# DYNAMIC SYSTEMS THEORY AND DUAL CHANGE SCORE MODELS: SEEING TEAMS THROUGH THE LENS OF DEVELOPMENTAL PSYCHOLOGY

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Empirical research examining team development has long lagged behind purely conceptual work. Moreover, traditional designs and logics frequently employed in the organizational sciences generally preclude the possibility of studying the trajectories of various team properties. This is problematic as continuity, nonlinearity, and within-construct feedback are implicit in many eminent conceptualizations of teams. Hence, the present investigation integrates dynamic logic, theory, and methodology from the discipline of developmental psychology-wherein the nature of the topic has necessitated a more careful examination of change over time-into the organizational literature. As a product of this integration, we propose and test a novel theoretical perspective that provides several contributions to teams research. First, we extend theory that has thus far been primarily used to explain intraindividual development in children to detail three testable principles of dynamism in team properties. Second, and utilizing a within-construct logic, we demonstrate that teams are indeed dynamic systems, but that the extent to which any particular team property may be considered dynamic is contingent upon characteristics of the property itself. Finally, we illustrate how teams' unique pasts may be leveraged to predict their asymmetric reactions to disruptive events in the future by employing a contemporary modeling technique.

A science advances through an iterative process that involves proposing *and* empirically scrutinizing precise theories (Popper, 1959). As such, the ongoing proliferation of untested (and often untestable; Hill & Gruner, 1973; Kozlowski & Klein, 2000) theories regarding team development (Collins, Gibson, Quigley, & Parker, 2016) represents a major shortcoming of the teams literature. Indeed, despite the existence of more than 100 models concerning team development (Collins et al., 2016), both eventoriented and longitudinal examinations of actual teams are noticeably scarce (Kozlowski & Bell, 2003; Morgeson, Mitchell, & Liu, 2015). This seems to run counter to the conceptual consensus that teams are open, dynamic systems influenced by their environment and embedded in the flow of time (Cronin, Weingart, & Todorova, 2011; Ilgen, Hollenbeck, Johnson, & Jundt, 2005).

Herein, we attempt to bridge this disconnect between theoretical and empirical research regarding team development by proposing and testing a dynamic perspective that encourages researchers to leverage the past to predict the reaction(s) of certain team properties to events in the future. We argue that, as open, dynamic systems (Collins et al., 2016; Kozlowski & Klein, 2000), the reaction of a team's properties to a change in the environment is partially a product of the prior states of the team (McGrath, Arrow, & Berdahl, 2000; Thelen, 2005). This is because the dynamism inherent in team development implies that a team's future is contingent upon its

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past, as the term "dynamic" literally means that the state of an entity "at any point in time depends on its previous states and is the starting point for future states" (Thelen, 2005: 262). Given that teams often have unique histories (McGrath et al., 2000), we contend that different teams could react in very different ways to the same event as a direct result of their pasts.

To formulate and test our arguments, we draw upon theory, logic, and methodology from the discipline of developmental psychology, wherein the nature of the topic has necessitated a more nuanced study of change over time. Consequently, we make several contributions to the organizational literature on teams. First, we extend dynamic systems theory (hereafter, "DST") (Thelen & Smith, 1994), a grand theory of individual development (Spencer, Clearfield, Corbetta, Ulrich, Buchanan, & Schoner, 2006), to detail three testable principles of dynamism in team properties. Although researchers frequently invoke systems perspectives when describing teams (Kozlowski & Bell, 2003), this widespread practice has thus far offered little in the way of falsifiable propositions. Second, we leverage a withinconstruct logic to examine change in various team properties after an event occurs, incorporating teams' histories into our theorizing and embodying the intraindividual philosophy of developmental psychology (Baltes & Nesselroade, 1979). This approach to examining team properties (and constructs, more generally) is largely missing from the literature, despite recognition by organizational scholars that a construct's past can shape its present and future states (e.g., Wang, Zhou, & Zhang, 2016). Third, we utilize a contemporary analytical technique to provide evidence that teams are indeed dynamic, as previously suggested (e.g., Cronin et al., 2011), but also demonstrate that the extent to which any particular team property may be considered dynamic depends upon characteristics of the property itself. Finally, we assess our theoretical framework in the context of an increasingly common and disruptive change in work design: the transition from standalone teams to teams nested in multiteam systems. What we ultimately find is that this transition has adverse effects for a wide variety of team properties, yet these adverse effects manifest themselves in different ways depending upon the observability of the evidence associated with the property in question (Carter, Carter, & DeChurch, 2018).

In terms of article organization, we begin by explaining our within-construct logic and the relevance of our event (the transition from standalone teams to teams nested in multiteam systems). We then review systems theories based in organizational research—namely, event system theory (hereafter, EST) (Morgeson et al., 2015) and structural adaptation theory (SAT) (Johnson, Hollenbeck, Humphrey, Ilgen, Jundt, & Meyer, 2006)-and integrate them with DST, a systems theory from developmental psychology. Next, we use this integrated theoretical perspective to explain the effects that our event will have on various team properties, depending upon the property under examination. Specifically, we argue that the extent to which there is overt, perceptible evidence associated with a team property dictates the pattern of change observed in that property after the event occurs, such that properties informed by observable, and often behavioral, cues (e.g., team backup behavior) will exhibit less dynamic change than those lacking such cues (e.g., team identification), due to their temporal anchoring and susceptibility to conformity pressures. Finally, we provide an overview of the unique strengths of our analytical approach, highlighting how it can open new lines of research, and test our integrative framework.

#### **TEAM DYNAMICS**

#### Within-Construct Development

Although continuity is central to many theories concerning teams (e.g., Ilgen et al., 2005; Kozlowski, Gully, Nason, & Smith, 1999; Marks, Mathieu, & Zaccaro, 2001; McGrath, 1964), the dearth of empirical research examining teams as they actually evolve over time represents an ongoing concern in the literature (Cronin et al., 2011; Kozlowski & Bell, 2003; Mathieu, Hollenbeck, van Knippenberg, & Ilgen, 2017). Moreover, the consistent failure to formulate and evaluate developmental models that embrace teams' unique histories has been identified as a major obstacle to advances in teams research as teams are, theoretically speaking, dynamic systems (Cronin et al., 2011; Johnson et al., 2006; McGrath et al., 2000). As dynamic systems (Thelen, 2005; Thelen & Smith, 1994), teams are embedded in the continuous flow of their maturation and may therefore exhibit asymmetric reactions to occurrences in the present or future as a result of their pasts. Accordingly, continued reliance on traditional designs and comfortable, nondynamic logics (i.e., those that do not take each team's unique history into account) places a severe upper limit on our potential understanding of team development.

To better appreciate the incompatibility of such designs and logics with the general notion that teams are dynamic systems (Cronin et al., 2011; Ilgen et al., 2005), researchers need to reflect on the meaning embodied in the term "dynamic." When one claims that a team is dynamic, she or he is directly implying that the current state of the team is partially a product of the prior states of the team (McGrath et al., 2000; Thelen, 2005; Thelen & Smith, 1994). This suggests that team development demonstrates temporal interdependence, such that the team's past shapes its future. This also means that a team's past can be leveraged as a predictor of the team's future, and therefore research that fails to take a longitudinal, dynamic perspective is potentially overlooking a major determinant of team development.

Regrettably, most research in the organizational sciences fails to take such a perspective. Although the idea that the past can be used to predict the future is evident in some purely theoretical work, empirical research has largely overlooked this possibility, and has, instead, employed "variance-oriented" or "process-oriented" approaches (Morgeson et al., 2015: 517). Variance-oriented research focuses on covariation among constructs, and pays little attention to time beyond that which is required to establish temporal precedence. Process-oriented research focuses on patterns of events, activities, and choices, and, often retrospectively, relates these patterns to various outcomes. Thus, the former draws attention to properties of the entity of interest and attempts to make relational inferences at the expense of a dynamic perspective, while the latter draws attention to series of events yet generally neglects properties (or "features") of the entity under observation (Morgeson et al., 2015). As a result, neither of these approaches explicitly capture dynamic development in teams or team properties themselves as doing so would demand a longitudinal, intra-team orientation focused on past-dependent, within-construct evolution.

Accordingly, we employ a within-construct approach in our invocation and application of theory throughout the remainder of this article, reflective of the intraindividual approach characteristic of developmental psychology (Baltes & Nesselroade, 1979). By this, we mean that we examine if, and by how much, prior states of a given team property affect subsequent states of that *same team property*, thus heeding team history in our theorizing (the properties examined herein are summarized in Table 1). Although within-construct evolution is rarely examined in teams research, it is indeed

aligned with how dynamic properties have been conceptualized in the literature (e.g., "dynamics can feed back upon each other within a single construct to create nonlinear growth" and thus "evolve independently of other constructs"; Cronin et al., 2011: 582–583). The value of this dynamic, withinconstruct approach becomes more apparent when one attempts to predict how a given team's properties will respond to a disruptive, external event.

#### **Disruptive Events**

Much like living organisms (Thelen & Smith, 1994), teams may be conceptualized as "open systems" (Collins et al., 2016). Open systems import energy and information from their environment (Kozlowski & Klein, 2000) and therefore may be stimulated by external events (Morgeson et al., 2015; Okhuysen, 2001; Zellmer-Bruhn, 2003). Although teams (Kozlowski & Klein, 2000), like organisms (e.g., children; Thelen, 2005), may be characterized by periods of relative stability (or homeostasis), events can instigate evolution, development, or even team "metamorphosis" (McGrath et al., 2000: 99). Events, in this sense, infuse energy into teams, knocking them out of states of homeostasis.

Attempts at identifying and examining the dynamics inherent in the development of team properties would benefit from the introduction of a disruptive event to the system because it puts the system in motion. Indeed, disciplines such as developmental psychology recognize the value in studying dynamics in the presence of disruptive events; developmental psychologists have previously argued that the occurrence of an event enables researchers to answer questions regarding the strength of the relationship(s) between prior and present states of an entity of interest (Salvatore, Tschacher, Gelo, & Koch, 2015; Thelen, 2005) because the occurrence of an event helps ensure that change in fact takes place. Therefore, to quantify the within-construct relationship(s) between past and present states, pertinent to the theorizing we develop below regarding team properties, we have elected to examine within-construct evolution as teams encounter and adapt to a disruptive event.

