Microfoundations of collaborative networks: The impact of social capital formation and learning on investment risk assessment

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Abstract

Both traditional financial and intangible asset (IA) performance measures aid in the design of micromanagement organizational systems. We shed light on the microfoundational processes of collaborative networks and their impact on investment risk assessment by exploring IA performance measures in response to decomposing macro-level constructs. The IA measures focus on the exploration of individual human capital and their actions and interactions that influence investment risk assessments, which is critical for long-term prosperity. Additionally, human capital herein includes social factors such as social capital, which research has demonstrated can be developed from intellectual capital, and vice versa. Findings from an experiment with 40 professional investors (resulting in 160 independent observations) suggested that belonging to a company's collaborative networks—where they would gain access to IA performance information—led them to adjust their investment risk assessments downward or upward in response to material weakness or strength disclosures pertaining to IA performance. Additionally, a laboratory experiment revealed that 121 novice investors who learned how to interpret and use their social networks to gain access to IA performance information also led them to adjust their investment risk assessments in response to material IA information deficiencies in target companies. The results showed IA knowledge can be learned and transferred to impact social change.

***Keywords*:** Intangible assets; Knowledge transfer; Learning; Microfoundations; Social change; Collaborative networks

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1. Introduction

Microfoundational approaches can support sound investment risk assessments that are critical for social change (i.e., long-term prosperity, in the form of sustainable social impact, derived from sound investment decisions underpinned by socially sharing intangible asset (IA) performance information in collaborative networks). However, to date, few studies have examined how collaborative networks—processes reliant on social capital formation and learning—provide a useful organizational context to understand the achievement of a sound investment risk assessment. Collaborative networks have emerged as central organizational phenomena (e.g., Child, Faulkner and Tallman, 2005; Ghouri, Akhtar, Shahbaz and Shabbir, 2019) for knowledge diffusion and/or sharing (e.g., Aklamanu, Degbey and Tarba, 2016; Hughes et al., 2020; Singh, 2005), and, ultimately, as a source of technological innovation and social change (Jamali, Yianni and Abdallah, 2011; Stephan, Patterson, Kelly and Mair, 2016). Achieving this social change calls for collaborative networks that take into consideration a sound valuation of microfoundations, such as managerial cognition, the motivational antecedents of human capital-based competitive advantage, and individual actions and interactions that influence organizational performance (Foss and Pederson, 2016). These aforementioned microfoundations are described in this study as IA measures. Moreover, due to globalization, competition, technological sophistication, and speed, a

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company's property, plant, and assets do not adequately capture its social capital (Hoskisson, Gambeta, Green and Li, 2018). More and more companies will have to depend on socially sharing their valued information to widen the gap between them and their competitors (Dubey, Gunasekaran, Childe, Blome and Papadopoulos, 2019). That is, successful companies' IAs are growing as a proportion of total shareholder value (Lev, 2001), and they must be accounted for, controlled for, and acknowledged by management as critical in assessments of internal control weaknesses. Hence, the arrival of powerful information technologies is proving to be a major challenge to organizations in terms of producing and processing knowledge.

One purpose of valuing IAs or knowledge-based assets is to afford valuation for difficult-to-measure assets. For example, the valuation of key IAs is essential in order to establish profit sharing for collaborative networks. Because the performance of IAs is critical to success, it follows that providing information about the performance of IAs would lead to the kind of transparency that collaborative networks desire to create. To be useful, this kind of IA performance information has to be shared among the network actors, such as a firm's management, its professional investors, as well as novice investors. This kind of social sharing of valued information is a means by which to increase the social capital and learning among the actors in the collaborative network, and thereby generate sound investment risk assessments that are critical for long-term prosperity. Prior research has indicated that "social capital increases the efficiency of action" (Nahapiet and Ghoshal, 1998, p. 245), presumably thereby increasing not only the efficiency of a firm, but more importantly, generating a social change in the way investment risk assessment knowledge can be learned and shared by both novice and professional investors. The implications contribute to the

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microfoundation research agenda by decomposing macro-level IA constructs in terms of the actions and interactions of lower level organizational members, such as novice and professional investors who collaboratively network with an organization's management (Foss and Pedersen, 2016). It is also important to mention that microfoundations are not solely about individuals or processes, as they also incorporate the interactions being undertaken in the context of organizations (e.g., Barney and Felin, 2013; Whetten et al., 2009). With specific reference to human capital, it has been described as a firm-level microfoundational capability, enabling such organizations to gain a competitive advantage (Raffiee and Coff, 2016). Similarly, learning has been found to be strongly linked to human capital development at the firm level from a microfoundational perspective (e.g., Coff and Kryscynski, 2011; Raffiee and Coff, 2016). Additionally, Becker's (1964) early conceptualization of human capital also showed a strong link with learning by referring to the concept as "learned skills and knowledge that individuals develop through their prior experience, training, and education" (Helfat and Martin, 2015, p. 1286). Relatedly, Wright, Coff, and Moliterno (2014) added that the core dimensions of individual human capital consist of knowledge, education, experience, and skills. It is noteworthy in recognizing that while some types of individual human capital may be specific (e.g., to particular technologies, functional areas, firms, and industries), others may be generic knowledge (Bailey and Helfat, 2003; Castanias and Helfat, 2001; Kor, Mahoney and Michael, 2007). However, human capital does not need to be firm-specific in order to create value for firms (Campbell, Coff and Kryscynski, 2012). In line with other human capital scholars (e.g., Ployhart and Moliterno, 2011), we recognize the concept to be complex and functioning beyond individual-level factors to also include social factors such as

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social capital (Barney and Felin, 2013). Regarding the latter, prior studies have underscored the intertwined connection between human and social capital by highlighting how human capital can be driven by social capital (e.g., Aklamanu et al., 2016)—social interactional-level microfoundations. Therefore, both of these constructs are essentially microfoundations rooted in prior research.

The microfoundational lens fundamentally focuses on the individual and his/her actions, but the broader microfoundational work indicates that the interactions between individuals in terms of sharing knowledge is equally vital in that socially aggregated behaviors usually differ from individual behaviors (Coleman, 1990; Felin, Foss, Heimeriks and Madsen, 2012; Foss and Pedersen, 2016). In addition, many of today's interactions between individuals when sharing knowledge occur in less routinized contexts, such as in collaborative networks, and during M&As, and they are not without complexity and tension (Degbey, 2015, 2020a; Degbey and Pelto, 2013, 2015; Khan, Shenkar and Lew, 2015; Paruchuri and Eisenman, 2012; Tarba et al., 2019), and thus this also makes the channels for sharing and transferring knowledge critical (Im and Rai, 2008; Stadler, Rajwani and Karaba, 2014). Moreover, research shows that a major feature of networks relates to the collaboration of individuals across traditional organizational boundaries (Graebner, Heimeriks, Huy and Vaara, 2017). Nonetheless, the current understanding of collaborative networks in investment decision-making is limited, and, therefore, a specific focus on the human-side microfoundations (i.e., individuals, their behaviors, and social interactions in organizations) is critical in order to clarify the macro-level outcomes (Liu, Sarala, Xing and Cooper, 2017). This approach can assist in understanding how firm-level IA performance measures emerge from social

interaction or from the collaboration between individual novice and professional investors and organizations when using IA variables to foster a sound investment risk assessment. As such, the current study takes advantage of measuring the impact of IA performance information on investors' decision-making processes as an indirect means through which to measure the impact of social capital and learning that help in fostering long-term prosperity for managers, investors, and society as a whole.

The IA measures can be viewed as shared information that engenders greater cooperation, particularly in collaborative networks—among a firm's micromanagement and its investors—with the goal of improving investors' decision-making processes. This sharing of the IA performance information with investors can be seen as a form of social capital formation: "Social capital is the goodwill available to individuals or groups. Its source lies in the structure and content of the actor's social relations. Its effects flow from the information, influence, and solidarity it makes available to the actor" (Adler and Kwon, 2002, p. 23). The current study's definition is consistent with Adler and Kwon's (2002) general definition, making it concise enough to rule out the distracting side issues discussed by others (e.g., Portes, 1998).[1] Moreover, the groundbreaking work of Nahapiet and Ghoshal (1998) underlined the intertwined nature of social capital and intellectual capital (IC). The latter authors equated the formation of social capital to the formation of IC (i.e., defined as IA in the current study) and determined that IC facilitates the development of social capital. While measuring the impact of social capital has proven difficult (Labianca and Brass, 2006), measuring

[1] Kemper, Schilke, and Brettel (2013) used a similar definition for social capital, as they "formally define social capital as the sum of the actual and potential benefits embedded in, available through, and derived from an individual's or social unit's network or relationships" (p. 590).

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the impact of IA performance has proven to be less problematic (Edvinsson and Malone, 1997; Housel and Bell, 2001; Lev, 2001; Rodgers, 2007). Measuring the influence of social capital via IA performance information among investors and management reduces the problem of "what to measure" to determine the impact of social capital (Labianca and Brass, 2006) that would foster a sound investment risk assessment.

The purpose of the current research was to determine whether professional investors and novice investors augmented their decision-making via access to the social network that provided IA-based knowledge to aid them in assessing the target firms' riskiness, thereby helping them make more informed investment decisions. In addition, we also examined whether investors could learn to utilize new IA performance knowledge in their decision-making. Specifically, we examined *how* novices' learning about how IA performance information was derived would affect their investment decisions. The results of the current study demonstrated that such IA information significantly influenced both novice and professional investors' decision-making. This is an indication that IA knowledge can be learned and transferred by both novice and professional investors to improve investment decision-making, which is critical for long-term prosperity (e.g., in the form of sustainable social impact—a social change in itself).

2. Microfoundations of collaborative networks and investment risk assessment for social change: A conceptual model

Forecasting and assessing risks such as technological, environmental, or investment risks constitute an important part of social change, particularly in our 21st-century knowledge-based society. Indeed, some of the recent studies published in *Technological Forecasting and Social Change* underscored forecasting or assessment for major technological and social changes. For

example, Frey and Osborne (2017) pinpointed the susceptibility of future jobs to computerization in the US labor market. Mazzucato and Semieniuk (2018) drew attention to the role of actors financing renewable energy to underscore how finance affects the directionality of innovation with implications for renewable energy policies. In a similar vein, Wang, Kung, and Byrd (2018) highlighted the importance of big data analytics and built an architecture to understand its potential benefits in healthcare organizations (see also Blazquez and Domenech, 2018 on big data analytics for forecasting social and economic change). Moreover, Ramani, SadreGhazi, and Gupta (2017) explored the role of social enterprises in the India sanitation sector and pinpointed that forecasting social change should incorporate the incentives within the national system of innovation for social entrepreneurship to harness high-quality sustainable social impacts. Along with studies published in *Technological Forecasting and Social Change*, established scholars in other journals such as *Business Ethics: A European Review*, The *Journal of Product Innovation Management*, The *Journal of Business Venturing*, and The *Journal of Management Studies* have presented similar arguments (see e.g., Estrin et al., 2016; Jamali et al., 2011; Stephan et al. 2016, 2019). This point is also highlighted in a very recent book where creative social change is linked to relevant technological developments (Jenkins, Shresthova and Peters-Lazaro, 2020). Hence, such studies serve to further underline the vital role of social change in 21st-century society.

However, these important examples in the area of technological forecasting and social change predominantly forecast the emergence of social change from macro- (country or global environment) and meso- (firm) level factors/processes (e.g., Ramani et al., 2017; Wang et al., 2018) while also crudely ignoring the emergence of social change from the actions and interactions

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of individuals, particularly in a collaborative network context. Our paper is predicated on the notion that investment risk assessment for social change also emerges from the actions and interactions of individual novice investors who are able to learn and transfer IA knowledge from social capital-generating networks with professional analysts and internal company management. Thus, a complete understanding of investment risk assessments for social change is inherently multilevel in nature, involving intricate relations between not only macro- and meso-level factors/processes, but also micro-level ones in a collaborative network context (see also Villani, Rasmussen and Grimaldi, 2017 for micro-level-based evidence of technology transfer in a collaborative network).

