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Industry Exposure to Artificial Intelligence, Board Network Heterogeneity, and Firm Idiosyncratic Risk

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ABSTRACT Despite the growing impact of artificial intelligence (AI) in business, there is little research examining its effects on firm idiosyncratic risk (IR). This is an important issue for boards: as key conduits of firm–environment information flows via board interlock networks, traditional risk oversight functions are being increasingly augmented with strategic decision-making and communications. Accordingly, we explore how AI and board interlocks independently and interactively affect IR, focusing on the heterogeneity of the board's network ties. We hypothesize these effects within signalling theory, positing that a firm's AI exposure and board network will differentially affect market perceptions of risk contingent on their perceived cost and relative signal strength under different environmental conditions. We find that while AI and board network heterogeneity both favourably affect risk, operating in a high-AI industry while occupying a network position that spans industry boundaries mitigates these effects, leading to an increase in IR for firms in the most technologically advanced industries. Additional analyses of diversification corroborate these theoretical mechanisms: as a costly signal of competence across multiple domains, diversification enables firms to simultaneously engage with AI and diverse knowledge networks without market penalties. Our findings offer practical insights for directors and avenues for theoretical development.

Keywords: Artificial intelligence, board interlocks, board of directors, idiosyncratic risk, corporate strategy, signalling theory

INTRODUCTION

Boards of directors are serving an increasingly active role in strategic decision-making, while also maintaining their traditional functions in monitoring and governance (Afzali et al., 2024; Chen et al., 2024). Ensuring the management of firm risk

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while identifying and capitalizing upon strategic opportunities has therefore become an essential tension in the contemporary role of directors (Boivie et al., 2021; Vera et al., 2022). This is exemplified by artificial intelligence (AI), which is presently creating both unprecedented disruption and opportunity within firms and leading to a demanding role for the board: 'keeping the organization at the forefront of this latest technological development yet intensely mindful of the risks' (McKinsey and Company, 2024).

AI refers to the ability of machines to perform tasks that presently require human discernment, such as those related to decision-making, problem-solving, and creativity (Benbya et al., 2020). More than any preceding technological discontinuity, AI requires fundamental changes to business processes, products, and organizational structures (Chalmers et al., 2020; Faraj and Pachidi, 2021), posing numerous risks for implementation within established firms (Prügl and Spitzley, 2020) and introducing uncertainty into investors' evaluations of their future value (Li et al., 2021). However, failure to capitalize upon these opportunities is also risky: when technology radically alters the bases of competition, these changes are necessary to avoid underperformance or obsolescence (Davenport et al., 2020; Litov et al., 2012).

Understanding the risk implications of AI is therefore imperative, not only for directors' ability to balance the increasing demands it places upon their role but also to inform a broader theoretical and practical understanding of how its effects will follow or diverge from previous waves of technological change (see Goos and Savona, 2024; Townsend et al., 2024). However, a dearth of research examining how boards interact with the technological environment to affect firm risk (Hoppmann et al., 2019) and a growing but increasingly fragmented body of research on AI in firms (see Bailey et al., 2022; Kellogg et al., 2020; Raisch and Krakowski, 2021) means that the literature presently lacks a cohesive theoretical approach for examining this understudied issue. The extant evidence suggests no clear pattern of effects and highly firm-specific reactions from financial markets (Mishra et al., 2022; Padigar et al., 2022). This indicates a need to clarify the mechanisms and conditions under which AI can positively or negatively affect firm risk (Li et al., 2021) and suggests that the board – as a key manager of risk, facilitator of strategic change, and informational bridge between a firm and its external stakeholders (Recendes et al., 2024; Vera et al., 2022) – is a pertinent unit of analysis for pursuing this objective.

Considering the necessity for firms to both acquire and communicate novel information in this emergent stage of AI (Mishra et al., 2022; Townsend et al., 2024) and the centrality of market perceptions in determining firm risk (Benner and Beunza, 2023; Litov et al., 2012), we utilize *signalling theory* (Bergh et al., 2014; Connelly et al., 2011) as a framework to integrate and investigate these issues. Operating at the interface of the firm and its environment, boards facilitate the use of external information in strategic decisions (Westphal et al., 2001) and, in turn, provide firm–market signals regarding the nature and legitimacy of these decisions (Certo, 2003; Park et al., 2016). Board interlock networks, which develop from the connections formed when a director serving at one firm is appointed to the board of another (Shropshire, 2010), are the main conduit for these information gathering and dissemination activities (Mizruchi, 1996; Withers et al., 2020). These networks serve an especially relevant role during technological change, when both the requirements for external information (Li, 2019) and need to

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reduce information asymmetries between a firm and its stakeholders (Litov et al., 2012) are heightened.

Our empirical analysis therefore focuses on two variables: (1) the *prevalence and importance of AI in a firm's industry* (*AI exposure*), representing the degree of opportunity and/or threat posed by AI (Felten et al., 2021), and (2) *board network heterogeneity*, representing the extent and diversity of market intelligence to which a firm can gain access via the interlock network (Li, 2019). We conceptualize board network heterogeneity as a signal which will differ in strength and perceived cost according to a firm's level of AI exposure, thus altering investors' interpretations and consequently shareholder value (Mishra et al., 2022; Srinivasan and Hanssens, 2009). Accordingly, we examine how these factors independently and interactively affect firm *idiosyncratic risk* (*IR*) to answer two underexamined questions: (1) How does AI affect firm risk? and (2) How can boards influence firm risk in the context of technological disruption and uncertainty?

In a ten-year panel of more than 1700 US firms, we find that AI exposure and board network heterogeneity independently *decrease* IR, suggesting that investors perceive greater risk in the opportunity cost of organizational inertia and isolation than in the pursuit of change (see Gilbert, 2005; Matthews et al., 2022). However, a heterogeneous network of inter-industry board interlocks *increases* IR in industries in which AI is most prevalent and important, and it attenuates the risk-reducing effect of AI exposure across firms.

Signalling theory suggests that this may be because operating in a high-AI industry while occupying a network position that spans industry boundaries signals to market actors that a firm's technological exploration extends beyond its core competence (Benner and Tushman, 2002; Li et al., 2021), increasing investor uncertainty and therefore IR. We conduct additional analyses to test this theoretical mechanism, examining the impact of *diversification* as a costly signal of competence across multiple domains (Mackey et al., 2017; Ng, 2007). Our findings show that diversification attenuates this effect and enables firms to simultaneously engage with AI and heterogeneous knowledge networks without market penalties, supporting the premise that the interaction we observe is a function of the market signals communicated by board networks.

Advances in signalling theory have been driven by its application to an increasingly uncertain range of management contexts which offer new insights into the forms, mechanisms, and effects of firm-level signals (Bergh et al., 2014; Connelly et al., 2011). Our study extends this, contributing to nascent research that expounds the role of board characteristics and strategy as market signals (e.g., Paruchuri et al., 2021; Recendes et al., 2024). Specifically, we show that board networks act as value-relevant signals that can attenuate IR (see Carter, 2006; Fombrun and Shanley, 1990) but also interact with environmental factors to induce unfavourable investor perceptions. This explicates contextual differences in the significance of signal characteristics – and consequently, their implications for shareholder value – of which signalling theory presently provides limited understanding (e.g., see Gomulya et al., 2017; Park and Mezias, 2005).

Through the first empirical examination of AI and firm risk in the corporate governance context, we also show that firm–market signals interact with AI exposure to jointly inform evaluations of IR, countering the common view that AI is inherently perceived as risky by investors (see Babina et al., 2024; Padigar et al., 2022). For further research on AI, this

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demonstrates signalling theory as an important framework for understanding its implications, beyond the 'first-order' effects within firms to incorporate stakeholders' perceptions and their 'second-order' consequences for firm performance (Recendes et al., 2024).

This study also has practical implications for the management of firm risk. Our results raise a difficult question: In industries in which AI is both prevalent and important, how can firms capitalize upon the knowledge resources accessible via board interlocks while exploring this new technology? We demonstrate the tensions between the monitoring and informational role of directors (Boivie et al., 2021; Vera et al., 2022), suggesting that boards' responsibility for risk management may be undermined by their own engagement in otherwise beneficial knowledge networks. Our additional analyses highlight diversification as a potential buffer against market penalties in this situation, and we discuss the novel questions this raises for future research on corporate governance and strategy during periods of technological disruption.

PERTINENT LITERATURE AND THEORETICAL BACKGROUND

Firm-Market Signalling during Technological Change

Research on the implications of AI for firm value and risk is in its infancy. However, recent studies are increasingly providing empirical evidence for impacts on shareholder value, moving beyond internal firm-based measures of performance to examine these market-based indicators (see Table I for an overview). These studies suggest significant but ambiguous population-level effects: for example, Babina et al. (2024) report that AI investments by recruitment firms increase market valuations among large firms and in concentrated industries, and Mishra et al. (2022) find both increases and decreases in efficiency-based financial performance metrics among AI-focused firms (for an extensive review of further studies in the wider AI domain, see Online Appendix 1 in Mishra et al., 2022).

This trend implies a large firm-specific, idiosyncratic component to the AI–shareholder value relationship, and therefore a need for greater understanding of how firms can influence investor reactions to strategic changes in this context (Padigar et al., 2022). *Signalling theory* is among the foremost approaches to understanding this relationship (Recendes et al., 2024).

Signalling theory posits that financial markets are characterized by information asymmetry between firms and market actors (e.g., Park et al., 2016; Paruchuri et al., 2021). To develop accurate expectations about the future, both parties will therefore be motivated to seek additional information and attempt to corroborate the veracity of present knowledge (Connelly et al., 2011). A sender (firm) can influence the behaviour of a receiver (market actor) through signals that communicate proprietary knowledge and reduce information asymmetry (Spence, 1973).