Although there are a wide variety of disruptive events that teams may encounter (Zellmer-Bruhn, 2003), an increasingly common and practically relevant change in work design that has yet to receive scholarly attention involves the transition from standalone teams to component teams nested in interdependent multiteam systems. As teams, rather

Construct	Definition	Nearest Team Process or Emergent State Categorization	Blended?	Observability in Our Context
Team Goal Commitment	The team's "determination" to extend effort toward achieving its specified goals (Klein, Wesson, Hollenbeck, & Alge, 1999: 885)	Team process: Transition (LePine et al., 2008; Marks et al., 2001)	Yes	Observable
Backup Behavior	The act of team "members going out of their way to assist other members in the performance of their tasks" (LePine, Piccolo, Jackson, Mathieu, & Saul, 2008: 276)	Team process: Action (LePine et al., 2008; Marks et al., 2001)	No	Observable
Relationship Conflict	The existence of "incompatibilities among group members, which typically includes tension, animosity, and annoyance among members in a group" (Jehn, 1995: 258)	Team process: Interpersonal (DeChurch, Mesmer-Magnus, & Doty, 2013; Loignon, Woehr, Loughry, & Ohland, 2019; Mathieu, Maynard, Rapp, & Gilson, 2008)	Yes	Observable
Psychological Empowerment	The "team members' collective belief that they have the authority to control their proximal work environment and are responsible for their teams' functioning" (Mathieu, Gilson, & Ruddy, 2006: 98)	Emergent state: Motivational (Mathieu et al., 2008; Waller et al., 2016)	No	Unobservable
Team Identification	The extent to which team members perceive their teams to be an important part of their self- definition—"group membership is an important part of who they are" (Roccas et al., 2008: 283)	Emergent state: Cognitive (Kearney, Gebert, & Voelpel, 2009; Pearsall & Venkataramani, 2015)	No	Unobservable
Cohesion	The "degree to which members of a group are attached to each other and are motivated to maintain their membership of the team" (Chang, Jia, Takeuchi, & Cai, 2014: 669)	Emergent state: Affective (Mathieu et al., 2008; Waller et al., 2016)	No	Unobservable

 TABLE 1

 Definitions and Categorizations of the Team Properties Examined<sup>a</sup>

<sup>a</sup> Whereas some team properties may be cleanly categorized as either a "team process" or an "emergent state," other properties may not (i.e., they are a "blend" of the two; Mathieu et al., 2008). We argue that team goal commitment and relationship conflict are two of these constructs, at least in our context. This is because goal commitment may be conceptualized as a psychological construct (Klein, Molloy, & Brinsfield, 2012), yet both Marks et al. (2001) and LePine et al. (2008) have explained that an important part of team transition processes involves identifying and prioritizing goals (which our participants did together in their teams immediately before reporting their goal commitment). Similarly, relationship conflict has been categorized as both an interpersonal process (Mathieu et al., 2008) and a state (DeChurch et al., 2013) by prior teams researchers. Given that these properties were observed by participants in our context, as well as the fact that Carter et al. (2018) considered processes more observable than states, we consider these two constructs to be closer to team processes than emergent states and categorized them accordingly.

than individuals, come to be considered the basic unit of work organization (Mathieu, Tannenbaum, Donsbach, & Alliger, 2014), relationships between teams have become increasingly important. As a result, many organizations have adopted multiteam systems, or tightly coupled, interdependent networks of teams pursuing both superordinate and component team goals (Luciano, DeChurch, & Mathieu, 2018; Mathieu, Marks, & Zaccaro, 2001). Given that the multiteam system context is associated with externally imposed and, potentially, unprecedented constraints on team autonomy, it may very well elicit adverse reactions from teams (see Beersma, Hollenbeck, Conlon, Humphrey, Moon, & Ilgen, 2009; Hollenbeck, Ellis, Humphrey, Garza, & Ilgen, 2011; Johnson et al., 2006; Moon et al., 2004).

With explanations of our dynamic, withinconstruct approach and disruptive external event in hand, we now turn to theoretical integration. In doing so, we draw heavily from DST (Thelen, 2005; Thelen & Smith, 1994), a theory of development with foundations in developmental psychology, to propose testable principles of dynamism in team properties. The delineation of testable principles is particularly important in light of our conceptualization of teams as open systems. Although this conceptualization has heuristic value, a major limitation associated with open systems logic is that it has thus far "contributed relatively little to the development of *testable principles* in the organizational sciences" (emphasis in original; Kozlowski & Klein, 2000: 6).

## THEORETICAL INTEGRATION

When it comes to understanding within-construct development in team properties after the transition to multiteam systems, we believe three systems theories are of particular relevance: EST (Morgeson et al., 2015), SAT (Johnson et al., 2006), and DST (Thelen & Smith, 1994). However, when each is taken alone, it can explain only one aspect of teams' reactions to this event. In the following section, we integrate these three systems theories into a single, coherent, theoretical perspective, with the intention of providing a broader conceptual foundation for examining the developmental consequences this event has for teams. Additionally, we supplement our theorizing with research regarding the "observability" of the evidence associated with team properties, or the extent to which team properties are informed by overt, perceptible, and (often) behavioral cues (Carter et al., 2018). We ultimately argue that those team properties that are informed by observable evidence are characteristically less dynamic than those that are not, due to differences in temporal anchoring and pressures for conformity. The differences in these properties should result in quantifiably distinct patterns of within-construct change after the event takes place.

#### **Event System Theory**

As noted, there are two dominant research approaches in the organizational sciences that have been applied to the study of teams: the varianceoriented and the process-oriented approaches (Morgeson et al., 2015). Although researchers studying teams have gainfully employed both approaches, each has major shortcomings. While the varianceoriented approach draws limited attention to temporal phenomena, change, or development, the process-oriented approach gives limited attention to features, is customarily retrospective in nature, and primarily offers descriptive accounts. In recognition of the limitations associated with these two research traditions, Morgeson and colleagues (2015) proposed EST.

EST diverges from the variance- and processoriented approaches by drawing attention to the influential role that "events," defined as discrete, external actions and circumstances resulting from the interaction of entities (e.g., teams), play in future development (Morgeson et al., 2015). Drawing upon open systems theory and logic (Morgeson et al., 2015: 517), EST posits that a concentration on nonroutine events not only facilitates the prediction of downstream consequences but also calls greater attention to dynamics because such events import energy into and, consequently, destabilize the system under observation. This perspective is largely consistent with our conceptualizations of teams as open systems and events as catalysts for change: as open systems, teams acquire energy from external events, which act as destabilizing forces that instigate development. In fact, much of the primary research informing EST was focused on disruptive events in the context of teams (Morgeson, 2005; Morgeson & DeRue, 2006). As such, we invoke EST to bolster our claims that the occurrence of an event, such as a "meeting" (Morgeson et al., 2015: 519) or, in our context, coupling of formally independent teams can trigger change in various team properties.

This said, we go a step further by arguing that dynamic team properties may react differently to the same event depending upon the history of those properties. These differential reactions are not necessarily due to other features or properties of the teams (a variance-oriented perspective) but due to the past states of the properties themselves. More specifically, we develop theory below suggesting that, when a team transitions from a standalone team to a component team in a multiteam system, the amount of change that occurs in dynamic team properties after the event occurs is often contingent upon the level of those team properties before the event occurs. This within-construct logic differs from the variance-, process-, and event-oriented approaches just discussed as the first highlights betweenconstruct relations, the second provides narratives, and the third concentrates heavily on events and their strength.

## **Structural Adaptation Theory**

With EST in hand, we next turn our attention to SAT. According to SAT, which also draws upon open systems logic, "structures that initially foster independent behaviors are not conducive to structural changes that are designed to promote interdependent action" (Johnson et al., 2006: 104). This theory explains that structural changes imposing constraints on team autonomy, inducing negentropy, or involving greater structural complexity will elicit negative reactions from the affected teams. This general proposition has been empirically documented for teams with respect to role scope (broad vs. narrow roles; Moon et al., 2004), decisionmaking authority (decentralized vs. centralized structures; Hollenbeck et al., 2011), and reward allocations (cooperative vs. competitive structures; Beersma et al., 2009). Indeed, the results of each of these prior studies showed that teams reacted negatively to any structural change that shifted the team from independent to interdependent states.

An extension of this theory implies that the transition from operating as a standalone team to a team embedded in an interdependent, multiteam system should generally elicit adverse reactions from the affected teams. For example, the associated threats to teams' structural empowerment (or control over physical assets and decision-making procedures) and entitativity (or the clarity of the teams' boundaries and goals) should coincide with decreases in team members' psychological empowerment, identification with their team, and cohesion (Ashforth & Mael, 1989; Hogg, 2004; Kozlowski & Chao, 2012; Maynard, Mathieu, Gilson, O'Boyle, & Cigularov, 2012; Menon, 2001). Similarly, the externally imposed, interdependent goal hierarchies (Marks, DeChurch, Mathieu, Panzer, & Alonso, 2005), increased number of members, and greater diversity of personality, opinions, and values associated with larger systems (Shuffler, Jiménez-Rodríguez, & Kramer, 2015) are likely to constrain component teams' pursuits of their own goals (i.e., team goal commitment), decrease intrateam backup behavior, and create greater opportunities for conflicts related to values, styles, and preferences (i.e., relationship conflict). Hence, our general, unconditional hypothesis is that the transition from standalone teams to teams embedded in multiteam systems will have negative consequences for a variety of team properties.

Hypothesis 1. Restructuring from standalone teams to teams embedded in multiteam systems will have adverse effects on component team properties, such as (a) team goal commitment, (b) backup behavior, (c) relationship conflict, (d) psychological empowerment, (e) team identification, and (f) cohesiveness.

Thus far, we have conceptualized teams as open systems (consistent with EST and SAT), argued that events import energy into teams and instigate change (consistent with EST), and explained why this particular event—the transition from standalone teams to teams nested in multiteam systems-will elicit adverse reactions from teams (consistent with SAT; other structural events, such as those that afford greater power or resources, may not necessarily elicit negative reactions). However, we have not specified the precise patterns of development in team properties that will occur, which is essential in crafting hypotheses that are falsifiable (Ployhart & Vandenberg, 2010). We have yet to do so because neither EST nor SAT explicitly address patterns of change or within-construct evolution, even though SAT heeds team history and EST implies the possibility of within-construct evolution given its emphasis on dynamics. Therefore, we draw upon a theory of dynamics from developmental psychology in the following section to detail three testable principles of within-construct change and formulate more explicit hypotheses regarding the dynamics underlying various team properties.

#### **Dynamic Systems Theory**

DST has been lauded as an integrative, metatheoretical framework for the study of stability and change in child development (Witherington, 2007). Often referred to as a "grand" theory of development, DST has been credited with (a) refocusing scholarly attention on individuality and (b) challenging the notion that development occurs in a universal, stepwise fashion (Spencer et al., 2006). DST also emphasizes the importance of dynamic continuity, or the idea that an entity's (e.g., child's) state in the past shapes its state in the present, and dictates his or her reaction(s) to current events (Thelen, 2005). To better understand the theoretical logic underlying DST, consider the following metaphor:

There is another way in which development is like a mountain stream. Depending on the conditions of the stream, similar actions may have very different results. Thus, if I throw a rock into a deep pool, the pool may be disturbed by ripples for a short time, but it will remain largely unchanged. The same rock tossed into a shallow part may divert the stream completely, with permanent consequences downstream. (Thelen, 2005: 260)

In other words, DST conceptualizes children as open systems and child development as continuous or "stream-like." As open systems, children are constantly in transaction with their environment (Thelen & Smith, 1994), and are thus affected by events. Being continuous, the current state of a child's development is a product of his or her past, and therefore his or her history ultimately shapes what he or she is like today and how they respond to occurrences in the present. Much like the effects of throwing a rock in a stream are contingent upon the state of the stream, which itself is a function of the stream's past (e.g., historical weather patterns; Thelen, 2005), a disruptive event (e.g., divorce) can have very different effects on a child depending upon his or her history (Emery, 1999; Kelly, 2000) and current state of development (i.e., a between-person approach). Moreover, an even more nuanced notion in this literature is that the same disruptive event can have very different effects on various characteristics of the same child depending on the nature and current state of the characteristic in question (i.e., a within-person approach).

When it comes to differences between individuals, consider two children of the same age (e.g., adolescence) reacting to divorce. The impact of this event may differ considerably in magnitude between the two individuals due to their idiosyncratic histories (Kelly, 2000). For example, one study suggests that young adults from divorced families characterized by low levels of predivorce conflict exhibit higher levels of internalizing disorders (e.g., psychological distress) than do young adults from divorced families characterized by high levels of predivorce conflict (Amato, Loomis, & Booth, 1995). Ultimately, this experience has a negative effect on both groups of individuals, yet divorces may be more jarring for young adults from low-conflict families because these individuals are relatively happier with their predivorce homelives. Accordingly, one should not generalize the dynamics of one of these groups to the other.

