Generalist Managers and Firm Innovation Worldwide: The Role of Innovation-Specific Institutions

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Abstract

We examine how generalist CEOs influence innovation outcomes across 25 countries from 2001 to 2019. We assemble a novel, extended dataset of generalist CEOs and find that generalist CEOs positively affect innovation, particularly in countries with abundant innovation resources. This finding aligns with the notion that generalist CEOs leverage their broad knowledge and cross-industry experience to integrate resources across institutional environments, thereby fostering innovation activities. However, in countries with stricter patent systems, the increased need for specialized knowledge and resources limits the value that generalist CEOs can contribute, leading to decreased innovation activities. Our research highlights how institutional environments shape the efficacy of CEO human capital in driving innovation, thus offering insights for the design of innovation policies that maximize leadership potential across different institutional contexts.

Keywords: *Generalist CEO; Human capital; Managerial ability; Innovation; Innovation-specific institution; Stringency of patent systems; Availability of innovation resources*

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1. Introduction

In today's rapidly evolving and highly competitive global environment, what enables generalist CEOs to effectively drive innovation? This study explores how specific institutional environments shape the effectiveness of these CEOs in fostering innovation. Generalist CEOs are recognized for their broad knowledge and cross-industry experience, and can navigate the inherent uncertainty and complexity of innovation initiatives (Custódio et al., 2019; Chen et al., 2021). However, empirical findings regarding the impact of generalist CEOs on innovation remain inconclusive. Most studies in the U.S. market suggest a beneficial effect (Custódio et al., 2019; Lin et al., 2021), while others, including those conducted in less developed markets, suggest more complex or even negative outcomes (Koo, 2019; Agnihotri and Bhattacharya, 2021). These divergent findings may arise from insufficient consideration of the influence of firms' external institutional environments on innovation.

Although the literature highlights the pivotal role of the institutional environment in shaping firms' strategies (Schout, 1991; Peng, 2003), its effect on the strategic value of CEOs' human capital in driving innovation remains underexplored (Glaeser and Lang, 2024). Our study bridges this gap by examining how innovation-specific institutional factors influence the relationship between generalist CEOs and innovation. We focus on two institutional features that can significantly affect innovation outcomes: innovation resources and patent system stringency (Guan and Chen, 2012; de Saint-Georges and de la Potterie, 2013; Freitas et al., 2013).

We propose that the availability of innovation resources enhances the impact that generalist CEOs have on innovation activities. Countries with a diverse talent pool, numerous research institutions, and strong university–industry collaborations provide firms with a richer knowledge base compared with those where such resources are more constrained (Guan and Chen, 2012; Freitas et al., 2013; Lepori et al., 2015). By capitalizing on these institutional advantages, generalist CEOs can increase the success of innovation activities. Their broad strategic skills enable them to leverage external resources and connections, thus promoting the exchange of ideas and cross-fertilization, which often leads to creative solutions and breakthrough innovations (Cohen and Levinthal, 1990; Carpenter et al., 2004).

The stringency of the patent system can affect how generalist CEOs drive innovation (Kim and Valentine, 2021; Hegde et al., 2023; Dyer et al., 2024). Establishing novelty and non-obviousness in innovation becomes more challenging under more stringent patent systems, which demand a greater understanding of specific technical domains (Cohen et al., 2019; Hou et al., 2023). Generalist CEOs, who typically lack such specialized knowledge, may struggle to comprehend the intricacies of innovations, and thus they may be discouraged from pursuing innovative solutions. Unlike specialist CEOs, whose long-term wealth is more closely tied to their current firms, generalist CEOs typically enjoy broad career opportunities (Mishra, 2019) and may pursue alternative options if their current firms' long-term growth prospects diminish. Consequently, a high patentability threshold may lead generalist CEOs to be more conservative in their innovative efforts, as the relative costs, such as those related to potential patent failure and forgone career opportunities, may outweigh potential benefits. Thus, we hypothesize that the stringency of patent systems negatively affects the relationship between generalist CEOs and their firms' innovation activities.

We test these hypotheses using hand-collected biographical profiles of CEOs across 25 countries. Our final sample comprises 125,264 firm-CEO-year observations for 28,076 unique CEOs across 18,334 distinct firms from 2001 to 2019. Building on the approach of Custódio et al. (2013), we develop a novel international measure of the general managerial ability index (*GAI*) using CEO biographical data from countries worldwide.[1] Drawing on the innovation

[1] International *GAI* data are available at https://sites.google.com/view/myresearch-2024/data/general-managerial-ability-index.

literature (e.g., Fagerberg and Srholec, 2008; Yang and Sonmez, 2013; Fagerberg, 2017; Cirillo et al., 2019), we develop two novel indices to encapsulate innovation-specific institutional features. The first index assesses the availability of innovation resources. This is constructed based on a principal component analysis of six country-level measures: *University–Industry Collaboration*, *Quality of Research Institutions*, *Availability of Scientists and Engineers*, *Researchers in R&D*, *Public Investment in R&D*, and *International Co-inventors*. The second index measures the stringency of the patent system, and is formulated via a principal component analysis of three country-level measures: the patent protection index (*PPI*), the patent enforcement index (*PEI*), and *Patent Office Strictness*. [2]

We find a positive and significant relationship between *GAI* and corporate innovation in the international setting. Economically, a one standard deviation increase in *GAI* is associated with a 2.5% increase in patents and a 4.0% increase in citations. These findings contribute to the literature on generalist CEOs and innovation by extending their applicability to an international context. In addition, we observe that the positive influence of generalist CEOs on innovation activities increases with the availability of innovation resources in the institutional environment. An interquartile shift in the level of available innovation resources is associated with a 6.5-fold (2.6-fold) increase in the effect of *GAI* on firms' patent counts (forward citations). This increase in innovative output suggests that generalist CEOs can effectively span boundaries and leverage external resources to catalyze innovation. We also observe a relative decline in the innovation activities of firms led by generalist CEOs in countries with stringent patent systems. An interquartile shift in patent system stringency is associated with a 4.3-fold (1.6-fold) decrease in the effect of *GAI* on firms' patent counts (forward citations). This finding

[2] Country-level datasets on innovation-specific institutions are available at https://sites.google.com/view/myresearch-2024/data/innovation-specific-country-institution.

suggests that the rigidity of strict patent systems reduces the value that generalist CEOs contribute to their firms, leading to a relative decline in innovation activities.

We conduct several supplementary analyses to assess the sensitivity of our primary inferences. These include investigating the effects of individual components of innovation-specific institutions and general managerial ability, and using alternative measures of innovation and general managerial ability. To alleviate endogeneity concerns when comparing heterogeneous firms, we conduct numerous robustness tests, including: (1) using a propensity score matched sample; (2) controlling for trade secrets protection, CEO talent, firm–CEO fixed effects, and other high-dimensional fixed effects; and (3) using a two-stage least squares (2SLS) analysis. The positive (negative) effects of innovation resource availability (patent system stringency) on the association between *GAI* and corporate innovation remain unchanged after these tests.

Our study makes several contributions to the literature. First, it extends the literature on CEO human capital and innovation by revealing how innovation-related institutional factors can affect the generalist CEO–innovation relationship. We propose that the interplay among the availability of innovation resources, the design of the patent system, and the value that generalist CEOs bring to innovation endeavors impacts innovation outcomes. Different from prior studies that examine the role of institutional environment or managerial abilities in isolation,[3] we assess and provide insights into their interrelationships. We also inform the literature on how patent system designs can stimulate or discourage innovation by identifying

[3] International studies document that firm innovation is directly influenced by various country-level institutional factors, such as credit market domination (Hsu et al., 2014), financial market development (Tadesse, 2006; Hsu et al., 2014), bankruptcy codes (Acharya and Subramanian, 2009), intelligence property rights protection (Lerner, 2009; Zhong, 2018), investor protection (Belloc, 2013; Xiao, 2013), and policy uncertainty (Bhattacharya et al., 2017).

how patent system stringency impacts the value of human capital in innovation (Kim and Valentine, 2021; Hegde et al., 2023; Dyer et al., 2024).[4]

Second, our work contributes to the accounting literature on innovation management. Unlike much of the literature, which focuses on how managers design control systems or on the productivity of individual inventors (e.g., Abernethy and Brownell, 1997; Chenhall et al., 2011; Grabner et al., 2018; Glaeser et al., 2023; see also Glaeser and Lang, 2024 for a comprehensive review), we consider different types of CEOs and assess their abilities to leverage institutional environments and drive firm innovation. Our findings indicate that in countries with extensive resources for innovation, generalist CEOs can foster innovation by leveraging their broad expertise and experience to effectively extract, consolidate, and utilize these resources. However, we find that generalist CEOs' positive effect on innovation diminishes if patent systems are stricter, as greater specialized knowledge is then required (Cohen et al., 2019; Hou et al., 2023). Our study extends the findings in the accounting literature indicating that flexible management control systems effectively encourage innovation (Glaeser and Lang, 2024) by revealing how institutions shape the effectiveness of CEOs in driving innovation.

Third, our study adds to the literature on the comparative value of generalist versus specialist CEOs. While some studies suggest that generalist rather than specialist CEOs are preferred in the labor market (Custódio et al., 2013; Ma et al., 2021), the preference for generalist CEOs remains a topic of debate (Gounopoulos and Pham, 2018; Custódio et al., 2019; Li and Patel, 2019; Mishra, 2019; Betzer et al., 2020). Unlike prior studies that focus on a single country, and particularly the U.S., we examine a diverse pool of CEOs internationally,

[4] For example, Kim and Valentine (2021) find that mandatory patent disclosures decrease innovation for firms whose disclosures are exposed to competitors, suggesting that these disclosures incur proprietary costs for the disclosing firms. Dyer et al. (2024) show that patents approved by examiners who are notably more lenient with respect to patent disclosure quality requirements contain disclosures of significantly lower quality and lead to considerably less follow-on innovation. Hegde et al. (2023) report that patents receive more and faster follow-on citations following mandatory disclosures, indicating greater technology dissemination.

thus offering a more nuanced assessment of the impact of generalist CEOs on corporate policies and outcomes. To the best of our knowledge, our study is the first to explore the global economic impact of the managerial abilities of CEOs and to suggest that the benefits of hiring generalist versus specialist CEOs depend on country-level institutions.

Our study offers valuable insights for policymakers, regulators, and practitioners. Our finding that the influence of managerial human capital on firm innovation is contingent on the design of innovation policy instruments and patent regulation underscores the need for policymakers to consider these complexities. We document that these institutional features affect executive incentives and behaviors *ex ante*, depending on a CEO's skill set, experience, and labor market opportunities. Our research thus provides practical guidance to managers on how managerial human capital and strategies should be aligned with specific institutional settings.

The remainder of this paper is organized as follows. Section 2 introduces our hypotheses. Section 3 details the research design. Section 4 presents the results from the baseline regressions and various robustness tests. We address endogeneity concerns in Section 5. Finally, Section 6 offers our concluding remarks.

2. Related Literature and Hypothesis Development

2.1. Board considerations in hiring generalist versus specialist CEOs

CEOs' general managerial ability represents their transferable human capital across firms and industries (Becker, 1962). Although firms increasingly choose generalist CEOs with broad managerial skills (Custódio et al., 2019), firm-specific human capital remains valuable (Coff and Kryscynski, 2011), and executives often need to develop specialized expertise (Baruch and Vardi, 2016). The literature suggests that a firm's strategic objectives influence whether the board of directors hires a generalist or specialist CEO. Generalist CEOs are typically preferred in uncertain and dynamic business environments due to their ability to navigate complex situations. This is often the case in larger firms, conglomerates, and firms experiencing industry shocks, operational distress, or increased competition, as generalist CEOs' broad skill sets enable them to perform challenging tasks effectively (Custódio et al., 2013; Mishra, 2014; Brockman et al., 2016; Betzer et al., 2020; Ma et al., 2021). In contrast, specialist CEOs may be more suitable for firms requiring in-depth expertise in specific areas or specialized knowledge (Mueller et al., 2021). The competitive nature of the executive labor market also influences boards' decisions. Generalist CEOs represent scarce managerial human capital, and thus firms may compete for them to maximize firm value net of compensation costs (Betzer et al., 2020).

Despite the extensive literature examining CEO selection and its implications for firm innovation, the main focus is on the internal factors driving the selection and effectiveness of generalist versus specialist CEOs. The role of external institutional factors in shaping the effectiveness of these types of CEO remains underexplored. Our study addresses this gap by examining how generalist CEOs interact with national innovation resources and regulatory environments to drive innovation, thereby providing new insights into the complex interplay between CEO characteristics and external institutional factors.