When information asymmetries are especially observable and empirically unresolvable, such as in the case of novel technologies and environmental uncertainty (Mishra et al., 2022; Padigar et al., 2022), firm–market signals assume a more significant role in informing analysts' and investors' evaluations (e.g., Benner, 2007, 2010; Benner and Ranganathan, 2012; Litov et al., 2012). In these environments, the inherent unknowability of the future state of technology and success of its application within a given

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Table I. Representative recent empirical studies on firm-level consequences of AI

					Dependent variable		
Study	*Scope*	*Theoretical framework*	*Empirical focus*	*AI definition*	*Definition*	*Market-based outcome*	*Firm risk outcome*
Li et al. (2021)	Chinese firms	Resource-based theory	CSR	AI-related patents	Idiosyncratic risk	✓	✓
Lui et al. (2022)	Large US firms	Operations management theory	AI capability	AI investments	Stock returns	✓	–
Padigar et al. (2022)	S&P 500	Signalling theory	Marketing department power	AI-embedded new products	Stock returns	✓	–
Mishra et al. (2022)	Large US firms	Marketing theory	Advertising and sales expenditure	Management AI focus	Operating efficiency	–	–
Babina et al. (2024)	US recruiting firms	Economic theory	Product innovation	AI skills demanded/ provided	Market value	✓	–
This study	Large US firms	Signalling theory	Board information networks	AI exposure	Idiosyncratic risk	✓	✓

Note: Studies were identified from a literature search of prominent journals (*CABS Academic Journal Guide* rank 4 or 4* and/or listed in the *Financial Times 50*) across business disciplines (including management, strategy, marketing, operations, finance, and innovation) for all articles published with the keywords 'AI' or 'artificial intelligence' published since 2020. These were manually reviewed to identify empirical studies of firm-level outcomes and refined to the above sample to provide a representative overview across disciplines.

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firm or industry means that other firm-specific factors will exert a greater influence on market actors' perceptions (see Guo and Yu, 2024, for a review). These signals convey value-relevant information about broader characteristics of the firm that indicate its ability and intentions to deal with the uncertainty (Bansal and Clelland, 2004; Recendes et al., 2024; Richards et al., 2017).

While firms can intentionally formulate and communicate these signals in attempts to influence market perceptions (Li et al., 2022; Whittington et al., 2016), evidence suggests that investors place greater weight on *costly signals*: those that demonstrate action and commitment and thus convey more credible evidence of the firm's intentions or capabilities (Certo et al., 2001). These signals may also be deliberate but can also arise incidentally from observable characteristics of the firm (Guo and Yu, 2024). Whether this occurs will depend on the salience of a particular characteristic to investors in informing their valuations, and thus the degree to which market attention is directed towards this factor (Hill et al., 2019; Recendes et al., 2024) – its *signal strength*. Critical to the context of technological change, a signal's strength is environmentally contingent (Gomulya et al., 2017) and can influence its effects independently of cost (Goranova et al., 2007; Park and Mezias, 2005).

Firm Value, Idiosyncratic Risk, and Technological Change

Shareholder value is a function of two aspects of a firm's stock market performance: valuation, reflecting predictions of future revenues (e.g., abnormal returns, Tobin's Q), and risk, reflecting the expected volatility of these revenues (Srinivasan and Hanssens, 2009). Perceptions of risk inform and shape market participants' valuations, particularly in situations of environmental disruption (Benner and Beunza, 2023; Litov et al., 2012), with firm-level changes that are seen to reduce risk leading to improved market performance (Harrison et al., 2020; Recendes et al., 2024). Idiosyncratic risk (IR) refers the component of risk that arises from actions and events at the firm or industry level (Bansal and Clelland, 2004). IR represents 80 to 85 per cent of the total risk associated with a stock, and investors consequently place greater emphasis on IR than systematic, market-level risk metrics (Goyal and Santa-Clara, 2003). IR is therefore a significant outcome for firms to monitor, as this aspect of firm risk can be influenced by strategic decisions (Li et al., 2021; Mishra et al., 2022). Despite this practical significance, theoretical and empirical research on the influence of strategic decisions on firm risk remains underdeveloped (Edeling et al., 2021).

IR is most important during periods of environmental uncertainty: when systematic shocks cause investors to doubt firms' ability to service debt and generate predictable revenues, the market will prefer firms that are better able to manage IR (Chen and Strebulaev, 2019; Herskovic et al., 2016). AI, and the associated disruptive technological change, represents one systematic uncertainty that is profoundly impacting the macroeconomic environment (Chalmers et al., 2020; Goldfarb and Tucker, 2019), making IR an increasingly important aspect of how firms generate returns to shareholders (Mishra et al., 2022).

This uncertainty is often equated to risk, particularly in current discussions of business applications of disruptive technologies (e.g., Brynjolfsson and McAfee, 2017; Tabrizi

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et al., 2019). However, these concepts are distinct (Alvarez et al., 2018), and the unknowable uncertainties of this change (i.e., which AI technologies will be relevant in the future) does not necessitate that firm IR is adversely affected. In fact, historical lows in average IR have coincided with the most rapid developments in disruptive technologies (Bartram et al., 2018), reflecting the fact that firms can take actions to manage IR in the face of systematic threats (Mishra et al., 2022). The relationship between AI and IR remains largely unexplored in the literature. However, the few studies of this topic have found non-significant population-averaged effects of AI innovations on IR (Li et al., 2021) and substantial variability in returns following AI-related new product introductions (Padigar et al., 2022).

Evidently, the emergence and application of AI does not inherently imply a rise in IR, demonstrating that it is not only the first-order risk implications of new technologies that affect firm performance but also the downstream effects on market outcomes arising from *perceptions* of risk, independent of the tangible impact of AI within the firm itself (see Recendes et al., 2024). Differences in analysts' and investors' evaluations of a firm give rise to these 'second-order' effects on firm risk, and therefore market performance (see Briscoe et al., 2014; Hill et al., 2019). This reflects an emerging perspective in which the role of firm–market signalling via a firm's leadership is an important mechanism for understanding these underexplored second-order effects (Connelly et al., 2016; Gomulya and Boeker, 2014; Recendes et al., 2024). Establishing the nature and effects of these signals in the context of AI is the focus of our study.

The information asymmetries induced by periods of systemic technological disruption therefore alter the landscape of firm–market signalling from two perspectives: (1) increased attention to IR, and therefore to factors seen as relevant to this aspect of performance, among market actors; and (2) a heightened need – and opportunity – for firms to influence market actors' evaluations of firm risk via signalling (Higgins and Gulati, 2006; Ndofor and Levitas, 2004; Park and Mezias, 2005). Figure 1 depicts these key relationships in the context of the ongoing advancement of AI. In the following sections, we derive the hypotheses shown therein and explain the operationalizations used for their empirical examination.

CONCEPTUAL FRAMEWORK AND HYPOTHESES

AI Exposure and Idiosyncratic Risk

Previous research has largely studied AI *implementation*; for example, with regard to its effects on labour (Faulconbridge et al., 2023), consumer behaviour (Huang and Rust, 2021), and innovation (Li et al., 2021; Padigar et al., 2022). However, examining forward-looking outcomes such as IR requires a level of analysis that accounts for the opportunities and threats posed by AI, rather than the present state of AI application within a given firm. For this reason, we focus on the degree of *AI exposure* faced by the firm, defined by the present state of AI application within its core industry (Felten et al., 2021), thus capturing the future-facing and idiosyncratic factors that influence IR (Mishra et al., 2022).

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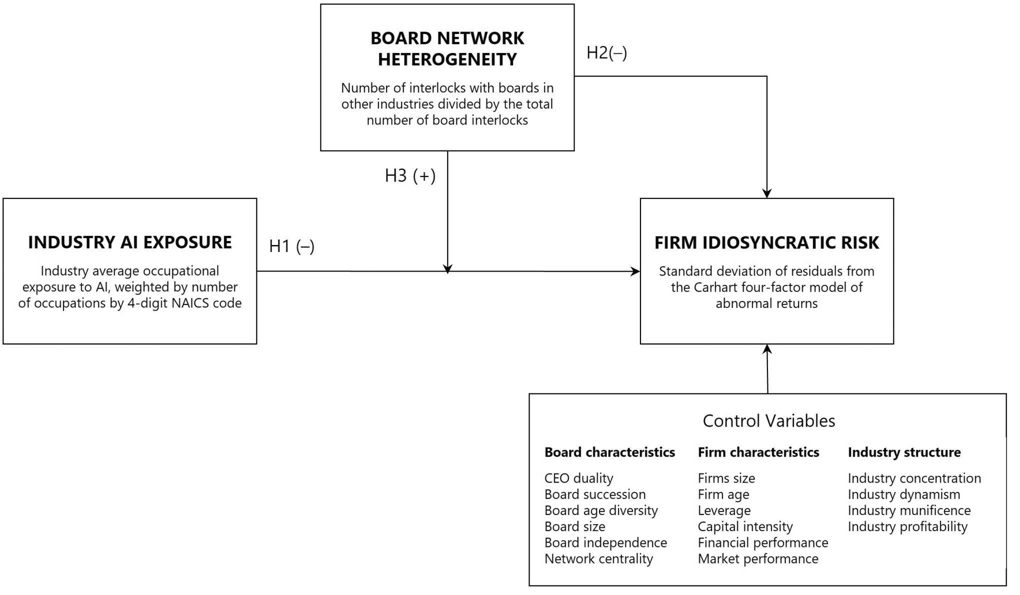

Figure 1. Hypothesized relationships between board network heterogeneity, AI exposure, and firm idiosyncratic risk

Note: This figure depicts the hypothesized relationships we test, but we also undertake further analyses to investigate whether diversification can attenuate the increase in idiosyncratic risk among firms with high levels of both artificial intelligence exposure and network heterogeneity. However, these relationships are not illustrated here.