When it comes to differences within individuals, various properties of the same person may react differently to a disruptive event due to dissimilarities in the properties' natures. For example, an adolescent may demonstrate continuous increases in externalizing behavior after a divorce (e.g., aggression) as adolescents tend to endure consistent social (e.g., emerging romantic relationships), academic (e.g., progressively difficult courses), and personal (e.g., identity development) pressures (Johnson, 2012; Lansford, 2009). These consistent pressures exacerbate the stress of the divorce, and consequently lead adolescents to increasingly lash out over time. In contrast, this same adolescent may exhibit a sharp, nonlinear spike in internalizing disorders (e.g., depression) that plateaus quickly after a divorce (Johnson, 2012), given the sensitivity and malleability of psychological and emotional development at this age (Pickhardt, 2005). That is, there may be a continuous, linear increase in aggression after a divorce, but a dramatic, nonlinear increase in depression after a divorce, in the same child.

As was the case with EST and SAT, DST's perspective on child development is largely consistent with our own conceptualization of teams: teams, like children, are open systems that interface directly with their environments and operate within the passage of time. Furthermore, there may be divergent patterns of change both between and within entities (e.g., teams or children) after the occurrence of a disruptive event. The major contribution of DST to the present investigation is that it overcomes the limitations associated with open systems logic by outlining testable principles of dynamism. These three interrelated principles are "continuity in time," "dynamic stability" (i.e., reactivity), and "complexity" (i.e., nonlinearity) (Thelen, 2005).

In the following subsections, we explain each of these principles and use them to specify the form of change we anticipate in team properties (Ployhart & Vandenberg, 2010). Throughout, we make a distinction between team properties that are informed by overt, perceptible, and, often, behavioral cues (e.g., team backup behavior; see Table 1) and properties that are not informed by such cues (e.g., cognitive, affective, and motivational properties) (Carter et al., 2018) to formulate arguments regarding their developmental differences. Specifically, we argue that these principles are more appropriate for describing development in properties that are informed by considerably less observable evidence, such that events are far more "phase-shifting" (Thelen & Smith, 1994) for these properties.<sup>1</sup>

<sup>&</sup>lt;sup>1</sup> We are not the first to suggest that open systems may not exhibit dynamic development after an event. In fact, DST, since its inception, has acknowledged that events are not always "phase shifting," meaning that they do not always result in dynamic, dramatic, or nonlinear change. Indeed, DST recognizes that open systems "may respond in a linear and continuous manner" to events or other changes the system encounters (Thelen & Smith, 1994: 275), and that these three tenets of dynamism would not be met in such cases (Thelen, 2005). Extending this notion, we argue that certain team properties will not exhibit dynamic development after the occurrence of our event; specifically, those that are accompanied by relatively observable, concrete, and, often, behavioral evidence (Carter et al., 2018) due to the conformity pressures and temporal anchoring associated with these properties.

**Continuity in time.** The first principle of dynamism is continuity in time. Recall that this is a defining characteristic of dynamism; we have emphasized throughout that the designation of a system as *dynamic* means that the current state of the system, at any particular point in time, depends upon the prior state and is the starting point for the next. Thus, dynamic team properties would include those that are heavily influenced by the past, or those that are highly contingent upon the team's history (McGrath et al., 2000; Thelen, 2005). We argue that this is less characteristic of team properties that are typically informed by overt, perceptible, and behavioral cues as these properties are heavily anchored in the present.

The reason for this anchoring is that team members can readily discern behavioral cues in the "here and now"-team activities and team members' actions and statements serve as salient external evidence of some team properties (e.g., backup behavior) in the moment they occur (Carter et al., 2018). Given that team members can easily observe actions and statements in real time, the team properties affiliated with these actions and statements are informed by (and thus anchored in) the present. Conversely, other team properties (e.g., cognitive, motivational, or affective properties) lack such concomitant observable evidence (Carter et al., 2018), meaning that there are few, if any, salient external cues associated with them (e.g., identification is more likely to be felt or inferred than directly observed). As a result, team members may reflect more heavily on the past when interpreting these properties in the present because the past serves as the most readily accessible referent. That is, how team members are *feeling* in the present is compared to how they *felt* in the past.

In sum, current activities, actions, and statements may serve as the most salient referents in the case of some team properties, whereas past states may serve as the most salient referents in the case of others. That is, the former are more anchored in the present, whereas the latter are more anchored in the past. Hence, a key difference between (a) team properties informed by behavioral and observable evidence and (b) team properties not informed by behavioral and observable evidence is that the former are less continuous in time (i.e., dependent on the past).

**Dynamic stability.** The second principle of dynamism is dynamic stability. Per DST, events may or may not be phase shifting (Thelen & Smith, 1994); open systems may experience linear, continuous adaptation or major destabilization (followed by homeostasis at a new attractor state) after a

disruptive event (Kozlowski & Klein, 2000; Spencer et al., 2006; Thelen & Smith, 1994). It is the latter possibility that suggests dynamism (Thelen, 2005). Although an event can lead to change in many team properties, differences in conformity pressures between those team properties accompanied by behavioral, observable cues and those team properties not accompanied by such cues may dictate how reactive they are to an event (i.e., how phase shifting the event is). Specifically, the former are likely to be less reactive than the latter, and thus change more gradually and linearly, as they are more vulnerable to conformity pressures.

It is a natural human tendency to monitor others and adjust one's behavior, statements, and actions to fit the ostensible norms of the group (Cialdini & Goldstein, 2004). Indeed, research often shows behavioral conformity in group settings (Myers, 2008), such that people have a variety of incentives to avoid dramatically altering their behavior (Cialdini & Goldstein, 2004; Cialdini & Trost, 1998), even if their feelings have dramatically altered. Moreover, the team member actions and statements that feed into certain team properties (e.g., backup behavior) are readily observable by others. This facilitates the determination of "normative" group member conduct and, consequently, adaptation of one's individual conduct to meet these norms. Thus, after the transition to multiteam systems, team properties informed by overt, perceptible, and behavioral cues will indeed undergo change. However, this change is likely to be continuous and gradual, rather than nonlinear and dramatic, as group members will engage in a process of mutual behavioral adjustment.

Conversely, team properties not informed by overt, observable evidence are less susceptible to such conformity pressures due to their inherent lack of behavioral elements. Furthermore, and reflecting back on our arguments regarding temporal anchoring, the changes these team properties endure may be more dramatic because how team members are feeling in the present, after the event has occurred, is juxtaposed to how they felt before the event, as they have fewer, if any, clear external signals to rely on. For example, the deleterious effects that the placement into a multiteam system has on a team's psychological empowerment (a relatively unobservable, motivational team property) is likely contingent on the team's initial level of psychological empowerment, such that declines may be more precipitous if this team initially had a particularly strong sense of empowerment. Hence, another key difference between (a) team properties informed by behavioral

**Complexity.** The final principle of dynamism is complexity, or nonlinearity. Along the same vein as our prior theorizing, team properties informed by behavioral and observable evidence are more likely to change gradually and linearly given human tendencies toward behavioral conformity in group contexts (Cialdini & Trost, 1998). That is, because team members can draw upon external cues and others' behavioral adjustments in response to an event, adaptation in the associated team properties may take place in a more systematic, linear fashion as team members gain experience working together, they conform and converge.

However, team properties not informed by behavioral, observable evidence may exhibit a more complex pattern of development, for two reasons. First, as noted, these properties are not as susceptible to conformity, and therefore are under less pressure to acclimate gradually. Second, their dependence on the past makes them more reactive-they may undergo more precipitous change after an event occurs. Consequently, these properties should undergo nonlinear development whereas properties informed by overt, perceptible, and behavioral cues should undergo linear, gradual development, as the latter essentially reflects behavioral adaptation to teams' new realities. Hence, a final key difference between (a) team properties informed by behavioral and observable evidence and (b) team properties not informed by behavioral and observable evidence is that the former are less likely to exhibit nonlinearity than the latter.

Taken altogether, team properties generally lacking concomitant observable cues (e.g., affective, cognitive, and motivational properties) are more continuous in time (i.e., dependent on the past), reactive (i.e., exhibit dynamic stability), and complex (i.e., nonlinear) than properties that are informed by such cues. As such, the former are more likely to exhibit dynamic patterns of development than the latter after a team transitions to a multiteam system. In terms of what these trajectories look like (Ployhart & Vandenberg, 2010), the former will exhibit a dramatic decline immediately after the transition to multiteam systems (i.e., a high level of reactivity), followed by more gradual declines (i.e., nonlinearity) that signify an approach toward dynamic stability (Thelen, 2005). Furthermore, the amount of change that these properties undergo will be a

function of their pasts (i.e., greater continuity in time), given their temporal anchoring. Conversely, properties informed by observable, behavioral evidence will not exhibit dramatic changes immediately after the transition to multiteam systems (i.e., a low level of reactivity), but will instead exhibit continuous, gradual changes due to tendencies toward behavioral conformity (i.e., linearity). Furthermore, the amount of change that these properties undergo will not be a function of their pasts due to their temporal anchoring (i.e., less continuity in time). Thus:

Hypothesis 2. Restructuring from standalone teams to teams embedded in multiteam systems will result in linear, non-past-dependent (nondynamic) change in team properties informed by behavioral and observable evidence, such as (a) team goal commitment, (b) backup behavior, and (c) relationship conflict.

Hypothesis 3. Restructuring from standalone teams to teams embedded in multiteam systems will result in nonlinear, past-dependent (dynamic) change in team properties not informed by behavioral and observable evidence, such as (a) psychological empowerment, (b) team identification, and (c) cohesiveness.

## METHOD

## Methodological Approach: Dual Change Score Models

When it comes to the study of team dynamics, the methodological gaps are more apparent than the theoretical ones (Cronin et al., 2011; Waller, Okhuysen, & Saghafian, 2016). Fortunately, more advanced, contemporary approaches for modeling dynamic phenomena can be found in alternative disciplines such as developmental psychology. Developmental psychology utilizes models that focus not only on the general trajectories of latent variables but also capture proportional change effects, or within-construct estimates that operate as a function of prior levels of latent variables (McArdle & Nesselroade, 2014). More specifically, the univariate "dual change score model" (the most foundational latent change score model; Clark, Nuttall, & Bowles, 2018) can capture exponential, nonlinear trajectories by providing estimates of underlying, constant change (i.e., a "maturational" effect, or linear change) in addition to proportional change (the effect that the prior status of a variable has on the change that occurs in that variable between measurement occasions) (Grimm, Ram, & Estabrook, 2017). Thus, dual change score models (a) capture

continuity, or the extent to which the level of a given construct at time t affects the change that occurs in that construct between time t and time t + 1; (b) demonstrate convergence to or divergence from some "equilibrium," given their exponential nature (i.e., reactivity and dynamic stability); and (c) model nonlinearity as a direct result of greater complexity in development (i.e., both constant and proportional change).

Given their capabilities, we believe dual change score models can be used to test the three principles of DST previously delineated, and therefore provide an appropriate modeling approach for our purposes. Furthermore, the linear model (or the "constant change" model) is nested within the dual change score model, meaning that researchers can directly test whether the additional complexity provided by the dual change score model, over the linear model, is necessary and appropriate (more information on this nesting is provided below).

