Accounting & Finance

ACCOUNTING & FINANCE afaanz

RESEARCH ARTICLE OPEN ACCESS

Migrant Top Management Team and Corporate Innovation: Evidence From China

Ying Liu | Ahsan Habib | Hedy Jiaying Huang

School of Accountancy, Economics and Finance, Massey Business School, Massey University, Auckland, New Zealand

Correspondence: Ahsan Habib (a.habib@massey.ac.nz)

Received: 28 September 2024 | **Revised:** 10 August 2025 | **Accepted:** 19 August 2025

Keywords: innovation | migrants | real earnings management | risk-taking | top management team

ABSTRACT

This study explores the association between top management teams (TMT) comprised of migrant managers (migrant TMT) and corporate innovation. Using hand-collected data for a sample of Chinese A-share listed firms spanning the period 2008–2020, we find a positive and significant association between a migrant TMT and corporate innovation. Our results remain robust to a set of endogeneity tests, including entropy-balanced regression and instrumental variable regression. We then show that real earnings management and risk-taking are the channels through which the positive relationship between migrant TMTs and corporate innovation manifests itself: migrant TMTs engage less in real earnings management and are more likely to take risks. Finally, we find that the positive relationship between migrant TMTs and corporate innovation is more pronounced in state-owned firms and remains significant in both high- and low-cultural diversity regions, suggesting that the observed effect is not primarily driven by cultural adaptability but reflects a robust migration-driven mechanism. Our findings contribute to the literature by providing novel evidence on how a migrant TMT affects corporate decision-making.

JEL Classification: O31, M40, G30

1 | Introduction

As individuals with diverse human capital, migrants have increasingly garnered attention for their role in human capital formation, knowledge transfer and regional economic development (Amendola et al. 2020; Gagliardi 2015). However, the literature has largely concentrated on international migration, especially cross-border relocation in developed countries, focusing on migration's impact on wages and employment (Borjas 1985; Chiswick 1978; Duleep et al. 2022; Kuziemko and Ferrie 2014). Prior research also highlights that migrants infuse host regions with fresh dynamism, contributing diverse perspectives, skills and entrepreneurial behaviours that foster regional innovation (Bosetti et al. 2015; Lissoni and Miguelez 2024). Lissoni and Miguelez (2024) further document that, in addition to knowledge transfer and self-selection into science and technology jobs of inventor immigrants, immigrants also contribute to innovation by increasing diversity, which can foster the generation of new ideas, and by helping to alleviate skill shortages.

However, despite internal migrants comprising 75% of total migrants globally (United Nations 2016), research on internal migration has received relatively limited attention, particularly regarding the managerial implications of internal migration at the firm level. This oversight contrasts with the significant scale and long-term impact of internal migration. Generally, compared to international migrants, internal migrants often enjoy greater cultural and institutional proximity, potentially accelerating knowledge integration and reducing barriers to innovation adoption. Focusing on Italian provinces, Pinate et al. (2023), for example, document that internal migration is more significantly related to regional innovation than international migration.

While extensive research has documented the macro-level impact of migration on economic vitality, little is known about how migrant managers influence firm-level outcomes, particularly in managerial roles. Gao et al. (2021) is a notable exception, revealing that migrant entrepreneurs can improve corporate innovation, as they are more likely to take risks compared with their local peers. One problem with this stream of literature, however, is that it solely focuses on individuals, leaving the team-related issues under-researched. With limited information, managers may not always make optimal decisions and thus must act within the social context of the firm (Zhang 2019). Migrant managers, working with other managers in the top management team (TMT), could collectively influence corporate decision-making at both the strategic and operational levels. Their migration background, therefore, is not only related to managerial decision-making but is inseparable from corporate strategy and firm value.

To fill this gap, we examine the association between top management teams (TMTs) comprised of one or more migrants (migrant TMTs) and corporate innovation.[1] On one hand, migrant managers may promote innovation through their personal characteristics, such as higher risk tolerance and openness (Chiswick 1999). Having faced uncertainties and challenges in adapting to new environments, migrants are often more psychologically prepared to embrace change and take risks (Chiswick 1999; Wu and Eesley 2022). In addition, migration experiences can lead to cognitive transformations that foster integrative thinking and a greater willingness to challenge conventional norms, all of which are crucial for navigating the uncertainties inherent in innovation. As such, a migrant TMT, comprising individuals from diverse social and cultural backgrounds, may encourage more equal and inclusive communication within the team, facilitating the exchange of novel ideas and enhancing innovation (West and Anderson 1996).[2] On the other hand, migrant managers may face social identity barriers and limited access to local resources (Xu et al. 2021), which can restrict their influence within the TMT and undermine their ability to foster an innovative team environment. These competing mechanisms raise a critical question about whether, and under what conditions, migrant TMTs contribute to firm-level innovation.