A growing number of studies have underscored the benefit of micro-level-based evidence in the context of interorganizational relationships and collaborative networks and have established their relationships to macro- and meso-level outcomes. For example, Haapanen et al. (2019) explored the function-specific microfoundations of dynamic capabilities in mergers and acquisitions (M&As), and highlighted that the alignment of function-specific microfoundations is critical to achieving post-merger success rather than the assessment of relatedness and complementarities, which may not reveal M&A pitfalls. In addition, Paruchuri and Eisenman (2012) focused on inventor networks to examine how the activities underlying firms' R&D change following a merger, and found that the effect of knowledge that is prominent and widely available in the intra-firm network increased but the effect of knowledge that is less easily accessible, although richer, decreased after the merger. Further, Angwin, Paroutis, and Connell (2015) examined why companies fail to proceed with major opportunities for strategic renewal through

M&As and found the centrality of an overlooked microfoundational process: the authorization routine. Similarly, Friedman, Carmeli, Tishler, and Shimizu (2016) conceptually explored the micro-behavioral sources of failure in M&As. Based on an in-depth review and processual framework, they argued that behavioral factors at the individual and organizational levels impede rational and effective decision-making before, during, and after an M&A, and underscored the pivotal role of the communication climate for effective integration and as a base to improve M&A performance (Degbey, Rodgers, Kromah and Yaakov, 2020b; Friedman et al., 2016).

We build on these prior works to specifically advance the literature on the microfoundational perspective of collaborative networks and their linkage to social change as an outcome by empirically investigating how the microfoundational processes of learning and transferring IA knowledge in a collaborative network setting lead to a sound investment risk assessment for social change. We posit that a sound investment risk assessment for social change is a collective phenomenon that emerges from learning and transferring IA knowledge in networks. The learning and transfer of IA knowledge facilitates the social capital generated in the collaborative network. Without learning and transferring IA knowledge among individuals, knowledge assets resident in individuals remain inert (Argote et al., 2003; Gavetti, 2005; Grant, 1996; Sarala et al., 2016), and we need to activate them to bring about social change. The aforementioned microfoundational processes of collaborative networks are represented in Figure 1.

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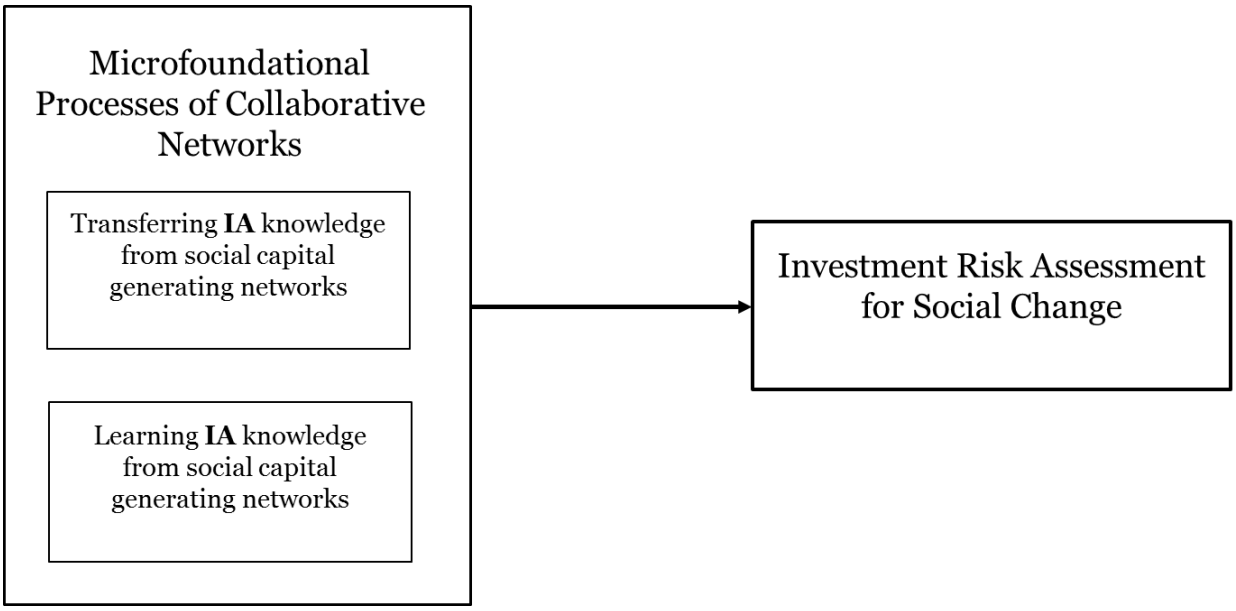

Figure 1: Microfoundations of Collaborative Networks in Investment Decision-Making

The current research advances research scholarship on the microfoundational processes of collaborative networks and their impact on investment risk assessments for social change by exploring investors' perceptions of risk derived primarily from IA performance information. This new source of investor information allows them to infer that there is a relationship between the IA performance information and the strength of internal controls. The logic is that without such performance information, it would be nearly impossible to accurately assess the strength of the company's operations. This study uses an IA performance measurement ratio to signal whether a firm's IA base is growing or retarding the firm's value. The US Congressional Act Section 404 requirements for reporting on the effectiveness of internal controls, certified by both management

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and the entity's independent accountants, may provide useful signals about investors' risks produced by potentially unreliable or incomplete (i.e., when IA performance information is not included) financial reports (Sarbanes-Oxley Act of the US House of Representatives, 2002). That is, the report should include the management's assessment of the effectiveness of its internal controls, the framework used to evaluate such controls, the disclosure of any material weaknesses in the system of controls, and a formal statement that the company's auditors have issued an attestation report on the management's evaluation of the internal controls regarding reporting (Rose, Norman and Rose, 2010). Hence, with this information, investors may be able to improve their forward-looking assessments of a company's investment riskiness (COSO, 2006; PCAOB, 2004, 2007).

Most of the prior research on knowledge transfer in this context has focused on how management can benefit from this kind of information to reduce costs and increase profitability. However, the current study focused on how this kind of information would be useful to society learning and transferring how to assess the riskiness of a firm by participating in the collaborative network (e.g., social network) of the entity. Exemplary prior research on this by Kogut and Zander (1993) focused on how knowledge resides in repositories within a firm and is transferred within the firm to improve the firm's performance. We argue that when investors are included in a firm's social network, this facilitates the development of social capital through the transfer of internal performance knowledge, and thus this can foster a sound investment risk assessment for social change. This social capital provides investors with information that they can use to pressure the firm to improve its performance, and they will tend to invest in those firms that they can see have

improved as a result; that is, a social change has occurred in the risk assessment of the investors. This new form of social capital, generated through the sharing of IA performance information, will also reduce their perception about the riskiness of the firm as an investment opportunity. One prior study (Rose, Norman and Rose, 2010) focused on how management credibility, based on investors' "perceptions about the pervasiveness of control weaknesses" (p. 1800), affected investors' perceptions about the riskiness of a firm and, consequently, their investment decision-making.

Prior research (Clark-Murphy and Soutar, 2004) demonstrated that an improvement in internal controls, based on understanding IA performance information, had a significant impact on investors' decision-making. Extending this line of research, this study will examine the impact of internal control systems that include IA performance information on experienced and novice investors who are included in the social networks of the target firms to determine if a social change has occurred in terms of their investment risk assessments. Previous experimental (e.g., Rose et al., 2010) and archival research (e.g., Beneish et al., 2008; Hammersley et al., 2008) provided evidence that investors perceived increased risks related to material control weaknesses, which in the current study will include material control weaknesses as a result of poor IA performance information.

In the first experiment of this study, we used two groups of participants—a group of professional investors from the USA and a second group from Sweden—to isolate the differences in their perceptions of the riskiness of the target companies based on IA performance information that was included as part of the target companies' information. In both cases, the assumption was

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that investors were included in the social network of the target companies and, therefore, would have access to this social capital-based information.

Prior research has examined the impact of social capital on resource transfer (Hansen et al., 2005; Muthusamy and White, 2005), although no prior studies have yet focused on the impact of IA performance information on investment decision-making. Consistent with our hypothesis that this new IA performance information would influence the investors' assessment of the target companies' riskiness, we found that IA information significantly affected the investors' decision-making processes. These results were interpreted within a knowledge-transfer theoretical framework that permitted new insights to be made about the effect of such information in changing both professional and novice investors' risk assessments in our knowledge society.

The knowledge-transfer theoretical framework seeks to arrange, generate, capture, or distribute knowledge and ensure its availability for future users (Argote, Ingram, Levine and Moreland, 2000). Knowledge is a vital, if not the most essential, strategic resource of firms (Grant, 1996; Housel and Bell, 2001) and a source of its competitive advantage (Argote et al., 2003). The ability to share knowledge about the relationship between a company's IA performance and the strength of its internal controls provides stakeholders (e.g., investors, management, analysts, and creditors) with an important basis for assessing the riskiness of the company.

In our study, knowledge transfer represents the practical problem of transferring knowledge about the performance of IAs obtained from the company's internal control systems to investment analysts as a result of the entity's social capital network. We found that analysts who had received favorable IA performance information expressed a greater willingness to invest in a

target company. We reasoned that this information was provided by more comprehensive internal control systems that accurately and adequately reported on the performance of these assets via social capital-generating networks.

Interestingly, these results differed based on the country of origin. Our results indicated that professional Swedish investors more readily included IA information as a part of their judgments compared to professional US investors. We had hypothesized that this result would be due to the greater importance of IA performance information in the Swedish business culture. This finding suggests that Swedish professionals may experience greater levels of knowledge transfer from internal controls that provide information about IA performance than their USA counterparts do, who may not treat such information as critical in their perceptions of the investment riskiness of companies.

In a second experiment, we examined whether novices utilize IA performance information after training over a three-month period. It was also reasoned that novice investors were part of the social capital network of the company and, therefore, received this information and could benefit from it. In this scenario, an IA learning program was assumed to enable better social networking communication for the novices. Consistent with our expectations, the results indicated that novice investors who were knowledgeable about what IA performance information analyses implied would likely utilize this information after appropriate training. These results also suggest that the differences between the Swedish and US professionals (in the first experiment) can be mitigated after US professionals receive exposure to and training about IA performance information that can be used to enhance their knowledge.

In a knowledge-based economy, training and learning to develop additional skills and expertise is essential for a company's performance (Hinds, Patterson and Pfeffer, 2001; Housel and Bell, 2001; Yan and Zhang, 2003). Fiol and Lyles (1985, p. 803) define learning as "the process of improving actions through better knowledge and understanding." Many researchers (Dutton and Thomas, 1984; Graham and Steinbart, 1992; Lapré, Mukherjee and van Wassenhove, 2000; Lieberman, 1987; Lucas, 1993) have emphasized that a better understanding of the contributions of learning is needed. Early research in this area focused more on the processes of learning and knowledge transfer as outcomes, but later works include the element of identifying a firm's knowledge assets for competitive advantage (Helfat, 2000; Kogut and Zander, 1996). Extending this prior general area of research to an IA information decision-making context, the final goal of the current study was to determine whether investors could learn to utilize new IA performance knowledge in their decision-making. Specifically, we examined *how* novices' learning about how IA performance information was derived would affect their investment decisions.

3. Background and development of the hypotheses: Intangible assets

Taking full account of the value of IAs denotes valuing, among other things, all of the company's innovations in terms of procedures and products. Globally, many research studies and consultants' reports have suggested that the important drivers of today's businesses are largely accounted for by IA performance (e.g., Ashton, 2005; Eccles et al., 2001; Eckstein, 2004; Edvinsson and Malone, 1997; Lev, 2001). According to Carmeli and Tishler (2004), an

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organization's competitive position is derived from a combination of organizational elements; that is, on the successful integration of various strategic and non-strategic resources. Considering that IAs are viewed as more likely to produce a competitive advantage (Hitt et al., 2001), firms need to focus on investments in intangible as well as in tangible assets (Kaufman and Englander, 2005; Mouritsen et al., 2001, 2002). It follows that this change in emphasis will also require greater functionality in the internal control systems to ensure their likelihood of providing timely and relevant information about IA performance. Since IAs contributing to knowledge-based competitive advantages are assumed to contribute to higher company performance (Barney, 1991; Delios and Beamish, 2001; Gardberg and Fombrun, 2006; Morgan, Zou, Vorhies and Katsikea, 2003), it follows that social capital that includes IA performance information would be helpful in producing an improved investment risk assessment for social change, and should lead to well-informed investment decisions and efficient capital markets (Branco and Rodrigues, 2006; Mouritsen et al., 2001). In the context of the kinds of information investors require, the acquisition and exploitation of this tacit knowledge about a company's IA performance would lead investors to a better understanding of a company's organizational capabilities (Grant, 1996; Kogut and Zander, 1992; Sabherwal and Sabherwal, 2005). However, prior research has not examined questions regarding investors' adjustments of their assessments of investment risk in response to material control weaknesses resulting from the lack of IA performance measure information.

To date, the bulk of research on this kind of knowledge focuses solely on traditional financial knowledge (Rodgers, 2003), with little inquiry into the impacts of knowledge transfer relating to new IA performance information. Previous accounting studies (e.g., Barron, Byard,

Kile and Riedl, 2002; Lang and Lundholm, 1996) have indicated that investors augment their review of standard information with IA performance information. While extensive research has examined investors collecting a firm's performance information, little is known about the procedures they use in weighting and integrating the information into their decision-making processes.