The degree to which AI is prevalent among peer firms and/or important to business operations within the industry determines the abundance of potential applications and strength of competitive pressure to adopt AI, yet the response to these opportunities and threats will depend on the actions of each individual firm (Felten et al., 2021). Signalling theory therefore suggests that the heightened information asymmetry in an industry of high AI exposure increases both the necessity and the ability to influence market perceptions (and consequently IR) through firm-specific signals (Guo and Yu, 2024; Ndofor and Levitas, 2004).

In the absence of the information conveyed by firm–market signalling, it is possible that the baseline effect of AI exposure on IR may be positive or negative. Supporting the former argument, AI is a novel technology with limited present application compared with its potential uses (Davenport et al., 2020; Huang and Rust, 2021). This means that many of the opportunities available to firms exposed to AI will involve speculative R&D that diverges from firms' extant capabilities (Kleis et al., 2012). These projects are likely to be perceived as necessary when AI is important in an industry, as a failure to match other firms' progress in disruptive technologies may result in a loss of competitive position and long-term obsolescence (see Litov et al., 2012). However, this explorative form of R&D has a high rate of failure, often generating zero return on investment (Hoberg and Phillips, 2016). This has clear negative implications for IR, raising both upside and downside variability in forecasts. Furthermore, the need for additional financing and/or diversion of resources from other revenue-generating activities for such projects implies risk to a firm's cash flows (Li et al., 2021). Even if firms ultimately succeed in pursuing

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AI opportunities, they may therefore incur short-term market penalties in the form of higher IR.

Compounding this issue, these forms of R&D generate attention for firms among market actors (Mishra, 2017). Securities analysts, who mediate the flow of information between firms and investors (Bradley et al., 2020), face incentives to cover firms with easy-to-analyse strategies as they can employ generalizable mental models to cover more firms without compromising the accuracy of forecasts (Benner, 2010; Washburn and Bromiley, 2014). When firms pursue technological change, analysts cannot rely on experience and heuristics and must pay greater attention to firm-specific factors (Benner, 2007). Analysts, as outsiders to the firm, necessarily lag internal decision-makers in terms of their expertise regarding each specific firm. This results in a short-term loss of accuracy and increase in variability in forecasts while analysts update their mental models (Benner and Ranganathan, 2017). Regardless of the effectiveness of a firm's internal approach to AI and the degree to which this is communicated via signalling, both firms and analysts must extend beyond their areas of established competence when assessing the likely returns to AI within an industry, impairing the ability to accurately predict future revenues from this technological change and potentially increasing IR.

Paradoxically, however, these same factors may induce the opposite market response to firms' AI exposure. We may equally expect that a lack of extant competence among both firms and analysts in assessing the returns to AI will lead to a joint understanding of the need to pursue developments in this area. Given that AI is broadly accepted as being central to the future of business by both firms and investors (Brynjolfsson and McAfee, 2017; Padigar et al., 2022), analysts' uncertainty may be driven not by the prospects of any one firm but by the adequacy of their present mental models. Perceiving shortfalls in their current knowledge of the relevance and likely impact of firm-specific factors, assessment of risk may therefore rely more on systematic factors (Merkl-Davies and Brennan, 2007; Washburn and Bromiley, 2014), reducing IR.

The literature on analyst–firm interactions supports this. There is strong evidence that analysts actively seek to update their valuation heuristics during periods of technological change (Benner, 2007, 2010; Benner and Ranganathan, 2017; Matthews et al., 2022), indicating that stock market penalties for firms' early adoption of these innovations does not reflect negativity towards the technology itself but rather a lack of information, for which analysts accordingly attempt to compensate (Litov et al., 2012). Furthermore, as analysts specialize by industry (Washburn and Bromiley, 2014), the opportunity to improve their knowledge of the likely implications of AI – and consequently, confidence in their forecasts – will be greater when covering industries in which AI is prevalent and/or important (see Benner and Beunza, 2023), suggesting that this updating process is facilitated by AI exposure. AI exposure thus represents a situation in which market actors will seek additional information in order to adapt their mental models, but with this information first sought and available at the industry level (Benner and Beunza, 2023; Litov et al., 2012), implying that AI exposure will decrease IR.

Research in finance further supports the notion that AI exposure may decrease IR, demonstrating historically low IR at the market level over the previous decade (e.g., Bartram et al., 2018). This coincides with the perception of AI's future importance being

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at its height (Brynjolfsson and McAfee, 2017) and the most rapid period of advancement in AI applications within businesses (Davenport et al., 2020; Padigar et al., 2022).

A baseline decrease in IR also reflects the premise that the increase in information asymmetry will motivate investors to seek firm-specific signals to inform their valuations, as the environment is no longer sufficiently predictable or informative (Benner and Beunza, 2023; Matthews et al., 2022). In accordance with signalling theory and the extant empirical evidence, we therefore propose the following hypothesis and next turn to these firm-specific factors:

Hypothesis 1: Artificial intelligence exposure decreases firm idiosyncratic risk.

Board Characteristics as Market Signals

We hypothesize the effects of AI exposure on IR as a function of the information available to analysts and investors regarding the impact of AI on firms' ability to predictably generate revenues. Whether we empirically observe the 'risk-reducing' effect of AI exposure predicted by Hypothesis 1 may therefore be contingent upon the additional, firm-specific information available to the market. As we are considering the implications of AI in terms of both current strategy and future opportunities (i.e., exposure; see Felten et al., 2021, and the preceding section), the value relevance of a firm's signalling activity in this context will depend on its ability to communicate information regarding the general *strategic direction* of the firm (Mishra et al., 2022), rather than the past or current implementation of AI that has largely been the focus of previous research (e.g., Li et al., 2021; Padigar et al., 2022).

Prior research in signalling theory (Certo, 2003; Certo et al., 2001; Park et al., 2016) identifies the *board of directors* as a key determinant of this. As a key conduit of information flows between a firm and its environment (Finkelstein et al., 2009; Tuggle et al., 2010), the board disseminates firm-specific intelligence both through direct communication with market participants and in the incidental signals conveyed through board characteristics, such as the credentials and experience (Certo, 2003; Withers et al., 2012) and network ties (Park et al., 2016; Pollock et al., 2004) of directors. Both provide value-relevant information to investors about the competence and strategic orientation of firms (Connelly et al., 2011), but the incidental signals conveyed by board characteristics are likely to be perceived as more credible indicators of a firm's true capabilities or intentions than the 'cheap talk' of deliberate investor communications (Li et al., 2022; Whittington et al., 2016). Although these incidental signals may be less observable, evidence indicates that investors and analysts actively seek access to information on these factors when forming their evaluations of firms (Hill et al., 2019; Recendes et al., 2024).

Literature on the signalling role of boards is limited in scope (Recendes et al., 2024), being primarily focused on IPOs (e.g., Certo, 2003; Certo et al., 2001; Park et al., 2016; Pollock et al., 2004). Examinations of board–environment information flows in the context of technological change are also scarce (Srinivasan et al., 2018). However, combining these research streams with the established literature on board interlock networks suggests that a key characteristic of boards that will influence market responses (particularly in terms of IR) to firms' AI exposure is *board network heterogeneity*.

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Board interlocks are formed when a director serves on the board of two firms (Mizruchi, 1996). The configuration of these ties between firms forms the board interlock network, with individual firms occupying distinct positions in this network based on both the extent and nature of their connections to others (Srinivasan et al., 2018). A firm's network *centrality* – i.e., its number of connections to other firms – affects the *volume* of information flows to and from the firm within the network and has been shown to affect multiple strategic decisions such as innovation (Li, 2019, 2021), acquisitions (Beckman and Haunschild, 2002), and adoption of business practices (Westphal et al., 2001). Network *heterogeneity* – i.e., the nature and diversity of connections – accounts for the fact that the *content* of information flows can differentially affect the impact of interlocks on a focal firm (Geletkanycz and Hambrick, 1997).

Heterogeneity in industry ties is a well-established influence on firm-level outcomes in the context of technological change (e.g., Cohen and Levinthal, 1990; Levitt and March, 1988). Industrial heterogeneity in interlocks has been shown to affect the degree to which firms pursue disruptive innovations (Li, 2019), whereas network homogeneity (i.e., primarily within the focal firm's industry) improves the success of incremental new product development (Srinivasan et al., 2018). These findings are attributed to the informational content of the networks to which inter- and intra-industry interlocks provide access, and upon which directors' contributions to strategic decisions thus rely (Beckman and Haunschild, 2002). Access to other industries encourages exploration of novel ideas, untested in the focal firm's industry (Ahuja and Katila, 2001; West and Bogers, 2014), whereas ties within the same industry facilitate the acquisition of deeper knowledge about a firm's existing markets; for example, with regard to changing consumer tastes, competitors' activities, or technology adoption (see also Li, 2021; Srinivasan et al., 2018). Overall, information gained from interlocks appears to promote imitation of technological changes to which a firm is exposed, rather than exploration of novel technologies beyond those utilized by connected firms (Li, 2021).

These forms of information, gained from dissimilar and similar network ties, respectively, have been termed *variance-increasing* versus *variance-reducing*, according to the degree to which the strategic opportunities they provide represent 'departure from a focal firm's store of current skills and capabilities' (Benner and Tushman, 2002, p. 679; see also Li, 2019). In a way similar to AI exposure, this has implications for the degree of information asymmetry between a firm and market actors and thus raises two potential effects on IR.