2.2. Generalist CEOs, innovation-specific institutions, and firm innovation

Previous studies in the U.S. market show a positive relationship between generalist CEOs and innovation (Custódio et al., 2019; Lin et al., 2021). These studies suggest that the ability of generalist CEOs to drive corporate innovation stems from their capacity to integrate resources and thus effectively address complex innovation challenges. However, research in less developed markets suggests a more nuanced or negative relationship. For instance, Agnihotri and Bhattacharya (2021) indicate that in emerging markets like India, generalist

CEOs face greater resource and institutional constraints, resulting in lower investment in innovation.

These mixed findings imply that the effectiveness of generalist CEOs in promoting innovation depends on both their personal capabilities and the availability of supportive resources within the institutional environment. Such resources can be an important determinant of innovation outcomes. Guan and Chen (2012) highlight that the availability and quality of resources such as research and development (R&D) investments, skilled labor, and technological infrastructure are essential for encouraging firm innovation. They enable firms to develop new products, processes, and technologies, which can lead to competitive advantages and economic growth. Freitas et al. (2013) further emphasize the importance of innovation resources by showing how the presence of a robust R&D ecosystem that includes collaborations with universities and research institutions enhances a firm's innovation capabilities. They find that firms with greater access to diverse innovation resources are better positioned to undertake complex and high-risk innovation projects.

We propose that the availability of innovation resources enhances the influence of generalist CEOs on innovation activities. Top managers rationally make strategic choices within the constraints of a given institutional framework (Peng et al., 2009). This perspective is particularly relevant in innovation-specific institutional environments, such as those involving innovation resources and patent activities, which can significantly influence managerial efforts and innovation outcomes (Shu et al., 2015; Kraft and Bausch, 2018). Countries with abundant innovation resources typically feature a diverse talent pool, numerous research institutions, and strong university–industry collaborations (Freitas et al., 2013; Lepori et al., 2015). Firms in these countries benefit from a richer knowledge base than firms in countries with limited innovation resources (Guan and Chen, 2012).

By leveraging resources from such institutional environments, generalist CEOs can increase the success of innovation activities. The broad strategic skill sets of generalist CEOs enable them to utilize external resources and connections to facilitate the exchange of ideas and cross-fertilization, often leading to creative solutions and breakthrough innovations (Cohen and Levinthal, 1990; Carpenter et al., 2004). When innovation resources are abundant, generalist CEOs can span an extensive range of resources by leveraging their extensive networks and attract exceptional individuals to drive the innovation process. However, in environments where resources for innovation are limited, firms may find it advantageous to appoint specialist CEOs who can actively engage in innovation activities themselves. Although a specialist CEO may not contribute to the broader vision of the company to the same extent as a generalist CEO, their direct involvement in innovation can be essential in resource-constrained environments. Thus, we propose that generalist CEOs, with their adept resource management skills and extensive networks, are likely to excel in fostering innovation within resource-rich environments. Our first hypothesis is thus stated as follows:

H1 The availability of innovation resources at the country level positively influences the relationship between generalist CEOs and their firms' innovation activities.

Patent offices apply standards covering industrial applicability, novelty, and inventiveness to determine whether patents are eligible for protection. The patent system plays a crucial role in influencing firms' patent activities by providing a legal framework that grants inventors exclusive rights to their inventions for a limited period. This exclusivity incentivizes innovation by allowing firms to recoup R&D investments and profits from their inventions (Van Pottelsberghe de la Potterie, 2011). However, the stringency of such systems varies considerably across countries, leading to concerns about how the quality of a patenting process can affect innovation activities (de Saint-Georges and de la Potterie, 2013). Integral to these differences are variations in the judicial environment related to the patenting process (Cuny et al., 2022; Dyer et al., 2024; Kim et al., 2024), as well as intellectual property protection and enforcement across countries (e.g., La Porta et al., 1998; Fang et al., 2017). Patent protection allows firms to prevent others from using their patented technologies without consent, thus encouraging investment in new technologies and processes. Enforcement mechanisms like infringement lawsuits and post-grant proceedings enable challenges to the validity of patents, with their effectiveness hinging on the judicial system's quality. Thus, examining how the design of patent systems impacts the role of managerial human capital in innovation activities is crucial for promoting a sustainable competitive advantage and economic growth.

Previous studies provide some evidence on how the design of the patent system can stimulate or discourage innovation (Kim and Valentine, 2021; Hegde et al., 2023; Dyer et al., 2024). For example, Dyer et al. (2024) examine the effect of patent disclosure quality on follow-on innovation. They show that variations in patent examiner stringency affect disclosure quality, and that detailed patent disclosures encourage a broader geographic and technological diffusion of knowledge. Our research complements these studies, which focus on the disclosure aspect of patent systems, by highlighting the influence of patent system stringency on the value of human capital for innovation activities.

The design of a patent system, and particularly its level of stringency, can significantly influence how generalist CEOs drive innovation. As patent systems become more stringent, establishing novelty and non-obviousness in innovation becomes increasingly challenging. Stricter patent systems necessitate a profound understanding of specific technical domains (Cohen et al., 2019; Hou et al., 2023). Generalist CEOs, who typically lack specialized technical knowledge, may struggle to grasp the complexities of innovations, potentially dissuading them from pursuing innovative initiatives. Additionally, generalist CEOs can often obtain more external career opportunities than specialist CEOs, whose long-term wealth is closely tied to their current firms' success (Mishra, 2019). Thus, if the long-term growth prospects of their current firms appear limited, generalist CEOs may pursue alternative opportunities. A high patentability threshold can then lead generalist CEOs to take a conservative approach to innovation. The relative costs, including the potential failure to secure patent protection and the opportunity costs associated with their career advancement, may outweigh the perceived benefits. This dynamic can ultimately reduce generalist CEOs' willingness to engage in innovative efforts.

Thus, we hypothesize that the stringency of the patent system negatively affects the relationship between generalist CEOs and their firms' innovation activities. We therefore state our second hypothesis as follows:

H2 The stringency of the patent system at the country level negatively affects the underlying relationship between generalist CEOs and their firms' innovation activities.

3. Research Design

3.1. Sample and data

We collect data from several sources. We start by identifying firms in Worldscope with non-missing financial data during our sample period of 2001–2019. We exclude firms in the financial (SIC codes 6000–6999) and utility (SIC codes 4900–4999) industries because they are highly regulated. Next, we merge the Capital IQ People Intelligence database with Worldscope to identify the CEOs of publicly listed companies from 2001 to 2019.[5] We identify 34,222 CEOs associated with 21,024 publicly listed firms and 139,434 firm-CEO-year observations. We then manually match the executives with biographical profiles sourced from the Capital IQ People Intelligence database, BoardEx, and the Amadeus database from Bureau

[5] Our sample period begins in 2001 because data for non-U.S. countries are relatively limited before this year, even though the Capital IQ People Intelligence database has been collecting data since 1998. Our sample ends in 2019 (and therefore patent data conclude in 2020 as we use one-year-forward innovation variables) to mitigate the truncation bias of patent data resulting from the lag between the application year and the actual grant year of patents.

van Dijk (BvD). Additional profile information is obtained where necessary via Google searches. We exclude CEO profiles with unidentified starting years in the corresponding positions when constructing *GAI*.[6] We therefore obtain a final sample of 29,192 (85.3%) CEOs associated with 19,096 (90.8%) unique firms and 130,393 (93.5%) firm-CEO-year observations, for which we construct the *GAI* measure.

Next, we collect firm-year patent data from BvD's Orbis patent database, which covers global patent applications and sourcing data from over 40 patent authorities (Tsang et al., 2019, 2021). For patent applications filed in more than one patent office, we include only the first application to avoid double counting.[7]

Data including SIC codes, business segments, and financial figures are gathered from Worldscope and country-level variables are collected from the World Bank, World Economic Forum global competitiveness reports, the OECD database, and previous international studies (e.g., Park, 2008; de Saint-Georges and de la Potterie, 2013; Lippoldt and Schultz, 2014; Isidro et al., 2020; Papageorgiadis and Sofka, 2020). We exclude small countries with fewer than 100 observations (Bushman and Piotroski, 2006; Kim et al., 2016). Finally, we exclude countries without data on innovation-specific institutions. Table 1 provides details of the sample attrition. Our final sample consists of 125,264 firm-CEO-year observations for 18,334 unique firms and 28,076 unique CEOs located in 25 countries, over a sample period of 19 years (2001–2019).

3.2. Variable construction

3.2.1. GAI

We construct an index of CEOs' general managerial abilities, *GAI*, based on their biographical profiles and lifetime work experience before they assumed their current CEO

[6] In robustness checks, we incorporate CEO profile information that lacks a starting year into the construction of *GAI* by designating the missing starting year as 2000, the year prior to our sample start year. Our findings remain consistent when using this alternative *GAI* measure.
[7] Our inferences remain unchanged when we include patents subsequently filed in other countries in the firm-year patent count.

positions.[8] Following Custódio et al. (2013), we derive *GAI* from a principal component analysis of five measures that capture the general human capital of CEOs in various dimensions. Using a single principal factor of five proxies enhances the power of the regression tests by avoiding problems of multicollinearity and measurement error that can arise when these variables are used individually in the same regression model (Custódio et al., 2013). The five measures are *Number of Positions*, *Number of Firms*, *Number of Industries*, *CEO Experience*, and *Conglomerate Experience*. Appendix A provides details of these measures.

The results of our principal component analysis of the proxies for general managerial ability are presented in Panel A of Internet Appendix I. We find that only the first principal factor has an eigenvalue exceeding 1 (2.752).[9] Consistent with the results of Custódio et al. (2013), all five variables exhibit positive loadings, indicating their positive correlations with *GAI*. Thus, a higher *GAI* value represents greater general managerial ability, while a lower value indicates more specialized managerial ability. *GAI* assigns approximately equal weights to the number of positions, firms, and industries, and a lower weight to previous CEO experience and conglomerate experience. Thus, the *GAI* of CEO_i in year t is calculated as follows:

$$GAI_{i,t} = 0.513\ \textit{Number of Positions}_{i,t} + 0.527\ \textit{Number of Firms}_{i,t} + 0.552\ \textit{Number of Industries}_{i,t} + 0.371\ \textit{CEO Experience}_{i,t} + 0.130\ \textit{Conglomerate Experience}_{i,t} \quad (1)$$

The index is standardized to have a mean of 0 and a standard deviation of 1.[10]

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[8] We construct *GAI* based on CEOs' lifetime work experience in both privately held and publicly listed companies. As a robustness check, we also construct a general managerial ability measure using only CEOs' experience in publicly traded firms and rerun our regression tests. Our untabulated results show that our inferences remain unchanged.

[9] The components with eigenvalues above 1 have greater explanatory power than any single original proxy. The eigenvalue of the second factor is less than 1.

[10] We standardize *GAI* in our firm-CEO-year population, which is larger than our regression sample. Thus, the mean of *GAI* is not 0, and its standard deviation is not 1 in our regression sample. This is consistent with the statistics of *GAI* in previous studies on general managerial ability (e.g., Custódio et al., 2019). We obtain similar results when we standardize *GAI* within our sample.

We conduct a series of tests to validate the reliability of our global *GAI* measure. First, we compare the correlation between our measure and that of Custódio et al. (2013). We find that the indices are strongly correlated, with a Pearson correlation coefficient of 0.72.[11] To further validate our measure, we investigate the relationship between *GAI* and innovation based on a U.S. subsample, using both our *GAI* measure and that of Custódio et al. (2013). The regression results are available in Internet Appendix II. The findings indicate that both measures of general managerial ability are positively associated with firm innovation for the U.S. sample, further reinforcing the validity of our global *GAI* measure.[12]

3.2.2. Innovation measures

In line with the literature on innovation (e.g., Zhong, 2018; Tsang et al., 2021), we use two patent-based measures in our main analyses to capture corporate innovation: patent counts (*PATENT*) and citation counts (*CITATION*).[13] *PATENT* is the natural logarithm of one plus the

[11] We construct our *GAI* measure based on CEOs' past work experience in both publicly traded and privately held firms worldwide up to 2019, using information collected from multiple sources, including Capital IQ, BoardEx, BvD Amadeus database, and Google searches. The *GAI* measure of Custódio et al. (2013) is constructed based only on CEOs' past work experience in publicly traded firms up to 2007 using data collected from BoardEx for Standard and Poor's 1500 firms. The differences in the data sources and coverage of CEO profiles may explain why we do not observe a stronger correlation between our measure of *GAI* and that of Custódio et al. (2013).