Knowledge about a company's IA performance is an essential strategic company resource (Grant, 1996; McEvily and Chakravarthy, 2002; Szulanski, 1996), and the ability to share knowledge between units of the organization is a vital basis for the competitive advantage of companies (Argote et al., 2000; Nonaka and Takeuchi, 1995; Noorderhaven and Harzing, 2009). In the current study, the knowledge-transfer framework provides a theoretical basis for describing investors' adoption of IA performance metrics provided by other units that may reduce investors' tendency to discount ambiguous IA performance information (Van Dijk and Zeelenberg, 2003). Management professionals from around the world, most notably from Sweden (Edvinsson and Malone, 1997), have learned how valuable IA performance information is for improved management and investment decision-making. Professional investors in Sweden would therefore be more likely to exploit IA performance information as a result of prior exposure to IA performance metrics compared to professionals from the USA, where the use of this type of information is not regarded favorably (Lev, 2001). A secondary goal of the current study was to examine the cultural differences in exploiting tacit IA performance knowledge.

The remainder of the paper is organized as follows. The second section (Experiment I) summarizes the background about knowledge transfer and the IA literature as it pertains to the

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focus of the experiment. The third section (Experiment II) summarizes the potential impact of learning how to use IA performance information for investment decision-making, leading to the hypotheses. A description of the participants, the methodology, and the results follow the hypotheses. Finally, we discuss the results and provide conclusions, including limitations and suggestions for further research.

4. Knowledge transfer and intangible asset performance information: Experiment I

Many terms denote intangible resources in the literature, such as *intellectual capital, knowledge assets,* and *IAs* (Andriessen, 2004; Edvinsson and Malone, 1997; Lev, 2001). We use "intangible" in place of "knowledge," in that these resources can consist of knowledge and non-knowledge items (e.g., trademarks, goodwill, etc.). The IA perspective comes from the resource-based view that examines an organization, a company, or the economy as a combination of stocks, flows, and the transformation of resources into valued outputs (Wernerfelt, 1995). A very important dimension of the social capital use of IA performance information concerns the organizational learning component operationalized as a result of novice investors learning how the traditional financial and IA performance information was derived. In the current study, exploitative learning relates to the refinement and extension of traditional financial statements in a predictable manner. In contrast, explorative learning occurs when investors experiment with new performance information alternatives such as IA performance measures (March, 1991). Investors use

exploitative learning when new knowledge[2] about the performance of a firm's resources is transferred by way of an enhancement of traditional financial information that includes IA performance information. Managers of a firm can also transfer their knowledge about the firm's performance to investors when they use explorative learning as they begin to experiment with new performance metrics such as IA performance metrics.

The use of IA performance information is a fundamental component of the resource-based perspective. That is, privately held, internal, corporate performance knowledge is a basic source of competitive advantage. The resource-based view generally addresses performance differences among companies using asymmetries in knowledge (see Barney, 1991). Therefore, different kinds of knowledge vary in their transferability. The theoretical underpinnings of the IA concept range from the psychological emphasis on cognition, to the focus of economics on the market structure and competition, to the sociological orientation toward social structure. During the early 1990s, different ideas and streams of research intersected to produce what has come to be known as the knowledge-based view. These ideas and streams include the resource/capability analysis of a firm (Barney, 1991), basic epistemetic assumptions (Polanyi, 1966), and organizational learning/knowledge transfer (Levitt and March, 1988). The perspective we take in this paper stems from the knowledge-transfer literature.

[2] Knowledge has been viewed as an elusive concept that has been categorized and described in a variety of ways. *Knowledge* as used in this paper is defined as a combination of framed experience, values, contextual information, expert insight, and grounded intuition. That is, knowledge can be viewed as contextually dependent and subjectively constructed (Mohrman, Gibson and Mohrman, 2001).

Knowledge transfer is viewed as an event through which an individual or organization learns from informational sources (Argote, 1999; Darr and Kurtzberg, 2000). The knowledge-transfer framework provides a well-developed theoretical basis for describing how individuals' adoption of new knowledge is influenced by refining and innovating (i.e., exploitative and explorative learning). Given this relationship between the two types of learning and the resulting knowledge adoption within their decision-making processes, it follows that investment analysts may utilize both learning strategies to transfer new financial IA performance knowledge when assessing investment opportunities.

Earlier research (Earley, 2001; Moreland and Myaskovsky, 2000) implied that the knowledge transfer of IA performance information would take place with the evolution of IA training. However, it did not resolve the issue of how influential the new knowledge would become in an investment decision-making context. Given the oft-stated importance of IA performance information to firms' future benefits, the present research focuses on determining whether knowledge about IA performance information actually would be transferred, thus allowing investors to use such new knowledge in their decision-making processes.

Previous research (Argote et al., 2000, 2003; Cohen and Sproull, 1996; Spender and Grant, 1996) indicated that the knowledge transfer of traditional accounting metrics, such as earnings per share and cash flow potential ratios, can be used to predict a company's performance outcomes. In addition, knowledge transfer in the form of IA performance information may assist investors in responding more appropriately to investment opportunities. Relying upon earlier studies on knowledge transfer among markets and individuals (Haunschild and Beckman, 1998; Kogut and Zander, 1996), we examined the transfer of two key types of market knowledge: public (e.g., financial statements) and private (e.g., IAs). However, unlike published financial statements, private knowledge is not publicly available or guaranteed by a third party. Instead, it is "soft" information that lacks benchmarks and depicts idiosyncratic and nonstandard information about

the firm. We conducted an experiment to determine whether professional investment analysts (American and Swedish) would include IA metrics provided by a company's internal control system in their decision-making. Prior research has shown that analysts do not rely upon net present values alone when making decisions (Bradshaw, 2004), and the current research investigated whether IA performance information would influence analysts' judgments in connection with typical financial-statement information.

4.1. Hypotheses tested

Previous studies (Argote et al., 2000, 2003; Cohen and Sproull, 1996; Helfat, 2000; Spender and Grant, 1996) indicated that knowledge transfer can predict firms' performance outcomes. In addition, knowledge transfer in the form of IA information may assist analysts in responding better to investment opportunities (Borgatti and Cross, 2003). For example, Amir and Lev (1996) argued persuasively that traditional accounting metrics alone do not provide analysts with all the information needed to evaluate the potential value of a given company. One of the theses of the current study is that firms using social capital (i.e., sharing and support) can generate social change that can help improve the integration of a new IA measure requiring search, variation, risk taking, experimentation, flexibility, discovery, and innovation (Adler and Kwon, 2002; Grant, 1996). An analyst needs to consider IA performance information even though it is not benchmarked to industry standards due to its newness; hence, support from the analyst's firm may help in its use. Training in the derivation and interpretation of such a new IA performance metric may mitigate the risks of using such new and potentially useful information.

Previous research investigated whether the properties of IA measures enhance individuals' abilities to forecast future financial performance (Rodgers and Housel, 2004). This research concluded that investment banking firms providing social capital about IA information would have an impact on the investment-decision processes. In addition, although both Sweden and the USA are often classified as similar cross-cultural countries (Griffith, Myers and Harvey, 2006; Hofstede, 2001), we expect the integration of IA performance information will be more relevant to Swedish investment analysts' decision-making (Edvinsson and Malone, 1997). The differences between the analyst groups in Sweden and the USA may indicate the differences in the analysts' social capital use of IA performance information and their corresponding investment judgments may significantly impact capital markets. These arguments led to two hypotheses:

> **H_{1a}.** The IA performance information (as part of the internal control system) will have a positive significant impact on analysts' investment decision-making processes.
>
> **H_{1b}.** Due to greater emphasis in the Swedish business environment on the importance of IA performance information, Swedish investment analysts' decisions will be influenced more by new IA performance information metrics compared to American analysts.

4.2. Participants, instrument, and procedure

The present study provided the participants with the assurance that IA performance reporting was in place, and that management, along with the investment banking firm's social capital, will depict IA performance information (for professional investors) and provide training (for novice investors) that is necessary to interpret the performance reporting and provide society with a novel method of assessing organizational performance. The study participants were informed that the

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entity's social capital network provided the information that would enable them to bridge the transparency gap between social capital and IA performance measurements. Two assumptions were made: (1) that a company would include investors within its social network where information (e.g., IA information) would be received and shared among the various interested parties; and (2) that the IC generated from the IA performance information would lead to the development of beneficial social capital. The social capital generated via access to the IA performance information facilitates knowledge transfer among networks of investors, analysts, and internal company management.

The total sample size represented 40 investment bankers (investment bankers x 4 distinct cases = 160). Each investment banker received randomized and unnamed cases from two good and two bad companies. The selection of these companies was random and was based on Moody's classification of bonds and stocks (B = good companies; C = bad companies). The company data were taken from the Center for Research in Security Prices (CRSP). This procedure allowed for a sampling of independent responses from the subjects, similar to previous commercial loan officers and auditors' studies (e.g., Rodgers, 1992, 1999; Rodgers and Housel 1987; Rodgers and Johnson, 1988). This experimental design has been reported in the aforementioned publications.

The data were collected from employees at several investment banking firms in the Gothenburg area of Sweden and in Southern California in the USA. The participants for this research included 15 professional analysts from Gothenburg and 25 professional analysts from Southern California. The average age was 34 years old for the Swedish participants and 35 for the Americans. The average tenure for both groups was five years and all were college graduates. The

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research assistants of the authors administered the survey during work time to employees at the investment banking firms. This approach resulted in a 97 percent response and ensured the consistent application of the survey. Pretests were conducted in Borås, Sweden and Southern California (Rodgers, 2002) in order to insure the reliability and validity of the instrument questions. We found no differences in the Swedish and American subjects' ability to analyze the performance information about the four different companies used in the experiment. The participants were provided with financial-statement information, prospective financial information, and IA performance information on the four test company cases. As a proxy of IA performance information, we selected the return on knowledge (ROK) metric (see appendix A), a relatively new performance ratio measure (Housel and Kanevsky, 1995). ROK is essentially a measure of the return on investment (ROI) in IAs and, as such, in the following, the ROK metric is a surrogate for the ROI on IAs. Taking revenue and cost allocation independently derives ROK. In this regard, ROK establishes a productivity ratio (revenue over cost). This ratio allocates a percentage of revenue to a given process based on the amount of knowledge required to produce the process outputs in the numerator, over the cost to employ the knowledge in the denominator. The ROK metric was presented in a format that analysts were most likely to understand because it was a performance ratio similar to those used in traditional financial information. For all participants, ROK was defined as a ratio that measures the revenue attributable to an IA divided by the cost to use the IA. The IA is operationalized as a proxy for Revenue[k]/Cost[k]; that is, revenues and costs of operations, selling, general and administrative costs (SG&A), and corporate

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management in their assessment of the company stock's potential value. This proxy measure has been derived from the knowledge value-added (KVA) theory (Housel and Kanevsky, 1995).

The ROK metric has been in use for some time in various accounting and financial contexts. For instance, the former President of the American Institute of Certified Public Accountants (AICPA), Robert K. Elliot, has applied concepts from this line of research, such as the "virtual information dual" to various problems in auditing and accounting (Elliot, 1994). Just as historical financial return-based ratios can be used for benchmarking and projecting future firm performance, ROK can be used in the same way (Rodgers, 2002). This ROK metric has been used by corporate management as well as by analysts in prior research (Housel and Bell, 2001; Pavlou, Housel, Rodgers and Jansen, 2005).

In this experiment, the participants evaluated the four different test case companies as potential investment opportunities. The four business cases provided the manipulations for the experimental design. Appendix B presents detailed measurement scales and appendix C provides the information presented to the participants. Five years' annual financial information, five years' financial ratios, earning estimates for the coming two years, and three years' ROK information were provided to the participants. Two of the companies were classified (with traditional financial metrics) as positive trending earnings, and two were classified as negative earnings. For one of the two positive-profit trending companies, ROK information showed an increasingly positive trend for the three-year period; for the other positive-profit trending firm, the ROK information showed an increasingly negative trend for the same three-year period. Likewise, for one of the negative-

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profit trending companies, the ROK information was increasingly positive over the three-year period; for the other negative-profit trending firm, the ROK information was increasingly negative over the three-year period. The order of presentation of these companies was randomized across all participants.

We instructed the participants to compare the importance of various information items in forming their decisions about whether a firm should receive an investment of $1,000,000. The participants gave a rating about their willingness to invest or not to invest in each of the four companies on a continuous scale ranging from 0 (not approved) to 200 (approved). Rating scales ranged from 1–100 (investment is not approved) and from 101–200 (investment is approved). The participants could take as much time as they wanted to make their decisions. The participants' average time of completion for the four business case analyses and responses was one hour.