In terms of how this modeling approach relates to approaches commonly used by organizational scientists, dual change score models essentially combine the strengths of growth curve and autoregressive models (Clark et al., 2018). By capturing general trajectories, modeling latent change, and providing a proportional change estimate (predicting this latent change), dual change score models allow researchers to examine general trends (like growth curve models) as well as quantify the effect of past status on future status (like autoregressive models). In this sense, dual change score models may be considered both *descriptive* and *explanatory* (Ployhart & Vandenberg, 2010: 99)-they describe overall trajectories and demonstrate whether past levels of a variable itself predict the change that occurs in that variable over time. Although the dual change score model provides only one additional, proportional estimate beyond those provided by the linear (or constant change) model, this estimate is critical. It not only tells us whether the value of variable X at time t effects the change that takes place in X between time t and time t + 1, but also the direction and strength of this effect. Thus, a statistically significant and large proportional change estimate indicates that (a) the construct is indeed dynamic, per the definition previously provided, and (b) prior values of the construct are influential with respect to the amount of change that takes place (Ferrer & McArdle, 2003).

The adoption of dual change score models by the organizational sciences offers several unique benefits. First, for theoretical reasons previously stipulated, we believe that the empirical distinctions between linear and dual change score models reflect conceptual distinctions between nondynamic and dynamic team properties, respectively. Ultimately, we provide evidence that linear models are indeed more appropriate for properties informed by concomitant observable evidence, while dual change score models are more appropriate for those that lack it. In other words, dual change score models provide us with a new way of identifying dynamism that does not currently exist in the organizational literature, and therefore could be used inductively for theory generation or deductively for theory testing in future research.

Second, dual change score models allow researchers to capture the concept of change without calculating difference scores (see Appendix A for annotated syntax). Traditional difference scores, calculated by subtracting the value at the initial or previous assessment from the value of the subsequent assessment, do not take the measurement error of each assessment into account and thus yield values with questionable reliability (Cronbach & Furby, 1970; Edwards, 2001). By adding a set of fixed values to an autoregressive model, dual change score models capture change in a variable across assessment points while accounting for measurement error (King, King, McArdle, Saxe, Doron-LaMarca, & Orazem, 2006; McArdle, 2009). This approach reduces biases in parameter estimates by modeling change in reliable "true" scores, allowing future researchers to more confidently test multivariate models that contain either or both time-varving and time-invariant predictors of this change (i.e., predictors other than the prior values of the variable itself).

Finally, and relatedly, dual change score models can be "conceived as a disaggregation of a longerterm trajectory or growth curve into a sequence of latent difference segments, each of which is a potential outcome to be examined and understood" (King et al., 2006: 783). This means that what may have been a single index of change in a growth curve analysis (e.g., slope) becomes several latent change variables, each signifying predictable change over a different time period. Thus, dual change score models allow for the examination of more nuanced trajectories (Bernard, Peloso, Laurenceau, Zhang, & Dozier, 2015). Whereas many nonlinear growth models pose challenges for understanding determinants of change given their general inability to capture change over discrete intervals (Grimm, Castro-Schilo, & Davoudzadeh, 2013), intraindividual (or intra-team) change over specific intervals is represented by a latent variable in dual change score models and thus can be directly predicted by covariates.

#### **Research Context**

The context in which we tested our hypotheses involved a change in work design; namely, the placement of formerly standalone teams into multiteam systems. Although our primary purpose was the delineation of differential dynamics underlying various team properties through the integration of concepts and methods from developmental psychology, we purposively chose the multiteam system context. The lure of reaping the benefits of both capacity and flexibility has made multiteam systems an increasingly attractive design option for organizations seeking to manage complexity, including organizations in business, government, medicine, and the military (Shuffler & Carter, 2018). Moreover, researchers in the social and behavioral sciences have noticed the increased use of multiteam systems and responded accordingly (Shuffler et al., 2015).

Despite the fact that the body of work on multiteam systems is expanding, the focus of this research has been on the performance of the multiteam system as a whole—prior literature has largely overlooked the effects that placing formerly independent teams into a multiteam system has on those "component" teams. Indeed, multiteam system research has generally considered the multiteam system to be the unit of analysis rather than the component teams that comprise it. Given that organizations are increasingly adopting multiteam systems, and thus may be redesigning work so that teams become interdependent, examination of the team-level implications of this work design event appears to be of considerable practical relevance.

#### **Participants and Procedure**

The data analyzed herein were collected as part of a larger program of research focused on examining multiteam systems as they function over time. As a result, there exists another study that has utilized a subset of the data presented shortly (Porck, Matta, Hollenbeck, Oh, Lanaj, & Lee, 2019). Specifically, Porck and colleagues (2019) have examined the effects of team identification, multiteam system identification, and depletion on multiteam system performance in a sample of 22 multiteam systems. Their study came before the present one, and it therefore utilized a subset (n = 22) of the multiteam systems that we examine (n = 47). Importantly, Porck and colleagues (2019) were interested in multiteam system performance, and therefore aggregated responses to the multiteam system level, whereas we are interested in team-level phenomena, and thus aggregate responses to the team level. Furthermore, the variable overlap between this prior study and the present one only involves the construct of team identification. Nevertheless, future researchers, and particularly meta-analysts (given the nonindependence of these two studies), should take this overlap into consideration when reviewing the team and multiteam system literature(s).

**Participants.** Participants included 634 undergraduate students from a large Midwestern university who took part in a yearlong study to fulfill requirements for entry-level courses. These courses were part of a larger, selective residential curriculum program meant to prepare students for majors in the business college. Participants ranged in age from 17 to 20 years old, with an average age of 18.08 years. Approximately 55.1% of participants were male, and 70.6% identified as Caucasian, 12.4% as Asian, 9.8% as African American, 3.4% as Hispanic or Latino, 1.1% as Arab or Middle Eastern, and the rest as Native American or "other." Participants were randomly placed into one of 141 four- or five-person teams, for an average of 4.5 students each.

Procedure. Data were collected across four waves over the course of one school year. As mentioned, participation in this study represented a portion of participants' course requirements. A major objective of the course was to foster strong connections among team members in the small four- or five-person standalone teams. Team members generally lived in the same building, took the same classes, and were assigned team projects in those classes. These standalone teams also underwent training in the leadership development exercise (LDX) simulation, the task used in all four waves, before participating in any actual simulations (more information on this task is provided below). Therefore, each of the standalone teams lived and worked together closely for several months prior to placement in multiteam systems, and, thus, these teams had their own unique histories prior to multiteam system membership.

In the first wave, participants worked on LDX in their standalone teams. LDX is the next-generation version of a 10-round, virtual simulation developed through a collaboration between the United States Airforce and a large Midwestern university. This task requires participants to identify various hidden targets on a virtual game grid, integrate information collected using assorted assets, and efficiently use assets to eliminate identified targets (for more details, see Davison, Hollenbeck, Barnes, Sleesman, & Ilgen, 2012, and Lanaj, Hollenbeck, Ilgen, Barnes, & Harmon, 2013). In short, participants must use unique combinations of information-collecting, defensive, and offensive assets to locate and eliminate enemy targets.

In the three subsequent waves of the study, the teams once again worked on variations of the LDX simulation. However, teams were now placed in larger, three-team multiteam systems. Each multiteam system consisted of three component teams, referred to as the "point" (or "operations"), "support" (or "intel"), and "leadership" teams. Participants remained in the same four- to five-person team that they were members of in the first wave (i.e., their component teams consisted of the same individuals that comprised their standalone teams from the first wave and training), and they remained in this group for the entirety of the study. That is, teams from Wave 1 simply transitioned from standalone teams to component teams during Wave 2, and remained in these component team roles and multiteam systems throughout the remainder of the study. All the component teams in the multiteam system were, for the first time, together in one room while completing LDX. In addition, above being confronted with a much larger number of people in one place, each of the component teams now did only one of the three major functions for the multiteam system, and had to rely on other teams to perform functions that they were able to do for themselves when they were a standalone team. Each wave took place approximately three to four weeks apart.

At the beginning of each of the four waves, we provided participants with goal sheets. These goal sheets were the same for all teams during the first wave, and specific to their team roles (e.g., support) in the three subsequent waves. These goal sheets provided participants with information regarding how we calculated team performance, in addition to what performance targets they should strive for if they sought to outperform "75% of teams who [had] already completed this exercise." We also provided teams with strategies to achieve these goals. Shortly after receiving this information, teams discussed goals among themselves and prioritized the goals they wished to pursue. Participants then reported (a) their commitment to their discussed goals and (b) their identification with their team in the first of two surveys. At the end of each of the four waves, after completing the 10-round LDX simulation, teams

reported their (c) psychological empowerment, (d) backup behavior, (e) cohesion, and (f) relationship conflict.

We chose team psychological empowerment, identification, and cohesion as the three team properties that were *not* informed by observable, behavioral evidence (i.e., those anchored in the past and not susceptible to conformity pressures) because we wanted to be comprehensive in scope. We chose one team property that was largely motivational (i.e., psychological empowerment), one that was largely cognitive (i.e., team identification), and one that was largely affective (i.e., cohesion). Situating these constructs in the broader teams literature (see Table 1), these properties are conceptually closest to what may be termed "emergent states," or motivational, cognitive, and affective "properties of the team that are typically dynamic in nature" and reflect states of teams rather than team member interactions (Marks et al., 2001: 357). Carter and colleagues (2018) considered emergent states less observable than "team processes."

We chose team goal commitment, backup behavior, and relationship conflict as the three team properties that were informed by observable, behavioral evidence (i.e., those anchored in the present and susceptible to conformity pressures), and therefore were similarly comprehensive in scope. We chose one team property that was informed by a team exercise that took place before the 10-round simulation (i.e., team goal commitment), and two that reflected behaviors and statements that took place during the simulation itself—one that was positive in connotation (i.e., backup behavior) and one that was negative in connotation (i.e., relationship conflict). Once again situating these constructs in the broader teams literature (see Table 1), these properties are conceptually closest to what may be termed "team processes," or members' "cognitive, verbal, and behavioral activities directed toward organizing taskwork to achieve collective goals" (Marks et al., 2001: 357). Team processes may be further categorized as "transition," "action," or "interpersonal" (see Marks et al., 2001). Carter and colleagues (2018) considered team processes more observable than emergent states.

Although the construct of team goal commitment itself is arguably less observable than the constructs of backup behavior and relationship conflict, team members reported their goal commitment immediately after engaging in a team goal specification and prioritization exercise with their teammates. This exercise involved concrete numbers, explicit performance targets, and interpersonal dialogue. Therefore, participants reported on goal commitment after they had literally observed relevant behavior and utilized physical materials; there were clear behavioral, vocal, and interpersonal cues, as well as tangible materials, participants could leverage. Thus, in light of Carter et al.'s (2018) conceptualization of "observability," we considered team goal commitment to be a property that was highly informed by observable evidence in our setting.

#### Measures

All items were measured using a 5-point Likert-type scale that ranged from "strongly disagree" to "strongly agree," unless stated otherwise. Intraclass correlation coefficients (ICCs) were calculated using output from repeated measures analyses of variance. Responses were aggregated to the team-level as acceptable ICC(1) values of approximately .44, .32, .33, .22, .45, and .38, and  $r_{WG(l)}$  index values of approximately .92, .91, .82, .84, .82, and .89, averaged across sessions, were achieved for team goal commitment, backup behavior, relationship conflict, psychological empowerment, identification, and team cohesion, respectively (Bliese, 2000; James, 1982; James, Demaree, & Wolf, 1984). ICC(2) values of .78, .68, .69, .55, .79, and .73 were achieved for team goal commitment, backup behavior, relationship conflict, psychological empowerment, identification, and cohesion, respectively. Although some ICC(2) values were below .70, we note that ICC(2) is highly dependent on group size (James, 1982) and we had relatively small teams ( $\sim$ 4.5 individuals per team). See Table 2 for these interrater agreement and reliability indices.

