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How the Threat of Knowledge Loss Drives Firms' R&D Dynamism: A Threat Rigidity Perspective

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ABSTRACT Drawing on threat rigidity theory, this paper argues that the threat of knowledge loss gives rise to a threat rigidity effect in firms' R&D function, that is, reduces their R&D dynamism. It further argues that the dampening of R&D dynamism is greater for firms more vulnerable to the threat of knowledge loss due to facing greater product market competition, yet lower for firms that can better respond to the threat due to having relatively higher absorptive capacity and/or greater financial slack. Using a sample of publicly listed US manufacturing firms tracked over a 15-year observation period from 1991 to 2015 and leveraging the quasi-natural experiment created by the staggered rejection of the inevitable disclosure doctrine (IDD) across fourteen US states, it empirically tests and finds support for the above hypotheses.

Keywords: difference-in-differences, inevitable disclosure doctrine, R&D dynamism, threat of knowledge loss, threat rigidity theory

INTRODUCTION

For firms competing in knowledge-intensive industries, privately held knowledge is a key source of competitive advantage (Grant, 1996; Kogut and Zander, 1992). Yet, such knowledge-based competitive advantage can be undermined if firms face the risk of losing their valuable knowledge to rivals who can benefit from it without incurring the costs of creating it (Agarwal et al., 2009; Coff, 1997; Martinez-Noya et al., 2013). That risk is substantial and growing, as highlighted by a recent PwC survey on the theft of trade secrets (Passman et al., 2014). It notes that '*U.S. employees' loyalty to their employers is changing*

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because of the much higher rate of lifetime job changes'. This is making it more likely that employees could transfer proprietary knowledge to a new firm, posing a real and significant threat to their former employers.[1]

To mitigate the resulting threat of knowledge misappropriation, firms seek the aid of legal institutions and mechanisms (Teece, 1986). One such mechanism is the inevitable disclosure doctrine (IDD), a theory of common law based on state court rulings (Patel and Devaraj, 2022). As per the IDD, threatened misappropriation is inevitable when a knowledge worker possessing trade secrets of her current employer quits her job to join a rival firm or establish a competing one. The IDD provides employers with a legal mechanism to prevent their knowledge workers from working for another firm in the immediate future. Whenever a state court rules against (rejecting) the IDD, it removes a mobility restriction for knowledge workers, increasing a focal firm's likelihood of losing knowledge in the future (Flammer and Kacperczyk, 2019; Patel and Devaraj, 2022). The rejection of IDD therefore poses a real threat to firms by restricting their ability to prevent employees with valuable knowledge from working for a rival, raising expectations of a potential knowledge loss (e.g., Gilson, 1999; Kahnke and Bundy, 2013; Png and Samila, 2015).

Prior research on the threat of knowledge loss has primarily focused on strategic responses firms can adopt to prevent knowledge loss through mechanisms such as contracts and incentives (e.g., Agarwal et al., 2009; Carnahan et al., 2012; Flammer and Kacperczyk, 2019; Ganco et al., 2015; Gilson, 1999). While these studies have explored various economic mechanisms a firm could rationally make use of to mitigate the threat of knowledge loss, there is still a paucity, a gap in the literature when it comes to developing behavioural accounts of the actual responses of firms confronted with a threat of knowledge loss. This study seeks to address that gap by leveraging the behavioural lens of threat rigidity theory (Connelly and Shi, 2022; Ocasio, 1995; Staw et al., 1981). Threat rigidity theory offers a behavioural framework for examining how firms respond when faced with an external threat. According to threat rigidity theory, when faced with an external threat, firms become less capable of processing new information and ideas and more reliant on constriction of control and adherence to established standardized procedures (Griffin et al., 1995; Zhou et al., 2008), resulting in more mechanistic, familiar responses to external threats (Chattopadhyay et al., 2001).

Such threat rigidity behaviour is particularly likely to manifest in the organizational functions most affected by a focal threat (Cyert and March, 1963; Staw et al., 1981). Given one of the primary ways innovative firms create knowledge is through investments in R&D (Grant, 1996; Pisano, 1990), rigidity (vs. dynamism) in firms' R&D investment is a prime area where threat rigidity effects induced by an increased threat of knowledge loss could manifest. This study, thus, explores whether and when the threat of knowledge loss due to rejection of IDD triggers a threat rigidity response in firms' R&D investment, that is, alters their R&D dynamism. R&D dynamism – making considerable adjustments in R&D investments to add resources to R&D or release resources from R&D – is essential to R&D strategy (Bloom, 2007; Mudambi and Swift, 2011, 2014) as it facilitates adaptation to environmental change (Pennetier et al., 2019) and influences key organizational outcomes such as innovation quantity, innovation quality, firm growth, and financial performance (Bloom, 2007; Kor and Mahoney, 2005; Mudambi and Swift, 2011, 2014).

Drawing on threat rigidity theory (Staw et al., 1981), we argue that the rejection of IDD, which increases firms' risk of losing knowledge in the future, will trigger a threat rigidity effect that dampens their R&D dynamism. We further posit that the effect will vary based on firms' vulnerability to the threat of losing knowledge, proxied by firm-level product market competition (Chen, 1996; Hoberg and Phillips, 2010), their information processing capacity, proxied by relative absorptive capacity (Cohen and Levinthal, 1990; Zahra and George, 2002), and/or their need to constrict control, proxied by relative financial slack (George, 2005; Mount et al., 2024). Leveraging the quasi-natural experiment created by the staggered rejection of the inevitable disclosure doctrine (IDD) across US states and a sample of publicly listed US manufacturing firms tracked over the 15-year observation period from 1991 to 2015, we empirically test and find robust support for our hypotheses.

This paper makes several contributions to the literature. First, it contributes to the literature on firm responses to the threat of knowledge loss. Prior research has primarily adopted an economics lens to examine strategic responses that firms can adopt to prevent knowledge loss using mechanisms such as contracts and incentives (e.g., Agarwal et al., 2009; Carnahan et al., 2012; Flammer and Kacperczyk, 2019; Ganco et al., 2015; Gilson, 1999). We contribute a new direction for this literature by contributing a behavioural examination that leverages threat rigidity theory (Connelly and Shi, 2022; Ocasio, 1995; Staw et al., 1981). We argue and demonstrate empirically that the threat of knowledge loss posed by rejection of IDD gives rise to a threat rigidity effect in firms' R&D dynamism. We further examine heterogeneity in this response, identifying product market competition, relative absorptive capacity, and relative financial slack as key moderators. Second, this paper contributes to research on R&D dynamism (Kor and Mahoney, 2005; Mudambi and Swift, 2014; Pennetier et al., 2019; Swift, 2016), which has primarily focused on the *consequences* of R&D dynamism. We identify the threat of knowledge loss created by rejection of IDD as a significant *antecedent* of R&D dynamism. Finally, our study extends the scope of threat rigidity theory by examining the impact of a novel threat – rejection of IDD – on a hitherto unexplored outcome, namely R&D dynamism.

THEORY DEVELOPMENT

Loss of Knowledge Due to Employee Departures

Privately held knowledge is a key source of competitive advantage (Grant, 1996; Kogut and Zander, 1992). According to a report on knowledge protection by the US Chamber of Commerce (2014), on average, proprietary knowledge is estimated to make up two-thirds of the value of firms' intangible assets, an estimated total value of $5 trillion for publicly listed US companies. Even though proprietary knowledge holds tremendous value, it is vulnerable to misappropriation. Indeed, theft of trade secrets and other critical business information costs US businesses 'billions of dollars in annual losses' according to the U.S. Chamber of Commerce (U.S. Chamber of Commerce, 2014). Sustaining a knowledge-based competitive advantage depends on a firm's ability to prevent the loss of proprietary knowledge and its imitation by competing firms (e.g., Barney, 1991).

A key challenge in that regard stems from the fact that knowledge often resides in a firm's employees, who could take it with them if/when they leave their employer. Innovative firms thus face a dilemma: investing in knowledge creation over time is essential for innovating successfully (Kor and Mahoney, 2005) but a firm that finances knowledge creation may find it difficult to prevent its employees from taking that knowledge with them when they quit to move to a competitor or start a competing business (Coff, 1997). The loss of knowledge disrupts established firm knowledge creation routines and hampers the functioning of teams and networks (Hambrick et al., 1983; Phillips, 2002; Wezel et al., 2006). Moreover, knowledge embedded in employees can facilitate competitive imitation as employees with valuable knowledge can join a rival firm (Campbell et al., 2012; Song et al., 2003). In most legal cases on knowledge misappropriation, the defendants are current or former employees of the firms bringing the claims (Almeling et al., 2009; The Economist, 2013; U.S. Chamber of Commerce, 2014). In sum, the potential loss of knowledge due to employee departures can threaten the value of a firm's investments in knowledge creation, impeding its ability to profit from proprietary knowledge.

Background on the Rejection of the Inevitable Disclosure Doctrine (IDD)

Firms seek recourse to legal tools to mitigate the risk of knowledge misappropriation (Teece, 1986). The Uniform Trade Secrets Act (UTSA) defines misappropriation as the use or disclosure of the trade secret by the defendant to the detriment of the plaintiff (Klitzke, 1980). The inevitable disclosure doctrine (IDD) is a theory of common law based on state courts' interpretation of the concept of threatened misappropriation (Patel and Devaraj, 2022). According to the IDD doctrine, threatened misappropriation is inevitable when a knowledge worker in possession of trade secrets of her current employer quits her job to join a rival firm or establishes a competing firm. Therefore, the IDD provides employers with a legal tool to prevent knowledge workers from working for another firm without proving that the individual disclosed any trade secret or even threatened to do so.

Unlike non-compete laws, which require knowledge workers to have signed specific contracts that include a non-compete clause and for actual misappropriation to occur to be applicable, IDD is applicable on the mere possibility of knowledge misappropriation. An example of applying the IDD is the prominent case of PepsiCo, Inc. v. Redmond (1995)[2]. William Redmond Jr., who worked in the top management of PepsiCo, sought to join a rival firm, Quaker. PepsiCo, Inc. (the plaintiff) filed an action to enjoin William Redmond and the Quaker Oats Company (the defendants) to prevent Redmond from divulging PepsiCo trade secrets and confidential information in his new job with Quaker and from assuming any duties with Quaker relating to beverage pricing, marketing, and distribution. The court granted a preliminary injunction, prohibiting Redmond from joining Quaker on the basis that his new job would 'inevitably lead him to rely on the plaintiff's [PepsiCo's] trade secrets'. (Kahnke and Bundy, 2013). Another notable case is that of IBM v. Mark Papermaster (2008).[3] Papermaster, a former senior executive at IBM, was hired by Apple Inc. as a senior executive in its hardware engineering division. Papermaster did not have a non-compete agreement with IBM, but IBM argued that the inevitability of disclosure warranted legal protection. IBM relied on this doctrine, which suggests that even without direct evidence of trade secret misuse, the mere fact of Papermaster's knowledge and his new role at a competitor could lead to an unavoidable disclosure of confidential information. The court granted a temporary injunction preventing Papermaster from starting his position at Apple. The court found that IBM had shown a likelihood of success on the merits of its case and that Papermaster's insider knowledge created a substantial risk of inevitable disclosure (see also Reder and O'Brien, 2011). As the PepsiCo, Inc. v. Redmond and IBM v. Papermaster cases illustrate, a state court ruling in favour of IDD provides employers with a strong mechanism to reduce the inter-firm mobility of their knowledge workers by obtaining a court injunction against departing inventors (e.g., Contigiani et al., 2018; Gilson, 1999).