First, a heterogeneous network may direct the attention of market actors to a firm's variance-increasing activities. It indicates that a firm has access to inter-industry information, and whether this has been deliberately cultivated by the focal firm (i.e., by appointing directors that serve on boards in other industries) or is a by-product of director selection according to other criteria (see Withers et al., 2012, 2020), this may be seen as a signal that the firm is exploring opportunities outside of its own industry. Furthermore, board network heterogeneity is a relative concept (Li, 2019): the greater the degree of inter-industry interlocks, the lesser will be the firm's focus on industry-specific market intelligence (Srinivasan et al., 2018). This may signal a lack of attention to the core competences and activities that predictably generate revenues for the firm, which could increase perceptions of risk among investors.

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Conversely, rather than focusing on the *heterogeneity* of board networks, market actors may instead attribute salience to the *board*-level nature of this heterogeneity. Firms can gain access to information about other industries in many ways; for example, through alliances, acquisitions, or purchasing market intelligence services (Ahuja and Katila, 2001; Li, 2019; West and Bogers, 2014). Despite the significant resources that firms may devote to director selection, these other modes of information gathering necessitate greater disruption of strategic- and operational-level activities within the firm and/or require higher levels of commitment than the establishment of social and professional ties among interlocked firms (Withers et al., 2012). Furthermore, these ties may be perceived as a form of relational capital that can mitigate the effects of firm-specific risk (Withers et al., 2020).

Relative to other actions in which firms can engage to signal exploration of new industries, board network heterogeneity may therefore act as a less costly signal, assuaging analysts' and investors' concerns regarding the variance-increasing nature of these intentions and/or activities. Following the predictions of signalling theory, we therefore hypothesize:

> *Hypothesis 2:* Board network heterogeneity decreases firm idiosyncratic risk.

AI Exposure and Board Network Heterogeneity

The preceding discussion illustrates the theoretical plausibility of positive or negative effects on IR in the case of both AI exposure and board network heterogeneity. While the strength of evidence leads us to posit that both will independently decrease IR, the combination of these factors may change the meaning of the signal conveyed by their presence and thus elicit a different response from market actors (see Higgins and Gulati, 2006; Ndofor and Levitas, 2004; Park and Mezias, 2005). Specifically, we hypothesize that firms with heterogeneous board networks operating in high-AI industries may experience an *increase* in IR.

We base this prediction on the difference in *signal strength* that this combination implies. The salience and observability of firm signals has been shown to alter their effects on market actors, independent of their cost (Goranova et al., 2007; Park and Mezias, 2005). Two key determinants of signal strength are the *attention* of the receiver and the *environment* in which the signal is conveyed (Connelly et al., 2011; Gomulya et al., 2017; Gulati and Higgins, 2003). Signalling theory suggests that firms with heterogeneous board networks operating in high-AI industries will experience a change in both factors, leading to increased perception of risk.

Empirical corroboration of Hypothesis 2 would suggest that market actors place greater emphasis on the fact that board network heterogeneity represents variance-increasing behaviour at a relatively early, low-commitment stage of the strategic decision-making process (see Li, 2019). If analysts and investors assume the board to be primarily concerned with environmental scanning and strategic direction-setting (e.g., Finkelstein et al., 2009), then this signal is unlikely to raise concerns about future cash flows relative to the more costly and concrete actions in which a firm could engage to signal their engagement in technological exploration (e.g., Padigar et al., 2022). However, in environments of

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increased baseline uncertainty or change, boards tend to adopt a more active role in strategic decisions (Carpenter and Westphal, 2001), as the value of external knowledge takes on greater importance relative to the firm-specific expertise of senior executives (Boivie et al., 2021; Rindova, 1999). Under these conditions, market actors may therefore pay closer attention to board-level signals due to their heightened implications for firm-level outcomes (Connelly et al., 2011; Park et al., 2016). This situation of baseline uncertainty and change characterizes industries in which AI is a prevalent and important technology (Felten et al., 2021; Huang and Rust, 2021). Accordingly, we expect board network heterogeneity to be a *stronger* signal of variance-increasing behaviour in this environment, suggesting a negative effect on risk perceptions. We therefore hypothesize:

> *Hypothesis 3:* Board network heterogeneity positively moderates the effect of artificial intelligence exposure, such that board network heterogeneity attenuates the decrease in IR when artificial intelligence exposure is high.

Importantly, this prediction holds regardless of whether the board's role in decision-making changes in practice: the difference in signal strength is contingent on market actors' *perception* that greater discretion and input are likely, which is widely held (Gupta et al., 2019; Hambrick and Finkelstein, 1987; Recendes et al., 2024).

METHOD

We combine four main sources of data for this study. Firm-level variables are calculated from monthly stock price data from S&P Capital IQ and annual financial data from Compustat Fundamentals. Board-level data, used for controls and in our construction of the board interlock network, is obtained from BoardEx. Finally, we use the Artificial Intelligence Occupational Exposure Index (AIOE) developed by Felten et al. (2021) to measure industry-level AI exposure. Combining these sources yields a sample of 11,878 observations of 1736 firms across 424 industries (by four-digit NAICS code), covering the period 2010–19.

Dependent Variable: Firm Idiosyncratic Risk

As outlined above, we focus on IR as our dependent variable as the indicator of market participants' perceptions that is most pertinent in uncertain environments (Mishra et al., 2022) and precedes evaluations of a firm's likely future performance (Harrison et al., 2020; Recendes et al., 2024). We measure firm IR using the Fama-French-Carhart four-factor model of abnormal returns (Carhart, 1997). The model for calculating the abnormal return for firm *i* in month *m* is specified as

$$\mathrm{R_{im}} = \alpha_{\mathrm{i}} + \beta_{\mathrm{iMKR}}\mathrm{MKR_m} + \beta_{\mathrm{iHML}}\mathrm{HML_m} + \beta_{\mathrm{iSMB}}\mathrm{SMB_m} + \beta_{\mathrm{iUMD}}\mathrm{UMD_m} + \varepsilon_{\mathrm{im}} \quad (1)$$

where $\mathrm{R_{im}}$ represents the monthly returns for firm i in excess of the one-month Treasury bill risk-free rate; $\mathrm{MKR_m}$ is the difference between the value-weighted returns of the NYSE, AMEX, and NASDAQ and the risk-free rate, $\mathrm{HML_m}$ is the book-to-market risk premium factor, $\mathrm{SMB_m}$ the size-based factor, and $\mathrm{UMD_m}$ the momentum factor. The intercept α_{i} represents the abnormal return. Using the results of this calculation, we

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compute our dependent variable of IR as the standard deviation of the residuals at the firm-year level:

$$\mathrm{IR}_{\mathrm{it}} = \left[\frac{1}{12}\sum_{\mathrm{m}=1}^{12}\left(\varepsilon_{\mathrm{im}} - \bar{\varepsilon}_{\mathrm{it}}\right)^2\right]^{\frac{1}{2}} \tag{2}$$

Independent Variables: AI Exposure and Board Network Heterogeneity

To measure a firm's exposure to AI, we rely on the industry-level index provided in the AIOE. Full details of the development of this index are provided in Felten et al. (2021). Briefly, a firm's score on this index represents the degree to which that firm's industry (at the four-digit NAICS code level) comprises occupations in which AI is prevalent and/or important to the key abilities required for that occupation. These two attributes, along with the overall skill level and number of occupations within an industry, are weighted such that the measure captures AI exposure relative to other industries rather than the level or variety of labour employed. This is important for the purposes of this study: the index does not measure the degree to which AI has been implemented within an industry but captures in a broad sense the *opportunity* for AI application (cf. Brynjolfsson and McElheran, 2016; Felten et al., 2021).

To measure board network heterogeneity, we use BoardEx to identify the firms for which each individual director serves on the board. From this we construct the board interlock network, where two firms are connected by a shared director. For each connected pair, we then use the four-digit NAICS code of the firms' primary industries to identify whether the interlock is *inter-industry* or *intra-industry*. Board network heterogeneity is then computed as the ratio of inter-industry interlocks to the total number of interlocks (Li, 2019; Srinivasan et al., 2018). We reconstruct the network for each firm-year in the sample, allowing board network heterogeneity to vary over time according to changes in board composition.

Control Variables

We include a comprehensive set of control variables at the board, firm, and industry levels. Detailed operationalization and measurement for each control variable can be found in Table II; below, we discuss the most theoretically pertinent of these.

