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Social Learning in Information Technology Investment: The Role of Board Interlocks

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Abstract: We use a social learning perspective to extend our understanding of information technology (IT) investment and return. Specifically, we investigate social learning in the context of interlocks between corporate boards, which allow firms to share knowledge and experiences with respect to their IT investments. Using a large dataset of firm-years from 2001 to 2008, we find (a) a positive relationship exists between a focal firm's IT investment and that of its interlocked firms; (b) this positive relationship is amplified by the interlocked firms' IT capability, but only if the focal firm has an active board, which devotes time to allow sufficient communication among directors; and (c) the component of the focal firm's IT investment that is attributable to board interlock influence is positively related to the firm's performance, but only if the firm has an active board. Collectively, these findings support our central thesis: *social learning through board interlocks can play a significant role in influencing a firm's IT investments and enhancing their payoff*. That said, attaining such benefits requires boards to incorporate those firms with high IT management capability and to strengthen board activity so interlocked members can substantively share their knowledge and experiences with IT investments.

Keywords: IT investment, IT return, social learning, board interlocks

1. Introduction

Firms continue to invest heavily in information technology (IT).[1] While prior studies generally find that the average return to IT investment is positive, many also find notable variations of return across firms (e.g., Han and Mithas 2013, Saldanha et al. 2013, Tanriverdi and Uysal 2011). This range of findings implies that many contingencies that influence firm IT investment and returns have yet to be uncovered. With this study, we examine social learning as one such contingency, because theories of social learning suggest that it may influence firm IT investment decision-making and, importantly, the performance impact of a resultant investment (Bikhchandani et al. 1998, Young 2009).

Generally, social learning, which refers to a decision maker learning from others' choices and experiences (Bikhchandani et al. 1998, Young 2009), falls into two major types: conversational learning and observational learning (Cai et al. 2009, Li et al. 2014, Sorensen 2006). As documented in the literature, social learning "includes the mechanism in which individuals learn from each other through direct communications [i.e., conversational learning]; it also includes the mechanism of observational learning where the behavior of individuals is influenced by their observation of other people's choices" (Cai et al. 2009, p.864). A decision maker obtains different information through conversational learning and observational learning: "in some cases [observational learning], other individuals' choices serve as signals of private information, so learning comes from merely observing their actions . . . [i]n other cases [conversational learning], information and experiences are shared directly through conversation" (Sorensen 2006, p.929). These two types of social learning are therefore expected, at least in theory, to impact performance differently (Young 2009).

Research on social learning not only develops our theoretical understanding of how and why IT investment relates to returns, but also offers decision makers practical implications that underscore the importance of particular types of social learning. Intuitively, if convincing evidence supports the benefits of conversational (or observational) learning, then decision makers should create conditions that foster that type of learning to improve IT investment decisions. Although the information systems (IS) literature (e.g., Teo et al. 2003) has long documented the role that mimicking—a concept related to social learning, which we discuss below—plays as firms adopt new technologies, research that explores firm IT investment and returns in terms of social learning remains sparse. The literature particularly lacks research on conditions in which specific types of social learning (e.g., observational, conversational) may

[1] According to the US Bureau of Economic Analysis, information-processing equipment accounted for 28.7% of fixed investment in the US private sector in 2015 (https://www.bea.gov/iTable/index_FA.cfm).

occur and the subsequent influence on IT investment and returns. With our study, we aim to bridge this gap by illuminating the role that social learning plays with respect to IT investment decision-making and returns.

To that end, we identify a social learning channel for IT investment decision-making and, in particular, identify the conditions in which conversational learning or observational learning likely takes place through that channel. We choose to focus on *board interlocks* as such a channel, as directors in one firm often sit on the boards of others, creating opportunities for social learning (Brown and Drake 2014).

We focus on board interlocks for several important reasons. First, key decision makers who allocate a firm's financial resources to IT—especially to strategic IT—include a firm's board and top management (Salge et al. 2015), with the board holding the ultimate authority (Benaroch and Chernobai 2017). The board is responsible for overseeing investment decisions with strategic significance (Jensen 1986). Since the 2000s, firms are spending more on IT than on research and development (R&D) and advertising (Mithas et al. 2012). Moreover, IT investment bears high uncertainty (Dewan et al. 2007). The sheer magnitude of IT spending, coupled with the high uncertainty of related payoffs, makes IT investment decisions highly relevant for boards (Nolan and McFarlan 2005). In particular, IT investments are of strategic significance when "differing levels of these investments can significantly expand or constrain a firm's strategic choice sets" (Mithas et al. 2013, p.520). Typical examples include enterprise systems for customer relationship management (CRM) and supply chain management (SCM) that became practical since the late 1990s (McAfee and Brynjolfsson 2008). Different levels of investment in CRM and SCM applications determine how firms conduct strategically important value-chain processes (Ranganathan and Brown 2006). In practice, boards closely scrutinize such strategic IT investments, as "[c]ompanies have huge investments in applications software . . . [and boards] must ensure that management knows what information resources are out there, what condition they are in, and what role they play in generating revenue" (Nolan and McFarlan 2005, p.102). In recent years, increasingly more IT-related issues (e.g., cybersecurity, digital disruptions of operations, compliance with data protection regulations) have risen to the agendas of boards of directors. Thus, research that explores the role of boards with respect to IT-related decision-making can offer timely, impactful, and practical implications.

Second, board interlocks are perhaps the most widespread channel by which firms share information about strategic decisions (Chiu et al. 2013), such as strategic IT investment. Although public roundtable forums that share information about IT costs and benefits exist, learning will be limited to the extent that firms are reluctant to make such information available to their competitors (Zhu 2004). In contrast, interlocked directors cannot, by regulation, come from direct competitors (Brown and Drake 2014). When those interlocked directors sit on a focal firm's board, it is their responsibility to advise the firm on investment decisions; in executing this responsibility, they bring the tacit knowledge and experience they have gained elsewhere (Fama and Jensen 1983). Given that more than 64 percent of board directors in U.S. public firms were outsiders during the 1990s and 2000s (Linck et al. 2008) and that a typical S&P 1500 firm has a median of five interlocks with other boards during this same period (Chiu et al. 2013), social learning via interlocked directors may well be widespread.

Furthermore, social learning via interlocked directors will be boosted by board activity. Prior literature on corporate boards has long recognized that boards differ in their levels of activity, or the extent to which board members collectively devote time and exchange ideas to enhance board effectiveness (Conger et al. 1998, Lipton and Lorsch 1992). Board activity operationally manifests in board meetings (Vafeas 1999), which are the formal mechanism for board members to collectively contribute their time, expertise, and experience to a firm's decision-making process. On the one extreme, a corporate board is not active. Such a board is symbolic, meets rarely, does not engage in in-depth discussions about a firm's strategic decisions, and functions primarily as a requisite legal entity. On the other extreme, a corporate board is active. Such a board meets frequently to engage in substantive discussions about a firm's strategic decisions, which allows interlocked firms' knowledge and experience to flow into the firm (Brick and Chidambaran 2010, Carpenter and Westphal 2001, Vafeas 1999). As such, an active board strengthens a focal firm's social learning, particularly conversational learning, from its interlocked partners.

Third, information about IT investment and impacts is indeed discussed in board meetings. According to a recent survey by PricewaterhouseCoopers (2013), about 35 percent of directors spent six to ten percent of their annual board hours elaborating upon IT-related topics (e.g., overseeing major IT applications, approving annual IT budgets). The Deloitte Global Center for Corporate Governance (2011, p.8), summarizing the experiences of member firms around the world, finds that discussions in board meetings "track the [IT] investment to ensure that the organization fully realizes the benefits of the new technology." Also, a survey of 455 directors of publicly traded firms reports that "whether returns on [IT] investments are hitting predetermined targets" is a key issue that directors elaborate upon in board meetings; in turn, about half of those surveyed directors reported that measures of IT value are used in their board meetings to justify IT expenditures (Corporate Board Member 2007). Collectively, these reports indicate that IT topics are elaborated upon in board meetings.

We summarize our research context as follows:

- We focus on board interlocks as a conduit of social learning for IT investment decision-making.
- We address IT investment that is of strategic significance to a focal firm. Strategic IT is within the scope of board attention, while social learning at the board level may not be needed to address mundane IT that supports routine functions.
- We identify an active board as a facilitating context for conversational learning.

We formulate our research questions and investigate them in this research context. In doing so, we respond to the call by Johns (2006, 2017) to achieve significant theoretical advances by foregrounding key context-specific characteristics to formulate research questions, build theory, and make empirical assessments. Our first question is ***whether*** board interlocks influence IT investment decision-making. Specifically, we ask: if board interlocks facilitate social learning, do they lead a focal firm to make IT investments similar to those of its interlocked firms? The board interlocks literature has investigated social learning primarily in the context of decisions on financial policies (to be reviewed below). Given that (strategic) IT investment requires different skill sets than other corporate decisions studied in the board interlocks literature, exploring the extent to which prior findings apply to our research context warrants investigation.

Next, we consider the role of discrete contextual characteristics, those "particular aspects or levers of context that shape behavior" (Johns 2006, p.361), which, in our case, is social learning regarding IT investment from board interlocks. Informed by this learning perspective, which suggests that the learning source will influence what is learned (Conley and Udry 2010, Young 2009), as well as by the conversational learning perspective, which emphasizes the need for communication to achieve IT knowledge transfer (Li 2004, Li et al. 2014), we identify interlocked firms' IT capability and a focal firm's board activity as two discrete ***contextual levers*** that should shape a focal firm's social learning from interlocked firms. Accordingly, we ask how such board interlock influence, if any, may hinge on interlocked firms' IT capability and board activity.

Last, we ask a "***so what?***" question concerning performance impact: if a focal firm's IT investment is impacted by social learning through board interlocks, does that impact improve the firm's performance? Since performance impact ultimately matters to boards and top management (Salge et al. 2015), research that investigates this question has economically significant implications.

2. Literature and Hypotheses

2.1 Literature on Board Interlocks

Ample research has related firm decisions to board interlocks, and financial policies are among the most widely examined of these decisions. Prior studies document that board interlocks facilitate the propagation of earnings management, financial disclosure, and tax avoidance (Brown 2011, Cai et al. 2014, Chiu et al. 2013, Jiang et al. 2017). Also, Rao et al. (2000) find that NASDAQ-listed firms are more likely to migrate to the NYSE when their directors serve on the boards of companies that have already done so. Further, Bizjak et al. (2009) report that firms with interlocked directors from firms that backdate employee stock options are more likely to backdate their own employee stock options. Finally, Bouwman and Xuan (2012) find that a firm is more likely to adopt financial decisions (e.g., equity issuance, dividend policy, and earnings restatements) similar to those of firms with which it has interlocked directors. Other firm decisions that the board interlock literature explores include mergers and acquisitions and corporate governance structures.[2]

This literature has two important implications for our research. First, many of the financial decisions studied in the literature (e.g., option backdating, earnings management, tax avoidance) are not transparent to the public; hence, focal firms require *private* channels, such as board interlocks, to learn about the details and impacts of these financial decisions (Chiu et al. 2013).

Second, the influence of board interlocks on a focal firm's decisions can be attributed to *communication with interlocked firms*, through which details pertaining to the decisions are discussed. Davis (1991, p.594) attributes the spread of a new financial policy through board interlocks to a mechanism by which "to the extent that one's contacts have adopted some innovation and communicated their reasoning, the perceived value of adoption will increase." Connelly et al. (2011, p.690) contend that "a manager seeking to resolve the uncertainty around the benefits of using a new practice wants hard data on the benefits of adopting, such as the performance of prior adopters," while interlocked firms "gain an inside look at the major accomplishments and setbacks those firms [with which they are interlocked] encounter after they have adopted." However, this communication and the resultant conversational learning have not been explored empirically in the board interlocks literature. To the best of our knowledge, no research on board interlocks has explicitly identified settings in which conversational learning is likely to take place.

[2] Haunschild and Beckman (1998) find that firms that have interlocked directors from acquisitive firms tend to become more acquisitive. Stuart and Yim (2010) find that a firm is more likely to offer private equity if it has interlocked directors from firms that have private equity deal experience. Shipilov et al. (2010) find positive associations of governance practices among firms with common directors.

2.2 Social Learning

As defined earlier, social learning generally refers to a decision maker learning from others' choices and experiences. Such decisions, which can be made by individuals (Cai et al. 2009, Sorensen 2006) or by firms (Brown and Drake 2014, Lieberman and Asaba 2006, Kaustia and Rantala 2015, Yiu et al. 2014), include decisions for new technologies (Bikhchandani et al. 1998, Li et al. 2014).

For firms, motives for social learning can stem from the institutional environment. Information systems (IS) studies have applied the two lenses—social learning and institutional theory—to study firm investment in new technologies (Teo et al. 2003, Li et al. 2014). Both lenses concern uncertainty embedded in new technologies and help us better understand firms' behaviors when they face uncertainty. Specifically, three types of pressure in a firm's institutional context generally make such uncertainty salient. Coercive pressure is often driven by standards and regulations; in turn, when a firm is uncertain how to comply with new IT-related standards and regulations, it may be motivated to learn socially from other firms. Mimetic pressure, meanwhile, is closely driven by uncertainty in that, when a new technology appears, its embedded uncertainty will push firms to model themselves on others. This modeling process may make the technology trendy, and if so, more firms will be exposed to the new technology and may be motivated to learn about the new technology. In contrast, normative pressure is driven by professional values. Emerging technologies (e.g., big data and analytics, artificial intelligence, cognitive computing, cloud technology) all entail significant uncertainties with respect to appropriate codes for professional conduct, and these uncertainties require firms to address data privacy and security issues, ethics, and associated risk/return tradeoffs. That said, these professional standards of conduct and codes of ethics that accompany such emerging technologies have not yet been developed fully. As a result, firms facing such dilemmas as they struggle to make related trade-off decisions may be motivated to learn socially from other firms' decisions, values, and codes of conduct.