[12] We also compare our *GAI* measure with the managerial ability measure developed by Demerjian et al. (2012), which first estimates total firm efficiency, defined as a firm's ability to generate more revenue from a given set of inputs, and then uses the component of total efficiency attributable to the manager to define managerial ability within a U.S. sample. The correlation coefficient between our *GAI* measure and the managerial ability measure of Demerjian et al. (2012) is 0.028. Similarly, the correlation between the measure of Demerjian et al. (2012) and that of Custódio et al. (2013) is 0.06. This finding aligns with the notion that our *GAI* measure captures the generality of CEOs' human capital rather than solely focusing on their profit creation ability as proxied by the managerial ability measure of Demerjian et al. (2012). To alleviate the concern that the correlation between our *GAI* measure and that of Demerjian et al. (2012) may confound our findings, we construct a global managerial ability measure following their approach and include its interaction with our innovation-specific institutional measures in the regression model as a robustness check. The results (not tabulated) indicate that our findings remain unchanged.

[13] One limitation of using patents to measure innovation is that not all new innovations are patented (Horstmann et al., 1985). Additionally, firms sometimes consider alternative methods of protecting innovation, such as trade secrecy, as more important than patents, as indicated by the Community Innovation Survey and the Business R&D and Innovation Survey (e.g., Arundel and Kabla, 1998; Arundel, 2001; Glaeser, 2018). However, despite these limitations, patents are the most frequently used measure of innovation in international studies because their standardized nature facilitates comparisons across various jurisdictions. Acs et al. (2002, p. 1080) show that "patents provide a fairly reliable measure of innovative activity." In Section 4.4, we also use input-oriented innovation measures (i.e., R&D expenditure and patent efficiency) in our additional analysis. However, we exercise caution when using these measures in an international context, due to differences in accounting standards between countries regarding the accounting treatment of R&D activities (Tsang et al., 2021). In addition, to address the concern that our findings on firms' patenting activities may not result from increased innovation but

number of patent applications a firm filed in a given year that were eventually granted, reflecting the level of innovation output. To more accurately capture the timing of innovation activity (Griliches et al., 1986), we calculate the number of patents based on the application year rather than the year a patent is granted. *CITATION* represents the natural logarithm of one plus the number of citations received by patents filed by a firm in a given year that were eventually granted, which measures the influence or importance of patents. To mitigate endogeneity concerns, we follow recent innovation research (e.g., Zhong, 2018) and use one-year-forward *PATENT* and *CITATION*.

3.2.3. Innovation-specific institutions

The literature highlights two critical elements that significantly influence a country's innovation performance: innovation resource availability and patent system stringency (Fagerberg and Srholec, 2008; Yang and Sonmez, 2013; Fagerberg, 2017; Cirillo et al., 2019). Innovation resources encompass access to knowledge and skill pools, public investment in innovation, and the attraction of foreign innovation (Fagerberg and Srholec, 2008; Fagerberg, 2017; Cirillo et al., 2019). Patent system stringency represents the strictness of the national system in legislating patent laws, enforcing patent protection, and administering patent filing and granting procedures (Yang and Sonmez, 2013). To identify the relevant indicators, we use Atkinson's (2020) national innovation system (NIS) framework and conduct an extensive literature review to identify innovation-specific country institutions that affect firm innovation. We select country variables that are the core elements of the NIS because they directly influence the creation, development, and diffusion of new technologies and ideas, and are often viewed as central drivers of innovation within a country (Nelson, 1993; Lundvall, 2007; Shearmur, 2011). In addition, we focus on regulatory environment variables within the NIS

rather from a shift from trade secrecy to patenting (e.g., Png, 2017; Glaeser, 2018), we control for the interaction between country-level trade secrets protection and general managerial ability as a robustness check. Our findings remain unchanged, as detailed in Section 5.3.

framework that are related to the patent system, as these play a crucial role in shaping the innovation environment for a firm's patent-related strategies and activities. We initially screen over 50 potentially relevant indicators derived from previous studies.[14] Our final set of institutional variables consists of nine country-level measures: six associated with three dimensions of innovation resource availability and three linked to patent system stringency.[15]

3.2.3.1. Availability of innovation resources

We construct measurements of innovation resource availability across three dimensions. The first is knowledge and skill pools, which reflect the contributions of research and educational institutions (such as universities) to societal innovation. We use four country-level indicators to capture this dimension: *University–Industry Collaboration*, *Quality of Research Institutions*, *Availability of Scientists and Engineers*, and *Researchers in R&D*. The literature on innovation-specific institutions emphasizes the importance of these indicators in the development of an NIS (e.g., WEF, 2016, 2021; Cirillo et al., 2019). *University–Industry Collaboration* reflects the extent to which businesses and universities collaborate on R&D in a country, with higher values indicating broader and more extensive collaboration. *Quality of Research Institutions* assesses the caliber of scientific research institutions in the focal country, with higher values indicating better quality. *Availability of Scientists and Engineers* gauges the

[14] We conduct a literature review to identify an initial list of variables, including those from Bergek et al. (2008), Fagerberg and Srholec (2008), Park (2008), Fu and Yang (2009), Filippetti and Archibugi (2011), Castellacci and Natera (2013), de Saint-Georges and de la Potterie (2013), Picard and de la Potterie (2013), Radosevic and Yoruk (2013), Lippoldt and Schultz (2014), Campi and Nuvolari (2015), Jandhyala (2015), Liu and La Croix (2015), Bilgili et al. (2016), Zhong (2018), Cirillo et al. (2019), Prud'homme (2019), Huang et al. (2020), and Papageorgiadis and Sofk (2020). Our initial list of 52 variables reflects various factors affecting firms' innovation activities under the NIS framework. The definitions of these variables, their connections to Atkinson's (2020) NIS framework, references that use them, and their data sources are in Internet Appendix III. We then exclude 29 country-level variables associated with social and macroeconomic instruments (Panel A), two variables specific to the pharmaceutical and agriculture industries (Panel B), nine that are subindices or subcomponents of our chosen variables (Panel C), and three that exclusively focus on non-patent intellectual property rights protection (Panel D). Our screening process ultimately identifies six country-level variables associated with innovation policy systems that enhance innovation resource availability, and three related to regulatory environments that capture patent system stringency (Panel E).

[15] We acknowledge the potential influence of other country-specific factors that may moderate the underlying relationship. While our focus on innovation resource availability and patent system stringency is driven by theoretical and empirical considerations, it is not exhaustive.

extent to which scientists and engineers are accessible in the focal country, and *Researchers in R&D* quantifies the number of researchers engaged in R&D activities, expressed per million people in the country. Data for *University–Industry Collaboration*, *Quality of Research Institutions*, and *Availability of Scientists and Engineers* are obtained from World Economic Forum global competitiveness reports, and data for *Researchers in R&D* are collected from the World Bank database.

The second dimension is public investment in innovation. As Cirillo et al. (2019) note, the government plays a crucial role in developing a country's innovation-related institutions, and higher investment in R&D is associated with a greater availability of innovation resources. We measure public innovation investment as government expenditure on R&D divided by gross domestic product (*Public Investment in R&D*). This expenditure represents the portion of gross expenditure on R&D incurred by government units, and thus quantifies the government sector's intramural R&D expenditure over a specific period. The data for this variable are obtained from OECD Statistics.

The final dimension considers the openness of innovation, as defined by the World Economic Forum. Fagerberg and Srholec (2008) emphasize that a higher degree of openness is positively correlated with technology spillover, thus fostering innovation. We gauge the openness of innovation with *International Co-inventors*, which represents the number of patent family applications in which the co-inventors are located abroad, per million people. This measure is obtained from the World Economic Forum's Global Competitiveness Report series.

Isidro et al. (2020) identify significant interdependencies among the characteristics, institutions, and policies of countries, which leads to the attribution conundrum that can occur in international accounting research. To address this, we conduct a principal component analysis of the six innovation resource-related institutions to create a composite country factor that reflects the availability of innovation resources (*RAW_Resource*). The results of this analysis are presented in Panel B of Internet Appendix I. We observe that only the first principal factor has an eigenvalue exceeding 1 (3.910), and all six country-level innovation resource-related institution variables have positive loadings, indicating a positive correlation with *RAW_Resource*. Thus, a higher *RAW_Resource* value signifies a greater availability of innovation resources.

3.2.3.2. Patent system stringency

Yang and Sonmez (2013) propose that a patent system comprises three interrelated components: patent law legislation, patent enforcement, and administration. We therefore assess patent system stringency through the patent protection index (*PPI*), the patent enforcement index (*PEI*), and administrative adherence (*Patent Office Strictness*). *PPI* measures the stringency of national patent protection. This index is the unweighted sum of five categories of patent laws, namely, the coverage of protection, membership of international treaties, duration of patent protection, enforcement mechanism, and restrictions on patent rights (Ginarte and Park,1997; Park, 2008). A higher *PPI* value indicates more stringent patent protection in a specific country. *PEI* reflects the strengths of patent protection enforcement, taking into account the cost of legal patent trading services, patent protection, and monitoring (Papageorgiadis and Sofka, 2020). A higher *PEI* value signifies the stronger enforcement of patent protection. *Patent Office Strictness* assesses the extent to which a patent office adheres to transparent and stringent legal patentability standards (de Saint-Georges and de la Potterie, 2013). This index is the weighted average of nine categories of patent office implementation policies: invention ownership, search report disclosure, examination requirement and examination term, post-grant opposition, grace period, hidden application, continuation-inparts and other mechanisms, resource allocation per examiner, and examiner workloads.[16] A higher value denotes stricter patent filing and examination.

We apply a principal component analysis to construct a composite factor (*RAW_Stringency*). The results are presented in Panel C of Internet Appendix I. We find that only the first principal factor has an eigenvalue exceeding 1 (1.764), and all three country-level variables have positive loadings. Thus, a higher *RAW_Stringency* value represents a higher level of patent system stringency.

To address concerns that *RAW_Resource* and *Raw_Stringency* may merely reflect socio-economic fundamentals that happen to be correlated with resource availability and patent system stringency, we orthogonalize these two variables against the four latent country factors of economic, legal, and social attributes (*FACTOR1*), the development of the capital market (*FACTOR2*), the development of the political and regulatory system (*FACTOR3*), and societal openness (*FACTOR4*). Following Isidro et al. (2020), we derive these four country factors from a principal component analysis based on 72 explanatory country-level variables that are used in the literature to measure countries' economic, institutional, and societal characteristics. We calculate the residuals, *Resource* and *Stringency*, by regressing *Raw_Resource* and *Raw_Stringency* on these four latent country factors, respectively, using ordinary least squares regression, and then use these residuals in our regression analyses.[17]

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[16] The weighting scheme is based on a bilateral comparison of all components (see Table B2 in de Saint-Georges and de la Potterie, 2013). Our results remain consistent when we construct *Patent Office Strictness* using two alternative weighting schemes: equal weighting and relevance weighting (de Saint-Georges and de la Potterie, 2013).

[17] The use of residuals as a generated regressor is a well-established approach in the literature (e.g., Brown et al., 2012; Liang et al., 2018; Dyck et al., 2019; Yan et al., 2022). Chen et al. (2023) find that consistent with the studies of Pagan (1984) and Murphy and Topel (1985), no standard error bias is evident when using residuals as the generated regressors. This suggests that in the context of our study, using the residuals from orthogonalizing *Raw_Resource* and *Raw_Stringency* with socio-economic factors will not bias our estimates. Nevertheless, we conduct two robustness tests to further alleviate this concern. First, following the recommendations of Chen et al. (2023), we implement a bootstrapping procedure to correct the standard errors in Eq. (2). Second, we re-estimate Eq. (2) by replacing *Stringency* and *Resource* with *Raw_Stringency* and *Raw_Resource*, respectively, and directly control for the four latent country factors and their interaction terms with *GAI*. Our results (untabulated) remain economically and statistically significant in both tests, indicating that our findings are not sensitive to the choice of research methodology.

Internet Appendix IV shows that a country's innovation resource availability and patent system stringency have a significant positive association with its economic, legal, and cultural attributes, in addition to its capital market development and societal openness.