Conversely, a state court ruling against (rejecting) the IDD removes this significant mobility restriction for knowledge workers, increasing a firms' likelihood of losing knowledge in the future (Flammer and Kacperczyk, 2019; Patel and Devaraj, 2022). Cases such as Whyte v. Schlage Lock Co (2002) show that some states, like California, reject the IDD. Lynn Whyte, a former high-ranking executive at Schlage Lock Company, resigned to take a position with a competitor[4]. Schlage sought to prevent Whyte from joining the competitor, arguing that her knowledge of Schlage's business operations, strategies, and trade secrets would be inevitably disclosed in her new role. Schlage Lock Co. based its argument on the IDD, which suggests that even without direct evidence, the nature of Whyte's new job would inevitably lead to the disclosure of Schlage's trade secrets. The California Court of Appeals rejected the IDD. The court held that preventing Whyte from working for the competitor without direct evidence of trade secret misuse would contradict California's public policy, which prioritizes employees' right to seek employment freely. The Whyte v. Schlage Lock Co. decision is a pivotal case for understanding California's legal environment, which prioritizes employee mobility. It underscores that in California, an employer must provide concrete evidence of actual misuse of trade secrets rather than rely on speculation of inevitable disclosure.

In sum, the rejection of IDD does not lead to a direct loss of knowledge. Yet it poses a threat to firms by restricting their ability to prevent employees with valuable knowledge from working for a rival in the immediate future, thus elevating their risk of a potential loss of knowledge (e.g., Gilson, 1999; Kahnke and Bundy, 2013; Png and Samila, 2015).

R&D Dynamism

R&D dynamism is a key feature of firms' R&D strategy. Given that uncertainty is inherent in the innovation process, firms benefit from adjusting their R&D investments dynamically in response to a shifting opportunity set (Holmstrom, 1989). For instance, firms may reallocate resources – either by increasing investment in promising R&D areas or by scaling back in others – based on shifting priorities (Bloom, 2007). Significant changes in

R&D allocation are often linked to major adjustments, such as pivoting into entirely new research domains or discontinuing unproductive projects.

Significant increases in R&D spending are linked to the synthesis of new knowledge (Mudambi and Swift, 2011, 2014; Swift, 2016). A substantial body of empirical evidence indicates that exploratory R&D, which focuses on discovering new technologies or fields, tends to be more costly (DiMasi et al., 2003; Dyer, 1996; Gagnon and Lexchin, 2008; Harryson, 2008). While shifting R&D resources from explorative R&D to exploitative R&D, which optimizes and refines existing knowledge and capabilities, is associated with significant R&D cuts (Mudambi and Swift, 2014). For instance, Mudambi et al. (2015) examined R&D investments of Cisco and found that '*During exploratory periods, when new opportunities are opening up, Cisco spends generously in search of radical innovations for competitive advantage; once it has identified a good number of them, it shifts to exploitation, which allows the company to cut its R&D budget while producing large numbers of valuable patents, although with narrower scope than during the exploration phase*'.

The following two contrasting examples from our sample help illustrate the point. The first example is that of DuPont, one of the most prominent, historic firms in the US chemical industry. During the 1990s DuPont undertook a bold strategic transformation, shifting its focus increasingly towards biotechnology, agricultural products, and advanced materials. This pivot required strong investment in exploratory research, often in unfamiliar scientific and technological domains. As a result, DuPont's R&D spending became much more volatile, reflecting high R&D dynamism during this period, as reflected by its R&D dynamism being, on average, above our sample average. A contrasting example is provided by Tupperware Brands, a firm known for its kitchen storage solutions, which has followed a less volatile, more stable approach to R&D focused on incrementally improving its existing products. Over the years Tupperware Brands has steadily invested in R&D with minimal deviations in its R&D spending over time, thereby exhibiting lower R&D dynamism (reflected by its R&D dynamism value being, on average, below our sample average). Overall, DuPont's higher R&D dynamism reflects its greater extent of change, while the lower R&D dynamism of Tupperware Brands represents greater R&D stability, a consistent pattern of investments in its core product portfolio.

Ultimately, a firm's decision to adopt a more or less dynamic approach to managing R&D investments has been found to influence firms' innovation and performance outcomes (e.g., Kor and Mahoney, 2005; Mudambi and Swift, 2014; Pennetier et al., 2019; Swift, 2016).

Threat Rigidity Theory

Threat rigidity theory examines the behavioural patterns that emerge when individuals, groups, or organizations are confronted with an external threat, defined as 'an environmental event that has impending negative or harmful consequences for the entity' (Staw et al., 1981). We build on threat rigidity research that focuses specifically on the organizational level (the predominant body of research), that is, how organizations respond to external threats. The theory is grounded in the concept of bounded rationality, which recognizes the inherent limitations of human cognitive capacities (Simon, 1955, 1979). These cognitive constraints underpin the two central mechanisms proposed by the theory that give rise to the 'threat rigidity effect', that is, the tendency of organizations to respond to external threats with increased rigidity, that is, greater reliance on established routines and more mechanistic, conservative, familiar, tried-and-tested behaviours.

The first mechanism of threat rigidity theory is restricted information processing. The stress, anxiety, and arousal triggered by the external threat an organization faces restrict the range of information that it can attend to. For instance, Withey (1962, p. 118) suggests that exposure to an external threat leads to '*a narrowing of the perceptual field and a limitation of the information that can or will be received*'. Staw et al. (1981, p. 512) noted that when responding to threats, this narrowing effect may 'restrict alternatives to those that are similar to information that the organization already possesses', reducing the organization's ability to assimilate, process and utilize new information. Thus, organizations rely more on previously learned solutions and become less flexible when considering alternative approaches, resulting in problem-solving rigidity (Cowen, 1952; Shi et al., 2018).

The second mechanism of threat rigidity theory is constriction of control. When an organization is faced with an external threat, there is a shift towards increased centralization of authority, more formalization, and greater reliance on standardized procedures (Chattopadhyay et al., 2001). In essence, decision-making becomes more concentrated, typically shifting upwards within the firm hierarchy. As Staw et al. (1981, p. 502) note, 'power and influence can become more concentrated or placed at higher levels of a hierarchy'. This shift often leads to marginalization of the role of peripheral or lower level members as organizations prioritize familiar routines that have worked in past situations (Gladstein and Reilly, 1985). While this approach may enhance control and coordination under pressure, it suppresses diverse perspectives and the organizational ability to adapt, ultimately reinforcing rigidity in organizational behaviour when faced with a threat (Connelly and Shi, 2022).

Empirical research on threat rigidity theory at the organizational level shows that when faced with an external threat firms often restrict information and/or tighten control, which influences their behaviour and outcomes (Mazzei et al., 2024). For instance, adopting a threat rigidity perspective, Shi et al. (2018) find that firms with high short interest tend to respond by narrowing the range of growth opportunities they pursue. Similarly, Barbero et al. (2020) examine turnaround performance due to threat rigidity, while Fay et al. (2022) consider more conservative modes of expansion as a threat rigidity response adopted by retailers. Importantly, the threat rigidity effect described in the literature should not be interpreted as inherently negative or irrational. Indeed, threat rigidity theory is agnostic about the financial, economic, or survival consequences of threat rigidity. It does not assume a negative impact of threat rigidity on organizational performance per se; it simply predicts a specific change in organizational behaviour in response to an external threat. As Mazzei et al. (2024) note, '*At times, then, leaning in on tried-and-true behaviours can lead to stability, risk mitigation, and the further development of core competencies*'. In other words, increased organizational rigidity could also be a potentially performance-enhancing response for a 'boundedly rational' organization (Simon, 1955, 1979) facing an external threat.

In sum, the literature grounded in threat rigidity theory suggests that exposure to an external threat would prompt firms to restrict information processing and/or constrict control, thereby leading to greater reliance on more familiar, conservative, tried-and-tested responses, that is, threat-induced rigidity in organizational behaviour.

HYPOTHESES

Effect of Rejection of IDD on R&D Dynamism

The rejection of IDD presents an external threat for firms by increasing their risk of knowledge loss in the future (Flammer and Kacperczyk, 2019; Gilson, 1999; Kahnke and Bundy, 2013; Patel and Devaraj, 2022; Png and Samila, 2015). According to threat rigidity theory (Staw et al., 1981), when faced with an external threat such as the rejection of IDD, firms are likely to restrict information processing by reducing the amount and type of information they attend to in order to focus on the focal threat and/or constrict control in order to gain greater control over organizational behaviour while operating under threat.

Nevertheless, managing R&D investments in a dynamic way demands substantial attention and information processing. R&D decisions are especially difficult to evaluate due to their inherent uncertainty, lengthy time horizons, and intangible outcomes (Holmstrom, 1989). This complexity is further compounded by the accelerating pace of technological and scientific change, which continually reshapes competitive dynamics. As noted in a Cisco White Paper on Technology Strategy for Manufacturers, active scanning for new technologies, along with monitoring ecosystem partners and the market environment, is essential for effectively repositioning or pivoting the technology strategy of firms (Sullivan and Muthukrishnan, 2012). That is, firms must interpret subtle environmental cues and assess their internal capabilities before making significant R&D resource allocation decisions – an inherently difficult task (Cockburn et al., 2000). This challenge is further compounded when information processing is restricted in response to an external threat. Restricted information processing narrows managerial attention and as a result, firms are less likely to initiate bold changes in R&D (Bloom, 2007).

At the same time, constriction of control, characterized by more centralized decision-making authority at higher levels of the hierarchy, may constrain a firm's ability to act dynamically, especially in uncertain or fast-evolving environments. As Benjamin Laker, Forbes Senior Contributor, recently put it, such constriction of control can lead to top-down decision making where '*decisions flow from the top down…employees are often seen as cogs in a well-oiled machine, valued more for their ability to follow instructions than for their creative input…Over time, this leads to a culture of conformity, where the safest, least creative ideas are the ones that prevail*' (Laker, 2024). As such, the centralization brought about by constriction of control can limit the responsiveness and autonomy of lower level units, including R&D teams, which are typically closer to emerging knowledge and technological shifts. This can retard the recognition of novel opportunities or R&D setbacks, both of which are critical to managing R&D dynamically. Moreover, centralized control often reinforces existing routines and risk-averse behaviour, reducing the likelihood of bold resource reallocation, thus dampening R&D dynamism.

Overall, threat rigidity theory suggests that restriction of information processing and/or constriction of control leads to greater formalization and reliance on established routines (Connelly and Shi, 2022; Shi et al., 2018). As a result, in the face of an external threat, firms may become less open to change, less willing to experiment, and more reliant on previously learned routines and behaviours (Griffin et al., 1995). These responses make it difficult for firms to handle the complex decision-making associated with entering novel areas of research or overhauling R&D projects. Thus, they can be expected to be less likely to make bold changes when it comes to the addition of resources to R&D or the release of resources from R&D (Bloom, 2007). In sum, the above arguments suggest that when faced with the threat of losing knowledge due to the rejection of IDD, firms will be less inclined to make substantial adjustments to their R&D investments, dampening their R&D dynamism.