**Team goal commitment.** We measured team goal commitment using Hollenbeck, Klein, O'Leary, and Wright's (1989) 9-item measure, adapting it slightly to fit our context (Cronbach's  $\alpha = .84$ ).

TABLE 2
Interrater Agreement and Reliability Indices

Variables	ICC(1)	ICC(2)	r <sub>WG(J)</sub>
Goal Commitment	.44	.78	.92
Backup Behavior	.32	.68	.91
Relationship Conflict	.33	.69	.82
Psychological Empowerment	.22	.55	.84
Identification	.45	.79	.82
Cohesion	.38	.73	.89

Notes: n = 139 teams nested in 47 multiteam systems. ICCs calculated using the output generated from repeated measures analyses of variance.

**Backup behavior.** We measured backup behavior with a measure taken from Dalal, Lam, Weiss, Welch, and Hulin (2009), again adapting it to our context (Cronbach's  $\alpha = .78$ ).

**Relationship conflict.** We measured relationship conflict using the measure described by Jehn (1995). Items were measured using a 5-point Likert-type scale that ranged from "*to a very small extent*" to "*to a very large extent*." We adapted the items to fit our context (Cronbach's  $\alpha = .97$ ).

**Psychological empowerment.** We measured psychological empowerment using three items from Spreitzer (1995). Specifically, we used those items meant to assess self-determination because this dimension is the most relevant to our theorizing (we believe that the multiteam system impairs team autonomy). We then adapted these items to fit our context (Cronbach's  $\alpha = .82$ ).

**Team identification.** We measured team identification using four items from Roccas, Sagiv, Schwartz, Halevy, and Eidelson's (2008) measure of group identification. Specifically, we used those items meant to assess the "importance" of the team to one's identity as this dimension is most relevant to our theorizing (i.e., entitativity is necessary to view the group as important to one's identity; Roccas et al., 2008). We then adapted these items to fit our context (Cronbach's  $\alpha = .90$ ).

*Team cohesion.* Finally, we measured team cohesion using three items from Podsakoff, Niehoff, Mackenzie, and Williams (1993) (Cronbach's  $\alpha = .75$ ).

#### Analyses

The four waves of data were analyzed with Mplus 6.12 (Muthén & Muthén, 2012). Several model fit indices were used to determine acceptable fit, including the chi-squared test (Bollen, 1989), the root mean square error of approximation (RMSEA) (Hu & Bentler, 1999), and the comparative fit index (CFI) (Bentler, 1990). We chose the best model for our team properties through comparisons of competing, unconditional, univariate models. The three models we attempted to fit included the univariate interceptonly (i.e., no change), linear (i.e., constant change), and dual change score models. These models are nested and increase in complexity, such that the intercept-only model is nested within the linear model, and the linear model is nested within the dual change score model. We accounted for nonindependence in our data by clustering by multiteam system (i.e., component teams nested in multiteam systems). As previously noted, our initial sample size

Variables	Mean	SD	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Goal Commitment <sub>1</sub>	3.73	.38										
Goal Commitment <sub>2</sub>	3.65	.38	.58*	_								
Goal Commitment <sub>3</sub>	3.58	.41	.61*	.58*	_							
Goal Commitment <sub>4</sub>	3.51	.38	.45*	.53*	.65*	_						
Backup Behavior <sub>1</sub>	3.78	.38	.48*	.42*	.36*	.39*	_					
Backup Behavior <sub>2</sub>	3.72	.50	.15	.30*	.18*	.22*	.26*	_				
Backup Behavior <sub>3</sub>	3.66	.50	.32*	.30*	.35*	.41*	.45*	.28*	_			
Backup Behavior <sub>4</sub>	3.62	.53	.37*	.37*	.40*	.51*	.44*	.30*	.64*	_		
Relationship Conflict <sub>1</sub>	1.55	.55	37*	24*	22*	22*	29*	05	13*	15	_	
Relationship Conflict <sub>2</sub>	1.68	.52	19*	28*	31*	38*	29*	08	31*	19*	.26*	_
Relationship Conflict <sub>3</sub>	1.79	.64	24*	28*	17*	18*	16	.06	09	13	.38*	.33*
Relationship Conflict <sub>4</sub>	1.82	.61	20*	27*	21*	39*	18*	09	23*	35*	.19*	.41*
Team Identification <sub>1</sub>	3.66	.39	.58*	.33*	.44*	.35*	.49*	.08	.27*	.32*	20*	16
Team Identification <sub>2</sub>	3.59	.54	.46*	.55*	.56*	.48*	.44*	.27*	.35*	.35*	29*	27*
Team Identification <sub>3</sub>	3.53	.54	.43*	.43*	.64*	.58*	.40*	.29*	.47*	.51*	21*	23*
Team Identification <sub>4</sub>	3.51	.57	.37*	.41*	.57*	.58*	.41*	.27*	.50*	.54*	13	20*
Cohesion <sub>1</sub>	4.28	.43	.48*	.44*	.44*	.41*	.64*	.12	.31*	.29*	54*	29*
Cohesion <sub>2</sub>	4.06	.66	.14	.36*	.22*	.28*	.19*	.82*	.17*	.22*	13	22*
Cohesion <sub>3</sub>	4.09	.41	.38*	.32*	.44*	.44*	.48*	.19*	.59*	.48*	25*	44*
$Cohesion_4$	3.97	.50	.34*	.40*	.42*	.50*	.30*	.19*	.38*	.61*	23*	34*
Psych Empowerment <sub>1</sub>	3.84	.42	.47*	.46*	.36*	.31*	.51*	.21*	.34*	.32*	38*	28*
Psych Empowerment <sub>2</sub>	3.67	.63	.11	.30*	.21*	.23*	.13	.76*	.18*	.12	03	06
Psych Empowerment <sub>3</sub>	3.67	.42	.19*	.20*	.23*	.21*	.29*	.31*	.41*	.29*	08	13
Psych Empowerment <sub>4</sub>	3.66	.46	.12	.23*	.29*	.25*	.12	.18*	.28*	.38*	05	14

 TABLE 3

 Descriptive Statistics of and Correlations among Focal Variables<sup>a</sup>

consisted of 141 teams. We dropped two teams due to missing data, and thus we analyzed data for 139 teams. Annotated syntax for the dual change score model for team identification is provided in Appendix A.

#### RESULTS

Table 3 presents the means, standard deviations, and correlations among variables.

#### **Unconditional Growth Models**

As noted, each of the six focal team properties was fit with a series of three nested models. The first model—the intercept-only model—contained three freely estimated parameters: the intercept mean, the intercept variance, and a residual variance (constrained to equality across measurements). The second model—the linear (or constant change) model—contained six freely estimated parameters: intercept and constant change means, the intercept and constant change variances, their covariance, and a residual variance (constrained to equality across measurements). The final model—the dual change score model—contained seven freely estimated parameters: the six from the linear model in addition to a proportional change estimate (constrained to equality). Once again, the intercept-only model was nested in the linear model, which was nested in the dual change score model. Tables 4 and 5 provide comparisons of these models, including fit statistics and parameter estimates, for each set of team properties.

**Team goal commitment.** The intercept-only model did not provide an acceptable fit to the data,  $\chi^2(11) = 66.30$ , p < .001 (RMSEA = .19, CFI = .67, SRMR<sub>within</sub> = .06). However, the linear model did provide an acceptable fit to the data,  $\chi^2(8) = 8.81$ , p = .359 (RMSEA = .03, CFI = 1.0, SRMR<sub>within</sub> = .03), as did the dual change score model,  $\chi^2(7) = 8.19$ , p = .316 (RMSEA = .04, CFI = .99, SRMR<sub>within</sub> = .03). A chi-square difference test was conducted to determine if the addition of the proportional change estimate (i.e., the dual change score model) provided a significant improvement in fit over the linear model, using the procedures recommended by Satorra and Bentler (2010) due to the nested nature of the data.

Results indicated that the addition of the proportional change estimate did not significantly improve model fit, scaled  $\chi^2(1) = 0.33$ , p = .563. Furthermore, neither the constant change estimate,

						TABLE (Continu	E 3 1ed)						
(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)

_													
.31*	_												
15	11												
22*	15	.54*	—										
17*	15	.48*	.64*	—									
12	18*	.48*	.64*	.73*	_								
26*	21*	.51*	.46*	.42*	.33*	—							
03	18*	.01	.23*	.23*	.21*	.20*	_						
24*	30*	.35*	.40*	.43*	.37*	.42*	.27*	—					
19*	40*	.20*	.35*	.47*	.43*	.33*	.28*	.50*	—				
17*	23*	.40*	.38*	.29*	.30*	.61*	.34*	.43*	.33*	—			
.21*	03	03	.21*	.19*	.22*	.09	.79*	.20*	.20*	.20*	—		
05	00	.12	.24*	.26*	.19*	.20*	.35*	.53*	.22*	.24*	.39*	_	
03	.01	.22*	.31*	.42*	.38*	.15*	.24*	.31*	.54*	.09	.18*	.34*	—

 $^{a}$  n = 139 teams nested in 47 multiteam systems. All constructs are at the team level, with subscripts denoting the wave of data collection.  $^{*}p < .05$ 

b = 0.34, p = .608, nor the proportional change estimate, b = -0.11, p = .533, were significant in the dual change score model, suggesting that it was not an appropriate model for the data. Thus, the linear model was retained. The linear model provided a

significant intercept estimate, b = 3.73, p < .001, and a negative, significant slope, or constant change, estimate, b = -0.07, p < .001, suggesting that team goal commitment decreased, on average, by .07 *per measurement interval*.

TABLE 4
Comparisons of Models for Team Properties Informed by Observable Evidence: Intercept-Only, Linear, and Dual Change
Score Models

	Team	Goal Commi	tment	Team	Backup Beh	avior	Team Relationship Conflict			
Fit Statistics and Estimates	Intercept Only	Linear Change	Dual Change	Intercept Only	Linear Change	Dual Change	Intercept Only	Linear Change	Dual Change	
$\overline{\chi^2}$	66.30*	8.81	8.19	60.93*	13.92	12.57	27.88*	15.42	19.40*	
Degrees of freedom	11	8	7	11	8	7	11	8	7	
RMSEA	.19	.03	.04	.18	.07	.08	.11	.08	.11	
CFI	.67	1.00	.99	.82	.98	.98	.73	.91	.80	
SRMR (within) <sup>a</sup>	.06	.03	.03	.05	.02	.02	.05	.02	.02	
Intercept estimate	3.62*	3.73*	3.73*	3.69*	3.78*	3.79*	1.73*	1.63*	1.62*	
Slope estimate		-0.07*	0.34		-0.06*	1.64		0.07*	0.29	
Proportional change			11			46			13	

*Note:* n = 139 teams nested in 47 multiteam systems.

<sup>a</sup> SRMR = standardized root mean square residual (model fix index).

p < .05

	Team P	sych Empow	erment	Tea	m Identificat	ion	Team Cohesion			
Fit Statistics and Estimates	Intercept Only	Linear Change	Dual Change	Intercept Only	Linear Change	Dual Change	Intercept Only	Linear Change	Dual Change	
$\chi^2$	69.48*	19.18*	7.31	58.06*	16.37*	8.13	38.58*	n.a.	n.a.	
Degrees of freedom	11	8	7	11	8	7	11	n.a.	n.a.	
RMSEA	.20	.10	.02	.18	.09	.03	.13	n.a.	n.a.	
CFI	.76	.96	1.0	.81	.97	1.0	.00	n.a.	n.a.	
SRMR (within)	.07	.03	.02	.07	.03	.02	.08	n.a.	n.a.	
Intercept estimate	$3.59^{**}$	3.68*	3.71*	3.58*	3.65*	3.66*	3.71*	n.a.	n.a.	
Slope estimate		-0.06*	2.38*		-0.05*	2.29*		n.a.	n.a.	
Proportional change			68*			65*			n.a.	