We first control for direct, internal board-level influences on information gathering and decision-making (e.g., Withers et al., 2012, 2020), enabling a clearer examination of the signalling effects posited in our hypotheses. *Board size* (number of directors) and *board independence* (proportion of outside directors) affect the extent to which directors bring external perspectives to the board and the degree to which they can exert influence over strategic decisions (Chen et al., 2020; Joseph et al., 2014), with *CEO duality* (whether the CEO also serves as board chair) representing a particularly influential form of inside directorship (Krause et al., 2014) and thus included as a separate control variable. We further control for *board age diversity*, measured using the standard deviations in directors' age, and include the BoardEx *succession factor* to account for similar potential implications of director age, commitment, and tenure (Darouichi et al., 2021). Together, these variables comprehensively account for factors that have been shown to affect the breadth and diversity of

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Table II. Variable descriptions

Variable	*Operationalization*	*Data sources*
Idiosyncratic risk	Standard deviation of residuals from the Carhart (1997) four-factor model of abnormal returns	S&P CapitalIQ
Board network heterogeneity	Number of interlocks with boards in other industries divided by the total number of board interlocks	BoardEx, Compustat
AI exposure	Index of the weighted average occupational exposure to AI by four-digit NAICS code, developed by Felten et al. (2021)	AIOE Index
CEO duality	Indicator that takes the value of 1 if the CEO is also board chair; 0 otherwise	BoardEx
Board succession factor	Clustering of directors around retirement age	BoardEx
Board age diversity	Standard deviation of the age of directors	BoardEx
Board size	Number of directors	BoardEx
Board independence	Proportion of outside directors	BoardEx
Network centrality	Eigenvector centrality (EVC), calculated as the weighted centrality of the board in the interlock network, with weights for each connected firm determined by the EVC of that firm	BoardEx
Industry concentration	Hirschmann-Herfindahl Index (HHI), calculated as the sum of the squared market shares of firms in the focal firm's industry	Compustat
Industry dynamism	Standard error of the regression slope coefficient of the five-year trend in industry sales revenue, divided by mean industry sales revenue over the preceding five years (Dess and Beard, 1984)	Compustat
Industry munificence	Regression slope coefficient of the five-year trend in industry sales revenue, divided by mean industry sales revenue over the preceding five years (Dess and Beard, 1984)	Compustat
Industry profitability	Mean financial performance across firms in the focal firm's industry, as calculated below	Compustat
Firm size	Natural log of number of employees	Compustat
Firm age	Number of years since the firm first appears in financial databases	Compustat
Leverage	Long-term debt divided by total assets	Compustat
Capital intensity	Capital investments divided by total assets	Compustat
Financial performance	Return on assets (ROA), calculated as net income divided by total assets	Compustat
Market performance	Cumulative abnormal returns, calculated as the intercept from the Carhart (1997) four-factor model	S&P CapitalIQ

Note: All industry-based measures are calculated using four-digit NAICS codes, for consistency with the classification of AI exposure developed in Felten et al. (2021).

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information to which the board is likely to be attentive, and thus the nature of directors' deliberation and decision-making (e.g., Hudson and Morgan, 2023; Li, 2021; Srinivasan et al., 2018). Including these controls therefore allows us to more confidently attribute board-level effects to the informational and/or signalling implications of network heterogeneity rather than the more direct, internal effects that directors and executives can exert on firm-level outcomes (e.g., see Chin and Semadeni, 2017; Gupta and Wowak, 2017; Withers et al., 2020).

Finally, we derive a measure of *network centrality* from the network graph constructed above to capture a firm's overall exposure to information. We use eigenvector centrality (EVC) to account for both the number of interlocks for the focal firm and the centrality of connected firms (Srinivasan et al., 2018). This measures the extent to which these connections are likely to influence the focal firm, as connections to other well-connected firms provide more exposure to information within the network (Borgatti and Everett, 2006). The EVC of the focal firm, C_i, is calculated as

$$C_i = \frac{1}{\lambda} \sum_{j \in M(i)} a_{ij} C_j \tag{3}$$

where the interlock network of N firms consists of connections between each focal firm i and $M(i)$ other firms. For each specific firm j in $M(i)$, a_{ij} is an indicator that takes the value of 1 if firm i is connected to firm j and zero otherwise. C_j represents the vector of centralities for the connected firm j, and λ the vector of eigenvalues.

At the industry level, we control for key characteristics that have been shown to affect firm IR (Mishra et al., 2022): *concentration*, representing competitive influences; *dynamism*, capturing uncertainty in revenues; *munificence*, to measure growth opportunities; and *profitability*, to account for industry-level differences in average financial performance. These variables are calculated at the four-digit NAICS code level to correspond with the operationalization of the AIOE (full details are provided in Table II). At the firm level, we control for *size, age*, and four financial variables: *leverage* (long-term debt as a proportion of total assets), *capital intensity* (capital investments as a proportion of total assets), *financial performance* (return on assets), and *market performance* (CAR, derived from the four-factor model in equation 1 used to calculate IR). These firm-level controls account for the key financial influences on IR (Gulen and Ion, 2016; Li and Zhang, 2010).

In *Supplementary Analyses*, we also control for *institutional ownership*, as well as three additional board-level variables to capture experience and knowledge arising from the breadth and depth of directors' knowledge: *educational experience*, *industrial experience*, and *network experience*. These are presented in Table V and discussed below. Table III provides descriptive statistics and correlations for all variables.

Model Specification and Estimation

We specify the effects of board network heterogeneity and AI exposure on IR as

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Table III. Descriptive statistics and correlations

	Variable	*Mean*	*SD*	*Min.*	*Max.*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*
1	Idiosyncratic risk	28.499	9.717	9.083	346.918								
2	Board network heterogeneity	0.890	0.196	0.000	1.000	−0.061*							
3	AI exposure	0.433	0.985	−1.999	2.216	0.009	−0.142*						
4	CEO duality	0.583	0.493	0.000	1.000	−0.043*	0.114*	−0.014					
5	Board succession factor	0.297	0.147	0.000	1.600	0.041*	−0.011	0.081*	−0.050*				
6	Board age diversity	7.688	2.466	0.800	21.500	0.045*	0.009	0.045*	−0.026*	0.619*			
7	Board size	8.577	2.233	3.000	19.000	−0.111	0.125*	−0.118*	0.054*	−0.077*	−0.054*		
8	Board independence	0.229	0.153	0.000	0.875	−0.048*	0.036*	−0.016	0.116*	−0.089*	−0.084*	0.117*	
9	Network centrality	−24.490	5.719	−44.348	−3.299	−0.021*	−0.012	−0.018*	−0.000	−0.080*	−0.136*	0.047*	0.083*
10	Industry concentration	0.172	0.154	0.020	1.000	−0.017	0.196*	−0.237*	0.058*	0.043*	0.061*	0.010	−0.025*
11	Industry dynamism	0.054	0.303	0.000	10.871	−0.012	0.057*	−0.085*	0.037*	0.018*	0.058*	−0.038*	0.002
12	Industry munificence	−0.610	3.888	−181.867	14.385	0.052*	−0.049*	0.069*	−0.034*	−0.033*	−0.061*	0.031*	−0.013
13	Industry profitability	−3.855	37.304	−2218.351	214.940	0.028*	0.026*	−0.010	−0.006	0.015	0.001	0.019*	−0.001
14	Firm size	0.756	2.141	−6.908	6.342	−0.143*	0.223*	−0.160*	0.124*	−0.130*	−0.142*	0.563*	0.176*
15	Firm age	28.399	16.877	1.000	70	−0.058*	0.157*	−0.200*	0.109*	−0.199*	−0.147*	0.373*	0.257*
16	Leverage	0.199	0.291	0.000	18.410	0.035*	0.032*	−0.131*	0.030*	0.001	−0.017	0.132*	−0.005
17	Capital intensity	0.043	0.053	−0.001	1.457	−0.027*	0.051*	−0.206*	0.011	−0.012	−0.040*	0.013	−0.041*
18	Financial performance	−0.051	2.878	−276.022	5.281	−0.065*	0.004	−0.002	−0.005	−0.023*	−0.019*	0.038*	−0.014
19	Market performance	−99.218	112.146	−542.132	1507.386	0.067*	−0.006	0.007	0.001	0.027*	0.013	−0.025*	0.021*

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Table III. Variable descriptions

	Variable	*9*	*10*	*11*	*12*	*13*	*14*	*15*	*16*	*17*	*18*
10	Industry concentration	0.014									
11	Industry dynamism	−0.061*	0.278*								
12	Industry munificence	0.043*	−0.224*	−0.787*							
13	Industry profitability	0.017	−0.035*	0.001	−0.006						
14	Firm size	0.444*	0.124*	−0.025*	0.026*	0.022*					
15	Firm age	0.224*	0.005	0.004	0.011	0.004	0.347*				
16	Leverage	0.089*	0.013	−0.012	0.014	0.016	0.112*	0.052*			
17	Capital intensity	−0.051*	−0.030	−0.011	0.017	0.022*	0.038*	0.035*	0.069*		
18	Financial performance	0.021*	0.018	0.004	−0.003	0.001	0.071*	0.038*	−0.005	0.006	
19	Market performance	−0.038*	−0.002	0.013	−0.012	−0.023*	−0.024*	−0.030*	−0.008	−0.031*	0.002

Note: CEO duality is omitted from this table as it is an indicator variable. *$p < 0.05$.

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$$IR_{it} = \beta_0 + \beta_1 BNH_{it} + \beta_2 AI_{ijt} + \beta_3 \left(BNH_{it} \times AI_{ijt} \right) + \sum_{k=1}^{K} \beta_k K_{ijbt} + \varepsilon_{it} \quad (4)$$

where IR_{it} represents the IR of firm i in year t; BNH_{it} the firm's board network heterogeneity score; and AI_{ijt} the index of AI exposure in the industry j in which the firm operates. The vector of k control variables includes all variables at the firm (i), industry (j), and board (b) levels. We estimate equation 4 using generalized estimation equations (GEE), specifying a Gaussian distribution (IR is normally distributed), an exchangeable correlation structure, and identity link function. This approach follows precedent in the literature, addressing common concerns in the study of board-level influences on firm outcomes: GEE is well-suited to this context as it accounts for unobserved inter-firm heterogeneity and the relative temporal stability of board-level variables (e.g., see Chin and Semadeni, 2017; Gupta and Wowak, 2017), while alleviating estimation concerns regarding the use of panel data, such as intertemporal correlations between variables within firms (Liang and Zeger, 1986). Nevertheless, we provide a series of supplementary analyses (see Table V) using alternative model specifications and estimation methods. Results of these robustness checks are consistent with the GEE model presented below.