> *Hypothesis 1:* Rejection of IDD is negatively related to firms' R&D dynamism.

Moderators of Threat Rigidity

We also examine the influence of key mechanisms that, according to threat rigidity theory, can be expected to moderate the threat rigidity effect. Specifically, we examine factors that change a firm's vulnerability to the threat, its capacity to process information, or its need to constrict control in response to the threat.

Moderating effect of threat vulnerability. According to threat rigidity theory, a firm's response to an external threat depends on its *vulnerability* to that threat (Connelly and Shi, 2022). Vulnerability captures the likelihood that the firm will be adversely affected by the focal threat. In particular, a firm's vulnerability to the rejection of IDD may vary based on the motivation and ability of rival firms to take advantage of the focal firm's vulnerable position (Chen et al., 2007). Exposure to rejection of IDD can lead to misappropriation of the firm's R&D investments, that is, rivals could benefit from the knowledge of the focal firm without incurring the costs of creating it (Agarwal et al., 2009; Coff, 1997; Martinez-Noya et al., 2013). This, in turn, can enable rival firms to better compete with the focal firm, eroding its competitive advantage (Almeida and Kogut, 1999; Song et al., 2003). Therefore, the product market competition faced by a focal firm may moderate the effect of rejection of IDD on its R&D dynamism as it influences the vulnerability of the firm to that external threat.

Each firm in an industry can face a different level of product market competition based on its similarities to other firms in terms of the products and services on which they compete (Chen, 1996). Since firms that offer similar products and/or services often have similar factor inputs or suppliers, production technologies, and markets or customers, greater product market competition exists between them (Porac et al., 1989) and they focus their attention primarily on each other (Peteraf and Shanley, 1997). The higher the level of product market competition, the more rival firms offering similar products or services to the focal firm would have the necessary experience and expertise to exploit the knowledge of the focal firm by hiring away its knowledge workers. Thus, firms facing greater product market competition are more aware of, and exposed to, possible misappropriation of valuable knowledge by rivals (Chen and Miller, 2007; D'aveni, 1989), making them more vulnerable to external threats such as the rejection of IDD, which weakens their ability to protect knowledge. Thus, by making a firm more vulnerable to the external threat of knowledge loss created by the rejection of IDD, the product market competition faced by a focal firm may exacerbate the negative effect of the rejection of IDD on its R&D dynamism.

> *Hypothesis 2:* The negative effect of rejection of IDD on R&D dynamism is stronger for firms facing greater product market competition.

Moderating effect of information processing. According to threat rigidity theory, *restricted information processing* is one of the mechanisms that can give rise to a 'threat rigidity' effect. Firms differ considerably in their ability to process external information, largely driven by their absorptive capacity. Firms with greater absorptive capacity are better equipped to acquire, assimilate, and utilize external knowledge to create value (Cohen and Levinthal, 1989, 1990; Escribano et al., 2009; Zahra and George, 2002). In contrast, firms with lower absorptive capacity may struggle to process and leverage new information effectively, limiting their potential to capitalize on new opportunities or deal with new threats (Wales et al., 2013).

A firm's absorptive capacity is largely determined by its prior knowledge (Tsai, 2001), which plays a critical role in how effectively it can absorb and utilize new information (Jansen et al., 2005). The greater a firm's existing knowledge base, the better it can interpret and apply new insights, enabling the development of innovative solutions or responses and enhancing value. By enhancing information processing, absorptive capacity increases the firm's 'degrees of freedom', reducing constraints imposed by bounded rationality, thus enabling greater flexibility and variability in its strategic responses. Insights gained from processing external information are especially important when contemplating and making substantial changes to R&D investments, which may involve stark increases or decreases (Mudambi and Swift, 2011, 2014; Swift, 2016). Thus, absorptive capacity plays a role in shaping how firms adjust their R&D dynamism under external threats, such as the threat of knowledge loss triggered by rejection of IDD.

When firms have lower absorptive capacity relative to other firms, they can be expected to be more inclined to limit their information processing in response to external threats (Shi et al., 2018). This limitation occurs because, under threat, firms often redirect their attention and resources towards addressing that threat, leaving them with lower capacity to process information to make informed decisions about significantly increasing or decreasing their R&D investments. In contrast, firms with greater absorptive capacity are better equipped to attend to external threats without significantly reducing activities that require information processing. Their enhanced ability to acquire, assimilate, and utilize information flows means that they can continue to process and integrate valuable insights even when facing external threats. Therefore, the threat rigidity response of reducing R&D dynamism may be more severe for firms with lower levels of relative absorptive capacity.

What is more, greater absorptive capacity relative to other firms in the same industry generally enhances a firm's attractiveness to knowledge workers (Cohen and Levinthal, 1990; Zahra and George, 2002). Conversely, lower absorptive capacity makes firms less attractive to knowledge workers who value learning opportunities, collaboration, and innovation (Lane et al., 2006; Lepak and Snell, 1999). For instance, a survey supported by the Office of Science of the US Department of Energy's Early Career Award program found that practicing scientists and engineers cited the '*ability to work on innovative research*' and '*working with outstanding people*' as the most important factors that attracted them to their current positions (Northen et al., 2019). Firms with greater relative absorptive capacity may therefore be able to offset the risk of loss of knowledge by capitalizing on mobility-induced knowledge inflows, notably when rejection of IDD leads to displacement of knowledge workers. As a result, firms with greater absorptive capacity can maintain a more active engagement in R&D by leveraging external knowledge flows (Arora and Gambardella, 1994; Cohen and Levinthal, 1989; Zahra and George, 2002) and capitalizing on externally sourced expertise to adjust their R&D portfolios, directing resources to promising areas or scaling back investments in less promising ones. The above arguments suggest that firms with greater relative absorptive capacity can be expected to be better at maintaining their R&D dynamism under external threats compared to firms with lower relative absorptive capacity.

> *Hypothesis 3:* The negative effect of rejection of IDD on R&D dynamism is weaker for firms with greater relative absorptive capacity.

Moderating effect of constriction of control. Another mechanism that can drive threat rigidity is constriction of control. When a firm faces an external threat, decision-making tends to shift upwards, concentrating power among more senior leaders (Staw et al., 1981) and the firm becomes more dependent on familiar routines and formalized, standardized procedures (Chattopadhyay et al., 2001; Gladstein and Reilly, 1985). This realignment increases centralization (Argote et al., 1989) and reduces job autonomy for frontline employees (Sutton and D'Aunno, 1989). The focus is on increasing oversight and improving coordination at the lower levels to reduce implementation errors and improve alignment in response to the external threat. The following practitioner quote vividly illustrates the above role of centralization in the context of R&D: '*[Centralization] ensures that the R&D activities are closely aligned with the company's core objectives and culture. This alignment is crucial for maintaining a unified direction and preventing the fragmentation of research efforts. Centralized R&D also simplifies management oversight and resource allocation*' (Henike, 2024).

A critical factor influencing the degree to which firms may need to constrict control in response to external threats is organizational slack: potentially utilizable resources that can be redirected to achieve organizational goals (Haleblian et al., 2012; Mount et al., 2024). This is because slack serves two essential functions. First, slack acts as a cushion against environmental fluctuations, allowing firms to absorb internal and external pressures without disrupting ongoing operations. Second, slack reduces goal conflicts at the lower levels of firms, facilitating coordination and progress towards long-term goals.

Readily accessible and easily repurposed slack resources, such as financial slack (e.g., cash reserves) provide firms with greater discretion in navigating external threats. Studies suggest that cash is the most easily redeployed and fungible resource, providing firms with the greatest freedom in reallocating it towards alternative goals and priorities (George, 2005; Kim and Bettis, 2014). In contrast, firms with limited financial slack face more difficult resource allocation decisions, often compelling them to tighten control for greater efficiency (Chattopadhyay et al., 2001; Shi et al., 2018). Therefore, financial slack can be expected to moderate the likelihood/extent to which, when faced with an external threat, firms adopt more familiar, conservative responses.

Firms with greater financial slack tend to have a higher tolerance for errors (Bradley et al., 2011), thus lower need to tighten control when facing threats such as the increased risk of knowledge loss. As a result, lower-level employees often enjoy greater autonomy and their insights into environmental conditions are more likely to be considered during strategic discussions (Damanpour, 1991). This is especially important when firms are contemplating substantial changes in their R&D. Conversely, firms with less financial slack are more likely to respond to the rejection of IDD by constricting control, that is, more likely to reinforce centralization and formalization in their decision-making processes. This tends to limit flexibility and increase the likelihood of adopting more familiar, mechanistic responses. As a result, such firms are more likely to be more conservative and more hesitant to deviate from their existing R&D trajectories.

> *Hypothesis 4:* The negative effect of rejection of IDD on R&D dynamism is weaker for firms with greater relative financial slack.

DATA AND METHOD

To test our hypotheses, we use data of publicly listed US manufacturing firms (SIC codes 2000 to 3999). The US manufacturing industry exhibits high R&D (Hall et al., 2005; Mudambi and Swift, 2014) and mobility-induced knowledge leakages, which weaken the appropriability of R&D. We obtain financial and R&D productivity data from Compustat and Research Quotient databases through WRDS. This sample is merged with the data from Hoberg and Philipps Data Library (Hoberg and Phillips, 2010) for information on product market competition, DISCERN for information on patenting activities of the firms (Arora et al., 2021), and Bureau of Economic Analysis for information on the state-level characteristics. Each observation represents one firm-year. As a time series of R&D investments is needed to study R&D dynamism, we exclude firms that do not report their R&D for at least 10 uninterrupted years during the sampling period. The final sample consists of 584 unique firms and 6671 firm-year observations from 1991 to 2015.

Variables

Dependent variable. The dependent variable is *R&D dynamism*. Dynamism in R&D investments is an observable marker of changes in firms' R&D investments (Mudambi and Swift, 2011, 2014). As the prospect of innovation can become more exciting or lose its appeal over time (Nelson and Winter, 1977), firms may make adjustments to their allocation of investment to R&D, a central feature of the innovation processes.

R&D dynamism (i.e., variability in R&D investments) captures such adjustments in R&D investments over time. While R&D intensity captures whether firms invest more or less in R&D, R&D dynamism captures the flexibility with which firms adjust their investments in R&D by adding resources to R&D and/or releasing resources from R&D. A high value of R&D dynamism indicates flexibility in the allocation of resources to R&D, that is, proactive R&D management through significant addition of resources to R&D and/or significant withdrawal of resources from R&D relative to a firm's existing investment trend. Conversely, a low value of R&D dynamism indicates low flexibility in the allocation of resources to R&D, that is, cautious R&D management by refraining from significant addition of resources to R&D and/or significant withdrawal of resources from R&D. Evidence from management research and practice suggests that firms make careful decisions regarding adjusting their R&D investments as such adjustments affect a variety of firm-level outcomes such as innovation quantity and quality (Pennetier et al., 2019), firm growth, or financial performance (Mudambi and Swift, 2011, 2014).