The Chinese market provides a suitable setting to study the association between migrant TMT and corporate innovation for several reasons. First, in China, there are 34 provincial administrative regions, 56 ethnic groups and more than 20 different dialects (Bian et al. 2019). Throughout China's vast territory and diverse environment, unique cultures and traditions have developed in different regions, which profoundly influence individual personalities and behaviours (Du et al. 2014). For example, people from the northern part of China are generally considered more frank and outspoken, while southern people are considered to be gentler and more introspective. Consequently, individuals in a particular region are inevitably affected by the cultural environment in which they live (Tian et al. 2018). Such variations in culture and environment across regions in China provide a natural setting for exploring the association between migrant TMTs and corporate innovation. Second, China has witnessed a rapid increase in internal migration during the past few decades. The Chinese seventh national census conducted in 2020 states that the number of internal migrants grew from 21.35 million in 1990 to 376 million in 2020. The surge in internal migration within China provides an opportunity to examine whether migrant TMTs are related to corporate innovation.

To examine our hypothesis, it must first be determined whether a TMT member is a migrant or not using hand-collected birthplace data (see Section 4 for more details). The results show a positive association between migrant TMTs and corporate innovation. The result is also economically significant, with findings suggesting that a one-standard-deviation increase in the proportion of migrant managers in the TMT (*Mig_Prop*) in year t is associated with an 18.7% increase in the total number of patent applications, a 16.8% increase in the total number of patents granted and a 23.6% increase in the citations per patent in year $t+1$. This association is robust to a series of endogeneity tests, including the entropy matching approach and instrumental variable regression. Furthermore, mediating effect tests are run to explore the potential channels through which migrant TMT influences corporate innovation. The findings show that migrant TMT has a longer time horizon and is more willing to take risks, which likely increases corporate innovation.

We further find that the association between migrant TMT and corporate innovation is more pronounced for state-owned enterprises (SOEs) than their non-SOE counterparts. This finding suggests that migrant TMTs in SOEs are more innovative, which would lead to more innovative outputs. Second, subsample analyses reveal that the positive association between migrant TMTs and corporate innovation holds in both high- and low-cultural-diversity regions, suggesting that the observed effect is not primarily driven by cultural adaptability but reflects a robust migration-driven mechanism. Finally, we find that firms with migrant TMTs also invest more in R&D.

This study makes several contributions to the literature. First, it extends the growing body of literature examining how managerial characteristics affect firm decisions and performance. Prior literature has documented that the characteristics of top managers, such as their overseas background (Yuan and Wen 2018), educational experiences (Beladi et al. 2022) and early life experience (Wan et al. 2021; Zhou et al. 2021), are important factors in corporate decision-making. However, research on the consequences of the migration background of TMT members on firm outcomes is largely missing from the literature. This research fills this void in the literature.

Second, this research sheds light on the impact of *team dynamics* on managerial decisions, compared with research that solely focuses on the effects of individuals such as CEOs or CFOs on corporate outcomes (Zhang 2019). Although the characteristics of TMTs are widely studied in management literature, it remains an emerging study in the field of accounting and finance, leaving the impact of the TMT a fruitful area of research in accounting (Hanlon et al. 2022). This research examines the shared experience and heterogeneity of migrant TMTs in China, a country characterised by an institutional setting with complex administrative divisions. Empirical findings in such a complex institutional setting will provide useful insight into understanding the influence of migrant TMTs on business decisions in the world's second-largest economy.

The remainder of the paper proceeds as follows. Section 2 introduces the institutional background in terms of internal migration and innovation development in China. Section 3 reviews the related literature and develops the hypothesis. Section 4 outlines the sample and specifies the regression models and variables. Section 5 provides the main test results, and Section 6 concludes the paper.

