unpredictable allergic reaction to a medication in a patient not known to have allergies, and preventable events caused by errors (~2/3 of adverse events), often exacerbated by the complex sociotechnical environment of an emergency room, stress, and working under pressure (Rafter et al., 2014). Major adverse event cases can garner national and international attention (Altman, 1995; Resnick, 2003), but even in less dramatic cases (Rafter et al. 2014), the occurrence of such events often prompts management to initiate intensive study and remediation of the processes contributing to such errors. Management attention following adverse events leads to a better understanding of the underlying causes and to processes reducing reoccurrence.

We likewise assume that management attention will display similar effects for proactive events. For example, research shows that managerial attention is a key factor in driving the success of environmental improvement (Dhanorkar, Siemsen, & Linderman, 2018). In the context of our research, installing real-time energy consumption monitoring technology is simply a vehicle for generating data; it is only when managers use the data as a catalyst for change that expected benefits will occur. The more managers engage in new initiative-related behaviors, the more pronounced the changes. Thus, behaviors that signal event criticality through management attention should amplify initial event-based changes leading us to hypothesize that:

Hypothesis 3a: Pre-Post event-based declines in energy consumption will be greater for units with greater managerial behavior criticality, as indexed by managers devoting more effort and attention to critical components of the event.

Importantly, the impact of criticality should be evident for both initial and longer-term event-based changes associated with *Post-Event Trajectories*. According to EST, event criticality is likely to impact the "horizon" (Morgeson et al., 2015: 521). Managerial attention and new behaviors signal that the unit has changed in a meaningful way that can continue to capitalize on desired changes over time. Critical events impact both performance and interpersonal interactions within units (Morgeson & DeRue, 2006), and require greater attention (Chen et al., 2021; Gersick & Hackman, 1990). The implication is that individuals within a unit spend a considerable amount of cognitive effort interpreting critical events (Shipp & Jansen, 2011; Weick, 1979). Therefore, the effects of criticality do not always end at the discrete conclusion of an event but may continue to unfold over time. As this sensemaking process unfolds over time, units experiencing more critical events are apt to have more beneficial ongoing post-event trajectories of outcome change. Unlike duration and timing, criticality can also be assessed beyond the conclusion of the event itself. Therefore, we examine the role of criticality during the event and in the first three months of the post-event phase. In both cases, we hypothesize that units with greater managerial behavior criticality will achieve more significant long-term reduction in energy consumption leading to the hypotheses that:

Hypothesis 3b: Post-deployment energy consumption trends will be more favorable for units with greater managerial behavior criticality, as indexed by managers devoting more effort and attention to critical components of the event *during* the event.

Hypothesis 3c: Post-deployment energy consumption trends will be more favorable for units with greater managerial behavior criticality, as indexed by managers devoting more effort and attention to critical components of the event *after* the event.

Novelty and Disruption. Our primary hypotheses center on duration, timing, and criticality. Within EST, event strength is considered a function of three factors – novelty, disruption, and criticality. Novelty refers to the extent to which an event represents something new or unexpected. Novelty has been shown to drive improvisation (Chen et al., 2021), while perceptions of novelty associated with the Covid-19 pandemic led to feelings of job insecurity and decreased work engagement (Lin, Shao, Li, Gui, & Zhan, 2021; Liu, Chen, & Li, 2021). As noted, we assume that our smart meter installation event is similarly novel for each unit (see the footnote quote from an organizational leader further supporting this assumption[1]).

Disruption describes the degree to which an event represents a change in usual activities. Unlike novelty, disruption is likely to vary across units. Unlike criticality, however, disruption is challenging to operationalize in this context because potential measures of disruption tend to be correlated with duration (Morgeson & DeRue, 2006). While the link between disruption and duration is logical (a short installation is likely less disruptive than a long installation), the link makes it difficult to isolate disruption effects. Nonetheless, we identify a proxy for disruption in the *post-hoc* analysis and consider ways future research may operationalize disruption in the Discussion section.

METHOD

We tested our hypotheses using data from a large multinational company that produces many types of consumer goods. The sample organization is a Fortune 200 firm with over 100,000 employees and a global network of manufacturing units. In 2009, the organization began an initiative to reduce energy consumption by implementing an energy monitoring system to provide managers with real-time data about their unit's energy consumption. The sample organization identified units and assigned implementation characteristics (i.e., timing, duration) at the corporate level and event implementation was staggered across units[2].

At the unit level, we define the event as the period of time between the first and last smart meter installation. As these beginning and ending times varied between units in terms of both calendar time of event onset and duration, we built a dataset comparing the 12-month period before each unit's event to the 12-month period after each unit's event and centered the data around the event. The length of time between the initial and final installation month was captured for event duration (described below). For example, one unit had its initial installation in December 2013 and its final installation in October 2017, so the pre-event observation period was January-December 2013, and the post-event observation period was October 2017-September 2018. 104 units experienced the implementation in the dataset, and our design required a 24-month observation period (12 months prior to event onset and 12 months following event conclusion); 93 of the units met these criteria (with a total of 2,232 monthly observations). There were 58 observations with a value of 0 for our dependent variable, indicating that the unit was closed in that particular month. We eliminated units that were closed for four or more months within the 24-month observation period, resulting in a final sample of 87 units (with a total of 2,079 monthly observations).

We arranged the panel data in a floating baseline format, aligning the month of the onset of the event as the twelfth observation for each unit and the month of the conclusion of the event as the thirteenth observation for each unit. The resulting dataset had 2,079 monthly observations nested in 87 independent units. Because of the floating baseline, the time-related covariate matrix is specified based on event onset and duration for each unit. *Time* captures the baseline linear effects of time and was indexed as a vector where each observation was coded 0 through 23. *Pre-Post* captures outcome differences across the event and was coded with a value of 0 for the 12 months prior to the event and a value of 1 for the 12 months following the event. *Post-Event Trajectory* captures post-event outcome trajectory changes compared to the baseline outcome trajectory prior to the event and was coded with a value of 0 for the 12 months prior to the event and a vector from 0 through 11 for the 12 months following the event. We used the absolute coding of *Time* (*Time.A*) to test our hypothesized interaction effects because this specification is most aligned with the form of our hypotheses related to between-unit differences for *Pre-Post* and *Post-Event Trajectory* (Bliese & Lang, 2016). Absolute coding for *Time.A* uses a vector of values from 0 to 11 until the event and then holds the value constant at 11.

Measures

Previous EST research has typically leveraged validated survey scales (Morgeson, 2005; Morgeson & DeRue, 2006) to capture outcomes and post-hoc perceptions of event strength and duration, while limited research has tested objective measures of event attributes (e.g., Jiang et al., 2019). Our study leveraged objective measures related to the outcome and event attributes, offering external validity to the growing stream of event-based research.

Energy Consumption. We obtained monthly energy consumption in gigajoules (GJ) for each manufacturing unit. Monthly energy consumption was our repeated outcome measure.

Duration. Event duration was operationalized as the number of elapsed months between the onset of the event (month of first smart meter installation) and the conclusion of the event (month of final smart meter installation). Duration ranged from 1 to 108 months across units, with an average of 37.73 months and a median of 27 months.

Timing. Event onset represented the calendar month in which a unit's first smart meter was installed. For the units in our sample, the earliest event onset was January 2009, and the latest event onset was January 2018. Timing was operationalized as a vector from 1 to 123, corresponding to calendar months, with lower values indicating earlier onset.

Criticality. The sample organization launched an energy monitoring app for managers concurrent with the onset of smart meter installation in each unit. Usage-related indices measure the extent to which unit managers used the app to access smart meter data, representing new behavioral routines that coincide with the event. Footnote 3 presents a full quote from the Global Director of the Sustainability Metering System, verifying that the portal was designed to monitor plant usage[3].

Event criticality was operationalized in two ways. First, *App Views During Event* measures the number of times a unit manager interacted with the app during a unit's event. Second, *App Views After Event* measures the number of times a unit manager interacted with the app in the three-month period immediately following the event. Because the latter metric only captures behavior following the event, we used it exclusively to test Hypothesis 3c. In terms of measurement reliability, we tested whether unit means reliably differed by estimating the ICC(2) or group-mean reliability (Bliese, Maltarich, Hendricks, Hofmann, & Adler, 2019) for *App Views After Event*. We estimated the ICC(2) on *App Views After Event* to ensure a consistent number of observations per unit (3 months for each unit) given that duration lengths differed. The ICC(2) value of .86 indicates reliable mean differences across units.

Controls. We utilized several controls to help rule out alternative explanations for the event-based energy consumption changes. To control for unit size and energy consumption per output, we added a time-varying covariate for unit production (in tons) for each month. *Production* is a critical control because there is a potential for larger units to experience greater changes in energy consumption compared to smaller units. As seen in the correlation matrix below (Table 1), *Production* is highly correlated with energy consumption (r= .62 at Level 1 across all our repeated measurement occasions and between .61 and .64 at Level 2). Importantly, however, production is not significantly correlated with any of our proposed moderators. That is, *Production* was not related to *Event Duration* (r= .08, ns before the event; r= .15, ns after the event) or *Event Timing* (r= -.16, ns before the event; r= -.17, ns after the event). Nor was production related to either index of criticality (r= .06, ns before the event; r= -.02, ns after the event for *App Views During Event*; r= .08, ns before the event; r= -.01, ns after the event for *App*

Views After Event). We cross-validated these null findings with growth models of the pre-event baseline period. Neither *Event Duration* nor *Event Timing* had a significant main effect on energy consumption or a significant interaction effect with *Time*. Overall, these non-significant relationships make it unlikely that any effects we observe to be related to these predictors are simply due to differences in levels of plant size and production.

Insert Table 1 Here

To control for industry effects related to the product categories manufactured in a unit, we added dummy codes for the three industries in which the sample organization operates. Finally, to rule out any potential geographic effects, since different regions may use different approaches to energy consumption and sustainability, we created dummy codes for the three geographic regions in which units operate.

Analytic Strategy

Our theory provides directional predictions for most of our hypotheses (H1a, H2a, H3a, H3b, and H3c). Because these hypotheses specify a particular direction *a priori*, we tested them with one-tailed significance tests. In our analyses, we first ran models testing each hypothesis separately. For instance, we ran separate models testing *Event Duration* on *Pre-Post* and *Post-Event Trajectory*. In subsequent models we explored combined effects and with multiple predictors in the models. Our decision to test hypotheses separately was based on the observations that (a) *Pre-Post* and *Post-Event Trajectory* effects tend to be related, for both conceptual and methodological reasons (see Bliese, McGurk, Thomas, Balkin, & Wesensten, 2007) and (b) effects such as timing, duration, and criticality, while conceptually distinct, are likely to be related in practice. We elaborate on both these decisions below.

First, with respect to the conceptual and methodological reasons *Pre-Post* and *Post-Event Trajectories* tend to be related, entities that have large declines in energy usage in the *Pre-Post* phase may subsequently have little room for long-term declines in the *Post-Event Trajectory* phase, causing the two effects to be correlated. This correlation is a general phenomenon characteristic of many DGM models (e.g., Bliese et al., 2007), but highlights the value of understanding effects independently to avoid over-fitting a model where shared variance can negate both effects. Second, with respect to duration, timing, and criticality, we note that entities that start the event earlier likely have longer durations and having longer durations will provide more opportunities for a plant to record more app views. This general phenomenon, where duration, timing, and indices of criticality are related, is likely present in many contexts. Nonetheless, shared variance among the three variables could produce over-fit models, where meaningful shared variance is cancelled out. While these inter-relationships complicate the interpretation of this real-world event, we show how inferences can be drawn by starting with simple effects and subsequently testing more complex models.