We were careful to ensure a correct translation on the structured survey instrument for the Swedish participants. A Swedish native who spoke English as a second language was selected to translate the instrument from English into the native language. After the survey was translated, a native English speaker along with a Swedish research assistant translated the instrument back into English. Where discrepancies occurred, both translators and one of the authors met to reconcile the differences. All differences were reconciled prior to the administration of the instrument.

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4.3. Results

A manipulation check was undertaken by performing an ANOVA on whether the Swedish and American investment bankers treated the manipulated variables regarding the financial information variables similarly (Oppenheimer, Meyvis and Davidenko, 2009). We found that the manipulation check was successful (F [1, 38] = 1.095, $p > 0.302$) in that there were no differences among the investment bankers (i.e., based upon their experiences). Hence, we rule out that the manipulation may have failed.

The data, which included both Swedish and American professional analysts, were analyzed by a two (country: Sweden vs. USA) x two (traditional financial information: positive vs. negative) x two (i.e., ROK: positive vs. negative) mixed ANOVA. The results across countries yielded a marginally significant main effect from traditional financial information (F [1, 38] = 3.06, p = 0.09), indicating that the professional analysts were more willing to invest in companies with positive traditional financial information (Table 1). However, the main effect of IA performance information was significant (F [1, 38] = 7.46, p = 0.01). Investment ratings were higher for the companies with positive IA performance information than for the companies with negative IA performance information. The interaction between traditional financial information and IA performance information was not significant (p = 0.13). The findings suggest that knowledge transfer was evident in that professional analysts consider both financial and IA information in making investment decisions, as stated in Hypothesis 1a.

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Hypothesis 1b was partially supported in that no main effect or interactions related to the country of the analysts was significant, except for a marginally significant interaction among the country of the investor, traditional financial information, and IA performance information (F [1, 38] = 3.92, p = 0.05). Apparently, this difference was due to IA performance information influencing the Swedish analysts' investment decisions more than the American analysts (see Table 1).

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Insert Table 1 about here
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5. Learning process and intangible asset performance information: Experiment II

The judgment and decision-making literature provides evidence that experts and non-experts differ in their representations of judgment and decision-making situations (Önkal-Atay, Yates, Simga-Mugan and Öztin, 2003; Shanteau, Weiss, Thomas and Pounds, 2002; Yates, 1990, p. 372). When making investments, the decision maker has to consider all relevant criteria in the decision-making process. Different criteria will vary in importance to a decision maker, and s/he has to decide whether the cost of the search for information outweighs the value of the added information (Bazerman, 2002). Understanding how analysts use IA information is a step toward focusing research on the kinds of information that will allow analysts to become more familiar with emerging intangible investment opportunities at the lowest search cost, and research has shown that increasing familiarity leads to greater investment (Merton, 1987). As analysts become more familiar with IA information, they may tend to put greater emphasis on this information in

the context of traditional financial-statement information (Barney, 1991). Gardberg and Fombrun (2006) found that corporate citizenship activities may help a company create IAs and develop a competitive advantage over its competitors, which, in turn, may enhance its financial performance. Similarly, Delios and Beamish (2001), Morck and Yeung (1992), and Mishra and Gobeli (1998) found positive linkages between multinational firms' possession of IAs and their subsidiaries' market values.

In a second experiment, training sessions were used to allow novice analysts to learn how to derive the new IA metric: ROK. Given their earlier accounting and finance courses, along with readings that focused on deriving and interpreting traditional financial information, the general research question was whether novices would actually use the new IA metric, ROK, along with traditional financial information to help them make investment decisions. Considering that these valuations are currently not reported in traditional financial statements, we felt the time was ideal to begin the assessment of their potential effect on novice investors' decision-making processes.

5.1. Hypotheses tested

Based on the work of Adler and Kwon (2002), perhaps the most fundamental meaning of social capital is captured in what is known as "bonding." Bonding in social capital is indicated in the current study by the strength of the ties between the social actors, for example, novice investors, professional investors, and the management of investment banking firms. This was measured by communicating how IA performance information was derived and what it represented to novice investors. Therefore, we trained a student group in the derivation and use of the IA performance metric (e.g., ROK) to determine whether knowledge about the performance of IAs (in the context

of traditional financial information) could be transferred and, hence, influence their investment decisions. This was part of the novice's general learning about how to derive and use a supplemental non-traditional financial analysis (i.e., IA performance information), which was available to them for extra credit if they chose to participate. Nonetheless, 95 percent of the students participated because they wanted the extra credit. Students (i.e., representing the novice investors) were questioned about their prior knowledge of IA measures. None was aware of IA measures before the training sessions.

We examined whether training about how to derive and use ROK (i.e., IA performance information) influenced their reliance on traditional financial information in investment decision-making processes. We predicted that, before the training, investment decisions were more likely to be influenced by traditional financial information with which the students were more familiar. It follows that ROK information would not influence their investment decisions prior to them becoming more familiar with it through the knowledge-transfer process (i.e., training sessions). This led to the following hypothesis:

> **H_2.** Before ROK training, when social capital knowledge sharing is initiated, novice investors' investment decisions will only be influenced by traditional financial information.

We reasoned that after ROK training, individuals would consider both traditional financial information and ROK information because they had become more familiar with it (e.g., via the social capital sharing training process) and were therefore more likely to incorporate it into their decision processes. That is, social capital specifies that relationships confer various advantages to

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those with differential access to valuable information conferred upon them via social networks. Training provides a means for increasing social capital by linking novice investors with the professional group level. Therefore, we predicted that ROK information would influence investment decisions after novice analysts had learned how to derive ROK as a result of their education and training. This is supported by the findings by Barney (1991) that information derived from training can provide valuable information about a firm's efficiency or effectiveness. Researchers (Delaney, Reder, Staszewski and Ritter, 1998; Mazur and Hastie, 1978) have also noted that the time individuals took to perform a task and the number of errors they made decreased as task-related experience increased.

Further, positive IA information supports or adds to favorable financial information because it leverages positive financial information, producing sustainable capabilities in the investors (Carmeli and Tishler, 2004; Miller, 2003). Miller (2003, p. 968) stated the significance of sustainable capabilities in the following way: "By identifying key asymmetries, managers are able to make them a high priority, fund them, and turn them into valuable resources or capabilities. Formal aspects include policies and priorities, structure (authority, task, and role definitions, accountability, liaison devices) and information, human resources, and planning systems. Informal aspects include corporate culture (values, beliefs, styles of interaction), personal contacts, and communication networks."

Hence, we hypothesized that the influence of ROK information on investment-decision processes would be stronger when financial information was positive rather than negative. Novice

investors would use ROK as an auxiliary source of information to confirm positive traditional financial information, while the negative ROK information would not be sufficient to confirm negative traditional financial information. In addition, based on past research, we hypothesized that additional supportive information would lead to an increase in novice analysts' confidence and accuracy (Peterson and Pitz, 1988). This leads to the last two hypotheses:

> **H_{3a}.** After ROK training, ROK information will influence novice investors to invest more in companies with a positive ROK trend.
>
> **H_{3b}.** After ROK training, there will be an interaction between traditional financial and non-financial information resulting in stronger investment decisions when financial information is positive than when it is negative.

5.2. Participants, instrument, and procedure

A total of 121 business students taking a second accounting class participated in a two (ROK training: before vs. after training) x two (financial information: positive vs. negative) x two (ROK information: positive vs. negative) within-subject experimental design. This type of repeated measure design is frequently used to test the manner in which a treatment (i.e., ROK training) affects the performance of participants in an experimental setting. The students ranged in age from 19 to 24 years old and were approximately 50 percent male and 50 percent female. Most had very limited experience in analyzing financial statements to make investment decisions. This type of class was selected to use novices who had not been exposed to ROK performance information.

The participants received the financial and ROK information for four companies in the same way and with the same content as in Experiment I. No particular emphasis was placed on the

IA methodology. If anything, the students appeared to have been a bit skeptical about the methodology since it was not included in their course textbook, and therefore, they may have been less persuaded by the ROK findings. Each of the participants was instructed to assume the role of an investor. The participants received the same information about the four companies and made investment decisions for each firm *before* and *after* the ROK training. Before the ROK training began, the participants were asked the same decision question as was given to the professionals; that is, to review the information and decide to invest or not to invest in the companies on a continuous scale ranging from 0 (not approved) to 200 (approved). The participants received 25 hours of education and training over a period of three months (i.e., about how to calculate and interpret ROK information in the context of various case studies, lectures, and exercises) in addition to the standard training on common financial information analyses they would receive in a semester-long course of 15 weeks. Following the education and training, the participants were asked to review the same company information and respond to the same questions as before training about whether they would invest in the company or not.

5.3. Results

The investment decisions were analyzed by a 2 (before vs. after ROK training) x 2 (traditional financial information: positive vs. negative) x 2 (ROK information: positive vs. negative) repeated measure ANOVA. The overall results (i.e., summed over the conditions "before" and "after" training) indicated that there was a marginal main effect for traditional financial information (F [1,118] = 3.18, p = 0.08) and for ROK information (F [1,118] = 3.32, p = 0.07). This indicated that their investment intention was higher when a firm's financial information

($M_{positive}$ = 101.0 vs. $M_{negative}$ = 99.0) or ROK information was positive ($M_{positive}$ = 104.6 vs. $M_{negative}$ = 99.2). We also found a significant interaction between financial information and ROK information (F [1,118] = 4.63, p = 0.03) and a marginally significant interaction between before and after ROK training and ROK information (F [1,118] = 2.86, p = 0.09).

Hypotheses 2 and 3(a,b) were tested by examining the contrasts of the cell means and partial interactions. Table 2 presents the investment intention ratings by condition. Hypothesis 2 predicts that, without ROK training, investment decisions will only be influenced by the traditional financial information of a firm. Hypothesis 2 was supported by the results showing the main effects of financial and ROK information and the interactions indicate that the marginal main effect of financial information was significant (t_{118} = 1.55, p = 0.06). The investment decision rating was higher for companies with positive financial information (M = 105.3) than for companies with negative financial information (M = 95.8).

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Hypothesis 3a tests the effect of financial and ROK information on investment decisions after ROK training. We tested the main effects and partial interaction effect in the after-ROK-training condition. When individuals had knowledge about ROK, investment decisions were significantly influenced by the firm's ROK information (t_{118} = 1.74, p = 0.04). Individuals expressed more willingness to invest in companies with a positive ROK trend (M = 108.2) than in companies with a negative ROK trend (M = 97.5). However, the effect of financial information was not significant (p = 0.20; $M_{positive}$ = 105.6 vs. $M_{negative}$ = 100.3). More importantly, the

interaction between financial and ROK information on the investment decision was significant (t_{118} = 2.50, p = 0.01). The significant interaction was further analyzed by separate cell mean comparisons for companies with positive and negative financial information. As predicted by Hypothesis 3b, when the financial information was positive, the investment rating was higher for the firm with a positive ROK trend than for a firm with a negative ROK trend (t_{118} = 3.52, p = 0.001; $M_{positive}$ = 116.2 vs. $M_{negative}$ = 94.6). However, when the financial information was negative, there was no significant difference between companies with positive (M = 100.2) and negative (M = 100.4) ROK information (p = 0.49).

5.4. Additional results on the effect of ROK training on investment

We hypothesized that the effect of ROK training and ROK information would be stronger for companies with positive financial information. This potential effect was further analyzed by comparing the investment ratings of the four types of companies between before and after ROK training. As hypothesized, when the financial information was negative, ROK training did not significantly change the investment ratings for companies with either positive (p = .30) or negative (p = 0.37) ROK information. When the financial information was positive, however, ROK training significantly influenced investment decisions. Investment ratings for the firm with positive ROK information became higher after ROK training (t_{118} = .1.84, p = 0.03) and the investment intention for the firm with negative ROK information decreased after ROK training (t_{118} = .14, p = 0.08) (see Table 2).

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6. Discussion and conclusion

The results of this research are relevant for the future of IA performance reporting since corporate disclosures and information are critical for the effective functioning of capital markets in our global society (Lev, 2001). Above all, a more useful and transparent disclosure of IA performance allows investors to make informed decisions by understanding companies' underlying strategic elements leading not only to competitive advantages over their rivals (Gardberg and Fombrun, 2006; Hitt et al., 2001), but also fostering long-term prosperity (a social change in itself). It has also been widely recognized that the value relevance of a firm's traditional financial information is marginal in investor decision-making. The current study's results support this concern about the relevance of traditional financial information in assessing a company's investment prospects. In fact, investors are finding a paucity of information in financial statements about key value drivers for businesses in general, and for knowledge-intensive businesses in particular. This research also aligns with many societies that are now addressing the issue of the need for companies to provide investors with financial statements that have comparable information regarding IA performance information.