Following earlier research (Mudambi and Swift, 2011; Patel et al., 2018), we measure R&D dynamism using the standard deviation of the residuals from the firm's R&D investment trend, divided by the mean R&D investment. The calculation is performed using a two-step process. First, we regress R&D investment $RD_{i,t}$ on a linear time trend over the preceding 5 years:

$$RD_{i,t} = \alpha_i + \beta_i t + \varepsilon_{i,t}$$

That is, for firm *i* in year *t* we regress over a rolling five-year period from year *t* to year *t-4*. The above equation gives us the trend value of R&D investments over the last 5 years. The residuals around this trend capture the dynamism of R&D investments for each firm. However, because larger R&D spenders would have a larger standard deviation, in the second step, we divide the standard deviation of the residuals around the R&D trend by the mean of R&D investments over the last 5 years:

$$\text{R\&D Dynamism}_{i,t} = \frac{S_{i,t}}{\overline{X_{it}}}$$

where $S_{i,t}$ is the 5-year rolling standard deviation of R&D investment residuals around the trend line of firm *i*, while $\overline{X_{it}}$ is the 5-year rolling mean of R&D investment of firm *i*.

Independent variables. Our main independent variable is *Rejection of IDD*. To rule out potential endogeneity concerns, we exploit the exogenous variation in firms' likelihood of losing knowledge created by the staggered rejection of the inevitable disclosure doctrine (IDD) across US states. The adoption of IDD prevents employees with valuable know-how from working for a competitor or founding a rival firm on the grounds that they would inevitably disclose trade secrets (Contigiani et al., 2018, Gilson, 1999: Lowry, 1988). Conversely, the rejection of IDD reduces a firm's ability to restrict the mobility of its knowledge workers, thus increasing the firm's expectations of losing knowledge in the future (Flammer and Kacperczyk, 2019; Patel and Devaraj, 2022). We computed a dummy variable that equals 1 for years that follow the rejection of IDD in a state where the focal firm is located and zero otherwise. The IDD does not apply to the state of incorporation but to the state of location, which we proxied using the state of headquarters' location provided in Compustat. During the period of observation, 14 states in the US had rejected the IDD (Flammer and Kacperczyk, 2019; Kahnke and Bundy, 2013). The states rejecting IDD are (by year of decision) Virginia (1999), Florida (2001), California (2002), Michigan (2002), Maryland (2004), Ohio (2008), Arkansas (2009), New York (2009), Wisconsin (2009), New Hampshire (2010), Massachusetts (2012), New Jersey (2012), Washington (2012), and Georgia (2013). Table I presents the number of firms headquartered in each state at the time the state rejected IDD. In total, 183 firms were present across the states during their respective IDD rejection years. The years of rejection of the IDD in the above states and the relevant court rulings are taken from Flammer and Kacperczyk (2019).

We also operationalize our moderating variables. Since the threat rigidity effect depends on firms' vulnerability to the rejection of IDD, we expect it to be severe for firms facing greater product market competition. Product market competition is measured as proposed by Hoberg and Phillips (2010), who construct the variable as follows. First, they combine web crawling and text parsing algorithms to analyse the text of product descriptions of firms' 10-K filing statements. The product descriptions in a firm's 10-K are legally required to be accurate and current. Second, they use these product descriptions to compute firm-by-firm similarity scores using a hotelling-like product location space (Hotelling, 1929). Third, as 10-Ks are filed annually, they repeat the two steps above and update the calculation of

Table I. Firms headquartered in state at the time of IDD rejection

State	*Year of the rejection of IDD*	*Firms headquartered in state at the time of rejection of IDD*
Virginia	1999	6
Florida	2001	7
California	2002	74
Michigan	2002	13
Maryland	2004	5
Ohio	2008	11
New York	2009	18
Wisconsin	2009	7
Massachusetts	2012	19
New Jersey	2012	12
Washington	2012	6
Georgia	2013	5

product similarity for each firm-year, before computing the Herfindahl–Hirschman Index (HHI) based on sales to obtain a dynamic measure of product market competition for each firm. Specifically, we measure *Product Market Competition* as 1 minus HHI provided in the Hoberg and Phillips database. It is a continuous variable in which a larger number indicates a higher degree of product market competition.

Next, we examine the moderators' associated mechanisms proposed by threat rigidity theory. The theory asserts restricted information processing and tightening of control as two central mechanisms that give rise to the threat rigidity effect. To evaluate the impact of rejection of IDD on R&D dynamism of firms with strong versus weak information processing abilities, we consider the moderating influences of absorptive capacity (Zahra and George, 2002). Consistent with earlier research, we use the size of the firm's existing patent portfolio as a proxy for absorptive capacity (Zahra and George, 2002). To capture relative absorptive capacity, we compute the ratio between the focal firm's patent portfolio and the industry average patent portfolio each year.

To evaluate the impact of Rejection of IDD on R&D Dynamism of firms with high versus low levels of organizational control, we consider the moderating influences of relative financial slack. Financial slack plays a key role in shaping how much firms centralize and formalize control under threat, as it helps cushion environmental shocks and reduces internal goal conflicts – thereby lessening the need to tighten control in the face of external threats. Consistent with earlier research, we use the size of the firm's cash reserves as a proxy for financial slack (George, 2005). To capture relative financial slack, we compute the ratio between the focal firm's cash reserves and industry average cash reserves each year.

Control variables. We controlled for several factors that may be simultaneously related to our dependent and independent variables. We control for firm *Size* using the natural logarithm of total assets. To account for financial performance, we include *Return on Assets*, calculated as the ratio of earnings before interest, taxes, depreciation, and amortization to total assets. Given the inherent risk and uncertainty associated with R&D activities, creditors may impose stricter monitoring and constraints on such investments (Acharya et al., 2011). To capture this effect, we control for *Leverage*, measured as the ratio of long-term debt to total assets. Additionally, since dividend policy may signal a firm's expectations of future cash flows (Hoberg and Prabhala, 2009), we include a control for *Dividends*, measured as the ratio of total dividends on common and preferred shares to total assets.

To account for the firm's focus on knowledge-based competitive advantage, we control for *R&D intensity*, measured as the ratio of the amount invested in R&D to total assets each year. We also control for the firm's research productivity using *Research Quotient*, which captures how effectively a firm translates R&D investment into output. For this we use the Cobb–Douglas production function (see Knott, 2008). Further, a firm's focus on R&D could also depend on whether it owns manufacturing facilities to bring the inventions to product markets (Hall and Ziedonis, 2001). Accordingly, we control for *Capital Intensity*, measured as the ratio of the net property, plant, and equipment to total assets each year.

Following previous studies on IDD (Castellaneta et al., 2016; Contigiani et al., 2018; Flammer and Kacperczyk, 2019), to account for location-based differences in economic activity we control for the *State GDP*, measured as the log of the GDP of the state in which the firm is headquartered. Further, we accounted for unobserved time-invariant heterogeneity at the firm level and the state level by including firm fixed effects in the regressions.[5] We also controlled for year fixed effects in the regressions. Finally, we account for time-varying industry effects (by including interaction terms between industry and year) and time-varying regional effects (by including interaction between region and year)[6] that may correlate with the treatment. We did not include interaction terms between state and year in the regression because the treatment (rejection of IDD) is at the state-year level.

Method

To examine whether the Rejection of IDD affects firms' R&D dynamism, we use a difference-in-differences methodology based on the staggered rejection of IDD. We follow the difference-in-differences methodology in the presence of staggered treatments at the state level as applied by Bertrand and Mullainathan (2003) and estimate the models using firm fixed effects ordinary least squares regressions.

We control for time trends by including year dummies in all models. Further, to account for a serial correlation of the error terms, we cluster the standard errors at the state-of-firm-location level (Imbens and Wooldridge, 2009). The main specification that we estimate is the following:

$$\text{R\&D Dynamism}_{i,t+5} = \alpha_i + \alpha_t + \alpha_{jt} + \alpha_{rt} + \beta.\,\text{Treatment}_{s,t} + \lambda.\,Z_{i,t} + \gamma.\,X_{i,t} + \varepsilon_{i,t} \quad (1)$$

where i indexes the firm, t indexes the time, j indexes the two-digit SIC industries, s indexes the state of the firm's headquarters, and r indexes Bureau of Economic Analysis regions. α_i are firm fixed effects, α_t are year fixed effects, α_{jt} are industry by year fixed effects, and α_{rt} are region by year fixed effects.[8] Treatment is the rejection of IDD, $Z_{i,t}$ is a vector of other independent variables (in this case, product market competition, relative absorptive capacity, and relative financial slack), $X_{i,t}$ is a vector of control variables, and $\varepsilon_{i,t}$ is the error term. As R&D dynamism is calculated using a rolling 5-year window, we use the R&D dynamism of year $t+5$ in the main specification to avoid regressing on a backward-looking dependent variable.

In the regression Equation (1), α_i accounts for unobserved heterogeneity at the firm level. The inclusion of α_{jt} accounts for time varying industry effects that may correlate with the treatment. Similarly, the inclusion of α_{rt} accounts for time varying regional effects that may correlate with the treatment (we did not include interaction terms between state and year in the regression because the treatment is at the state-year level).

The rejection of IDD is staggered over time across US states, which alleviates some of the concerns related to exogeneity of the treatment in our identification strategy. However, recent research has questioned the traditional difference-in-differences estimation because of treatment heterogeneity arising from variation in treatment timings (Goodman-Bacon, 2021; Goodman-Bacon et al., 2019). To address that concern, as a robustness check we also use the Goodman-Bacon decomposition to examine the impact of the staggered rejection of IDD on R&D dynamism.

RESULTS

We first provide descriptive statistics for our sample. The number of firm-years in the states that rejected the IDD is 2870, representing about 43 per cent of the total sample size. Table II reports descriptive statistics and simple pairwise correlations between the variables used to test our hypotheses. The results of pairwise correlations and the mean of variance inflation factors (mean VIF: 1.25) associated with our explanatory variables raised no noteworthy concerns regarding multicollinearity.

Table III reports the results of difference-in-differences OLS regressions that test H1. In all regressions, the dependent variable is R&D dynamism. To ensure the robustness of our results and to assess any potential bias introduced by control variables, we included them sequentially across the regression models (Carlson and Wu, 2012; Certo et al., 2020). In the estimation for Model 1 the control group at a given time consists of all the firms in the sample that are not treated up to year *t*. This model accounts only for firm and year fixed effects, without incorporating control variables. Supporting H1, the coefficient for rejection of IDD is negative and statistically significant $\left(-0.031, \mathrm{p} < 0.05\right)$. In the subsequent model, organizational size is introduced as a control. Supporting H1, in Model 2 the coefficient of the rejection of IDD is negative and significant $\left(-0.030, \mathrm{p} < 0.05\right)$. In Model 3, non-ratio based control variables are introduced, and the coefficient of the rejection of IDD is negative and significant $\left(-0.023, \mathrm{p} < 0.05\right)$, In Model 4, after including all the control variables the coefficient of the rejection of IDD is negative and significant $\left(-0.023, \mathrm{p} < 0.05\right)$, supporting H1. In Models 5 and 6 we sequentially include the interaction terms between industry and year and the interaction terms between region and year, respectively, which may correlate with the treatment (rejection of IDD). Supporting H1, in Model 5 $\left(-0.025, \mathrm{p} < 0.05\right)$ and Model 6 $\left(-0.026, \mathrm{p} < 0.05\right)$ the coefficients of rejection of IDD are negative and significant. The coefficients lie between −0.023 and −0.031 and are always significant at the 5 per cent level. The effect is quite sizable. As the average value of R&D dynamism is 0.13, our results imply that rejection of IDD dampens R&D dynamism by 18 per cent–24 per cent.