The full Level 1 model for the change in the first condition of our framework is presented in Equation 1, with the Level 2 components listed in Equation 2. Note that the Level 2 model initially only includes an error term for the intercept (u_{0j}), resulting in the variance term τ_{00}.

$$\text{Level 1:} \quad Y_{tj} = \beta_{0j} + \beta_{1j} Time_{tj} + \beta_{2j} Pre\ Post_{tj} + \beta_{3j} Post\ Event\ Trajectory_{tj} + e_{tj} \qquad (1)$$

$$\text{Level 2:} \quad \beta_{0j} = \gamma_{00} + u_{0j} \qquad (2)$$
$$\beta_{1j} = \gamma_{10}$$
$$\beta_{2j} = \gamma_{20}$$
$$\beta_{3j} = \gamma_{30}$$

To our test hypothesized between-unit differences in the form of change, we expand the model to consider how specific predictors influence *Pre-Post* and *Post-Event Trajectory*. Equation 3 shows the fixed effects while Equation 4 represents Level 2 and uses a unit-level predictor to account for differences in the magnitude of the *Pre-Post* and *Post-Event Trajectory* parameters between units.

Level 1: $Y_{tj} = \beta_{0j} + \beta_{1j}Time.A_{tj} + \beta_{2j}Pre\ Post_{tj} + \beta_{3j}Post\ Event\ Trajectory_{tj} + e_{tj}$ (3)

Level 2: $\beta_{0j} = \gamma_{00} + \gamma_{01}Predictor_j + u_{0j}$ (4)

$\beta_{1j} = \gamma_{10} + u_{1j}$

$\beta_{2j} = \gamma_{20} + \gamma_{21}Predictor_j + u_{2j}$

$\beta_{3j} = \gamma_{30} + \gamma_{31}Predictor_j + u_{3j}$

While the DGM can be specified to take on a non-linear form (i.e., Lang & Bliese, 2009), our theory provided little basis to expect non-linear effects, which was further supported by model comparison. Therefore, our analysis used the parsimonious linear DGM.

RESULTS

Descriptive statistics and correlations at the unit level are shown in Table 2. For simplicity, we aggregated monthly repeated measures for the outcomes for the 12-month baseline prior to the event and the 12-month period following the event and standardized both by annual production for the descriptive statistics in Table 1.

Our framework focused on the three key time-related effects of *Time*, *Pre-Post*, and *Post-Event Trajectory*. First, we estimated the intraclass correlation coefficient (ICC) from a null model at the unit level to quantify the degree of non-independence among observations in the specified hierarchical structure (Bliese & Ployhart, 2002; Raudenbush & Bryk, 2002). We used a two-level model, where Level 1 was the monthly observation of a unit's energy consumption and Level 2 was the unit. The ICC was .87, indicating 87% of the variance in energy consumption is between units. While an ICC in this range is larger than many metrics in management research, it is based upon a highly reliable measurement source and is similar to other DGM research using objective measures. For example, Kramer and Chung (2015) found an ICC of .91 in their DGM exploring BMI. Importantly, however, the 13% of the variance which resides within-unit level still provides the possibility of explaining meaningful levels of change within units in a context where a very small percentage change results in substantial monetary savings – a point we elaborate on later.

The first condition of our conceptual and analytic framework posited that, across all units, there would be (a) pre-post declines in energy consumption and (b) that post-event energy consumption trajectories over the subsequent 12 months will be more favorable than the 12-month pre-event baseline trajectories. We empirically examined this condition by examining the main effects of *Pre-Post* and *Post-Event Trajectory* in the random intercept model (Table 2). As the model shows, *Pre-Post* was negative and significant (t= -3.98, p<.001) with observed power of .98, suggesting that 98% of values in the 95% confidence interval would be significant (Bliese & Wang, 2020). *Post-Event Trajectory* was negative but not significant (t= -1.33, p=.18). Figure 2 illustrates a decline in energy consumption around the event. Thus, the pre-post change around the event was validated for our sample, but across all plants there was not a significant trajectory of declining energy consumption in the 12 months after the last meter was installed.

Insert Table 2 and Figure 2 Here

While the *Post-Event Trajectory* was not significant across the sample, the second condition underlying our framework posited that there would be significant between-unit differences in the *Pre-Post* and *Post-Event Trajectory* parameters. We empirically examined this condition by contrasting a series of models where the slopes were fixed or were allowed to vary across entities (Bliese & Ployhart, 2002). The random intercept model used to assess the main effects of the event assumes that the event-based changes (both *Pre-Post* and *Post-Event Trajectory*) are consistent across units. Establishing random effects for the different parameters helps support the idea that between-unit event characteristics might explain different patterns of change and could in part explain why *Post-Event Trajectory* was not significant for the first condition. As shown in Table 3, model comparison found strong evidence of differences across units with likelihood values of 525.19 (p<.001), 340.43 (p<.001), and 72.45 (p<.001) for *Time*, *Pre-Post*, and *Post-Event Trajectory*, respectively. Together, the model comparisons support the second condition and show that units did not uniformly react to the event-based change. In subsequent tests, we found evidence of autocorrelation in our model (likelihood= 262.80, p<.001), so we included an autocorrelation control term. We failed to find evidence of heteroscedasticity in that the model failed to converge which suggested effects at or near zero.

Insert Table 3 Here

Our first hypothesis proposed that event duration would moderate changes in energy consumption such that *Pre-Post* event declines in energy consumption would be greater for units with longer event duration. The hypothesis was tested by the interaction between *Pre-Post* and *Event Duration* (Model 2, Table 4). The parameter was negative and significant (t= -2.05, p<.05) with observed power of .66 for the one-tailed test. The predicted plot in Figure 3 illustrates that units with longer event durations had a larger decline in *Pre-Post* energy consumption than those with shorter event durations. Thus, Hypothesis 1a was supported.

Insert Table 4 and Figure 3 Here

Hypothesis 1b proposed that event duration would moderate the event-based changes in energy consumption such that post-event energy consumption trajectories would differ as a function of event duration. The hypothesis was tested by the interaction between *Post-Event Trajectory* and *Event Duration* (Model 2, Table 5). The parameter was negative but not significant (t= -.92, *p*=.36) failing to support Hypothesis 1b.

Insert Table 5 Here

Hypothesis 2a proposed that event timing would moderate the event-based changes in energy consumption such that *Pre-Post* declines in energy consumption would be greater for units selected earlier than those selected later. The hypothesis was tested by the interaction between *Pre-Post* and *Event Timing* (Model 3, Table 4). The parameter was positive and directionally significant (t= 1.67, *p*<.05). In this case, the observed power was .51 for the one-tailed test, suggesting that 49% percent of the values represented by the 95% confidence interval would not be significant, implying a less robust finding (Bliese & Wang, 2020). The predicted plot in Figure 4 illustrates that units with an earlier event onset had a more pronounced decline in *Pre-Post* energy consumption. Thus, Hypothesis 2a was supported.

Insert Figure 4 Here

Hypothesis 2b proposed that event timing would moderate the event-based changes in energy consumption but did not specify a direction. The hypothesis was tested by the interaction between *Post-Event Trajectory* and *Event Timing* (Model 3, Table 5). The parameter was positive but not significant (t= .65, *p*=.52) failing to support Hypothesis 2b.

Hypothesis 3a proposed that managerial behavior (criticality) indexed by the number of app views would moderate the event-based changes in energy consumption such that *Pre-Post* declines in energy consumption would be greater for units when manager behaviors indicate higher levels of accessing the energy consumption-monitoring platform. The hypothesis was tested by the interaction between *Pre-Post* and *App Views During Event* (Model 4, Table 4). The parameter was negative and significant (t= -3.25, p<.001). The observed power was .95 which is indicative of a robust finding. Notice in Figure 5 that units with a high number of app views *during* the event had large *Pre-Post* declines in energy consumption. Thus, Hypothesis 3a was supported.

Insert Figure 5 Here

Hypothesis 3b proposed that managerial behavior (criticality) indexed by the number of app views *during* the event would moderate the *Post-Event Trajectory* such that energy consumption would be more favorable when managers demonstrated higher levels of accessing the app. The hypothesis was tested by the interaction between *Post-Event Trajectory* and *App Views During Event* (Model 4, Table 5). The parameter was negative but not significant (t= -1.37, p=.09) failing to support Hypothesis 3b.

Hypothesis 3c proposed that managerial behavior (criticality) indexed by the number of app views *after* the event would moderate the *Post-Event Trajectory* in the same way as app views *during* the event. Hypothesis 3c was tested by the interaction between *Post-Event Trajectory* and *App Views After Event* (Model 5, Table 5). The parameter for *App Views After Event* was negative and significant (t= -1.95, p<.05) with observed power for the one-tailed test of .62. As the predicted plot in Figure 6 shows, units with a greater number of app views in the online platform immediately after the event also had more favorable post-event energy consumption trajectories. Thus, Hypothesis 3c was supported.

Insert Figure 6 Here

Post-Hoc Analyses

We conducted post-hoc tests with a series of additional models that are detailed in tables and figures in the online supplement. We begin with alternative operationalizations of event disruption and event criticality that were inspired by suggestions from the review team, followed by sensitivity tests. All the models included the same control terms as our hypothesis tests.

Disruption. We explored whether the distribution of meter installations across time within units could provide an index of disruption. Units with a more uniform distribution over time undergo more ongoing interruptions compared to units that experience most of the installations in a short time period. In Footnote 4, two unit-level managers confirmed that more ongoing interruptions create considerable disruption[4]. We calculated the relative frequency of meter installations for each month in which meters were installed and then identified each unit's maximum value. For instance, a unit with a value of .25 would, in its maximum month, have had 25% of its meters installed whereas a unit with a .75 would, in its maximum month, had 75% of its meters installed. This measure ranged from .15 to 1.00. In models that controlled for production levels and the other covariates, we found a significant interaction with *Pre-Post* but not with *Post-Event Trajectory*. The plot in the supplement shows that units with low maximum installations (more chronic disruptions) experienced greater sustainability gains. Note, however, that the measure is negatively correlated with duration (r= -.61, p<.001) – units with a low percentage of installations in a single month tended to have long durations – so it is not clear if we are observing a disruption or duration effect. That is, even though less than 50% of the variance is shared, we believe the results could simply reflect duration. Unsurprisingly, when we modeled simultaneous effects for both disruption and duration on *Pre-Post*, neither effect was significant.

Alternative Criticality Measures. First, instead of *App Views*, we modeled criticality as the number of *App Sign Ins* to the online portal for each unit during its event, and the three months immediately after the event. System users may view the app multiple times per sign in, so *App Sign Ins* potentially represents a related metric for capturing the degree to which an event is treated as a priority, which was reliable[5]. In analogous models to those used to test Hypotheses 3a, 3b, and 3c, we found that *App Sign Ins During Event* predicted differences in initial (*Pre-Post*) change but that neither *App Sign Ins During Event* nor *App Sign Ins After Event* predicted differences in long-term (*Post-Event Trajectory*) change. The plot in the supplemental materials illustrates that units with more sign ins during the event had more favorable post-event energy consumption changes.

Next, we tested a model in which criticality was indexed as the increase (or decrease) in managerial attention after the event. Operationalizing managerial attention as a differential captures a shift in attention where more (or less) attention is given to the focal metric after the event. Based on adverse events research (Leape, 1994), units with increased attention after the event likely have greater sustainability changes. Change was captured by subtracting app views per month during from app views per month after, which ranged from -543 to 592. We a found significant interaction with *Post-Event Trajectory*. The plot in the supplemental materials shows that units with increased managerial attention after the event had a more favorable negative *Post-Event Trajectory*. This finding has implications for theory and practice that we address in the Discussion.

Sensitivity Analyses. Detailed sensitivity tests and tables are included in the online supplement. Our first set of sensitivity tests explored the potential for each moderator to simultaneously influence both *Pre-Post* and *Post-Event Trajectory*. Next, we ran a series of models with various predictor interaction combinations based on our significant results. We also replicated this approach to examine the significant effect of *App Views After Event* with *Post-Event Trajectory* in the presence of *Event Duration* and *Event Timing* effects on *Pre-Post*. In summary, results showed that during the *Pre-Post* phase, manager criticality had effects beyond effects of duration and timing. A final sensitivity test examined the implications of retaining the full sample of 93 that met the criteria even with the closed observations, versus restricting the analyses to the 87 with fewer closed months. The results largely reflect the pattern of significance in our hypothesis tests providing support for our findings.