 TABLE 5

 Comparisons of Models for Team Properties not Informed by Observable Evidence: Intercept-Only, Linear, and Dual Change

 Score Models<sup>a</sup>

<sup>a</sup> n = 139 teams nested in 47 multiteam systems.

\* *p* < .05

**Backup behavior.** The intercept-only model did not provide an acceptable fit to the data,  $\chi^2(11) =$ 60.93, p < .001 (RMSEA = .18, CFI = .82, SRMR<sub>within</sub> = .05). However, both the linear,  $\chi^2(8) =$ 13.92, p = .084 (RMSEA = .07, CFI = .98, SRMR<sub>within</sub> = .02), and the dual change score,  $\chi^2(7) =$ 12.57, p = .083 (RMSEA = .08, CFI = .98, SRMR<sub>within</sub> = .02), models provided acceptable fit statistics. A chi-square difference test was conducted to determine if the addition of the proportional change estimate provided a significant improvement in fit over the linear model, once again using the procedures recommended by Satorra and Bentler (2010).

Results from the chi-square difference test indicated that the dual change score model did not provide a significantly better fit than the linear model, scaled  $\chi^2(1) = 1.59$ , p = .207. Furthermore, neither the constant change, b = 1.64, p = .153, nor the proportional change, b = -0.46, p = .140, estimates were significant in the dual change score model, suggesting that it was not an appropriate model for the data. Thus, the linear model was retained. The linear model provided a significant intercept estimate, b = 3.78, p <.001, and a negative, significant slope, or constant change estimate, b = -0.06, p < .001, suggesting that team backup behavior decreased by .06 per measurement interval, on average.

**Relationship conflict.** The intercept-only model did not provide an acceptable fit to the data,  $\chi^2(11) = 27.88$ , p = .003 (RMSEA = .11, CFI = .73, SRMR<sub>within</sub> = .05). However, the linear model did provide an acceptable fit to the data,  $\chi^2(8) = 15.42$ , p = .051 (RMSEA = .08, CFI = .91, SRMR<sub>within</sub> = .02).

The addition of the proportional change estimate did not improve model fit, as the dual change score model did not provide an acceptable fit to the data,  $\chi^2(7) = 19.40$ , p = .007 (RMSEA = .11, CFI = .80, SRMR<sub>within</sub> = .02). Thus, the linear model was retained. The linear model provided significant, positive intercept, b = 1.63, p < .001, and slope, or constant change, b = .07, p = .002, estimates, suggesting that team relationship conflict increased by .07 per measurement interval, on average.

Taken together, the results of the models for team properties informed by behavioral and observable evidence provide preliminary support for Hypothesis 1, in which we argued that the transition from standalone teams to teams embedded in multiteam systems would have adverse (i.e., connotatively negative) effects on team properties, and fully support Hypothesis 2, in which we argued that the change these team properties would undergo, as a result of this transition, would not be dynamic (i.e., less continuous in time, less reactive to events, and linear). Figure 1 provides an example, visual representation of the linear model for team backup behavior.

**Psychological empowerment.** Neither the interceptonly,  $\chi^2(11) = 69.48$ , p < .001 (RMSEA = .20, CFI = .76, SRMR<sub>within</sub> = .07), nor the linear,  $\chi^2(8) = 19.18$ , p = .014 (RMSEA = .10, CFI = .96, SRMR<sub>within</sub> = .03), model provided an acceptable fit to the data, based on RMSEA estimates. However, the dual change score model did provide an acceptable fit to the data,  $\chi^2(7) = 7.31$ , p = .397 (RMSEA = .02, CFI = 1.0, SRMR<sub>within</sub> = .02). To ensure that the addition of the proportional change estimate provided a significant





Notes: \* p < .05. e variables represent residual variances.  $h_0$  represents the intercept/initial true score.  $h_1$  represents the constant change component. x variables within squares represent observed scores. x variables within ellipses represent latent true scores. x variables within triangle/delta in ellipses represent the latent change scores.

improvement in model fit over the linear model, we once again conducted a scaled chi-square difference test. Results suggested that the addition of the proportional change estimate significantly improved model fit, scaled  $\chi^2(1) = 8.99$ , p = .003, so the dual change score model was retained. This model provided an intercept estimate of b = 3.71, p < .001, a constant change estimate of b = 2.38, p = .001, and a proportional change estimate of b = -0.68, p = .001.

To examine the overall shape of team psychological empowerment's trajectory, the constant change component, proportional change component, and mean of the initial true score (i.e., intercept) must be taken together (Grimm et al., 2017). We used the following formula from Grimm et al. (2017) to calculate the trajectory:

$$d_{ti} = g_{2i} + \pi \times I y_{t-1_i}$$

where  $g_{2i}$  is the constant change component,  $\pi$  is the proportional change parameter, and  $ly_{t-1i}$  is the value of the latent variable at the prior point in time.

For team psychological empowerment, the mean trajectory begins at the initial score of approximately

3.71 and changes based on the two estimates of constant and proportional change. These parameters suggest that team psychological empowerment drops the most between the first wave and the second wave, or the critical point at which teams transitioned from standalone teams to teams nested in multiteam systems. This downward trend continues at a more gradual pace thereafter, before reaching a point of relative stability. Importantly, the proportional change estimate suggests that teams characterized by relatively higher levels of team psychological empowerment in the first wave of data collection experienced larger declines between Wave 1 and Wave 2. Figure 2 provides a visual representation of the dual change score model for team psychological empowerment, and Figure 3 depicts its estimated trajectory at the mean initial true score (3.71) as well as one (i.e., 4.13) and two (i.e., 4.55) standard deviations above this mean.

**Team identification.** The intercept-only model did not provide an acceptable fit to the data,  $\chi^2(11) = 58.06$ , p < .001 (RMSEA = .18, CFI = .81, SRMR<sub>within</sub> = .07). However, both the linear,

## FIGURE 2 Dual Change Score Model for Team Psychological Empowerment



Notes: \* p < .05. e variables represent residual variances.  $h_0$  represents the intercept/initial true score.  $h_1$  represents the constant change component. x variables within squares represent observed scores. x variables within ellipses represent latent true scores. x variables within triangle/delta in ellipses represent the latent change scores.



 $\chi^2(8) = 16.37, p = .037$  (RMSEA = .09, CFI = .97, SRMR<sub>within</sub> = .03), and the dual change score,  $\chi^2(7) =$ 8.13, p = .321 (RMSEA = .03, CFI = 1.0, SRMR<sub>within</sub> = .02), models provided relatively acceptable fits. To determine whether the addition of the proportional change estimate significantly improved model fit, we once again conducted a scaled chi-square difference test. Results suggest that the addition of the proportional change estimate provided a significant improvement in model fit, scaled  $\chi^2(1) = 5.96, p = .015$ . Thus, the dual change score model was retained. This model provided an intercept estimate of b = 3.66, p < .001, a constant change estimate of b = 2.29, p = .006, and a proportional change estimate of b = -.65, p = .006.

Once more, we used the formula from Grimm et al. (2017), described above, to plot team identification's trajectory. Much like psychological empowerment, these parameters suggest that team identification drops the most between the first wave and the second wave, or the critical point at which standalone teams transitioned to component teams in multiteam systems. Once more, this downward trend continues at a more gradual pace thereafter, before reaching a point of relative stability. Similarly, these estimates suggest that teams higher in team identification in Wave 1 experience larger declines in identification between Wave 1 and Wave 2. Figure 4 provides a visual representation of the dual change score model for team identification, and Figure 5 depicts its estimated trajectory at the mean initial true score (3.66) as well as one (i.e., 4.05) and two (i.e., 4.44) standard deviations above this mean.

**Team cohesion.** The intercept-only model did not provide an acceptable fit to the data,  $\chi^2(11) = 38.58$ , p < .001 (RMSEA = .13, CFI = .00, SRMR<sub>within</sub> = .08), and both the linear and the dual change score models

FIGURE 4 Dual Change Score Model for Team Identification



Notes: \* p < .05. e variables represent residual variances.  $h_0$  represents the intercept/initial true score.  $h_1$  represents the constant change component. x variables within squares represent observed scores. x variables within ellipses represent latent true scores. x variables within triangle/delta in ellipses represent the latent change scores.

failed to converge. Unlike all other variables studied as part of this research, team cohesion showed an initial drop after our event, followed by an uptick, followed by another drop. In other words, team cohesion did undergo change, but this change was nonmonotonic. Thus, cohesion's pattern of change was inconsistent with all three models tested.

We took two additional steps in supplemental analyses to facilitate model convergence. First,

## FIGURE 5 Estimated Trajectory of Team Identification



following Clark and colleagues' (2018) recommendations to release equality constraints on residual variance estimates where theoretically appropriate, we allowed the residual variance at Time 2 to be freely estimated. This was the point in time in which teams transitioned from standalone teams to teams nested in multiteam systems. Second, and given the nonmonotonic change cohesion exhibited, we fit a "quadratic dual change score model" (Hamagami & McArdle, 2019), which, as the name implies, is a dual change score model that includes a quadratic change component. These extra steps led to convergence for all models in a series of four nested models. However, because the post hoc, retrofitted models applied to cohesion are not directly comparable to the other models examined herein (due to the inclusion of a quadratic term and a freely estimated residual variance at Time 2), they are detailed in Appendix B rather than reported here. Also, it should be noted that allowing residual variances to be freely estimated is a relatively new practice, and therefore we call for more research examining how this approach affects parameter estimates (rather than endorse it or heed researchers against it).

Taken together, the results of the models for team properties not informed by behavioral and observable evidence provide additional support for Hypothesis 1, in which we argued that the transition from standalone teams to teams embedded in multiteam systems would have adverse (i.e., connotatively negative) effects on team properties, and provide some support for Hypothesis 3, in which we argued that the change these team properties would undergo as a result of this transition would be dynamic (i.e., more continuous in time, more reactive to events, and nonlinear).

#### DISCUSSION

Dynamics are integral to the study of teams. Indeed, both teams and multiteam systems are frequently referred to as dynamic entities (e.g., Cronin et al., 2011; Kozlowski & Bell, 2003; Mathieu et al., 2017; Shuffler & Carter, 2018; Shuffler et al., 2015), teams researchers have advanced more than 100 models regarding team development (Collins et al., 2016), and systems perspectives pervade the literature (Kozlowski & Bell, 2003; Kozlowski & Klein, 2000). Although these various conceptual models and perspectives have heuristic value, we believe the literature would benefit from a more explicit, testable conceptualization of team dynamics.

We say this because the term "dynamic" has arguably been loosely and inconsistently applied in this domain. Theories regarding team dynamics have discussed everything from feedback loops to stage models, to fluctuations in team properties (Collins et al., 2016), and the terms "emergence," "recursion," and "longitudinal" have become metonyms for the term "dynamic." By (a) leveraging an open systems approach, (b) integrating three specific principles of dynamism from a systems theory based in developmental psychology, (c) highlighting conceptual differences between team properties that are and team properties that are not informed by observable evidence (i.e., differences in temporal anchoring and susceptibility to conformity pressures), and (d) providing empirical evidence of these differences with a contemporary modeling approach, we hope that we have brought the field a bit closer to understanding team dynamics.