3.2.4. Control variables

Following prior international innovation studies (e.g., Zhong, 2018; Tsang et al., 2021), we control for a range of firm-, industry-, and country-level variables that may influence firm innovation. At the firm level, we control for access to external financing (*External Finance*) because the availability of external financing can affect innovation activities (Cornaggia et al., 2015). Profitability and growth opportunities are captured using return on assets (*ROA*), the market-to-book ratio (*MTB*), and sales growth (*Sales Growth*). We include firm size (*Size*) and capital intensity (*K/L*), as larger or more capital-intensive firms may appear more innovative (Fang et al., 2014). We also account for capital structure through firm leverage (*Leverage*) and the cash ratio (*Cash*), ownership structure using the percentage of closely held shares (*Closely Held*), global market expansion through foreign sales (*FSALE*), and firm age (*Firm Age*). At the industry level, we include product market competition using the Herfindahl–Hirschman Index (*HHI*) and its square term (HHI^2) to control for the non-linear relationship between competition and innovation (Roberts, 1999). At the country level, GDP per capita (*GDPpc*) is included to control for the influence of the broader economic environment on firm innovation. We also control for year, industry, and country fixed effects in all regression tests and interact *Resource* and *Stringency* with these fixed effects. We cluster standard errors at the firm and year levels to address cross-sectional dependence and time-series correlation in the data (Gow et al., 2010). All continuous variables are winsorized at the top and bottom one percentiles. Appendix A provides detailed definitions of the variables.

3.3. Descriptive statistics

Table 2 provides the country distribution of our sample along with the means of key variables for each country. Consistent with other international studies (e.g., Zhong, 2018; Tsang et al., 2021), we observe a significant variation in the number of observations across countries. The highest proportion of sample firms comes from the U.S., followed by the U.K., China, India, and Hong Kong. The five countries with the highest availability of innovation resources (*Resource*) are Finland, Singapore, Malaysia, India, and the U.S. In terms of patent system stringency (*Stringency*), India has the most stringent patent system, followed by Finland, Denmark, and Singapore. We find a notable disparity in general managerial ability across countries, with Denmark having the highest average *GAI*, followed by Canada, Switzerland, Finland, and France. We also observe extensive variation in innovation across countries, with larger economies such as Japan, China, Germany, the U.S., and France exhibiting higher levels of innovation.[18]

Table 3 presents the descriptive statistics of the key variables for the full sample and the generalist and specialist CEO subsamples. Firms led by generalist CEOs apply for significantly more patents (7.784 vs. 4.333) and receive about three times more citations than those led by specialist CEOs. These firms are also generally larger and older, with higher market-to-book ratios, greater capital intensity, higher leverage, and more foreign sales. However, they have a lower percentage of closely held shares, less access to external financing, and lower cash reserves and sales growth than firms led by specialist CEOs.

4. Empirical Analysis and Regression Results

4.1. Main results

[18] Consistent with previous studies (e.g., Tsang et al., 2021; Xie et al., 2022), we find a higher number of patents and citations in Japan. Our results remain robust when we exclude Japan from the sample (untabulated).

To test our hypotheses regarding the effects of innovation-specific institutions on the relationship between general managerial ability and firm innovation, we estimate the following model that links *Innovation* in year t+1 to innovation-specific institutions and their interaction terms with *GAI* and a set of control variables in year t:

$$Innovation_{ijt+1} = \beta_0 + \beta_1 Resource_{jt} \times GAI_{ijt} + \beta_2 Stringency_{jt} \times GAI_{ijt} + \beta_3 GAI_{ijt} + \beta_k \Sigma Controls_{ijt} + \beta_m \Sigma(Resource_{jt} \times Controls_{ijt}) + \beta_n \Sigma(Stringency_{jt} \times Controls_{ijt}) + Year\ FE + Industry\ FE + Country\ FE + Resource_{jt} \times Year\ FE + Resource_{jt} \times Industry\ FE + Resource_{jt} \times Country\ FE + Stringency_{jt} \times Year\ FE + Stringency_{jt} \times Industry\ FE + Stringency_{jt} \times Country\ FE + \varepsilon_{ijt+1} \quad (2)$$

where i indexes the firm, j indexes the country, and t indexes the year. We assign a firm to country j based on the location of its headquarters.[19] The variables of interest are *GAI* × *Resource* and *GAI* × *Stringency*, which capture the effects of the availability of innovation resources and patent system stringency on the association between general managerial ability and innovation, respectively. In this model, *GAI* is considered potentially endogenous,[20] while *Resource* and *Stringency* are considered exogenous. Therefore, following best practices for testing the interactive effects between endogenous and exogenous variables, as recommended by deHaan et al. (2023), we interact *Resource* and *Stringency* with all control variables and fixed effects.[21] This approach enables us to obtain an unbiased estimate of the interaction effects between endogenous and exogenous variables while alleviating concerns of potential correlated and omitted variable bias (deHaan et al., 2023). To mitigate multicollinearity resulting from the incorporation of interaction terms (Aiken and West, 1991) and to aid in the interpretation of coefficients, we mean-center and standardize all of the interacting variables in

[19] Our inferences remain unchanged when we use a firm's country of incorporation to identify its country (untabulated).
[20] In Section 5, we conduct a series of tests to address endogeneity concerns about *GAI*.
[21] We thank the anonymous referee for this helpful suggestion. Eq. (2) does not include the main effects of *Resource* and *Stringency* because these effects are absorbed by their interactions with year, industry, or country fixed effects.

all regression analyses before calculating the interaction, with the exception of the indicator variables.[22]

Table 4 reports the results. Panel A shows the results of baseline regressions without the interactions between innovation-specific institutions and control variables as well as the fixed effects. Columns (1) and (2) present the results without the interaction of *GAI* with innovation-specific institutions. The significant and positive coefficients of *GAI* suggest that firms with generalist CEOs on average generate more patents and receive more citations. The relationship is also economically significant. A one standard deviation increase in *GAI* is associated with increases in patents and citations of 2.5% and 4.0%, respectively.[23] These findings extend the literature by demonstrating the relevance of generalist CEOs to innovation in an international context. In general, the results for the control variables are consistent with those in the international innovation literature (e.g., Zhong, 2018; Tsang et al., 2021).[24] Columns (3) and (4) include the interaction between *GAI* and *Resource*. We find that the coefficients on the interaction term between *GAI* and *Resource* are positive and statistically significant for both patent and citation models, indicating that the positive impact of general managerial ability on firm innovation is greater in countries with more available innovation resources. This finding supports H1 and is consistent with the interpretation that generalist CEOs leverage external resources to catalyze innovation within their organizations. Columns (5) and (6) include the interaction between *GAI* and *Stringency*. The significantly negative coefficients on the interaction term *Stringency* × *GAI* suggest that the positive effect of general managerial ability on innovation is weaker in countries with stricter patent systems, thus supporting H2. This result indicates that the limited maneuverability within strict patent systems reduces the value

[22] We standardize the interacting variables according to the within-fixed-effect standard deviation, to more accurately capture the variation examined by the model (Breuer and deHaan, 2024).
[23] Given that the coefficients of *GAI* are 0.025 and 0.039 in the patent and citation models, respectively, the economic significance is calculated as follows: 2.5% = $e^{0.025} - 1$; 4.0% = $e^{0.039} - 1$.
[24] To address the potential concern about bad controls (Angrist and Pischke, 2009), we re-estimate our baseline regression without any control variables. Our inferences remain unchanged (untabulated).

that generalist CEOs contribute to firms, leading to a relative decline in innovation. Our conclusions remain unchanged when we include both *Resource* × *GAI* and *Stringency* × *GAI* in the same regression in columns (7) and (8).

To alleviate the concern of potential correlated and omitted variable bias, we estimate Eq. (2), where we interact *Resource* and *Stringency* with all of the control variables and fixed effects, and report the results in Panel B. Columns (1) and (2) show the moderating effect of innovation resource availability, and columns (3) and (4) show that of patent system stringency. The regression results of Eq. (2) are reported in columns (5) and (6). Across all columns, we find that the effect of general managerial ability on innovation is stronger in countries with more innovation resources available and less stringent patent systems.

Economically, the full model results in columns (5) and (6) indicate that a one standard deviation increase in *GAI* leads to patent (citation) increases of 3.69% (4.29%) and 0.76% (2.00%), respectively, in countries with median levels of innovation resource availability and patent system stringency.[25] The results also indicate that an interquartile shift from the 25th to the 75th percentile in *Resource* is associated with a 6.5-fold (2.6-fold) increase in the average effect of *GAI* on increasing firms' patent counts (citations). Conversely, an interquartile shift from the 25th to the 75th percentile in *Stringency* is associated with a 4.3-fold (1.6-fold) decrease in the average effect of *GAI* on increasing firms' patent counts (citations).[26]

Overall, the results in Table 4 suggest that the influence of general managerial ability on innovation depends on both the availability of innovation resources and on patent system stringency. Compared with specialist CEOs, generalist CEOs have a greater impact on

[25] The standardized *Resource* and *Stringency* values at the median level are 0.527 and 0.104, respectively. Given that the coefficients of *GAI* are 0.012 and 0.023 in the patent and citation models, respectively, the calculations are as follows: $3.69\% = e^{0.012+0.046\times0.527} - 1$; $4.29\% = e^{0.023+0.036\times0.527} - 1$; $0.76\% = e^{0.012-0.043\times0.104} - 1$; $2.00\% = e^{0.023-0.031\times0.104} - 1$.

[26] As the interquartile shift in *Resource* is 1.637 (0.792– (–0.845)) and the interquartile shift in *Stringency* is 1.251 (0.741– (–0.510)), the economic magnitude of the coefficients is calculated as follows: $6.49 = (e^{0.046\times1.637} - 1)/(e^{0.012}-1)$; $2.61 = (e^{0.036\times1.637} - 1)/(e^{0.023}-1)$; $-4.34 = (e^{-0.043\times1.251} - 1)/(e^{0.012}-1)$; $-1.63 = (e^{-0.031\times1.251} - 1)/(e^{0.023}-1)$.

innovation in countries with more available innovation resources and less stringent patent systems.

4.2. Dimensions of innovation-specific institutions

In this section, we examine whether the effects of innovation resource availability and patent system stringency on the relationship between general managerial ability and innovation vary across the individual components of innovation-specific institutions. We re-estimate Eq. (2) by replacing *Resource* (*Stringency*) with each of the six innovation resource-related institutions (three patent system-related institutions) and report the results in Table 5 (Table 6). Of the innovation resource-related measures, we find that the impact of generalist CEOs on innovation is enhanced by the quality of research institutions, the availability of scientists and researchers, and public investment in innovation. This finding suggests that the accumulation of a talent pool and knowledge base, along with government support in innovation, complement the ability of generalist CEOs to drive innovation activities. Table 6 shows that all three individual components of patent system stringency negatively affect the relationship between generalist CEOs and innovation activities.

4.3. Components of general managerial ability

We next investigate whether our results vary across the five components of the general managerial ability measure. Table 7 presents the regression results, which are generally consistent with those using the aggregate measure of general managerial ability. We find that both the availability of innovation resources and patent system stringency affect the promotion of innovation by generalist CEOs, mainly for those who gain more work experience by holding different positions and working at multiple firms or across different industries.[27]

4.4. Alternative measures of innovation

[27] The results align with those of Betzer et al. (2020), who find that investors regard CEOs' work experiences, and specifically their transitions between positions, firms, and industries, as valuable. We also devise an alternative *GAI* measure, formulated as the principal factor when applying principal component analysis to *Number of Positions*, *Number of Firms*, and *Number of Industries*. The results remain in line with our initial findings.

Our main measures of innovation, *PATENT* and *CITATION*, gauge both the quantity and quality of innovation output. In our supplementary analyses, we examine firms' innovation activities using input-oriented innovation measures. We first investigate their innovation input (*R&D Intensity*), measured as R&D expenditure scaled by total sales, multiplied by 100.[28] The results are presented in column (1) of Panel A in Table 8. We then examine the efficiency of firms when utilizing innovation input to generate patents through two efficiency metrics, *PATENT/RDC* and *CITATION/RDC*, representing the number of patents and the number of forward citations normalized by R&D capital (*RDC*), respectively.[29] The results are presented in columns (2) and (3) of Panel A in Table 8. Consistent with our main findings, innovation resource availability (patent system stringency) facilitates (attenuates) the positive effect of general managerial ability on innovation input and efficiency.

Some patent applications from the later years of our sample period may still be under evaluation and hence absent from patent databases, leading to an underrepresentation of the number of patents for recent years within our sample period (Fang et al., 2014; Zhong, 2018). We thus minimize potential truncation bias by ensuring that we only include patent data up to 2020, although we obtain these data up to 2022. To further address this bias, we adjust the number of patents using the application-grant lag distribution function (Fang et al., 2014).[30]

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[28] We follow previous research and replace missing R&D with the country-industry-year average, as many firms engage in patenting but do not report their R&D expenditure (Koh and Reeb, 2015; Koh et al., 2017). We obtain consistent results when using alternative approaches to deal with missing R&D data, such as excluding firm-years with missing R&D expenditure, replacing missing R&D expenditure with 0 for firm-years with no patent activities, and replacing missing R&D with country-industry-year average R&D expenditure for firm-years with patent activities (Tsang et al., 2021).