DISCUSSION

We used an EST framework and a variant of DGM to conceptualize proactive events and examine how event characteristics related to the installation of a smart meter sustainability system could be used to predict the degree to which manufacturing units were able to obtain desired changes. We showed that, on average, the event led to initial changes in energy consumption representing a 7.46% decline. We shared our findings with the Global Director responsible for the system who commented that “The most important element for us was that, had we not installed smart meters, we would have seen a substantial increase in our overall energy consumption. The smart meters were instrumental in helping us reduce our environmental impact and how many resources we consume to produce our products. The avoidance resulted in decreases of over $41 Million annually."

Despite benefits associated with smart meter installation, the models provided strong evidence that units did not uniformly show the same degree of positive effects. Using EST propositions related to duration, timing, and criticality, we found that units with longer event durations and (to a lesser degree) units that were selected to begin the process earlier had more pronounced initial *Pre-Post* declines associated with the event. We also found that units with greater criticality, indexed by managerial attention to event information (app views) during the installation, had a highly robust (observed power of .95) relationship to *Pre-Post* declines. We found weaker evidence to suggest that app views *after* the installation were associated with more favorable long-term trajectories. In post-hoc analyses, we found a relative increase in app views following the event was favorably related to longer-term sustainability outcomes. Additionally, we found some evidence to suggest that units with more disruptions, as indexed by a low percentage of installations in any month, tended to garner more benefit, but as we noted, this measure was confounded with event duration.

Theoretical Implications

Our exploration of EST in the context of proactive events has several implications for event-based research. First, we differentiate two forms of change and illustrate that event characteristics are differentially related to these two forms of change. Our framework answers calls for event-based research to leverage "sophisticated analytic methods…to capture pre-event, in-event, and post-event dynamics" (Liu et al., 2023: 2178). In our study, it was informative to be able to determine whether event characteristics impacted the *Pre-Post* change, the *Post-Event Trajectory*, or both, and we anticipate that this distinction will be useful to model the impact of many events in many different contexts. Relatedly, we also illustrated how a variant of DGM can formally test propositions about event duration. In situations where event duration varies across entities, it is possible to set up the design matrix as though the event occurred at a single observation point. Doing so and capturing amount of time as a predictor provides a way to model the impact of event duration as a predictor of both the *Pre-Post* change and the *Post-Event Trajectory*. We anticipate that this variant of DGM can be useful for understanding event duration effects in many contexts.

Second, our results showed that while facets of events such as duration, timing, and disruption have clear conceptual distinctions, they may be related in practice. As we have already noted, our index of disruption was moderately correlated to duration, and it seems likely that if novelty is held constant, duration and disruption will often be correlated. Beyond this link, we speculate that in many applied situations involving proactive events, duration and timing will be empirically related. Entities that initiate proactive events later are likely to have shorter event durations for at least two reasons. First, the organization likely becomes more efficient in implementing the proactive event. Second, organizations may announce end-dates to key stakeholders and feel that changing these end-dates represents a risk. Therefore, entities within the organization that delay starting may not have the luxury of having a prolonged implementation duration. In this latter case, an entity might opt for superficial adoption, potentially limiting the degree of desired change.

Importantly, the role of criticality suggests that other factors, such as the people (Liu et al., 2023), the location of the event's origin (Morgeson et al., 2015) in the organization, or even subsequent events or system features, stand to offer beneficial conditions where proactive events can still achieve desired changes. While our study has provided an empirical basis for several event characteristics, future research is needed to explore how additional characteristics apply to proactive events. For example, research can consider how characteristics of the agent of proactivity (i.e., personality, hierarchical position, status) interact with event strength, duration, or timing to influence proactive event outcomes.

Third, in addition to testing specific propositions related to a proactive sustainability event, our study provides contributions relevant for empirically testing EST in many other settings. We illustrate how focusing on outcome trajectories can help refine theory around a variety of events with respect to both initial change and long-term change. Additionally, as both Morgeson et al. (2015) and Liu et al. (2023) note in their discussions of future research, not all events are negative or exogenous. In fact, both articles called for more research with a proactive view of events. Thus, we formally define and empirically test a proactive event. To the broader point of studying proactive events, much of the prior research has looked at the immediate response to an event (e.g., Jiang et al., 2019) and conceptualizes change through relatively feature-oriented static mean difference changes. For example, stock prices tend to improve after announcing a change in sustainability index performance (Hawn, Chatterji, & Mitchell, 2018), implementation of a sustainability policy or program (Dam & Petkova, 2014), inclusion in a sustainability ranking (Lyon & Shimshack, 2015), winning a sustainability award (Eroglu, Kurt, & Elwakil, 2016), or obtaining sustainability certification (Narasimhan, Schoenherr, Jacobs, & Kim, 2015).

Using relatively static approaches to understanding change may under-represent the temporal elements (Roe, 2008) of the longitudinal processes surrounding the event (Liu et al., 2023). In contrast, our study shows the importance of parsing proactive event impact into initial and longer-term aspects. Our focus on a proactive event also extends EST to cover such events that are deliberate, planned, and with a strategic goal in mind. This work opens the door to further delineating how event attributes function for proactive events. Future work can also build up our approach to understand chains of events or event clusters (Liu et al., 2023) by modeling a series of discontinuities (Abramov, Kautz, Miellet, & Deane, 2022) or further addressing the temporal dynamics of event-based changes (e.g., delays: Pieper, Maltarich, Nyberg, Reilly, & Ray, 2023). Other work can use this approach to proactive events to study a variety of phenomena, such as the temporal effects of workplace interventions (World Health Organization, 2022). In this case, the researcher team would be the agent of proactivity. In an ideal case, the research team would randomly assign treatment and control conditions to employees and track outcomes over time; however, even if random assignment is not feasible, careful attention to collecting and analyzing changes over time and individual or group differences in response to the intervention could potentially provide important insights.

Finally, our research has relevance at the intersection of theory and practice by extending EST to the context of a sustainability event. On the theory side, the opportunity to make and test predictions about the rate of change, direction of change, and subsequent trajectories has implications for a variety of research investigations. For example, previous research using event study methodology has provided important insights regarding stock price fluctuations following a firm announcement (Hendricks & Singhal, 2003). Utilizing discontinuous growth modeling can expand such efforts by contrasting post-announcement stock price trajectories against pre-announcement baselines and, more specifically, capture the form of change over time. On the practical side, because capital-intensive manufacturing plants consume substantial amounts of energy (Lukić, Radenković, Despotović-Zrakić, Labus, & Bogdanović, 2017; Manno, Bravo, Manfredo, & Leon, 2013), many forms of change in consumption impact both economic and environmental sustainability; for example, we estimate that even a 1% decrease in energy consumption across our firm's manufacturing units could represent more than 400,000 gigajoules annually. The combination of theoretical and practical impact addresses calls for responsible research in business and management (i.e., Markman, 2022; Tsui, 2022) with a rigorous approach to theory testing and study design that has the potential for real-world impact. This model can be extended to a variety of other important real-world challenges as a means of advancing theory using scientific rigor to create practical insights.

Practical Implications

This study has several practical implications. Most importantly, managerial attention (Ocasio, 1997) in the form of prioritizing critical factors appears to play a vital role in facilitating initiative-related changes for proactive events. Broadly speaking, our findings are in line with the attention-based view of the firm, highlighting the role of local management in achieving desired changes from proactive events. Organizations make considerable efforts to initiate events, such as strategic initiatives, or training employees, or making considerable investments, such as pursuing certifications, installing enterprise Human Resource Management systems, or implementing digital record keeping, to achieve specific goals. The significant role of lower-level manager criticality likely applies in all these contexts. Therefore, our study reaffirms the importance of working with managers to achieve success.

Importantly, our extended view of the forms of event-based change and a helpful reviewer comment illustrated that *Post-Event Trajectory* changes are more pronounced when managerial attention to the event increases immediately following the event. This finding points to something specific about managerial attention, in that it may be most vital in the period immediately following a proactive event. Therefore, firms seeking to capitalize on proactive events can work to orient and focus managerial attention during the event itself and direct even greater resources toward managerial attention in the period immediately following.

In our specific context, EST proposes that firm leadership might reasonably focus on several aspects of implementation, such as timing, duration, and criticality. Our findings refine these propositions to highlight that the degree to which lower-level entities view the event as critical and devote managerial attention is a primary driver of positive outcomes. With this sustainability initiative, headquarters might routinely monitor how often unit management accesses smart meter information as the best "early warning system" for predicting whether a manufacturing unit will likely show benefits. Early adopters and units that take a long time to implement clearly benefit, but there is no indication that these two facets of the event are related to continued gains. These facets appear less strongly related to gains during the implementation phase, so they provide a less useful diagnostic for the organization. Therefore, devoting resources to continued managerial attention after the event ends is a vital opportunity for continued initiative-related sustainability performance gains.

In our context, the criticality finding highlights the need to take a socio-technical systems approach to understanding the full impact of technology implementation events. Socio-technical systems theory is based on two tenets (Bednar & Welch 2020; Leitch & Warren 2010; Winter, Berente, Howison, & Butler, 2014). First, technical factors, alone, do not create successful outcomes; the sustainability technology we examined was not turnkey. Rather, the impact of a technology implementation event should be considered in light of the human and structural factors that interface with it, such as managerial interaction with the energy monitoring app. Second, optimizing either technical or human factors, alone, leads to suboptimal outcomes. It is important to optimize *both* the technology and the way humans interact with it. Installing even the best sustainability technology will not lead to improved outcomes if managers do not interact effectively with it and use it to drive changes to practices and processes.

Generalizability

First, with respect to the generalizability of EST principles, we note that EST was primarily developed to explain a wide variety of events that are typically unexpected and/or negative in nature. Drawing motivation from Morgeson et al.'s (2015) and Liu et al.'s (2023) calls for future research on proactive events, we extended the theory to consider deliberate events initiated with desired changes in mind. Overall, we believe that our study clearly illustrates the utility of applying EST principles to proactive events.

Second, with respect to the generalizability of our findings, we anticipate that our results would likely generalize most directly to other organizations undergoing similar events. Based on the research and theoretical foundations behind our hypotheses, which were largely supported in our data, we expect that early onset, long duration, and managerial attention (criticality) advantages will generalize to other proactive event contexts. We do not expect the specific form of our findings to generalize to unexpected events, particularly if such events were negative. For instance, units within an organization that were the first to experience an unexpected labor dispute that ultimately embroiled the entire firm would probably not experience an early adopter or long-duration advantage. Likewise, criticality (operationalized as manager involvement in a labor dispute) could end up being a proxy for the intensity of the labor dispute in the unit. If so, high values would not likely be associated with better outcomes. It would be valuable to study unexpected negative events to learn which of our findings do generalize, but we believe the theoretical foundations surrounding such events differ substantially from the theoretical foundations surrounding proactive, positive events.

Third, much of the existing EST literature has captured event attributes using validated survey assessments. For example, Morgeson & DeRue (2006) captured criticality with items including “to what extent was this event critical for the long-term success of the team” and “to what extent was this an important event for the team”. While surveys are beneficial, especially for unexpected events, they are also open to potential confounding of post-event outcomes with perceptions of the event itself. Alternatively, our study captures objective indicators for duration, timing, and criticality in real time, and our results enhance the validity of EST research broadly.

Finally, we believe our study provides generalizability in terms of a framework to understand the impact of factors such as timing, duration, and other event-related parameters on both immediate and longer-term outcome changes. Obviously, our DGM approach still leaves some ambiguity. For instance, our attempts to disentangle duration and disruption illustrate the challenges associated with measuring and identifying the unique roles of separate constructs. That said, we believe the variant of the DGM we provide can be particularly useful in future work for both planned and unplanned events that have more chronic rather than acute durations.

Limitations and Future Directions

As with all research, there are limitations associated with this project. First, although we examined 87 manufacturing units, they were all within the same organization. This helps control for the impact of organizational factors, yet it could potentially limit the generalizability to other organizations. Thus, an important future step in research on proactive events involves comparing how these types of events unfold across different organizations and accounting for between-unit variance in event novelty.

Second, despite a promising pattern of findings, using 87 units limits our statistical power at Level 2. This may, in part, explain why some of our findings are no longer significant when accounting for other significant findings. For example, with a larger sample at Level 2, we may see that manager criticality is a significant predictor for both *Pre-Post* and *Post-Event Trajectory* together rather than have the simultaneous effects cancel each other out.