RESULTS

Table IV displays coefficients from the GEE models examining the relationships between AI exposure, board network heterogeneity, and IR. Model 3, including the interaction between the two focal independent variables, contains the effects of interest. We find that both AI exposure (-1.112, $p = 0.010$) and board network heterogeneity (-1.768, $p = 0.001$) independently reduce IR, supporting Hypotheses 1 and 2. Our conceptual framework recognizes that market actors' evaluation of firm risk may be contingent on two opposing factors: (a) present deficits in information and competence, versus (b) the perceived necessity of technological exploration among firms, analysts, and investors. These results lend support that the importance of the latter dominates in the case of both AI exposure and board network heterogeneity.

In contrast, we observe a positive interaction effect (0.958, $p = 0.038$). Across firms, this indicates that board network heterogeneity mitigates the risk-reducing effect of AI exposure, and the effect becomes negative when AI exposure reaches around 1.8. Given that AI exposure is approximately normally distributed, this means that around 9 per cent of firms experience detrimental effects from this interaction (see Figure 2). While a small proportion, this represents those firms operating in industries on the technological frontier, where managing firm risk is most important (Hoppmann et al., 2019; Li et al., 2021). Our results therefore support Hypothesis 3, based on the notion that board network heterogeneity in high-AI industries provides a credible signal that a firm is exploring applications of disruptive technology outside of its core competences, thus increasing the risk perceived by market actors.

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Table IV. Effects of board network heterogeneity and AI exposure on firm idiosyncratic risk

	(1) Controls			*(2) Main effects*			*(3) Interaction*		
	Coef.	*p*	*SE*	*Coef.*	*p*	*SE*	*Coef.*	*p*	*SE*
Effects of interest									
Board network heterogeneity				−1.150	0.006	0.417	−1.768	0.001	0.512
AI exposure				−0.233	0.004	0.081	−1.112	0.010	0.431
Board network heterogeneity × AI exposure							0.958	0.038	0.461
Board-level controls									
CEO duality	−0.347	0.008	0.132	−0.306	0.047	0.154	−0.309	0.045	0.154
Board succession factor	0.978	0.094	0.584	0.563	0.407	0.679	0.520	0.443	0.678
Board age diversity	0.070	0.042	0.034	0.105	0.009	0.040	0.105	0.009	0.040
Board size	−0.299	0.000	0.030	−0.294	0.000	0.045	−0.291	0.000	0.045
Board independence	−1.211	0.006	0.440	−1.369	0.008	0.516	−1.327	0.010	0.515
Network centrality	0.101	0.000	0.013	0.121	0.000	0.017	0.121	0.000	0.017
Industry-level controls									
Industry concentration	0.804	0.055	0.419	−0.167	0.750	0.524	−0.093	0.859	0.525
Industry dynamism	0.406	0.067	0.221	2.365	0.000	0.447	2.363	0.000	0.447
Industry munificence	0.056	0.000	0.014	0.273	0.000	0.035	0.273	0.000	0.035
Industry profitability	−0.007	0.002	0.002	−0.006	0.008	0.002	−0.006	0.009	0.002
Firm-level controls									
Firm size	−0.420	0.000	0.038	−0.552	0.000	0.046	−0.552	0.000	0.046
Firm age	0.007	0.127	0.004	−0.002	0.733	0.005	−0.002	0.726	0.005
Leverage	1.186	0.000	0.246	1.447	0.000	0.276	1.443	0.000	0.275
Capital intensity	0.136	0.916	1.293	−3.720	0.013	1.501	−3.830	0.011	1.500
Financial performance	−0.216	0.000	0.028	−0.196	0.000	0.029	−0.196	0.000	0.029
Market performance	0.005	0.000	0.001	0.005	0.000	0.001	0.005	0.000	0.001
Constant	−0.420	0.000	0.538	35.536	0.000	0.748	36.087	0.000	0.794
Wald χ^2	684.230	0.000		678.260	0.000		615.210	0.000	

Note: 11,878 yearly observations of 1736 firms.

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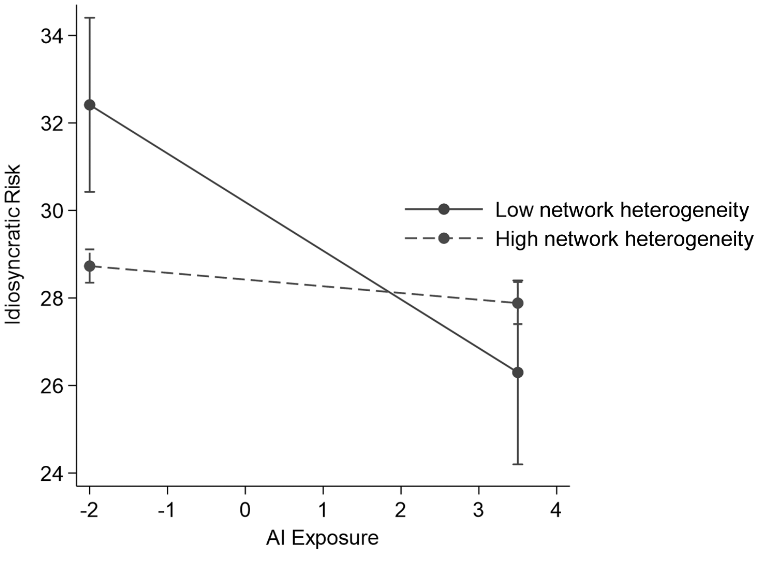

Figure 2. Interaction effect of board network heterogeneity and AI exposure on firm idiosyncratic risk

Supplementary Analyses

To ensure the robustness of our results, we conduct a series of supplementary analyses utilizing variations on the model specification and estimation technique detailed above. First, we estimate the above model with robust standard errors, to account for any remaining concerns regarding autocorrelation or heteroskedasticity (Liang and Zeger, 1986). Second, we estimate a random-effects model. Although we do not consider fixed or random effects estimation appropriate in this context, as board-level variables can be relatively persistent over time and these are consequently not well-suited to explaining between-firm differences, this facilitates comparison with other common panel regression techniques (Gupta and Wowak, 2017). These concerns apply particularly to fixed effects; hence the choice of random effects estimation here (Chin and Semadeni, 2017). Third, we estimate a panel instruments model using the generalized method of moments approach of Arellano and Bond (1991) (AB-GMM), to account for endogeneity issues resulting from the dynamic properties of panel data (e.g., Girod and Whittington, 2017). Finally, we estimate the above model with four additional control variables. Considering the significant effects of some firm-level controls in Table IV, we see it prudent to account for other firm-level variables that may affect our results. *Institutional ownership*, measured as the proportion of a firm's shares outstanding held by institutional investors, is thus included to account for other structural influences at the firm level. We also include three additional board characteristics, measured using the standard deviation among directors along three attributes: *education experience* (number of qualifications held), *industrial experience* (time served at the firm), and *network experience* (number of other boards on which the director serves). Together, these comprehensively measure the breadth and depth of directors' experience and knowledge.

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Table V. Supplementary analysis: Robustness checks

	(1) GEE with robust SE			(2) Random effects			(3) AB-GMM			(4) Additional controls		
	Coef.	*p*	*SE*	*Coef.*	*p*	*SE*	*Coef.*	*p*	*SE*	*Coef.*	*p*	*SE*
Effects of interest												
Board network heterogeneity	−1.769	0.007	0.658	−1.691	0.003	0.573	−10.831	0.028	4.918	−1.759	0.001	0.512
AI exposure	−1.112	0.008	0.420	−1.026	0.033	0.481	−15.475	0.014	6.283	−1.104	0.010	0.430
Board network heterogeneity × AI exposure	0.958	0.032	0.447	0.871	0.091	0.515	18.455	0.006	6.759	0.947	0.040	0.461
Board-level controls												
CEO duality	−0.309	0.042	0.151	−0.363	0.041	0.178	−6.925	0.003	2.353	−0.275	0.074	0.154
Board succession factor	0.520	0.558	0.886	0.153	0.839	0.755	−32.389	0.000	6.814	0.273	0.698	0.702
Board age diversity	0.105	0.033	0.049	0.119	0.008	0.045	4.297	0.000	0.492	0.122	0.004	0.042
Board size	−0.291	0.000	0.046	−0.320	0.000	0.051	−0.768	0.201	0.600	−0.300	0.000	0.045
Board independence	−1.327	0.018	0.560	−1.550	0.009	0.590	−7.113	0.262	6.343	−1.214	0.019	0.518
Network centrality	0.120	0.000	0.021	0.132	0.000	0.019	0.340	0.036	0.162	0.111	0.000	0.017
Educational experience										0.033	0.860	0.186
Industry experience										−0.033	0.152	0.023
Network experience										0.121	0.028	0.055
Industry-level controls												
Industry concentration	−0.093	0.858	0.521	−0.030	0.961	0.614	−9.420	0.297	9.026	−0.041	0.938	0.524
Industry dynamism	2.363	0.013	0.950	2.419	0.000	0.463	60.997	0.000	4.676	2.367	0.000	0.447
Industry munificence	0.273	0.003	0.091	0.282	0.000	0.036	5.227	0.000	0.278	0.274	0.000	0.035
Industry profitability	−0.006	0.002	0.002	−0.006	0.010	0.002	−0.046	0.005	0.016	−0.006	0.009	0.002
Firm-level controls												
Firm size	−0.552	0.000	0.070	−0.569	0.000	0.053	−1.863	0.000	0.528	−0.545	0.000	0.046

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Table V. (Continued)

	(1) GEE with robust SE			(2) Random effects			(3) AB-GMM			(4) Additional controls		
	Coef.	*p*	*SE*	*Coef.*	*p*	*SE*	*Coef.*	*p*	*SE*	*Coef.*	*p*	*SE*
Firm age	−0.002	0.649	0.004	0.005	0.358	0.006	0.116	0.045	0.058	0.001	0.829	0.005
Leverage	1.443	0.000	0.359	1.694	0.000	0.299	1.538	0.016	0.641	1.433	0.000	0.275
Capital intensity	−3.830	0.050	1.951	−4.431	0.008	1.670	−11.698	0.008	4.382	−3.735	0.013	1.498
Financial performance	−0.195	0.005	0.070	−0.181	0.000	0.030	−0.087	0.034	0.041	−0.196	0.000	0.029
Market performance	0.005	0.128	0.004	0.005	0.000	0.001	0.001	0.391	0.001	0.005	0.000	0.001
Institutional ownership										−0.019	0.650	0.042
Constant	36.087	0.000	1.030	36.349	0.000	0.884	35.198	0.000	7.716	35.648	0.000	0.821
Wald χ^2	346.440	0.000		561.680	0.000		684.217	0.000		692.620	0.000	

Note: 11,878 yearly observations of 1736 firms.