Robustness Checks

Parallel trends. The causal interpretations using difference-in-differences methodology rely on the parallel trends assumption, that is, the treatment and control groups follow parallel trends before the treatment occurs, in this case, rejection of IDD (Bertrand and Mullainathan, 2003). We explore the temporal trends in R&D dynamism. Figure 1 shows the average values for R&D dynamism for observations in the treatment and control groups. It provides evidence that both groups of observations follow a similar trajectory in the pre-treatment period. However, the parallel trends in R&D dynamism between the firms in the treatment and control groups seem to sharply diverge once IDD is rejected. The sharp decrease in R&D dynamism for the firms located in the states that rejected IDD compared to the firms in other states provides initial evidence in favour of the idea that anticipated loss of knowledge dampens R&D dynamism.

In addition to depicting the parallel trends graphically, we inspect the parallel trend assumption of the difference-in-differences methodology in Model 7 (Table IV). We test

Table II. Descriptive statistics and correlations

		Mean	*SD*	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*	*(13)*	*(14)*
(1)	R&D dynamism	0.13	0.13	1													
(2)	Rejection of IDD	0.22	0.41	**−0.03**	1												
(3)	Product market competition	0.73	0.28	**0.09**	**0.14**	1											
(4)	Relative absorp-tive capacity	1.00	0.70	0.00	**0.02**	−0.00	1										
(5)	Relative finan-cial slack	1.00	0.56	**−0.02**	**0.03**	**0.01**	**0.03**	1									
(6)	Size	6.71	1.84	**−0.12**	**0.05**	**0.07**	**−0.09**	**−0.14**	1								
(7)	Return on assets	0.14	0.11	**−0.09**	**−0.21**	**−0.07**	**−0.14**	0.00	**0.19**	1							
(8)	Leverage	0.28	0.50	−0.01	**−0.05**	**−0.10**	**0.03**	**−0.11**	**0.16**	0.01	1						
(9)	Dividends	0.02	0.03	**−0.11**	**−0.05**	**−0.12**	−0.01	0.01	**0.20**	**0.23**	**0.03**	1					
(10)	Capital intensity	0.23	0.14	**−0.10**	**−0.30**	**−0.14**	**0.03**	**−0.16**	**0.15**	**0.20**	**0.12**	**0.14**	1				
(11)	Sales volatility	0.10	0.09	**0.27**	**0.02**	**0.16**	**0.04**	**0.08**	**−0.16**	**−0.20**	**−0.07**	**−0.16**	−0.09	1			
(12)	R&D intensity	0.06	0.07	**0.04**	**0.21**	**0.29**	**0.29**	**0.09**	**−0.24**	**−0.41**	**−0.10**	**−0.09**	**−0.23**	**0.20**	1		
(13)	Research productivity	0.12	0.05	0.01	**−0.02**	**0.10**	**−0.02**	**0.13**	**−0.12**	**0.06**	**−0.06**	−0.01	**−0.15**	**0.06**	**0.11**	1	
(14)	State GDP	12.84	1.02	**0.04**	**0.54**	**0.20**	0.00	**0.04**	**0.08**	**−0.17**	**−0.02**	**−0.08**	**−0.29**	**0.11**	**0.22**	**−0.03**	1

Note: Correlations that are significant at the 10% level are shown in bold.

Table III. Difference-in-differences models of R&D dynamism

Variables	*Model 1*	*Model 2*	*Model 3*	*Model 4*	*Model 5*	*Model 6*
Rejection of IDD	−0.031*	−0.030*	−0.023**	−0.023**	−0.025*	−0.026*
	(0.013)	(0.012)	(0.008)	(0.008)	(0.010)	(0.012)
Product market competition				−0.023**	−0.021†	−0.021†
				(0.009)	(0.011)	(0.011)
Relative absorptive capacity				0.000	−0.000	−0.002
				(0.005)	(0.005)	(0.005)
Relative financial slack				−0.000	0.000	−0.001
				(0.005)	(0.005)	(0.005)
Size		−0.015†	−0.011	−0.013	−0.012	−0.013
		(0.009)	(0.009)	(0.009)	(0.009)	(0.010)
Return on assets				−0.012	−0.018	−0.015
				(0.037)	(0.039)	(0.040)
Leverage				0.003	0.003	0.002
				(0.004)	(0.006)	(0.006)
Dividends				0.031	0.069	0.067
				(0.074)	(0.070)	(0.074)
Capital intensity				−0.007	−0.011	−0.013
				(0.020)	(0.022)	(0.020)
R&D intensity				−0.101	−0.094	−0.083
				(0.115)	(0.109)	(0.106)
Sales volatility			0.259**	0.259**	0.254**	0.250**
			(0.048)	(0.047)	(0.046)	(0.045)
Research productivity			0.032	0.035	0.025	0.041
			(0.080)	(0.078)	(0.067)	(0.072)
State GDP			−0.135*	−0.132*	−0.109†	−0.125
			(0.058)	(0.057)	(0.059)	(0.078)
Constant	0.112**	0.201**	1.804*	1.807*	1.498*	1.706†
	(0.006)	(0.054)	(0.702)	(0.691)	(0.710)	(1.013)
AIC	−11,201.7	−11,223.8	−11,399.0	−11,397.9	−11,773.5	−11,843.8
BIC	−11,024.8	−11,040.0	−11,194.9	−11,139.3	−11,480.9	−11,564.7
Number of observations	6671	6671	6671	6671	6671	6671
Number of firms	584	584	584	584	584	584
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
SIC × Year FE	No	No	No	No	Yes	Yes

(Continues)

Table III. (Continued)

Variables	*Model 1*	*Model 2*	*Model 3*	*Model 4*	*Model 5*	*Model 6*
Region × Year FE	No	No	No	No	No	Yes

Note: Robust standard errors clustered at state level are in parentheses.
†Significant at 10%;
*Significant at 5%;
**Significant at 1%.

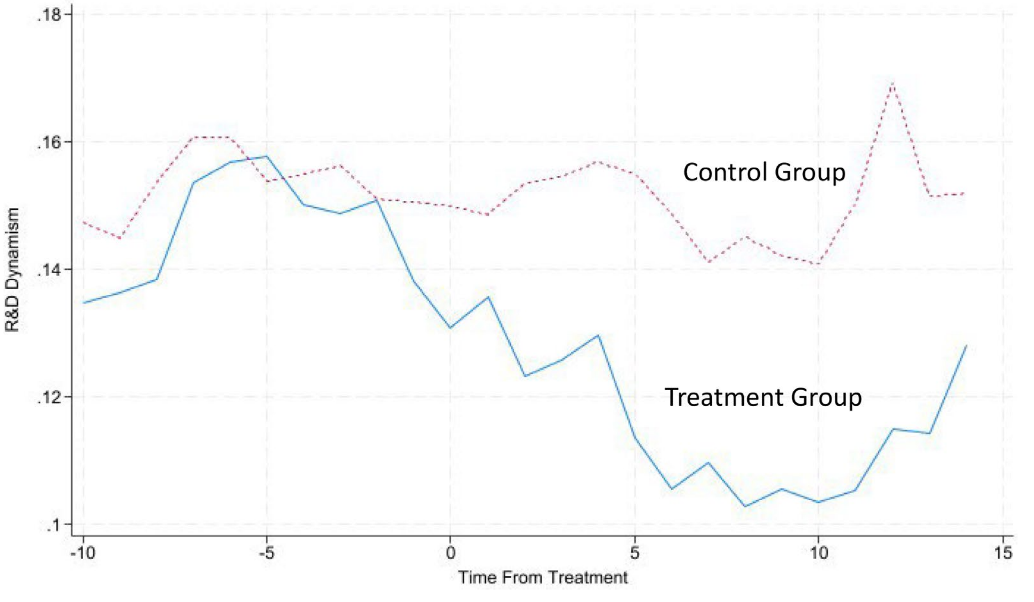

Figure 1. The impact of rejection of IDD on R&D dynamism

Note: The graph shows the effect of the rejection of IDD on firm R&D dynamism. The Y-axis is R&D dynamism. The X-axis is time from treatment, where treatment is the rejection of IDD. The control group consists of firms headquartered in states that did not reject IDD. Since R&D dynamism is calculated using a rolling window of the preceding 5 years, from year *t* to year *t*-4, the rejection of IDD in year *t* is regressed on the R&D dynamism of year *t* + 5 for a given firm. This explains why the decline in R&D dynamism visually appears to begin before the treatment period.

the parallel trends assumption by including the rejection of IDD (−2), rejection of IDD (−1), rejection of IDD (0), rejection of IDD (+1), and rejection of IDD (+2), which respectively equal 1 if the firm is headquartered in a state that will reject the IDD in 2 years, will reject the IDD in 1 year, rejected the IDD in the current year, rejected the IDD 1 year ago, rejected the IDD 2 years ago, and zero otherwise (Flammer and Kacperczyk, 2019). There is no evidence of an existing pre–trend, as the coefficients of the rejection of IDD (−2) $\left(-0.019, \mathrm{p} > 0.10\right)$ and rejection of IDD (−1) $\left(-0.007, \mathrm{p} > 0.10\right)$ are not significant. As expected, the coefficients of rejection of IDD (0) $\left(-0.029, \mathrm{p} < 0.01\right)$, rejection of IDD (+1) $\left(-0.022, \mathrm{p} < 0.10\right)$, and rejection of IDD (+2) $\left(-0.033, \mathrm{p} < 0.05\right)$ are negative and significant. The temporal trends of R&D dynamism in Figure 1 and the dynamic difference-in-differences model suggest that rejection of IDD reduces R&D dynamism.

Location of headquarters. Following earlier research that leverages the quasi-natural experiment created by the rejection of IDD (Flammer and Kacperczyk, 2019; Patel and Devaraj, 2022), we obtain the location of the focal firm's headquarters from Compustat. The state of headquarters in Compustat is backfilled, that is, the historical data for a firm report only the current state of incorporation. The measurement error in the threat of loss of knowledge, which is based on the location of headquarters, could have biased our results. To mitigate this concern, following Flammer and Kacperczyk (2019) we perform a robustness check by limiting the sample to firms that have at least 80 percent of their operations in the state of headquarters location. The assumption we make is that firms with highly concentrated operations in the state of the headquarters would be more reluctant to relocate. We use the data provided by García and Norli (2012) on the state-wise dispersion of firm operations based on the 10-K filings. The results for the restricted sample are presented in Model 8. Supporting H1, the coefficient of the Rejection of IDD is negative and significant $\left(-0.041, \mathrm{p} < 0.10\right)$.