Third, we were limited to archival data. Our findings could be enriched by understanding *a priori* differences between manufacturing unit managers' motivation towards the sustainability event. It would be interesting to compare outcomes between units genuinely motivated to achieve desired changes with those more influenced by pressures for mimetic isomorphism and legitimacy. Likewise, we would have benefitted from a systematic survey-based measure of disruption. Even having a single item rating on a simple measure (e.g., "during the last week/month our operations were disrupted") from a key informant could be useful for the organization and for future research. Indeed, there would almost certainly be benefits to collecting standardized survey measures in real time from key informants to assess a number of event-related factors for organizations undergoing proactive changes.

Finally, studies of proactive events will always have challenges resolving issues of causality unless firms randomly assign units to undergo the changes. In contrast, when the event is exogenous to an entity, causal inferences are considerably stronger. For instance, in a DGM of collective turnover in stores focused on Covid-19, the event would be exogenous to the stores. That is, nothing about the store characteristics (i.e., between-unit differences; Liu et al., 2023) would make Covid-19 more or less likely to occur. In this case, causal inferences would be much stronger for a finding that a store-level attribute collected prior to the Covid-19 event mitigated negative effects. A similar approach could be used on a more macro level to track the effects of *a priori* differences on sustainability outcomes following a natural disaster, which could potentially illustrate important factors that facilitate more favorable post-disaster outcome trajectories. As we detail in our conceptualization of proactive events, such events are fundamentally endogenous in that an agent of proactivity creates the event. However, many characteristics of the event should be fairly exogenous to lower-level entities who experience the event without having planned it themselves. For example, in our case, we find no evidence that units were selected in terms of timing and duration based on the key attributes of pre-event production or pre-event energy usage. Nonetheless, because lower-level units were not randomly assigned to a condition, we cannot rule out the possibility that our observed findings were in some way driven by unmeasured attributes of the lower-level entities.

Thus, while this paper presents an important step in studying proactive events, it is imperative to note that proactive event research is more limited than exogenous event research in its ability to make inferences. For example, if firms routinely target the worst-performing lower-level units to be the first to undergo improvement initiatives, one could observe reverse causation where levels of performance are causally related to timing. As a result, careful research design choices and transparent analyses are necessary for the study of proactive events, along with the knowledge that not all proactive events can be effectively explored using current empirical approaches.

Conclusion

This research tests several EST propositions in a novel context. More broadly, it contributes to the literature through a longitudinal exploration of proactive events with desired changes in mind. The application of EST propositions with DGM provides a way to capture two forms of event-based change and explore between-unit differences in these forms of change. Together, we found that both event duration and timing play a role in explaining initial energy declines following the installation of a new sustainability initiative, but that neither of these facilitated differences in long-term change. On the other hand, manager criticality behaviors were associated with greater degrees of both initial and long-term change, reinforcing the importance of local management in driving proactive event-based change.

REFERENCES

Abrahamson, E. 1991. Managerial fads and fashions: The diffusion and rejection of innovations. *Academy of Management Review*, *16*(3): 586-612.

Abramov, G., Kautz, J., Miellet, S., & Deane, F. P. 2022. The influence of attachment style, self-protective beliefs, and feelings of rejection on the decline and growth of trust as a function of borderline personality disorder trait count. *Journal of Psychopathology and Behavioral Assessment*, *44*(3), 773-786.

Ainin S., Naqshbandie, M. N., & Dezden, S. 2016. Impact of adoption of green IT practices on organizational performance. *Quality and Quantity*, *50*:1029-1048.

Allen, P. 2005. How Disney saves energy and operation costs. *HPAC Engineering,* http://www.hpac.com/building-controls/how-disney-saves-energy-and-operating-costs.

Altman, L. K. 1995. Big doses of chemotherapy drug killed patient, hurt 2d. *New York Times,* 3/24/95.

Arthur, J. B., & Huntley, C. L. 2005. Ramping up the organizational learning curve: Assessing the impact of deliberate learning on organizational performance under gainsharing. *Academy of Management Journal*, *48*(6): 1159-1170.

Atasu A., & van Wassenhove L. N. 2012. An operations perspective on product take-back legislation for E-waste: Theory, practice, and research needs. *Production and Operations Management,* 21(3): 407-422.

Baron, J. N., Dobbin, F. R., & Jennings, P. D. 1986. War and peace: The evolution of modern personnel administration in US industry. *American Journal of Sociology*, *92*(2): 350-383.

Bednar, P. M., & Welch, C. 2020. Socio-technical perspectives on smart working: Creating meaningful and sustainable systems. *Information Systems Frontiers, 22*(2): 281-298.

Bliese, P. D., Adler, A. B., & Flynn, P. J. 2017. Transition processes: A review and synthesis integrating methods and theory. *Annual Review of Organizational Psychology and Organizational Behavior*, *4*: 263-286.

Bliese, P. D., & Lang, J. W. 2016. Understanding relative and absolute change in discontinuous growth models: Coding alternatives and implications for hypothesis testing. *Organizational Research Methods*, *19*(4): 562-592.

Bliese, P. D., Maltarich, M. A., Hendricks, J. L., Hofmann, D. A., & Adler, A. B. 2019. Improving the measurement of group-level constructs by optimizing between-group differentiation. *Journal of Applied Psychology*, *104*, 293-302.

Bliese, P. D., McGurk, D., Thomas, J. L., Balkin, T. J., & Wesensten, N. 2007. Discontinuous growth modeling of adaptation to sleep setting changes: Individual differences and age. *Aviation, Space, and Environmental Medicine*, *78*(5): 485-492.

Bliese, P. D., & Ployhart, R. E. 2002. Growth modeling using random coefficient models: Model building, testing, and illustrations. *Organizational Research Methods*, *5*(4): 362-387.

Bliese, P. D., & Wang, M. 2020. Results provide information about cumulative probabilities of finding significance: Let's report this information. *Journal of Management*, *46*: 1275-1288.

Bonanno, G. A. 2004. Loss, trauma, and human resilience: Have we underestimated the human capacity to thrive after extremely aversive events?. *American Psychologist*, *59*(1): 20-28.

Bonini, S., & Görner, S. 2011. The business of sustainability. *McKinsey*. http://www.mckinsey.com/business-functions/sustainability-and-resourse-productivity/our-insights/the-business-of-sustainability-mckinsey-global-survey-results.

Bradley, B. H., Postlethwaite, B. E., Klotz, A. C., Hamdani, M. R., & Brown, K. G. 2012. Reaping the benefits of task conflict in teams: The critical role of team psychological safety climate. *Journal of Applied Psychology*, *97*(1): 151-158.

Buerhaus, P. I., 1999. Lucian Leape on the causes and prevention of errors and adverse events in health care. *Journal of Nursing Scholarship, 31*(3), 281-286.

Campbell, J. L. 1997. Recent trends in institutional political economy. *International Journal of Sociology and Social Policy*, *17*(7): 15-56.

Dam, L., & Petkova, B. N. 2014. The impact of environmental supply chain sustainability programs on shareholder wealth. *International Journal of Operations & Production Management*, *34*(5), 586-609.

Dhanorkar, S. S., Siemsen, E., & Linderman, K. W. 2018. Promoting change from the outside: Directing managerial attention in the implementation of environmental improvements. *Management Science*, *64*(6), 2535-2556.

Davis, F.D. 1989. Perceived usefulness, perceived ease of use and user acceptance of information technology. *MIS Quarterly.,* 13(3): 319-340.

Davis, F. D., Bagozzi, R. P., Warshaw, R. P. 1989. User acceptance of computer technology: A comparison of two theoretical models. *Management Science,* 35(8): 982-1003.

DiMaggio, P. J., & Powell, W. W. 1983. The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. *American Sociological Review*: 147-160.

Eroglu I., Kurt A. C., Elwakil O. S. 2016. Stock market reaction to quality, safety, and sustainability awards in logistics. *Journal of Business Logistics,* 37(4): 329-345.

Frayne, C. A., & Geringer, J. M. 2000. Self-management training for improving job performance: A field experiment involving salespeople. *Journal of Applied Psychology*, *85*(3), 361-372.

Fontenot, S. F. 2013. The Affordable Care Act and electronic health care records. *Physician Executive*, *39*(6): 72-76.

Gersick, C. J., & Hackman, J. R. 1990. Habitual routines in task-performing groups. *Organizational Behavior and Human Decision Processes*, *47*(1): 65-97.

Hale Jr, D., Ployhart, R. E., & Shepherd, W. 2016. A two-phase longitudinal model of a turnover event: Disruption, recovery rates, and moderators of collective performance. *Academy of Management Journal*, *59*(3): 906-929.

Hawn O., Chatterji A. K., Mitchell W. 2018. Do investors actually value sustainability? New evidence from investor reactions to the Dow Jones Sustainability Index. *Strategic Management Journal, 39*(4): 949-976.

Hendricks, K. B., & Singhal, V. R. 2003. The effect of supply chain glitches on shareholder wealth. *Journal of Operations Management*, *21*(5), 501-522.

Hofmann, D. A., & Stetzer, A. 1998. The role of safety climate and communication in accident interpretation: Implications for learning from negative events. *Academy of Management Journal*, *41*(6): 644-657.

Hoch, J. E., & Dulebohn, J. H. 2013. Shared leadership in enterprise resource planning and human resource management system implementation. *Human Resource Management Review*, *23*(1): 114-125.

Jiang, L., Yin, D., & Liu, D. 2019. Can joy buy you money? The impact of the strength, duration, and phases of an entrepreneur's peak displayed joy on funding performance. *Academy of Management Journal*, *62*(6), 1848-1871.

Joshi, S., & Li, Y. 2016. What is corporate sustainability and how do firms practice it? A management accounting research perspective. *Journal of Management Accounting Research*, *28*(2), 1-11.

Khuntia S., Pattanayak J. K., & Hiremath G. S. 2018. Is the foreign exchange market adaptive? The empirical evidence from India. *Journal of Asia-Pacific Business, 19*(4):261-285.

Kim, Y., & Ployhart, R. E. 2014. The effects of staffing and training on firm productivity and profit growth before, during, and after the Great Recession. *Journal of Applied Psychology*, *99*(3): 361-389.

Kramer, A., & Chung, W. 2015. Work demands, family demands, and BMI in dual-earners families: A 16-year longitudinal study. *Journal of Applied Psychology, 100*(5), 1632.

Krass, D., Nedorezov, T., & Ovchinnikov, A. 2013. Environmental taxes and the choice of green technology. *Production and Operations Management*, 22(5):1035-1055.

Lang, J. W. B., & Bliese, P. D. 2009. General mental ability and two types of adaptation to unforeseen change: Applying discontinuous growth models to the task-change paradigm. *Journal of Applied Psychology, 92*, 411-428.

Leape, L. L., 1994. Error in medicine. *Journal of the American Medical Association, 272*, 1851-1857.

Leape, L. L., Bates, D. W., Cullen, D. J., Cooper, J., Demonaco, H. J., Gallivan, T., Hallisey, R., Ives, J., Laird, N., Laffel, G. 1995. Systems analysis of adverse drug errors. *Journal of the American Medical Association, 274*, 35-43.

Leitch, S., & Warren, M. J. 2010. ETHICS: The past, present and future of socio-technical systems design. In *IFIP International Conference on the History of Computing* (pp. 189-197). Springer, Berlin, Heidelberg.

Li, H., Hausknecht, J. P., & Dragoni, L. 2020. Initial and longer-term change in unit-level turnover following leader succession: Contingent effects of outgoing and incoming leader characteristics. *Organization Science*, *31(2)*, 458-476.

Lin, W., Shao, Y., Li, G., Guo, Y., & Zhan, X. 2021. The psychological implications of COVID-19 on employee job insecurity and its consequences: The mitigating role of organization adaptive practices. *Journal of Applied Psychology*, *106*(3), 317-329.

