A TEMPORAL PERSPECTIVE ON BOUNDARY SPANNING: ENGAGEMENT DYNAMICS AND IMPLICATIONS FOR KNOWLEDGE TRANSFER

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Inter-firm knowledge flows have important implications for the innovative performance of individuals (Dahlander, O'Mahony, & Gann, 2016; ter Wal, Criscuolo, & Salter, 2017; Tortoriello & Krackhardt, 2010) and firms (Cohen & Levinthal, 1990; Laursen & Salter, 2006). Yet, there is still little scholarly insight into how boundary spanners—individuals who stand at the interface of the firm and its environment (Tushman & Scanlan, 1981)—can increase the inflow of external knowledge. Boundary spanners face the problem of knowledge "stickiness": relevant knowledge is often complex and deeply embedded—and, thus, difficult to transfer between firms (Kim & Anand, 2018; Szulanski, 1996; von Hippel, 1994). While such transfer difficulties are well documented, our understanding of how boundary spanners can facilitate external knowledge flows remains underdeveloped (Tortoriello, 2015).

Prior work suggests that effective boundary spanning entails two functions: engaging with external parties to gather knowledge and engaging within the organization to link external knowledge to internal constituencies (Allen, Tushman, & Lee, 1979). Thus, boundary spanners need to be "stars" of both external and internal communication (Tushman & Scanlan, 1981) and adopt the dual roles of "cosmopolitans" and "locals" (Dahlander et al., 2016; Gouldner, 1957). Some studies suggest that a certain degree of specialization—in either internal or external engagement—is a viable boundary-spanning strategy (Dahlander et al., 2016; Salter, ter Wal, Criscuolo, & Alexy, 2015). Others emphasize that a single individual needs to balance external and internal efforts, while acknowledging that doing both equally well can be tricky (Lifshitz-Assaf, 2018; ter Wal et al., 2017; Tushman & Scanlan 1981). It has thus remained unclear how boundary spanners can best combine external and internal engagement for knowledge-transfer purposes. One potential reason for this lack of understanding is that prior investigations have neglected that boundary spanning is a dynamic process (Majchrzak, Cooper, Neece, 2004). In addition to investigating static engagement levels at particular points in time, we need to pay attention to *engagement dynamics*, especially to the degree to which individuals switch their focus from one engagement type to the other over time. Yet, extant quantitative studies are cross-sectional (Dahlander et al., 2016; Salter et al., 2015; Ter Wal et al., 2017) and have not yet addressed the following question: *How do boundary spanners' engagement dynamics affect external knowledge transfer?*

We address this question by theorizing that the degree to which individuals switch between external and internal engagement across consecutive time periods has important knowledge-transfer implications. We build on the boundary-spanning (e.g. Dahlander et al., 2016; Monteiro & Birkinshaw, 2017; ter Wal et al., 2017; Tushman & Scanlan, 1981) and knowledge-transfer literatures (e.g. Carlile, 2004; Majchrzak et al., 2004; Szulanski, 1996; 2000; Zhao & Anand, 2013), and draw from a cognitive lens (e.g. Cornelissen & Werner, 2014; Dougherty, 1992; Walsh, 1995) to explain under which conditions switching between external and internal engagement is conducive to, or hinders, knowledge transfer. We argue that switching strongly between engagement types generates cognitive advantages for "channeling" knowledge. In contrast, weak or no switching is associated with cognitive advantages for "translating" and "transforming" knowledge. Correspondingly, we adopt a contingency perspective and theorize that the cognitive advantages associated with stronger vs. weaker switching weigh differently, contingent on the stickiness of knowledge to be transferred and the nature of boundary-spanning activities that vary in importance over time. Specifically, we hypothesize that the association between switching and knowledge transfer becomes increasingly negative as the degree to which the knowledge to be transferred is (1) more trans-specialist in nature, (2) has to span a greater organizational distance between source and recipient units, and (3) as boundary-spanning activities shift from scouting and matching (in early phases) to problem re-definition, technical integration, and conflict resolution (in later phases). We argue that under these conditions, knowledge transfer requires more translation and transformation, which benefits from cognitive advantages that we associate with weak or no switching.

To gain a better understanding of boundary spanners' engagement dynamics and knowledge transfer, we studied participants of a multi-firm collaborative innovation program. This research setting is very well suited to answer our research question. Firms assigned designated boundary spanners to the collaborative program with the aim of transferring external knowledge—i.e., knowledge from other firms participating in the program—to the home organization. The program structure comprises four one-week "modules" in which all participating individuals co-locate to intensify their engagement with each other. Given this program structure, all participants switch at the same time and with the same frequency (i.e., when they simultaneously co-locate), allowing us to focus on the association between the *degree of switching* and external knowledge transfer. Fixed-effects panel analyses of eight waves of survey data reveal that the association between switching and knowledge transfer becomes increasingly negative (1) the more boundary spanners access knowledge that is trans-specialist in nature, (2) the greater the organizational distance between source and recipient units, and (3) in later phases of the boundary-spanning process.

We contribute to the literature on boundary spanning and knowledge transfer by theorizing and showing that the benefits of engaging both externally and internally depend on the underlying engagement dynamics. Our findings add to extant work that has developed important insights into how differences *between* boundary spanners—for instance, differences in engagement levels or network characteristics—influence knowledge transfer (Dahlander et al. 2016, Obstfeld, 2005; Reagans & McEvily, 2003; Salter et al. 2015; Tortoriello, Reagans, & McEvily, 2012). By shifting the focus to the degree of change *within* boundary spanners—i.e., how much they switch between external and internal engagement across consecutive time periods—we provide a new lens to look at the effectiveness of boundary-spanning individuals as conduits of external knowledge. Further, combining the knowledge-transfer literature with a cognitive perspective, we provide a framework along the dimensions of (1) trans-specialist knowledge, (2) organizational distance, and (3) boundary-spanning phases that explicates the circumstances under which switching between external and internal engagement hinders knowledge transfer.

THEORETICAL BACKGROUND AND HYPOTHESES

Knowledge Transfer across Boundaries

The benefits of boundary spanning in terms of transferring knowledge across inter- (Dahlander et al., 2016; Lifshitz-Assaf, 2018) and intra-organizational boundaries (Bechky, 2003; Carlile, 2004; Tortoriello et al., 2012) are well established. Prior work has investigated a range of antecedents and conditions of knowledge-transfer effectiveness. For instance, transfer effectiveness depends on the strength of the ties between sources and recipients (Hansen, 1999; Reagans & McEvily, 2003); the nature of these ties (Hansen, 2002; Obstfeld, 2005; Tortoriello & Krackhardt, 2010; Zhao & Anand, 2013); and the range, cohesion, and social capital engrained within a network (Tortoriello et al., 2012). In addition to individual boundary spanners, effective cross-boundary knowledge transfer can require a collective bridge whereby "all relevant members of a recipient unit communicate with and learn from all relevant members of a source unit, with a minimum possible number of ties" (Kim & Anand, 1996, p. 1966). Transfer effectiveness further depends on the characteristics of the recipients, such as their willingness and ability to absorb external knowledge (Cohen & Levinthal, 1990; Katz & Allen, 1982; Lane & Lubatkin, 1998), and the characteristics of the sources, such as their motivation and ability to engage in the transfer (Szulanski, Ringov, & Jensen, 2016; Zhao & Anand, 2009).

Studies focusing on the underlying mechanisms of knowledge transfer (Lingo & O'Mahony, 2010; Majchrzak et al. 2004; Monteiro & Birkinshaw, 2017; Szulanski 1996; 2000) complement this structural line of research. According to an information-processing approach (Lawrence & Lorsch, 1967), knowledge can be *channeled* across boundaries if there is a shared and stable syntax across the boundary (Carlile, 2002). When knowledge is channeled, the focus is on knowledge "processing" through storage and retrieval (Carlile, 2004). When there is a lack of common ground between external and internal parties, however, knowledge needs to be *translated* to create common meaning (Carlile, 2002; 2004). Moreover, when accumulated knowledge is at stake (Carlile, 2004) and recipients are reluctant to accept external knowledge (Katz & Allen, 1982), knowledge *transformation* is required. This entails reconceptualizing the problems about which external knowledge is sought (Bechky, 2003), assessing how knowledge on one side of the boundary generates consequences for knowledge on the other side, and transforming "current" knowledge to create common interests (Carlile 2004). We argue that these mechanisms – channeling, translation, transformation – provide a useful lens for theorizing about the association between boundary spanners' engagement dynamics and knowledge transfer.

Boundary Spanners' Engagement Dynamics

Boundary-spanning individuals facilitate knowledge transfer across organizational entities by engaging externally and internally (Aldrich & Herker, 1977; Allen et al., 1979; Keller & Holland 1975; Tushman 1977; Tushman & Scanlan, 1981). While external engagement creates a larger and more diverse pool of potentially relevant knowledge, internal engagement is required to share external knowledge with colleagues and ensure its diffusion. Accordingly, higher levels of external and internal engagement yield positive outcomes, such as individual-level innovativeness (Dahlander et al., 2016; ter Wal et al., 2017; Salter et al., 2015). Yet, prior work also suggests that the relationship between engagement and relevant outcomes is more complex. For instance, too wide a range of external engagement may yield negative effects due to increasing cognitive efforts and coordination costs associated with the use of diverse sets of external knowledge (Salter et al., 2015). And while simultaneously engaging in both external and internal engagement is difficult for a single individual (Dahlander et al., 2016; Lifshitz-Assaf, 2018; Tushman & Scanlan 1981), combining both engagement types may yield synergies as high internal engagement facilitates the "repackaging" of a large amount of external knowledge and will make it more meaningful to insiders (ter Wal et al., 2017). Empirically, results regarding diminishing returns and synergistic effects of external and internal engagement have been mixed (Dahlander et al., 2016; Salter et al., 2015; ter Wal et al., 2017).

We aim to shed new light on the relationship between boundary spanners' engagement and knowledge transfer by shifting the spotlight from engagement *levels* to engagement *dynamics*. While prior work has examined between-person differences (Dahlander et al., 2016; ter Wal et al., 2017)—thus adhering to the logic of engagement levels—it has not yet addressed within-person engagement dynamics. We argue that beyond the levels of external and internal engagement and their potential curvilinear and synergetic effects, it is the *switching* between external and internal engagement across consecutive time periods that has important knowledge-transfer implications. Note that there can also be a change in levels across consecutive time periods without a switch. For instance, a boundary spanner could have high external & high internal engagement at time t and low external & low internal engagement at t+1. We are not interested in this change in levels but in the switching *between* external and internal engagement over time. As such, switching can be conceptualized twofold: (1) the frequency with which individuals switch, i.e., *how often* or in which intervals individuals switch between external and internal engagement, and (2) the degree of the switch at each switching occasion, i.e., *how much* individuals switch from focusing relatively more on one engagement type during a time period (t) to focusing relatively more on the other engagement type during the next time period (t+1). We focus on the latter.