2 | Institutional Environment

2.1 | Internal Migration in China

The term "migrant" refers to people who move from one place to another, especially to find a job or better living conditions. They can be individuals moving across international borders or individuals simply moving within a country from one region to another. Unlike international immigrants, most migrants in China tend to be of the same ethnicity. However, internal migrants might still be culturally, economically and socially different from local residents due to differences in social environments between the host city and the migrant's birthplace (Wang and Fan 2012).

The results of the 2020 population census also show the trend of internal migration in China over the past decades. In terms of educational background, 57% of internal migrants have a bachelor's degree or above, choosing Beijing, Shanghai, Guangzhou, Shenzhen and Hangzhou as the most popular destinations for internal migration. The upward migration trend shows that more-educated, highly skilled individuals are more willing to migrate to more economically developed cities (Kopi and Clark 2015). However, it is also possible for individuals to migrate to a less economically developed city where they could have a competitive advantage in the job market. These downward migrants may pursue a less stressful lifestyle and can enjoy lower living costs despite the less challenging job environment and fewer career progression opportunities.

While most studies on migration and innovation focus on international contexts, internal migration in China presents a distinct and underexplored phenomenon with important implications for managerial behaviour and firm outcomes. Unlike international migrants, who often face visible linguistic, cultural and institutional barriers, internal migrants in China, despite sharing the same nationality and ethnicity, encounter subtle but persistent challenges in social assimilation. These challenges arise from the country's vast geographic and cultural diversity, as well as institutional restrictions rooted in the *hukou* (household registration) system (Chan 2009; Wang and Fan 2012). China spans multiple climate zones and dialect regions, and local identity is strongly shaped by regional affiliation, customs and language (Talhelm et al. 2014). Even though the *hukou* system has been gradually relaxed over time and non-*hukou* migration has been tolerated, the conversion to local hukou and related social benefits (such as pension, education, medical insurance and permission to purchase housing and vehicles) is still quite restrictive for non-hukou migrants (Chan 2009), making migration in China predominantly temporary and individualised. While the written language is unified, spoken dialects vary significantly across regions, reflecting historical patterns of migration and political boundaries. Dialect similarity is often indicative of shared cultural identity, while dissimilarity may signal deeper social divides (Falck et al. 2012).

These cultural and institutional frictions not only hinder migrants' social integration but also shape how they behave in organisational settings. Migrant managers may face barriers to accessing local networks, resources and support, affecting their influence and role within TMTs (Ren et al. 2021; Xu et al. 2021). As a result, internal migration in China is not merely a background demographic factor but a meaningful social experience that may influence cognitive styles, leadership behaviour and strategic decision-making. By explicitly focusing on internal migrant managers, rather than international migrants, this study contributes to the migration literature by highlighting a unique form of within-country relocation and its implications for corporate innovation in a context marked by significant regional, market and cultural disparities.

2.2 | Innovation Policies and Development in China

Since the early 2000s, innovation has been a key factor in China's sustained economic growth. In 2006, the 'National Guideline on Medium and Long-term Plan for Science and Technology Development (2006–2020)' was issued by the State Council of China to change the mindset of the economy from 'made-in-China' to 'invented-in-China'.[3] Thereafter, several policies and regulations have been issued at different administrative levels to foster innovation.

At present, tax relief policies and government subsidies are the main methods by which the Chinese government encourages firms to innovate (Liu et al. 2011). Several circulars have been issued by the central government regarding R&D expenses eligible for "super deduction". For example, in 2015 the government decided to expand the scope of the super deduction for R&D expenses incurred by firms domiciled in China (Circular 119).[4] Since then, R&D expenses, including testing expenses for trial products, labour costs of external R&D personnel and other expenses which can be directly related to R&D activities, have also been considered for the super deduction. Over the past few years, in addition to providing R&D subsidies directly to local firms, provincial governments have also provided other government-funded research projects to local firms. Owing to these efforts, a positive impact of these government policies and guidelines is seen in the R&D investment of China as a whole. As reported by the World Bank[5], the R&D/GDP ratio in China increased from 1.37% to 2.07% between 2005 and 2016.