Liu, D., Chen, Y., & Li, N. 2021. Tackling the negative impact of COVID-19 on work engagement and taking charge: A multi-study investigation of frontline health workers. *Journal of Applied Psychology*, *106*(2), 185-198.

Liu, D., Morgeson, F. P., Zhu, J., & Fan, X. 2023. Event-oriented organizational behavior research: A multilevel review and agenda for future research. *Journal of Management*, *49*(6), 2148-2186.

Lucas, R. E. 2007. Adaptation and the set-point model of subjective well-being: Does happiness change after major life events?. *Current Directions in Psychological Science*, *16*(2): 75-79.

Lukić, J., Radenković, M., Despotović-Zrakić, M., Labus, A., & Bogdanović, Z. 2017. Supply chain intelligence for electricity markets: A smart grid perspective. *Information Systems Frontiers*, *19*, 91-107.

Lyon, T. P., & Shimshack, J. P. 2015. Environmental disclosure: Evidence from Newsweek's green companies rankings. *Business & Society*, *54*(5), 632-675.

Manno, P. T., Bravo, J., Manfredo, M., & Leon, R. C. 2013. Water markets and sustainable water use in Almeria, Spain–assessing the readiness for organizational change. *World Journal of Entrepreneurship, Management and Sustainable Development*, *9*(4), 208-222.

Markman, G. D. 2022. Will your study make the world a better place?. *Journal of Management Studies*, *59*(6), 1597-1603.

Marler, J. H., & Fisher, S. L. 2013. An evidence-based review of e-HRM and strategic human resource management. *Human Resource Management Review*, *23*(1): 18-36.

Matsuo, H. 2015. Implications of the Tohoku earthquake on Toyota's coordinating mechanism: Supply chain disruption of automotive semiconductors. *International Journal of Production Economics*, *161*: 217-227.

McFarland, L. A., Reeves, S., Porr, W. B., & Ployhart, R. E. 2020. Impact of the COVID-19 pandemic on job search behavior: An event transition perspective. *Journal of Applied Psychology*, *105*(11): 1207-1217.

Morgeson, F. P. 2005. The external leadership of self-managing teams: intervening in the context of novel and disruptive events. *Journal of Applied Psychology*, *90*(3), 497-508.

Morgeson, F. P., & DeRue, D. S. 2006. Event criticality, urgency, and duration: Understanding how events disrupt teams and influence team leader intervention. *The Leadership Quarterly*, *17*(3): 271-287.

Morgeson, F. P., Mitchell, T. R., & Liu, D. 2015. Event system theory: An event-oriented approach to the organizational sciences. *Academy of Management Review*, *40*(4): 515-537.

Muthulingham, S., Corbett, C. J., Benartzi, C., & Oppenheim, B. 2013. Energy efficiency in small and medium-sized manufacturing firms: Order effects and the adoption of process improvement recommendations. *Manufacturing and Service Operations Management, 15*(4):596-615.

Narasimhan R., Schoenherr T., Jacobs B. W., Kim M. K. 2015. The financial impact of FSC certification in the United States: A contingency perspective. *Decision Sciences,* 46(3):527-563.

Ni, J. Z., Melnyk, S. A., Ritchie, W. J., & Flynn, B. B. 2016. Why be first if it doesn't pay? The case of earlier adopters of C-TPAT supply chain security certification. *International Journal of Operations & Production Management*, 36(10): 1161-1181.

Ngwenyame, O., & Nielsen, P. A. 2014. Using organizational influence processes to overcome information system implementation barriers: Lessons from a longitudinal case study of SPI implementation. *European Journal of Information Systems*, *23*: 205-222.

Ocasio, W. 1997. Towards an attention-based view of the firm. *Strategic Management Journal*, *18*(S1), 187-206.

Pieper, J. R., Maltarich, M. A., Nyberg, A. J., Reilly, G., & Ray, C. 2023. Collective turnover response over time to a unit-level shock. *Journal of Applied Psychology*, *108*(6), 1001-1026.

Pirola-Merlo, A., Härtel, C., Mann, L., & Hirst, G. 2002. How leaders influence the impact of affective events on team climate and performance in R&D teams. *The Leadership Quarterly*, *13*: 561–581.

Rafter, N., Hickey, A., Condell, S., Conroy, R., O'Connor P., Vaughn, D., & Williams, D. 2014. Adverse events in healthcare: Learning from mistakes. *QJM: An International Journal of Medicine*, 108, 273-277.

Resnick, D. 2003. The Jessica Santillan tragedy: Lessons learned. *The Hastings Center Report, 33*(4): 15-20.

Raudenbush, S. W., & Bryk, A. S. 2002. *Hierarchical linear models: Applications and data analysis methods* (2nd Ed.). Newbury Park: Sage Publications.

Roe, R. A. 2008. Time in applied psychology: The study of "what happens" rather than "what is". *European Psychologist*, *13*(1): 37-52.

Schepker, D. J., & Bliese, P. D. 2023, "Using mixed-effect growth models to examine time as a predictor of interest and between-firm differences over time", Hill, A.D., McKenny, A.F., O'Kane, P. and Paroutis, S. (Ed.) *Methods to improve our field* (Research Methodology in Strategy and Management, Vol. 14), Emerald Publishing Limited, Bingley, pp. 79-99. https://doi.org/10.1108/S1479-838720220000014005

Shipp, A. J., & Jansen, K. J. 2011. Reinterpreting time in fit theory: Crafting and recrafting narratives of fit in medias res. *Academy of Management Review*, *36*(1): 76-101.

Singer, J. D., & Willett, J. B. 2003. *Applied longitudinal data analysis: Modeling change and event occurrence*. Oxford: Oxford university press.

Sroufe, R. 2003. Effects of environmental management systems on environmental management practices and operations. *Production and Operations Management*, *12*(3), 416-431.

Tsui, A. S. 2022. From traditional research to responsible research: The necessity of scientific freedom and scientific responsibility for better societies. *Annual Review of Organizational Psychology and Organizational Behavior*, *9*, 1-32.

Tolbert, P. S., & Zucker, L. G. 1983. Institutional sources of change in the formal structure of organizations: The diffusion of civil service reform, 1880-1935. *Administrative Science Quarterly*, *28*: 22-39.

Tushman, M. L., Neuman, W. H., and Romanelli, E. 1981. Convergence and upheaval: Managing the unsteady pace of organizational evolution. *California Management Review*, *29*(1): 29-44.

UN DESA. 2022. The Sustainable Development Goals Report 2022 - July 2022. New York, USA: UN DESA. © UN DESA. https://unstats.un.org/sdgs/report/2022/

Venkatesh, V., & Davis, F. D. 2000. A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, *46*(2): 186-204.

Weick, K. 1979. *The social psychology of organizing*. Boston: Addison-Wesley.

Westphal, J. D., Gulati, R., & Shortell, S. M. 1997. Customization or conformity? An institutional and network perspective on the content and consequences of TQM adoption. *Administrative Science Quarterly*, 366-394.

Westphal, J., & Zajac, E. J. 1994. Substance and symbolism in CEOs' long-term incentive plans. *Administrative Science Quarterly*, *39*: 367-390.

Winter, S, Berente, N., Howison, J., Butler, B. 2014. Beyond the organizational "containers:" conceptualizing 21st century sociotechnical work. *Information & Organization*, *24*(4): 250-269.

World Health Organization. 2022. WHO guidelines on mental health at work. Geneva: World Health Organization; 2022. Licence: CC BY-NC-SA 3.0 IGO. https://www.who.int/publications/i/item/9789240053052

Zampou, E., Plitsos, S., Karageannaki, A., Mourtos, I. 2014. Towards a framework for energy-aware information systems in manufacturing. *Computers in Industry*, *65*(3): 419-433.

FOOTNOTES

1. We conducted an interview with the Global Director of the Sustainability Metering System who was responsible for the global deployment and management of the system. In the interview, the Director stated that "All connected meters upload data directly into that system, and all users access the data through an identical system interface. The system was newly developed for this purpose, it was equally new for any facility that had the system installed. We never developed global training for the program, we just provided the training for the site as they received the new system being installed."
2. In the interview, the Global Director of the Sustainability Metering System also shared "Once we identified and developed the global system, we began to identify how to deploy it at the factories. We would identify a factory, inform them to prepare for deployment, and then we would send the team. Due to our corporate structure, we were able to initiate deployment at the global level, and then initiate deployment at the factories."
3. In the interview, the Global Director of the Sustainability Metering System also shared "While we were developing the system, we needed to identify how the system was being used and if it was worth the investment. While we could just look at how much we invested in the system or how widely deployed it was, it was extremely important to understand how well it was being used. While app sign ins to the system are important, we wanted to identify how users were genuinely interacting with the system. Interacting with the systems and viewing the app is an excellent proxy for us to understand the ROI of the system. This helps us show the executive leadership team that the investment was worth it. It also serves the purpose of helping us understand which plants are actually using the system to the fullest of its

capabilities. By viewing the app more users should be better able to understand where the opportunities are to improve sustainability performance."

4. We conducted interviews with two Factory Managers who oversee operations for their respective manufacturing units. The first Factory Manager shared "When we have a team from HQ come to change how we do things its very distracting for my local team. The longer they are here the more distractions they cause, and the demands they make on my teams' time. My team has to deal with doing their regular jobs and they also have to worry about the installation team being there. The longer the external install the more distraction that we have to deal with." The second Factory Manager shared "Whenever we integrate something new we have to generate new standard processes and we need to identify which team members will be responsible for these new processes. When we had the metering team come back again to further build out the metering system most of the changes that we had done had to get thrown out and we had to do the process again."
5. ICC(2) for *App Sign Ins After Event* was .94, demonstrating reliability.

Table 1

Unit-Level Descriptive Statistics and Correlations

	M	sd	1	2	3	4	5	6	7	8
1. Pre-Event Energy Consumption	15933.22	13596.00								
2. Post-Event Energy Consumption	14239.90	11980.97	.89***							
3. Pre-Event Production	10462.12	11730.67	.64***	.43***						
4. Post-Event Production	9849.95	9812.02	.59***	.61***	.80***					
5. Event Duration	37.73	34.27	.10	.08	.08	.15				
6. Event Timing	71.91	34.54	-.16	-.17	-.07	-.16	-.88***			
7. App Views During Event	2080.67	5253.48	.11	.06	-.06	-.02	.31**	-.24*		
8. App Views After Event	277.18	533.82	.10	.08	-.07	-.01	.23*	-.12	.67***	

Note: *n*= 87 manufacturing units. Pre-Event Energy Consumption and Production are the 12-month averages for Energy Consumption and Production before the event onset. Post-Event Energy Consumption and Production are the 12-month averages for Energy Consumption and Production following the event.
*p< .05; **p< .01; ***p< .001

Table 2

Energy Consumption Discontinuous Growth Model Regression Results

Variable	Model 1	
	Coef.	SE
Level 1 Model		
(Constant)	4828.97	3437.35
Production	.77***	.02
Time	26.29	30.95
Pre-Post	-1209.77***	303.69
Post-Event Trajectory	-58.44	43.81
Level 2 Model		
Industry Category (A v. B)	1859.09	3686.31
Industry Category (A v. C)	2917.87	3210.48
Geographic Region (A v. B)	527.14	2701.75
Geographic Region (A v. C)	1173.96	2735.31
Goodness-of-fit		
-2 Log-likelihood (REML)	-20054.50	
AIC	40131.00	
BIC	40192.98	

Note: Unstandardized regression coefficients presented for n= 2,079 observations in k= 87 manufacturing units. Unit-level intercepts were allowed to randomly vary.
*p< .05; **p< .01; ***p< .001

Table 3

Energy Consumption Mixed Effects Model Comparisons

	df	AIC	BIC	Likelihood Ratio	p-value
Fixed effects	5	45310.19	45338.38		
Random Intercepts	6	41465.57	41499.39	3846.62	<.001
Random Time	8	40944.38	40989.48	525.19	<.001
Random Time & Pre-Post	11	40609.95	40671.96	340.43	<.001
Random Time, Pre-Post, & Post-Event Trajectory	15	40545.50	40630.06	72.45	<.001