[29] Based on the premise that successful patent applications filed in year t are the outcome of R&D investment over the preceding five years (Lev et al., 2005), R&D capital (*RDC*) is calculated as $RDEXP_{t} + 0.8 \times RDEXP_{t-1} + 0.6 \times RDEXP_{t-2} + 0.4 \times RDEXP_{t-3} + 0.2 \times RDEXP_{t-4}$, where *RDEXP* is annual R&D expenditure. We replace missing *RDC* with the country-industry-year average. Missing *RDEXP* is set to 0 for the calculation of *RDC*, and zero *RDC* is then replaced with its country-industry-year average.

[30] The application-grant lag distribution (W_S) is the percentage of patents applied for in a given year that are granted in s years. This is estimated by calculating the time interval in the number of years between a patent's application year and its grant year. We follow Fang et al. (2014) and choose a 10-year interval (2001−2010) to estimate W_S to calculate the truncation-adjusted number of patents for the last 10 years of our sample period (2011−2020), as 99% of patents in our sample are granted within 10 years. We then estimate the truncation-adjusted number of patents by computing the adjusted number of patents $P_{adj} = \frac{P_{raw}}{\sum_{s=0}^{2020-t} W_S}$, where P_{raw} is the raw number of patent applications filed (and eventually granted) in a year between 2011 and 2020.

We also make a similar adjustment for the number of citations. The results for the adjusted values are presented in columns (4) and (5) in Panel A. Our inferences remain unchanged.

4.5. Alternative measures of general managerial ability

In the above analyses, we treat our *GAI* measure as a continuous variable, but to check robustness we categorize CEOs as generalists or specialists using the annual median *GAI* as the cut-off, following Custódio et al. (2013). We introduce the indicator *Generalist* for general managerial ability, which equals one if a CEO's *GAI* exceeds the yearly sample median, and zero otherwise. We then replace *GAI* with *Generalist* in Eq. (2) and re-estimate the model. The regression results are presented in Panel B of Table 8. The coefficients of the interaction term *Resource* × *Generalist* are significant and statistically positive in both the patent and citation models and the coefficients of the interaction term *Stringency* × *Generalist* are significant and negative. The results are consistent with our main findings: an environment with abundant innovation resources increases the likelihood that generalist CEOs promote innovation, whereas a stringent patent landscape reduces their effect on innovation.

5. Endogeneity and Identification Strategies

In this section, we apply various strategies to alleviate endogeneity concerns arising from omitted variables and reverse causality.

5.1. Propensity score matched sample

Our regression analysis in Table 4 may be subject to bias if specific firm attributes simultaneously affect both CEOs' general managerial ability and firm innovation. In our main regression analyses, we account for potential confounding factors by including variables that may affect both *GAI* and innovation. We further address this concern by constructing a matched sample through one-to-one nearest neighbor propensity score matching without replacement, using all control variables in Eq. (2), along with year, industry, and country fixed effects. We calculate the propensity scores as the predicted probabilities from a Probit model. To optimize our matching, we apply a tight caliper distance of 0.001. This yields a matched sample of 43,986 observations.

We provide a univariate comparison of all control variables in Panel A of Internet Appendix V. In this matched sample, the differences in control variables between firms led by generalist CEOs and those led by specialist CEOs are not statistically significant, indicating that our matching technique effectively increases the comparability of the two groups. We then re-estimate our main regression using the matched sample, and the results, presented in Panel B of Internet Appendix V, remain quantitatively and qualitatively similar.

5.2. Two-stage least squares analyses

To further alleviate endogeneity concerns arising from reverse causality and omitted variable bias, we estimate a 2SLS regression, following prior studies (e.g., Angrist and Pischke, 2009; Brockman et al., 2016; Armstrong et al., 2022a, 2022b). We use the predecessor CEO's *GAI* (*Predecessor GAI*) as an exogenous predictor of the current CEO's *GAI*. Firms that prioritize generalist leadership often aim to retain such CEOs over extended periods (Brockman et al., 2016). Nonetheless, a predecessor CEO's general managerial ability is unlikely to influence the firm's subsequent innovation activities unless an innovation initiative persists beyond the CEO's tenure. Following the approach outlined by Angrist and Pischke (2009), we generate two additional instruments by interacting *Predecessor GAI* with both *Resource* and *Stringency* to instrument the interaction terms in the model. These three variables then serve as exogenous instruments for *GAI*, *GAI* × *Resource*, and *GAI* × *Stringency* in the first stage.

We report the first-stage results in Panel A of Internet Appendix VI. Consistent with our prediction, *Predecessor GAI*, *Predecessor GAI* × *Resource*, and *Predecessor GAI* × *Stringency* have significant and positive associations with *GAI*, *GAI* × *Resource*, and *GAI* × *Stringency*, respectively, suggesting that the instrument relevance conditions are satisfied. The Kleibergen–

Paap Wald F-statistic is 34.9 and statistically significant at the 1% level, indicating that the model is not subject to weak instrument problems.

Panel B of Internet Appendix VI presents the results of the second-stage estimation. We continue to find a significant and positive (negative) coefficient of the interaction term between *GAI* and *Predicted Resource* (*Predicted Stringency*).

5.3. Alternative explanation: Trade secrets protection

An alternative explanation of our findings is that a surge in patenting activity may not necessarily signify an uptick in innovation but rather a shift from other protective methods like trade secrecy to patenting (Png, 2017; Glaeser, 2018). For instance, generalist CEOs may prefer to use patents rather than trade secrecy to protect their innovations, as patents offer a credible platform for showcasing their capabilities to the external labor market. However, specialist CEOs may not feel the need to externally validate their skills in such a manner. Institutional frameworks could influence this dynamic by affecting the depth and dynamism of the external labor market, which in turn could influence generalist CEOs in terms of publicizing their capabilities. To address this concern, we re-estimate our regression by controlling for the degree of trade secrets protection at the country level (*Trade Secrets Protection*) and its interaction with *GAI*. The trade secrets index is a comprehensive summary of factors (i.e., definition and coverage; specific duties and misappropriation; remedies and restrictions on liability; enforcement, investigation, and discovery; and system functioning and related regulations) that indicate the stringency level of trade secrets protection (Lippoldt and Schulz, 2014).[31] We measure *Trade Secrets Protection* using the residual value obtained through a regression of the raw index value on the four latent country factors (*FACTOR1*, *FACTOR2*, *FACTOR3*, and *FACTOR4*). We do not include the main effect of *Trade Secrets Protection* in

[31] The index is available every five years from 1985 to 2010. Thus, we determine *Trade Secrets Protection* for a given year using the value derived from the most recent year available for that specific country and year in our sample. The data are sourced from Lippoldt and Schulz (2014).

the regression because it is absorbed by its interactions with the fixed effects. Panel A of Internet Appendix VII presents the results. We continue to observe significant coefficients of the interaction terms *Resource* × *GAI* and *Stringency* × *GAI* for both patent and citation models, suggesting that our results are unlikely to be driven by a firm's change in preference regarding the method of protection.

5.4. Alternative explanations: CEO talent and *firm–CEO matching*

The potential correlation between CEO talent and *GAI* is also a concern, as this may not be fully addressed by firm-level controls. Our *GAI* measure provides a comprehensive gauge of CEOs' general managerial ability, developed through a lifetime of professional experience, including adaptability, decision-making acumen, and innovation-oriented thinking. Such factors are distinct from CEO talent, so we should not assume that our findings are systematically driven by CEO talent. Nevertheless, we address this concern by using CEOs' academic credentials, i.e., whether they have a PhD degree (*PhD*) or MBA degree (*MBA*), as indicators of their talent (Islam and Zein, 2020; He and Hirshleifer, 2022). We then add their interaction terms with both *Resource* and *Stringency* as additional controls. Columns (1) and (2) in Panel B of Internet Appendix VII show the results. We find that both the coefficients of *Resource* × *GAI* and *Stringency* × *GAI* remain similar to those in our main analysis.[32]

The literature suggests that the board of directors' decision to hire a generalist versus a specialist CEO is influenced by the strategic objectives of the firm. Generalist CEOs are typically preferred in uncertain and dynamic environments and in larger firms, conglomerates, and firms experiencing operational distress or increased competition (Custódio et al., 2013; Mishra, 2014; Brockman et al., 2016; Betzer et al., 2020; Ma et al., 2021). In our main analysis,

[32] To further alleviate the concern that CEOs' general managerial ability may be correlated with other CEO characteristics that influence innovation and its success, we include additional control variables for CEO age, gender, compensation, tenure, and their interaction terms with both *Resource* and *Stringency* to mitigate any potential confounding effects that these characteristics may have on firm innovation. The untabulated results of these tests are consistent with those of our main results.

we control for determinants such as firm size, financial performance, sales growth, and industry competition, to account for endogeneity problems arising from the potential firm–CEO matching process. The propensity score matched sample and 2SLS approach discussed in Sections 5.1 and 5.2 further help address these issues. Additionally, endogenous matching is likely to be more prominent in firms with shorter CEO tenures, and their CEOs have less opportunity to influence the firms' innovation processes. Therefore, we follow Custódio et al. (2019) by excluding observations in which a CEO's tenure is less than three years and find that our inferences remain unchanged. Our results also remain robust when using alternative CEO tenure cut-offs of five and ten years. In addition, to alleviate endogeneity issues arising from unobserved time-invariant factors at the firm–CEO pair level, we control for firm–CEO paired fixed effects and interact them with *Resource* and *Stringency*. Columns (3) and (4) in Panel B of Internet Appendix VII present the results. Again, we find that our inferences remain unchanged.[33]

5.5. Other robustness tests

Our results may also be affected by time-varying country- and industry-level shocks in our global sample that simultaneously affect both general managerial ability and firm innovation. We address this in additional (untabulated) tests by including a high-dimensional fixed effect structure that captures intra-country and intra-industry shifts over time. In the first test, we include *Country* × *Year* fixed effects, *Industry* × *Year* fixed effects, and interactions of *Industry* × *Year* fixed effects with *Resource* (*Industry* × *Year* × *Resource*) and *Stringency* (*Industry* × *Year* × *Stringency*) in our regression model. These fixed effects account for any time-varying macro shocks or industry shocks that may affect the underlying relationship. Next,

[33] We exclude 6,878 singleton observations (or 5.5% of our main sample) due to the use of firm-CEO fixed effects in the analysis. Including these observations in regressions with firm-CEO fixed effects can overestimate statistical significance, potentially resulting in incorrect inferences (Breuer and deHaan, 2024).

we include *Country* × *Industry* × *Year* fixed effects as an additional robustness check.[34] Our inferences remain unchanged in both tests.

6. Conclusion

Our study extends the literature on CEO characteristics and innovation by examining the role of generalist CEOs and the interplay between innovation-specific institutions and general managerial ability in fostering innovation globally. We hypothesize that the strategic value of a generalist CEO's human capital in promoting innovation depends on the firm's institutional environment, specifically the availability of innovation resources and the stringency of the patent system. The results support our hypotheses, showing that generalist CEOs have a greater positive impact on innovation in environments with abundant innovation resources. This supports the notion that generalist CEOs can more effectively align and mobilize external resources to facilitate innovation activities in such contexts. Thus, generalist CEOs are particularly valuable in complex, innovation-driven landscapes where adapting and leveraging external resources is crucial. Our results also indicate that the relationship between generalist CEOs and innovation is weaker in countries with stringent patent systems, which may limit the advantages generalist CEOs bring to the innovation process. This finding suggests that policymakers should consider not only firms' innovation capacities but also the leadership characteristics that foster innovation in such regulatory environments.

Our study therefore has implications for the design of innovation-related policies and institutional structures. Our findings suggest that overly stringent patent systems may inhibit innovation, especially under generalist leaders, while the availability of extensive innovation resources can serve as a catalyst for innovation. Our study also contributes to the ongoing

[34] In these two tests, we do not interact *Country* × *Industry* × *Year* (*Country* × *Year*) fixed effects with *Resource/Stringency* because *Resource* and *Stringency* vary at the country-year level, and these interactions are thus absorbed by the *Country*× *Industry* × *Year* (*Country* × *Year*) fixed effects.

debate regarding the comparative value of generalist versus specialist CEOs. While previous research indicates a labor market preference for generalist CEOs (e.g., Custódio et al., 2013; Ma et al., 2021), we find that their impact on innovation outcomes depends on the institutional environment. By considering an extensive pool of CEOs in an international setting, our study offers a more nuanced assessment of the impact of generalist CEOs on corporate policies and outcomes.

In conclusion, our study reveals the nuanced relationships between generalist CEOs, innovation-specific institutional factors, and corporate innovation in an international context. Our findings can therefore stimulate further research on how CEO human capital and institutional designs—broadly or specifically related to innovation (e.g., inventor mobility restrictions, trade secrets protection)—shape corporate innovation and other strategic outcomes across various institutional environments.