Switching—i.e., focusing more on one type of engagement over the other at different points in time—is often triggered by mobility. To tap into locally embedded external knowledge, boundary spanners tend to physically move across boundaries. Examples include participation in trade shows or conferences (Chai & Freeman, 2019), secondments to short-term assignments with a partner organization (Kolympiris, Hoenen, & Klein, 2019), temporary and often repeated co-location in scouting units (Monteiro & Birkinshaw, 2017; Tippmann et al., 2017), or collaborative innovation programs (Furr et al., 2016). Such programs are the context of our study. Prior work shows that physical proximity increases personal engagement (Almeida & Kogut, 1999; Chai & Freeman, 2019; Rosenkopf & Almeida, 2003). Thus, individuals have a switching tendency under conditions of mobility such that they prioritize external engagement during co-location and switch to internal engagement during periods at home. Hence, switching is a widespread phenomenon in boundary spanning. Yet, we know little about its implications for knowledge transfer.

Even when boundary spanners have identical average engagement *levels*, they may differ in how they temporally arrange their engagement activities. On the one hand, they may strictly focus on external engagement at one point in time (e.g., during co-location) and on internal engagement at a subsequent point in time (e.g., when they return home). These individuals switch strongly between external and internal engagement. On the other hand, individuals may maintain more of a balance in their allocation between external and internal engagement across consecutive time periods. An example helps to illustrate. Ann and Christian are boundary spanners participating in the same collaborative innovation program. They differ in how they temporally allocate their external and internal engagement across two consecutive time periods. Ann, at time t (during co-location), engages intensively with seven external knowledge sources and one internal unit. Note that we are interested in both the number and the intensity of external knowledge sources as indicators of engagement. When she returns home (t+1), she remains engaged with just one external source and increases her internal engagement to seven units. Ann thus switches strongly between external and internal engagement over time. Christian, during co-location (time t), engages with five external knowledge sources and three internal units. When he returns home (t+1), he stays connected with three external knowledge sources and increases his internal engagement from three units to five. Christian's degree of switching across the two time periods is weaker.

In such a situation, cross-sectional studies would provide an incomplete picture. Considering only time t, one could theorize that Ann benefits from her higher level of external engagement (i.e., 7) (e.g., Dahlander et al. 2016), whereas Christian may benefit from the higher synergy between external and internal engagement (i.e., 5 and 3) (e.g., ter Wal et al. 2017). When combining both time points (t and t+1) into an aggregated measure of engagement levels across a longer time period (as is typical for cross-sectional surveys), one would assume the same "average" levels of external and internal engagement (i.e., 4 and 4) for Ann and Christian, thus predicting identical knowledge transfer implications – all else equal. By investigating multiple consecutive time periods, we shift the focus to the degree of switching as a dynamic aspect of a boundary spanner's engagements that adds to our existing understanding of engagement levels and synergies (Dahlander et al., 2016; Salter et al., 2015; ter Wal et al., 2017). While Ann and Christian switch with the same frequency (triggered by their participation in the same collaborative program with periods of co-locating and returning), they differ in *how much* they switch between external and internal engagement on each switching occasion—i.e., the degree of switching.

Drawing from a cognitive perspective, we theorize why, and under which conditions such engagement dynamics shape knowledge transfer. In the following, we argue that engagement dynamics activate different mental knowledge structures and forms of knowledge processing, which differ in how they support the channeling, translation, and transformation of knowledge.

A Cognitive Perspective on Engagement Dynamics

Knowledge is transmitted across boundaries via the intervention of a cognizing mind (Ringberg & Reihlen, 2008). Knowledge-transfer mechanisms, such as channeling, translation, and transformation, involve a sense-making aspect, as boundary spanners interpret and act upon certain cues in their context (Birkinshaw, Ambos & Bouquet, 2017; Weick, 1995). Thus, spanning organizational boundaries requires the development of new cognitive knowledge structures or schemas (Roberts & Beamish, 2017; Weick, 1979). A knowledge structure is a mental template that individuals impose on an information environment to give it form and meaning (Kaplan, 2011; Walsh, 1995; Weick, 1995) and that directs and guides information processing (Cornelissen & Werner, 2014).

Drawing from a cognitive perspective, we argue that individuals who focus more on just one type of engagement during a specific time (before they switch to the other engagement type) are likely to employ a cognitive knowledge structure that segments knowledge more strictly according to its source (external or internal). Individuals need to make conscious decisions regarding how to focus their limited information-processing capacity (Ocasio, 2011). Individuals' foci of attention are "situated" within—and shaped by—the network of channels within which they interact (Ocasio & Joseph, 2005). Thus, the more individuals focus on just one (e.g., external) engagement type at a certain point in time (e.g., before they switch to internal engagement), the more they will focus their information-processing capacity on these (e.g., external) stimuli and organize incoming (e.g., external) information into a rather distinct knowledge structure. This is in line with prior work that suggests that knowledge structures are formed by experience (Fiske & Dyer, 1985). Since knowledge is interpreted differently in intra- and interorganizational "thought worlds" (Dougherty, 1992), structural segmentation allows individuals to cognitively isolate information and to concentrate on demands more singularly (Tempelaar & Rosenkranz, 2019). Individuals with segmented knowledge structures can thus engage in the *categorical processing* of knowledge, which involves autonomic and less-mindful categorization of incoming stimuli (Levinthal & Rerup, 2006; Ringberg & Reihlen, 2008).

Categorical processing allows boundary spanners to process stimuli from their external and internal engagement activities more quickly by keeping them rather separate in their segmented "external" and "internal" mental models. This is because such schemata facilitate the interpretation of incoming information, which can then be processed in a conceptually fluent manner (von Hippel et al., 1993; 1995). As categorical processing facilitates selective attention, it enables individuals to ignore irrelevant information and devote their attention only to relevant information (von Hippel et al., 1993). Categorical processing can thus be more efficient as it facilitates the encoding of both category-consistent and category-inconsistent information even when a boundary spanner's attentional capacity is low (Macrae & Bodenhausen, 2000). In addition, focusing attention more singularly on a particular knowledge source (i.e., external or internal) enables individuals to retrieve a larger quantity of information (von Hippel et al., 1993) with less effort (Haas & Ham, 2015). This is particularly important for knowledge channeling when knowledge primarily needs to be accessed, stored, and then retrieved for internal dissemination (Szulanski, 2000). Let's return to Ann: as she focuses more on external engagement at time t and then switches strongly to internal engagement at time t+1, she is more likely to segment stimuli from external and internal sources. With this engagement dynamic, she can quickly and efficiently channel knowledge, as it requires less effort to categorically process incoming information and retrieve it for internal dissemination.

Individuals who switch less or not at all tend to keep engaging with *both* external and internal sources across consecutive time periods. They are less likely to segment knowledge from the two sources and more likely to construct a blended knowledge structure in which structures and elements from two input mental frames are combined (Cornelissen & Durand, 2012). On the one hand, blending is cognitively more complex (Smith & Lewis, 2011) as individuals proactively and deliberately engage with stimuli rather than processing them automatically into separate categories (Ringberg & Reihlen, 2008). Without a clear (segmented) knowledge structure, individuals must rely on a more effortful, piecemeal integration of available information (von Hippel et al., 1993). On the other hand, blending enables individuals to derive *novel inferences* through a more abstract knowledge structure that comprises elements from both external and internal sources (Cornelissen & Werner, 2014; Kaplan, 2011). The emerging representations and inferences developed in the blended knowledge structure can lead boundary spanners to change their view of the corresponding situation and develop inferences not provided by the input (Cornelissen & Durand, 2012). As such, blended structures enable more reflective (rather than categorical) knowledge processing, during which individuals combine mental models in more mindful and novel ways (Levinthal & Rerup, 2006). Abstraction and novel inferences, in turn, facilitate the translation and transformation of knowledge (Ringberg & Reihlen, 2008). Following this logic, Christian, from our example above, who does not switch so strongly between external and internal engagement, has advantages for knowledge translation and transformation as he is more likely to blend stimuli from external and internal sources and derive novel inferences.

In sum, we combine a cognitive perspective on engagement dynamics with a knowledge transfer perspective. We argue that individuals who switch strongly between external and internal engagement are likely to exhibit a more segmented knowledge structure and apply categorical thinking, which facilitates quick and efficient processing of external and internal stimuli, thus supporting knowledge channeling. In contrast, individuals who switch less or not at all are more likely to have a blended knowledge structure and engage in reflective knowledge-processing that facilitates novel inferences and thus, knowledge translation and transformation. Such knowledge structures and processing mechanisms are difficult to identify directly (Walsh, 1995) and we thus propose them as unobserved mechanisms that help to explain the association between engagement dynamics and knowledge transfer.

In the following, we adopt a contingency perspective and theorize that the cognitive advantages associated with stronger vs. weaker switching weigh differently, contingent on the stickiness of knowledge to be transferred and on the varying nature of boundary-spanning activities in different phases of the boundary-spanning process. As the cognitive perspective suggests advantages of both segmented knowledge structures (for knowledge channeling) and blended knowledge structures (for knowledge translation and transformation), we do not hypothesize a main association of the degree of switching but develop more nuanced relationships between switching and knowledge transfer under different conditions.

A Contingency Framework of Engagement Dynamics and Knowledge Transfer

Although all transfers of knowledge require some degree of effort, some transfers experience more difficulty than others, given different degrees of knowledge "stickiness" (Szulanski, 1996; 2000; von Hippel, 1994). The characteristics of the knowledge that is subject to the transfer are amongst the most important determinants of transfer difficulty (Kim & Anand, 2018; Szulanski, 2000; Szulanski et al., 2016). A key knowledge characteristic that has been identified as a contingent factor in knowledge transfer is knowledge complexity (Kim & Anand, 2018; Rivkin, 2005; Zhao & Anand, 2013)–the number of knowledge elements and the degree to which these elements interact with each other and are thus interdependent (Rivkin, 2005; Simon, 1962; Zander & Kogut, 1995). We argue that under conditions of higher knowledge complexity, simple "storage and retrieval" becomes difficult and that more sophisticated transfer mechanisms are required. This decreases the cognitive advantages of strong switching (i.e., knowledge segmentation and categorical processing) and elevates the cognitive advantages of weak/no switching (i.e., knowledge blending and reflective processing).