Institutional theory (DiMaggio and Powell 1983) focuses on institutional isomorphism that makes firms similar without necessarily making them efficient. Specifically, taken-for-granted assumptions (underlying mimicry) and political forces (coercion and norm) drive conformity as firms pursue legitimization, so they may survive in institutional environments rife with uncertainty that do not necessarily make conformity efficient. As DiMaggio and Powell (1983, pp.153-4) note, "each of the institutional isomorphic processes [coercive, mimetic, and normative] can be expected to proceed in the absence of evidence that they increase internal organizational efficiency. … [S]imilarity can make it easier for organizations to transact with other organizations, to attract career-minded staff, to be acknowledged as legitimate and reputable, and to fit into administrative categories that define eligibility for public and private grants and contracts. None of this, however, insures that conformist organizations do what they do more efficiently than do their more deviant peers."

We recognize that the institutional environment can present uncertainty pertaining to IT for the focal firm, but we are concerned about the firm learning how to deal with uncertainty from various sources (institutional and other) regarding IT investment so as to make its decisions more efficient. Hence, we focus on a firm's social learning. Firm-level research has used the perspective of social learning. Lieberman and Asaba (2006) submit that social learning and institutional theory are two related lenses that help answer the question: why do firms imitate each other? Theory of firm-level social learning itself emphasizes how a focal firm (learner) acquires knowledge from other firms and how the learner's decisions rely heavily on outcome expectations (i.e., impacts on firm performance) (Yiu et al. 2014). Empirical studies also document evidence that supports social learning in firms' decision-making, including IT investment decisions.

Following the literature, we distinguish between two types of social learning: observational and conversational. In our research context (IT investment and return), observational learning and conversational learning differ in important ways, including (i) the mechanism for learning, (ii) the information obtained by a focal firm, and (iii) the uncertainty reduced for a focal firm (Table 1).

[Insert Table 1 about here]

First, observational learning is based on "watching others" (Li et al. 2014), while conversational learning requires communication between learners and sources of learning. There is a long stream of research in economics on such communication-based, conversational learning (Conley and Udry 2010, Sorensen 2006). In our research context, conversational learning is likely in boards that are active in sharing and exchanging ideas through multiple board meetings, in which a focal firm and its interlocked partners discuss the firm's strategic decisions (Carpenter and Westphal 2001), including a variety of IT-related decisions (e.g., IT budgets, plans, priorities, value) governed by the board (Benaroch and Chernobai 2017). As ideas are shared and exchanged, focal firms can elaborate upon IT decisions under consideration, and their interlocked firms can share related knowledge and experiences.

Second, through observational learning, a focal firm observes others' choices and then *infers* their private information; conversational learning, in contrast, allows a focal firm to obtain information directly through communication (e.g., board meetings). The social learning literature confirms that information learned through conversational learning can include: (a) interlocked firms' IT investment decisions (Li et al. 2014); (b) details of the investment, such as costs, risks, and performance impacts (Young 2009); and (c) interlocked firms' experiences of how to manage IT after an investment is made (Conley and Udry 2010). [3]

Third, both observational learning and conversational learning from interlocked firms can reduce a focal firm's uncertainty when it makes IT investment decisions, albeit in different ways. According to the observational learning literature, learning by observation reduces a decision maker's uncertainty based on the assumption that interlocked firms use their private information when they make decisions. However, focal firms are unable to observe whether interlocked firms possess relevant private information and how they use such information, which requires focal firms to make assumptions (Bikhchandani et al. 1992, 1998). The economics literature concludes that, because these assumptions may or may not be true, "blind" imitation is likely to occur (Bikhchandani et al. 1992, 1998). Similarly, the IS literature contends that imitation may result in investment decisions "regardless of the technical value of a practice or innovation" (Teo et al. 2003, p.22). The IS literature even documents cases in which observational learning led firms to adopt the wrong technologies (Li 2004). In contrast, conversational learning reduces the uncertainty related to IT investments that focal firms face by allowing them to learn from interlocked partners about investment details, various associated costs, as well as the risks and performance impacts of IT (Young 2009). Conversational learning also reduces uncertainty associated with IT management by allowing focal firms to learn from the interlocked firms' experiences (Conley and Udry 2010). Therefore, it is reasonable to expect conversational learning to improve firm performance.

2.3 Hypotheses

We develop a research model (Figure 1) that (i) uses *interlocked firms' IT investment* and *interlocked firms' IT capability* to explain a focal firm's social learning through board interlocks about IT investment decisions, (ii) integrates *board activity* as a contextual factor that facilitates conversational learning, and

[3] Li et al. (2014) study the role of social learning with respect to IT investment. Young (2009) and Conley and Udry (2010) provide implications for innovation adoption in general. Young (2009) examines innovation adoption in general and discusses evidence from farmers' adoption of a new seed. From an economic perspective, a farmer can be considered a profit-seeking small enterprise. As Young (2009) notes, "farmers delayed so long in adopting a technology that could have substantially increased their profits" (p.1917) and "the rate of adoption in each region was positively correlated with the estimated monetary gain from adoption" (p.1919). Similarly, Conley and Udry (2010) suggest that pineapple farmers learn from each other about how to manage a new farming technology, and that high profits achieved by a given farmer's information neighbors will influence his or her decision. These studies (Young 2009, Conley and Udry 2010) have implications that are applicable to our work, which examines how firms make IT investment decisions with the ultimate goal of improving firm performance.

(iii) examines the impact of social learning on a *focal firm's performance*. We list key model components (including their conceptualization and operationalization) in Table 2 and put forward our corresponding hypotheses below.

[Insert Figure 1 about here]

[Insert Table 2 about here]

Influence of board interlocks on IT investment

To hypothesize the influence of board interlocks, we discuss (a) the subject of our theorization (i.e., strategic IT), (b) the role of board interlocks in social learning beyond other possible channels for social learning, and (c) the ways in which social learning reduces uncertainty for a focal firm.

As we state in the Introduction, our theorization focuses on strategic IT, as opposed to mundane IT that may not require a board's attention. Based on the literature (Ranganathan and Brown 2006, Mithas et al. 2013), strategic IT has several key features. First, strategic IT can influence a firm's strategically important processes. Second, the investment is large. Third, return to the investment is highly uncertain. For instance, in the 2000s, enterprise systems applications—CRM and SCM, in particular—entailed "radical improvements in strategically important processes, greater investment in complementary resources, and organizational learning due to the implementation of cross-functional processes" (Ranganathan and Brown 2006, p.150). Investment in these applications accounted for much of corporate IT spending during the 2000s (Keil and Tiwana 2006). They were shown to have high financial returns (Anderson et al. 2003) but also high failure risks (Morris and Venkatesh 2010). Therefore, such investments need to be incorporated into board-level strategic deliberations (Nolan and McFarlan 2005).

We next identify board interlocks as a practical channel for information sharing with respect to strategic IT, beyond other typical channels (e.g., standard financial reports, media coverage, vendors, and consulting firms). "Although information management has assumed an increasingly important role in defining the strategic direction of businesses, there is no standard for reporting IT initiatives under current accounting rules" (Anderson et al. 2003, p.91). Some firms announce IT investment to the business press, but such announcements are not common. For instance, Ranganathan and Brown (2006), collecting firm announcements of enterprise system investment, found only 116 that had been made over a period of five years. Firms only reluctantly release public information about strategic IT initiatives such as CRM and SCM investments, which informs their competitors (Zhu 2004), and only a few firms allow vendors and consulting firms to share related information with others (Liu et al. 2013). Communication via board interlocks, in contrast, can help firms transfer information about strategic IT initiatives. The Clayton Act prohibits board interlocks among direct competitors, but not intra-industry or cross-industry interlocks (Brown and Drake 2014).[4] Since interlocked firms are not direct competitors, a focal firm's board is unlikely to share information considered harmful to the interlocked firms. Although prior studies on board interlocks have not examined strategic IT investment, they have accumulated rich evidence suggesting the sharing of information via board interlocks about strategically significant decisions, such as mergers and acquisitions, and even the sharing of sensitive information, such as earnings management and tax avoidance. If board interlocks can then be considered a conduit of social learning for such strategic decisions involving sensitive information, then board interlocks may very well serve as a channel for social learning about strategic IT.

Social learning via board interlocks—in particular, conversational learning—reduces a firm's uncertainty concerning strategic IT investment decisions. What the focal firm can learn via conversational learning includes not only detailed IT investment information (e.g., amounts, specific technology details), but also performance impact and how to manage IT after making an investment. First, the impacts of strategic IT such as CRM and SCM applications are embedded in business processes (Ray et al. 2004). A focal firm's learning about the impacts of strategic IT therefore demands communication with others who have experienced them in their own firms. Board interlocks offer reliable and credible knowledge sources, both because of board directors' fiduciary roles and because of their direct, vivid experiences and related knowledge from their own firms. Second, after making IT investments such as CRM and SCM applications, firms generally need to manage the co-evolutionary changes in processes and business strategies (Bharadwaj et al. 2007); some of these changes are even ingrained in inter-firm relationships (Rai et al. 2012). In order to realize IT payoffs, a focal firm then needs to manage IT in ways that accommodate these complementary changes in processes and strategies. Because such changes are typically invisible to outsiders, social learning via board interlocks is arguably an important way for a firm to learn about these changes.

Now we turn to the consequence of social learning for a firm's IT investment decisions. As a focal firm obtains detailed information about certain IT investments by its interlocked firms, including investment amounts (likely obtained from both observational learning and conversational learning), costs and benefits (likely obtained from conversational learning), and how to manage IT (likely obtained from conversational learning), that focal firm reduces uncertainty associated with its own IT investment

[4] Since firms in the same SIC-4 industry are likely to be director competitors, we test the sensitivity of our main results by excluding interlocked firms in a focal firm's SIC-4 industry and find similar results.

decisions. The focal firm, therefore, will likely make the same or a similar IT investment, made manifest in a positive relationship between the focal firm's IT investment and that of its interlocked firms.

H1a: A focal firm's IT investment is positively related to that of its interlocked firms.

Further, we expect the relationship in H1a to be moderated by interlocked firms' *IT capability*, which refers to their ability to effectively deploy IT with other firm resources (Bharadwaj 2000, Rai et al. 2012). As we discuss earlier, successful IT applications require firms to manage complementary changes in processes and strategies. By definition, firms with high IT capability are better able to manage these complementary resources. There are two reasons for expecting a stronger impact of interlocked firms with higher IT capability on a focal firm's IT investment decision-making. First, firms with higher IT capability are more likely to obtain positive IT payoffs, and the literature supports this expectation (e.g., Bharadwaj et al. 1999, Mithas et al. 2011, Muhanna and Stoel 2010). Therefore, the information that interlocked firms with higher IT capability share with a focal firm is more about investment that worked out well than about investment that didn't, which then reduces the focal firm's uncertainty about investment return to a greater extent. Second, interlocked firms with higher IT capability can better inform a focal firm how to manage IT with complementary resources; the more such knowledge is transferred, the more it reduces the focal firm's uncertainty about how to manage IT strategically. The focal firm is therefore more likely to make an IT investment that is the same as or similar to that of its interlocked firms.

H1b: The relationship between interlocked firms' IT investment and a focal firm's IT investment is positively moderated by the interlocked firms' IT capability.

This moderation effect of interlocked firms' IT capability, however, depends on the level of board activity. The level of board activity, which manifests itself as the number of board meetings, reflects the extent to which board members collectively contribute their time and devote into exchanges of ideas with respect to a firm's decision-making processes (Conger et al. 1998, Lipton and Lorsch 1992). Accordingly, we expect board activity to be a contingency in the focal firm learning about interlocked firms' IT investments.

At the low end of the spectrum, a corporate board is not active; such a board is symbolic in that it does not engage in in-depth discussions about a firm's strategic decisions, but rather functions solely as a necessary legal entity for corporate governance. When a board functions symbolically, the focal firm will be unable to execute learning processes effectively because the board does not provide substantive ideas and knowledge as inputs for the firm's decision making. From the vantage of the focal firm's IT investment decisions, such a board may simply be a vehicle for the firm to obtain information about the interlocked firms' IT investment decisions (e.g., amount) but without attaining detailed knowledge about these IT investments. In such a case, even if the interlocked firms possess high IT capability, they lack the opportunities to transfer related knowledge and experiences to the focal firm. As a result, the focal firm will more likely observe and imitate interlocked firms' IT investment decisions, regardless of how well those decisions actually worked.

At the high end of the spectrum, a board is active; the board devotes substantial time to board meetings that institutionalize communication among directors and promote the flows of external knowledge and experiences to inform the focal firm's strategic decisions (Brick and Chidambaran 2010, Carpenter and Westphal 2001, Vafeas 1999). As such, an active board strengthens the focal firm's social learning, particularly conversational learning, from its interlocked partners. With respect to the focal firm's IT investments, such a board can be a vehicle for the firm to keep abreast of constant and rapid IT changes.[5] Through communications in board meetings, an active board enables the focal firm to learn, for example, details about the interlocked firms' IT investments, where to strategically target IT investments, and how to implement and manage IT investments. Based on this discussion, we expect the moderation effect of interlocked firms' IT capability to be stronger when a focal firm has an active board.

H1c: The positive moderation effect of the interlocked firms' IT capability (proposed in H1b) is stronger when the focal firm has an active board (vs. when the firm's board is not active).

Performance effect

We define *interlock-driven IT investment* as the component of a focal firm's IT investment that is made due to learning from its interlocked firms. This investment captures the *joint* impact of the interlocked firms' IT investment and their IT capability (graphically illustrated in Figure 1).

The interlock-driven IT investment may impact performance for two reasons. First, social learning—especially conversational learning—helps the focal firm make the "right" investment decisions (i.e., those more likely to pay off). After obtaining detailed information about the costs and benefits of IT investments made by its interlocked firms, a focal firm can follow their successful examples to avoid

[5] For example, when Equifax in 2017 suffered IT failures (i.e., a cybersecurity breach), its board meetings increased from 6 times in the previous year to 26 times. See the proxy statement of Equifax in 2017 (https://www.sec.gov/Archives/edgar/data/33185/000130817918000113/lefx2018_def14a.htm).

mistakes. Because interlocked firms with higher IT capability have more successful investments, a focal firm is more likely to follow those firms (as hypothesized in H1a). In other words, the outcome of social learning (particularly conversational learning) is to follow successful examples (i.e., firms with higher IT capability) rather than unsuccessful ones.