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Appendix A. Variable Definitions

Variable	Definition	Data Source
Innovation Variables		
PATENT	The natural logarithm of one plus the total number of patents filed (and eventually granted) by a firm in a year.	Orbis
CITATION	The natural logarithm of one plus the total number of citations received by patents filed (and eventually granted) by a firm in a year.	Orbis
R&D Intensity	Research and development (R&D) expenditure scaled by total sales, multiplied by 100.	Worldscope
PATENT/RDC	A measure of innovation efficiency calculated as the number of patents scaled by R&D capital (*RDC*). *RDC* is calculated as $DEXP_t$ + 0.8 × $RDEXP_{t-1}$ + 0.6 × $RDEXP_{t-2}$ + 0.4 × $RDEXP_{t-3}$ + 0.2 × $RDEXP_{t-4}$, where *RDEXP* is R&D expenditure in millions. We set missing R&D expenditure (*RDEXP*) to zero in computing *RDC* and replace zero *RDC* with the country-industry-year average. We use the natural logarithm transformation of the variable to correct for excessive skewness.	Orbis; Worldscope
CITATION/RDC	A measure of innovation efficiency calculated as the number of citations scaled by R&D capital (*RDC*). We use the natural logarithm transformation of the variable to correct for excessive skewness.	Orbis; Worldscope
Adj. PATENT	Patent counts adjusted for truncation bias. We compute the application-grant lag distribution function (W_s) for all patents filed and granted between 2001 and 2010. We then estimate the truncation-adjusted number of patents by computing the adjusted number of patents $P_{adj} = P_{raw} / \sum_{s=0}^{2020-t} W_s$), where P_{raw} is the raw number of patent applications filed (and eventually granted) in year t and $2011 <= t <= 2020$.	Orbis
Adj. CITATION	Citation counts adjusted for truncation bias.	Orbis
General Managerial Ability Variables		
GAI	The first factor of principal component analysis using five measures of general managerial ability: *Number of Positions*, *Number of Firms*, *Number of Industries*, *CEO Experience*, and *Conglomerate Experience*.	Capital IQ; BoardEx; Orbis; Internet; Worldscope
Number of Positions	Number of different positions that the CEO has held.	Capital IQ; BoardEx; Orbis; Internet
Number of Firms	Number of different firms in which the CEO has worked.	Same as above
Number of Industries	Number of 4-digit SIC industries in which the CEO has worked.	Same as above
CEO Experience	An indicator variable that equals one if the CEO held a CEO position at another firm, and zero otherwise.	Same as above
Conglomerate Experience	An indicator variable that equals one if the CEO worked in a firm with multiple business segments, and zero otherwise.	Capital IQ; BoardEx; Orbis; Internet; Worldscope
Generalist	An indicator variable that equals one if the CEO's *GAI* is greater than the sample median value in the year, and zero otherwise.	Same as above
Predecessor GAI	The predecessor CEO's *GAI*.	Same as above
Innovation-Specific Country Variables		
Availability of Innovation Resources		
Resource	The residual value obtained by regressing *RAW_Resource* on the four latent country factors (*FACTOR1*, *FACTOR2*, *FACTOR3*, and *FACTOR4*) constructed following Isidro et al. (2020). These four factors represent the first four factors resulting from a principal component analysis with varimax rotation applied to 72 explanatory country-level variables identified in Isidro et al. (2020). These variables collectively encompass a range of	World Economic Forum; Executive Opinion Survey; OECD Statistics; World Bank

	macroeconomic, social, and cultural conditions, along with indicators of capital market development, the political system, and societal openness.	
RAW_Resource	The principal factor among the six distinct measures of country-level innovation resources: *Availability of Scientists and Engineers*, *International Co-inventors*, *Public Investment in R&D*, *Quality of Research Institutions*, *Researchers in R&D*, and *University–Industry Collaboration*.	Same as above
Availability of Scientists and Engineers	An index reflecting the extent to which scientists and engineers are available within a specific country. This index is measured on a scale of 1 (not available at all) to 7 (widely available).	World Economic Forum; Executive Opinion Survey
International Co-inventors	The number of patent family applications with co-inventors located abroad per million population.	World Economic Forum; Executive Opinion Survey
Public Investment in R&D	Government expenditure on R&D (i.e., the portion of gross R&D spending incurred by government sector entities) divided by GDP.	OECD Statistics
Quality of Research Institutions	An index reflecting the quality of scientific research institutions within a specific country. This index is measured on a scale of 1 (poor quality–among the worst in the world) to 7 (good quality–among the best in the world).	World Economic Forum; Executive Opinion Survey
Researchers in R&D	The number of researchers engaged in research and development in a country, presented as a ratio per million.	World Bank
University–Industry Collaboration	An index reflecting the level of collaboration between businesses and universities for research and development within a specific country. This index is measured on a scale of 1 (no collaboration) to 7 (high collaboration).	World Economic Forum; Executive Opinion Survey
Patent System Stringency		
Stringency	The residual value obtained by regressing *RAW_Stringency* on the four latent country factors (*FACTOR1*, *FACTOR2*, *FACTOR3*, and *FACTOR4*).	Park (2008); de Saint-Georges and de la Potterie (2013); Papageorgiadis and Sofka (2020)
RAW_Stringency	The principal factor of the three individual patent system-related country institution measures: *Patent Office Strictness*, the patent enforcement index (*PEI*), and the patent protection index (*PPI*).	Same as above
Patent Office Strictness	An index reflecting the quality of a national patent office, calculated as the weighted average of nine variables related to the rules, regulations, and resource allocation policies of the patent office. The index is measured on a scale of 0 to 1, with higher levels indicating a more rigorous patent application examination process. The weighting scheme for the index is constructed using a bilateral comparison of all variables.[a]	de Saint-Georges and de la Potterie (2013)
PEI	Patent enforcement index (*PEI*), which gauges the effectiveness of patent enforcement and captures variations in enforcement practices across various countries and over time. It is measured on a scale of 0 (no protection at all) to 10 (full protection) and is the weighted sum of three sub-indices: the servicing cost index, the IP protection cost index, and the monitoring cost index.[b]	Papageorgiadis and Sofka (2020)
PPI	Patent protection index (*PPI*), which assesses the strength of patent protection based on legislation and case law that establish how such legislative provisions are interpreted and enforced. The values of *PPI* range from 0 to 5, with higher values indicating that a country has more stringent patent protection. This index is the unweighted sum of the values of five categories of patent legislation: (1) coverage of protection; (2) membership of international treaties; (3) duration of patent protection; (4) enforcement mechanisms; and (5) restriction on patent rights.[c]	Park (2008)
Control Variables and Variables Used in the Robustness Tests		
Cash	Cash holdings scaled by total assets.	Worldscope

Closely Held	The total number of closely held shares as a percentage of the total number of shares outstanding.	Worldscope
External Finance	The sum of the firm's net equity issues (scaled by total assets) over a rolling five-year window ending in the current fiscal year.	Worldscope
FACTOR1/ FACTOR2/ FACTOR3/ FACTOR4	The first/second/third/fourth factors from a principal component analysis with varimax rotation applied to 72 explanatory country-level variables, as identified by Isidro et al. (2020). *FACTOR1* captures a country's economic, legal, and social attributes. *FACTOR2* captures the development of the capital market. *FACTOR3* captures the development of political and regulatory systems. *FACTOR4* captures societal openness.	Own construction based on Isidro et al. (2020)
Firm Age	The natural logarithm of one plus the number of years the firm is listed on Worldscope.	Worldscope
FSALE	Foreign sales scaled by total sales.	Worldscope
GDPpc	The natural logarithm of gross domestic product per capita.	World Bank
HHI	Industry Herfindahl–Hirschman Index based on all firms within each country, where industries are defined by 3-digit SIC codes.	Worldscope
HHI^2	The squared term of HHI.	Worldscope
K/L	The natural logarithm of the ratio of net property, plant, and equipment (in thousands) to the number of employees.	Worldscope
Leverage	Total liabilities scaled by total assets.	Worldscope
MBA	An indicator variable that equals one if the CEO obtained an MBA degree, and zero otherwise.	Capital IQ
MTB	The market value of equity divided by the book value of equity.	Worldscope
PhD	An indicator variable that equals one if the CEO obtained a PhD degree, and zero otherwise.	Capital IQ
ROA	Net income before extraordinary items scaled by beginning total assets.	Worldscope
Sales Growth	Annual change in net sales scaled by beginning total assets.	Worldscope
Size	The natural logarithm of net sales.	Worldscope
Trade Secrets Protection	The residual value obtained by regressing the trade secrets index on the four latent country factors (*FACTOR1*, *FACTOR2*, *FACTOR3*, and *FACTOR4*). The trade secrets index reflects the degree of stringency in trade secrets protection at the country level and comprises five components: (1) definition and coverage; (2) specific duties and misappropriation; (3) remedies and restrictions on liability; (4) enforcement, investigation, and discovery; and (5) system functioning and related regulation. The index is rated on a scale of 0 to 5, with higher values indicating stronger trade secrets protection within a given country.	Lippoldt and Schultz (2014)

[a] de Saint-Georges and de la Potterie (2013) also use two alternative weighting schemes to measure the quality of a patent office: an equal weighting scheme and a weighting scheme based on the relevance score for each variable. Our inference remains unchanged when measuring *Patent Office Strictness* based on these alternative weighting schemes.

[b] The servicing cost index is constructed based on the "bureaucracy quality index" published in the International Country Risk Guide (ICRG) and the "bureaucracy does not hinder business activity" indicator published in the World Competitiveness Yearbook (WCY). The IP protection cost index is constructed based on the "justice is fairly administered" indicator published in the WCY, the "law and order" indicator published in ICRG, the "judicial independence" indicator published in the Global Competitiveness Report (GCR) of the WEF, and the "corruption perceptions index" from Transparency International. The monitoring cost index is constructed based on the "intellectual property rights" indicator reported in the WCY, the "intellectual property protection" indicator reported in the GCR, the "software piracy rate" indicator, and country listings from the Special 301 Report.

[c] Coverage of protection encompasses patent protection for seven items: pharmaceuticals, chemicals, food, plant and animal varieties, surgical products, microorganisms, and utility models. Membership of international treaties includes the Paris Convention, International Convention for the Protection of New Varieties of Plants, Patent Cooperation Treaty, Budapest Treaty, and the Agreement on Trade-Related Aspects of Intellectual Property Rights. Enforcement mechanisms includes the availability of preliminary injunctions, contributory infringement pleadings, and burden-of-proof reversals. Restriction on patent rights is based on working requirements, compulsory licensing, and the revocation of patents.

Table 1. Sample Attrition

Procedures	# of unique firms	# of unique CEOs	# of observations
All publicly listed non-financial and non-utility firms in the Worldscope with non-missing financial data during 2001–2019	32,835		217,904
(1) After matching CEOs from Capital IQ	21,024	34,222	139,434
(2) After removing CEOs without data on *GAI*	19,096	29,192	130,393
(3) After removing small countries with fewer than 100 observations	18,861	28,869	129,412
(4) After removing country-years without data on innovation-specific institutions	18,334	28,076	125,264
Final Sample	**18,334**	**28,076**	**125,264**

This table details the sample attrition. The final sample comprises 125,264 observations representing 28,076 CEOs from 18,334 unique firms in 25 countries over the 2001–2019 period.