This study examined professional and novice analysts' potential propensity to use IA information, in addition to traditional financial statements, in their investment decision-making in an experimental setting. In both experiments, the participants belonged to a social capital network of the entity (i.e., brokerage, investment company) and, therefore, could benefit from the provision and sharing of this information (cf. Aklamanu et al., 2016; Inkpen and Tsang, 2005). In our study, we examined how the formation of social capital and learning in collaborative networks involving

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novice and professional investors and company management were key to achieving more informed investment decisions that are critical for long-term prosperity (e.g., Angelstam et al., 2017; Klus et al., 2019). The findings support previous research (Carmeli and Tishler, 2004; Rodgers and Housel, 2004) showing the significant impact of a combined use of traditional financial information and new IA information in investment decision-making. However, the results were more obvious for Swedish professionals perhaps because they have developed a culture of proactive training in IA awareness utilization. The professional American analysts seemed to have a more skeptical view of this kind of new information perhaps because they have had little or no training in the use of IA metrics and the resulting information.

As a practical matter, because IA information is important in IA knowledge accumulation, it makes sense that more awareness training should be considered for investment analysts and business management, especially in the USA. In today's business environment, stakeholders and shareholders are demanding greater transparency regarding the productive activities of a firm and, over time, these activities have become an increasingly larger share of the value-producing activities of firms. Greater transparency relating to the impact of these activities may best be reflected in IA performance information.

The results of the study also indicated that learning about IA performance information assisted novice analysts in addressing this need by examining how knowledge about the performance of IAs can be transferred by incorporating it into standard reporting procedures between the reporting units of companies and analysts (cf. Cabello-Medina, López-Cabrales and

Valle-Cabrera, 2011). Additionally, the results also imply that social capital takes time to build via the knowledge-transfer process (cf. Inkpen and Tsang, 2005). Social capital can assist in knowledge transfer based on information about traditional financial and IA performance information, which will ultimately lead to better-informed investment analysts. In turn, this should lead to more efficient capital markets. Further, the firm's management can provide a consistent focus on achieving improved IA performance reporting that will meet or exceed investment analysts' expectations. Investment analysts, in turn, can use this new knowledge to provide investors with a better understanding of stock selection options. Hence, the knowledge-transfer framework can provide insights about the best ways in which to structure information systems for the inclusion of IA performance information as well as traditional financial information. Furthermore, the social capital of the entity, understood in a broad sense (Maurer et al, 2011) as the actual and potential resources provided by and derived through actors' social relations, allows investors to benefit from the provision of this information.

In a nutshell, we develop the argument that social capital generated by access to IA performance information serves as the microfoundation for assessing investment risks in collaborative networks including investors, analysts, and internal company management. In addition, we suggest that the effect of this microfoundation (i.e., social capital resulting from access to IA performance information) on investment risk goes beyond downward or upward risk assessments in collaborative networks to also include a wider benefit of knowledge-based social change (e.g., sustainable social impact). Consistent with prior studies on collaborative networks, the appropriation of knowledge-based assets poses a challenge, especially in knowledge-intensive

collaborative networks (e.g., Degbey, 2016a, 2016b; Lamont, King, Maslach, Schwerdtfeger and Tienari, 2019; Puranam, Singh and Zollo, 2006; Reus, Lamont and Ellis, 2016), due to their tacit nature (Polanyi, 1966), as well as their embeddedness in individual managers, groups, or networks (Nonaka and Von Krogh, 2009). This therefore emphasizes the primacy of social capital generated by access to IA performance information to aid in the sharing, transfer, or use of such knowledge that is critical to fostering long-term prosperity in our 21st-century knowledge-based society.

The current study has *limitations* that future research may resolve. In a practical sense, this study should stimulate further research and other interested parties in identifying IA value drivers and, subsequently, in collecting information regarding IA performance information. Future studies should examine which specific factors contribute to the relevance of IAs and how its relevance can be identified, measured, and legitimized in reporting a firm's performance. Such an understanding will help determine which metrics are most desired by analysts based on the use of such metrics in actual investment decision-making settings. This will require benchmarks for the impact of IAs and social capital on actual firm performance over time.

Finally, further ongoing research that improves the reliability and validity of such IA performance metrics will ultimately also improve analysts' and other investors' decision-making processes.

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Appendix A: Return on Knowledge (ROK)

A very simplistic example of how ROK can be estimated is found in Pavlou et al. (2005). Let's assume that we teach the "average" person everything she needs to know, including how to produce all the outputs of IT investments and how to produce all outputs for any given firm. In a very real sense then, her knowledge of the firm would be the embodiment of the firm's value-added processes. Therefore, it is these core processes (e.g., selling, marketing, production, accounting, finance) that change process inputs to value-added outputs. When combined, these outputs generate the firm's revenue.

We can put this understanding to the test with a simple example. In the widget company, there is one person, the owner, who makes and sells widgets. This person knows all there is to know about how to make widgets, which sell for $1. The owner's sales-production knowledge can be used as a surrogate for the $1 of revenue generated by his application of the core process knowledge. We can ascertain how long it would take the widget company owner to transfer all the necessary sales and production knowledge to a new owner. Furthermore, we could use these learning times to allocate the $1 of revenue between the sales and production processes. In this sense, the knowledge is a surrogate for the amount of change produced by the sales and production processes.

For simplicity's sake, let's assume that it takes 100 hours for a new owner to learn both processes, with 70 hours spent on learning how to make the widget and 30 hours on learning how to sell it. Of the 70 hours of learning time, let's assume that 20 hours were used to learn how to produce the outputs of the IT used to support the production process. This would indicate that 70% of the knowledge, elementary changes, or complexity, and value added were contained in the production process and 30% in the sales process. It would follow that $0.70 of the revenue was generated by the production knowledge and $0.30 by the sales knowledge.

Having determined how much it will cost to use the sales and production knowledge, we would then have a ratio of knowledge revenue to knowledge cost or return on knowledge (ROK). It is a simple extrapolation from there to generate the ROIT ratio by partitioning the amount of knowledge the IT used to produce the outputs of these two processes. Then, by allocating revenue to these IT outputs and subtracting the cost to produce these IT outputs (divided by the cost to produce the IT outputs), we would have an ROIT estimate. Let's assume that the total cost of selling and producing the widget was $0.50: $0.25 cost for sales and $0.25 for production. Of the production cost, $0.05, was the cost to use the IT supporting the production process. We would conclude that the production process provided a better utilization of the knowledge asset (ROK = 0.70/0.25 = 280%) than the sales process (ROK = 0.30/0.25 = 120%). Further assume that the IT in the production process accounted for 20 units of output and cost $0.05 to produce. Thus, the ROIT would be 0.20−0.05/0.05 or 300%.

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Appendix B: Questionnaire for Investing Situations

This study is designed to determine the information that you, as an investor, need to make investment decisions for your organization. The company information contains financial information and IA performance information from the internal control system. Your responses will be kept strictly confidential and only aggregate responses will be reported.

Attached you will find a number of investment cases and response forms for evaluating these cases. Please respond to these cases as if they had occurred in your company (e.g., an investment company). Evaluate them as you would any other new investment opportunity. Assume that the investment amount is ***$1,000,000.*** After reading each case, you will be asked to evaluate it in three different dimensions:

(1) your impression of the economic and management information;
(2) your analysis and evaluation of the investment; and
(3) your approval of the investment.

Please mark your answers on the following questionnaire along the scale in the manner indicated on the "example" below

Low degree of Confidence High Degree of Confidence
/_____/

Please answer the following question

Decide whether you would invest in this company

Approved Low degree of Confidence High Degree of Confidence
/_____/

Not Approved Low degree of Confidence High Degree of Confidence
/_____/

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Appendix C: Financial and ROK Information Presented for Experiments I and II

	AI					EX				
Annual financial information										
	Y2009	**Y2008**	**Y2007**	**Y2006**	**Y2005**	**Y2009**	**Y2008**	**Y2007**	**Y2006**	**Y2005**
Sales	5.551	4.071	2.796	2.192	1.804	242	53	12	3	#NA
Pretax income	1.383	992	807	716	592	-130	-66	-25	-4	#NA
Income taxes	398	324	256	256	207	0	0	0	0	#NA
Net income	1.052	690	582	484	372	-130	-68	-25	-4	#NA
EPS	0.680	0.450	0.380	0.320	0.240	-0.780	-0.55	-0.32	-0.27	#NA
Current assets	1.251	967	800	512	494	1.093	167	13	4	#NA
Current liabilities	2.468	2.395	1.661	891	717	151	47	17	2	#NA
Total assets	5.877	4.186	3.970	2.692	2.284	1.743	293	41	8	#NA
Total debt	2.442	1.893	1.184	336	285	1.599	247	23	2	#NA
Common equity	1.834	1.076	857	214	227	1.575	227	15	1	#NA
Operating cash flow	1.314	472	1.262	1.560	1.325	18	19	-31	-5	#NA
	1.296	1.125	785	786	463	-47	-46	-15	3	#NA
Ratios										
	Y2009	**Y2008**	**Y2007**	**Y2006**	**Y2005**	**Y2009**	**Y2008**	**Y2007**	**Y2006**	**Y2005**
Return (Ret) on equity	222.43	54.54	37.23	36.50	35.81	-654.2	#NA	#NA	#NA	#NA
Ret. on assets	27.50	19.18	23.04	21.95	23.92	-33.40	-134.5	-293.1	#NA	#NA
Ret. on sales	18.95	16.95	20.80	22.09	20.60	-53.82	-129.8	-203.9	-132.0	#NA
Current ratio	0.51	0.40	0.48	0.57	0.69	7.26	3.54	0.78	1.77	#NA
Quick ratio	0.33	0.25	0.32	0.35	0.41	7.16	3.44	0.70	1.72	#NA
Debt to equity	139.57	227.68	67.91	13.70	17.13	8.939	1.186	-49.06	-28.09	#NA
Cash flow/sales	26.28	26.77	29.33	33.10	32.27	-32.02	-96.94	-167.5	-117.3	#NA
R&D/sales ratio	1.10	1.36	1.90	1.93	1.76	3.66	6.11	13.27	14.19	#NA
Interest. coverage ratio	10.24	10.45	14.79	28.61	131.45	-1.55	-2.48	-35.19	-37.63	#NA
Earnings Estimates										
	Curr-ent	**EPS Y2010**	**DPS**	**EPS Y2011**	**DPS**	**Curr-ent**	**EPS Y2010**	**DPS**	**EPS Y2011**	**DPS**
Current EPS	0.27					-0.96				
Mean Estimate		0.63	#NA	0.92	#NA		-0.94	#NA	-0.12	#NA
Nbr. Estimates		15	#NA	15	#NA		28	#NA	30	#NA
Projected P/E		62.01	#NA	42.83	#NA		-79.28	#NA	-579.8	#NA
Year/Year Growth		-4.3%	#NA	44.8%	#NA		41.9%	#NA	-87%	#NA
ROK [Revenue(k)/Cost(k)]										
	Y2009	**Y2008**	**Y2007**			**Y2009**	**Y2008**	**Y2007**		
Operations	118%	160%	246%			106%	190%	310%		
SG&A	163%	191%	283%			163%	287%	480%		
Corporate Management	125%	148%	250%			125%	148%	186%		

Notes:

1. Upward (downward) trending implies that the financial (e.g., earnings) and non-traditional information (i.e., return on knowledge [ROK]) is increasing or improving (decreasing or not improving) over the 3-to-5-year period of time.
2. AI: upward trending financial information/downward trending ROK.

3. EX: downward trending financial information/downward trending ROK.
4. The financial information is in millions of US dollars.
5. R&D = research and development; Nbr = number of experts' estimates; EPS = earnings per share; DPS = dividend per share; P/E = stock price/earnings per share; SG&A = selling, general, and administrative expenses.
6. The ROK ratio allocates a percentage of revenue to a given process based on (1) the amount of knowledge required to produce the process outputs in the numerator, over (2) the cost to employ the knowledge in the denominator.