Table 4

Energy Consumption Discontinuous Growth Model Regression Results for *Pre-Post*

Variable	Model 1		Model 2		Model 3		Model 4	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Level 1 Model								
(Constant)	17492.68*	7646.58	2535.82	3886.43	6943.52	3966.23	2993.00	3380.81
Production	.80***	.03	.80***	.03	.80***	.03	.80***	.03
Time.A	11.26	37.12	11.09	37.10	11.14	37.05	11.39	37.29
Pre-Post	-1177.73*	506.74	-326.63	649.07	-2502.76**	939.27	-704.82	513.22
Post-Event Trajectory	-20.10	35.40	-19.95	35.41	-19.96	35.41	-20.12	35.41
Level 2 Model								
Industry Category (A v. B)	1619.08	3597.35	1987.30	3617.86	2541.34	3590.03	1806.75	3571.78
Industry Category (A v. C)	3710.16	3143.59	4497.71	3175.61	4847.65	3123.71	4475.01	3105.21
Geographic Region (A v. B)	2444.49	2741.11	1588.15	2678.1	2367.56	2728.54	1351.33	2620.31
Geographic Region (A v. C)	437.82	2880.56	395.70	2689.74	176.94	2644.94	-220.56	2778.75
Event Duration	-122.27	65.65	26.33	36.31				
Event Timing	-131.60*	64.86			-55.16	36.14		
App Views During Event	.19	.22					.43	.23
Pre-Post X Event Duration			**-22.53***	10.97				
Pre-Post X Event Timing					**18.44***	11.06		
Pre-Post X App Views During Event							**-.23*****	.07
Goodness-of-fit								
-2 Log-likelihood (REML)	-19734.99		-19736.41		-19736.65		-19743.36	
AIC	39517.99		39518.82		39519.3		39532.72	
BIC	39653.20		39648.41		39648.89		39662.31	

Note: Unstandardized regression coefficients presented for *n*= 2,079 observations in *k*= 87 manufacturing units. Unit-level slopes and intercepts were allowed to randomly vary. Time.A describes absolute coding for contrasting absolute differences in the moderation effects. **Significant directional hypothesized results** were interpreted using a one-tailed test.
*p< .05; **p< .01; ***p< .001

Table 5

Energy Consumption Discontinuous Growth Model Regression Results for *Post-Event Trajectory*

Variable	Model 1		Model 2		Model 3		Model 4		Model 5	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Level 1 Model										
(Constant)	18286.63*	7644.09	3424.43	3853.85	5647.35	3875.87	3476.66	3378.82	3188.01	3382.41
Production	.80***	.03	.80***	.03	.80***	.03	.80***	.03	.80***	.03
Time.A	11.26	37.23	11.20	37.25	11.22	37.16	11.23	37.36	11.29	37.20
Pre-Post	-1177.89*	507.34	-1177.43*	504.90	-1177.74*	505.35	-1176.79*	515.18	-1175.55*	501.36
Post-Event Trajectory	-20.10	35.48	11.75	49.69	-62.74	74.64	-2.92	37.67	11.95	39.01
Level 2 Model										
Industry Category (A v. B)	1736.30	3601.19	1975.45	3614.94	2528.20	3589.02	1789.77	3570.90	1936.41	3555.00
Industry Category (A v. C)	3655.80	3144.91	4481.52	3173.14	4822.72	3122.86	4460.35	3104.72	4482.50	3102.39
Geographic Region (A v. B)	2462.11	2742.77	1583.36	2675.96	2357.48	2727.75	1348.88	2619.66	1373.62	2613.54
Geographic Region (A v. C)	143.87	2793.40	384.00	2687.55	169.51	2644.18	-223.52	2777.98	-285.05	2771.05
Event Duration	-130.15	66.34	3.59	34.11						
Event Timing	-141.74*	65.95			-36.56	34.04				
App Views During Event	.04	.28					.21	.21		
App Views After Event	2.29	2.68							2.46	2.09
Post-Event Trajectory X Event Duration			-0.84	.92						
Post-Event Trajectory X Event Timing					.59	.92				
Post-Event Trajectory X App Views During Event							-.01	.01		
Post-Event Trajectory X App Views After Event									**-.12***	.06
Goodness-of-fit										
-2 Log-likelihood (REML)	-19732.77		-19740.63		-19740.31		-19749.96		-19744.27	
AIC	39515.54		39527.25		39526.62		39545.91		39534.55	
BIC	39656.38		39656.84		39656.21		39675.50		39664.14	

Note: Unstandardized regression coefficients presented for n= 2,079 observations in k= 87 manufacturing units. Unit-level slopes and intercepts were allowed to randomly vary. Time.A describes absolute coding for contrasting absolute differences in the moderation effects. **Significant directional hypothesized results** were interpreted using a one-tailed test.
*p< .05; **p< .01; ***p< .001

Figure 1

Illustrative plot of initial and long-term event-based changes, and between-unit differences in those changes. Path a represents the pre-event comparison baseline. Path b represents the initial event-based change. Path c represents the long-term event-based change.

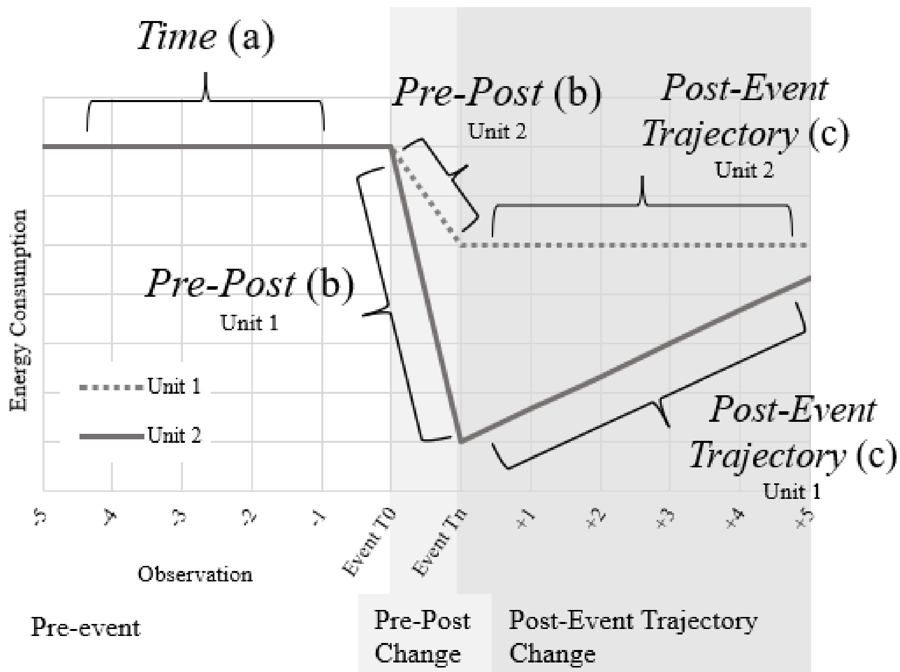


Figure 2

Predicted plot of energy consumption around the proactive event of a new managerial system for sustainability.

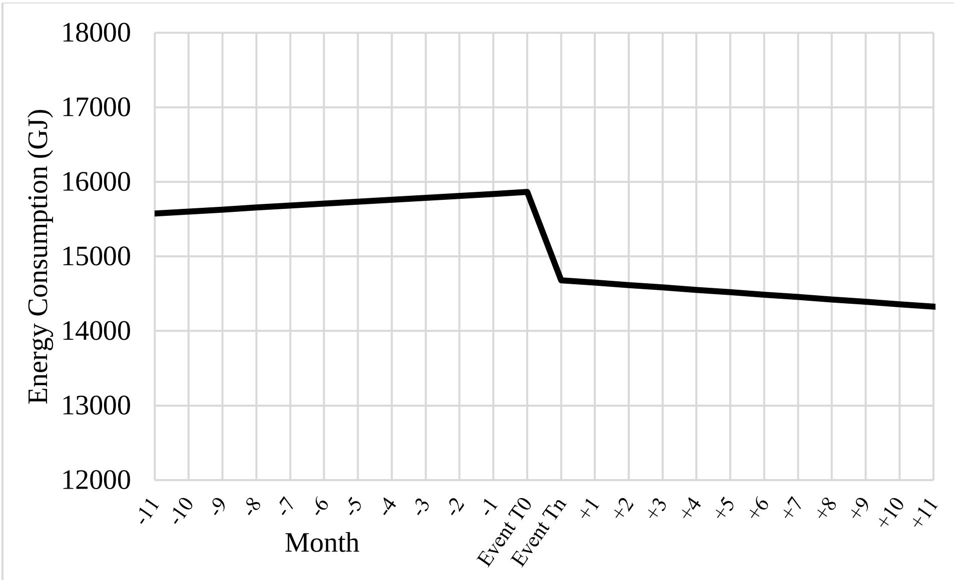


Figure 3

Predicted plot for the moderating effect of event duration on energy consumption around the proactive event.

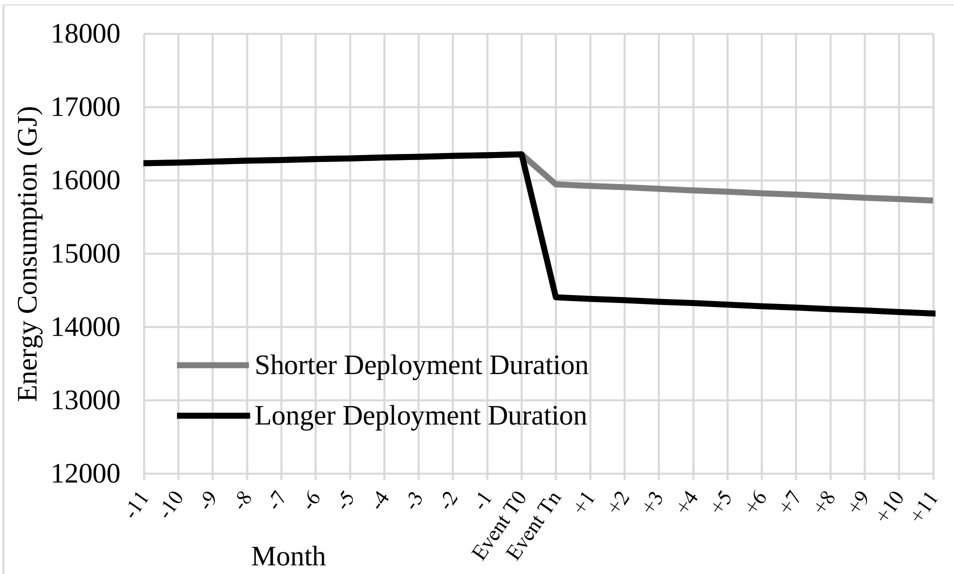


Figure 4

Predicted plot for the moderating effect of event timing on energy consumption around the proactive event.

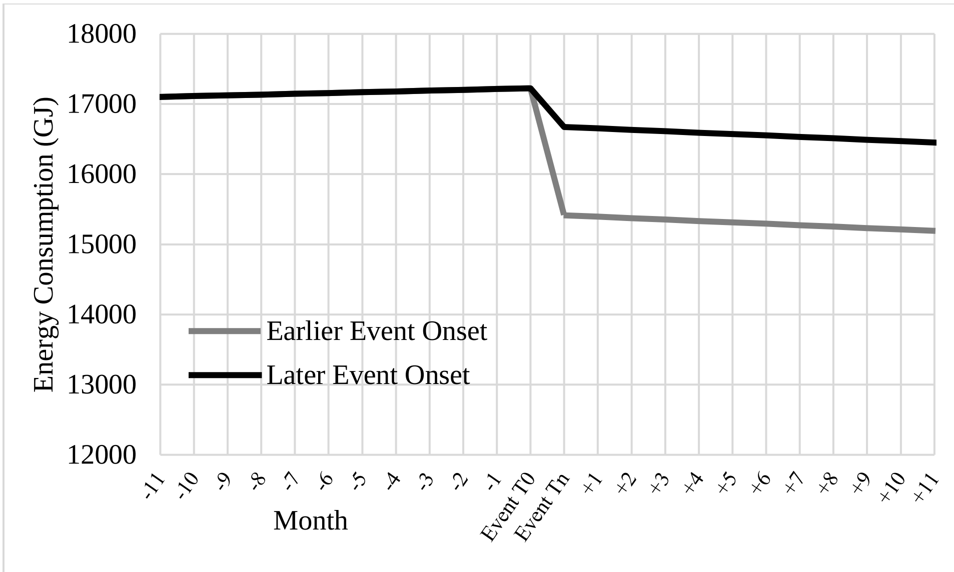


Figure 5

Predicted plot for the moderating effects of event criticality during the event on energy consumption around the proactive event.