#### **Theoretical Contributions**

As it pertains to theoretical contributions, we extended a dynamic theory from developmental psychology (i.e., DST) and applied it to team development after the occurrence of a disruptive event. In doing so, we integrated systems theories based in the organizational sciences (i.e., EST and SAT) to provide a broader conceptual foundation for examining the full developmental consequences associated with the transition to multiteam systems. This extension and integration of DST not only necessitated a new way of conceptualizing team properties. but also allowed us to identify three defining principles of dynamism. This represents a contribution because disproportionately few models of team development have been explicitly tested (Collins et al., 2016; Cronin et al., 2011), and a major limitation associated with the widespread notion that teams are "open systems" is that open systems logics often fail to elicit testable principles (Kozlowski & Klein, 2000). As noted at the outset, a science can only advance by putting forth and testing precise theories (Popper, 1959).

In some respects, the theory we develop herein is consistent with concepts already ubiquitous in the teams literature. Noted throughout, the teams literature considers teams to be open, dynamic systems (Ilgen et al., 2005), much as we do. The team's literature has also documented the implications that events have for teams (Summers, Humphrey, & Ferris, 2012; Tyre & Orlikowski, 1994; Zellmer-Bruhn, 2003), including those associated with changes in interdependence requirements (e.g., Beersma et al., 2009; Hollenbeck et al., 2011; Johnson et al., 2006; Moon et al., 2004). Where we diverge from the broader teams literature is in our (a) specific conceptualization of team dynamics (i.e., the past dictating future change within constructs) and (b) explicit designation of certain team properties as *non*dynamic.

In discussing dynamics, some researchers have focused on "bottom-up," emergent processes. For example, Kozlowski and colleagues (e.g., Kozlowski & Bell, 2003; Kozlowski & Chao, 2012; Kozlowski & Klein, 2000) frequently discuss how higher-level (e.g., team-level) properties emerge over time from individual-level cognition, affect, and behavior, as well as interpersonal interactions among team members. Similarly, Morgeson and Hofmann (1999) explain how collective constructs can emerge through various interactions among individuals. Although we do not disagree with this premise (or provide evidence that discredits it), prior researchers have deemed this bottom-up, emergent perspective static as it ignores recursion, and have even gone so far as to argue that its prominence has stifled research on within-construct evolution (e.g., Cronin et al., 2011).

On the topic of recursion, other researchers have offered alternative models that expressly address the possibility of feedback loops in their discussions of dynamics. For example, Marks and colleagues (2001) examined reciprocal influences between team states and processes, and Ilgen and colleagues (2005) captured iterative cycles in their amendment to the input-process-output model, the inputmediator-output-input model. Although we, again, do not necessarily disagree with these models, they generally provide theoretical insight on what may be considered global dynamics (i.e., how variable X and variable Y reciprocally or iteratively affect each other over time) (Cronin et al., 2011). Considering the dearth of substantive research on team dynamics, we believe that the fresh theoretical perspectives that inform future empirical research should start at a more foundational level. In a sense, we believe we need to walk before we attempt to run if we hope to gain a better understanding of team dynamics. Hence our focus on univariate, within-construct dynamics.

Although the literature on teams rarely studies within-construct evolution, we believe there is a great deal of value in undertaking this work. As noted, a second area where we diverge from prior researchers is in our designation of certain team properties as explicitly *non*dynamic; specifically, those informed by observable, behavioral evidence. Whereas eminent scholars such as McGrath (Arrow, McGrath, & Berdahl, 2000; McGrath & Argote, 2001; McGrath et al., 2000) have broadly labeled teams dynamic, we argue and show that the designation of relatively behavioral team properties as dynamic may be a technical misnomer. Indeed, our theorizing and results suggest that these properties are less (a) contingent upon their past and (b) reactive to the transition to multiteam systems, and thus (c) may respond relatively linearly and adaptively to the new system. Although it is arguably true that prior engagement in a behavior is related to subsequent engagement in that same behavior (e.g., routines), as theory pertaining to performance episodes would suggest, we argue that the designation of observable team properties as "dynamic" may be inappropriate. Accordingly, future researchers may want to be more selective when applying this label to teams and various team phenomena.

## **Methodological Contributions**

As it pertains to methodological contributions, we introduced an analytical technique that allows organizational researchers to test the theoretical dynamism underlying constructs of interest in a modeling language they frequently use (i.e., structural equation modeling; Wang et al., 2016). It should be reiterated that the differences between linear (or constant change) and dual change score models are not purely statistical-the conceptual distinctions we make between dynamic and nondynamic team properties, as specified in our integration of DST, map on to the differences between these models. As such, the differences we achieved in model fit suggest that team properties lacking concomitant observable evidence are more (a) continuous in time, (b) reactive to the transition to multiteam systems, and (c) complex (i.e., nonlinear) than their more behavioral counterparts. In other words, our results suggest that some team properties fulfill the three principles of dynamics derived from DST, and some do not.

Although researchers could use methods such as latent growth modeling to examine change in various team properties, we argue that these methods do not explicitly provide evidence of dynamism. This is because latent growth models are primarily used to determine the overall trajectory of a construct (*patterns* of change are "the focus" of growth modeling; Collins et al., 2016: 67)—they do not provide the detail necessary to claim that a construct is indeed dynamic (i.e., the past predicts *change* in the present). In this sense, these models are purely descriptive (Ployhart & Vandenberg, 2010). Conversely, other analytical techniques, such as autoregressive models, could be used to quantify the effect of past status on future status, but such techniques often "fail to provide information on the absolute trajectories of change over time" (Clark et al., 2018: 172). Thus, neither latent growth curve models nor autoregressive models allow us to test DST's principles in a single analysis like dual change score models do.

Importantly, the adoption of dual change score models by the organizational sciences offers benefits beyond their ability to provide a new way of identifying and testing dynamic development. These models also allow researchers to model change without the calculation of unreliable difference scores, as well as disaggregate trajectories into latent difference segments that can be directly predicted through the inclusion of additional covariates (King et al., 2006). Thus, these models can be used deductively for theory testing or inductively for theory development, as well as used to reliably capture change and examine nuanced trajectories.

#### **Empirical Contributions**

As it pertains to empirical contributions, a search of the literature on multiteam systems suggests a marked imbalance between conceptual and empirical work. Moreover, researchers have yet to examine the component teams nested within multiteam systems as the unit of analysis. Much of the research conducted on multiteam systems takes the perspective of the larger system and seeks to either determine the antecedents of effective multiteam system performance (DeChurch & Marks, 2006; Firth, Hollenbeck, Miles, Ilgen, & Barnes, 2015) or test the generalizability of findings on standalone teams to the multiteam system context (Davison et al., 2012; Lanaj et al., 2013). Thus, our focus on component teams represents an unprecedented effort and heeds calls to examine teams' differential responses to the instantiation of multiteam systems (Shuffler et al., 2015). Generally speaking, and consistent with what would be expected per SAT, this change in work design represented a major exogenous shock to these component teams that harmed them in several ways.

Because there have been no studies that have explicitly examined component teams in multiteam systems, the consequences associated with the transition from standalone teams to component teams may go overlooked. Given that multiteam systems are often considered a solution to practical problems (such as those that require specialization; Shuffler & Carter, 2018), it is important that researchers and practitioners recognize the consequences associated with component teams' loss of autonomy when they undergo this transition. Of relevance to researchers, the failure to observe change over time could have empirical consequencesnamely, the underestimation of effects. Consistent with what Mitchell and James (2001) referred to as "Configuration 3" in their series of theoretical models, we find that the effects of our event may persist (and even build) over time, depending on the construct under consideration. Simple pre- postdesigns would have captured only the immediate change that took place.

#### **Implications and Recommendations for Practice**

Our results also suggest that practitioners need to closely manage the transition from independent teams to interdependent multiteam systems, especially in the beginning. When it comes to team members, there may be an initial overreaction to the experience, but, when it comes to managers, there may be an initial under-reaction to the experience. In terms of team member reactions, our results showed an immediate and steep decline in team properties not informed by observable evidence (e.g., psychological empowerment). Because these properties are quite salient to team members, but perhaps unobservable by management, team members may worry this precipitous decline is going to progress in a continuous fashion over time and management may fail to intervene and address these concerns. Fortunately, we find that this steep slope does not persist in a linear fashion (it instead flattens out and re-stabilizes), and therefore the picture initially painted in the minds of team members is likely worse than what they actually end up experiencing. Much like how internal states of adolescents are highly reactive to the news of parental divorce (e.g., sharp, nonlinear spikes in depression immediately following the event), these initial spikes will flatten out (or plateau) given time.

In contrast, when it comes to managers, there may be an initial under-reaction to the experience because the decline in observable properties (e.g., backup behavior) may not seem extreme at first glance. Although the manager might assume that this small dip will quickly flatten out and re-stabilize, our evidence suggests that this small drop may persist in a linear fashion over time (i.e., it may not flatten out, or plateau), and in fact accumulate. Much as the externalizing behaviors of adolescents may steadily increase in intensity with time (e.g., incremental increases in aggression as adolescents encounter the various pressures associated with the transition to adulthood), changes in behavioral team properties could persist at steady rates and indeed become something to fear.

Another practical implication of this research is that, ironically and perhaps counterintuitively, the component teams that might need the most support during the transition to multiteam systems are those that are the strongest to begin with, given our findings pertaining to the continuity of certain team properties. That is, the teams that experienced the most precipitous drops in empowerment and identification were those that were the "strongest" on these dimensions before our event took place. In contrast, there was a less pronounced negative effect of this change for teams that were not experiencing highly positive cognitive and motivational states. Although a parent might believe that a child who started out low in depression and aggression might be highly resilient to a divorce (i.e., this child "will get over it" fairly easily), this may actually be the child most at risk.

Accordingly, practitioners may wish to be particularly selective in the standalone teams they choose to undergo this transition (assuming they have this discretion). Just as teams should not always be staffed with "all-stars" when there is a need for interdependence, those composing multiteam systems may not want to put all their best standalone teams into one multiteam system. In other words, those teams with heightened levels of identification and psychological empowerment may not necessarily be ideal component team candidates because the transition to multiteam systems represents a greater shock for them.

## Limitations and Directions for Future Research

A limitation of this investigation is that we provided a very a concrete test of a fairly abstract theory. As noted, systems perspectives are notorious for their historical inability to elicit falsifiable propositions (Kozlowski & Klein, 2000), and DST itself has been described as metatheoretical (Witherington, 2007). In contrast, dual change score models have been described as fairly direct tests of dynamism (Grimm et al., 2017; McArdle & Hamagami, 2001). Given the contrast between the rather high-level theorizing we invoke and the relatively concrete tests we employ, we acknowledge that our empirical tests may not do full justice to our broader theoretical model, and thus call for more research testing the principles we derived from DST.

One way this may be accomplished is by examining a broader array of events than we did herein. We elected to focus on a single, specific event-the transition from standalone teams to teams nested in multiteam systems-due to its increasing practical relevance. Although our focus on this particular event provides some evidence for our claims that (a) events precipitate change and influence development, and (b) properties lacking observable, behavioral evidence are more dynamic than properties informed by such evidence, future researchers varying the type of event that takes place may or may not provide additional support. For example, a change in team membership has serious implications for established coordination patterns (Summers et al., 2012), which are arguably behavioral and observable. Given the relevance that this event has for team member coordination, the resultant flux in observable, behavioral properties may be characterized by patterns of change that diverge from those we witnessed.