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Appendix C (Continued): Financial and ROK Information Presented for Experiments I and II

	SB					SP				
Annual financial information.										
	Y2009	**Y2008**	**Y2007**	**Y2006**	**Y2005**	**Y2009**	**Y2008**	**Y2007**	**Y2006**	**Y2005**
Sales	49.489	28.777	24.856	13.898	12.670	17.016	16.017	14.874	14.045	12.765
Pretax income	9.941	6.138	2.136	3.023	2.636	2.797	2.474	2.405	2.186	1.480
Income taxes	4.280	2.306	863	1.166	903	1.061	936	631	721	534
Net income	6.577	4.068	1.474	2.101	1.889	1.613	1.540	952	1.192	958
EPS	1.900	2.050	0.800	1.730	1.550	1.820	1.780	1.090	1.400	1.370
Current assets	11.930	7.538	7.062	3.912	3.679	4.282	4.042	3.773	4.353	3.619
Current liabilities	19.313	9.989	10.252	5.820	5.056	4.301	3.293	3.077	3.314	5.142
Total assets	83.215	45.066	42.132	23.449	22.003	21.803	19.275	18.219	16.953	15.196
Total debt	20.849	13.163	13.972	7.227	7.352	5.607	4.716	3.880	3.281	5.677
Common equity	17.475	11.612	12.019	5.505	5.672	4.531	4.683	3.749	2.982	3.253
Operating cash flow	26.726	12.780	9.892	6.835	6.256	10.514	9.025	9.059	8.520	4.643
	16.578	8.381	6.970	4.824	4.021	3.713	3.971	3.379	2.404	2.729
Ratios										
	Y2009	**Y2008**	**Y2007**	**Y2006**	**Y2005**	**Y2009**	**Y2008**	**Y2007**	**Y2006**	**Y2005**
Return (Ret) on equity	22.71	38.62	14.04	33.70	22.60	13.90	16.84	10.95	21.13	20.84
Ret. on assets	20.20	11.10	8.95	10.96	-2.30	8.79	9.58	6.35	8.64	3.80
Ret. on sales	13.29	14.14	5.93	15.12	14.91	9.48	9.62	6.40	8.49	7.50
Current ratio	0.62	0.75	0.69	0.67	0.73	1.00	1.23	1.23	1.31	0.70
Quick ratio	0.51	0.63	0.56	0.57	0.57	0.79	0.89	1.00	1.09	0.59
Debt to equity	65.39	90.86	121.50	80.54	90.67	43.09	51.89	41.38	34.99	70.07
Cash flow/ sales	30.15	33.13	26.12	33.69	35.81	24.32	22.78	24.21	21.69	21.35
R&D/sales ratio	#NA	#NA	#NA	#NA	#NA	0.00	0.00	0.00	0.00	#NA
Interest coverage ratio	7.53	6.82	4.91	7.09	6.03	13.24	6.48	9.02	8.07	5.68
Earnings Estimates										
	Curr-ent	**EPS Y2010**	**DPS**	**EPS Y2011**	**DPS**	**Curr-ent**	**EPS Y2010**	**DPS**	**EPS Y2011**	**DPS**
Current EPS	1.92					1.82				
Mean Estimate		2.29	#NA	2.59	#NA		1.99	#NA	2.44	#NA
Nbr. Estimates		28	#NA	22	#NA		24	#NA	11	#NA
Projected P/E		19.75	#NA	17.42	#NA		30.16	#NA	24.59	#NA
Year/Year Growth		-1.9%		13.4%			9.97%		22.7%	
ROK [Revenue(k)/Cost(k)]										
	Y2009	**Y2008**	**Y2007**			**Y2009**	**Y2008**	**Y2007**		
Operations	219%	160%	136%			210%	137%	102%		
SG&A	203%	151%	113%			163%	129%	115%		
Corporate Management	185%	148%	104%			148%	108%	80%		

Notes:

1. Upward trending (downward) implies that the financial (e.g., earnings) and non-traditional information (i.e., return on knowledge [ROK]) is increasing or improving (decreasing or not improving) over the 3-to-5-year period of time.
2. SB: downward trending financial information/upward trending ROK.

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3. SP: upward trending financial information/upward trending ROK.
4. The financial information is in millions of US dollars.
5. R&D = research and development; Nbr = number of experts' estimates; EPS = earnings per share; DPS = dividend per share; P/E = stock price/earnings per share; SG&A = selling, general, and administrative expenses.
6. The ROK ratio allocates a percentage of revenue to a given process based on (1) the amount of knowledge required to produce the process outputs in the numerator, over (b) the cost to employ the knowledge in the denominator.

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Table 1

Investment decisions and descriptive statistics as a function of nationality, financial information, and ROK information (Experiment I)

	United States				Sweden			
Financial information	Positive Financial		Negative Financial		Positive Financial		Negative Financial	
ROK information	Positive ROK	Negative ROK	Positive ROK	Negative ROK	Positive ROK	Negative ROK	Positive ROK	Negative ROK
Mean	93.8	92.3	107.7	82.0	131.8	110.1	110.9	71.7
	(10.4)	(9.3)	(10.8)	(11.1)	(13.4)	(11.9)	(13.9)	(14.3)
95% confidence interval for mean	[68, 120]	[74, 111]	[88, 127]	[60, 103]	[119, 143]	[83, 137]	[75, 146]	[38, 104]
Std. Deviation	63.2	44.9	46.7	52.9	21.4	48.9	64.3	59.6
Minimum	0	10	26	6	74	5	22	0
Maximum	194	153	182	191	163	168	186	190

Notes:
1. Standard errors are in parentheses.
2. Rating scales ranged from 1–100 (investment is not approved) and from 101–200 (investment is approved).
3. ROK = return on knowledge.

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Table 2
Investment decisions and descriptive statistics as a function of nationality, financial information, and ROK information (Experiment II)

	Before ROK Training				After ROK Training			
Financial information	Positive Financial		Negative Financial		Positive Financial		Negative Financial	
ROK information	Positive ROK	Negative ROK	Positive ROK	Negative ROK	Positive ROK	Negative ROK	Positive ROK	Negative ROK
Mean	104.9	103.4	97.0	98.3	116.2	94.6	100.2	100.3
	(4.40)	(4.11)	(4.34)	(4.75)	(4.55)	(3.60)	(4.45)	(4.33)
95% confidence interval for mean	[96, 115]	[93, 110]	[91, 109]	[85, 105]	[108, 125]	[84, 102]	[95, 110]	[88, 107]
Std. Deviation	51	49.1	48.9	55.2	47.0	49.5	41.4	54.1
Minimum	7	2	3	0	4	2	5	0
Maximum	197	187	199	200	199	189	189	193

Notes:
1. Standard errors are in parentheses.
2. Rating scales ranged from 1–100 (investment is not approved) and from 101–200 (investment is approved).
3. ROK = return on knowledge.

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References

Adler, P.S., & Kwon, S.W. 2002. Social capital: Prospects for a new concept. *Academy of Management Review*, 27(1), 215-234.

Aklamanu, A., Degbey, W. Y., & Tarba, S. Y. 2016. The role of HRM and social capital configuration for knowledge sharing in post-M&A integration: a framework for future empirical investigation. *The International Journal of Human Resource Management*, *27*(22), 2790-2822.

Amir, E., & Lev, B. 1996. Value-relevance of nonfinancial information: the wireless communications industry, *Journal of Accounting and Economics 22*(1/3), *3-30.*

Andriessen, D. 2004. *Making sense of intellectual capital*: *Designing a method for the valuation of intangibles.* NY: Elsevier.

Angelstam, P., Barnes, G., Elbakidze, M., Marais, C., Marsh, A., Polonsky, S., ... & Stafford, W. 2017. Collaborative learning to unlock investments for functional ecological infrastructure: Bridging barriers in social-ecological systems in South Africa. *Ecosystem Services*, *27*, 291-304.

Angwin, D. N., Paroutis, S., & Connell, R. 2015. Why good things Don't happen: the micro-foundations of routines in the M&A process. *Journal of Business Research*, *68*(6), 1367-1381.

Argote, L. 1999. *Organizational Learning. Creating, Retaining and Transferring Knowledge*. MA: Norwell, Kluwer Academic Publishers.

Argote, L., Ingram, P., Levine, J.M. & Moreland, R.L. 2000. Knowledge transfer in organizations: Learning from the experience of others, *Organization Behavior and Human Decision Processes 82*(1), 1-8.

Argote, L., B. McEvily, & Reagans, R. 2003. Introduction to the special issue on managing knowledge in organizations: Creating, retaining, and transferring knowledge, *Management Sciences 49*(4), v-viii.

Ashton, R. H. 2005. Intellectual capital and value creation: A review. *Journal of Accounting Literature*, 24: 53-134.

Please cite as: Rodgers, W., Degbey, W.Y., Housel, T.J., & Arslan, A (2020). Microfoundations of collaborative networks: The impact of social capital formation and learning on investment risk assessment. *Technological Forecasting & Social Change, 161* (December 2020), 120295.
DOI: https://doi.org/10.1016/j.techfore.2020.120295

Bailey, E. E., & Helfat, C. E. 2003. External management succession, human capital, and firm performance: An integrative analysis. *Managerial and Decision Economics*, *24*(4), 347-369.

Barney, J. B. 1991. Firm resources and sustained competitive advantage, *Journal of Management* 17(1), 99-120.

Barney, J. A. Y., & Felin, T. 2013. What are microfoundations?. *Academy of Management Perspectives*, *27*(2), 138-155.

Barron, O. E., Byard, D., Kile, C., & Riedl, E. J. 2002. High-technology intangibles and analysts' forecasts. *Journal of Accounting Research*, *40*(2), 289-312.

Bazerman, M. H. 2002. *Judgment in managerial decision making* (Fifth Edition). NY: John Wiley and Sons.

Becker, G. S. 1964. *Human capital: A theoretical and empirical analysis, with special reference to education*. Chicago: University of Chicago Press.

Beneish, M.K, Billings, M, & Hodder, L. 2008. Internal Control Weaknesses and Information Uncertainty. *The Accounting Review*: 83(3), 665-703

Blazquez, D., & Domenech, J. 2018. Big Data sources and methods for social and economic analyses. *Technological Forecasting and Social Change*, 130, 99-113.

Borgatti, S. P., & R. Cross. 2003. A relational view of information seeking and learning in social networks, *Management Science 49*(4), 432-445.

Bradshaw, M.T. 2004. How do Analysts use their earnings forecast in generating stock recommendations? *The Accounting Review*, January, 79, 1, 25-50

Branco, M., & Rodrigues, L. 2006. Corporate social responsibility and resource-based perspectives, *Journal of Business Ethics 69*(2), 111-132.

Cabello-Medina, C., López-Cabrales, Á., & Valle-Cabrera, R. 2011. Leveraging the innovative performance of human capital through HRM and social capital in Spanish firms. *The International Journal of Human Resource Management*, 22, 807–828.

Campbell, B. A., Coff, R., & Kryscynski, D. 2012. Rethinking sustained competitive advantage from human capital. *Academy of Management Review*, *37*(3), 376-395.

Please cite as: Rodgers, W., Degbey, W.Y., Housel, T.J., & Arslan, A (2020). Microfoundations of collaborative networks: The impact of social capital formation and learning on investment risk assessment. *Technological Forecasting & Social Change*, *161* (December 2020), 120295.
DOI: https://doi.org/10.1016/j.techfore.2020.120295

Carmeli, A., & Tishler, A. 2004. The relationships between intangible organizational elements and organizational performance, *Strategic Management Journal, 25*(13), 1257-1278.

Castanias, R. P., & Helfat, C. E. 2001. The managerial rents model: Theory and empirical analysis. *Journal of Management*, *27*(6), 661-678.

Child, J., Faulkner, D., Tallman, S., & Tallman, S. B. 2005. *Cooperative strategy*. Oxford University Press, USA.

Clark-Murphy, M., & Soutar, G. N. 2004. What individual investors value: Some Australian evidence, *Journal of Economic Psychology*, *25*(4), 539-555.

Cohen, M., & Sproull, L. 1996. Special issue on organizational learning, *Organization Science*, *2*(special issue), 1-145.

Coff, R., & Kryscynski, D. 2011. Invited editorial: Drilling for micro-foundations of human capital–based competitive advantages. *Journal of Management*, *37*(5), 1429-1443.

Coleman, J. S. 1990. *Foundations of social theory*. Cambridge: Harvard University Press.

Committee of Sponsoring Organizations (COSO) 2006. Internal Control over Financial Reporting—Guidance for Smaller Public Companies. New York, NY: AICPA.

Darr, E. D., & Kurtzberg, T.R. 2000. An investigation of partner similarity dimensions on knowledge transfer. *Organizational Behavior and Human Decision Processes 82*(1), 28-44.

Degbey, W.Y. 2015. Customer retention: A source of value for serial acquirers. *Industrial Marketing Management, 46*, 11-23.

Degbey, W.Y. 2016a. Why good things may not happen in knowledge-intensive acquisitions: The neglect of acquired firm's customers. In Y. Weber and S. Tarba (Eds.) Mergers and Acquisitions, Entrepreneurship and Innovation (Technology, Innovation, Entrepreneurship and Competitive Strategy, Volume 15). UK: Emerald Group Publishing Limited.