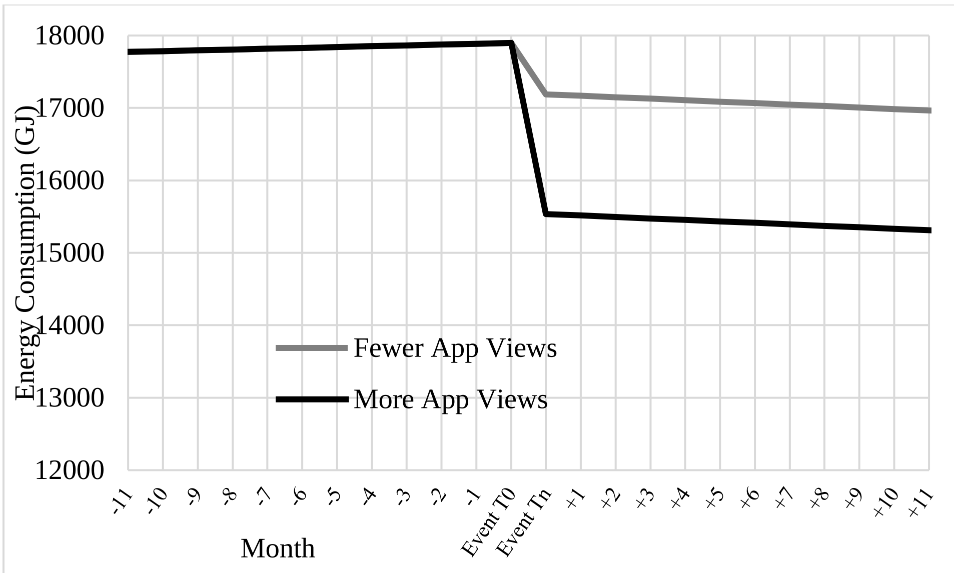
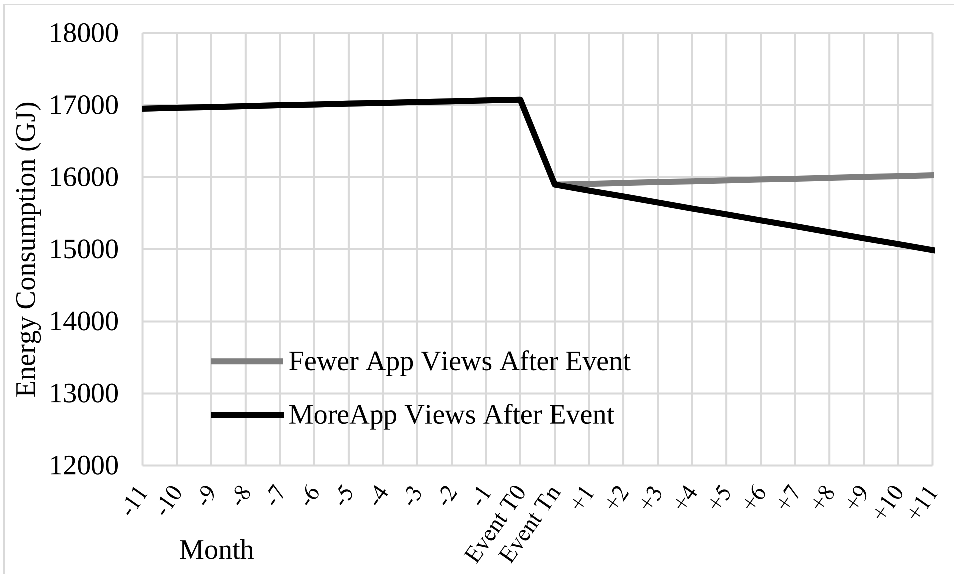


Figure 6

Predicted plot for the moderating effects of event criticality after the event on energy consumption around the proactive event.



Supplemental Table 1

Energy Consumption Discontinuous Growth Model Regression Results for *Pre-Post* and *Post-Event Trajectory*

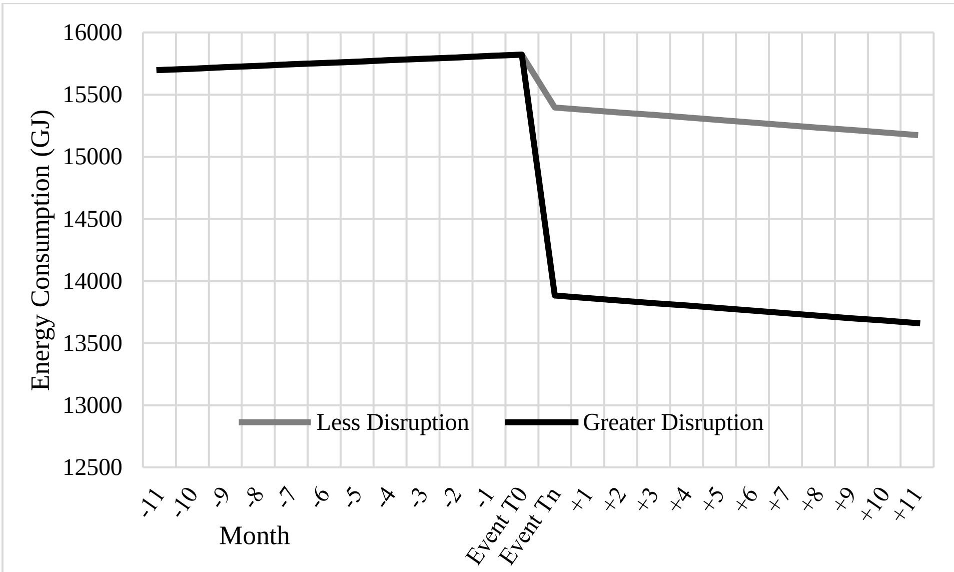
Variable	Model 1		Model 2	
	Coef.	SE	Coef.	SE
Level 1 Model				
(Constant)	4115.28	4418.41	2246.98	4264.07
Production	.80***	.03	.80***	.03
Time.A	11.29	36.95	11.28	37.20
Pre-Post	-3159.20**	1107.24	-1177.31*	503.83
Post-Event Trajectory	-20.03	35.42	-122.26	90.01
Level 2 Model				
Industry Category (A v. B)	1518.51	3607.76	1529.54	3606.44
Industry Category (A v. C)	4184.56	3144.95	4176.73	3143.87
Geographic Region (A v. B)	1485.42	2617.67	1481.25	2616.68
Geographic Region (A v. C)	704.89	2684.12	703.03	2683.12
Event Disruption	-555.47	5125.77	2473.22	4770.22
Pre-Post X Event Disruption	**3205.86***	1600.26		
Post-Event Traj. X Event Disruption			165.33	133.80
Goodness-of-fit				
-2 Log-likelihood (REML)	-19726.31		-19741.70	
AIC	39498.62		39529.40	
BIC	39628.21		39658.99	

Note: Unstandardized regression coefficients presented for n= 2,079 observations in k= 87 manufacturing units. Unit-level slopes and intercepts were allowed to randomly vary. Time.A describes absolute coding for contrasting absolute differences in the moderation effects. **Significant hypothesized results** were interpreted using a one-tailed test.

*p< .05; **p< .01; ***p< .001

Supplemental Figure 1

Predicted plot for the moderating effect of event disruption, indexed by maximum installation, on energy consumption around the proactive event. Units with lower maximum installation have greater disruption (more disruptive installations) while units with higher maximum installation have lower disruption (fewer disruptive installations).



Supplemental Table 2

Energy Consumption Discontinuous Growth Model Regression Results for *Pre-Post* and *Post-Event Trajectory* with *App Sign Ins*

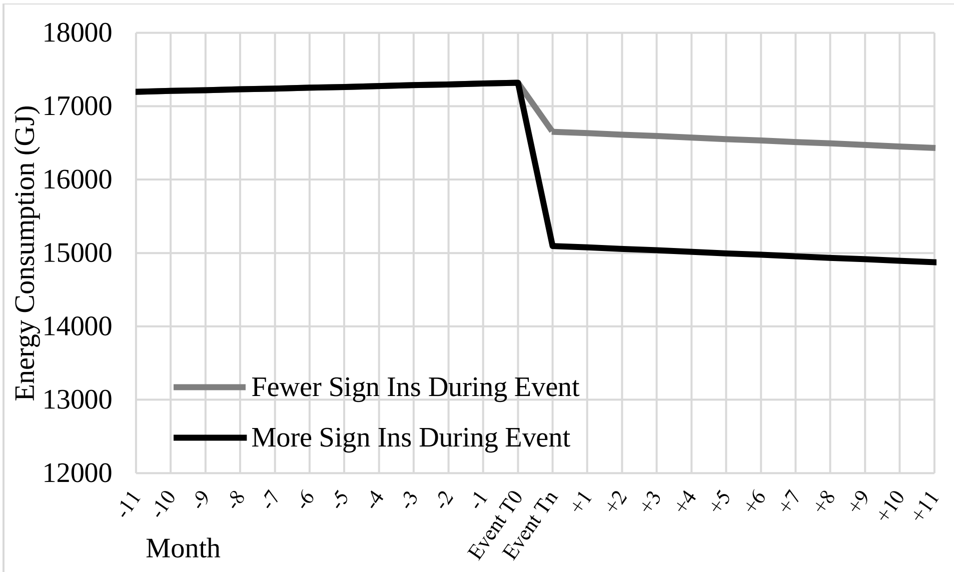
Variable	Model 1		Model 2		Model 3	
	Coef.	SE	Coef.	SE	Coef.	SE
Level 1 Model						
(Constant)	2756.60	3411.77	3260.55	3407.10	3310.71	3404.92
Production	.80*	.03	.80*	.03	.80*	.03
Time.A	11.25	37.10	11.27	37.22	11.26	37.14
Pre-Post	-661.45	524.12	-1176.26*	502.78	-1176.21*	505.17
Post-Event Trajectory	-19.99	35.44	2.94	38.64	2.62	39.44
Level 2 Model						
Industry Category (A v. B)	2108.94	3572.27	2104.34	3572.79	2043.44	3570.77
Industry Category (A v. C)	4613.64	3130.13	4598.18	3130.79	4542.75	3115.19
Geographic Region (A v. B)	1493.13	2629.21	1482.12	2629.56	1571.83	2652.75
Geographic Region (A v. C)	24.84	2850.34	22.55	2850.70	292.28	2744.08
App Sign Ins During Event	3.81	2.76	1.60	2.60		
App Sign Ins After Event					4.76	13.49
Pre-Post X App Sign Ins During Event	**-2.36*** **	.83				
Post-Event Traj. X App Sign Ins During Event			-.11	.07		
Post-Event Traj. X App Sign Ins After Event					-.50	.39
Goodness-of-fit						
-2 Log-likelihood (REML)	-19739.71		-19744.96		-19741.91	
AIC	39525.42		39535.91		39529.82	
BIC	39655.01		39665.50		39659.41	

Note: Unstandardized regression coefficients presented for n= 2,079 observations in k= 87 manufacturing units. Unit-level slopes and intercepts were allowed to randomly vary. Time.A describes absolute coding for contrasting absolute differences in the moderation effects. **Significant directional hypothesized results** were interpreted using a one-tailed test.

*p< .05; **p< .01; ***p< .001

Supplemental Figure 2

Predicted plot for the moderating effect of event criticality, indexed by app sign ins, on energy consumption around the proactive event.