3 | Literature Review and Hypothesis Development

3.1 | Literature on Migrant TMT

Migration research has predominantly developed through several theoretical lenses to explain migrants' distinctive characteristics and economic outcomes. For example, human capital theory conceptualises migration as a self-selection process where

individuals with greater ambition, risk tolerance and achievement motivation are more likely to relocate (Borjas 1985; Chiswick 1999). These inherent characteristics foster entrepreneurship, innovation and adaptability in unfamiliar environments (Chiswick 1999). Building on this view, prior studies argue that the personal characteristics of migrants shape their post-migration behaviour (Duleep 2015; Hart and Acs 2011). Such individuals typically demonstrate greater openness to new experiences, cognitive flexibility and problem-solving capabilities, which are characteristics particularly valuable in uncertain and dynamic contexts.

Although human capital theory is commonly used to explain how human capital contributes to individual and regional development, other perspectives, such as social identity theory, highlight the importance of migrants' adaptation across economic, cultural, behavioural and psychological dimensions, which also significantly influence migration outcomes (Cai and Zimmermann 2024). While these theoretical insights are compelling, migration research has traditionally focused on the macro-level economic consequences of international migration, particularly in developed countries. A large body of literature examines how immigration affects host-country labour markets, including wages, employment and productivity (Dustmann et al. 2016; Lewis and Peri 2015). However, this focus overlooks a critical demographic reality: while international migrants accounted for 3.5% of the global population in 2019, internal migrants made up a much larger share, 10.8% in 2009 (McAuliffe and Khadria 2020). In rapidly urbanising economies such as China, internal migration plays a central role in shaping not only labour dynamics but also organisational behaviour.

Recent studies have begun exploring the implications of internal migration in the Chinese context. An et al. (2024) examine labour market outcomes among internal migrants, while Cai and Zimmermann (2024) investigate identity formation and cultural adaptation. Wu and Eesley (2022) find that rural-to-urban migrants demonstrate greater entrepreneurial tendencies, likely due to the enhanced resilience and lower risk aversion developed through migration experiences. These studies suggest that migration experiences may systematically alter economic behaviours. Social identity theory offers valuable insights applicable to the internal migration context as well. In China, internal migrants frequently move across regions with significant differences in dialect, culture, economic development and social norms. Despite sharing ethnicity and citizenship with local residents, these migrants often encounter outsider status and limited access to informal networks and resources (Chan 2010; Wang and Fan 2012). Research shows that individuals perceived as outgroup members typically face greater trust deficits and integration challenges within organisations (Hogg et al. 2012). These social barriers likely influence both migrants' behaviour and how they are perceived within corporate structures.

However, few studies have systematically examined how these migrant characteristics manifest in managerial roles or affect firm-level outcomes. Notable exceptions include He et al. (2024), who find that internal migrant auditors, possessing a higher level of human capital, provide high-quality audits. Gao et al. (2021) show that migrant entrepreneurs tend to pursue more innovative business strategies than their local counterparts, as migrant entrepreneurs are more risk-taking. Building on the social identity theory, Huang, Li, and Li (2023) document that migrant CEOs, who are perceived as outgroup members by local stakeholders, would engage in a higher level of ESG activities to overcome the intergroup bias they face. However, research specifically addressing how internal migrant managers in top leadership positions influence corporate innovation remains limited.

We argue that internal migrant managers bring both the distinct cognitive characteristics associated with migration and the identity-based challenges of outsider status. This combination of capability and context jointly influences their innovation behaviour. Our approach extends existing research by connecting individual migration experiences to organisational innovation outcomes in a setting where internal migration is both widespread and institutionally complex.

3.2 | Literature on Corporate Innovation

Unlike routine tasks, innovation involves exploring unknown knowledge, which involves a higher risk of failure and long-term, multi-stage investments, which can generate positive returns with significant delays (Holmstrom 1989). As such, to encourage managers to be oriented towards innovation, short-term failures must be tolerated, and managers must be shielded from external short-term pressure (Manso 2011).

Extensive studies in the fields of accounting, finance and corporate governance have been conducted to explore the determinants of innovation (see Huang et al. 2021, for a comprehensive review). First, the stream of literature in accounting highlights the importance of quality accounting information and transparency in promoting innovation. As innovation is more information-sensitive than other investments, these studies demonstrate that a better accounting information environment promotes firm innovation by reducing information asymmetries (Brown and Martinsson 2019). Consistent with this, research on financial reporting quality shows that more transparent and comparable disclosure of accounting information improves innovation efficiency (Chircop et al. 2020; Zhong 2018). Jia (2019) finds that firms which restate their financial information to improve transparency tend to innovate more in exploratory rather than exploitative innovation projects, suggesting that these firms are associated with a greater appetite for risk. However, increases in financial reporting quality may also be detrimental to innovation, given the risk of information leakage about product development to competitors (Bhattacharya and Ritter 1983; Healy and Palepu 2001).