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Results, presented in Table V, are fully consistent with our original model in the relative magnitude, direction, and significance of parameter estimates, with one minor exception: in Model (2), the interaction effect of board network heterogeneity and AI exposure is only marginally significant at the 10 per cent level ($p = 0.091$). As we do not consider the random effects model to be appropriate in this context, this remains qualitatively supportive of our main results.

Additional Analyses: Diversification

Our results raise a difficult question for corporate strategy: If board network heterogeneity is detrimental to IR – and consequently to shareholder value (Mishra et al., 2022) – in situations where AI is both prevalent and important in a firm's industry, how can firms capitalize upon the knowledge resources accessible via board interlocks while exploring new technologies? While the primary purpose of this analysis was to understand the underexplored relationships between AI exposure, board network heterogeneity, and IR, the pertinence of this problem to strategic decision-making warrants further exploration.

To offer additional insight into whether and how firms may benefit from both AI exposure and board network heterogeneity while avoiding the associated increase in IR, we conduct further analyses, incorporating *diversification* as a factor. Like our focal variables, diversification entails both benefits and costs to a firm, and the implications for firm value are heavily contingent on numerous firm-specific factors (Mackey et al., 2017). However, in relation to IR, diversification across multiple operating segments inherently reduces a firm's vulnerability to sector- and market-specific shocks in any one line of business (Teece, 1982). This suggests that IR should be lower among firms that are diversified across multiple business segments (though this remains unexplored in the empirical literature – see Sun and Govind, 2017).

For these reasons, examining the effects of diversification provides a more direct test of the proposed theoretical mechanism underlying the effects observed above. Diversification requires firms to develop or acquire competence in areas outside of their core business (Mackey et al., 2017). If the joint effect of AI exposure and board network heterogeneity is due to signalling, whereby the market views the firm as venturing beyond its competence, we may expect this effect to be attenuated in diversified firms: established operations across multiple lines of business provides a *costly* and therefore credible counter-signal that the firm possesses competence in other sectors or markets (see Carter, 2006; Fombrun and Shanley, 1990; Paruchuri et al., 2021). Diversification may therefore reduce information asymmetries in financial markets (Ahuja and Novelli, 2017), alleviating uncertainty regarding the firm's ability to explore AI across multiple domains.

We therefore investigate whether diversification can attenuate the increase in IR among firms with high levels of both AI exposure and board network heterogeneity. We split our sample into diversified and non-diversified firms based on whether they operate in more than one business segment (identified in Compustat for each firm-year; see Table VI for additional details of this measure) and re-estimate equation 4 for each subsample. This dichotomous measure enables direct comparison of diversified and non-diversified

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Table VI. Effects of board network heterogeneity and AI exposure on firm idiosyncratic risk in diversified and non-diversified firms

	(1) Diversified firms			*(2) Non-diversified firms*		
	Coef.	*p*	*SE*	*Coef.*	*p*	*SE*
Effects of interest						
Board network heterogeneity	−1.161	0.056	0.608	−3.774	0.000	0.796
AI exposure	−0.960	0.057	0.504	−1.775	0.010	0.690
Board network heterogeneity × AI exposure	0.793	0.141	0.538	1.792	0.016	0.742
Board-level controls						
CEO duality	−0.345	0.053	0.178	−0.329	0.187	0.249
Board succession factor	0.047	0.955	0.834	0.155	0.875	0.984
Board age diversity	0.129	0.008	0.048	0.140	0.023	0.062
Board size	−0.298	0.000	0.052	−0.366	0.000	0.074
Board independence	−0.967	0.138	0.652	−3.408	0.000	0.675
Network centrality	0.106	0.000	0.020	0.205	0.000	0.025
Industry-level controls						
Industry concentration	0.051	0.932	0.597	0.105	0.909	0.917
Industry dynamism	2.105	0.000	0.468	15.395	0.000	2.086
Industry munificence	0.306	0.000	0.041	1.036	0.000	0.132
Industry profitability	−0.007	0.005	0.002	0.012	0.191	0.010
Firm-level controls						
Firm size	−0.539	0.000	0.054	−0.486	0.000	0.074
Firm age	0.003	0.627	0.006	0.013	0.161	0.009
Leverage	1.562	0.000	0.321	1.623	0.000	0.455
Capital intensity	−6.747	0.000	1.836	3.795	0.080	2.171
Financial performance	−0.105	0.003	0.035	−0.456	0.000	0.045
Market performance	−0.002	0.047	0.001	0.039	0.000	0.002
Constant	33.812	0.000	0.935	42.742	0.000	1.245
Wald χ^2	419.600	0.000		940.840	0.000	
Observations	8811			3067		

Note: Diversification is measured by an indicator variable that takes the value of 1 (diversified) if the firm operates in multiple business segments, and 0 (non-diversified) otherwise. Network heterogeneity is measured based on the firm's primary operating segment. It is plausible that diversified firms may have inherently more heterogeneous board networks as a consequence of operating across multiple industries. However, network heterogeneity is not significantly different between diversified (mean = 0.895, SD = 0.191) and non-diversified (mean = 0.874, SD = 0.209) firms in our sample.

firms, for which continuous measures are poorly suited (Hoskisson et al., 1993; Mackey et al., 2017). Table VI presents the results.

We note two key features of these results. First, we observe that the effects of board network heterogeneity (NH) and AI exposure on firm IR are substantially greater in

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magnitude for non-diversified firms (NH: −3.774, $p < 0.001$; AI: −1.775, $p = 0.010$), and only marginally significant among diversified firms (NH: −1.161, $p = 0.056$; AI: −0.960, $p = 0.057$). Further, the interaction effect is not significant in diversified firms, indicating that diversification protects against increases in IR from simultaneously high levels of AI exposure and board network heterogeneity. These findings lend theoretical support to signalling as the mechanism underlying the interactive effects of board network heterogeneity and AI exposure, and they suggest that firms can attenuate the market penalties associated with this if extant operations across multiple businesses provides a costly and therefore credible signal of broad-based competence.

DISCUSSION

With growing attention and exposure to AI among businesses, directors are serving an increasingly demanding role: balancing greater involvement with strategic decision-making with traditional risk management responsibilities (Afzali et al., 2024; McKinsey and Company, 2024). Understanding how boards can capitalize upon technological opportunities while effectively controlling risk is therefore of primary theoretical and practical importance; yet, empirical studies of both firm risk (Li et al., 2021) and governance (Goos and Savona, 2024) in the context of AI remain scarce. We therefore sought to address two unresolved questions: (1) How does AI affect IR? and (2) How can boards influence IR in the context of this technological disruption?

Drawing on signalling theory, we conceptualize and corroborate two key findings. First, both AI exposure and board network heterogeneity independently *decrease* IR, suggesting that in assessing firms' exposure to disruptive technologies and diverse knowledge networks, analysts and investors place greater weight on signals of organizational inertia or isolation than the uncertainty of exploration (see Gilbert, 2005; Matthews et al., 2022). Second, a heterogeneous board network *increases* IR in industries in which AI is most prevalent and important, and attenuates the risk-reducing effect of AI exposure across firms, suggesting that the interaction between these two factors alters the perceived meaning of board characteristics as firm–market signals (see Bergh et al., 2014; Gomulya et al., 2017). Additional analyses support this mechanism, showing that this detrimental effect is significant only for non-diversified firms. This suggests that firms can benefit from both AI exposure and diverse knowledge networks by first demonstrating, through costly signalling, a broad base of internal competence that facilitates exploration of technological uncertainty. These empirical contributions offer a novel extension of the limited research on AI and firm risk, with several implications for theory and practice.

Implications for Theory

This study contributes to the nascent and imperative research on the role and implications of AI within firms, highlighting signalling theory as an avenue for theoretical development. Given that AI remains shrouded in uncertainty in terms of the future state and implications of this technology (Benbya et al., 2020; Chalmers et al., 2020), firm–market information asymmetries cannot (currently) be resolved empirically. The

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deliberate or unintentional ways in which firms can influence analysts' and investors' perceptions may therefore be critical to gaining greater insight into the implications of AI: while evidence of the 'first-order' effects of AI-related strategic change within firms is rapidly accruing (Gama and Magistretti, 2023; Mishra et al., 2022), this would facilitate understanding of the 'second-order' effects on shareholder value via stakeholders' perceptions (see Padigar et al., 2022; Recendes et al., 2024). This theoretical shift in the examination of AI's consequences has the potential to improve the managerial relevance of research in this domain: under the common assumption that all firms and industries will be disrupted by AI to some extent (Chalmers et al., 2020; Gama and Magistretti, 2023), a greater focus on the ability of firm-specific characteristics to affect the subjective perceptions of market actors may uncover new routes to competitive advantage.