Supplemental Table 3

Energy Consumption Discontinuous Growth Model Regression Results for *Pre-Post* and *Post-Event Trajectory*

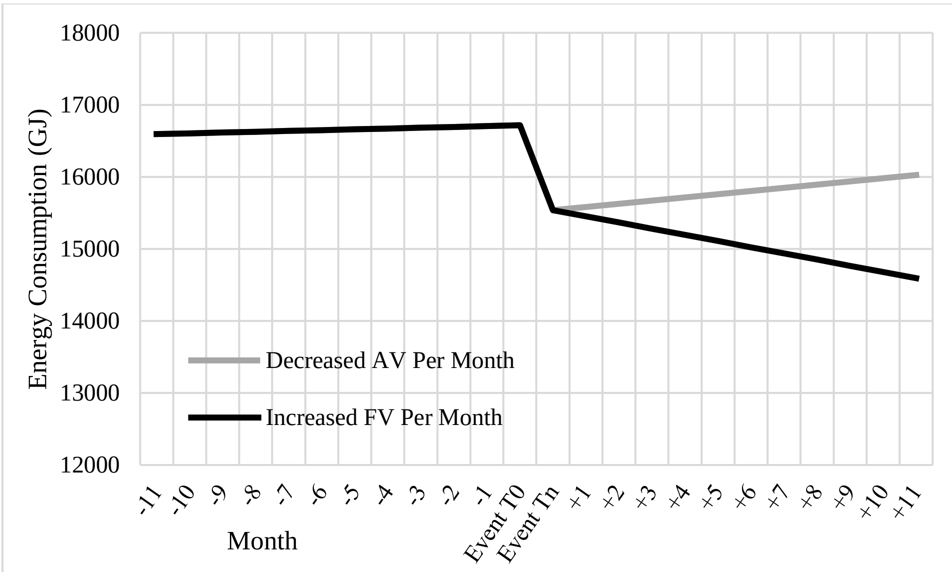
Variable	Model 1	
	Coef.	SE
Level 1 Model		
(Constant)	3316.44	3387.72
Production	.80***	.03
Time.A	11.30	37.14
Pre-Post	-1175.31*	502.50
Post-Event Trajectory	-3.17	36.32
Level 2 Model		
Industry Category (A v. B)	2010.13	3560.75
Industry Category (A v. C)	4617.97	3115.78
Geographic Region (A v. B)	1558.88	2611.19
Geographic Region (A v. C)	-6.67	2727.85
Δ Event Criticality	7.02	7.90
Post-Event Traj. X Δ Event Criticality	**-.43***	.21
Goodness-of-fit		
-2 Log-likelihood (REML)	-19741.70	
AIC	39529.40	
BIC	39658.99	

Note: Unstandardized regression coefficients presented for n= 2,079 observations in k= 87 manufacturing units. Unit-level slopes and intercepts were allowed to randomly vary. Time.A describes absolute coding for contrasting absolute differences in the moderation effects. **Significant directional hypothesized results** were interpreted using a one-tailed test.

*p< .05; **p< .01; ***p< .001

Supplemental Figure 3

Predicted plot for the moderating effect of event criticality change, indexed by an increase or decrease in app views per month, on energy consumption around the proactive event.



Sensitivity Analyses. Our first set of sensitivity analyses explored the potential for each moderator to simultaneously influence both *Pre-Post* and *Post-Event Trajectory*. Matching our results, *Event Duration* had a significant interaction with *Pre-Post* and a non-significant effect on *Post-Event Trajectory*. Similarly, *App Views During Event* a significant interaction with *Pre-Post* but not with *Post-Event Trajectory*. *App Views During Event* also had a significant interaction with *Pre-Post* in a model that interacted *App Views After Event* with *Post-Event Trajectory*. The latter interaction was in the expected direction but no longer significant (t= -1.06). Finally, *Event Timing* did not have a significant interaction with either *Pre-Post* or *Post-Event Trajectory*.

Next, we ran a series of models with various predictor interaction combinations based on our significant results, for a total of seven models. First, we explored each combination of the significant hypothesized moderators on *Pre-Post*. *App Views During Event* remained significant for models with *Event Duration* or *Event Timing*. *App Views During Event* was also significant in a model that had interactions for *Event Duration* and *Event Timing* simultaneously. In sum, during the Pre-Post phase, manager criticality had the most robust effects beyond effects of duration and timing.

We replicated this approach to examine the significant effect of *App Views After Event* with *Post-Event Trajectory* in the presence of *Event Duration* and *Event Timing* effects on *Pre-Post*. We tested separate models for *Event Duration* and *Event Timing* and a third model that included both of their interactions together. The interaction of *App Views After Event* remained significant in each model. A model with *Event Duration* and *App Views After Event* revealed that *Event Duration* still had a significant interaction with *Pre-Post* in the expected direction. The effects of *Event Duration* and *Event Timing* on *Pre-Post* were no longer significant in the other two models.

A final set of sensitivity analyses examined the implications of retaining the full sample of 93 that met the criteria even with the closed observations, versus restricting the analyses to the 87 with less than 15% closed observations. This expanded dataset had 2,174 monthly observations in 93 units which were used in analogous models for our significant hypothesis tests. The results tests were largely the same. The conditional effects for *Duration*, *Timing*, and *App Views During Event* on *Pre-Post* were significant and in the anticipated directions while the interaction effect for *App Views After Event* on *Post-Event Trajectory* was in the expected direction but no longer significant. Overall, these results indicate that the effects were generally robust.

Supplemental Table 4

Energy Consumption Discontinuous Growth Model Regression Results for *Pre-Post* and *Post-Event Trajectory*

Variable	Model 1		Model 2		Model 3		Model 4	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Level 1 Model								
(Constant)	2539.15	3886.72	6948.59	3966.50	2995.21	3381.88	2817.14	3405.01
Production	.80***	.03	.80***	.03	.80***	.03	.80***	.03
Time.A	11.05	37.14	11.09	37.09	11.34	37.31	11.39	37.29
Pre-Post	-321.92	681.98	-2542.56*	1020.79	-700.60	518.68	-754.00	514.43
Post-Event Trajectory	-19.49	52.47	-12.70	81.60	-20.88	38.00	-1.96	39.34
Level 2 Model								
Industry Category (A v. B)	1986.34	3618.11	2540.07	3589.69	1805.30	3573.16	1865.75	3589.53
Industry Category (A v. C)	4495.46	3175.83	4846.60	3123.44	4474.42	3106.40	4477.28	3118.99
Geographic Region (A v. B)	1587.59	2678.28	2368.15	2728.28	1351.14	2621.31	1311.64	2632.62
Geographic Region (A v. C)	395.42	2689.92	176.11	2644.68	-218.39	2779.82	-403.63	2819.14
Event Duration	26.33	36.31						
Event Timing			-55.20	36.14				
App Views During Event					.43	.23	.32	.29
App Views After Event							1.68	2.71
Pre-Post X Event Duration	**-22.47***	12.29						
Pre-Post X Event Timing			19.00	12.38				
Pre-Post X App Views During					**-.23****	.08	**.20****	.07
Post-Event Traj. X Event Duration	-.01	1.03						
Post-Event Traj. X Event Timing			-.10	1.02				
Post-Event Traj. X App Views During Event					.00	.01		
Post-Event Traj. X App Views After Event							-.07	.06
Goodness-of-fit								
-2 Log-likelihood (REML)	-19735.47		-19735.71		-19747.38		-19742.42	
AIC	39518.94		39519.42		36542.76		3953.28	
BIC	39654.15		39654.63		39677.98		39676.11	

Note: Unstandardized regression coefficients presented for n= 2,079 observations in k= 87 manufacturing units. Unit-level slopes and intercepts were allowed to randomly vary. Time.A describes absolute coding for contrasting absolute differences in the moderation effects. **Significant directional hypothesized results** were interpreted using a one-tailed test.

*p< .05; **p< .01; ***p< .001

Supplemental Table 5

Energy Consumption Discontinuous Growth Model Regression Results for *Pre-Post* and *Post-Event Trajectory*

Variable	Model 1		Model 2		Model 3		Model 4	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Level 1 Model								
(Constant)	14966.74	8187.86	5541.35	3999.87	2931.37	3923.61	16254.59*	8138.59
Production	.80***	.03	.80***	.03	.80***	.03	.80***	.03
Time.A	11.08	37.08	11.26	37.22	11.27	37.25	11.25	37.22
Pre-Post	274.27	2503.55	-1515.68	965.75	-271.00	633.34	-179.52	2423.70
Post-Event Trajectory	-20.02	35.42	-20.00	35.37	-20.05	35.43	-20.07	35.36
Level 2 Model								
Industry Category (A v. B)	2036.93	3551.96	2323.00	3630.91	1632.01	3662.20	1650.21	3597.23
Industry Category (A v. C)	3917.64	3131.86	4787.29	3134.02	4333.62	3185.01	3717.87	3143.23
Geographic Region (A v. B)	2859.81	2704.09	2092.68	2774.56	1197.67	2718.59	2435.53	2740.97
Geographic Region (A v. C)	1032.03	2659.73	-252.77	2784.84	-160.28	2804.98	443.13	2770.55
Event Duration	-78.31	70.70			6.74	37.55	-105.75	71.02
Event Timing	-122.44	70.86	-41.65	36.85			-130.46	70.03
App Views During Event			.37	.23	.41	.24	.43	.23
Pre-Post X Event Duration	-27.56	23.05			-12.96	11.17	-13.73	22.83
Pre-Post X Event Timing	-5.72	23.01	10.79	10.91			-.88	22.28
Pre-Post X App Views During Event			**-.21****	.07	**-.20****	.07	**-.20****	.07
Goodness-of-fit								
-2 Log-likelihood (REML)	-19725.26		-19734.70		-19734.86		-19723.67	
AIC	39500.52		39519.39		39519.71		39501.34	
BIC	39641.36		39660.23		39660.55		39653.41	

Note: Unstandardized regression coefficients presented for *n*= 2,079 observations in *k*= 87 manufacturing units. Unit-level slopes and intercepts were allowed to randomly vary. Time.A describes absolute coding for contrasting absolute differences in the moderation effects. **Significant directional hypothesized results** were interpreted using a one-tailed test.

*p< .05; **p< .01; ***p< .001

Supplemental Table 6

Energy Consumption Discontinuous Growth Model Regression Results for *Pre-Post* and *Post-Event Trajectory*

Variable	Model 1		Model 2		Model 3	
	Coef.	SE	Coef.	SE	Coef.	SE
Level 1 Model						
(Constant)	2557.36	3884.91	6417.62	3966.79	16807.34*	8169.03
Production	.80***	.03	.80***	.03	.80***	.03
Time.A	11.15	37.03	11.17	37.22	11.10	37.19
Pre-Post	-398.33	644.18	-2422.14**	925.87	-129.70	2478.98
Post-Event Trajectory	9.05	39.03	10.95	39.13	8.88	39.09
Level 2 Model						
Industry Category (A v. B)	1832.41	3626.87	2455.39	3595.05	1827.14	3550.04
Industry Category (A v. C)	4398.68	3178.37	4810.67	3125.51	3702.80	3126.60
Geographic Region (A v. B)	1282.47	2697.28	2125.34	2741.95	2536.90	2704.91
Geographic Region (A v. C)	-221.74	2807.04	-456.83	2778.84	208.72	2754.20
Event Duration	18.90	36.53			-102.68	71.23
Event Timing			-52.07	35.94	-139.46	70.66
App Views After Event	2.44	2.13	2.35	2.10	3.20	2.12
Pre-Post X Event Duration	**-20.58***	10.94			-22.80	22.88
Pre-Post X Event Timing			17.35	10.87	-2.58	22.75
Post-Event Traj. X App Views After Event	**-.11***	.06	**-.11***	.06	**-.11***	.06
Goodness-of-fit						
-2 Log-likelihood (REML)	-19734.77		-19734.89		-19723.27	
AIC	39519.53		39519.79		39500.54	
BIC	39660.36		39660.62		39652.61	

Note: Unstandardized regression coefficients presented for *n*= 2,079 observations in *k*= 87 manufacturing units. Unit-level slopes and intercepts were allowed to randomly vary. Time.A describes absolute coding for contrasting absolute differences in the moderation effects. **Significant directional hypothesized results** were interpreted using a one-tailed test.

*p< .05; **p< .01; ***p< .001