A salient component of knowledge complexity is the degree to which knowledge is trans-specialist in nature (Postrel, 2002; Zhao & Anand, 2013). While within-expertise knowledge draws from a single area of expertise, trans-specialist knowledge draws from multiple expertise areas with inherent interdependencies (Kim & Anand, 2018; Postrel, 2002; Zhao & Anand, 2013). When the knowledge to be transferred is primarily within-expertise, it is less complex since knowledge can be more easily codified (Reagans & McEvily, 2003) and independent chunks of knowledge can simply be channeled between source and recipient units (Kim & Anand, 2018). Boundary spanners can then store and retrieve this codified knowledge and thus, may afford a segmented knowledge structure and categorical processing that is facilitated by stronger switching between external and internal engagement.

Trans-specialist knowledge, however, is more difficult to codify (Reagans & McEvily, 2003; Szulanski et al., 2016), requires more translation (Carlile, 2004), and is, as such, harder to automatically process and categorize via a segmented knowledge structure. Thus, the categorical processing associated with stronger switching becomes detrimental when knowledge is more trans-specialist in nature. In addition, when knowledge stems from multiple expertise areas, interdependencies are likely to arise such that decisions or activities in one area may impact the effectiveness of decisions or activities in another expertise area (Kim & Anand, 2018; Reagans & McEvily, 2003). To effectively transfer such trans-specialist knowledge, boundary spanners need to develop a cross-expertise understanding regarding how such decisions or activities of one specialist with a certain expertise may impact the effectiveness of the decisions or activities of another specialist with different expertise when they are working on an interdependent task (Zhao & Anand, 2013). Understanding these interdependencies and assessing how knowledge on one side of the boundary generates consequences for knowledge on the other side is the essence of knowledge transformation. Through a blended knowledge structure, individuals will be better able to see the broader template of interactions among different expertise areas (Reagans & McEvily, 2003; Zhao & Anand, 2013) and integrate different perspectives (Levinthal & Rerup, 2006). When individuals do not switch but, instead, maintain more of a balance between the two engagement types across consecutive time periods, they are more likely to continuously reflect upon their own as well as external and internal models. This reflective processing improves knowledge transfer when multiple divergent mental models are involved (Ringberg & Reihlen, 2008), such as in the case of trans-specialist knowledge transfer. Hence, we expect that:

H1: The relationship between switching and knowledge transfer becomes increasingly negative, the more the knowledge to be transferred is trans-specialist.

Given that knowledge is embedded in practice (Bechky, 2003), the organizational distance between source and recipient units further determines knowledge stickiness and thus, transfer difficulty (Simonin, 1999; Szulanski, 1996). Organizational distance can be described in terms of the degree to which organizations fundamentally differ in their institutional heritage, routines of behavior, practices, values, and professional language (Kogut & Zander, 1992; Simonin, 1999). A smaller organizational distance between source and recipient units implies that knowledge is less sticky and boundary spanners can focus relatively more on "simply" channeling and transmitting knowledge across the boundary. As both sides of the boundary possess similar routines, practices, and language, knowledge transfer occurs with fewer problems and requires less translation and transformation. It is under these conditions that boundary spanners may afford to draw from cognitively less demanding knowledge segmentation and categorical processing.

However, the greater the organizational distance between source and recipient units, the stickier the knowledge. The greater the differences between source and recipient in terms of institutional environment (Jensen & Szulanski, 2004; Gutierrez-Huerter et al. 2022), size (Baughn et al., 1997), corporate, organizational, and professional culture (Choi & Lee, 1997), or communication practices (Szulanski, 1996), the greater the difficulty of transferring knowledge. Transfer difficulty impedes individuals' abilities to directly channel the embedded knowledge to the other side of the boundary (Carlile, 2002; 2004; Lane & Lubatkin, 1998). The greater the distance that the individual spans, the more translation effort is required, given differences in language, symbolic communication, shared meaning, and heuristics (Grant, 1996; Zhao & Anand, 2013). Similarly, a lack of common cognitive schemas and frameworks (Roberts & Beamish, 2017; Weick, 1979) between source and recipient units requires that boundary-spanning individuals apply blended knowledge structures and reflective processing to facilitate the transformation of knowledge. Hence, we expect that:

H2: The relationship between switching and knowledge transfer becomes increasingly negative, the greater the organizational distance between source and recipient units.

Prior work has identified different boundary-spanning *activities* and has shown how these activities vary in importance across multiple phases of the boundary-spanning process (e.g., Gutierrez-Huerter, Moon, Gold, Chapple, 2020; Majchrzak et al., 2004; Monteiro & Birkinshaw, 2017). Early phases are characterized primarily by knowledge scouting (Hansen, 1999), evaluating the fit of external knowledge (Gutierrez et al., 2020; Monteiro & Birkinshaw, 2017), and making connections between actors who are unaware of each other's existence (Birkinshaw et al., 2017). Following Carlile's (2004) terminology, these activities primarily require information transfer, albeit some translation may be required if the novelty of knowledge is high (see also Birkinshaw et al., 2017). The main objectives in the early phases are to identify relevant external knowledge and channel it to internal units to enable the matching of external knowledge with internal needs (Szulanski, 1996).

In later phases of the process, activities shift towards more in-depth discussions about technical integration or redefining problems for which the knowledge was initially sought (Szulanski, 1996), re-architecting knowledge (Gutierrez et al., 2020), and resolving conflict and tensions (Birkinshaw et al., 2017; Schotter & Beamish, 2011). These constitute deeper activities that, following Carlile's (2004) terminology, require more translation and transformation (see also Tippmann et al., 2017). Once connections are established and facilitated, boundary spanners increasingly focus on overcoming different worldviews on each side of the boundary and reconciling different interests (Birkinshaw et al., 2017). Thus, as primary activities shift from scouting and matching towards problem re-definition, integration, and conflict resolution, the importance of channeling decreases and the importance of knowledge translation and transformation increases.

Studies across different boundary-spanning contexts provide empirical support for the varying importance of activities, as the boundary-spanning process progresses. For instance, Monteiro and Birkinshaw (2017) investigate a scouting unit tasked with transferring external knowledge from startups in Silicon Valley to internal business units in Europe. The scouting unit started by channeling knowledge about novel technologies and business models. Thereafter, it continued to deliver value by translating and transforming knowledge about whether and how external technologies and business models could be implemented at the internal units. Birkinshaw et al. (2017) study the boundary-spanning activities of headquarter executives and find that early in the process, the focus is on making connections, whereas during later stages, the focus shifts to overcoming different worldviews. Gutierrez et al. (2022) study the sequence of micro processes undertaken by individuals who transfer knowledge between headquarters and subsidiaries and discover that, over time, the intensity of translation and transformation activities increases. Hence boundary-spanning activities vary in relative importance over time and prior work suggests that activities require more translation and transformation efforts during later stages of the boundary-spanning process.

Building on this work and combining it with our cognitive perspective on engagement dynamics, we argue that during later phases, which require more knowledge translation and transformation, individuals benefit from switching less and forming blended knowledge structures. Accordingly, segmented knowledge structures associated with stronger switching become detrimental in later phases of the boundary-spanning process. We therefore hypothesize:

> *H3: The relationship between switching and knowledge transfer becomes increasingly negative as the boundary-spanning process progresses.*

METHODS

Research Context and Design

We were looking for a setting that would allow us to trace and measure boundary spanners' engagement dynamics and investigate their implications for knowledge transfer. We selected a collaborative innovation program embedded in the energy sector. Firms assigned designated boundary spanners to this program with the aim of transferring external knowledge—i.e., knowledge from other firms participating in the program—to the home organization. All boundary spanners were subject to the same program structure that comprised four one-week "modules" during which all participating individuals met in one place to intensify their engagement with each other. Given this program structure, all participants switched at the same time (i.e., when they simultaneously co-located and returned home), allowing us to focus on the association between the *degree of switching* and external knowledge transfer.

The program is comprised of 10 international energy utilities and 15 technology startups. Collaborative innovation has become a strategic necessity for energy utilities, which must cope with rapid changes in the industry, given the simultaneous rise of renewable electricity generation and decentralized energy systems (Bumpus & Comello, 2017). The participating startups are relatively mature, with an established product line, revenues, and business model in the areas of renewables, smart grids, energy storage and management, predictive maintenance, cybersecurity, and electric vehicles. To them, the program offers a platform where they can access the knowledge of some of the world's largest electricity utilities and learn about their customer needs, technologies, markets, and business models. Moreover, startups can access the knowledge of their peers, which have all been deemed "rising stars" in the industry through the prestige afforded to them by the program. While a large part of the knowledge transfer happens in informal settings and discussions, participants also form collaborative pilot projects in which utilities test startups' offerings by integrating their solutions within a new market. While most of these projects take place on a bilateral basis, learnings are shared among all other program participants. Taken together, the program is an organized venue that offers both startups and utilities the opportunity to tap into valuable external knowledge sources that would otherwise be difficult to access. This purpose of the program is also illustrated in the following quote:

"We want to find startups and do something that involves real money, real time and create impact to the business [and for this] we have to be involved in the program. It's a very powerful way, like rolling a hand grenade [i.e., external knowledge] into your company to get the innovation started. I think the opportunity to interact with a whole bunch of other global energy companies is enormously valuable because you can test, you can benchmark, you can share [knowledge]." (Innovation manager, participating utility)

Since its initiation in 2017, the collaborative innovation program has run annual programs (each year with a new startup cohort). Our study is set in the second edition in 2018. Using the second edition allowed us to operationalize variables based on in-depth contextual knowledge that we gathered through qualitative field research in the first edition of the program. The 10 utilities jointly selected 15 startups out of ~500 applications. In this process, the utilities' innovation managers analyzed the startups' applications and gathered input from business units about potential interests and needs. Finally, innovation managers of all 10 utilities rated the startups and discussed the selection of the final 15. This selection was based on the written material provided by startups in their applications. As such, the selection process already entails some degree of scouting and knowledge matching. However, most of the scouting and matching happens as part of the program when personal interactions between the participating firms and their boundary spanners begin.

The six-months program includes four "modules" during which individuals from each of the 25 firms are synchronously co-located at a designated geographic location for one week each (see Figure 1). Modules were scheduled to occur at equal intervals from each other. Each firm committed to participating in all modules; each startup sent two to three individuals, and each utility sent two to five. On rare occasions, utilities sent guests (e.g., a CEO to give a keynote speech); however, the set of continuous module participants stayed constant throughout the program. While some activities were pre-structured (e.g., company presentations), individuals self-determined the approach and intensity of their engagement (e.g., booking meetings) with other firms. Further, participants self-determined the approach and intensity of engagement with individuals and units who were recipients of knowledge but did not participate in the program (e.g., business-unit leaders of the home organization). The timing and duration of co-location/home periods is equal for all participants, allowing us to compare how individuals differ in how they temporally allocate their external and internal engagement in the same well-defined setting where the frequency of switching is the same for all individuals. We measured our dynamic variables within a narrow time window at the end of co-location (home) periods (see Figure 1) and clearly instructed participants to reflect only on their engagement since the start of each period. We thus capture individuals' external and internal engagement across clearly separated temporal periods.