Degbey, W. Y. 2016b. *Customer retention in a cross-border acquisition: a single-case study of a knowledge-intensive firm*. Turku, Finland: University of Turku-Annales Universitatis Turkuensis.

Please cite as: Rodgers, W., Degbey, W.Y., Housel, T.J., & Arslan, A (2020). Microfoundations of collaborative networks: The impact of social capital formation and learning on investment risk assessment. *Technological Forecasting & Social Change*, *161* (December 2020), 120295.
DOI: https://doi.org/10.1016/j.techfore.2020.120295

Degbey, W., & Pelto, E. 2013. Cross-border M&A as a trigger for network change in the Russian bakery industry. *Journal of Business & Industrial Marketing*, 28(3), 178–189.

Degbey, W., & Pelto, E. 2015. Uncovering different forms of customer network changes in M&A. *Management Research Review*, 38(11), 1191–1212.

Degbey, W. Y., Eriksson, T., Rodgers, P., & Oguji, N. 2020a. Understanding cross-border mergers and acquisitions of African firms: The role of dynamic capabilities in enabling competitiveness amidst contextual constraints. *Thunderbird International Business Review*. Advance online publication. https://doi.org/10.1002/tie.22138

Degbey, W. Y., Rodgers, P., Kromah, M. D., & Weber, Y. 2020b. The impact of psychological ownership on employee retention in mergers and acquisitions. *Human Resource Management Review*. Advance online publication. https://doi.org/10.1016/j.hrmr.2020.100745

Delaney, P. F., Reder, L. M., Staszewski, J. J., & Ritter, F. E. 1998. The strategy-specific nature of improvement: The power law applies by strategy within task, *Psychological Science 9*(1), 1-7.

Delios, A., & Beamish, P. W. 2001. Survival and profitability: the roles of experience and in foreign subsidiary performance, *Academy of Management Journal*, *44*(5), 1028-1038.

Dubey, R., Gunasekaran, A., Childe, S. J., Blome, C., & Papadopoulos, T. 2019. Big Data and Predictive Analytics and Manufacturing Performance: Integrating Institutional Theory, Resource-Based View and Big Data Culture. *British Journal of Management*, *30*(2), 341-361.

Dutton, J. M., & A. Thomas. 1984. Treating progress functions as a managerial opportunity, *Academy of Management Review*, 9(2), 235-247.

Earley, C. E. 2001. Knowledge acquisition in auditing: Training novice auditors to recognize cue relationships in real estate valuation, *The Accounting Review 76*(1), 81-97.

Eccles, R., Herz, R., Keegan, E. & Phillips, D.M. 2001. *The value reporting revolution*. NY: Wiley.

Eckstein, C. 2004.The measurement and recognition of intangible assets: then and now. *Accounting Forum* 28: 139-158.

Edvinsson, L., & Malone, M.S. 1997. *Intellectual capital*: *Realising your company's true value by fining its hidden brainpower*. London: Harper Business.

Estrin, S., Mickiewicz, T., & Stephan, U. 2016. Human capital in social and commercial entrepreneurship. *Journal of Business Venturing*, *31*(4), 449-467.

Elliot, R. 1994. Confronting the future: Choices for the attest function, *Accounting Horizons 8*(3), 106-124.

Felin, T., Foss, N.J., Heimeriks, K.H. and Madsen, T.L. 2012. Micro-foundations of routines and capabilities: Individuals, processes, and structure. *Journal of Management Studies*, 49(8), 1351-1374.

Fiol, C. M., & M.A. Lyles. 1985. Organizational learning, *Academy of Management Review 10*(4), 803-813.

Foss, N. J., & Pedersen, T. 2016. Microfoundations in strategy research. *Strategic Management Journal*, *37*(13), E22-E34.

Frey, C. B., & Osborne, M. A. 2017. The future of employment: how susceptible are jobs to computerisation?. *Technological forecasting and social change*, 114, 254-280.

Friedman, Y., Carmeli, A., Tishler, A., & Shimizu, K. 2016. Untangling micro-behavioral sources of failure in mergers and acquisitions: a theoretical integration and extension. *The International Journal of Human Resource Management*, *27*(20), 2339-2369.

Gardberg, N. A., & Fombrun, C.J. 2006. Corporate citizenship: Creating across institutional environments, *Academy of Management Review 31*(2), 329-346.

Gavetti, G. 2005. Cognition and hierarchy: Rethinking the microfoundations of capabilities' development. *Organization Science*, *16*(6), 599-617.

Ghouri, A. M., Akhtar, P., Shahbaz, M., & Shabbir, H. 2019. Affective organizational commitment in global strategic partnerships: The role of individual-level microfoundations and social change. *Technological Forecasting and Social Change*, *146*, 320-330.

Graebner, M. E., Heimeriks, K. H., Huy, Q. N., & Vaara, E. 2017. The process of postmerger integration: A review and agenda for future research. *Academy of Management Annals*, *11*(1), 1-32.

Please cite as: Rodgers, W., Degbey, W.Y., Housel, T.J., & Arslan, A (2020). Microfoundations of collaborative networks: The impact of social capital formation and learning on investment risk assessment. *Technological Forecasting & Social Change*, *161* (December 2020), 120295.
DOI: https://doi.org/10.1016/j.techfore.2020.120295

Graham, G., & Steinbart P.J. 1992. Interface style and training task difficulty as determinants of effective computer-assisted knowledge transfer, *Decision Sciences 23*(1), 128-145

Grant, R. M. 1996. Prospering in dynamically-competitive environments: Organizational capability as knowledge integration, *Organization Science 7*(4), 375-389.

Griffith, D. A., Myers, M.B., & Harvey, M.G. 2006. An investigation of national culture's influence on relationship and knowledge resources in interorganizational relationships between Japan and the United States, *Journal of International Marketing 14*(3), 1-32.

Haapanen, L., Hurmelinna-Laukkanen, P., Nikkilä, S., & Paakkolanvaara, P. 2019. The function-specific microfoundations of dynamic capabilities in cross-border mergers and acquisitions. *International Business Review*, *28*(4), 766-784.

Hammersley, J., Myers, L.A., & Shakespeare, C. 2008. Market reaction to the disclosure of internal control weaknesses and to the characteristics of those weaknesses under section 302 of the Sarbanes Oxley Act of 2002, *Review of Accounting Studies*, *13*(1), 141-165

Hansen, M.T., Mors, M.L, & Björn, L. 2005. Knowledge sharing in organizations: Multiple networks, multiple phases. *Academy of Management Journal*, 48, 776-793

Haunschild, P. R., & Beckman, C.M. 1998. When do interlocks matter?: Alternative sources of information and interlock influence, *Administrative Science Quarterly 43*(4), 815-844.

Helfat, C. E. 2000. Guest editor's introduction to the special issue: The evolution of firm capabilities, *Strategic Management Journal*, *21*(10/11), 955-959.

Helfat, C. E., & Martin, J. A. 2015. Dynamic managerial capabilities: Review and assessment of managerial impact on strategic change. *Journal of Management*, *41*(5), 1281-1312.

Hinds, P. J., Patterson, M. & Pfeffer, J. 2001. Bothered by abstraction: The effect of expertise on knowledge transfer and subsequent novice performance, *Journal of Applied Psychology 86*(6), 1232-1243.

Hitt, M. A, Biermant, L., Shimizu, K., &. Kochhar, R. 2001. Direct and moderating effects of human capital on strategy and performance in professional service firms: A resource-based perspective, *Academy of Management Journal 44*(1), 13-28.

Hofstede, G. 2001. *Culture's Consequence.* Beverly Hills: Sage.

Please cite as: Rodgers, W., Degbey, W.Y., Housel, T.J., & Arslan, A (2020). Microfoundations of collaborative networks: The impact of social capital formation and learning on investment risk assessment. *Technological Forecasting & Social Change*, *161* (December 2020), 120295.
DOI: https://doi.org/10.1016/j.techfore.2020.120295

Hoskisson, R.E., Gambeta, E., Green, C.D., & Li, T.X. 2018. Is my firm-specific investment protected? Overcoming the stakeholder investment dilemma in the resource-based view. *Academy of Management Review*, *43*(2), 284-306.

Housel, T., & Bell, A. 2001. *Managing and measuring knowledge*. Boston: McGraw-Hill.

Housel, T., & Kanevsky, V. A. 1995. Reengineering business processes: A complexity theory approach to value added. INFOR: *Information Systems and Operational Research*, *33*(4), 248-262.

Hughes, P., Hughes, M., Stokes, P., Leed, H., Rodgers, P. & Degbey, W. Y. 2020. Microfoundations of organizational ambidexterity in the context of cross-border mergers and acquisitions. *Technological Forecasting and Social Change*, *153*: https://doi.org/10.1016/j.techfore.2020.119932

Im, G., & Rai, A. 2008. Knowledge sharing ambidexterity in long-term interorganizational relationships. *Management Science*, *54*(7), 1281-1296.

Inkpen, A. C., & Tsang, E. W. 2005. Social capital, networks, and knowledge transfer. *Academy of Management Review*, 30(1), 146-165.

Jamali, D., Yianni, M., & Abdallah, H. 2011. Strategic partnerships, social capital and innovation: accounting for social alliance innovation. *Business Ethics: A European Review*, *20*(4), 375-391.

Jenkins, H., Shresthova, S., & Peters-Lazaro, G. 2020. Popular Culture and the Civic Imagination: Case Studies of Creative Social Change. New York: NYU Press.

Kaufman, A., & Englander, E. 2005. A team production model of corporate governance, *Academy of Management Executive 19*(3), 9-22.

Kemper, J., Schilke, O., & Brettel, M. 2013. Social Capital as a Microlevel Origin of Organizational Capabilities. *Journal of Product Innovation Management 30(3),* 589-603.

Khan, Z., Shenkar, O. & Lew, Y. K. 2015. Knowledge transfer from international joint ventures to local suppliers in a developing economy. *Journal of International Business Studies*, 46(6), 656–675.

Klus, M. F., Lohwasser, T. S., Holotiuk, F., & Moormann, J. 2019. Strategic alliances between banks and fintechs for digital innovation: Motives to collaborate and types of interaction. *The Journal of Entrepreneurial Finance*, *21*(1), 1-15.

Kogut, B., & Zander, U. 1992. Knowledge of the firm, combinative capabilities, and the replication of technology, *Organization Science 3*(3), 383-397.

Kogut, B., & Zander, U. 1993. Knowledge of the firm and the evolutionary theory of the multinational corporation. *Journal of International Business Studies* 24(4), 525-645

Kogut, B., & Zander, U. 1996. What firms do? Coordination, identity, and learning, *Organization Science 7*(5), 502-518.

Kor, Y. Y., Mahoney, J. T., & Michael, S. C. 2007. Resources, capabilities and entrepreneurial perceptions. *Journal of Management Studies, 44*(7), 1187-1212.

Labianca, G. & Brass, D.J. 2006. Exploring the social ledger: Negative relationships and negative asymmetry in social networks in organizations. *Academy of Management Review*, 31(3), 596-614.

Lamont, B. T., King, D. R., Maslach, D. J., Schwerdtfeger, M., & Tienari, J. 2019. Integration capacity and knowledge-based acquisition performance. *R&D Management*, 49(1), 103-114.

Lang, M., & Lundholm, R. 1996. Corporate disclosure policy and analyst behavior, *The Accounting Review 71*(4), 467-492.

Lapré, M. A., Mukherjee, A. S., & van Wassenhove, L. N. 2000. Behind the learning curve: Linking learning activities to waste reduction, *Management Science*, *46*(5), 597-613.

Lev, B. 2001. *Intangibles: Management, measurement, and reporting*. Washington, DC: Brookings Institution Press.

Levitt, B., & March J.G. 1988. Organizational learning, *Annual Review of Sociology 14*, 319-340.

Lieberman, M. B. 1987. The learning curve, diffusion, and competitive strategy, *Strategic Management Journal 8*(5), 441-452.

Please cite as: Rodgers, W., Degbey, W.Y., Housel, T.J., & Arslan, A (2020). Microfoundations of collaborative networks: The impact of social capital formation and learning on investment risk assessment. *Technological Forecasting & Social Change*, *161* (December 2020), 120295.
DOI: https://doi.org/10.1016/j.techfore.2020.120295

Liu, Y., Sarala, R. M., Xing, Y., & Cooper, S. C. L. 2017. Human side of collaborative partnerships: A microfoundational perspective. *Group & Organization Management*, 42(2) 151–162

Lucas, R. E. 1993. Making a miracle, *Econometrica 61*(2), 251-272.

March, J. G. 1991. Exploration and exploitation in organizational learning, *Organizational Science 2*(1), 71-87.