Second, through social learning (particularly conversational learning), a focal firm learns about IT management, which is useful once an investment is made. This differs from the first reason. An assumption of the first reason is that the performance impacts for the interlocked firms' IT investment have already been demonstrated, so that the interlocked firms can share relevant information. Even if the performance impacts of some interlocked firms' investments may not have surfaced yet, focal firms can still benefit from social learning by learning later how to manage that IT investment.

Although advice from interlocked directors is not guaranteed to be beneficial, the literature confirms that, as a *group*, interlocked directors provide useful advice (e.g., Cai et al. 2014, Haunschild and Beckman 1998; see also the literature review in Section 2.1). Interlocked directors are usually selected carefully as experts (Fama and Jensen 1983), including as IT experts.[6] As IT is increasingly ingrained in business models and firm strategies, we argue that interlocked directors have gained experience and knowledge regarding IT investment and management in their respective home companies, and that this experience and knowledge helps generate useful, collective advice that they can offer to focal firms.

Accordingly, we suggest that the performance impact of interlock-driven IT investment depends on the level of board activity. With an active board, communication and discussions with interlocked directors enable the focal firm to obtain detailed information about interlocked firms' IT investments and to learn how best to manage IT investments, based upon interlocked firms' knowledge and experience. In contrast, when the focal firm's board is not active, the firm lacks these opportunities to learn from the knowledge and experience of interlocked firms in managing IT investments. In such cases, observational learning is more likely to be at work; the focal firm may imitate interlocked firms' IT investments, but without the insights that require detailed explanations about the outcomes associated with IT investments and also without in-depth discussions regarding why and how interlocked firms managed the investments (Li 2004, Teo et al. 2003). This kind of social learning, regardless of interlocked firms' IT capability, may lead to

[6] For instance, General Electric's 2014 proxy statement states that the managerial responsibilities of its board include "standardized reviews of long-term strategic and operational planning … and information technology and security" and highlights the directors' areas of expertise, including IT management (see p. 13 of General Electric's Form DEF 14A: www.sec.gov/Archives/edgar/data/40545/000120677414000746/ge_def14a.htm).

suboptimal IT investment decisions for the focal firm. Based on this discussion, we expect a stronger performance impact of interlock-driven IT when a focal firm has an active board.

H2a: There is a positive relationship between a focal firm's interlock-driven IT investment and the focal firm's performance.

H2b: The positive relationship between a focal firm's interlock-driven IT investment and the focal firm's performance (proposed in H2a) is stronger when the focal firm has an active board (vs. when the firm's board is not active).

3. Methodology

3.1 Data and Sample

Our dataset covers the period 2001–2008 and comes from four sources. We elaborate upon the data sources and variables below (Table A1 in the Appendix presents definitions of all variables and summary statistics. Table A2 shows correlations of major variables.).

IT investment. We obtained IT investment data from the Computer Intelligence (CI) database, which has been widely used and is considered a reliable source (e.g., Chwelos et al. 2010, Dewan et al. 2007, Forman 2005, Kleis et al. 2012). The data contain detailed information about IT infrastructure in over 500,000 business establishments in the US and Canada. The data vendor, Harte Hanks Inc., is regarded as the authoritative source for data on companies' IT investments and applications, and Harte Hanks updates the database annually via surveys, site visits, physical audits, and telephone interviews. Harte-Hanks identifies three levels of business establishment: branches, divisional headquarters, and firm headquarters. Divisional headquarters represent business units, while firm headquarters represent firms. We use two measures to capture IT investment with strategic importance to firms: (a) enterprise systems applications covering a firm's customer relationship management (CRM) and supply chain management (SCM), and (b) IT labor expense. To avoid the potential misrepresentation of enterprise systems applications and IT labor, we include in our sample only those firms with non-missing values for their firm headquarters. We then aggregate enterprise systems applications and IT labor data from business units and firm headquarters, since strategically-focused IT investments are concentrated in those sites (Cotteleer and Bendoly 2006).

- ***Investment in CRM&SCM applications***: As explained earlier, CRM and SCM applications were strategic IT investments in the 2000s due to large investment amounts (Keil and Tiwana 2006), high potential returns associated with high risk (Anderson et al. 2003), and their role in shaping strategically important value-chain processes (Ranganathan and Brown 2006). Following Dewan and Ren (2011), we measure CRM&SCM applications as the sum of users of the two applications scaled by the number of employees. Because the number of users serves as the basis for license fees charged by enterprise systems vendors, the number of users serves as a good proxy for investment in enterprise systems (Eisenfeld et al. 2003).

- ***IT labor expense*** serves as a close proxy for investment in IT software and services (Hitt and Brynjolfsson 1996). Since the 2000s, a firm's IT labor expense has become two to three times the amount of its hardware spending and, as a result, bears greater strategic importance (Tambe et al. 2012). We estimate IT labor expense by aggregating each establishment's IT staff multiplied by average IT staff pay in the establishment's geographical area (we obtain this data from the US Bureau of Labor Statistics). To allow this measure to capture strategic components of IT investment, our computation includes establishments with CRM and SCM applications only. We then scale a firm's IT labor expense by the number of employees.

By measuring firm investment in CRM and SCM applications and IT labor expense, we have well captured the strategic elements of a firm's IT investment during our sample period.

Board interlocks**.** We obtain information about board interlocks from RiskMetrics, which provides information on boards of directors of S&P 1500 firms and is widely used for corporate governance studies (e.g., Brown et al. 2014, Cai et al. 2014, Chiu et al. 2013). We follow the methods used in prior research (Chiu et al. 2013) to identify interlocked directors. Specifically, the RiskMetrics data includes directors' names, ages, positions, and committee memberships from 1998 to 2008. Each director has a unique identifier over the whole sample period, so we can follow a director even as he or she moves from one firm to another. To construct our interlock variable, we start with a firm's board in one year and trace whether directors corresponding to that firm-year are also directors of other firms. In Table A3 of the Appendix, we list the 10 largest companies (by assets) in our sample in 2008 and their interlocked firms. Also, in Table A4 of the Appendix, we show the three most frequent SIC codes of interlocked firms across industries. On average, each focal firm has 6.75 interlocked firms, 3.53 (56.4%) of which have IT investment data available. To avoid introducing additional noise, we make no attempt to fill in missing data; in other words, when we calculate interlocked firms' average IT investment, we include only those for which we have IT investment data. The percentage of firms missing IT investment data seems to be consistent across observations, as evidenced by the high correlation (0.85) between the number of interlocked firms and the number of interlocked firms with IT investment data, indicating that the data is not missing in any systematic way. Therefore, we conclude that missing data should not bias our results.

IT capability. *InformationWeek*'s (IW) rank for IT leaders is a widely used proxy for firm IT capability during our sample period (e.g., Bharadwaj 2000, Muhanna and Stoel 2010, Santhanam and Hartono 2003). Because the IW website listed the top 500 IT leaders but did not provide ordinal rankings for those ranked between 251-500, we code a sample firm as 2 or 1 if it is ranked either in 1–250 or 251–500. Because we were only able to download ranking information for the years 2005–2008, our sample size shrinks when we test the moderation effect of interlocked firms' IT capability.

Board activity. We proxy for board activity by the number of board meetings. The literature on board effectiveness has used the number of board meetings as an indicator of board activity, as board meetings offer a formal mechanism through which board members exchange ideas and carry out their duties to improve board effectiveness (Conger et al. 1998, Lipton and Lorsch 1992, Vafeas 1999). After collecting information from the SEC proxy filings on the number of board meetings for a focal firm, we split the sample into two subsamples—a high and low number of board meetings, respectively—by comparing a focal firm's number of board meetings in a given year with the median number of board meetings for firms in its industry in the same year.

- ***#Meetings High*** is the label for the subsample in which a focal firm's number of board meetings is higher than or equal to the industry median. This represents that the subsample firms have active boards. Accordingly, this is the setting that facilitates conversational learning.
- ***#Meetings Low*** is the label for the subsample in which a focal firm's number of board meetings is lower than the industry median. This indicates that the subsample firms have boards that are not active. As a result, conversational learning is unlikely in this setting; to the extent learning is observed for firms in this subsample, it is likely observational learning.

In Table A5 of the Appendix, we report the median, minimal, and maximum number of board meetings by industry.

3.2 Regression Models

Test H1: Influence of board interlocks on IT investment

We use Equation (1) to test H1a and H1b, in which IT_{lt} is the IT investment of a focal firm l in year t, and $AvgIT\_InterlockFirm_{lt}$ is the average IT investment of firm l's interlocked firms (not including firm l itself) in year t. According to H1a, we expect the coefficient ω to be positive.

$$
\begin{aligned}
IT_{lt} = \varphi &+ \omega(AvgIT\_InterlockFirm_{lt}) + \rho(AvgIWRank\_InterlockFirm_{lt}) \\
&+ \sigma(AvgIT\_InterlockFirm_{lt} \times AvgIWRank\_InterlockFirm_{lt}) \\
&+ \sum_{k} \beta_k(Control\, Variable\ k_{lt}) + \varepsilon_{lt} \qquad (1)
\end{aligned}
$$

Equation (1) models the moderation effect of the interlocked firms' IT capability as proxied by IW rank. As we describe above, we construct a variable *IWRank* as follows: *IWRank* equals 2 if a firm is ranked between 1-250; 1 if ranked between 251-500; and 0 if not included in the top-500 list. Note that *larger values* of *IWRank* indicate higher IT capability. Again, because a firm typically has multiple interlocked firms, Equation (1) uses their average *IWRank* to proxy for their IT capability (*AvgIWRank_InterlockFirm*). According to H1b, we expect a positive moderation effect of *AvgIWRank_InterlockFirm*; that is, if interlocked firms have a higher IT capability, then we expect a greater effect of those interlocks on the focal firm and therefore a positive sign on the coefficient σ in Equation (1).

We estimate Equation (1) separately on the two subsamples, *#Meetings High* and *#Meetings Low*, which represent, respectively, settings in which conversational learning or observational learning is likely to happen. According to H1c, the estimated coefficient σ is greater on the *#Meetings High* subsample than on the *#Meetings Low* subsample, suggesting a stronger moderation effect of interlocked firms' IT capability when the focal firm has an active board (vs. when the firm's board is not active).

We add control variables in Equation (1). First, recent research (Chiu et al. 2013) suggests that the impact of board interlocks may be contingent upon the number of interlocked firms (*#InterlockFirm*). On the one hand, a larger pool of interlocked firms may exert a stronger influence, suggesting a positive interaction between *AvgIT_InterlockFirm* and *#InterlockFirm*. On the other hand, information may be more visible and thus have a greater impact in a less crowded space (Mithas et al. 2013). In our research context, a smaller number of interlocked partners sitting in the same board room (*#InterlockFirm*) represents a less crowded space; this is consistent with the prior literature, which finds that decision makers such as investors underreact to relevant news when there are many information cues grabbing attention at the same time (Hirshleifer et al. 2009). This suggests a negative interaction between *AvgIT_InterlockFirm* and *#InterlockFirm*.

Second, we include *MatchedInterlockIT*, which is the IT of matched firms that are similar to a focal firm's interlocked firms but do not have an interlock with the focal firm. For example, if a focal firm X has interlocked firms Y1, Y2, and Y3, we identify a matched firm for each of the interlocked firms (M1, M2, and M3) using the following criteria: that the matched firm is closest to the interlocked firm in total assets, has the same two-digit SIC industry code, and is not interlocked with X. The average of the IT investments of M1, M2, and M3 is *MatchedInterlockIT*, which helps control for unobserved common characteristics (if any) other than board interlocks that may cause the correlation of the focal firm's IT investment with that of its interlocked firms.

Third, while we argue that board interlocks enable social learning, one may ask: is there any other mechanism of knowledge spillover from the interlocked firms to the focal firm? We include industry IT (*IndustryIT*) to control for one such possibility: industry knowledge spillover. We also control for knowledge spillover within regions (i.e., a focal firm obtaining IT information from firms in the same region) (Aitken and Harrison 1999); this knowledge spillover may reflect employees moving from one firm to another, talking among local people, or simply observing nearby firms. We identify neighborhood firms as those within 100 kilometers of a focal firm and having no board interlocks with it[7] and then control for the average IT of these neighborhood firms (*NeighborhoodIT*).

We also control for contextual factors that the prior literature has found to influence IT investment. Studies show that firm scope increases IT investment and that firm growth also plays a role (Dewan et al. 1998).[8] Kobelsky et al. (2008), based on a comprehensive review of the literature, suggest that prior studies use three groups of contextual factors—environment (concentration, uncertainty, diversification, and industry benchmark), organization (profitability, debt ratio, and growth), and technology (strategic role of IT in a given industry and high-tech or low-tech industry)—to explain IT investment. We include the following contextual variables. *CR4*, the four-firm concentration ratio, is the fraction of an industry's (at the four-digit SIC level) total sales accounted for by its four largest firms. *Uncertainty* equals the standard deviation of earnings for the past five years. *Diversification* represents firm diversification, measured using the Herfindahl index across the firm's business segments. *AdjustedROA* equals the moving average of the return on assets for the past three years, adjusted by the corresponding industry performance benchmark.[9] *Leverage* equals the moving average of financial leverage for the past three

[7] Both matched firms and neighborhood firms may have interlocks with other firms, but we only need to ensure that they are not interlocked with the focal firm to avoid contamination with our measure of ***AvgIT_InterlockFirm*.**

[8] There are two views on firm growth and IT investment. On the one hand, firms facing growth opportunities may want to allocate financial resources to mainstream areas of their business, suggesting a negative relationship between growth and IT investment (Dewan et al. 1998). On the other hand, IT helps firms manage growing businesses, suggesting a positive relationship between growth and IT investment (Mitra 2005).

[9] For the three organizational factors (*AdjustedROA, Leverage, Growth*), we use the moving averages of the past three years (including the current year) because firms might consider past income, leverage, and growth and smooth out transient changes of these factors when they make IT investment decisions. Our results are robust when we use concurrent adjusted ROA, leverage, and growth. *AdjustedROA* is calculated as the deviation from the industry median because firms often benchmark against industry peers' performance (Farrell and Whidbee 2003). Industry-level factors are stable, so there is no need to use moving averages.

years. *Growth* equals the moving average of the year-to-year percentage change in sales for the past three years. *Auto* and *Trans* are dummy variables indicating that IT plays either an automating role or a transformative role, respectively, in the industry. *HighTech* is a dummy variable indicating whether a firm belongs to a high-tech industry.