Another limitation associated with this study is that we approached this investigation with relatively simple models. Although this was intentional (as we were introducing a new modeling technique), researchers can expand univariate dual change score models to more complex, multivariate models that (a) add predictors of the slope and intercept parameters, as well as the change that occurs over discrete time intervals, and (b) consider interrelations among dynamic constructs. Regarding the first possibility, future researchers should integrate time-varying and time-invariant covariates to predict the variables modeled in dual change score models (i.e., the intercept, constant change, and latent change components). For example, research suggests that extraversion is predictive of team member-rated influence early in the team's lifecycle, but not late in the team's lifecycle (Deuling, Denissen, van Zalk, Meeus, & van Aken, 2011). Assuming that we are interested in how extraversion affects fluctuations in influence as the team operates over time, we could apply a dual change score model to team member-rated influence, regress each latent change segment (or "factor"; Clark et al., 2018) on extraversion, and allow this effect to be freely estimated for each individual segment. As another example, research suggests that identification with one's team may be negatively affected by one's social power (Lammers, Galinsky, Gordijn, & Otten, 2012), which is an evolving, dynamic construct (Greer, van Bunderen, & Yu, 2017). Researchers interested in examining how one's social power affects one's identification with his or her team at various points in time could, similarly, apply a dual change score model to identification and regress the latent change segments on one's social power at various timepoints. Such nuanced trajectories are rare in organizational behavior, as dominant approaches for modeling longitudinal phenomena (e.g., latent growth curve models) are unable to reliably capture change over discrete intervals (Grimm et al., 2013).

Regarding the second possibility, the "bivariate dual change score model"-the most commonly fit bivariate latent change score model-allows for "coupling" among variables, or the ability to test whether dynamic constructs reciprocally influence one another over time (Grimm et al., 2017). This model combines aspects of both growth models and autoregressive cross-lag models, capturing withinunit change, differences between units in terms of change, and occasion-to-occasion associations among variables (Grimm et al., 2017). Thus, bivariate dual change score models allow one to test whether variables have reciprocal relationships with one another over time, a possibility proposed by teams researchers specifically (e.g., Mathieu et al., 2017), as well as other organizational scientists more generally (e.g., Mitchell & James, 2001).

Transitioning the focus from limitations to purely future research opportunities, we encourage researchers to (a) continue to employ "counter-normative" within-construct logic (Cronin et al., 2011: 589) and (b) study different forms of change. As it pertains to the first opportunity, prior researchers within our field have highlighted the importance in examining within-unit change. However, the emphasis has often been on general trajectories (Ployhart & Vandenberg, 2010) or the notion that change in some variable persists over time (e.g., "Configuration 3" in Mitchell & James, 2001). We suggest that researchers, instead, attempt to examine how prior levels of a given construct affect subsequent change in that same construct (especially after the occurrence of an event).

As it pertains to the second opportunity, our field needs to examine different forms of change (Ployhart & Vandenberg, 2010). Whereas most researchers examine whether manipulations, interventions, or events are beneficial or detrimental for teams (pretest-posttest designs), we advocate a longitudinal perspective and urge researchers to ask whether these changes are nonlinear or linear (and, similarly, dynamic or nondynamic), perhaps leveraging the dynamic principles we delineated herein. Progression in this realm has been hindered by factors such as a lack of methodological tools, standard academic performance metrics (i.e., quantity of publications, and thus simpler, often static research designs), and the difficulty associated with longitudinal data collection and analysis (Ployhart & Vandenberg, 2010; Waller et al., 2016). Still, a mature field should be asking more complex questions regarding change (Mitchell & James, 2001), especially one that has produced more than 100 different conceptual models.

## CONCLUSION

Empirical research capturing team dynamics, development, and within-construct evolution has fallen far behind purely theoretical work. In an attempt to reduce this discrepancy, we introduced and integrated a new perspective, theory, and analytical approach from developmental psychology, which collectively provide a new way of seeing change in team properties. Developmental psychology is a discipline with a long history of working with temporal-based theories and longitudinal data, and therefore the application of techniques and perspectives common within that field to research questions in our own may prove insightful to both teams researchers, narrowly speaking, and organizational scientists more broadly. That is, we believe that further infusion of this discipline's practices will provide organizational researchers in other topic areas with new ways of seeing, testing, and challenging long-standing assumptions and theoretical frameworks in their areas of interest.

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## APPENDIX A

## Example Mplus Syntax for the Dual Change Score Model for Team Identification ("TID")

USEVAR = TID\_time1 TID\_time2 TID\_time3 TID\_time4; ANALYSIS: TYPE= meanstructure; MODEL:

!Latent true scores; observed scores (i.e., TID\_time1-TID\_ time4), the data, are composed of latent "true scores" (i.e., ITID1-ITID4) and unique scores (error). By using the "BY" command, we create latent true scores (the circles containing  $x_1-x_4$  in Figures 1, 2, and 4) that are free of measurement error ( $e_{x1}-e_{x4}$  in Figures 1, 2, and 4). Loadings are fixed to 1 ("@1") in the syntax.

ITID1 BY TID\_time1@1; ITID2 BY TID\_time2@1; ITID3 BY TID\_time3@1; ITID4 BY TID\_time4@1;

#### 2019

!Allows the mean of first latent true score to be freely estimated. We allow this to be freely estimated as it provides our intercept estimate (or initial true score). This provides the first parameter estimate.

#### [lTID1];

!Allows the variance of the first latent true score to be freely estimated. We allow this to be freely estimated as it provides the variance of our intercept (or initial true score). This provides the second parameter estimate.

#### lTID1;

!The means (first line) and variances (second line) of subsequent latent true scores are constrained to zero ("@0").

#### [lTID2-lTID4@0]; lTID2-lTID4@0:

!The means of all observed scores are fixed to zero ("@0").

#### [TID\_time1-TID\_time4@0];

!Allows residual variances to be estimated, but constrained to equality over time (the purpose served by the constant label "(r)" following each observed score). This provides the third parameter estimate.

TID\_time1 (r); TID\_time2 (r); TID\_time3 (r); TID\_time4 (r);

!Accounts for autoregression; links latent true scores over time, with a regression weight set equal to one ("@1").

ITID2 ON ITID1@1; ITID3 ON ITID2@1; ITID4 ON ITID3@1;

!Creates latent change scores, which are free of measurement error (the circles containing  $\Delta_{x2}$ - $\Delta_{x4}$  in Figures 1, 2, and 4).

dTID2 BY lTID2@1; dTID3 BY lTID3@1; dTID4 BY lTID4@1;

!The means (first line) and variances (second line) of latent change scores are constrained to zero ("@0").

#### [dTID2-dTID4@0]; dTID2-dTID4@0;

!The constant change component; latent basis coefficients traditionally fixed to 1 (Clark et al., 2018; Grimm et al., 2017).

## h1 BY dTID2-dTID4@1;

!Allows the variance of the constant change component to be freely estimated. This is constrained to zero (@0) in the intercept only model, but freely estimated in both the constant change and dual change score models. This provides the fourth parameter estimate. h1;

!Allows the mean of the constant change component to be freely estimated. This is constrained to zero (@0) in the intercept only model, but freely estimated in both the constant change and dual change score models. This provides the fifth parameter estimate.

#### [h1];

!Allows the covariance between the constant change component and initial true score (intercept) to be freely estimated. This is constrained to zero (@0) in the intercept only model, but freely estimated in both the constant change and dual change score models. This provides the sixth parameter estimate.

#### lTID1 with h1;

!Allows for proportional change effects to be estimated, but constrained to equality over time (the purpose served by the constant label "(pe)" following each line of syntax). The latent change score (dTID2-dTID4) is regressed on the latent true score (ltid1-ltid3) of the prior timepoint. This is the portion of the syntax that makes the model a dual change score model. Thus, each of the following lines of syntax would be constrained to zero in the intercept only and constant change or linear models. This provides the seventh and final parameter estimate.

dTID2 on ltid1 (pe); dTID3 on ltid2 (pe); dTID4 on ltid3 (pe);

#### APPENDIX B

# Supplemental Analyses: Quadratic Dual Change Score Model for Team Cohesion

Although the norm is to constrain residual variances to equality over time (which is done by using a fixed label for each and all of these estimates, noted in the syntax in Appendix A), Clark and colleagues (2018) argued that such constraints may be relaxed when there is theoretical reason to do so. Rather than release constraints indiscriminately, we relaxed the equality constraint on the residual variance for the second timepoint only (the point at which teams transitioned to multiteam systems). Additionally, and considering that our data exhibited nonmonotonic change, we integrated a quadratic slope or change term to model what may be referred to as a "quadratic dual change score model" (Hamagami & McArdle, 2019). As the name implies, a quadratic dual change score model is a dual change score model that includes a quadratic change component.

We tested a series of four nested models with this approach: the intercept-only, constant change or linear, quadratic, and quadratic dual change score models. Our quadratic model built on the linear model by allowing the quadratic component, its variance, and its covariances to be freely estimated. Our quadratic dual change score model built on the quadratic model by allowing the proportional change effect to be freely estimated. All four models converged, but neither

## FIGURE B1 Quadratic Dual Change Score Model for Team Cohesion



Notes: \* p < .05. *e* variables represent residual variances.  $h_0$  represents the intercept/initial true score.  $h_1$  represents the constant change component.  $h_2$  represents the quadratic change component. *x* variables within squares represent observed scores. *x* variables within ellipses represent latent true scores. *x* variables within triangle/delta in ellipses represent the latent change scores.

the intercept-only model,  $\chi^2(10) = 34.14$ , p < .001 (RMSEA = .13, CFI = .13, SRMR<sub>within</sub> = .09), nor the linear model,  $\chi^2(7) = 16.31$ , p = .022 (RMSEA = .10, CFI = .66, SRMR<sub>within</sub> = .07), provided acceptable fit statistics. However, both the quadratic model,  $\chi^2(3) = 4.53$ , p = .209 (RMSEA = .06, CFI = .94, SRMR<sub>within</sub> = .03), and the quadratic dual change score model,  $\chi^2(2) = 1.74$ , p = .419 (RMSEA = .00, CFI = 1.0, SRMR<sub>within</sub> = .02), provided acceptable fit. A scaled chi-square difference test suggested that the addition of the proportional change estimate (the quadratic dual change score model) provided a marginally significant improvement in model fit, scaled  $\chi^2(1) = 3.42$ ,

## FIGURE B2 Estimated Trajectory of Team Cohesion



p = .064, over the quadratic model. Considering that these were post hoc, exploratory analyses, we decided to interpret the quadratic dual change score model.

The quadratic dual change score model provided significant intercept, b = 3.84, p < .001, constant change, b = 4.31, p = .016, and proportional change, b = -1.17, p = .013, estimates, but did not provide a significant estimate for the quadratic term itself, b = -0.01, p = .707. We plotted cohesion's trajectory using the following formula:

$$d_{ti} = g_{2i} + \alpha_q \times q_{2i} + \pi \cdot ly_{t-1_i}$$

where  $g_{2i}$  is the constant change component,  $\alpha_q$  is the quadratic basis coefficient (which took on the value of 1, 3, and 5 for  $\Delta_{x2}$ ,  $\Delta_{x3}$ , and  $\Delta_{x4}$ , respectively; Hamagami & McArdle, 2019),  $q_{2i}$  is the quadratic change component,  $\pi$  is the proportional change parameter, and  $ly_{t-1i}$  is the value of the latent variable at the prior point in time.

These results suggest that cohesion dropped the most between the first and second timepoint (the point at which teams transitioned from standalone teams to teams nested in multiteam systems), increased slightly between the second and third timepoint, and dropped slightly again thereafter, thus mirroring the descriptive statistics for cohesion provided in Table 3. Figure B1 provides a visual representation of the quadratic dual change score model for team cohesion (with 12 freely estimated parameters), and Figure B2 depicts its estimated trajectory at the mean initial true score (3.84) as well as one (i.e., 4.27) and two (i.e., 4.70) standard deviations above this mean.