Table 2. Country Distribution

	(1) Country	(2) Freq.	(3) *Resource*	(4) *Stringency*	(5) *GAI*	(6) *Patent* (Raw)	(7) *Citation* (Raw)
1	Australia	3,532	-0.539	0.085	-0.142	0.374	0.891
2	Austria	364	0.820	0.274	0.155	3.030	2.316
3	Belgium	507	0.701	0.236	0.061	3.075	2.550
4	Canada	5,196	0.114	-0.127	0.199	2.283	6.744
5	China	11,443	-0.794	0.374	-0.683	14.826	12.641
6	Denmark	354	0.245	0.544	0.439	7.249	17.653
7	Finland	1065	1.396	0.656	0.184	5.134	13.230
8	France	4,626	-0.153	-0.076	0.183	7.649	12.502
9	Germany	2,899	0.322	-0.335	0.071	13.113	26.712
10	Hong Kong	8,454	-1.909	-0.575	-0.198	0.150	0.110
11	India	8,752	1.214	0.667	-0.100	0.594	0.780
12	Japan	1,641	-0.612	0.046	-0.151	61.649	68.806
13	Malaysia	904	1.253	0.493	-0.120	0.008	0.008
14	Netherlands	1445	-0.101	0.250	0.117	2.746	8.708
15	New Zealand	122	-1.221	-1.434	-0.214	1.754	11.311
16	Norway	1159	-0.585	0.015	0.064	0.859	2.464
17	Poland	1,645	-1.201	0.295	-0.496	0.204	0.091
18	Singapore	613	1.285	0.507	0.178	2.666	18.078
19	South Africa	1655	-0.680	-0.084	0.022	0.086	0.020
20	Spain	518	-0.887	-0.478	0.018	0.645	0.261
21	Sweden	1,943	0.868	0.297	0.088	5.415	14.207
22	Switzerland	1574	1.024	-0.727	0.184	10.140	30.277
23	Thailand	616	0.179	-0.416	-0.101	0.180	0.242
24	United Kingdom	13,165	-0.754	0.305	-0.200	0.913	2.475
25	United States	51,072	1.026	0.305	0.149	6.624	29.689
	Overall	125,264	0.230	0.196	-0.030	6.060	16.874

This table reports the sample distribution and the mean values of *Resource* in column (3), *Stringency* in column (4), general managerial ability (*GAI*) in column (5), and the raw numbers of patents in column (6) and citations in column (7), by country. All variables are defined in Appendix A.

Table 3. Summary Statistics

Variable	Full Sample (N=125,264)		Generalist Subsample (N=62,691)		Specialist Subsample (N=62,573)		Difference	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	*p*-value
PATENT (Raw)	6.060	29.929	7.784	34.862	4.333	23.866	3.451	0.000
CITATION (Raw)	16.874	89.836	25.370	113.513	8.363	55.698	17.007	0.000
PATENT	0.473	1.106	0.538	1.202	0.408	0.996	0.130	0.000
CITATION	0.522	1.366	0.648	1.562	0.395	1.123	0.253	0.000
GAI	-0.030	0.905	0.637	0.841	-0.698	0.195	1.335	0.000
Resource	0.230	1.006	0.434	0.916	0.026	1.050	0.407	0.000
Stringency	0.196	0.378	0.207	0.365	0.185	0.389	0.022	0.000
External Finance	0.063	0.234	0.059	0.232	0.067	0.236	-0.008	0.000
Size	12.322	2.544	12.911	2.627	11.733	2.311	1.178	0.000
Firm Age	2.514	0.626	2.610	0.636	2.418	0.601	0.192	0.000
ROA	-0.015	0.212	-0.014	0.208	-0.016	0.216	0.001	0.319
MTB	2.689	5.007	2.735	5.133	2.643	4.877	0.092	0.001
Sales Growth	0.100	0.360	0.093	0.346	0.106	0.373	-0.012	0.000
K/L	3.695	1.637	3.856	1.693	3.533	1.563	0.323	0.000
Leverage	0.576	0.700	0.593	0.671	0.560	0.728	0.034	0.000
Cash	0.188	0.199	0.179	0.197	0.198	0.201	-0.019	0.000
Closely Held	0.359	0.267	0.301	0.264	0.417	0.257	-0.116	0.000
FSALE	0.310	0.343	0.346	0.346	0.275	0.336	0.071	0.000
GDPpc	10.241	1.043	10.418	0.952	10.063	1.099	0.355	0.000
HHI	0.296	0.262	0.296	0.259	0.296	0.265	0.000	0.886
HHI^2	0.156	0.260	0.155	0.258	0.157	0.263	-0.003	0.049

This table presents the summary statistics for the main variables used in this study for the full sample, as well as the generalist and specialist subsample, respectively. The generalist (specialist) CEOs are defined as CEOs with *GAI* higher (not higher) than the yearly median (Custódio et al. 2019). All variables are defined in Appendix A.

Table 4. Effect of Innovation-specific Institutions on the Relationship Between General Managerial Ability and Innovation

Panel A. Baseline Results: Excluding Interactions of Innovation-specific Institutions with Control Variables and Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.	*PATENT*$_{t+1}$	*CITATION*$_{t+1}$	*PATENT*$_{t+1}$	*CITATION*$_{t+1}$	*PATENT*$_{t+1}$	*CITATION*$_{t+1}$	*PATENT*$_{t+1}$	*CITATION*$_{t+1}$
Resource × GAI			**0.050*****	**0.054*****			**0.078*****	**0.084*****
			(0.008)	**(0.011)**			**(0.011)**	**(0.014)**
Stringency × GAI					**-0.017***	**-0.019***	**-0.052*****	**-0.055*****
					(0.010)	**(0.011)**	**(0.011)**	**(0.012)**
GAI	**0.025***	**0.039****	**0.014**	**0.026****	**0.021***	**0.032****	**0.009**	**0.019***
	(0.014)	**(0.015)**	**(0.011)**	**(0.011)**	**(0.011)**	**(0.012)**	**(0.009)**	**(0.010)**
Resource	0.100***	0.171***	0.112***	0.193***			0.093***	0.165***
	(0.028)	(0.036)	(0.029)	(0.036)			(0.030)	(0.037)
Stringency	-0.010	-0.171***			-0.008	-0.072***	-0.002	-0.062***
	(0.031)	(0.059)			(0.012)	(0.021)	(0.011)	(0.021)
External Finance	0.081***	0.090***	0.084***	0.092***	0.080***	0.088**	0.083***	0.092***
	(0.019)	(0.031)	(0.019)	(0.031)	(0.019)	(0.031)	(0.019)	(0.031)
Size	0.119***	0.143***	0.118***	0.142***	0.118***	0.142***	0.119***	0.143***
	(0.006)	(0.009)	(0.006)	(0.009)	(0.006)	(0.009)	(0.006)	(0.009)
Firm Age	0.077***	0.094***	0.080***	0.100***	0.076***	0.092***	0.078***	0.094***
	(0.017)	(0.022)	(0.017)	(0.022)	(0.017)	(0.022)	(0.017)	(0.021)
ROA	-0.135***	-0.120***	-0.138***	-0.123***	-0.133***	-0.116**	-0.137***	-0.122***
	(0.032)	(0.041)	(0.032)	(0.041)	(0.031)	(0.041)	(0.032)	(0.041)
MTB	0.010***	0.012***	0.010***	0.012***	0.010***	0.012***	0.010***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Sales Growth	-0.021	-0.025	-0.021	-0.026*	-0.022	-0.026	-0.022	-0.026
	(0.014)	(0.016)	(0.013)	(0.015)	(0.013)	(0.016)	(0.014)	(0.016)
K/L	0.049***	0.061***	0.049***	0.061***	0.049***	0.061***	0.049***	0.062***
	(0.006)	(0.009)	(0.006)	(0.009)	(0.006)	(0.009)	(0.006)	(0.009)
Leverage	0.030***	0.015	0.031***	0.016	0.031***	0.016	0.032***	0.017*
	(0.007)	(0.010)	(0.007)	(0.010)	(0.007)	(0.009)	(0.007)	(0.010)
Cash	0.643***	0.878***	0.646***	0.882***	0.642***	0.876***	0.648***	0.883***
	(0.041)	(0.066)	(0.041)	(0.066)	(0.041)	(0.066)	(0.041)	(0.066)
Closely Held	-0.190***	-0.230***	-0.187***	-0.220***	-0.188***	-0.226***	-0.189***	-0.229***
	(0.033)	(0.049)	(0.033)	(0.050)	(0.033)	(0.049)	(0.033)	(0.049)
FSALE	0.244***	0.281***	0.248***	0.286***	0.243***	0.280***	0.250***	0.287***
	(0.029)	(0.041)	(0.029)	(0.041)	(0.029)	(0.041)	(0.030)	(0.042)
GDPpc	0.307***	0.290***	0.303***	0.231***	0.307***	0.296***	0.273***	0.254***
	(0.059)	(0.064)	(0.057)	(0.076)	(0.056)	(0.060)	(0.057)	(0.063)

HHI	-0.256*	-0.311*	-0.263*	-0.316*	-0.252*	-0.308*	-0.252*	-0.307*
	(0.128)	(0.153)	(0.128)	(0.152)	(0.128)	(0.153)	(0.128)	(0.152)
HHI^2	0.245**	0.318**	0.249**	0.320**	0.244**	0.318**	0.243**	0.315**
	(0.114)	(0.136)	(0.114)	(0.135)	(0.114)	(0.136)	(0.114)	(0.135)
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	125,264	125,264	125,264	125,264	125,264	125,264	125,264	125,264
R-squared	0.280	0.245	0.282	0.247	0.280	0.245	0.284	0.248

Panel B. Main Results: Including Interactions of Innovation-specific Institutions with Control Variables and Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	***PATENT$_{t+1}$***	***CITATION$_{t+1}$***	***PATENT$_{t+1}$***	***CITATION$_{t+1}$***	***PATENT$_{t+1}$***	***CITATION$_{t+1}$***
Resource × GAI	**0.020*** **	**0.017** **			**0.046*** **	**0.036*** **
	(0.007)	**(0.008)**			**(0.010)**	**(0.011)**
Stringency × GAI			**-0.023** **	**-0.017** **	**-0.043*** **	**-0.031*** **
			(0.008)	**(0.008)**	**(0.010)**	**(0.011)**
GAI	0.018	0.029**	0.020*	0.032**	0.012	0.023*
	(0.012)	(0.012)	(0.011)	(0.012)	(0.010)	(0.011)
Controls	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES
Resource × Controls	YES	YES	NO	NO	YES	YES
Resource × Year FE	YES	YES	NO	NO	YES	YES
Resource × Industry FE	YES	YES	NO	NO	YES	YES
Resource × Country FE	YES	YES	NO	NO	YES	YES
Stringency × Controls	NO	NO	YES	YES	YES	YES
Stringency × Year FE	NO	NO	YES	YES	YES	YES
Stringency × Industry FE	NO	NO	YES	YES	YES	YES
Stringency × Country FE	NO	NO	YES	YES	YES	YES
Observations	125,264	125,264	125,264	125,264	125,264	125,264
R-squared	0.300	0.273	0.287	0.252	0.307	0.280

The table shows the results of the effect of innovation resource availability and patent system stringency on the relationship between general managerial ability and firm innovation. The dependent variables are measured at year *t*+1 while all other variables are measured at year *t*. Panel A shows the results of the baseline regression excluding interactions of innovation-specific institutions with control variables and fixed effects. Panel B shows the regression results of the full model, which includes interactions of control variables and fixed effects with *Resource* (columns (1) and (2)), *Stringency* (columns (3) and (4)), and both innovation-specific institutions (columns (5) and (6)). All interacted variables are mean-centered and standardized using the within-fixed effect standard deviation prior to computing the interaction, except for indicator variables. Intercepts are included but not reported in all regressions. All variables are defined in Appendix A. Standard errors for two-tailed tests in parentheses are clustered at the firm and year levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5. Effect of Individual Components of Innovation Resource Availability on the Relationship Between General Managerial Ability and Innovation

Panel A. Dependent Variable: $PATENT_{t+1}$

	(1)	(2)	(3)	(4)	(5)	(6)
Innovation-specific Institution Subcategory	**Construction of Knowledge & Skill Pools**				**Public Innovation Investment**	**Openness for Innovation**
Component of *Resource* =	***University–Industry Collaboration***	***Quality of Research Institutions***	***Availability of Scientists and Engineers***	***Researchers in R&D***	***Public Investment in R&D***	***International Co-inventors***
Component_Resource × GAI	**0.018**	**0.035*****	**0.033*****	**0.018***	**0.036*****	**0.010**
	(0.010)	**(0.008)**	**(0.007)**	**(0.009)**	**(0.008)**	**(0.010)**
Stringency × GAI	-0.029**	-0.037***	-0.037***	-0.035***	-0.030***	-0.022**
	(0.011)	(0.010)	(0.009)	(0.010)	(0.008)	(0.008)
GAI	0.021*	0.015	0.017*	0.018	0.015	0.018
	(0.011)	(0.010)	(0.010)	(0.012)	(0.010)	(0.011)
Controls	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES
Component_Resource × Controls	YES	YES	YES	YES	YES	YES
Component_Resource × Year FE	YES	YES	YES	YES	YES	YES
Component_Resource × Industry FE	YES	YES	YES	YES	YES	YES
Component_Resource × Country FE	YES	YES	YES	YES	YES	YES
Stringency × Controls	YES	YES	YES	YES	YES	YES
Stringency × Year FE	YES	YES	YES	YES	YES	YES
Stringency × Industry FE	YES	YES	YES	YES	YES	YES
Stringency × Country FE	YES	YES	YES	YES	YES	YES
Observations	125,264	125,264	125,264	125,264	125,264	125,264
R-squared	0.301	0.295	0.299	0.299	0.305	0.295