In addition, among the two roles of corporate boards—that of advisor and monitor—social learning mainly focuses upon a board's advisory role. We therefore control for board characteristics that are relevant to monitoring. Following Faleye et al. (2011), we construct a measure of monitoring intensity (*MonitorIntensive*) according to outside director memberships in principal monitoring committees (i.e., audit, compensation, and nominating/governance committees). Research (e.g., Goyal and Park 2002, Klein 2002) suggests that board independence (*IndependentDirector*) and the separation of the roles of board chairman and CEO (*CEO_Duality*) are good practices for monitoring. The three variables for monitoring have received consistent support in the literature. We report the details of these variable definitions in Table A1 (Variables) of the Appendix.

Test H2: Performance impact of interlock-driven IT investment

To calculate interlock-driven IT investment (*InterlockDrivenIT*), we estimate a reduced version of Equation (1) without the control variables so that the interlocked-driven IT investment varies only with interlock-related variables, namely, *AvgIT_InterlockFirm*, *AvgIWRank_InterlockFirm*, and their interaction (see Equation (2) below). Because different mechanisms underlying board interlock influence may be at work in the *#Meetings High* and *#Meetings Low* subsamples, we estimate Equation (2) on them separately. We then use *InterlockDrivenIT* and *ResidualIT*, as defined in Equations (2) and (3), to decompose a focal firm's IT investment into the element pertaining to board interlocks' influence and the residual.

$$\begin{aligned} InterlockDrivenIT_{lt} &= \hat{\varphi} + \hat{\omega}(AvgIT\_InterlockFirm_{lt}) + \hat{\rho}(AvgIWRank\_InterlockFirm_{lt}) \\ &+ \hat{\sigma}(AvgIT\_InterlockFirm_{lt} \times AvgIWRank\_InterlockFirm_{lt}) \end{aligned} \tag{2}$$

$$ResidualIT_{lt} = IT_{lt} - InterlockDrivenIT_{lt} \tag{3}$$

To test H2a, we use Equation (4), which uses Tobin's Q to measure firm performance because it is a forward-looking measure that accounts for IT's intangible and long-term impact (Bharadwaj et al.

1999).[10] H2a predicts that the impact of a focal firm's interlock-driven IT investment (*InterlockDrivenIT*) on Tobin's Q is positive; that is, the coefficient γ_1 in Equation (4) is positive.

We estimate Equation (4) separately on the *#Meetings High* and *#Meetings Low* subsamples. According to H2b, the estimated coefficient γ_1 is greater on *#Meetings High* than on *#Meetings Low*, suggesting a stronger performance impact by the interlock-driven IT investment when the focal firm's board is active (vs. when the board is not active).

$$\begin{aligned} TobinsQ_{lt} = \gamma_0 &+ \gamma_1(InterlockDrivenIT_{lt}) + \gamma_2(ResidualIT_{lt}) + \gamma_3(Lag\_TobinsQ_{lt}) \\ &+ \gamma_4(IndustryQ_{lt}) + \gamma_5(MarketShare_{lt}) + \gamma_5(PPE_{lt}) + \gamma_6(RD_{lt}) + \gamma_7(ADV_{lt}) \\ &+ \gamma_8(Size_{lt}) + \varepsilon_{lt} \end{aligned} \tag{4}$$

Following prior research relating IT investment to firm performance (e.g., Bharadwaj et al. 1999, Kobelsky et al. 2008), we add the following control variables in Equation (4): *Lag_TobinsQ* (the lagged Tobin's Q), *IndustryQ* (the industry average Tobin's Q), *MarketShare* (a focal firm's market share in its four-digit SIC industry), *PPE* (a focal firm's property, plant, and equipment investment intensity), *R&D* (a focal firm's R&D spending intensity), *Adv* (a focal firm's advertising spending intensity), and *Size* (a focal firm's size). We also include the three variables for board monitoring (*MonitorIntensive*, *IndependentDirector*, and *CEO_Duality*) as control variables. We define these variables in detail in Table A1 in the Appendix.

4. Empirical Results

In Section 4.1, we discuss our results for hypothesis testing, and we discuss our robustness tests in Sections 4.2 and 4.3. We provide a summary of these tests in Table 3.

[Insert Table 3 about here]

4.1 Hypothesis Testing

Results of testing H1: Influence of board interlocks on IT investment

In Table 4, we present our regression results when we test the influence of board interlocks on IT investment on sample splits that are based on the number of board meetings, for which the *#Meetings*

[10] As we report below, we also use the focal firm's future accounting profitability ratio as the dependent variable and obtain consistent results.

High subsample consists of firms whose number of board meetings was greater than or equal to the industry median and the *#Meetings Low* subsample consists of the rest.[11] We use two measures of IT investment—CRM&SCM applications and IT labor expense—and obtain consistent results. Specifically, we find that:

- For the *#Meetings High* subsample, (a) a focal firm's IT investment is positively associated with the average IT investment of its interlocked firms (*AvgIT_InterlockFirm*) and (b) the relationship is positively moderated by the interlocked firms' IT capability as proxied by IW rank.
- For the *#Meetings Low* subsample, the coefficient on *AvgIT_InterlockFirm* is positive and sometimes significant, but interlocked firms' IT capability does *not* play a role.

Together, these findings suggest that board interlocks can promote social learning, especially conversational learning, and that having an active board leads focal firms to be more influenced by interlocked partners that have higher IT capability. These findings support hypotheses H1a through H1c.

Regarding the controls, the interaction term of *AvgIT_InterlockFirm* and *Ln(#InterlockFirm)* is negative, which reflects that information in a less-crowded boardroom would be more visible and therefore have a greater impact on a focal firm; we articulate this view earlier when we specify our control variables. The coefficients on the contextual controls are largely consistent with those of papers in the prior literature. In particular, the coefficient on *AdjustedROA* is negative in most columns, possibly because when their performance lags behind industry peers, focal firms are motivated to increase IT investment to solve the performance problem (Salge et al. 2015).[12]

Results of testing H2: Performance effect

In Table 5, we report the regression results separately for the performance effect of interlock-driven IT investment (*InterlockDrivenIT*) on the *#Meetings High* and *#Meetings Low* subsamples. Interestingly, we find that:

- For the *#Meetings High* subsample, the performance impact of interlock-driven IT is positive and significant, suggesting a *positive* performance impact of social learning via board interlocks.

[11] The median split is parsimonious, compared to a more complicated three-way interaction model. When we use the median split, our analysis aligns with Iacobucci et al.'s (2015a, 2015b) two criteria. First, our analysis approach (i.e., using subsamples) aligns with our hypotheses of difference in relationships between two contexts: boards that are active vs. those that are not. Second, we find no multicollinearity in our sample. The mean variance inflator factors (VIF) for Equations (1) and (4) are 1.16 and 1.14, respectively, both well below the threshold of 10 for high multicollinearity (a lower level of multicollinearity).

[12] The estimate in Table 4, Panel A, column (5) suggests that a decrease of *AdjustedROA* by one standard deviation is associated with an increase of IT investment by $89 per employee (=(-0.084)*(-1.603)*1000), or an increase of 9.4% from the sample's average IT investment.

- For the *#Meetings Low* subsample, the performance impact of interlock-driven IT is not significant, suggesting *no* performance impact of social learning via board interlocks.

These results suggest that, in the context of IT investment and return, a focal firm benefits from social learning through board interlocks only when it has an active board that facilitates conversational learning. This finding supports hypotheses H2a and H2b.

We also evaluate the economic significance of the observed effects. Taking CRM and SCM applications as an example, when the number of board meetings is high (Table 5, Column (1)), the standardized coefficient of *InterlockDrivenIT* (0.034) is larger than that of *ResidualIT* (0.024), indicating that a one-standard-deviation increase in *InterlockDrivenIT* will increase *TobinsQ* by 0.034 standard deviations, which is 41.7 percent ((0.034-0.024)/0.024 = 41.7%) more than the impact of a one-standard-deviation increase in *ResidualIT*. This finding indicates an economically significant impact of board interlocks.[13]

[Insert Tables 4 and 5 about here]

4.2 Tests of Alternative Explanations

Knowledge overlap. In our research context, social learning reflects two steps: (1) an external director joins a focal firm, creating a knowledge overlap between the focal firm and the newly interlocked firm; and (2) the external director transfers knowledge to the focal firm's board. Although knowledge overlap remains the basis for social learning, this type of learning goes beyond knowledge overlap in that knowledge is transferred to the board, which ultimately makes decisions (rather than any individual member). To address this distinction between knowledge overlap and social learning, we use Equation (5) to explore the temporality of board interlocks. Specifically, we distinguish newly interlocked firms (interlocks formed in year *t*) from existing interlocked firms (interlocks formed prior to year *t*)[14] and identify firms that have left the interlock (i.e., those no longer linked with the focal firm) one, two, or three or more years earlier. If knowledge overlap is the sole driving force, then we expect the coefficient ω_1 to be positive (indicating knowledge overlap through existing interlocks), ω_2 to be positive (indicating knowledge overlap through new interlocks), and the coefficients ω_3 through ω_5 to be nonsignificant

[13] We also recognize that the focal firm's IT capability could signal its efficacy in realizing potential benefits from the IT investment. In an additional test (untabulated), we classify *InterlockDrivenIT* of the focal firm into two components: the interlock-driven IT for a focal firm with high IT capability, and the interlock-driven IT for a focal firm with low IT capability. Our empirical results suggest that the focal firm with high IT capability can better realize the potential benefits from IT investment than the focal firm with low IT capability.

[14] Newly interlocked firms are defined as firms never interlocked with the focal firm previously. It is possible that, as directors move around, some firms are interlocked, then not, then interlocked again. In our sample of 51,262 interlocks, only 196 (0.38%) exhibit this on-and-off pattern. Accordingly, to generate a "cleaner" definition, we define the newly interlocked firms as the firm-years that are "brand new" and classify the rest as existing interlocked firms.

(indicating no knowledge overlap once the interlocked director leaves the focal firm's board). The control variables are the same as in Equation (1).

$$\begin{aligned} IT_{lt} = \varphi &+ \omega_1(AvgIT\_ExistingInterlockFirm_{lt}) \\ &+\omega_2(AvgIT\_Newly\_InterlockFirm_{lt}) \\ &+\omega_3(AvgIT\_Firm\_Left\_Interlock\_1stYear_{lt}) \\ &+\omega_4(AvgIT\_Firm\_Left\_Interlock\_2ndYear_{lt}) \\ &+\omega_5(AvgIT\_Firm\_Left\_Interlock\_3rdYear_{lt}) \\ &+\sum_k \beta_k(Control\,Variable\;k_{lt}) + \varepsilon_{lt} \end{aligned} \tag{5}$$

In Table 6, we report our results. With a low number of board meetings (*#Meetings Low*), we find positive and significant coefficients for existing and newly interlocked firms (with comparable influence) and find no significant role once the interlock is broken. With a high number of board meetings (*#Meetings High*), we find that (a) the influence of existing interlocked firms' IT investment is stronger than that of newly interlocked firms (e.g., 0.181*** vs. 0.044** in Column (1) of Table 6; 0.176*** vs. 0.046** in Column (7)) and (b) firms that have ceased to be interlocked continue to play a significant role for the first year, suggesting an attenuating influence. These results *support a learning story* in that (a) *learning takes time*, such that existing interlocked firms tend to have a stronger influence than newly interlocked ones, and (b) the *effect of learning can last* after an interlock ceases. Knowledge overlap alone does not seem to fully explain our results. These results lend further support for social learning from interlocked firms, particularly when a focal firm has an active board that provides opportunities for a firm to learn about IT investment from interlocked firms' knowledge and experiences.

[Insert Table 6 about here]

Homophily. As documented in the literature, "socially proximate individuals also tend to be similar with respect to their individual-level characteristics. Thus, similarities in their behavior may be driven by similarities in individual-level characteristics" (Wang et al. 2016, p.9). This logic may be applied to a firm-level analysis of IT investment: a focal firm and its interlocked firms may be similar in certain characteristics (i.e., they may exhibit homophily), which leads to similar IT investment decisions even *before* they become interlocked. Following recent research (Aral et al. 2009, Wang et al. 2016), we leverage the timing of interlocks to help distinguish the impact of homophily from that of interlocks. We specify a regression equation as follows:

$$\begin{aligned} IT_{lt-1} = \varphi &+ \omega_1(AvgIT\_Newly\_InterlockFirm_{lt-1}) \\ &+\sum_k \beta_k(Control\,Variable\;k_{lt-1}) + \varepsilon_{lt} \end{aligned} \tag{6}$$

We divide each focal firm's interlocked firms in year *t* into two groups: newly interlocked firms (interlocks formed in year *t*) and existing interlocked firms (interlocks formed prior to year *t*). With Equation (6), we examine the relationship between a focal firm's and its interlocked firms' IT investments *prior to* being interlocked; that is, we examine the *lag* IT investment (or IT investment in year *t*-1) of both parties with the lagged control variables. If homophily were at work, then the *lag* IT investment of the newly interlocked firms should have a positive association with the focal firm's *lag* IT investment. However, Table 7 shows no such association exists, suggesting that interlocked firms' IT investments are not similar *prior to* interlocking. This finding thus rules out the argument that certain unobserved characteristics of the interlocked firms (homophily) drive our results.

[Insert Table 7 about here]

Alternative channels of co-movement**.** Alternative factors, including common ownership and common business partners, may explain the co-variation between the IT investment of the focal firm with that of interlocked firms (i.e., the co-movement of interlocked firms) because these factors may affect board interlocks and IT investment simultaneously (e.g., Tafti et al. 2013). We take the following steps to address this possibility:

(1) To address co-movement due to common ownership, we use Thomson-Reuters 13F institutional holding data to identify interlocked firm pairs in which the same long-term dedicated investor holds more than a five-percent equity in both (Columns (1) through (4), Table 8).[15]

(2) To address co-movement among firms within a business alliance, we use the SDC Platinum database to identify interlocked firm pairs that are members of a business alliance (Columns (5) through (8), Table 8).

(3) To address co-movement among major supply chain partners, we identify interlocked firm pairs that are also major supply chain partners.[16]

After excluding all these firm pairs, our results hold (as we show in Table 8), indicating the robustness of our results with respect to the impact of board interlocks.