INSERT FIGURE 1 ABOUT HERE

Data

We conducted a longitudinal survey following Dillman's (2007) "Tailored Design Method," administering eight survey waves to program participants. Two of the authors were present at all modules to gain a better understanding of the context, administer the surveys, and observe participants' behavior (~300 hours). Further, we conducted 26 semi-structured interviews (30–60 minutes) in phases of co-location, home, and after program conclusion. This helped us to better understand the research context, validate our operationalizations, and explicate the underlying mechanisms of our results. We pre-tested the survey with 20 academics and five practitioners. Across all eight surveys, we collected 398 out of 736 possible responses from 92 individuals, yielding an overall response rate of 54%. After excluding participants who responded to the survey only once, the final sample consists of 382 observations from 76 individuals representing all 25 firms in the program. The average number of completed surveys per individual was five (out of eight) and we collected, on average, 48 responses per survey wave. Most individuals are 41–50 years old with an average tenure of 7.8 years. Sample distribution of individuals across startups and utilities is ~50-50. For startups, typically, two to three program participants are senior managers—sometimes accompanied by a technical or business expert. For utilities, at least one senior manager is typically accompanied by two or three business or technical experts. The online appendix details the roles and demographics of representatives per firm, demonstrating that all the firms selected similar compositions of individuals as program participants. Both startups and utilities mostly sent highly educated employees—33% held a PhD or MBA, and the remainder had BSc/MSc degrees. The advanced technological/business expertise of participants, on average, indicates that firms selected individuals who had relevant technology and business acumen.

We conducted statistical and procedural remedies to mitigate sources of common method bias (Podsakoff et al., 2012). First, we addressed "item characteristic" and "item context" biases by giving detailed instructions; ensuring anonymity; applying reverse and disperse ordering of independent (IVs) and dependent variables (DVs); and extensive pre-testing. Second, by directly accounting for the location where individuals fill out the survey with our research design, we mitigated "measurement context" biases. Third, "common rater" bias is reduced, as it is unlikely that individuals develop implicit longitudinal theories. Accordingly, Harman's (1976) single-factor test indicates that no single factor accounts for a large portion of the variance. Finally, to test for non-response bias, we compared individuals who responded to all (many) surveys with those who responded to one (few) survey(s) and delayed vs. non-delayed respondents on key variables with t-tests; we found no significant differences. Yet, as we rely on survey data, we can only mitigate the risk of these biases, but cannot rule out endogeneity. Therefore, we aim to reveal meaningful associations between engagement dynamics and knowledge transfer rather than establish causal relationships.

Measures

DV: Knowledge transfer. To measure *knowledge transfer*, we followed Schulz (2001) to assess the amount of technological, market, and business-model knowledge (Cronbach's alpha = 0.80) that boundary spanners transferred from external knowledge sources that were part of the program to the home organization at each measurement occasion. An introductory sentence to the three-item question explicates that we are asking about knowledge accessed from external sources (i.e., other firms) in the program: "*We would like to assess the extent to which you were able to transfer knowledge from the [collaborative innovation program] to [your organization] since the end of [e.g., module 3]."* The three question items re-emphasize the assessment of knowledge transfer from the external innovation program to the home organization. For instance, one sample item is: *"I have been providing a great deal of knowledge about technologies developed in [the collaborative innovation program] to individuals inside [my organization]."* While prior work often relies on patents as performance indicators of boundary spanners, other studies highlight the importance of measuring the flow of knowledge directly with self-reported survey scales (Tortoriello et al., 2012; Wang, 2015).

IV: Degree of switching. To capture the degree to which boundary spanners switch between external and internal engagement, we first measured their external and internal engagement in each survey wave with scales adopted from prior studies (Dahlander et al., 2016; Salter et al., 2015; Wang 2015). In each wave, we provided respondents with lists of external parties (i.e., other firms in the program) and internal parties (i.e., functions within their own firm) and asked them to indicate those that they had engaged with during the specified time period. Second, they received a generated list based on the selected parties and were asked to assess the intensity of engagement with each one on a seven-point Likert scale. As we are less interested in the interplay between the breadth and intensity of engagement, we combined both items into a single measure by creating a count variable with an intensity cut-off value (see also Laursen & Salter, 2006). Thus, we constructed *External (Internal) engagement* as the number of external (internal) parties an individual *intensively* (moderately high, high, or very high) engaged with in each time period. For example, a value of 2 for *External engagement* implies that an individual intensively engaged with two external parties in the program in a given time period. H1 suggests that—on top of internal and external engagement *levels*—it is the *degree of switching* between the two engagement types across consecutive time periods that is associated with knowledge transfer. To capture the *Degree of switching*, we first subtracted the number of internal engagement parties from the number of external engagement parties at each point in time—i.e., the focus on external vs. internal engagement. Then we constructed the *within-person change* between two consecutive time periods by calculating the absolute change and dividing it by the total number of external and internal engagement parties.

(1) $Degree\ of\ switching = \frac{absolute\ ((External{-}Internal\ Engagement\ at\ time\ t) - (External{-}Internal\ Engagement\ at\ time\ t{-}1))}{Total\ number\ of\ external\ and\ internal\ engagement\ parties}$;

To illustrate the measure, we revisit our example of Christian and Ann. When Ann goes to the first module (time t) she focuses on external engagement and intensively engages with four external parties and just one internal party. After she returns home from the module (time t + 1) she switches strongly to internal engagement, engaging intensively with just one external party, but four internal ones. The strong switching would be captured in an absolute change of 6 in the focus on external vs. internal engagement from time t (external – internal = 4 – 1 = 3) to time t + 1 (external – internal = 1 – 4 = –3). Divided by the total number of engagement parties (external + internal = 5), the value for the *switching* variable for Ann at time t + 1 would be 6/5 (1.2). Christian switches less strongly, as he engages with three external and two internal parties at time t and two external and three internal parties at time t+1. This engagement dynamic would be captured in a lower absolute change of 2 in the focus on external vs. internal engagement from time period t (external – internal = 3 – 2 = 1) to t + 1 (external – internal = 2 – 3 = –1). Divided by the total number of engagement parties (external + internal = 5), the value for the variable for Christian at time t + 1would be 2/5 (0.4).

Moderators: Trans-specialist knowledge. To capture the extent to which individuals access knowledge that is trans-specialist in nature, we follow prior work (e.g., Reagans & McEvily, 2003; Zhao & Anand, 2013) and rely on two input measures. First, based on our field research, we identified relevant knowledge areas, which we included in an eight-item survey question that asked each individual whether they were "*comfortable addressing (1) technical aspects associated with the following [8] areas* [Yes/No]:" Clean Energy, Smart Grids, Energy Efficiency, Energy Management, E-Mobility, Customer Experience, IoT and Digitalization, Energy Access. Second, we rely on a proxy of the areas of expertise that a particular external knowledge source (i.e., firm) in the program represents. To create this proxy, we aggregated individuals' measures to the firm level by using the average expertise of all individual participants who belonged to a specific firm in our sample.

Based on this information, for each individual at each point in time, we could determine the extent to which they engaged with external parties (i.e., firms) that were within their own expertise vs. trans-specialist. We constructed the variable by accumulating the number of expertise areas of a boundary spanner's engagement parties that did not overlap with their own expertise at a certain point in time. To ensure that the measure is not inflated by the total number of engagement parties, we divided the number of non-overlapping expertise areas by the total number of external engagement parties.

The following example illustrates the construction of this variable. At t = 0, Christian engages deeply with two external parties in the program, namely firm A and firm B. Christian and firm A both have expertise in Smart Grids and IoT, but none of the other areas. Firm B has also expertise in Smart Grids and IoT but additionally in Energy Management. Accordingly, the value for the *Trans-specialist knowledge* variable would be 1 (as there is one trans-specialist knowledge area for Christian) divided by 2 (as he engages with 2 external parties in total). The low value of 0.5 reflects that Christian accesses more within-expertise knowledge. However, if Ann, who only has knowledge in Energy Management, deeply engages with firms A and B, the value for the trans-specialist variable would be 4 (as there are 2 trans-specialist areas in her engagement with firm A and 2 trans-specialist areas with firm B) divided by 2. The higher value of 2 reflects that Ann accesses more trans-specialist knowledge. As we have the information at each point in time, we can construct a time-varying variable. The logic of how we construct this variable is also illustrated in Figure 2.

INSERT FIGURE 2 ABOUT HERE

Moderators: Organizational distance. To capture the organizational distance between source and recipient, we presume that startups are more distant from utilities (and closer to other startups) and that utilities are more distant from startups (and closer to other utilities). Startups and incumbents fundamentally differ in their underlying routines, skills, shared meaning, mental frameworks, and professional languages (Chesbrough & Tucci, 2020). Further, we assume that the more time an individual spends engaging with the other organizational type (startup-utility) relative to the same organizational type (startup-startup; utility-utility), the more they attempt to transfer knowledge from that other type of organization. At each measurement point, we thus asked respondents how many hours they allocated to engaging with startups and utilities. We then constructed the time-varying variable as the ratio of hours spent with external parties of the other organizational type:

$$(2) \qquad Organizational\ distance = \frac{hours\ spent\ with\ ext.parties\ of\ other\ org.type_{t,j}}{hours\ spent\ with\ ext.parties\ of\ the\ same\ and\ other\ org.type_{(t),j}};$$

with time t ∈ [0-7] and individual j ∈ [1-76].

A value of (e.g.) 70 would imply that an individual, on average, spent 70% of their time engaging with external parties of the other organizational type (and 30% with the same organizational type), thus focusing more on transferring knowledge from the other (more distant) organizational type.

Moderators: Progression in boundary-spanning process. We exploit 'time' to proxy the varying importance of activities across the boundary-spanning process. This measure builds on prior empirical work that showed that early phases of the boundary-spanning process are characterized by the activities of knowledge scouting and matching, while later phases deal primarily with problem re-definition, technical integration, and conflict resolution (e.g., Gutierrez-Huerter et al, 2022. Monteiro & Birkinshaw, 2017). While it is difficult to delineate clearly separate phases of the boundary-spanning process, we assume a gradual and continuous shift in the relevance of boundary-spanning activities. We thus proxy the changing importance of boundary-spanning activities across different phases, by coding measurement occasions as a linear time trend (–4, –3, –2, –1, 0, 1, 2, 3). This assumption is in line with our observations of the program and illustrated in the following quotes from interviews with participating boundary spanners reflecting on (1) the early phases:

"*And then these first conversations were good to sort of … filter a bit. Like, okay; who is really interested in us? What kind of problems do they have? Which also allows us to filter as well*." (CTO, participating startup)

and (2) the shift of activities as the program progressed:

"I guess after the first modules, there were conversations about whether you might want to do something or where could be the fit. But they really didn't go too much into technical details. But then we really saw that at [the second module] stuff gets moving. And we started to get into the really technical conversations in [the third module]. And it looks like it's potentially going to sustain itself until we get to [the final module], because we're still discussing many problems that we discovered [in the technical discussions] but I think we can get everything sorted now." (Utility innovation manager)

The coding with 0 at the center follows best practice in longitudinal research, allowing for easier interpretation of interaction coefficients without changing the significance levels of time or interaction coefficients (Ployhart & Vandenberg 2010).