Beyond the context of AI, these findings also have broader implications for understanding the determinants and impacts of firm risk, an area in which theory and empirical evidence are underdeveloped (Edeling et al., 2021; Recendes et al., 2024). Returns to shareholders are ultimately determined by both valuation and risk (Srinivasan and Hanssens, 2009), with risk perceptions preceding assessments of value (Harrison et al., 2020). IR is therefore an important metric that warrants further exploration, particularly in the context of emerging technological threats and opportunities (Mishra et al., 2022) as prior research has predominantly focused only on valuation (see Padigar et al., 2022). A notable implication of our results is that, despite widespread perceptions of the future of AI as *uncertain* (Brynjolfsson and McAfee, 2017), exposure to AI is not inherently perceived as *risky* by investors. Accordingly, exposure to AI need not be detrimental to shareholder value, as extrapolation from prior research on disruptive technological change (e.g., Benner, 2010; Benner and Ranganathan, 2012; Litov et al., 2012) might suggest. Whether market actors penalize high-AI firms is contingent on the firm-specific factors of (a) the network position of the board and (b) diversification strategy, which interact with AI exposure to jointly inform market evaluations of a firm's IR. These findings highlight the importance of considering the role of second-order effects that occur via the perceptions of market actors and provide a framework that can be extended to examine other 'intuitively' risky phenomena to develop a rigorous and accurate understanding of their effects.

We also contribute to the development and extension of signalling theory by conceptualizing and empirically corroborating two novel categories of effects: (a) contextual interactions between signal characteristics and (b) unintentional signals, of which firms may be unaware but that communicate value-relevant information and can therefore be strategically leveraged to influence market perceptions. Regarding the first category, we explicate the interplay between two concepts that are central to signalling theory but rarely examined in combination: *signal cost* and *signal strength* (Connelly et al., 2011). Our main findings reveal that the heightened salience of board-level signals may outweigh their (relatively) low cost in uncertain environments, while our additional analyses of diversification indicate that other firm-level signals can moderate this effect if they are costly and therefore credible. This suggests contextual differences in the relative significance of strength and cost in determining the effect of signals. This warrants further exploration, particularly with regard to whether firms can influence these (see Recendes et al., 2024).

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For example, the effects of investor communications such as strategic announcements (Whittington et al., 2016) and earnings calls presentations (Callahan et al., 2024) suggest that these deliberate, prepared signals are often viewed by the market as a form of impression management rather than a credible signal of a firm's competence or real strategic intent (Guo and Yu, 2024). Our findings suggest that firms may more effectively influence investors' responses to these actions, outweighing their low cost by increasing signal strength.

Extending signalling theory to more comprehensively account for this interplay of signal characteristics may also be particularly beneficial in understanding how firms can leverage *unintentional* signals in a strategically advantageous manner. Much work in signalling theory assumes that signals are intentional attempts by the sender to reduce information asymmetry (see Connelly et al., 2011). This is debatable in the case of the factors identified here: AI remains a novel technology, meaning that firms are in the exploratory stage of determining the announcements and actions that may induce desirable responses from investors (Mishra et al., 2022). While board networks may be deliberately constructed to convey a desired signal, such as legitimacy (e.g., Withers et al., 2020), these are more likely to be incidental to the development of interlocks in order to gain access to information. Similarly, it is unlikely that diversification strategies are pursued with the primary aim of firm–market signalling. Nevertheless, evidence indicates that market actors actively seek information on these factors when forming their perceptions of firms (Hill et al., 2019; Recendes et al., 2024).

This has two key implications. First, research in signalling theory may be enhanced by relaxing the assumption of intentionality, considering incidental signals as alternative (and potentially more powerful) explanations for the effects of firms' communications and characteristics. For example, while the deliberate choice to disclose customer metrics can affect investor behaviour (Bayer et al., 2017), the incidental signals of customer orientation conveyed by the presence of marketing- or sales-experienced executives or directors has been shown to elicit similar responses (Borah and Skiera, 2021; Whitler et al., 2021). These signals are likely to co-occur; thus, disentangling the effects of deliberate and unintentional signals may be an important avenue for future development in signalling theory (cf. Bergh et al., 2014). This may require further research that follows the second key implication of our study: identifying and understanding the firm-level factors about which investors seek to gain information under different environmental contingencies (Guo and Yu, 2024; Hill et al., 2019; Recendes et al., 2024). The incidental development of unintentional signals implies that firms may possess capabilities or characteristics that have potentially valuable effects on investors' perceptions, and thus second-order effects on firm performance that are presently unaccounted for but could be leveraged for strategic advantage. Returning to the context of AI, this is especially pertinent in the case of novel environments or firm-level innovations where current knowledge of these factors will inherently be low (Benner and Beunza, 2023; Padigar et al., 2022). Development of theory in this area would therefore have important near-term implications for practice, enhancing the managerial relevance of this work.

Collectively, these implications highlight opportunities for development of signalling theory in understanding the incidental signals a firm may unintentionally convey, the

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characteristics of these signals (e.g., strength and cost), and their contextual and interactive effects. As a presently underexplored phenomenon in signalling theory, board-level signals may be a useful context in which to explore these mechanisms. Our findings that market perceptions of firm characteristics (e.g., board networks) can shift depending on the *strength* of the signals these characteristics convey in a particular environment (e.g., Connelly et al., 2011; Gomulya et al., 2017) and that *costly signals* of competence can overcome the negative risk perceptions associated with uncertain environments or activities (e.g., Certo et al., 2001; Goranova et al., 2007) align with the core premises of signalling theory, suggesting that this may be a powerful explanatory and predictive framework in this context. Through our conceptual development and corroboration of these effects, this study may therefore also contribute to the extension of theory and empirical study of the role of the board in signalling (e.g., Guo et al., 2020; Park et al., 2016).

Implications for Practice

In addition to evincing novel effects that firms can leverage to influence investor behaviour, these contributions have practical consequences for directors and senior executives involved in the management of firm risk and formulation of corporate strategy. Our results highlight the potential conflict between exploration of novel technologies and knowledge networks and the management of firm risk (see also Withers et al., 2020) and provide insight into how firms can alleviate this tension. Responsibility for both strategic decisions and risk management, previously associated with the executive level and board level, respectively, is increasingly placed on directors (Boivie et al., 2021). This points to a need for greater awareness of potential tensions between the monitoring and strategic decision-making roles of directors if these functions are to be fulfilled simultaneously (cf. Boivie et al., 2016; Huynh et al., 2022). Our findings suggest that boards' responsibility for risk management may be undermined by their own engagement in (otherwise beneficial) information networks, showing how strategic and governance objectives can conflict. However, we also show that corporate-level strategic decisions – also increasingly under the influence of the board – are protective against these detrimental effects. Specifically, our additional analyses demonstrate diversification as a buffer against market penalties in this situation. This points to a concrete strategic action that may allow firms to simultaneously benefit from the opportunities of AI and heterogeneous knowledge networks, but more broadly suggests that costly signals of competence across multiple domains may exert this effect. As the 'cost' of an action (in signalling terms) is determined by the investment of resources, time, or the attention and commitment of a firm's leaders, boards may be the most significant factor in determining the signals conveyed by strategic decisions (e.g., Certo, 2003; Filatotchev et al., 2023), particularly under conditions of environmental uncertainty (Gupta et al., 2019; Recendes et al., 2024). Accordingly, our findings demonstrate that the expanding role of the board presents both difficulties and opportunities, raising novel dilemmas for directors and future research on corporate governance during technological disruption (see also Hoppmann et al., 2019).

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Limitations and Directions for Future Research

Beyond the questions raised in the preceding sections, this study has several limitations that indicate avenues for further research. First, our use of secondary data provides advantages of scale but limits the depth of inquiry possible. This does not allow for examination of factors internal to the firm that play a key role in (a) whether, and to what degree, firms implement the advances in AI to which they are exposed (see Felten et al., 2021) and (b) the extent to which information gained via board interlocks is utilized in decision-making (see Mohammed et al., 2021). Combining large-scale studies with in-depth, qualitative research is therefore necessary for developing greater understanding of these nascent phenomena. For example, internal observations or surveys of senior leaders may elucidate the importance of AI and board networks to the operations of specific firms, offering opportunities to examine how firm-level contingencies affect IR via the relationships proposed here (see also Srinivasan et al., 2018).

Second, our data sources also restrict this analysis to large US firms. While interlock networks have been found to be most influential as sources of information (Mizruchi, 2013; Srinivasan et al., 2018) and mechanisms for signalling (Withers et al., 2020) in this context, further research may examine whether our findings are generalizable to other contexts. For example, Li et al. (2021) focus on the Chinese stock market in their investigation of how AI moderates the relationship between corporate social responsibility (CSR) and IR. In this context, the authors find no significant direct effect of AI on IR. This suggests differences across countries in market reactions to firms' AI exposure that warrant further exploration.

Third, we provide only a preliminary investigation of the effects of diversification, focusing on the dichotomy between diversified and non-diversified firms (see Hoskisson et al., 1993; Mackey et al., 2017). This points to opportunities for future research that utilizes more complex measures to examine how different forms of diversification affect risk perceptions among market actors when firms engage with AI and/or knowledge networks. For example, related diversification (where economies of scope can be leveraged across multiple operations) has long been accepted as most beneficial for firm performance, yet research is increasingly finding positive and novel effects of unrelated diversification strategies that require exploration of new resources and capabilities (Mackey et al., 2017; Ng, 2007). These emerging insights align with our findings that market actors do not inherently perceive exploration of uncertainty as detrimental to firm risk, and they indicate opportunities to examine the market signalling effects of diversification strategies that vary in nature and scope.

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