[Insert Table 8 about here]

[15] We follow the prior studies (e.g., Bushee 1998) to define long-term dedicated investors as institutional investors who have continuously held their equity investment in firms for more than two years.

[16] Specifically, we use the Compustat-Segment data to identify major supply chain partners because U.S. financial reporting standards require firms to report customers that account for more than 10 percent of total sales. When we merge the major supply-customer pairs with our board interlock data, we find that excluding those supply-chain-partner pairs has no effect on our main results (untabulated).

***Other unobservables*.** Other than the alternative explanations that we have previously discussed, unobserved factors could drive both interlock connection and IT investment. To address this possibility, we include two-digit SIC industry fixed effects in our model to control for time-invariant, industry-specific factors and also add year dummies to control for economy-wide fluctuations in all of our regressions. We also use firm-level random effects as an alternative specification to control for any unobserved firm-level time constant effects.[17] Our findings are robust to this alternative specification (as we report in Table 9). In addition, we address endogeneity by using the dynamic generalized method of moments (GMM), which is designed for datasets with a relatively short time dimension, such as our eight-year (2001–2008) sample (Arellano and Bond 1991).[18] We instrument the endogenous variables by their lagged values and lags of the exogenous variables because, by construction, those lagged variables are uncorrelated with the error term and partially correlated with the endogenous variables. Besides those internal instruments, we also use the average levels of the nine determinants of IT investment *of the interlocked firms* (*CR4, Uncertainty, Diversification, AdjustedROA, Leverage, Growth, Auto, Tran*, and *HighTech*) as the external instruments because they only affect the IT investment of the focal firm through their effect on the interlocked firms' IT investment. We then use the two-step robust GMM to ensure that the resulting standard errors are consistent with panel-specific heteroscedasticity.[19] In Table 9, we report our results for three tests: the Hansen test for overidentification restriction, the AR(1) (first-order serial autocorrelation), and the AR(2) (second-order serial autocorrelation). The Hansen tests turn out to be insignificant, indicating that the instruments as a group are exogenous and, thus, valid. The AR(1) and AR(2) tests show that panel-specific autocorrelation in our sample is not severe. As we show in Table 9, our results continue to hold with these econometric adjustments.

[Insert Table 9 about here]

***Competition concern*.** There is a concern that sharing information from an interlocked director to a focal firm may eventually cause further information to be leaked to direct competitors of the director's own firm. This competition concern may prevent interlocked directors from sharing IT investment information. To address this concern, we exclude interlocked firms in the focal firm's same four-digit SIC industry because the competition concern, if any, should be salient for these firms. After excluding these firms, we

[17] Hausman tests suggest no significant differences between random and fixed effects estimates. Due to the efficiency and generalizability advantages of random effects models, we choose to use random effects models.
[18] Endogeneity may be caused by unobserved variables being correlated with our independent variables. For example, the average IT investment of interlocked firms would be endogenous if causality goes both ways (i.e., from interlocked firms' IT investment to the focal firm's IT investment, and vice versa). We thank an anonymous reviewer for suggesting the dynamic generalized method of moments.
[19] Results from our one-step robust GMM are similar because the tests show that panel-specific autocorrelation in our sample is not severe.

continue to find consistent results with respect to the influence of board interlocks on the focal firm's IT investment (results not tabulated for brevity's sake).

4.3 Tests with Alternative Controls and Measures

#Meetings High versus #Meeting Low. In our main analysis, the *#Meetings High* subsample is defined as firms whose number of board meetings is *greater than* or *equal to* the industry median. Alternatively, we include in the *#Meetings High* subsample only those firms whose number of board meetings is *greater than* the industry median, in order to alleviate the concern that firms with the industry median number of board meetings would otherwise belong to neither subsample (Table 10).

[Insert Table 10 about here]

An alternative IT measure: IT hardware capital. Papers in the prior literature use hardware capital to capture a firm's overall IT investment (e.g., Chwelos et al. 2010, Dewan et al. 2007). Following Chwelos et al. (2010), we use the hedonic method to construct hardware capital scaled by total assets for each firm-year. When we use this measure to rerun our tests, we obtain the results that we show in Table 11. When the number of board meetings is high (*#Meetings High*), a focal firm's hardware capital is positively associated with that of its interlocked firms (Panel A) and the focal firm's interlock-driven hardware capital is positively associated with Tobin's Q (Panel B); this collective evidence is consistent with learning. However, interlocked firms' IW rank does not play a moderating role, which differs from our result in the main analysis when we examine strategic IT investment. A plausible explanation for this finding is that many hardware products are standard products and, overall, IT hardware capital is similar to a commodity. Thus, interlocked firms with varying levels of IT capability are not differentiable in their capacity to reveal information about commodity technology.

[Insert Table 11 about here]

Alternative ways to identify matched firms. In our main analysis, when we identify matched firms to calculate *MatchedInterlockIT*, we make sure that the matched firms also have IT data. Imposing this constraint may mean that the matched firm is not a close match to the interlocked firms in the matching dimension (i.e., total assets). To address this possibility, we therefore run an additional test by first restricting the matched firm's total assets to within 10% of the interlocked firm's total assets and then by identifying a matched firm that is closest to the interlocked firm with respect to total assets, that shares the same four-digit SIC code, and that is not interlocked with the focal firm. When we run this test, our results are similar to our main results (Table 12).

[Insert Table 12 about here]

Alternative ways to code IW ranking. In our main analysis, we code a sample firm as 2 or 1 if it is ranked either 1–250 or 251–500, given the availability of IW ranking information. To ensure our list is credible, we code unranked firms as 0, for stellar firms are more likely to be included in the IW ranking; in contrast, unranked firms are more likely to be mediocre firms with respect to their IT capability. We use an alternative coding scheme by including just the top 250 firms and using their ordinal ranking in our regression. We also code a sample firm as 2 or 1 if it is ranked either 1–100 or 101–500 because the top 100 firms are the outstanding IT leaders. When we re-run our main analysis with this alternative coding scheme, we obtain qualitatively consistent results (Table 13).

[Insert Table 13 about here]

Alternative measure for IT capability. In our analysis so far, we have used IW rank to proxy for IT capability. We now draw on interlocked directors' background to develop an alternative proxy. Specifically, we (a) collect their employment information from SEC proxy filings and RiskMetrics, (b) construct an indicator variable, *Interlock_IT_Industry_Experience*, to determine whether any interlocked directors have working experience in IT industries, and then (c) use that variable as an alternative proxy for interlocked firms' IT capability.[20] In Columns (1), (3), (5), and (7) of Table 14, we obtain results that are consistent with a learning story. Since CEOs are especially knowledgeable about their own firms' strategic decisions, we also test whether interlocked directors who are also CEOs of interlocked firms affect the transfer of strategic IT knowledge.[21] Our results from Table 14 (see Columns (2), (4), (6), and (8)) show that the relationship between a focal firm's IT investment and those of its interlocked firms becomes stronger when interlocked directors are CEOs in the interlocked firms and when there is an active board. This finding is consistent with the notion that CEOs, being knowledgeable about their own firms' strategic IT decisions, are a valuable source of such knowledge—and, hence, of social learning—for the focal firm.

[Insert Table 14 about here]

Alternative performance measure. In our main analysis, we use Tobin's Q to measure firm performance because it is a forward-looking measure. Alternative measures used in prior studies include the two-year average return to assets (ROA) subsequent to IT investment (Ho et al. 2011) and the three-year average

[20] Following prior studies (Brynjolfsson et al. 2002, Dehning et al. 2007, Gaba and Meyer 2008), we consider IT manufacturing (3-digit SIC: 357, 366-368) and IT services (481-484, 489, 737) as IT industries.

[21] Chief information officers (CIOs) are seldom found on corporate boards. In only three of our sample's 1,952 firm-year observations (around 0.15%) do interlocked directors hold a CIO title.

return on sales (ROS) subsequent to IT investment (Kobelsky et al. 2008). When we used these alternative measures, we found consistent support for our hypothesis. In Table 15, we show our regression results when we use future ROS as the dependent variable. In the *#Meetings Low* subsample, the interlock-driven IT is negatively related to the two-year average ROS, suggesting that the benefit of IT, if any, does not cover IT investment in the case of observational learning. In the *#Meetings High* subsample, we see a consistent positive impact of interlock-driven IT across different IT measures and accounting profitability measures, providing strong evidence of the beneficial impact of board meetings to promote conversational learning.

[Insert Table 15 about here]

5. Discussion

5.1 Major Findings and Contributions

This paper starts by asking questions of "whether," "the levers," and "so what" with respect to social learning for strategic IT investments through board interlocks. We now summarize findings that answer these questions. We first ask: if board interlocks facilitate social learning from interlocked firms (i.e., *whether* a focal firm makes IT investment similar to those of its interlocked firms). Our finding provides strong support for social learning in the context of IT investment decision-making, be it for conversational learning (facilitated by an active board) or observational learning (likely in a firm whose board is not active), as manifested in the similarity between a focal firm's IT investment and that of its interlocked firms. Regarding the *levers*, we find that the similarity is amplified by the interlocked firms' IT capabilities, but only if the board is active. The "*so what*" question, then, addresses the performance impact, and we do find evidence suggesting that social learning through board interlocks promotes economic benefits for firms; that is, the component of a focal firm's IT investment that is attributable to board interlock influence is positively related to firm performance, but only if the board is active, enabling sharing and communication in multiple board meetings with interlocked firms to learn about relevant IT investments and how to implement and manage IT.

With these findings, our paper makes the following contributions. To start with, *by theorizing and testing the influence of social learning as an input to IT investment decision-making, this study sheds light on how firms can make efficient IT investment decisions and how social learning contributes to IT investment returns.*

We depart from prior research on IT investment decision-making, which has focused mainly on the influence of contextual factors (e.g., Dewan et al. 1998, Kobelsky et al. 2008, Mitra 2005). Specifically, we provide a rationale for the influence of social learning on a firm's IT investment and offer supporting evidence. Unlike prior studies that assume firms align their IT investment with common contextual requirements, our paper significantly expands this view by controlling for common contextual factors and surfacing the role of social learning through board interlocks. Our results suggest that firms not only react to contextual requirements when they make IT investments, but also use private sources for learning, namely board members who also sit on the boards of other firms. In particular, when we consider cases in which the board is active (i.e., having frequent board meetings), we find that conversational learning allows a focal firm to obtain detailed knowledge of IT investments (e.g., what investments were made, how they were managed, what impacts were realized) from the interlocked firms, such that the focal firm differentially follows the IT investments of interlocked firms with different IT capabilities; in turn, we find that this knowledge transfer results in pronounced performance improvement.

While the IT business-value literature has accumulated rich theories to explain the heterogeneity of IT investment returns across firms, our paper is, to the best of our knowledge, the first to document performance benefits of social learning through board interlocks, which adds a novel theoretical perspective to that literature. In particular, our analysis highlights the magnitude of the performance impact of IT investment driven by social learning (see Table 5), which suggests that social learning with respect to IT investments and returns is not only economically meaningful and beneficial, but also warrants future research.

Furthermore, we investigate conditions in which a firm can socially learn about IT investments in the interlocked board network, thereby improving the returns from IT investments. In doing so, we make two unique contributions.

First, *we surface high board activity as a key contextual factor that facilitates conversational learning*. We highlight that to better learn about IT investments and realize their potential, a focal firm not only ought to put IT issues on board directors' agendas, but also ensures an active board that fosters the sharing of knowledge and experience of interlocked firms with IT investments. Moreover, only when board directors are active in sharing such knowledge and experience, can a focal firm conversationally learn, in any substantial manner, from the interlocked firms with high IT capability. In contrast, when the board is not active (i.e., the board is symbolic), we surface that mimicry or observational learning is likely to manifest.

Second, *we uncover* interlocked firms' *IT capability is another key contingency to improve social learning of a firm, but we also find doing so requires the focal firm to have an active board*. By showing that interlocked firms' IT capability and board activity together increase the influence of board interlocks, we identify the mechanism by which social learning plays a role for the board interlocks channel. These factors characterize the conditions for a focal firm seeking to acquire knowledge from board interlocks, thereby expanding the details of IT investments, performance impact, and how to manage IT after making an investment. In contrast, board interlocks for a focal firm whose board is not active may serve as a mimetic influence on the firm; nonetheless, such mimicking is unlikely to involve an important differentiation of IT investment by interlocked firms based on their IT capabilities. As a result, the focal firm is unlikely to improve performance.

5.2 Implications for Research

A direct implication for future research is to use the lens of social learning to examine a firm's IT decisions, especially those considered strategic and emergent. Various IT-related issues (e.g., cybersecurity risks, digital disruptions of operations) have recently risen to the top of the agendas of boards of directors (Benaroch and Chernobai 2017), and leveraging IT to transform business models (Rai and Tang 2014) deserves board attention as well. Our findings imply that boards can potentially use interlocks as a social learning mechanism to assess their firms' strategic IT investment issues. In turn, future research can examine whether social learning, especially via board interlocks, can help firms better deal with these important risk and transformation issues.

In the broad context of IT management, social learning can take place through other channels besides board interlocks; addressing these channels also offers an important direction for future research. Given that the dependent variable of our study is firm-level IT investment, we focus on a corresponding network for social learning that likely has a significant impact: board members. For other types of IT investment decisions (e.g., outsourcing), however, social learning may often take place at lower levels in a firm through various social networks of IT staff (e.g., social clubs, alumni gatherings, informal offline or online organizations). Moreover, employee mobility at the rank-and-file level or the executive level may contribute to social learning with respect to IT investment decisions. IT knowledge transfer can also occur at the macro-level among countries by means such as trade partnerships, the flow of IT expertise, and the exchange of scholars and students; these unexplored areas also possess great potential to help us understand IT-related knowledge transfer among networks of different types and at different levels of analysis. Future research can also examine social learning with respect to emerging technologies. As social learning using diverse channels can plausibly provide a focal firm with a broad range of learning possibilities and sources, future research can help reveal how different channels for social learning can be leveraged to make efficient investments in emerging technologies.