Control variables. We constructed the variable *Home* as a dummy that takes the value 0 for phases of co-location and 1 for phases at home (*Home* = 0, 1, 0, 1, 0, 1, 0, 1). Following previous studies on boundary spanning, we control for the *levels* of external and internal engagement and potential *complementarities* at each point in time (Dahlander et al., 2016; Salter et al., 2015; ter Wal et al., 2017). In addition, individuals and their colleagues might divide engagement activities among themselves, forming a "collective bridge" rather than following the typical one-person boundary-spanning model (Zhao & Anand, 2013). We thus control for *team collaboration* - the total number of hours an individual spent engaging with colleagues who were also participating in the program. These individuals are not the focal recipients of the knowledge transfer, but they are accessing external knowledge through the program. Furthermore, we control for the *unrelated internal engagement hours* – the total number of hours individuals spent on communicating with internal colleagues about issues not related to the focal program, which might influence their capacity to transfer knowledge from the program to their home organization. To enhance interpretation of the model estimates, we standardized our variables. Finally, we collected information on time-invariant variables such as demographic and job-related characteristics including *Gender*, *Age*, *Education*, *Tenure*, *Knowledge breadth*, *Not-invented-here syndrome*, *Perceived innovation climate*, and *Intrinsic motivation.* The time-invariant variable *Startup* is 1 for startups and 0 for utility participants. While the fixed-effects panel analysis accounts for these (and any potential other) time-invariant differences, collecting time-invariant control variables allows us to include them for determining the suitable estimation techniques. Details on all measures and descriptive statistics can be found in the online appendix (Table A1-A3 and Figure A1-A2). The correlation table and an estimation of variance inflation factors indicate that our estimations are not subject to multicollinearity issues.

Analysis

To investigate the associations between boundary spanners' engagement dynamics and knowledge transfer, we estimated a fixed-effects panel model. Since our longitudinal dataset violates the independence assumption of cross-sectional OLS regression analysis, we rely on panel data analysis (see Greene, 2012). First, we ran a random-effects panel model, where unobserved heterogeneity is assumed to be uncorrelated with the regressors. Second, we estimated a fixed-effects panel model that does not rely on this assumption as it accounts for unobserved heterogeneity by using the within-transformation. Subsequently, we conducted the Hausman specification test (Hausman, 1976), which tests the assumption of the random-effects model that unobserved heterogeneity is uncorrelated with the regressors. The p-value of 0.372 indicates that the assumption of the random-effects model does not hold. This indicates that coefficient estimates of the random-effects model would be contaminated by unobserved heterogeneity. Thus, we use the fixed-effects panel model. To test our hypotheses, we interact the switching variable with our three moderators in three separate models (Aiken & West, 1991). We use marginal-effects plots (also referred to as regions-of-significance plots) to further explore whether and in what regions of the moderator value the association between switching and knowledge transfer is significantly negative or positive (Johnson & Fay, 1950; McCabe, Kim, King, 2018; Murphy & Aguinis, 2022). We use the r-package "interplot" (Solt & Hu, 2021), which accounts for bias and overconfidence of estimates for distant values of the moderator (Berry et al., 2016; Murphy & Aguinis, 2022). To avoid Type I errors, we only plot the coefficient for observed ranges of the moderator variable (McCabe et al., 2018).

RESULTS

Engagement Dynamics and Knowledge Transfer

The results of the fixed-effects estimation model for knowledge transfer are shown in Table 1. In Models 1 and 2, we first examine the control variables and engagement levels. Model 1 shows that individuals' levels of external engagement (ß = 0.347, p-value = 0.041) and internal engagement (ß = 0.098, p-value = 0.478) in each time period have positive associations with knowledge transfer. However, the p-value for internal engagement fails to meet standard significance levels. Model 2 reveals that the interaction of external and internal engagement does not meet standard significant levels (ß = -0.023, p-value = 0.749), thus failing to support complementarities of both engagement types at a single point in time. Interestingly, in both Models 2 and 3, the variable *Home* shows a significant positive association with knowledge transfer (e.g., ß = 0.477, p-value = 0.04, Model 2). This implies that boundary spanners transfer more external knowledge sourced from the program when they are embedded in the home organizations compared to phases of co-location with external parties.

In Model 3, we find that switching between external and internal engagement has, overall, a negative association with knowledge transfer (ß = -0.187, p-value = 0.108). However, the p-value of 0.108 just fails to meet the 10% significance level. This indicates some inconclusiveness regarding the direct association between switching and knowledge transfer. This is, however, in line with our theorizing regarding the potential cognitive advantages of both stronger vs. weaker switching. This is also reflected in our contingency framework, which does not put forth any direct association between switching and knowledge transfer.

Model 4 shows that the extent of trans-specialist knowledge moderates the association between the degree of switching and knowledge transfer (ß = -0.146, p-value = 0.059). This result implies that an increase in the extent of trans-specialist knowledge by 1 standard deviation, changes the switching coefficient by -0.146. Thus, we find support for H1 at the 10% level. This is also visualized in the marginal-effects plot (see Figure 3). Interestingly, the plot indicates that the 95% confidence interval of the negative coefficient for switching does not include 0 for values of the moderator above -1 standard deviation. This implies that the association between the degree of switching and knowledge transfer is significantly negative when trans-specialist knowledge is -1 standard deviation or higher. Furthermore, as visualized in Figure 3, there is no crossover point for the coefficient. This indicates that, for the observed range of the moderator (trans-specialist knowledge), the estimated coefficient for the association between switching and knowledge transfer is always negative.

INSERT FIGURE 3 ABOUT HERE

Model 5 shows that organizational distance significantly moderates the association between the degree of switching and knowledge transfer (ß = -0.588, p-value < 0.01). This implies that an increase in organizational distance by 1 standard deviation changes the switching coefficient by -0.588. Thus, we find support for H1 at the 5% level. This is also visualized by the marginal-effects plot (see Figure 4), which indicates that the 95% confidence interval of the negative coefficient for switching does not include 0 for values of the moderator above -0.5 standard deviations. This implies that the estimated coefficient for the association between switching and knowledge transfer is significantly negative when organizational distance is high. Furthermore, we detect a cross-over point of the coefficient that lies just above -1 standard deviation of the moderator value. This indicates a possible positive association between switching and knowledge transfer when organizational distance is low. However, the plot also indicates that the 95% confidence interval of the positive coefficient always includes 0 for the observed range of the moderator.

INSERT FIGURE 4 ABOUT HERE

Model 6 reveals that progression in the boundary-spanning process significantly moderates the association between the degree of switching and knowledge transfer (ß = -0.107, p-value < 0.01). This implies that the progression from one time period to the next changes the switching coefficient by -0.107. Thus, we find support for H3 at the 5% level. This is also visualized by the marginal-effects plot (see Figure 5). The plot indicates that the 95% confidence interval does not include 0 for the last four time periods (0, 1, 2, 3). This implies that the coefficient is significantly negative in the later phase of the boundary-spanning process. Again, we detect a crossover point, where the coefficient turns positive between the second (-3) and third (-2) time period. This indicates a potential positive association between switching and knowledge transfer in early phases of the boundary-spanning process. However, the plot also indicates that the 95% confidence interval of the positive coefficient always includes 0 for the observed range of the moderator.

INSERT FIGURE 5 AND TABLE 1 ABOUT HERE

While the results are in line with our stipulated mechanisms, our research design and analyses do not allow us to measure the underlying cognitive and knowledge transfer mechanisms directly. We thus turn to our complementarity qualitative data for further illustrative insights. For example, one interviewee elaborates on the lack of blended knowledge when switching more strongly:

> *If you talk to [external parties at the module] and then you have all these ideas in your head about what could be done. Then you go back [home], and you're trying to convince people who weren't there to do what you've just thought about in your head. The moment they [people at home] give you some input, you will have to rethink what you've come up with in your head, a week or two or three weeks ago, and then you just start discussing [with external parties] from the start again.* (CEO, participating startup)

Another interviewee explains how the organizational distance between the source and recipient units increases the need for knowledge translation and how weaker switching between external and internal engagement may facilitate such translation:

> *One challenge is that utilities are just fundamentally thinking differently from us. And that's not a secret, that translation is needed there at all levels. And obviously, over the week [of co-location], I can understand what they mean. And then I try to pass it on again to my team [back home]. It is quite a useful exercise to report this back as quickly and as much in real time as possible during the week… Because otherwise, you create a gap, and the gap will be wider if I wait and [only switch to internal engagement] when I come back, then the follow-up will be more difficult.* (CEO, participating startup)

Similarly, in the following two quotes, participants reflect on the difficulty of transferring trans-specialist knowledge and why it requires more translation and transformation, further illustrating and corroborating both our operationalization of the variable and the underlying mechanisms of H1:

> *"If you think about electric vehicle charging, or electric micro grids […]. That is close to the harbor for people [in an energy utility], they understand it. They know what we're talking about. And it goes all the way up to the board level. But, if it becomes a horizon 2 topic, like blockchain solutions or other digital stuff it becomes very abstract [for people inside the utility]."* (Utility innovation manager)

> *"I mean, we were the "energy access" [one technology category] guys, everybody wanted to talk with us, but nobody wanted to actually do something with us --because nobody knew what to do [because it is outside their expertise], and it takes time to explain to them what we could actually do."* (CTO, participating startup)

Robustness of Results

We conducted several robustness tests, which are detailed in the online appendix. First, we included all interactions with our three moderators in one model. The results in Model 7 indicate that the interactions for the progression of the boundary-spanning process and organizational distance remain significant at the 5% level. However, the interaction with trans-specialist knowledge is less robust and fails to meet standard significant levels. To further explore boundary conditions of our results, we tested whether our findings differ for individuals employed by different organizational types. Given that startups and incumbents are quite different types of organizations (Chesbrough & Tucci, 2020), this would be a likely alternative explanation. Thus, we interacted the startup dummy with the switching variable and found that the coefficient does not significantly differ between individuals from startups vs. incumbents. Similarly, we explore alternative explanations with additional control variables (e.g., individuals' identification with the program) and find that our results are robust (see online appendix). We also tested whether there is a curvilinear relationship between switching and knowledge transfer by including the squared term of switching in the model. However, we found no support for a curvilinear relationship. Instead, our results indicate that the association between switching and knowledge transfer is contingent on the degree to which individuals access trans-specialist knowledge, the organizational distance between sources and recipient units, and the progression in the boundary-spanning process.