Another stream of literature suggests that corporate governance influences corporate innovation, where culture, as an informal governance mechanism, can shape individual behaviours and financial practices of a firm and thus can either facilitate or hinder innovation. Informal governance makes more sense in emerging markets, in particular where formal institutions are weak and less developed (Huang et al. 2021). Adhikari and Agrawal (2016), for example, find that firms headquartered in gambling-friendly areas are more

innovative, in the sense that gambling preferences instil a corporate culture which tolerates failures where there is a possibility of very large gains, leading to increased spending on exploration and experimentation, and ultimately to more innovation. Kong et al. (2021) document that social trust can enhance innovation output by alleviating the principal-agent problem and increasing the tolerance for short-term failures. Based on the *imprinting theory*[6], literature also examines how the experiences of top managers, such as disaster experience (Bernile et al. 2017), foreign experience (Yuan and Wen 2018), back-to-countryside experience (Zhou et al. 2021), birth order (Wan et al. 2021) and hometown identity (Ren et al. 2021) influence corporate innovation.

3.3 | Hypothesis on Migrant TMT and Innovation

As a risky, unpredictable and long-term investment (Holmstrom 1989), corporate innovation requires managers to have certain personality traits, including tolerance for failure, openness to novel ideas and an adventurous spirit (Galasso and Simcoe 2011; Hamilton et al. 2019; Hirshleifer et al. 2012). Individual attitudes towards risk and uncertainty have consistently been shown to explain variations in innovation and entrepreneurial activities (McGrath et al. 1992; Shane 1993). Within this context, we propose that migrant TMT may drive greater corporate innovation in three ways: inherent risk preferences, cognitive diversity and social identity transformation.

First, migrant managers may possess inherent risk preferences that align with innovative activities. The act of migration itself demonstrates a willingness to embrace uncertainty, as migrants must establish new social networks and acquire resources in an unfamiliar environment (Chiswick 1999; Wu and Eesley 2022). Behavioural genetics research supports this proposition, suggesting that the act of migration itself may be inherently linked to increased exploratory behaviour, novelty seeking and risk-taking, collectively considered to be innovative traits (Chen et al. 1999; Matthews and Butler 2011).

Second, cognitive adaptation theory explains how migration experiences transform managerial thinking patterns in ways that enhance innovative potential. The cross-cultural psychological literature demonstrates that adaptation to new cultural environments fosters cognitive flexibility and integrative complexity (Berry 2005). As migrants navigate unfamiliar social systems, they develop enhanced abilities to reconcile competing perspectives, recognise novel patterns and connect disparate ideas, which are cognitive processes that are foundational to innovation (Leung et al. 2008). These cognitive adaptations represent an acquired rather than innate advantage, suggesting that the migration experience itself cultivates innovation-enhancing cognitive capacities beyond any selection effects.

Third, migrant managers occupy a unique transitional position—having left behind their original social norms yet not fully absorbed into the institutional structures of their new environment (Cai and Zimmermann 2024). While this marginality creates identity challenges, it also provides the freedom to go beyond conventions. This flexibility enables a critical distance from established practices, reducing conformity pressures and enhancing the willingness to challenge institutional routines. Consequently, migrant managers may be less constrained by routine tasks and more inclined to pursue innovative initiatives.

On the flip side, social identity theory[7] suggests that migrant managers might face structural barriers that limit their ability to drive innovation, despite their innovative characteristics. These constraints largely stem from their potential outgroup status within the TMT (Tajfel 1982). In China, hometown is among the most common and distinctive bases upon which social networks are built (Xu et al. 2021). Non-migrant CEOs tend to receive greater board support due to shared local identity (Ren et al. 2021), while migrant managers, compared with their local counterparts, may have reduced access to key resources such as government support, local investment and supplier networks (Lai et al. 2020).