This study's social learning perspective suggests that directors' background, experience, and knowledge may moderate the impact of social learning. Extending our focus on interlocked firms' IT capability, future research can examine at a more granular level the impact of directors' IT and business backgrounds on the transfer of IT knowledge and the resulting impacts. Given that returns to IT investment appear highly uncertain, future research could also examine how directors' historical records of success and failure in major IT projects influence their effectiveness as sources of learning. Moreover, our study implies that active boards promote conservational learning. That said, future research should extend beyond board activity to examine whether other board attributes, such as board technology-related sub-committee composition, affect types of social learning for IT investments and strategic IT decisions in domains such as sourcing, security, and privacy. An overarching lens for future research would open up the "quality" of boards, which in theory moderates the performance impact of social learning via board interlocks.

In a similar vein, future research could also help us better understand how a focal firm chooses and invites interlocked firms to its board, especially in ways that highlight externalities that IT applications can generate. Many IT applications transcend organizational boundaries, such that firms may collaborate on IT-enabled platforms (Rai et al. 2012). Such firms thus can obtain an "insider look" at their partners' IT needs, resources, and capabilities. Considering the important role of IT externalities in a business ecosystem, identifying parts of business ecosystems that generate the most useful IT knowledge for boards offers another interesting direction for future research. In addition, future research could also explore how a firm selects interlocked partners to participate on boards, given this ecosystem perspective and the role of IT-enabled platforms that interlocked partners can provide.

More broadly, while interlocked partners' background is an example of contingencies in social learning, another direction for future research is to uncover other contingencies in social learning that influence IT investments and returns. For example, a focal firm's ability to use IT investment as a source of competitive advantage may be contingent on whether the focal firm is an early adopter of IT among its direct competitors, and the benefits of social learning for IT investment and return may thus be different for IT leaders and laggards. Future research that examines such contingencies can help develop theory to explain when and where the impact of social learning in IT investment and return is salient.

In the voluminous literature on IT business value, there is mixed evidence of the payoff from certain types of IT applications, such as SCM systems and CRM systems (Hendricks et al. 2007, Sabherwal and Jeyaraj 2015), while the evidence regarding the payoff from newer IT applications (e.g., business intelligence systems) is growing. We expect that the social learning perspective can help explain variations in payoffs across firms and highlight the learning approaches that work well for technologies of different types and at different levels of maturity. In particular, social learning will prove beneficial and salient for emerging technologies that involve high uncertainty. Further, future research can use the social learning lens to explore the impacts of IT on specific aspects of firm performance. For instance, recent research links IT investment to innovation (Kleis et al. 2012). Because innovation is expected to be significantly influenced by board directors (He and Wang 2009), future research can explore how social learning facilitates IT-enabled innovation. Future research can also address the role of social learning via board interlocks in investments that complement IT, such as business-process redesign, organizational restructuring, and the recruiting associated with IT investment (Bharadwaj et al. 2007, Mithas et al. 2011). These types of investments, along with IT, jointly influence firm performance; thus, knowing how social learning contributes to this influence would prove worthwhile. In short, there is a rich array of complementary investments to IT and of outcomes to those investments that may be subject to the influence of social learning via board interlocks.

5.3 Implications for Practice

For a firm to learn about IT investment from the knowledge and experience of its interlocked firms, it needs to set a formal agenda in board meetings. Agenda items can include elaborating and reviewing key periodic IT decisions (e.g., annual IT investment budgets) and key episodic IT decisions (e.g., strategic launch of a new platform for customer engagement, entry into strategic relationships with vendors, hiring IS leadership). They can also include seeking advice from external directors on how IT can enable key capabilities and business strategies, as well as solve or preempt IT-related strategic business problems (e.g., security breaches). To that end, a firm's board should include outside members who serve on the boards of companies with substantial IT management capability. There is also an important implication for industry consortia and policymakers, who can create collective learning platforms by gathering information from firms about their choices, practices, and outcomes regarding various IT investments. Making such information public can help firms leverage external knowledge, even if they lack opportunities for social learning via board interlocks. In addition, having an active board is crucial for a firm to effectively learn from its interlocked firms about their IT investments because social learning requires board directors to share their knowledge and experience with IT investments in ways that meaningfully inform a firm's strategic decisions.

5.4 Limitations

First, our inference for social learning through board interlocks is mainly based on the analysis of cross-sectional associations, although we do explore several dynamic tests for robustness. Future research can fully use a longitudinal research methodology to model the learning process, which would shed light on the causal impacts of social learning. An exemplary paper in agricultural economics that uses this methodology is Conley and Udry (2010), which uses data from a focal farmer's information neighbors (i.e., those communicating with the focal farmer) to model the process by which (1) the information neighbors make a decision, (2) the decision leads to certain outcomes, and (3) focal farmers observe the outcomes and make their own decisions. To apply such a methodology with survey details, future research can focus on a specific technology to examine (a) its implementation over time by firms within a business community in which members learn from each other and (b) the impacts of those implementations.

Second, due to *InformationWeek* data availability, we could only measure interlocked firms' IT capability using a proxy measure with three levels. Future research should further develop that measurement, perhaps by asking focal firms to rate the IT management capability of their respective interlocked firms' directors. In addition, while we source our IT investment data from Harte Hanks, widely considered an authoritative vendor for data related to firms' IT resources, and obtain the most complete version of the data from this vendor, the validity of our findings are subject to the quality of the data that that vendor provides. Future research can use multiple data sources to further test the role of social learning with respect to IT investments and returns.

Finally, because alternative explanations to social learning exist (e.g., homophily) even though we have been careful to rule them out, drawing a definitive conclusion on whether those alternative forces play a role proves challenging. To address this challenge, future research can further investigate IT investment decision processes in a boardroom by gaining access to board transcripts and/or by conducting interviews and surveys to capture granular information that captures a board's role with respect to specific IT investment decisions.

6. Conclusion

This paper contributes to our understanding of IT investment and return by shedding light on *social learning as an input* to a firm's IT investment decisions. In particular, we demonstrate the role played by interlocks between corporate boards in (a) determining the amount of a firm's IT investment and (b) increasing the return on that investment for the firm. Our findings show that the performance implication of board interlocks is economically meaningful and contingent upon two characteristics of board interlocks: interlocked firms' IT capability and board activity. Overall, this study highlights the importance of incorporating a *social learning* perspective in research and practice on IT investments and returns.

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Figure 1. Research Model

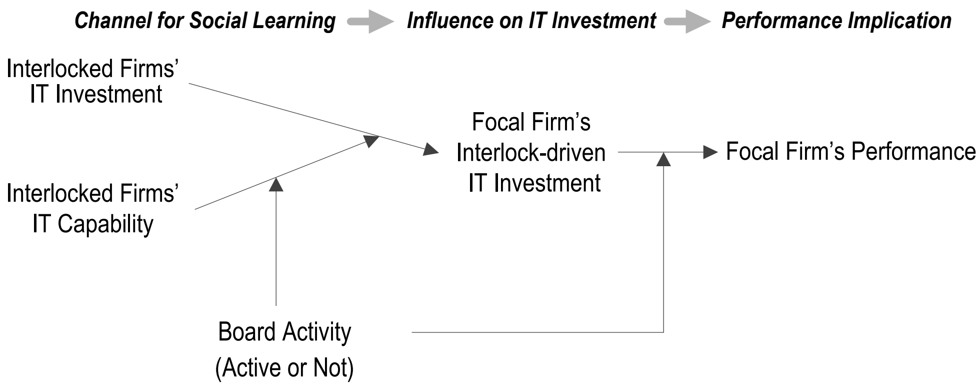

Table 1: Social Learning through Board Interlocks in the Context of IT Investment

	Learning mechanism / observation- or communication-based	Information obtained by the focal firm	Reduced uncertainty for the focal firm / performance impact	Selected references
Observational learning	Based on watching others	Interlocked firms' IT investment decisions (signals to infer their private information)	Reduced uncertainty concerning outcomes of the investment by assuming that interlocked firms have used their private information in decision making	Li et al. (2014)
Conversational learning	Requires communication with interlocked directors; board meetings are an institutionalized means for such communication	Interlocked firms' IT investment decisions (expanding *know-what*) How to manage IT (expanding *know-how*) Details of the investment and impacts (costs and risks, performance impacts) (expanding *know-why*)	Reduced uncertainty by learning about various costs and risks associated with IT investment and the performance impacts on the interlocked firms Reduced uncertainty concerning how to manage IT by learning from interlocked firms' experiences	Conley and Udry (2010), Li et al. (2014), Young (2009)

Table 2: Key Model Components

	Conceptualization	Operationalization	Selected references
Interlocked firms' IT investment	Refers to firm investment in IT that bears strategic significance to the interlocked firms	(i) Interlocked firms' investment in customer relationship management (CRM) and supply chain management (SCM) (ii) Interlocked firms' IT labor expense	(i) Dewan and Ren (2011) (ii) Hitt and Brynjolfsson (1996), Tambe et al. (2012)
Interlocked firms' IT capability	Refers to interlocked firms' ability to deploy IT with other firm resources	Firm ranking in the *InformationWeek*-500 list of interlocked firms	Bharadwaj (2000)
Board activity	Extent to which board members collectively contribute their time and devote into exchanges of ideas with respect to a firm's decision-making processes	The number of the focal firm's board meetings	Vafeas (1999)
Focal firm's interlock-driven IT investment	Refers to the component of the focal firm's IT investment that is made due to the influence of its interlocked firms	Predicted value based on interlocked firms' IT investment and IT capability	
Focal firm's performance	Focal firm's future performance; that is, performance following IT investment	(i) Tobin's Q (ii) Future accounting profitability	(i) Bharadwaj et al. (1999) (ii) Kobelsky et al. (2008)

Table 3: Summary of Results: Hypothesis Testing and Robustness Checks

	Tables	Found support?
Hypothesis testing		
H1a: A focal firm's IT investment is positively related to that of its interlock firms.	Table 4	Yes
H1b: The relationship between interlocked firms' IT investment and a focal firm's IT investment is positively moderated by the interlocked firms' IT capability.	Table 4	Partial support
H1c: The positive moderation effect of the interlocked firms' IT capability (proposed in H1b) is stronger when the focal firm has an active board (vs. when the firm's board is not active).	Table 4	Yes
H2a: There is a positive relationship between a focal firm's interlock-driven IT investment and the focal firm's performance	Table 5	Partial support
H2b: The positive relationship between a focal firm's interlock-driven IT investment and the focal firm's performance (proposed in H2a) is stronger when the focal firm has an active board (vs. when the firm's board is not active).	Table 5	Yes
Tests addressing alternative explanations		
1) Support for social learning above and beyond knowledge overlap	Table 6	Yes
2) Support for social learning rather than homophily	Table 7	Yes
3) Support for social learning after controlling for channels of co-movement (common ownership and business alliances)	Table 8	Yes
4) Support for social learning rather than impact of unobserved factors, using alternative econometric specifications (i.e., firm random effect and dynamic panel generalized method of moments)	Table 9	Yes
Tests with alternative controls and measures		
1) Support for social learning (and its performance implication) with an alternative definition of High #Meetings	Table 10	Yes
2) Support for social learning (and its performance implication) using an alternative IT measure: IT hardware capital	Table 11	Partial support
3) Support for social learning using alternative ways to identify matched firms	Table 12	Yes
4) Support for social learning using alternative ways to code IW ranking	Table 13	Yes
5) Support for social learning using interlocked directors' background as proxy for IT capability	Table 14	Yes
6) Support for social learning's performance implications with alternative performance measures	Table 15	Yes

Table 4: Influence of Board Interlocks on IT Investment

	IT=CRM&SCM				IT=IT Labor			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	#Meetings High		*#Meetings Low*		*#Meetings High*		*#Meetings Low*	
AvgIT_InterlockFirm	0.061***	0.295**	0.102***	0.257	0.069***	0.303**	0.107***	0.261
	(0.015)	(0.111)	(0.014)	(0.191)	(0.014)	(0.110)	(0.014)	(0.193)
AvgIT_InterlockFirm X AvgIWRank_InterlockFirm		0.609**		0.237		0.626**		0.223
		(0.204)		(0.227)		(0.214)		(0.234)
AvgIWRank_InterlockFirm		0.006		0.012		0.450		0.941
		(0.004)		(0.008)		(0.330)		(0.641)
Ln(#InterlockFirm)		-0.009**		0.003		-0.672**		0.241
		(0.003)		(0.005)		(0.233)		(0.387)
AvgIT_InterlockFirm X Ln(#InterlockFirm)		-0.512***		-0.209		-0.515***		-0.199
		(0.140)		(0.205)		(0.148)		(0.207)
MatchedInterlockIT		-0.028		-0.180		-0.031		-0.174
		(0.059)		(0.133)		(0.058)		(0.133)
NeighborhoodIT		0.168		-0.090		0.164		-0.086
		(0.114)		(0.114)		(0.114)		(0.115)
CR4	0.000	-0.008	-0.001	-0.007	0.061	-0.628	-0.120	-0.633
	(0.001)	(0.011)	(0.002)	(0.017)	(0.088)	(0.872)	(0.176)	(1.405)
Uncertainty	0.010	0.026	0.013***	-0.003	0.831	1.989	0.998***	-0.103
	(0.007)	(0.032)	(0.002)	(0.085)	(0.545)	(2.496)	(0.164)	(6.809)
Diversification	0.002**	-0.001	0.008***	0.011	0.113**	-0.055	0.615***	0.882
	(0.001)	(0.005)	(0.001)	(0.009)	(0.042)	(0.404)	(0.073)	(0.701)
AdjustedROA	-0.014***	-0.002	-0.008	0.058	-1.063***	-0.086	-0.570	4.609
	(0.004)	(0.018)	(0.005)	(0.049)	(0.267)	(1.399)	(0.391)	(3.962)
Leverage	0.002	-0.006	0.000	0.004	0.158	-0.552	0.005	0.280
	(0.002)	(0.011)	(0.002)	(0.016)	(0.121)	(0.855)	(0.186)	(1.280)
Growth	-0.011***	-0.032*	-0.010***	-0.032+	-0.863***	-2.518*	-0.792***	-2.577+
	(0.001)	(0.012)	(0.002)	(0.017)	(0.096)	(0.974)	(0.167)	(1.334)
Auto	-0.012	0.016*	0.052+	0.012	-0.889	1.257**	3.735	0.918
	(0.011)	(0.006)	(0.030)	(0.009)	(0.781)	(0.473)	(2,417.467)	(0.727)
Trans	-0.008*	0.017*	0.005	0.012	-0.627*	1.339*	-0.037	0.940
	(0.004)	(0.007)	(0.010)	(0.008)	(0.286)	(0.530)	(2,417.466)	(0.673)
HighTech	0.002	0.008	0.004**	0.015	0.144+	0.610	0.302**	1.181
	(0.001)	(0.007)	(0.001)	(0.010)	(0.085)	(0.558)	(0.117)	(0.813)
IndustryIT	0.315***	0.383	-0.005	-0.028	0.343***	0.419	-0.034	-0.065
	(0.073)	(0.339)	(0.106)	(0.517)	(0.077)	(0.343)	(0.104)	(0.557)
MonitorIntensive	0.001**	0.002	0.001*	0.002	0.072**	0.159	0.084*	0.185
	(0.000)	(0.002)	(0.000)	(0.004)	(0.025)	(0.188)	(0.036)	(0.358)
IndependentDirector	-0.004***	-0.002	-0.002**	0.005	-0.311***	-0.147	-0.169**	0.371
	(0.001)	(0.010)	(0.001)	(0.005)	(0.076)	(0.740)	(0.058)	(0.404)
CEO_Duality	-0.001**	-0.002	-0.001	-0.005	-0.063**	-0.205	-0.068+	-0.425