Second, while we acknowledge that we cannot fully address endogeneity issues, we undertook several steps to reduce potential sources of endogeneity as much as possible. We applied alternative modeling approaches to further substantiate the theorized direction of the association (see online appendix). We used structural equation modeling to implement a cross-lagged panel model that tests the direction of the association between our key IV (degree of switching) and DV (knowledge transfer) (Selig & Little, 2012). The results further support our theorizing that stronger switching from the previous time period to the current one is associated with lower knowledge transfer. In addition, we apply a Qualitative Comparative Analysis (QCA). QCA is a set-theoretic method that allows for more complex (configurational) relationships by using a minimization algorithm based on Boolean algebra and counterfactual analysis (Fiss, 2007). While QCA is less suited to analyzing dynamic processes, it does allow us to address concerns related small sample bias. The results confirm that weaker switching is consistently associated with knowledge transfer when boundary spanners source trans-specialist knowledge, or when both organizational distance is high, and the boundary-spanning process is in its later phase. Interestingly, we find one configuration that indicates that stronger switching is consistently associated with high knowledge transfer, but only in early boundary-spanning phases and when knowledge is within-expertise. This provides some indication that under certain conditions (i.e., in early phases and when knowledge is within-expertise) switching might generate knowledge-transfer advantages, even though we fail to find significant support in our regression analyses. Further supporting the findings from our fixed-effects panel regression, we find that strong switching is consistently associated with low knowledge transfer if organizational distance is high and in later phases of the boundary-spanning process.

Third, we probed whether our results could be driven by outliers. Outliers refer to data points that deviate sharply from the overall pattern of the data (see also Moore and McCabe, 1999). As such, outliers raise the suspicion of erroneous data that can lead to false conclusions. However, outliers do not necessarily represent erroneous data, but can instead convey important information and variance. Following best practice, we define outliers as data points that are more than 3 standard deviations above (below) the sample mean (Moore and McCabe, 1999) or above (below) the third (first) quartile and 3 times the interquartile range (Turkey, 1977). We detect five data points that can be classified as outliers in at least one of the distributions of our independent variable or moderators. For each of the data points, we manually inspected the data going back to the actual survey responses. From the manual inspection, we can conclude that the data points are not erroneous. We do not exclude them from our main analysis because they might carry important information and the overall sample size in this study is limited. However, for a robustness analysis, we removed the five outliers to run the fixed-effects models and plot the marginal-effects plots. The plots for all three interactions (see online appendix) indicate the same support for our hypotheses.

Fourth, for our DV, we relied on a self-reported survey scale. In a post-hoc analysis, we used information from pilot contracts signed between participating parties to construct an alternative DV. We assume that the signing of firm-level pilot contracts represents the outcome of a successful knowledge transfer, as it implies that boundary spanners identified an external technology/business model/market and were able to link it to internal parties who were willing and able to commit resources. Since the information was only available at the firm level and at the conclusion of the program, data points for this analysis are few. Hence, we used them to inspect to what extent this data displays patterns that are qualitatively similar to those we found in our quantitative analysis. We plotted the extent to which individuals from (1) the six best-performing firms (top quartile of contracts) and (2) the six worst-performing firms (bottom quartile of contracts) switched between external and internal engagement across time periods. Visual inspection of these plots (see online appendix) indicates that, on average, individuals from low-performing firms tend to switch more strongly and those from the best-performing firms tend to switch less strongly. While we cannot inspect our finer-grained conditional hypotheses with this firm-level data, the consistent finding further corroborates our results.

In sum, we reduce the risk of several biases through our research design and robustness tests. However, we cannot rule out endogeneity as we rely on observational survey rather than experimental data and do not have instruments for the hypotheses of interest. Thus, our results should be understood as meaningful associations that support our theorizing rather than causal relationships.

DISCUSSION AND CONCLUSION

In this study, we sought to gain insights into how and under which conditions boundary spanners' engagement dynamics are related with external knowledge transfer. This dynamic perspective advances extant work that has adopted a more static and cross-sectional lens. Prior research has primarily focused on how differences *between* boundary spanners' engagement levels (Dahlander et al. 2016; Salter et al. 2015; ter Wal et al., 2017) at single points in time shape relevant outcomes. Our study complements this research by revealing how changes *within* boundary spanners—the degree to which they switch between external and internal engagement—are associated with knowledge transfer.

Our longitudinal analysis of boundary spanners in a collaborative innovation program generated two key findings. First, the degree to which individuals switch between external and internal engagement across consecutive time periods has a significant association with knowledge transfer. Second, the association is contingent on (1) the degree to which the sourced knowledge is trans-specialist in nature (2) the organizational distance between source and recipient units; and (3) the phase of the boundary-spanning process. We theorized that the association between switching and knowledge transfer becomes increasingly negative, the greater the stickiness of the knowledge to be transferred and the more the boundary-spanning process has progressed. Under these conditions, effective transfer requires more knowledge translation and transformation, which benefit from knowledge abstraction, blending, and novel inferences, which we associate with weak/no switching. We find support for a negative association between switching and knowledge transfer when the sourced knowledge is trans-specialist in nature, when there is greater organizational distance, and in later phases of the boundary-spanning process.

Overall, these findings have important implications for research that aims at understanding individuals' roles in knowledge transfer across boundaries.

Theoretical Contributions

Our findings offer several contributions to the literature on boundary spanning and knowledge transfer. First, they highlight the importance of adopting a dynamic perspective for better understanding the relationship between boundary-spanning behavior and the inflow of external knowledge. So far, literature has remained unclear on how boundary spanners can most effectively combine external and internal engagement. While some studies suggest that a viable boundary-spanning strategy is external or internal specialization (Dahlander et al., 2016; Salter et al., 2015), other studies posit that individuals need to balance external and internal efforts (Lifshitz-Assaf, 2018; Monteiro & Birkinshaw 2017; ter Wal et al., 2017; Wang, 2015), whereas yet another line of work questions the effectiveness of individual boundary spanners for transferring complex knowledge (Zhao & Anand, 2009; 2013). We contribute to this discussion by showing that knowledge transfer varies based on how individuals allocate their external and internal engagement across consecutive points in time. We reveal that while under specific conditions, individuals may be able to afford to switch strongly between external and internal engagement, the association between switching and knowledge transfer becomes increasingly negative the more the knowledge to be transferred is trans-specialist in nature, has to span greater organizational distance, and the more progressed the boundary-spanning process is. We thus introduce an important new dimension to the discussion of boundary-spanning effectiveness: *engagement dynamics*. In addition to engagement levels (Dahlander et al., 2016; Salter et al., 2015; Wang, 2015), the degree of switching between external and internal engagement is significantly associated with knowledge transferred.

The notion of engagement dynamics relates to an emerging research stream that proposes that the study of organization outcomes should focus on the temporal sequencing of behaviors (Klarner & Raisch, 2012). Our findings add to the discussion of whether, and under which conditions, activities should be balanced at single points in time or should be pursued in sequence. They correspond, for instance, to recent insights on the concept of ambidexterity, which suggest that greater temporal separation between exploration and exploitation is associated with lower performance levels (Mathias, Mckenny & Crook, 2018). Recent research has also highlighted the role of "time" in understanding knowledge transfer (Szulanski et al., 2016). For instance, Burt and Merluzzi (2016) suggest that the way individuals' networks change over time has implications for the advantages they can draw from those networks. Others find that the timing of specific knowledge-transfer methods (Szulanski et al., 2016) and the shifting between efforts of knowledge channeling, translation, and transformation over time is crucial for knowledge-transfer effectiveness (Monteiro & Birkinshaw, 2017). We add to this line of research by uncovering boundary spanners' temporal allocation of external and internal engagement as an important factor in external knowledge transfer.

Second, our findings contribute to a better understanding of how boundary-spanning behavior is associated with the inflow of external knowledge under different conditions (Tortoriello, 2015). We elaborate on "knowledge stickiness" (e.g., Nonaka, 1994; Szulanski, 1996; von Hippel, 1994) as an important contingency of boundary-spanning effectiveness and theorize why switching between external and internal engagement is unsuited for knowledge transfers with high stickiness. Building on prior work, we differentiate between two forms of stickiness. First, transfers are less sticky when the knowledge to be sourced is lower in complexity, such as when it is primarily within-expertise rather than trans-specialist (Kim & Anand, 2018; Reagans & McEvily, 2003; Zhao & Anand, 2013). Second, stickiness is lower when the organizational distance between source and recipient units is smaller, due to similarity in routines, practices, values, and language (Grant, 1996, Simonin, 1999; Szulanski, 1996). It is under these conditions that knowledge can be transferred by "simply" channeling it across the boundary (Carlile, 2002). Under these conditions, boundary-spanning individuals may afford to switch more strongly between external and internal engagement across consecutive time periods. Our findings provide some support for these arguments as the marginal-effects plots (see Figures 3 and 4) and the crossover points suggest that the association between switching and knowledge transfer is positive (though not significant) when organizational distance is low and in early phases of the boundary-spanning process. However, as knowledge becomes stickier—i.e., when knowledge is complex, due to its trans-specialist nature, and when organizational distance is high—its effective transfer may require more translation and transformation. In line with this theorizing, our findings reveal that, under those conditions, switching is negatively associated with knowledge transfer. These results provide new insights into how boundary-spanning behavior—in terms of external and internal engagement—is related to knowledge transfer under different conditions.

Third, by combining a cognitive perspective with prior work on knowledge transfer, we offer a preliminary set of mechanisms that may help to explain the relationship between boundary spanners' engagement dynamics and external knowledge transfer. While in our quantitative research design, we cannot observe and measure the more detailed underlying mechanisms of knowledge transfer (e.g. Bechky, 2003; Carlile, 2004; Monteiro & Birkinshaw, 2017) and cognition (e.g. Cornelissen & Werner, 2014; Dougherty, 1992) that have been outlined in qualitative work, we theorize how engagement dynamics may trigger mental knowledge structures that differ in the extent to which they support knowledge channeling vs. knowledge translation and transformation. We argue that stronger switching between external and internal engagement activates segmented knowledge structures and categorical processing, which mainly support knowledge channeling and are thus helpful when knowledge is less sticky and in earlier phases of the boundary-spanning process. Weaker switching, in contrast, activates blended knowledge structures and reflective processing, which are more supportive of knowledge translation and transformation and thus facilitate knowledge transfer under "stickier" conditions. Our regression results and complementary qualitative insights align with this theorizing. Yet, as we could not directly observe and measure the proposed mechanisms, we consider this contribution only as a first step in providing explanations for why engagement dynamics are associated with knowledge transfer and call for further research to shed more light on these mechanisms.