Such exclusion and unsettled conditions would negatively influence a migrant's sense of belonging and identity formation (Du et al. 2018; Wang and Fan 2012), making them shy away from communicating and impeding their ability to stimulate constructive debates and evaluation of different strategic choices. Also, the cost of favouritism bias[8] may lead to in-group views being less likely to be challenged, which might weaken the monitoring of each member of the TMT on others (Zhang 2019). As a result, the TMT may be led more towards meeting short-term earnings expectations and engaging more in myopic behaviours, eventually resulting in biased decision-making (Huang, Yang, and Zhang 2023). As such, migrant managers may not be able to promote an innovative team environment at the TMT level, despite their innovative personalities.

Based on the competing arguments above, the following hypothesis is proposed:

Hypothesis 1. *There is no association between migrant TMT and corporate innovation in Chinese listed firms.*

4 | Research Methodology

4.1 | Sample Selection

The initial data for this study includes all A-share listed firms from 2008 to 2020. The sample period starts in 2008, as birthplace data for managers required for calculating migrant TMT was largely missing before 2008. The birthplace data is critically important to identify whether a TMT member is a migrant or not. Several sources were utilised as detailed below.

First, the China Stock Market Accounting Research Database (CSMAR) was used to retrieve birthplace data for TMT managers. Second, when this information was not available from CSMAR, we manually collected the ID number from the Initial Public Offering (IPO) prospectus and then retrieved birthplace data using the manager's ID number. Every Chinese citizen must register their residence after birth, and each resident is assigned a unique 13-digit ID number when registering their residence. The ID number cannot be

changed, even after migration. In most cases, a person's birthplace can be determined by the first 6 digits of the ID number. Specifically, the first 2 digits indicate the province of the residence, the third and fourth digits indicate the city, and the fifth and sixth indicate the district/county. Finally, to further validate the accuracy of the retrieval of birthplace information as described above, we cross-referenced the birthplace information provided on the ID with data retrieved from various sources, including newspapers, journals, alumni reports and public profiles.[9] These procedures resulted in an initial sample of 8335 firm-year observations. Some illustrative examples of tracking the migration status of TMT members are provided in Appendix A. Patent applications and granted data are collected from the Chinese Research Data Services Platform (CNRDS) database, which has been widely used in prior innovation studies (Chen et al. 2021; Cui et al. 2021; Luo et al. 2022; Tang et al. 2021). Patent citation data and the accounting and governance data come from the CSMAR database. To focus solely on mainland China, firms with migrant managers from foreign countries, Hong Kong, Taiwan and Macao were excluded. Migrant TMT data was then merged with innovation data. We then performed a series of filtering on our initial sample and used 4713 firm-year observations for the baseline regression. The detailed sample selection procedures are shown in Panel A of Table 1.

4.2 | Measurement of the Dependent and Main Independent Variable

4.2.1 | Migrant TMT

The CSMAR database lists the President, Vice Presidents, Secretary to the Board and other senior executives in the TMT as disclosed in annual reports. Consistent with prior literature, a migrant manager is defined as a manager whose birthplace is different from the place where the firm is located (Gao et al. 2021).[10] Based on the definition of migrant managers, we measure migrant TMT by the proportion of migrant managers in the TMT and denote this as *Mig_Prop*. Prior literature finds that individual behaviour is shaped not only by nature (i.e., innate characteristics) but also by experiences (Hanlon et al. 2022). To investigate whether migration experiences impact managers' preferences and beliefs and ultimately corporate innovation, we decompose *Mig_Prop* into two components, namely pure migration (*Mig_Pure*) and multiple migration (*Mig_Multiple*) based on the movements of their migration.[11] Specifically, *Mig_Pure* refers to the proportion of migrant managers who migrated just once, moving directly from their hometown to their current workplace. *Mig_Multiple* is defined as the proportion of migrant managers who have migrated more than once.

4.2.2 | Corporate Innovation

Corporate innovation is calculated using output-based measures, namely patent applications, patents granted and patent citations.[12] One-year-ahead patent measures were used in all regression specifications to account for the fact that migrant TMTs need time to make investments in innovative activities. Three variants of patent applications were used. *Apply*1 is the natural logarithm of one plus the total number of patent applications; *Apply2* is the natural logarithm of one plus the number of invention and utility model patents applied; and finally, *Iapply* is the natural logarithm of one plus the number of invention patents applied.[13] Similarly, three variants of patents granted are used. *Grant*1 is the natural logarithm of one plus the number of total patents granted. *Grant2* is the natural logarithm of one plus the number of invention and utility patents granted. *Igrant* is the natural logarithm of 1 plus the number of invention patents granted. *Citation* is the natural logarithm of 1 plus the number of citations received by the patent annually. We adjust a patent's annual citations for its technology class by dividing it by the average citation of that year received by all patents filed (and eventually granted) in the same cohort (the same two-digit technology class and application year) (Hall et al. 2001; Nguyen et al. 2020). This measure of innovation quality accounts for the heterogeneous propensity for patents in different technology classes to cite other patents.