State-level differences. As discussed, the rejection of IDD is likely to be driven by the merits of the precedent-setting cases rather than by state-level variables. Nevertheless, to deal with the potential endogeneity concerns we include controls on state-level economic conditions such as state GDP and per-capita income. To further control for the potential confounding factors, all regressions include region × year fixed effects, which account for unobservable trends at the regional level (see Model 3). However, the regions are broader than the states and do not completely mitigate the issue. To alleviate this issue to some extent, we restrict the control states of each state that rejected IDD to its neighbours. Suppose the rejection of IDD is driven by unobserved local conditions of the focal state and the firms adjust their R&D dynamism in response to those conditions. If so, then the firms in the neighbouring states would also spuriously respond to rejection of IDD as economic conditions are likely to spill across state borders. Using states that share border with the state rejecting IDD as the control group, we find that the effect of rejection of IDD on R&D dynamism continues to be significant. Supporting H1, in Model 9 the coefficient of the rejection of IDD is negative and significant $\left(-0.024, \mathrm{p} < 0.05\right)$.

To further alleviate concerns that our findings may be driven by differences between the states that rejected IDD and those that did not, we re-run Model 6 on just the subsample of firms that are headquartered in states that rejected the IDD. That is, we restrict the control group at a given time to all the firms in the sample that are not treated up to year t but would be eventually treated during our period of observation. The results of Model 9 are qualitatively similar in size and significance to the main results and thus provide additional support for H1. In Model 10 the coefficient of the rejection of IDD is negative and significant $\left(-0.029, \mathrm{p} < 0.01\right)$.

Coarsened exact matching. A potential challenge in estimating the effect of IDD rejection on R&D dynamism is that firms experiencing rejection of IDD may differ largely from those that do not. In addition to including various control variables, our models account for firm fixed effects, state fixed effects, and time-varying industry and regional effects. To further address potential imbalances between treated and untreated firms, we construct a matched sample for more robust comparison. We matched firms in states that rejected the IDD with firms in states that did not reject it, using coarsened exact matching (CEM) based on firm-level characteristics (Iacus et al., 2012). Specifically, we used the following observable factors related to market conditions: *Return on Assets, Size, Research Productivity, and Research Intensity*.

Our matched sample consists of 455 firms and 4906 observations. The CEM procedure reduced the multivariate imbalance in our sample from 0.63 to 0.41. In Model 11, we report the results of estimating our models using a CEM matched sample. The estimated coefficient of the rejection of IDD retains the same sign and similar significance levels compared to our main results ($-0.028, p < 0.05$). Thus, our results are robust to estimating our models using a CEM matched sample, offering additional empirical support for the results of our main hypothesis.

Placebo test. To establish exogeneity of the rejection of IDD, we also conduct placebo regressions. In each iteration of the placebo regression we randomly select and assign a pseudo rejection year to each state that rejected IDD. We use the placebo rejection year to create a dummy variable Placebo Rejection IDD that equals 1 for subsequent years if the focal firm is located in the state that has pseudo rejected the IDD by year t, and zero otherwise. Using the Placebo Rejection IDD variable we re-estimate Model 6 (Table III), repeating the exercise 500 times and recording the coefficient of the placebo rejection IDD variable in each regression. Figure 2 shows the distribution of the placebo coefficients obtained using these regressions. None of the estimates are lower than −0.026, which is the value of the coefficient in Model 6.

Goodman-Bacon decomposition. Due to within-treatment heterogeneity, recent research has questioned the estimates of difference-in-differences designs relying on staggered treatments (Goodman-Bacon, 2021; Goodman-Bacon et al., 2019). We examine the

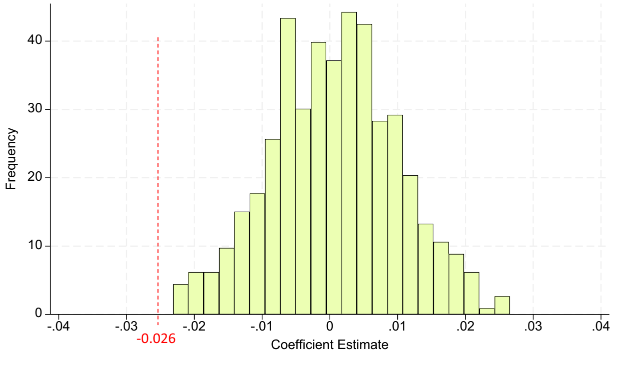

Figure 2. Placebo test results

Note: Please refer to results for a description of the placebo test. In Model 6, the coefficient for rejection of IDD is both negative and statistically significant (coefficient = −0.026, p-value < 0.05), indicated by the red dotted line in the figure.

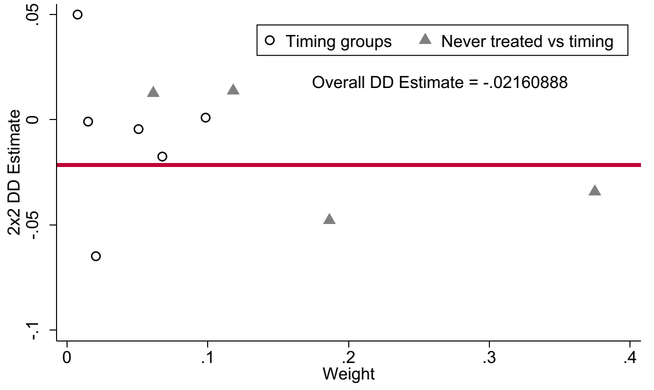

Figure 3. Goodman-Bacon decomposition results

Note: Please refer to results for a description of the Goodman-Bacon decomposition.

sources of variation in the effect of treatment by applying the Goodman-Bacon decomposition method in STATA 17 (Note that the bacondecomp procedure in STATA cannot be applied to an unbalanced panel). Figure 3 displays the effect (Y-axis) and weights (X-axis) for distinct groups formed due to variation in treatment (rejection of IDD) timings: timing groups (early vs. late IDD rejected groups; estimate of the treatment effect is −0.026 and total weight is 0.032) and never treated versus timing (IDD rejected vs. never rejected groups; estimate of the treatment effect is −0.026 and total weight is 0.741). The overall difference-in-differences estimate (weighted average of the estimates mentioned above) obtained from the Goodman-Bacon decomposition is −0.0216 ($p < 0.01$). Thus, the Goodman-Bacon decomposition provides further support for our findings.

Moderation Analysis

Models 12–15 test the moderation hypotheses (Table V). In H2 we propose that the threat of rejection of IDD on R&D dynamism would be stronger for firms that are more vulnerable, that is, facing higher product market competition. In Model 12 the coefficient of the interaction terms between rejection of IDD and product market Competition is negative and significant $\left(-0.077, p < 0.01\right)$, supporting H2. Next, we examine the two mechanisms proposed by threat rigidity theory, which include restricted information processing and tightening of control. To assess the impact of rejection of IDD on R&D dynamism in firms with varying information processing abilities, we consider Relative Absorptive capacity as a moderating variable. In Model 13, the coefficient of the interaction terms between Rejection of IDD and relative absorptive capacity is positive and significant $\left(0.023, p < 0.01\right)$, supporting H3. To assess the impact of rejection of IDD on R&D dynamism in firms with varying tightening of control, we consider relative financial slack as a moderating variable. In Model 14, the coefficient of the interaction terms between rejection of IDD and relative financial slack is positive and significant $\left(0.033, p < 0.01\right)$, supporting H4. Finally, Model 14 reports a full model that tests all moderating hypotheses simultaneously.

Table IV. Robustness checks for difference-in-differences models of R&D dynamism

Variables	*Model 7*	*Model 8*	*Model 9*	*Model 10*	*Model 11*
Rejection of IDD		−0.041*	−0.024*	−0.029**	−0.028*
		(0.017)	(0.010)	(0.008)	(0.012)
Rejection of IDD (−2)	−0.019				
	(0.012)				
Rejection of IDD (−1)	−0.007				
	(0.012)				
Rejection of IDD (0)	−0.029**				
	(0.009)				
Rejection of IDD (+1)	−0.022†				
	(0.012)				
Rejection of IDD (+2)	−0.033*				
	(0.015)				
Product market	−0.021†	−0.013	−0.021†	−0.012	−0.025†
Competition	(0.011)	(0.013)	(0.012)	(0.021)	(0.015)
relative absorptive	−0.002	−0.006	0.003	−0.001	−0.004
Capacity	(0.005)	(0.008)	(0.005)	(0.012)	(0.006)
Relative financial slack	−0.001	−0.012	−0.001	0.007*	0.003
	(0.005)	(0.008)	(0.005)	(0.003)	(0.008)
Size	−0.012	−0.031**	−0.011	−0.010	−0.004
	(0.010)	(0.007)	(0.010)	(0.009)	(0.008)
Return on assets	−0.015	−0.026	−0.008	0.068	0.008
	(0.040)	(0.054)	(0.043)	(0.079)	(0.046)
Leverage	0.001	0.016	0.001	−0.008*	0.011
	(0.006)	(0.011)	(0.005)	(0.003)	(0.010)
Dividends	0.065	0.007	0.065	0.082	0.130
	(0.073)	(0.085)	(0.075)	(0.186)	(0.163)
Capital intensity	−0.014	−0.002	−0.018	−0.054*	−0.056†
	(0.020)	(0.031)	(0.023)	(0.020)	(0.028)
R&D intensity	−0.082	−0.215	−0.077	0.145	0.036
	(0.105)	(0.199)	(0.111)	(0.150)	(0.105)
Sales volatility	0.249**	0.193*	0.246**	0.224*	0.210**
	(0.045)	(0.084)	(0.049)	(0.080)	(0.050)
Research productivity	0.038	0.175	0.007	0.061	0.031
	(0.073)	(0.109)	(0.071)	(0.108)	(0.060)
State GDP	−0.130	−0.251*	−0.131†	−0.197†	−0.062
	(0.079)	(0.109)	(0.073)	(0.093)	(0.084)

(Continues)

Table IV. (Continued)

Variables	*Model 7*	*Model 8*	*Model 9*	*Model 10*	*Model 11*
Constant	2.079*	3.657*	2.096*	2.872*	0.930
	(1.011)	(1.473)	(0.896)	(1.209)	(1.134)
AIC	−11,847.8	−4388.0	−10,630.8	−5154.5	−9230.5
BIC	−11,568.8	−4245.9	−10,422.6	−5088.9	−9003.5
Number of observations	6671	2173	6105	2870	4906
Number of firms	584	219	519	183	455
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES
SIC × Year FE	YES	YES	YES	YES	YES
Region × Year FE	YES	YES	YES	YES	YES

Note: Robust standard errors clustered at the state level are in parentheses.
†Significant at 10%;
*Significant at 5%;
**Significant at 1%.