	(0.000)	(0.002)	(0.001)	(0.004)	(0.024)	(0.187)	(0.040)	(0.313)
Observations	1,269	512	681	233	1,269	512	681	233
R-squared	0.191	0.329	0.205	0.323	0.192	0.330	0.210	0.319
Number of firms	482	267	321	148	482	267	321	148
Year&industry FE	YES	YES	YES	YES	YES	YES	YES	YES

Standard errors are in parentheses and calculated by clustering firms and using heteroscedasticity-consistent estimation; *** p<0.001, ** p<0.01, * p<0.05, +p<0.1

Table 5: Performance Effects of Interlock–Driven IT Investment

	DV=TobinsQ							
	IT=CRM&SCM				IT=IT Labor			
	(1)		(2)		(3)		(4)	
	#Meetings High		*#Meetings Low*		*#Meetings High*		*#Meetings Low*	
InterlockDrivenIT	9.551***	0.034	-0.599	-0.001	0.106***	0.029	-0.016	-0.003
	(0.994)		(3.443)		(0.016)		(0.043)	
ResidualIT	0.939***	0.024	1.266*	0.021	0.011***	0.022	0.015*	0.020
	(0.102)		(0.500)		(0.002)		(0.006)	
Lag(TobinsQ)	0.792***	0.798	0.766***	0.820	0.790***	0.796	0.767***	0.821
	(0.008)		(0.014)		(0.008)		(0.014)	
IndustryQ	0.271***	0.143	-0.082	-0.026	0.272***	0.143	-0.086	-0.028
	(0.010)		(0.066)		(0.010)		(0.066)	
MarketShare	0.001	0.000	-0.284***	-0.067	0.000	0.000	-0.291***	-0.069
	(0.011)		(0.044)		(0.011)		(0.043)	
PPE	0.143***	0.037	0.121	0.020	0.141***	0.036	0.113	0.018
	(0.017)		(0.117)		(0.017)		(0.116)	
RD	-0.041	-0.002	-0.053	-0.001	-0.043	-0.002	-0.110	-0.002
	(0.090)		(0.522)		(0.094)		(0.515)	
ADV	-0.022	-0.001	2.842***	0.051	0.023	0.001	2.823***	0.051
	(0.183)		(0.581)		(0.187)		(0.577)	
Size	0.066***	0.120	0.087***	0.085	0.067***	0.121	0.087***	0.085
	(0.003)		(0.011)		(0.003)		(0.011)	
MonitorIntensive	-0.041***	-0.025	0.025	0.010	-0.041***	-0.025	0.023	0.009
	(0.007)		(0.023)		(0.007)		(0.023)	
IndependentDirector	0.023	0.002	0.008	0.001	0.021	0.002	0.010	0.001
	(0.144)		(0.097)		(0.144)		(0.097)	
CEO_Duality	-0.038***	-0.023	-0.142***	-0.053	-0.041***	-0.025	-0.143***	-0.053
	(0.007)		(0.021)		(0.007)		(0.021)	
Observations	616		277		616		277	
R-squared	0.802		0.837		0.802		0.837	
Number of firms	301		159		301		159	
Year&industry FE	YES		YES		YES		YES	

Standard errors are in parentheses and calculated by clustering firms and using heteroscedasticity-consistent estimation; standardized coefficients are reported on the right side of each column. *** p<0.001, ** p<0.01, * p<0.05, +p<0.1

Table 6: Regressions Addressing Knowledge Overlapping

	IT=CRM&SCM						IT=IT Labor					
	(1)	(2) *#Meetings High*	(3)	(4)	(5) *#Meetings Low*	(6)	(7)	(8) *#Meetings High*	(9)	(10)	(11) *#Meetings Low*	(12)
AvgIT_ExistingInterlockFirm	0.181***	0.182***	0.171***	0.160***	0.139***	0.157***	0.176***	0.183***	0.184***	0.178***	0.156***	0.173***
	(0.019)	(0.019)	(0.019)	(0.027)	(0.028)	(0.025)	(0.020)	(0.019)	(0.019)	(0.025)	(0.027)	(0.024)
AvgIT_Newly_InterlockFirm	0.046*	0.048*	0.047*	0.158***	0.154***	0.157***	0.043*	0.045*	0.045*	0.173***	0.167***	0.169***
	(0.020)	(0.019)	(0.018)	(0.022)	(0.022)	(0.016)	(0.021)	(0.020)	(0.020)	(0.016)	(0.017)	(0.011)
AvgIT_Firm_Left_Interlock_1stYear	0.044**	0.043**	0.035*	0.019	0.025	0.031	0.046**	0.043**	0.033+	0.010	0.015	0.019
	(0.016)	(0.016)	(0.017)	(0.029)	(0.028)	(0.029)	(0.016)	(0.017)	(0.017)	(0.031)	(0.030)	(0.031)
AvgIT_ Firm_Left_Interlock_2ndYear		-0.007	-0.013		-0.023	0.016		-0.007	-0.012		-0.032*	0.010
		(0.018)	(0.016)		(0.015)	(0.020)		(0.018)	(0.016)		(0.013)	(0.020)
AvgIT_ Firm_Left_Interlock_3rdYear			-0.009			0.043			-0.009			0.045
			(0.012)			(0.041)			(0.012)			(0.028)
Ln(#ExistingInterlockFirm)	-0.004***	-0.004***	-0.004***	0.000	0.000	-0.000	-0.287***	-0.316***	-0.326***	0.018	0.009	0.004
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.028)	(0.026)	(0.025)	(0.041)	(0.040)	(0.042)
AvgIT_ExistingInterlockFirm X	-0.306***	-0.317***	-0.303***	0.009	0.006	0.029	-0.291***	-0.320***	-0.334***	0.021	0.014	0.034
Ln(#ExistingInterlockFirm)	(0.029)	(0.029)	(0.030)	(0.052)	(0.053)	(0.052)	(0.031)	(0.030)	(0.029)	(0.052)	(0.053)	(0.052)
Other controls	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Observations	978	978	978	522	522	522	978	978	978	522	522	522
R-squared	0.256	0.257	0.257	0.211	0.212	0.218	0.259	0.26	0.26	0.211	0.213	0.217
Number of firms	404	404	404	267	267	267	404	404	404	267	267	267
Year&industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Standard errors are in parentheses and calculated by clustering firms and using heteroscedasticity-consistent estimation; *** p<0.001, ** p<0.01, * p<0.05, +p<0.1
Other controls: MatchedInterlockIT, NeighborhoodIT, CR4, Uncertainty, Diversification, AdjustedROA, Leverage, Growth, Auto, Trans, HighTech, IndustryIT, MonitorIntensive, IndependentDirector, and CEO_Duality

Table 7: Regressions Addressing Homophily

	IT=Lag(CRM&SCM)		IT=Lag(IT Labor)	
	(1)	(2)	(3)	(4)
	#Meetings High	*#Meetings Low*	*#Meetings High*	*#Meetings Low*
Lag(AvgIT_NewlyInterlockFirm)	0.013	-0.037	0.015	-0.035
	(0.075)	(0.045)	(0.074)	(0.045)
Lag(MatchedInterlockIT)	-0.007	-0.033	-0.014	-0.037
	(0.060)	(0.088)	(0.059)	(0.089)
Lag(NeighborhoodIT)	0.143	0.118	0.143	0.109
	(0.089)	(0.120)	(0.088)	(0.120)
Lag(CR4)	-0.018+	-0.013	-1.416+	-0.982
	(0.010)	(0.011)	(0.768)	(0.839)
Lag(Uncertainty)	-0.000	0.021	0.095	1.676
	(0.028)	(0.048)	(2.173)	(3.642)
Lag(Diversification)	0.004	0.018**	0.300	1.321**
	(0.004)	(0.006)	(0.329)	(0.456)
Lag(ROA)	-0.016	0.023	-1.082	1.822
	(0.027)	(0.045)	(2.065)	(3.442)
Lag(Leverage)	-0.002	0.023	-0.057	1.688
	(0.012)	(0.015)	(0.893)	(1.183)
Lag(Growth)	-0.013	-0.019+	-1.023	-1.487+
	(0.009)	(0.011)	(0.721)	(0.825)
Lag(Auto)	0.007	-0.000	0.620	-0.056
	(0.006)	(0.006)	(0.441)	(0.497)
Lag(Trans)	0.005	-0.002	0.436	-0.304
	(0.006)	(0.013)	(0.418)	(1.021)
Lag(HighTech)	0.005	0.014	0.404	1.068+
	(0.005)	(0.008)	(0.401)	(0.641)
Lag(IndustryIT)	0.292	-0.643	0.364	-0.687
	(0.380)	(0.763)	(0.385)	(0.778)
Lag(MonitorIntensive)	0.003	-0.000	0.270	-0.015
	(0.002)	(0.003)	(0.164)	(0.240)
Lag(IndependentDirector)	-0.000	-0.004	0.036	-0.338
	(0.006)	(0.007)	(0.420)	(0.511)
Lag(CEO_Duality)	-0.004*	0.001	-0.313*	0.057
	(0.002)	(0.003)	(0.150)	(0.267)
Observations	796	447	796	447
R-squared	0.204	0.221	0.202	0.222
Number of firms	358	233	358	233
Year&industry FE	YES	YES	YES	YES

Standard errors are in parentheses and calculated by clustering firms and using heteroscedasticity-consistent estimation; *** p<0.001, ** p<0.01, * p<0.05, +p<0.1

Table 8: Regressions Excluding Common Ownership or Business Alliances as Channels of Co-movement

	Excluding interlocked firm pairs owned by common long-term investors (>=5% equity)				Excluding interlocked firm pairs that share common business alliances in the past five years			
	IT=CRM&SCM		IT=IT Labor		IT=CRM&SCM		IT=IT Labor	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	#Meetings High	*#Meetings Low*	*#Meetings High*	*#Meetings Low*	*#Meetings High*	*#Meetings Low*	*#Meetings High*	*#Meetings Low*
AvgIT_InterlockFirm	0.313**	0.289	0.321**	0.293	0.296**	0.257	0.303**	0.261
	(0.117)	(0.192)	(0.117)	(0.193)	(0.111)	(0.191)	(0.110)	(0.193)
AvgIT_InterlockFirm X AvgIWRank_InterlockFirm	0.780***	0.241	0.806***	0.220	0.605**	0.237	0.626**	0.223
	(0.223)	(0.241)	(0.229)	(0.248)	(0.205)	(0.227)	(0.214)	(0.234)
AvgIWRank_InterlockFirm	0.007	0.011	0.493	0.895	0.006	0.012	0.451	0.941
	(0.004)	(0.007)	(0.318)	(0.593)	(0.004)	(0.008)	(0.331)	(0.641)
Other controls	Included	Included	Included	Included	Included	Included	Included	Included
Observations	478	226	478	226	512	233	512	233
R-squared	0.348	0.329	0.350	0.325	0.330	0.323	0.330	0.319
Number of firms	254	146	254	146	267	148	267	148
Year&industry FE	YES	YES	YES	YES	YES	YES	YES	YES

Standard errors are in parentheses and calculated by clustering firms and using heteroscedasticity-consistent estimation; *** p<0.001, ** p<0.01, * p<0.05, +p<0.1

Other controls: Ln(#InterlockFirm), AvgIT_InterlockFirmXLn(#InterlockFirm), MatchedInterlockIT, NeighborhoodIT, CR4, Uncertainty, Diversification, AdjustedROA, Leverage, Growth, Auto, Trans, HighTech, IndustryIT, MonitorIntensive, IndependentDirector, and CEO_Duality

Table 9: Regressions Using Alternative Models of Firm Random Effects (Firm RE) and Dynamic Panel Generalized Method of Moments (DynGMM)

	Firm Random Effect Models				Two-step DynGMM			
	IT=CRM&SCM		IT=IT Labor		IT=CRM&SCM		IT=IT Labor	
	(1) *#Meetings High*	(2) *#Meetings Low*	(3) *#Meetings High*	(4) *#Meetings Low*	(5) *#Meetings High*	(6) *#Meetings Low*	(7) *#Meetings High*	(8) *#Meetings Low*
AvgIT_InterlockFirm	0.236**	0.204	0.246**	0.204	0.234+	0.118	0.257+	0.142
	(0.088)	(0.133)	(0.088)	(0.131)	(0.125)	(0.146)	(0.135)	(0.143)
AvgIT_InterlockFirm X AvgIWRank_InterlockFirm	0.360*	0.248	0.388*	0.216	0.422*	0.214	0.454*	0.222
	(0.170)	(0.159)	(0.177)	(0.153)	(0.190)	(0.193)	(0.206)	(0.219)
AvgIWRank_InterlockFirm	0.003	0.007	0.239	0.498	0.004	0.009	0.332	0.894+
	(0.004)	(0.005)	(0.279)	(0.375)	(0.006)	(0.007)	(0.435)	(0.525)
Other controls	Included	Included	Included	Included	Included	Included	Included	Included
Observations	512	233	512	233	512	233	512	233
Number of firms	267	148	267	148	267	148	267	148
Firm random effect	YES	YES	YES	YES				
Year&industry FE	YES	YES	YES	YES				
Hansen test of overidentification restrictions (χ^2)					13.11 (insig.)	11.53 (insig.)	13.32 (insig.)	9.35(insig.)
Arellano-Bond test for AR(1) (*z*)					0.02 (insig.)	-1.06 (insig.)	-0.15 (insig.)	-1.10 (insig.)
Arellano-Bond test for AR(2) (*z*)					-1.37 (insig.)	-1.29 (insig.)	-1.37 (insig.)	-1.29 (insig.)
Year FE					YES	YES	YES	YES

Standard errors are in parentheses and calculated by clustering firms and using heteroscedasticity-consistent estimation; *** p<0.001, ** p<0.01, * p<0.05, +p<0.1
Other controls: Ln(#InterlockFirm), AvgIT_InterlockFirmXLn(#InterlockFirm), MatchedInterlockIT, NeighborhoodIT, CR4, Uncertainty, Diversification, AdjustedROA, Leverage, Growth, Auto, Trans, HighTech, IndustryIT, MonitorIntensive, IndependentDirector, and CEO_Duality.