Limitations and Future Research

We acknowledge that our study is based on a very specific empirical setting in which switching was likely more pronounced and occurred in a regular rhythm due to the co-location schedule prescribed by the collaborative program. Future research should extend investigations to other settings in which switching is less prescribed and more variable across individuals and over time. This would enable the examination of other dimensions of engagement dynamics, such as differences in the frequency of switching or the duration of focus on a particular form of engagement and provide a more complete understanding of engagement dynamics. For instance, expanding on a cognitive perspective, one could argue for a U-shaped relationship between switching *frequency* and knowledge transfer. Specifically, blended knowledge structures may not only be triggered by weak/no switching but may also be facilitated by strong switching, if that switch occurs with a high frequency, thus causing quick iterations of focusing on external vs. internal stimuli (which future studies need to explore). Switching frequency is difficult to assess empirically since the number and timing of switches cannot be predicted ex-ante. Thus, scheduling surveys around switching occasions is difficult and recalling switching frequency ex-post would be cognitively demanding for individuals. Given this difficulty, simulation studies may complement empirical research as they would allow researchers to create and manipulate different dimensions of engagement dynamics (e.g., frequency) more freely.

Our setting represents an innovation-related context, where participants transfer knowledge regarding clean energy solutions. We are thus careful in claiming generalizability to other boundary-spanning contexts that do not entail any innovation component. In addition, we started collecting data after the process of selecting startups had already occurred. Hence, some information channeling may already have taken place when different applications to the program were screened. Thus, we might have missed the very early part of the boundary-spanning process in our empirical analysis. The marginal-effects plot (see Figure 5) and the crossover points indicate that switching might be beneficial in the early phases of the boundary spanning. Future research could focus on sampling boundary-spanning processes at earlier stages and further explore the conditions under which switching may be positively associated with knowledge transfer. In addition to exploring different boundary-spanning settings, future studies need to validate our results with larger samples.

One of the surprising outcomes of our analyses was that we could not detect any differences in the relationship between engagement dynamics and knowledge transfer between boundary spanners employed by large incumbents vs. startups. On the one hand, this might be supportive of our proposed cognitive mechanisms, which are unlikely to differ between incumbent and startup employees. On the other hand, this calls for further research on boundary conditions to better understand the "home-organizational" settings in which our findings apply.

A key limitation is that our empirical setting does not allow us to measure the underlying mechanisms of the relationship between switching and knowledge transfer. We combine a cognitive perspective with the knowledge transfer literature to delineate rather detailed mechanisms (i.e., segmented vs. blended knowledge structures and categorical vs. reflective processing) that we cannot empirically measure. While knowledge structures and cognitive processes are difficult to measure in general (Walsh, 1995), novel methodological approaches such as neuroscientific methods (Laureiro-Martinez et al., 2015) or lab experiments (Laureiro-Martinez et al., 2019) may shed further light on the underlying cognitive mechanisms of boundary-spanning behavior. Such alternative research designs may also help to establish causal relationships between engagement dynamics and knowledge transfer. Until then, we merely state that our findings align with our theorizing but do not claim that we have identified the mechanisms that explain a causal relationship between switching and knowledge transfer. While we implemented several remedies and robustness tests, we cannot completely rule out that our results are to some extent affected by endogeneity and thus suggest that future research builds on our findings to verify, detail, and extend the underlying causal mechanisms. Relatedly, the measures of our moderators are proxies. For instance, based on prior empirical work, we theorize that the nature of boundary-spanning activities changes over time. Yet, we simply measure 'time' and not boundary-spanning activities directly. This also implies that we cannot rule out that other aspects that may change over time—e.g., incentives or personal relationships—add to the explanation of why the relationship between switching and knowledge transfer changes as the boundary-spanning process progresses.

While our study addresses recent calls in the literature to better understand more direct outcomes of boundary spanning, such as knowledge transfer (Dahlander et al., 2016; Tortoriello, et al., 2012), we do not assess the ultimate success of boundary spanning (e.g., in terms of innovation outcomes). We hope that our dynamic perspective will inspire future research, relating engagement dynamics to other relevant outcomes and antecedents. Regarding the latter, our finding that switching has negative associations with knowledge transfer across most regions of the moderating variables raises the question of why boundary spanners switch in the first place. This is an opportunity for future work to investigate individual- and organizational-level factors that shape the engagement behavior and outcomes of boundary spanners. On the one hand, boundary-spanning individuals may incur costs (e.g., cognitive load or relational disadvantages) or may be unable to excel in other elements of their profession when pursuing a weak-switching strategy. It will thus be important to examine relevant outcomes – beyond knowledge transfer – to better understand the implications of engagement dynamics (and whether it is worthwhile to incur associated costs). On the other hand, organizational-level—e.g., organizational culture—or individual-level factors—e.g., identification with both internal and external constituencies – may facilitate a weak-switching strategy. Such investigations will be crucial for providing practical recommendations for selecting, instructing, and supporting boundary-spanning individuals.

Finally, while we control for some team-level variables, our study focuses on boundary-spanning behavior at the individual level. Thus, future research should investigate the knowledge-transfer effectiveness of dynamic engagement processes in teams (see also Marrone et al. 2007). For instance, scholars might examine the knowledge-transfer implications of how collective bridges—direct relationships between all relevant members of source and recipient units with a minimum number of ties – (Kim & Anand, 2018; Zhao & Anand, 2013) —build and change over time, or of how the structure of social networks (Burt & Merluzzi, 2016; Reagans & McEvily, 2003; Tortoriello et al., 2012) changes over time. A particularly promising avenue for future research would be to investigate how different organizational structures and behaviors for knowledge transfer (e.g., collective bridges and individual-level boundary spanning) may be best combined over time. Szulanski et al. (2016) already suggested that knowledge transfer may benefit from beginning with a collective bridge and then simplifying to a boundary spanning structure. At the very beginning of a knowledge transfer attempt, actors may not know one another or may be unable to communicate effectively, in which case there is a boundary-spanning opportunity (see also Birkinshaw et al., 2017). However, later in the process, actors inside and outside the organization may be in a better position to engage with each other directly and the boundary-spanning function may decrease in importance. The combination and sequence of different structures for knowledge transfer may further depend on the complexity of the knowledge that needs to be transferred (Szulanski et al., 2016). Hence, we encourage future research to extend our dynamic perspective that focuses on boundary-spanning individuals to a dynamic perspective that considers different temporal combinations of organizational structures and behaviors for knowledge transfer.

Our study has taken an important first step towards understanding the knowledge-transfer implications of engagement dynamics and thereby sheds more light on how and under which conditions boundary spanners can be successful conduits of external knowledge. We hope that the research agenda outlined above inspires further research on the antecedents and outcomes of an important dimension of boundary spanning: engagement dynamics.

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Table 1. Fixed-effects model results

	Knowledge Transfer						
Fixed Effects	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
Home	0.467*	0.477	0.501	0.505	0.477	0.561	0.534
	(0.227)	(0.230)	(0.230)	(0.228)	(0.226)	(0.226)	(0.224)
Team collaboration	0.098	0.101	0.110	0.109	0.090	0.110	0.093
	(0.137)	(0.138)	(0.138)	(0.137)	(0.136)	(0.135)	(0.134)
Level of external engagement	0.347*	0.351*	0.305*	0.218	0.354*	0.285*	0.309*
	(0.135)	(0.136)	(0.139)	(0.145)	(0.138)	(0.136)	(0.145)
Level of internal engagement	0.037	0.035	0.008	-0.020	-0.057	-0.028	-0.084
	(0.110)	(0.110)	(0.111)	(0.111)	(0.112)	(0.109)	(0.111)
Unrelated internal engagement hours	-0.170†	-0.173†	-0.178†	-0.177†	-0.163	-0.219*	-0.201*
	(0.101)	(0.102)	(0.101)	(0.100)	(0.100)	(0.100)	(0.099)
Progression in the boundary spanning	-0.063	-0.063	-0.065	-0.061	-0.072	-0.042	-0.050
process	(0.045)	(0.045)	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)
Organizational distance	0.025	0.028	0.026	0.029	-0.196	0.036	-0.151
	(0.125)	(0.126)	(0.125)	(0.125)	(0.150)	(0.123)	(0.150)
Trans-specialist knowledge	-0.132	-0.140	-0.222	-0.091	-0.158	-0.217	-0.135
	(0.140)	(0.144)	(0.152)	(0.166)	(0.152)	(0.149)	(0.163)
Ext. engagement*Int. engagement		-0.023	0.012	-0.002	-0.055	0.031	-0.031
		(0.087)	(0.092)	(0.089)	(0.092)	(0.088)	(0.091)
Degree of switching			-0.187	-0.363*	-0.553**	-0.287*	-0.619**
			(0.116)	(0.148)	(0.180)	(0.118)	(0.185)
Degree of switching* Trans-specialist				-0.146†			-0.031
knowledge				(0.077)			(0.082)
Degree of switching* Organizational					-0.588**		-0.494*
Distance					(0.224)		(0.230)
Switching*Progression in the boundary						-0.107**	-0.094*
spanning process						(0.035)	(0.037)
# of Individuals / Observations	69/258	69/258	69/258	69/258	69/258	69/258	69/258
R^2 / adj. R^2	0.09/0.06	0.09/0.06	0.10/0.07	0.12/0.08	0.13/0.1	0.15/0.11	0.17/0.13

Note. Standard errors in parenthesis. Continuous variables are standardized. † p < .10; * p < .05; ** p < .01.