Maurer, I.; Bartsch, V. & Ebers, M. 2011. The value of intra-organizational Social Capital: How it fosters knowledge transfer, innovation performance and growth. *Organization Studies*, 32 (2), 157-185

Mazur, J. E., & Hastie, R. 1978. Learning as accumulation: A reexamination of the learning curve, *Psychological Bulletin 85*(6), 1256-1274.

Mazzucato, M., & Semieniuk, G. 2018. Financing renewable energy: Who is financing what and why it matters. *Technological Forecasting and Social Change*, 127, 8-22.

McEvily, S. & Chakravarthy, B. 2002. The persistence of knowledge-based advantage: an empirical test for product performance and technological knowledge, Strategic Management Journal, 23, 4, 285-305

Merton, R. 1987. A simple model of capital market equilibrium with incomplete information, *Journal of Finance 42*(3), 483-510.

Miller, D. 2003. As asymmetry-based view of advantage: Towards an attainable sustainability, *Strategic Management Journal 24*(10), 961-976.

Mishra, C. S., & Gobeli, D. H. 1998. Managerial incentives, internalization, and market valuation of multinational firms, *Journal of International Business Studies 29*(3), 583-598.

Mohrman, S. A., Gibson, C. B., & Mohrman, A. M. 2001. Doing research that is useful to practice: A model and empirical exploration, *Academy of Management Journal 44*(2), 357-375.

Morck, R., & Yeung, B. 1992. Internalization: An event study test, *Journal of International Economics 33*(1/2), 41-56.

Please cite as: Rodgers, W., Degbey, W.Y., Housel, T.J., & Arslan, A (2020). Microfoundations of collaborative networks: The impact of social capital formation and learning on investment risk assessment. *Technological Forecasting & Social Change*, *161* (December 2020), 120295.
DOI: https://doi.org/10.1016/j.techfore.2020.120295

Moreland, R., & Myaskovsky, L. 2000. Exploring the performance benefits of group training: Transactive memory or improved communication?, *Organizational Behavior and Human Decision Processes 82*(1), 117-133.

Morgan, N. A., Zou, S., Vorhies, D. W., & Katsikeas, C. S. 2003. Experiential and informational knowledge, architectural marketing capabilities, and the adaptive performance of export ventures: A cross-national study, *Decision Sciences 34*(2), 287-323.

Mouritsen, J., Bukh, P. N. D., Larsen, H. T., & Johansen, M. R. 2002. Developing and managing knowledge through intellectual capital statements, *Journal of Intellectual Capital 3*(1), 10-29.

Mouritsen, J., Larsen, H. T., & Bukh, P. N. D. 2001. Intellectual capital and the 'capable firm': Narrating, visualizing and numbering for managing knowledge, *Accounting, Organization and Society 26*(7/8), 735-762.

Muthusamy, S.K. & White, M.A. 2005. Learning and knowledge transfer in strategic alliances, a social exchange view. *Organization Studies*. 26, 415-441.

Nahapiet, J. & Ghoshal, S. 1998. Social capital, intellectual capital, and the organizational advantage. *Academy of Management Review*, 23(2), 242-266.

Nonaka, I., & Von Krogh, G. 2009. Perspective-tacit knowledge and knowledge conversion: Controversy and advancement in organizational knowledge creation theory. *Organization Science*, 20(3), 635-652.

Nonaka, I. & Takeuchi, H. 1995. The knowledge creating company: how Japanese companies create the dynamics of innovation. Oxford University Press.

Noorderhaven, N & Harzing, A. 2009. Knowledge sharing and social interaction within MNEs. *Journal of International Business Studies*, 40, 719-741.

Önkal-Atay, D., Yates, J. F., Simga-Mugan, C., & Öztin, S. 2003. Professional vs. amateur judgment accuracy: The case of foreign exchange rates, *Organization Behavior and Human Decision Processes 91*(2), 169-185.

Oppenheimer, D.M., Meyvis, T., & Davidenko, N. 2009. Instructional manipulation checks: Detecting satisficing to increase statistical power. *Journal of Experimental Social Psychology, 45*(4), 867-872.

Please cite as: Rodgers, W., Degbey, W.Y., Housel, T.J., & Arslan, A (2020). Microfoundations of collaborative networks: The impact of social capital formation and learning on investment risk assessment. *Technological Forecasting & Social Change, 161* (December 2020), 120295.
DOI: https://doi.org/10.1016/j.techfore.2020.120295

Paruchuri, S., & Eisenman, M. 2012. Microfoundations of firm R&D capabilities: A study of inventor networks in a merger. *Journal of Management Studies*, *49*(8), 1509-1535.

Pavlou, P. A., Housel, T. J., Rodgers, W., & Jansen, E. 2005. Measuring the return on information technology: A knowledge-based approach for revenue allocation at the process and firm level, *Journal of the Association of Information Systems 6*(7), 199-226.

Peterson, D. K., & Pitz, G. F. 1988. Confidence, uncertainty, and the use of information, *Journal of Experimental Psychology: Learning, Memory, and Cognition 14*(11), 85-92.

Ployhart, R. E., & Moliterno, T. P. 2011. Emergence of the human capital resource: A multilevel model. *Academy of Management Review*, 36(1), 127-150.

Polanyi, M. 1966. *The Tacit Dimension*. London: Routledge and Kegan Paul.

Portes, A. 1998. Social capital: Its origins and applications in modern sociology. *Annual Review of Sociology*, 24, 1-24.

Public Company Accounting Oversight Board (PCAOB) 2004. An Audit of Internal Control over Financial Reporting Performed in Conjunction with an Audit of Financial Statements. Auditing Standard No. 2. Washington, D.C.: PCAOB.

Public Company Accounting Oversight Board (PCAOB) 2007. An Audit of Internal Control over Financial Reporting that is Integrated with an Audit of Financial Statements. Auditing Standard No. 5. Washington, D.C.: PCAOB.

Puranam, P., Singh, H., & Zollo, M. 2006. Organizing for innovation: Managing the coordination-autonomy dilemma in technology acquisitions. *Academy of Management Journal*, *49*(2), 263-280.

Raffiee, J., & Coff, R. 2016. Micro-foundations of firm-specific human capital: when do employees perceive their skills to be firm-specific?. *Academy of Management Journal*, *59*(3), 766-790.

Ramani, S. V., SadreGhazi, S., & Gupta, S. 2017. Catalysing innovation for social impact: The role of social enterprises in the Indian sanitation sector. *Technological Forecasting and Social Change*, 121, 216-227.

Please cite as: Rodgers, W., Degbey, W.Y., Housel, T.J., & Arslan, A (2020). Microfoundations of collaborative networks: The impact of social capital formation and learning on investment risk assessment. *Technological Forecasting & Social Change*, *161* (December 2020), 120295.
DOI: https://doi.org/10.1016/j.techfore.2020.120295

Reus, T., Lamont, B. & Ellis, K. 2016. A darker side of knowledge transfer following international acquisitions. *Strategic Management Journal*, 37, 932–944.

Rodgers, W. 1992. The effects of accounting information on individuals' perceptual processes, *Journal of Accounting, Auditing, and Finance*, 7, 67-96.

Rodgers, W. 1999. The influences of conflicting information on novices' and loan officers' actions, *Journal of Economic Psychology*, *20*, 123-145.

Rodgers, W. 2002. Knowledge based capital in accounting. *Collected abstracts of the 25th Annual Congress of the European Accounting Association*, Copenhagen, Denmark, April 25-27.

Rodgers, W. 2003. Measurement and reporting of knowledge-based assets, *Journal of Intellectual Capital 4*(2), 181-190.

Rodgers, W. 2007. Problems and resolutions to future knowledge-based assets reporting, *Journal of Intellectual Capital*, 8, 205-215.

Rodgers, W. & Housel, T. 1987. The effects of information and cognitive processes on decision-making, *Accounting and Business Research*, 69, 67-74.

Rodgers, W., & Housel, T. 2004. The effects of environmental risk information on Auditors' decisions about prospective financial statements, *European Accounting Review 13*(3), 523-540.

Rodgers, W. & Johnson, L. 1988. Integrating credit models using accounting information with loan officers' decision processes, *Accounting and Finance*, 28, 1-22.

Rose, J.M., Norman, C.S., & Rose, A.M. 2010. Perceptions of investment risk associated with material Control weakness pervasiveness and disclosure detail. *The Accounting Review, 85*(5) 1787–1807.

Sabherwal, R., & Sabherwal, S. 2005. Knowledge management using information technology: Determinants of short-term impact on firm value *Decision Sciences, 36*(4), 531-569.

Sarala, R.M., Junni, P., Cooper, C.L. and Tarba, S.Y. 2016. A sociocultural perspective on knowledge transfer in mergers and acquisitions. *Journal of Management*, *42*(5), 1230-1249.

Sarbanes-Oxley Act of U.S. House of Representatives, 2002. Public Law 107–204. H.R. 3763. Washington, D.C.: Government Printing Office.

Please cite as: Rodgers, W., Degbey, W.Y., Housel, T.J., & Arslan, A (2020). Microfoundations of collaborative networks: The impact of social capital formation and learning on investment risk assessment. *Technological Forecasting & Social Change*, *161* (December 2020), 120295.
DOI: https://doi.org/10.1016/j.techfore.2020.120295

Shanteau, J., Weiss, D. J., Thomas, R. P., & Pounds, J. C. 2002. Performance-based assessment of expertise: How to decide if someone is an expert or not, *European Journal of Operational Research 136*(2), 253-263.

Singh, J. 2005. Collaborative networks as determinants of knowledge diffusion patterns. *Management Science*, *51*(5), 756-770.

Spender, J. C., & Grant, R. M. 1996. Knowledge and the firm: Overview, *Strategic Management Journal* 17, 5-9.

Stadler, C., Rajwani, T., & Karaba, F. 2014. Solutions to the exploration/exploitation dilemma: Networks as a new level of analysis. *International Journal of Management Reviews*, 16(2), 172–193.

Stephan, U., Patterson, M., Kelly, C., & Mair, J. 2016. Organizations driving positive social change: A review and an integrative framework of change processes. *Journal of Management*, *42*(5), 1250-1281.

Stephan, U., Andries, P., & Daou, A. 2019. Goal Multiplicity and Innovation: How Social and Economic Goals Affect Open Innovation and Innovation Performance. *Journal of Product Innovation Management*, *36*(6), 721-743.

Szulanski, G. 1996. Exploring internal stickiness; Impediments to the transfer of best practice within the firm, *Strategic Management Journal*, *17*, 27-43

Van Dijk, E., & Zeelenberg, M. 2003. The discounting of ambiguous information in economic decision making, *Journal of Behavioral Decision Making 16*(5), 341-352.

Tarba, S. Y., Ahammad, M. F., Junni, P., Stokes, P., & Morag, O. 2019. The impact of organizational culture differences, synergy potential, and autonomy granted to the acquired high-tech firms on the M&A performance. *Group & Organization Management*, 44(3) 483–520.

Villani, E., Rasmussen, E., & Grimaldi, R. 2017. How intermediary organizations facilitate university–industry technology transfer: A proximity approach. *Technological Forecasting and Social Change*, *114*, 86-102.

Wang, Y., Kung, L., & Byrd, T. A. 2018. Big data analytics: Understanding its capabilities and potential benefits for healthcare organizations. *Technological Forecasting and Social Change*, *126*, 3-13.

Please cite as: Rodgers, W., Degbey, W.Y., Housel, T.J., & Arslan, A (2020). Microfoundations of collaborative networks: The impact of social capital formation and learning on investment risk assessment. *Technological Forecasting & Social Change*, *161* (December 2020), 120295.
DOI: https://doi.org/10.1016/j.techfore.2020.120295

Whetten, D. A., Felin, T., & King, B. G. 2009. The practice of theory borrowing in organizational studies: Current issues and future directions. *Journal of Management*, *35*(3), 537-563.

Wernerfelt, B. 1995. The resource-based view of the firm: Ten years after, *Strategic Management Journal 16*(3), 171-174.

Wright, P. M., Coff, R., & Moliterno, T. P. 2014. Strategic human capital: Crossing the great divide. *Journal of Management, 40*(2), 353-370.

Yan, Y., & Zhang, J. A. 2003. Performance of high-tech firms' resource and capability-based development: knowledge acquisition, organizational utilization and management involvement, *International Journal of Business Studies 11*(1), 45-67.

Yates, J. F. 1990. *Judgment and Decision Making*. Englewood Cliffs, NJ: Prentice Hall, Inc.

Please cite as: Rodgers, W., Degbey, W.Y., Housel, T.J., & Arslan, A (2020). Microfoundations of collaborative networks: The impact of social capital formation and learning on investment risk assessment. *Technological Forecasting & Social Change*, *161* (December 2020), 120295.
DOI: https://doi.org/10.1016/j.techfore.2020.120295