Panel B. Dependent Variable: CITATION$_{t+1}$

	(1)	(2)	(3)	(4)	(5)	(6)
Innovation-specific Institution Subcategory	**Construction of Knowledge & Skill Pools**				**Public Innovation Investment**	**Openness for Innovation**
Component of *Resource* =	***University–Industry Collaboration***	***Quality of Research Institutions***	***Availability of Scientists and Engineers***	***Researchers in R&D***	***Public Investment in R&D***	***International Co-inventors***
Component_Resource × GAI	**0.007**	**0.023****	**0.030*****	**0.005**	**0.025****	**0.002**
	(0.012)	**(0.009)**	**(0.008)**	**(0.010)**	**(0.009)**	**(0.010)**
Stringency × GAI	-0.017	-0.025**	-0.032***	-0.022**	-0.022**	-0.015*
	(0.011)	(0.010)	(0.009)	(0.010)	(0.008)	(0.008)
GAI	0.035**	0.025**	0.028**	0.031**	0.026**	0.031**
	(0.013)	(0.011)	(0.011)	(0.013)	(0.011)	(0.012)
Controls	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES
Component_Resource × Controls	YES	YES	YES	YES	YES	YES
Component_Resource × Year FE	YES	YES	YES	YES	YES	YES
Component_Resource × Industry FE	YES	YES	YES	YES	YES	YES
Component_Resource × Country FE	YES	YES	YES	YES	YES	YES
Stringency × Controls	YES	YES	YES	YES	YES	YES
Stringency × Year FE	YES	YES	YES	YES	YES	YES
Stringency × Industry FE	YES	YES	YES	YES	YES	YES
Stringency × Country FE	YES	YES	YES	YES	YES	YES
Observations	125,264	125,264	125,264	125,264	125,264	125,264
R-squared	0.277	0.262	0.270	0.263	0.280	0.263

This table presents the regression results of the effect of individual components of country-level innovation resource availability on the relationship between general managerial ability and firm innovation. The dependent variables are measured at year t+1, and all other variables are measured at year t. The components of innovation resource availability (*Component_Resource*) include *University–Industry Collaboration* in column (1), *Quality of Research Institutions* in column (2), *Availability of Scientists and Engineers* in column (3), *Researchers in R&D* in column (4), *Public Investment in R&D* in column (5), and *International Co-inventors* in column (6). All interacted variables are mean-centered and standardized using the within-fixed effect standard deviation prior to computing the interaction, except for indicator variables. Intercepts are included but not reported in all regressions. All variables are defined in Appendix A. Standard errors for two-tailed tests in parentheses are clustered at the firm and year levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6. Effect of Individual Components of Patent System Stringency on the Relationship Between General Managerial Ability and Innovation

Panel A. Dependent Variable: PATENT$_{t+1}$

	(1)	(2)	(3)
Component of *Stringency* =	***PPI***	***PEI***	***Patent Office Strictness***
Component_Stringency* × *GAI	**-0.032****	**-0.024***	**-0.029*****
	(0.013)	**(0.012)**	**(0.008)**
Resource* × *GAI	0.038***	0.033***	0.015*
	(0.010)	(0.011)	(0.007)
GAI	0.016	0.016	0.016
	(0.011)	(0.011)	(0.011)
Controls	YES	YES	YES
Year FE	YES	YES	YES
Industry FE	YES	YES	YES
Country FE	YES	YES	YES
Component_Stringency × Controls	YES	YES	YES
Component_Stringency × Year FE	YES	YES	YES
Component_Stringency × Industry FE	YES	YES	YES
Component_Stringency × Country FE	YES	YES	YES
Resource × Controls	YES	YES	YES
Resource × Year FE	YES	YES	YES
Resource × Industry FE	YES	YES	YES
Resource × Country FE	YES	YES	YES
Observations	125,264	125,264	125,264
R-squared	0.309	0.305	0.305

Panel B. Dependent Variable: CITATION$_{t+1}$

	(1)	(2)	(3)
Component of *Stringency* =	***PPI***	***PEI***	***Patent Office Strictness***
Component_Stringency* × *GAI	**-0.017****	**-0.015*****	**-0.023*****
	(0.007)	**(0.004)**	**(0.003)**
Resource* × *GAI	0.028***	0.024***	0.012***
	(0.006)	(0.003)	(0.003)
GAI	0.029***	0.028***	0.027***
	(0.008)	(0.007)	(0.007)
Controls	YES	YES	YES
Year FE	YES	YES	YES
Industry FE	YES	YES	YES
Country FE	YES	YES	YES
Component_Stringency × Controls	YES	YES	YES
Component_Stringency × Year FE	YES	YES	YES
Component_Stringency × Industry FE	YES	YES	YES
Component_Stringency × Country FE	YES	YES	YES
Resource × Controls	YES	YES	YES
Resource × Year FE	YES	YES	YES
Resource × Industry FE	YES	YES	YES
Resource × Country FE	YES	YES	YES
Observations	125,264	125,264	125,264
R-squared	0.279	0.278	0.283

This table presents the regression results of the effect of individual components of country-level patent system stringency on the relationship between general managerial ability and firm innovation. The dependent variables are measured at year t+1, and all other variables are measured at year t. The components of patent system stringency (*Component_Stringency*) include *PPI* in column (1), *PEI* in column (2), and *Patent Office Strictness* in column (3). All interacted variables are mean-centered and standardized using the within-fixed effect standard deviation prior to computing the interaction, except for indicator variables. Intercepts are included but not reported in all regressions. All variables are defined in Appendix A. Standard errors for two-tailed tests in parentheses are clustered at the firm and year levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7. Effect of Innovation-specific Institutions on the Relationship Between Individual Components of General Managerial Ability and Innovation

Panel A. Dependent Variable: $PATENT_{t+1}$

Component of *GAI*	(1) Number of Positions	(2) Number of Firms	(3) Number of Industries	(4) CEO Experience	(5) Conglomerate Experience
Resource* × *Component_GAI	**0.063*** **	**0.037*** **	**0.042*** **	**0.021**	**0.031**
	(0.011)	**(0.011)**	**(0.010)**	**(0.041)**	**(0.036)**
Stringency* × *Component_GAI	**-0.049*** **	**-0.040*** **	**-0.037*** **	**-0.042**	**-0.041**
	(0.009)	**(0.011)**	**(0.011)**	**(0.032)**	**(0.025)**
Component_GAI	0.019*	0.017	0.026**	-0.048	-0.072
	(0.010)	(0.011)	(0.012)	(0.031)	(0.036)
Controls	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES
Resource × Controls	YES	YES	YES	YES	YES
Resource × Year FE	YES	YES	YES	YES	YES
Resource × Industry FE	YES	YES	YES	YES	YES
Resource × Country FE	YES	YES	YES	YES	YES
Stringency × Controls	YES	YES	YES	YES	YES
Stringency × Year FE	YES	YES	YES	YES	YES
Stringency × Industry FE	YES	YES	YES	YES	YES
Stringency × Country FE	YES	YES	YES	YES	YES
Observations	125,264	125,264	125,264	125,264	125,264
R-squared	0.307	0.306	0.307	0.305	0.276

Panel B. Dependent Variable: $CITATION_{t+1}$

Component of *GAI*	(1) Number of Positions	(2) Number of Firms	(3) Number of Industries	(4) CEO Experience	(5) Conglomerate Experience
Resource* × *Component_GAI	**0.051*** **	**0.035*** **	**0.039*** **	**-0.018**	**0.020**
	(0.012)	**(0.012)**	**(0.012)**	**(0.037)**	**(0.038)**
Stringency* × *Component_GAI	**-0.039*** **	**-0.034*** **	**-0.028** **	**-0.010**	**-0.026**
	(0.009)	**(0.012)**	**(0.011)**	**(0.031)**	**(0.030)**
Component_GAI	0.032**	0.027**	0.037**	-0.043	-0.055
	(0.011)	(0.012)	(0.013)	(0.029)	(0.043)
Controls	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES
Resource × Controls	YES	YES	YES	YES	YES
Resource × Year FE	YES	YES	YES	YES	YES
Resource × Industry FE	YES	YES	YES	YES	YES
Resource × Country FE	YES	YES	YES	YES	YES
Stringency × Controls	YES	YES	YES	YES	YES
Stringency × Year FE	YES	YES	YES	YES	YES
Stringency × Industry FE	YES	YES	YES	YES	YES
Stringency × Country FE	YES	YES	YES	YES	YES
Observations	125,264	125,264	125,264	125,264	125,264
R-squared	0.281	0.280	0.281	0.279	0.249

This table presents the regression results of the effect of innovation-specific institutions on the relationship between each component of general managerial ability and firm innovation. The dependent variables are measured at year *t*+1. All other variables are measured at year *t*. Components of general managerial ability (*Component_GAI*) include *Number of Positions* in column (1), *Number of Firms* in column (2), *Number of Industries* in column (3), *CEO Experience* in column (4), and *Conglomerate Experience in* column (5). *Resource* and *Stringency* are omitted due to collinearity with their interactions with fixed effects. All interacted variables are mean-centered and standardized using within-fixed effect standard deviation prior to computing the interaction, except for indicator variables. Intercepts are included but not reported in all regressions. All variables are defined in Appendix A. Standard errors for two-tailed tests in parentheses are clustered at the firm and year levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8. Alternative Measures of Innovation and General Managerial Ability

Panel A. Alternative Measures of Innovation

Dependent Variable	(1) ***R&D Intensity$_{t+1}$***	(2) ***PATENT/ RDC$_{t+1}$***	(3) ***CITATION/ RDC$_{t+1}$***	(4) ***Adj. PATENT$_{t+1}$***	(5) ***Adj. CITATION$_{t+1}$***
Resource × GAI	**0.015***	**0.082*****	**0.044*****	**0.056*****	**0.034*****
	(0.008)	**(0.020)**	**(0.015)**	**(0.012)**	**(0.010)**
Stringency × GAI	**-0.015**	**-0.037***	**-0.033****	**-0.057*****	**-0.032*****
	(0.010)	**(0.019)**	**(0.013)**	**(0.013)**	**(0.010)**
GAI	0.014	-0.030	-0.023	0.008	0.026**
	(0.009)	(0.019)	(0.014)	(0.012)	(0.012)
Controls	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES
Resource × Controls	YES	YES	YES	YES	YES
Resource× Year FE	YES	YES	YES	YES	YES
Resource × Industry FE	YES	YES	YES	YES	YES
Resource × Country FE	YES	YES	YES	YES	YES
Stringency × Controls	YES	YES	YES	YES	YES
Stringency × Year FE	YES	YES	YES	YES	YES
Stringency × Industry FE	YES	YES	YES	YES	YES
Stringency × Country FE	YES	YES	YES	YES	YES
Observations	125,264	112,605	112,605	125,264	125,264
R-squared	0.334	0.263	0.245	0.310	0.276

Panel B. Alternative Measures of General Managerial Ability

Dependent Variable	(1) ***PATENT$_{t+1}$***	(2) ***CITATION$_{t+1}$***
Resource × Generalist	**0.068*****	**0.042****
	(0.014)	**(0.016)**
Stringency × Generalist	**-0.060*****	**-0.030***
	(0.014)	**(0.016)**
Generalist	-0.004	0.021
	(0.014)	(0.016)
Controls	YES	YES
Year FE	YES	YES
Industry FE	YES	YES
Country FE	YES	YES
Resource × Controls	YES	YES
Resource × Year FE	YES	YES
Resource × Industry FE	YES	YES
Resource × Country FE	YES	YES
Stringency × Controls	YES	YES
Stringency × Year FE	YES	YES
Stringency × Industry FE	YES	YES
Stringency × Country FE	YES	YES
Observations	125,264	125,264
R-squared	0.304	0.279

This table presents the regression results using alternative measures of firm innovation (Panel A) and general managerial ability (Panel B). The dependent variables are measured at year t+1, and all other variables are measured at year t. In Panel A, the alternative measures of firm innovation include *R&D Intensity*, which is measured as R&D expenditure scaled by total sales and then multiplied by 100 (column (1)), the number of patents scaled by R&D capital (column (2)), the number of forward citations received by the patents scaled by R&D capital (column (3)), and truncation-adjusted measures of *PATENT* (column (4)) and *CITATION* (column (5)). Panel B uses an indicator variable, *Generalist*, to signify generalist CEOs. All interacted variables are mean-centered and standardized using the within-fixed effect standard deviation prior to computing the interaction, except for indicator variables. Intercepts are included but not reported in all regressions. All variables are defined in Appendix A. Standard errors for two-tailed tests in parentheses are clustered at the firm and year levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.