Figure 1. Research context, program design, and administration of surveys

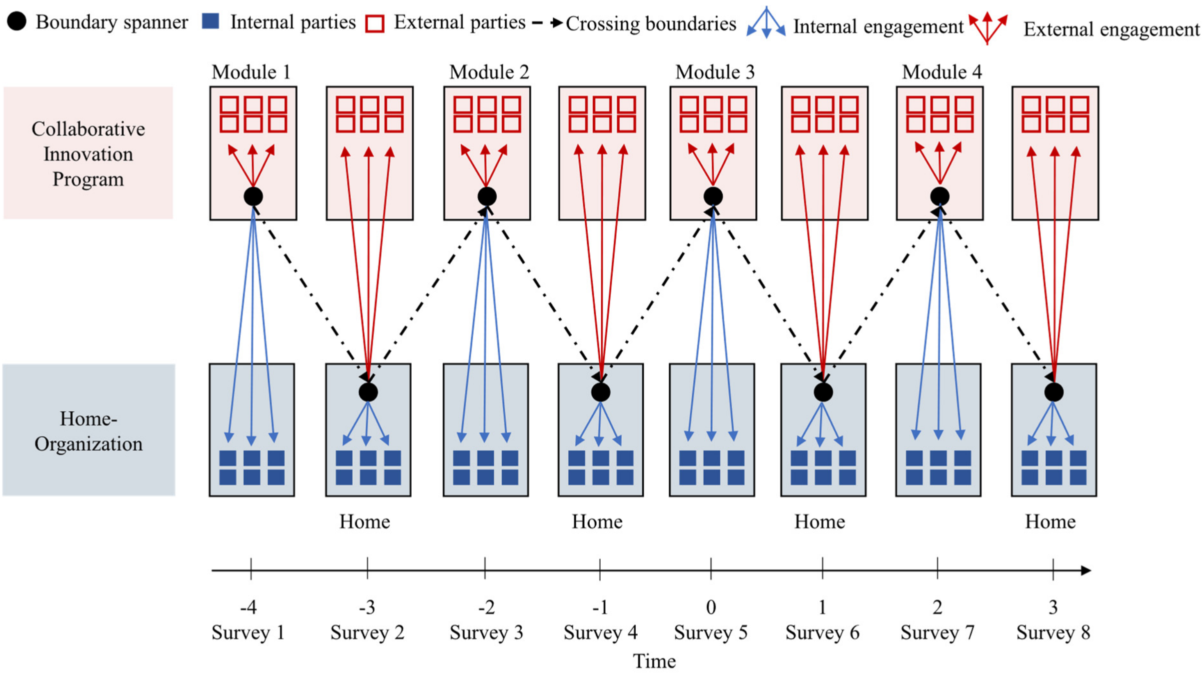

Figure 2. Measure for extent of trans-specialist knowledge

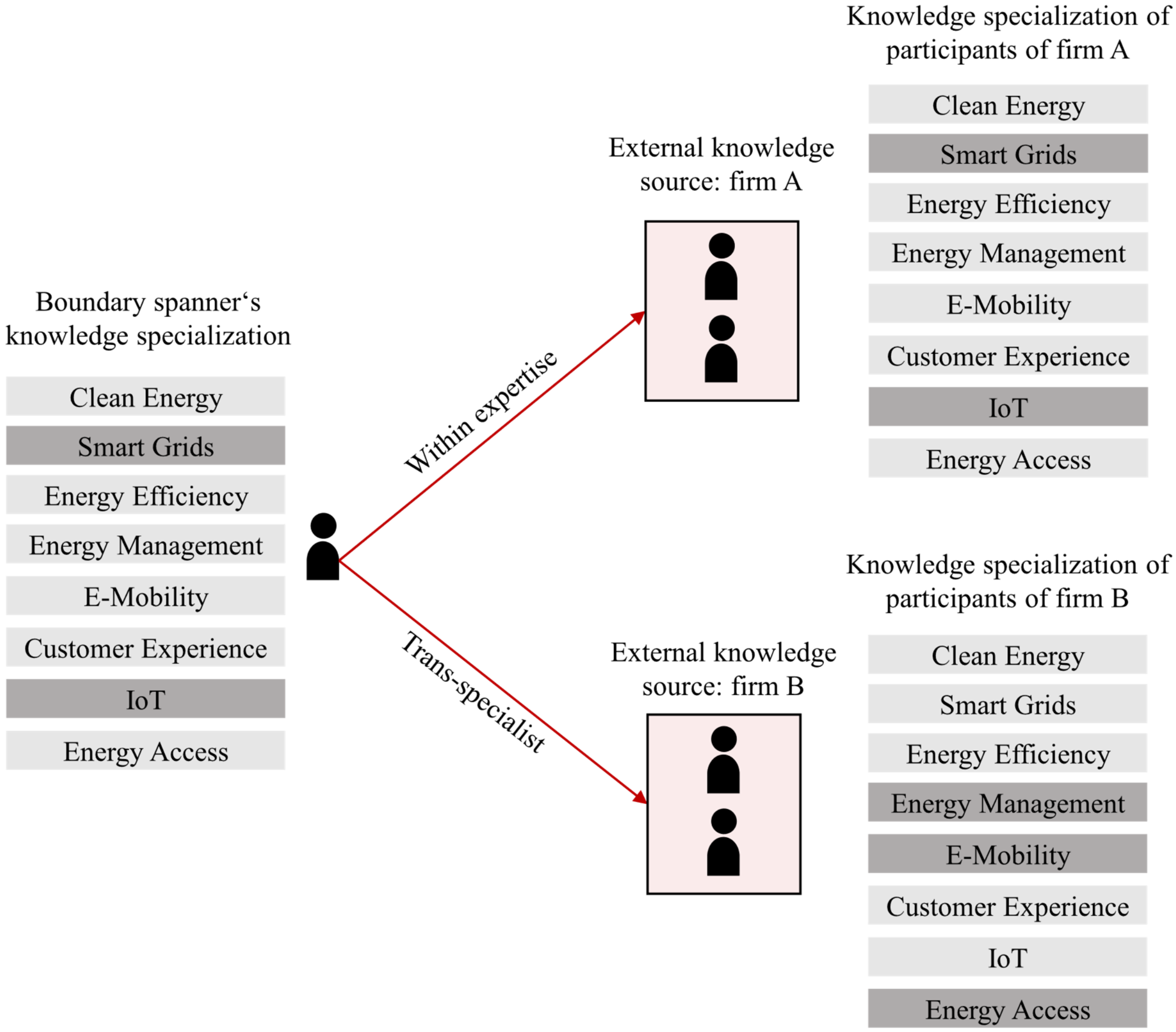

Figure 3. Marginal-effects plot with estimates and 95% confidence intervals of the association between the degree of switching and knowledge transfer, contingent on trans-specialist knowledge

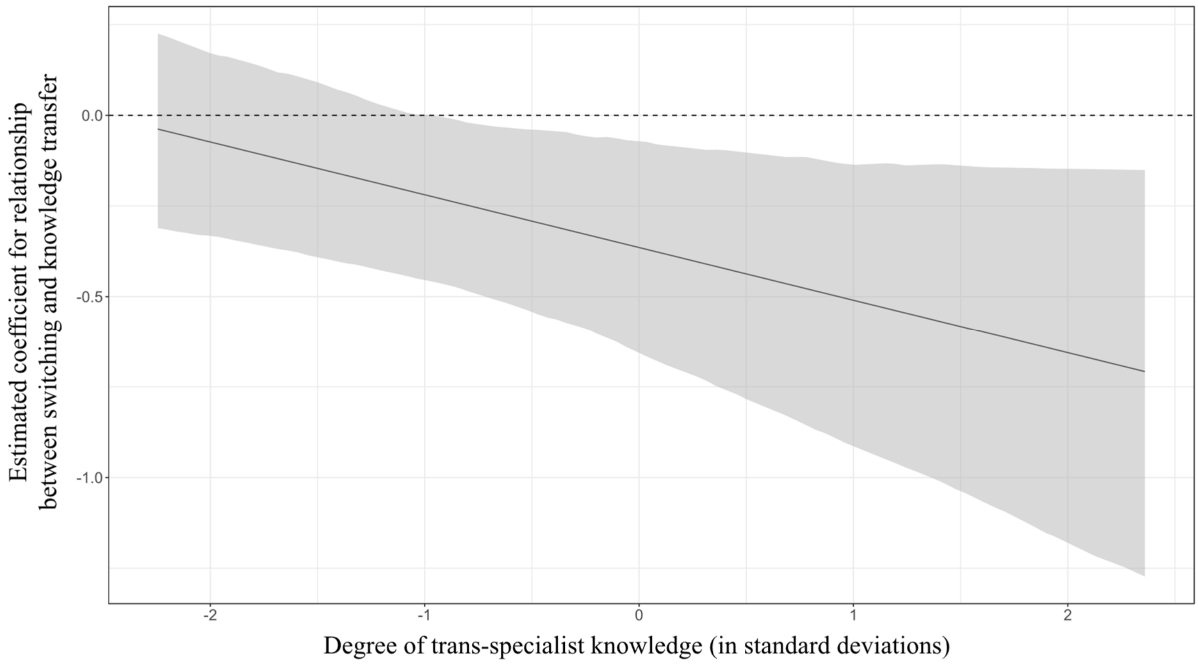

Figure 4. Marginal-effects plot with estimates and 95% confidence intervals for the association between the degree of switching and knowledge transfer, contingent on organizational distance

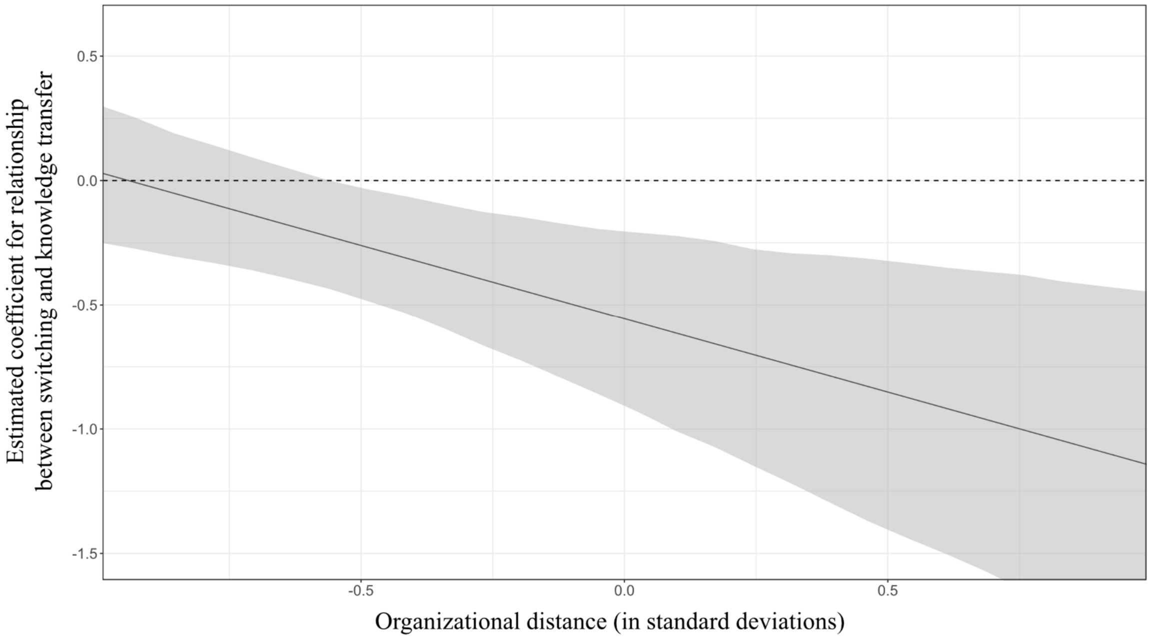

Figure 5. Marginal-effects plot with estimates and 95% confidence intervals for the association between the degree of switching and knowledge transfer, contingent on progression of the boundary-spanning process