Table 10: Influence of Board Interlocks on IT Investment and Performance Effects with High #Meetings Defined as Greater than Industry Median

Panel A: Influence of Board Interlocks on IT Investment

	IT=CRM&SCM		IT=IT Labor	
	(1) *#Meetings High*	(2) *#Meetings Low*	(3) *#Meetings High*	(4) *#Meetings Low*
AvgIT_InterlockFirm	0.098*	0.257	0.096*	0.261
	(0.046)	(0.191)	(0.046)	(0.193)
AvgIT_InterlockFirm X AvgIWRank_InterlockFirm	0.375***	0.237	0.375***	0.223
	(0.097)	(0.227)	(0.103)	(0.234)
AvgIWRank_InterlockFirm	0.009***	0.012	0.686***	0.941
	(0.001)	(0.008)	(0.094)	(0.641)
Other controls	Included	Included	Included	Included
Observations	348	233	348	233
R-squared	0.450	0.323	0.450	0.319
Number of firms	203	148	203	148
Year&industry FE	YES	YES	YES	YES

Standard errors are in parentheses and calculated by clustering firms and using heteroscedasticity-consistent estimation; *** p<0.001, ** p<0.01, * p<0.05, +p<0.1
Other controls: Ln(#InterlockFirm), AvgIT_InterlockFirmXLn(#InterlockFirm), MatchedInterlockIT, NeighborhoodIT, CR4, Uncertainty, Diversification, AdjustedROA, Leverage, Growth, Auto, Trans, HighTech, IndustryIT, MonitorIntensive, IndependentDirector, and CEO_Duality.

Panel B: Performance Effects

	IT=CRM&SCM		IT=IT Labor	
	(1) *#Meetings High*	(2) *#Meetings Low*	(3) *#Meetings High*	(4) *#Meetings Low*
InterlockDrivenIT	5.795***	-0.599	0.068***	-0.016
	(0.937)	(3.443)	(0.012)	(0.043)
ResidualIT	1.473***	1.266*	0.018***	0.015*
	(0.274)	(0.500)	(0.003)	(0.006)
Other controls	Included	Included	Included	Included
Observations	421	277	421	277
R-squared	0.812	0.837	0.812	0.837
Number of firms	230	159	230	159
Year&industry FE	YES	YES	YES	YES

Standard errors are in parentheses and calculated by clustering firms and using heteroscedasticity-consistent estimation; *** p<0.001, ** p<0.01, * p<0.05, +p<0.1
Other controls: lag_TobinsQ, IndustryQ, MarketShare, PPE, RD, ADV, Size, MonitorIntensive, IndependentDirector, and CEO_Duality.

Table 11: IT Hardware Capital as an Alternative IT Measure

Panel A: Influence of Board Interlocks on IT Investment

	IT=IT Hardware Capital	
	(1) *#Meetings High*	(2) *#Meetings Low*
AvgIT_InterlockFirm	0.269***	0.043
	(0.080)	(0.097)
AvgIT_InterlockFirm X AvgIWRank_InterlockFirm	0.009	-0.250
	(0.152)	(0.234)
AvgIWRank_InterlockFirm	0.000	-0.000
	(0.000)	(0.001)
Other controls	Included	Included
Observations	513	233
R-squared	0.513	0.533
Number of firms	268	148
Year&industry FE	YES	YES

Standard errors are in parentheses and calculated by clustering firms and using heteroscedasticity-consistent estimation; *** p<0.001, ** p<0.01, * p<0.05, +p<0.1
Other controls: Ln(#InterlockFirm), AvgIT_InterlockFirmXLn(#InterlockFirm), MatchedInterlockIT, NeighborhoodIT, CR4, Uncertainty, Diversification, AdjustedROA, Leverage, Growth, Auto, Trans, HighTech, IndustryIT, MonitorIntensive, IndependentDirector, and CEO_Duality.

Panel B: Performance Effects

	DV=TobinsQ	
	(1) *#Meetings High*	(2) *#Meetings Low*
InterlockDrivenIT	112.281***	-20.216
	(6.981)	(30.032)
ResidualIT	15.021***	32.837***
	(1.697)	(5.462)
Other controls	Included	Included
Observations	617	277
R-squared	0.808	0.839
Number of firms	302	159
Year&industry FE	YES	YES

Standard errors are in parentheses and calculated by clustering firms and using heteroscedasticity-consistent estimation; *** p<0.001, ** p<0.01, * p<0.05, +p<0.1
Other controls: lag_TobinsQ, IndustryQ, MarketShare, PPE, RD, ADV, Size, MonitorIntensive, IndependentDirector, and CEO_Duality.

Table 12: Alternative Ways to Identify Matched Firms

	Restricting matched interlocked firm's assets to be within 10% of the interlocked firms'				Restricting matched interlocked firm to be in the same 4-digit SIC as the interlocked firm			
	IT=CRM&SCM		IT =IT Labor		IT=CRM&SCM		IT =IT Labor	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	#Meetings High	*#Meetings Low*	*#Meetings High*	*#Meetings Low*	*#Meetings High*	*#Meetings Low*	*#Meetings High*	*#Meetings Low*
AvgIT_InterlockFirm	0.297***	0.271	0.308***	0.276	0.094***	0.166	0.099***	0.170
	(0.025)	(0.195)	(0.026)	(0.196)	(0.022)	(0.196)	(0.021)	(0.197)
AvgIT_InterlockFirm X AvgIWRank_InterlockFirm	0.519***	0.159	0.534***	0.145	0.424***	-0.239	0.436***	-0.247
	(0.062)	(0.260)	(0.060)	(0.267)	(0.050)	(0.328)	(0.049)	(0.333)
AvgIWRank_InterlockFirm	0.005***	0.012	0.344***	0.921	0.002*	0.015+	0.151*	1.214+
	(0.001)	(0.009)	(0.078)	(0.732)	(0.001)	(0.008)	(0.074)	(0.648)
MatchedInterlockIT	-0.038**	-0.137	-0.040**	-0.132	0.002	-0.027	0.002	-0.019
	(0.014)	(0.106)	(0.013)	(0.104)	(0.013)	(0.100)	(0.012)	(0.097)
Other controls	Included	Included	Included	Included	Included	Included	Included	Included
Observations	448	208	448	208	499	229	499	229
R-squared	0.328	0.332	0.326	0.329	0.336	0.324	0.335	0.322
Number of firms	242	137	242	137	264	140	264	140
Year&industry FE	YES	YES	YES	YES	YES	YES	YES	YES

Standard errors are in parentheses and calculated by clustering firms and using heteroscedasticity-consistent estimation; *** p<0.001, ** p<0.01, * p<0.05, +p<0.1
Other controls: Ln(#InterlockFirm), AvgIT_InterlockFirmXLn(#InterlockFirm), MatchedInterlockIT, NeighborhoodIT, CR4, Uncertainty, Diversification, AdjustedROA, Leverage, Growth, Auto, Trans, HighTech, IndustryIT, MonitorIntensive, IndependentDirector, and CEO_Duality.

Table 13: Alternative Ways to Code IW Ranking

	Using ordinal ranking of top 250 firms				Coding a sample firm as 2 if it is ranked 1–100; 1 if ranked 101–500; 0 if not Included in the top-500 list			
	IT=CRM&SCM		IT =IT Labor		IT=CRM&SCM		IT =IT Labor	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	#Meetings High	*#Meetings Low*	*#Meetings High*	*#Meetings Low*	*#Meetings High*	*#Meetings Low*	*#Meetings High*	*#Meetings Low*
AvgIT_InterlockFirm	0.481***	0.200	0.476***	0.142	0.281**	0.256	0.277**	0.259
	(0.076)	(0.173)	(0.076)	(0.170)	(0.100)	(0.223)	(0.098)	(0.225)
AvgIT_InterlockFirm X AvgIWRank_InterlockFirm	0.004***	-0.002	0.003***	-0.002	1.242***	0.092	1.216***	0.076
	(0.001)	(0.002)	(0.001)	(0.002)	(0.347)	(0.541)	(0.344)	(0.559)
AvgIWRank_InterlockFirm	0.000	0.000	0.000	0.000	0.009	0.007	0.603	0.577
	(0.000)	(0.000)	(0.001)	(0.002)	(0.006)	(0.010)	(0.468)	(0.833)
Other controls	Included	Included	Included	Included	Included	Included	Included	Included
Observations	239	96	239	96	379	174	379	174
R-squared	0.567	0.537	0.556	0.533	0.375	0.330	0.372	0.330
Number of firms	146	77	146	77	223	128	223	128
Year&industry FE	YES	YES	YES	YES	YES	YES	YES	YES

Standard errors are in parentheses and calculated by clustering firms and using heteroscedasticity-consistent estimation; *** p<0.001, ** p<0.01, * p<0.05, +p<0.1
Other controls: Ln(#InterlockFirm), AvgIT_InterlockFirmXLn(#InterlockFirm), MatchedInterlockIT, NeighborhoodIT, CR4, Uncertainty, Diversification, AdjustedROA, Leverage, Growth, Auto, Trans, HighTech, IndustryIT, MonitorIntensive, IndependentDirector, and CEO_Duality.

Table 14: Using Interlocked Directors' Background to Proxy for IT Capability

	IT=CRM&SCM				IT=IT Labor			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	#Meetings High	*#Meetings High*	*#Meetings Low*	*#Meetings Low*	*#Meetings High*	*#Meetings High*	*#Meetings Low*	*#Meetings Low*
AvgIT_InterlockFirm	0.181***	0.101***	0.169	0.218+	0.188***	0.110***	0.167	0.209
	(0.012)	(0.019)	(0.129)	(0.132)	(0.011)	(0.020)	(0.133)	(0.130)
Interlock_IT_Industry_Experience	0.002**		-0.000		0.145**		-0.031	
	(0.001)		(0.005)		(0.049)		(0.376)	
Interlock_IT_Industry_Experience X AvgIT_InterlockFirm	0.183**		0.181		0.200**		0.206	
	(0.070)		(0.242)		(0.071)		(0.242)	
InterlockCEO		0.002***	0.169	0.003		0.170***		0.252
		(0.000)		(0.002)		(0.026)		(0.163)
InterlockCEO X AvgIT_InterlockFirm		0.178***		-0.124		0.166***		-0.100
		(0.021)		(0.148)		(0.022)		(0.152)
Other controls	Included	Included	Included	Included	Included	Included	Included	Included
Observations	954	954	502	502	954	954	502	502
R-squared	0.266	0.261	0.219	0.225	0.268	0.263	0.222	0.227
Number of firms	398	398	256	256	398	398	256	256
Year&industry FE	YES	YES	YES	YES	YES	YES	YES	YES

Standard errors are in parentheses and calculated by clustering firms and using heteroscedasticity-consistent estimation; *** p<0.001, ** p<0.01, * p<0.05, +p<0.1
Other controls: Ln(#InterlockFirm), AvgIT_InterlockFirmXLn(#InterlockFirm), MatchedInterlockIT, NeighborhoodIT, CR4, Uncertainty, Diversification, AdjustedROA, Leverage, Growth, Auto, Trans, HighTech, IndustryIT, MonitorIntensive, IndependentDirector, and CEO_Duality.

Table 15: Performance Effects Using Future Accounting Profitability Measures

	DV=average(ROS_{t+1}, ROS_{t+2})				DV=average(ROS_{t+1}, ROS_{t+2}, ROS_{t+3})			
	IT=CRM&SCM		IT=IT Labor		IT=CRM&SCM		IT=IT Labor	
	(1) *#Meetings High*	(2) *#Meetings Low*	(3) *#Meetings High*	(4) *#Meetings Low*	(5) *#Meetings High*	(6) *#Meetings Low*	(7) *#Meetings High*	(8) *#Meetings Low*
InterlockDrivenIT	0.528*	-0.214	0.006+	-0.003	0.929***	-0.239	0.012***	-0.003
	(0.262)	(0.299)	(0.003)	(0.004)	(0.270)	(0.221)	(0.004)	(0.003)
ResidualIT	0.068*	0.177***	0.001*	0.002***	0.069**	0.184***	0.001**	0.002***
	(0.030)	(0.036)	(0.000)	(0.000)	(0.023)	(0.044)	(0.000)	(0.001)
ROS_t	0.497***	0.716***	0.497***	0.714***	0.467***	0.672***	0.467***	0.671***
	(0.021)	(0.033)	(0.021)	(0.032)	(0.022)	(0.031)	(0.022)	(0.031)
Other Controls	Included	Included	Included	Included	Included	Included	Included	Included
Observations	672	300	672	300	672	300	672	300
R-squared	0.557	0.643	0.557	0.643	0.533	0.617	0.533	0.618
Number of firms	328	172	328	172	328	172	328	172
Year&industry FE	YES	YES	YES	YES	YES	YES	YES	YES

Standard errors are in parentheses and calculated by clustering firms and using heteroscedasticity-consistent estimation; *** p<0.001, ** p<0.01, * p<0.05, +p<0.1
Other controls: MarketShare, PPE, RD, ADV, Size, MonitorIntensive, IndependentDirector, and CEO_Duality