The estimated coefficients of the interaction terms of rejection of IDD that test H2 to H4 are similar in sign and significance to those reported in Models 12–15. We used Model 15 to estimate the effect of moderating variables at values corresponding to the mean plus one standard deviation. The results indicate that product market competition amplifies the effect of threat rigidity on R&D dynamism effect by 62 per cent, whereas relative absorptive capacity and relative financial slack weaken it by 58 per cent and 48 per cent, respectively.

Additional Robustness Checks

Alternative measures of R&D dynamism. We perform additional robustness checks to support our findings (Table VI). First, we check the robustness of our results to alternative measures of our dependent variable. We re-estimate the impact of rejection of IDD on R&D dynamism using different time windows (7 and 10 years) for measuring R&D dynamism. In Model 16, (dependent variable: R&D dynamism measured using a 7-year window), the coefficient of rejection of IDD is negative and significant $(-0.033,\ p < 0.05)$. In Model 17, (dependent variable: R&D dynamism measured using a 10-year window), the coefficient of rejection of IDD is negative and significant $(-0.037,\ p < 0.10)$. We also re-estimate the model using a measure of R&D dynamism based on the time varying conditional variance estimate derived from an autoregressive conditional Heteroskedastic (ARCH) time trend of R&D spending that the organization exhibits over the period of the study. We use this R&D investment trend to estimate the extent to which an organization's R&D spending diverges from the predicted R&D spending obtained using the ARCH model (Anderson and Tushman, 2001; Folta and O'Brien, 2004; Oriani and Sobrero, 2008). The calculation is performed using a two-step process. First, to make the

Table V. Moderation analysis

Variables	*Model 12*	*Model 13*	*Model 14*	*Model 15*
Rejection of IDD	0.022	−0.049**	−0.058**	−0.035*
	(0.015)	(0.015)	(0.017)	(0.017)
Rejection of IDD × Product Market Competition	−0.077**			−0.071**
	(0.019)			(0.020)
Rejection of IDD × Relative Absorptive Capacity		0.023**		0.022**
		(0.006)		(0.007)
Rejection of IDD × Relative Financial Slack			0.033**	0.033**
			(0.011)	(0.010)
Product market competition	−0.007	−0.022†	−0.021†	−0.007
	(0.014)	(0.011)	(0.011)	(0.014)
Relative absorptive capacity	−0.001	−0.008	−0.002	−0.008
	(0.005)	(0.006)	(0.005)	(0.006)
Relative financial slack	−0.001	−0.001	−0.007	−0.008
	(0.005)	(0.005)	(0.006)	(0.006)
Size	−0.011	−0.012	−0.013	−0.010
	(0.009)	(0.009)	(0.010)	(0.009)
Return on assets	−0.013	−0.017	−0.016	−0.015
	(0.039)	(0.041)	(0.040)	(0.040)
Leverage	0.001	0.002	0.001	0.001
	(0.006)	(0.006)	(0.005)	(0.005)
Dividends	0.071	0.067	0.055	0.058
	(0.074)	(0.072)	(0.072)	(0.069)
Sales volatility	0.250**	0.249**	0.247**	0.246**
	(0.045)	(0.045)	(0.044)	(0.043)
R&D intensity	−0.074	−0.087	−0.082	−0.075
	(0.106)	(0.105)	(0.106)	(0.106)
Research productivity	0.042	0.040	0.040	0.042
	(0.073)	(0.071)	(0.070)	(0.070)
Capital intensity	−0.018	−0.011	−0.015	−0.016
	(0.020)	(0.021)	(0.020)	(0.020)
State GDP	−0.111	−0.119	−0.124	−0.105
	(0.076)	(0.078)	(0.077)	(0.075)
Constant	1.641	1.630	1.691†	1.786†
	(0.983)	(1.016)	(1.000)	(0.979)
AIC	−11,866.4	−11,861.4	−11,866.7	−11,907.8
BIC	−11,587.3	−11,575.6	−11,587.7	−11,628.8
Number of observations	6671	6671	6671	6671

(Continues)

Table V. (Continued)

Variables	*Model 12*	*Model 13*	*Model 14*	*Model 15*
Number of firms	584	584	584	584
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
State FE	YES	YES	YES	YES
SIC × Year FE	YES	YES	YES	YES
Region × Year FE	YES	YES	YES	YES

Note: Robust standard errors clustered at state-level are in parentheses.
†Significant at 10%.
*Significant at 5%.
**Significant at 1%.

time-series of organization-level R&D expenditures stationary we transform the R&D investments to log changes in R&D for each year (Hamilton, 1994). Second, we use the transformed time-series to estimate the R&D investment trend over time using an ARCH model. To capture the unexpected changes in the R&D investments, we measure the time-varying volatility of R&D investments using the conditional variance estimates for each year obtained from the ARCH model, represented as follows:

$$r_{i,t} = \beta . r_{i,t-1} + \varepsilon_{i,t}$$

$$\mathrm{Var}\left(\varepsilon_{i,t}\right) = \mathrm{Var}_{i,t} = \alpha_0 + \delta . \varepsilon_{i,t-1} + \upsilon_t$$

where $r_{i,t}$ is the continuous changes in R&D investments of an organization i at time t, and $Var\left(\varepsilon_{i,t}\right)$ is the conditional variance of the error term $\varepsilon_{i,t}$. υ_t is independent and identically distributed. The conditional variance of the error term captures the volatility of an organization's R&D expenditures for each year. Finally, to deal with the skewed distribution of the conditional variance of organization R&D investments, we take the conditional variance estimate. Our results are robust to using these alternative measures. In Model 18 (dependent variable: R&D dynamism measured based on ARCH model), the coefficient of rejection of IDD is negative and significant $\left(-0.012,\ \mathrm{p} < 0.01\right)$.

Additional control variables. To assess the robustness of our findings, we re-estimated the main model by incorporating additional control variables: *Board Size* (number of members on a firm's board), *Board Independence* (proportion of independent outside directors), *CEO Tenure* (number of years the CEO has held office), *Institutional Ownership* (percentage of firm shares held by institutional investors), *Earnings Underperformance* (lower partial moment of the focal firm's earnings relative to the industry level benchmark), *Enforcement of Non-compete Covenants* (enforcement index as developed by Starr, 2019), and *State* Per Capita *Income* (log of per capita income). These variables were included in Model 19, where the dependent variable remains R&D Dynamism, as measured in the main models. In this specification, the coefficient for rejection of IDD remains negative and statistically significant (−0.026, $p < 0.05$), supporting the robustness of our results.

Impact of IDD *rejection on R&D intensity*. Threat rigidity theory posits that when faced with threats, firms tend to restrict information processing and tighten control, responding with cautious, familiar behaviours. We argue that the threat rigidity effect in R&D manifests as a reduction in R&D dynamism, that is, avoiding major changes, staying close to the status quo in the domain of R&D investments. The narrowing of the perceptual field and a reduced capacity to process new information and ideas often lead firms to avoid major adjustments in their R&D programmes such as allocating significant resources to novel, exploratory initiatives, or drastically cutting back on existing R&D activities. As firms tend to rely more on previously learned solutions and become less flexible in considering alternative approaches, they often maintain their R&D resources within established and familiar R&D processes. Overall, the threat rigidity effect suggests that firms become more rigid and cautious, which can affect decision-making in R&D.

It is important to note that this does not imply that firms would substantially cut R&D spending. In high-tech industries, R&D is central to a firm's identity, competitiveness and survival. For example, an influential survey by McKinsey found that research-intensive firms are generally very reluctant to cut R&D – even during crisis times (Musso et al., 2009). R&D-intensive firms are deeply familiar with the R&D process, and significant cuts could pose more risk than continuing investments in ongoing research trajectories. In fact, sticking with familiar R&D routines can lead to valuable outcomes: quicker development cycles and more predictable results. A well-understood R&D model can be standardized, scaled, and rolled out across different units and locations. Familiarity also helps manage uncertainty and makes forecasting returns more reliable. In sum, given that investing in R&D is familiar and seen as reducing risks (market, technological, competitive, etc.) for R&D-intensive, innovative firms, sticking with tried-and-tested levels of investment and familiar processes (i.e., lowering R&D dynamism rather than reducing R&D investment) is what threat rigidity theory would predict in our setting. Yet, to probe for a possible impact on R&D investment levels, we also re-estimated our baseline specification with R&D intensity (the ratio of R&D investments to total assets) as the dependent variable. In line with our arguments above, in Model 20, we do not find a significant relationship between rejection of IDD and R&D intensity (−0.001, $p > 0.10$). Our finding is also consistent with that of Flammer and Kacperczyk (2019), who performed a similar robustness check and found no significant change in R&D spending following the rejection of IDD.

DISCUSSION

Leveraging the behavioural lens of threat rigidity theory, this paper argues that the threat of knowledge loss gives rise to a threat rigidity effect in firms' R&D function, that is, reduces their R&D dynamism. It further argues that the dampening of R&D

dynamism is greater for firms more vulnerable to the threat of knowledge loss due to facing greater product market competition, yet lower for firms that can better respond to the threat due to having relatively higher absorptive capacity and/or greater financial slack. Using a sample of publicly listed US manufacturing firms tracked over a 15-year observation period from 1991 to 2015 and leveraging the quasi-natural experiment created by the staggered rejection of the Inevitable Disclosure Doctrine (IDD) across 14 US states, it empirically tests and finds support for the above hypotheses.

The study contributes to the literature on organizational responses to the threat of knowledge loss. Prior research has largely viewed this threat from an economics lens and has focused on rational strategic responses, such as contracts and incentives, that firms could adopt in order to mitigate the threat of knowledge loss (e.g., Agarwal et al., 2009; Carnahan et al., 2012; Flammer and Kacperczyk, 2019; Ganco et al., 2015; Gilson, 1999). Yet, by focusing primarily on strategic mitigation – how to prevent knowledge loss – prior work has largely sidestepped the question of what consequences the threat of knowledge loss has for organizational behaviour to begin with. Because countering measures alone cannot fully pre-empt or prevent the potential for knowledge leakage, understanding firm behaviour under threat and the specific behavioural mechanisms at play is critical. Threat rigidity theory, we argue, offers a robust theoretical framework for better understanding and managing organizations operating under threat of knowledge loss.

Threat rigidity effects are most likely to emerge in functions most directly impacted by a focal threat (Cyert and March, 1963; Staw et al., 1981). Given R&D serves as a primary channel of knowledge creation, it is especially susceptible to a potential threat of knowledge loss. A central contribution of this study is showing that the threat of knowledge loss dampens the R&D dynamism of firms and identifying the key mechanisms and moderators that govern this relationship. We do so by examining the fundamental question of how firms respond to the threat of knowledge loss, from a novel, threat rigidity, perspective (Connelly and Shi, 2022; Staw et al., 1981). In addition to identifying the direct effect of threat rigidity on R&D dynamism, we are also able to show the moderating effects of relative absorptive capacity and relative financial slack, driven by underlying mechanisms of restricted information processing and constriction of control. What is more, we demonstrate that a firm's vulnerability to the threat of knowledge loss, proxied by product market competition, also moderates the effect of threat rigidity on R&D dynamism. Overall, our study sheds new light on important behavioural, threat rigidity mechanisms firms must pay attention to and consider when managing their R&D under the threat of knowledge loss.

The paper also contributes to research on R&D dynamism (Kor and Mahoney, 2005; Mudambi and Swift, 2014; Pennetier et al., 2019; Swift, 2016). Dynamism is a key aspect of R&D, identified in the literature to have strong implications for innovation and performance outcomes (Mudambi and Swift, 2014; Pennetier et al., 2019; Swift, 2016). While this stream of research has started to examine the *consequences* of more versus less dynamic R&D investment strategies, there is a limited understanding of the *antecedents* of R&D dynamism (Bloom, 2007; Triguero and Córcoles, 2013). Triguero and Córcoles (2013) and Bloom (2007) have made first steps in addressing

Table VI. Additional robustness checks

Variables	*Model 16*	*Model 17*	*Model 18*	*Model 19*	*Model 20*
Rejection of IDD	−0.033*	−0.037†	−0.012**	−0.026*	−0.001
	(0.015)	(0.020)	(0.004)	(0.012)	(0.003)
Product market competition	−0.016	−0.015	−0.001	−0.021†	0.004*
	(0.015)	(0.016)	(0.004)	(0.011)	(0.002)
Relative absorptive capacity	−0.002	−0.010	−0.006*	−0.002	0.014**
	(0.006)	(0.007)	(0.003)	(0.005)	(0.003)
Relative financial slack	0.001	0.006	−0.003	−0.000	−0.004**
	(0.008)	(0.008)	(0.003)	(0.005)	(0.001)
Size	−0.010	−0.020	−0.004	−0.012	−0.024**
	(0.010)	(0.014)	(0.003)	(0.010)	(0.006)
Return on assets	0.025	−0.046	−0.006	−0.012	−0.079**
	(0.033)	(0.033)	(0.013)	(0.042)	(0.023)
Leverage	0.003	0.003	0.001	0.002	−0.000
	(0.003)	(0.004)	(0.002)	(0.006)	(0.001)
Dividends	0.099	0.132†	0.057	0.066	0.029
	(0.067)	(0.070)	(0.036)	(0.074)	(0.020)
Capital intensity	−0.085	−0.033	−0.053**	−0.012	0.040*
	(0.054)	(0.099)	(0.017)	(0.020)	(0.015)
Sales volatility	0.273**	0.140*	−0.003	0.250**	0.005
	(0.047)	(0.066)	(0.013)	(0.045)	(0.010)
R&D intensity	0.056	0.058	0.017	−0.091	
	(0.081)	(0.103)	(0.024)	(0.110)	
Research productivity	0.137	0.175†	−0.020	0.042	0.022
	(0.117)	(0.093)	(0.041)	(0.073)	(0.020)
State GDP	−0.165*	−0.122	−0.007	−0.122	0.022
	(0.069)	(0.083)	(0.026)	(0.078)	(0.023)
Earnings underperformance				0.006	
				(0.081)	
Board size				0.001	
				(0.001)	
Board independence				−0.016	
				(0.025)	
Institutional ownership				−0.014	
				(0.020)	
CEO tenure				0.000	
				(0.000)	

(Continues)

Table VI. (Continued)

Variables	*Model 16*	*Model 17*	*Model 18*	*Model 19*	*Model 20*
Non-compete enforcement				0.008	
				(0.018)	
State per-capita income				−0.004	
				(0.072)	
Constant	2.222*	1.741†	0.312	1.720	−0.051
	(0.886)	(0.996)	(0.344)	(1.142)	(0.292)
AIC	−10,629.2	−8296.6	−24,058.4	−11,851.1	−29,791.0
BIC	−10,354.7	−8060.2	−23,779.3	−11,572.1	−29,498.3
Observations	5041	3710	6671	6671	6671
Number of firms	464	395	584	584	584
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors clustered at state level are in parentheses.
†Significant at 10%;
*Significant at 5%;
**Significant at 1%.

this gap by showing that a firm's past innovation activities are an important determinant of its current R&D activities and that higher economic uncertainty makes firms more cautious when adjusting their R&D, respectively. This paper contributes to this nascent line of research by arguing and offering evidence that the dynamism of R&D investments is not driven only by 'rational actor' strategic/economic considerations but also reflects significant behavioural differences in how firms respond to perceived threats. Specifically, we show that a dampening of R&D dynamism emerges as a behavioural threat rigidity effect in response to an increase in the threat of knowledge loss. By integrating insights from threat rigidity theory with research on R&D dynamism, this paper extends our understanding of how firm behaviour under threat shapes the dynamics of R&D investment.

In addition, this paper broadens the scope of threat rigidity theory to incorporate a new kind of external threat as well as a new kind of threat rigidity outcome. Previous management research has predominantly focused on threats that pose direct harm to firms, such as regulatory bans or shrinking markets (Bellavitis et al., 2022; Shimizu, 2007). Shi et al. (2018) recently began extending the scope of threat rigidity theory to the study of indirect threats, which may not cause direct harm but can still alarm top managers and have implications for organizational behaviour. We further this approach by leveraging threat rigidity theory to explore the impact of another indirect threat: rejection of IDD. Although rejecting IDD does not directly lead to a loss of knowledge, it weakens a firm's ability to prevent the departure of knowledge workers, thereby increasing its future risk/likelihood of knowledge loss. We also examine a novel threat rigidity outcome: R&D dynamism. While earlier work on threat rigidity theory has examined the effect of threats on growth opportunities (Shi et al., 2018), turnaround performance (Barbero et al., 2020), and expansion in retail (Fay et al., 2022), among others, our study is the first to theorize and show evidence of a threat rigidity effect affecting the R&D dynamism of firms. In doing so, we offer a more nuanced understanding of how behavioural constraints that emerge under perceived threat can shape firms' R&D trajectories over time, highlighting the relevance of threat rigidity theory for innovation research.

Implications for Managers and Policymakers

Our findings show that the effect of the threat of knowledge loss created by the rejection of IDD is quite significant – a reduction of a firm's R&D dynamism by 18 per cent–24 per cent, on average. These results carry important implications for policymakers, indicating that regulations aiming to balance employers' interest in protecting proprietary knowledge with knowledge workers' rights to freely pursue their career choices can have a rather sizable impact on the dynamism of firms' R&D investments. Importantly, the dampening effect of IDD rejection on R&D dynamism is not uniform: it is more pronounced in firms that are more vulnerable to the threat of knowledge loss, while it is less severe in firms with greater absorptive capacity and/or financial slack. The differential effect of the rejection of IDD on R&D dynamism suggests that policies and regulations that influence knowledge protection and mobility can indirectly shape the distribution of innovative activity across firms, with potential long-term implications for industry-level technological dynamism and competitiveness.

From a managerial perspective, our findings suggest that firms can buffer against the constraining effects of the threat of knowledge loss by investing in differentiated, 'sticky' product or service offerings to reduce direct competition, enhancing organizational absorptive capacity, and accumulating greater financial slack. These measures can enable firms to sustain dynamic R&D investments even when exposed to the threat of losing knowledge in the future. Overall, the study underscores the interplay between regulatory environments, firm capabilities, and behavioural responses to perceived threats, emphasizing the importance of proactive managerial and policy actions to preserve R&D dynamism in knowledge-intensive firms.

Limitations and Future Research

This study opens multiple exciting avenues that can serve as a powerful springboard for future research. Future research could build on the theoretical and empirical foundations set forth by our work to further advance scholarly understanding of the link between threat rigidity and R&D dynamism. For one, future research could explore what factors determine the duration of the threat rigidity effect on firms' R&D dynamism as well as what factors affect the evolution of its magnitude and duration over time. Moreover, while our study examines R&D dynamism at the firm level, future research could examine whether and how threat rigidity also manifests at the R&D project level as prior research on threat rigidity suggests that threat rigidity effects do not operate only at the organizational level but can also manifest at more granular levels, including group and individual levels (Staw et al., 1981). Such studies could investigate, for instance, the specific characteristics of R&D projects, such as technological complexity or strategic importance, that make them more susceptible to threat rigidity as a result of restriction of information processing and constriction of control. In addition, examining threat rigidity at the inventor level could provide critical insights into how individual-level behaviour under threat shapes R&D dynamism. By investigating threat rigidity effects in the R&D function at multi-levels – from projects to individual inventors – future research could provide a more nuanced understanding of how firms adjust their R&D dynamism over time when faced with the threat of knowledge loss.

Future studies could also investigate further organizational-level factors that could potentially moderate the effect of threat rigidity on R&D dynamism. For instance, future research could examine how the extent to which managers are held liable for R&D outcomes may affect their information processing and constriction of control which, in turn, modulates the effect of threat rigidity on R&D dynamism. Such research can shed new light on how an organization's degree of tolerance of failures (Shepherd et al., 2011) impacts how managers adjust R&D investments when operating under threat of knowledge loss. In addition, future research could investigate whether and how the threat rigidity effect varies with factors, other than absorptive capacity, that enhance a firm's attractiveness to knowledge workers (Lee et al., 2017) and whether and when such factors complement the effect of absorptive capacity to an extent that can fully mitigate/offset the rigidity effect of the threat of knowledge loss on R&D dynamism. What is more, future research could examine how differences in the enforcement of intellectual property rights (Somaya, 2012) or the distribution of intellectual property rights among firms in an industry (Asija et al., 2024) may shape firms' threat rigidity response. Such research would enhance our knowledge of factors, other than product market competition identified by our study, that increase a firm's vulnerability to the threat of knowledge loss. Overall, this study can be viewed as a powerful call for future research that would further advance our understanding of firms' R&D dynamism by fostering a deeper examination of the behavioural foundations of firms' R&D function.

Our study also has limitations future research could address. For one, the generalizability of our findings could be affected by contextual differences. While we provide robust empirical evidence using data of publicly listed US manufacturing firms, future research could examine the extent to which our hypotheses and findings generalize to other settings. For example, future studies could examine whether and when geo-cultural differences in job-hopping and/or the organization of R&D departments affect the impact of the threat of knowledge loss on the R&D dynamism of firms. Future research could also examine whether the generalizability of our results might be influenced by the ownership structure of firms, as it determines how different firms are regulated in terms of mandated disclosures that their rivals can exploit to the potential detriment of the firm (Doshi et al., 2013). Moreover, the threat of loss of knowledge may affect public and private firms differently as their risk profiles may also be different. Future research could probe the extent to which our arguments and results generalize to private firms, non-profits, and hybrid firms.

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NOTES

[1] For instance, the Administration Strategy on Mitigating the Theft of U.S. Trade Secrets (2013) report discusses the case of a former employee of an automotive company who copied 4000 documents on the design of engine-transmission and electric power supply systems and took these documents to the new job.
[2] PepsiCo, Inc. v. Redmond, 54 F.3d 1262, 1272 (7th Cir. 1995).
[3] IBM v. Papermaster, No. 7:08-cv-09078, 2008 U.S. Dist. LEXIS 95516.
[4] Whyte v. Schlage Lock Co., 101 Cal. App. 4th 1443 (2002).
[5] For the mapping of states to regions, see Bureau of Economic Analysis: https://www.bea.gov.
[6] Controlling for firm fixed effects subsumes state fixed effects, and thus state fixed effects are not included separately in the regression.

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