4.3 | Regression Model

To investigate the association between migrant TMT and corporate innovation, the following ordinary least squares (OLS) regression model is used:

$$\begin{aligned} Innovation_{i,t+1} = {} & \alpha_0 + \beta_1 Mig\_Prop_{i,t} + \beta_2 Size_{i,t} + \beta_3 Roa_{i,t} + \beta_4 Lev_{i,t} + \beta_5 Growth_{i,t} \\ & + \beta_6 Tobinq_{i,t} + \beta_7 TMT\_size_{i,t} + \beta_8 TMT\_age_{i,t} + \beta_9 TMT\_edu_{i,t} \\ & + \beta_{10} TMT\_gender_{i,t} + \beta_{11} Bind_{i,t} + \beta_{12} Top\_Holding_{i,t} + \beta_{13} Firm\_Age_{i,t} \\ & + \beta_{14} Home\_CEO_{i,t} + IndustryFE + YearFE + ProvinceFE + \varepsilon_{i,t} \end{aligned} \tag{1}$$

$$\begin{aligned} Innovation_{i,t+1} = {} & \alpha_0 + \beta_1 Mig\_Pure_{i,t} + \beta_2 Mig\_Multiple_{i,t} + \beta_3 Size_{i,t} + \beta_4 Roa_{i,t} + \beta_5 Lev_{i,t} \\ & + \beta_6 Growth_{i,t} + \beta_7 Tobinq_{i,t} + \beta_8 TMT\_size_{i,t} + \beta_9 TMT\_age_{i,t} + \beta_{10} TMT\_edu_{i,t} \\ & + \beta_{11} TMT\_gender_{i,t} + \beta_{12} Bind_{i,t} + \beta_{13} Top\_Holding_{i,t} + \beta_{14} Firm\_Age_{i,t} \\ & + \beta_{15} Home\ \ CEO_{i,t} + IndustryFE + YearFE + ProvinceFE + \varepsilon_{i,t} \end{aligned} \tag{2}$$

where *Innovation* is proxied by patent applications (*Apply*1, *Apply2* and *Iapply*), patents granted (*Grant*1, *Grant2* and *Igrant*) and patent citations (*Citation*). In Equation (1), the variable of interest, *Mig_Prop*, is the ratio of the number of migrant managers to the TMT size. In Equation (2) *Mig_Pure* and *Mig_Multiple* are the proportions of one-time migrants and multiple-time migrants in the TMT, respectively. Following prior literature (Hu et al. 2021; Wan et al. 2021), the set of control variables includes firm size (*Size*), return on assets (*Roa*), financial leverage of the firm (*Lev*), asset growth (*Growth*), Tobin's q (*Tobinq*), TMT size (*TMT_size*), the average age of TMT (*TMT_age*), the average education level of TMT (*TMT_edu*), the average gender of TMT (*TMT_gender*), board independence (*Bind*), ownership concentration proxied by the percentage of total shares held by the largest shareholder (*Top Holding*), firm age (*Firm Age*) and CEO hometown identity (*Home CEO*). In addition, we include industry, year and province fixed effects in the regression model to control for the unobservable industry, year and provincial-level invariant characteristics and time trends. Standard errors are clustered at the firm level. We winsorize all the continuous variables at the 1% and 99% levels to reduce the influence of the outliers. Appendix B details the variable definitions and their data sources.

TABLE 1 | Full sample distribution.

Panel A: Sample selection procedure	
Observations with available manager birthplace information	8335
Less	
Observations in the financial industry	157
Observations with no patent application and no patents granted in the same year	1089
Observations with TMT members from foreign countries	355
Observations with missing controls	546
Observations lost for using one-year ahead innovation measure	1475
Final Sample	4713

Panel B: Full sample distribution across industry

Industry		***N***	**%**	**Mean_*Mig_Prop***
(1)		**(2)**	**(3)**	**(4)**
A	Agriculture, forestry, animal husbandry and fishery	25	0.53	0.347
B	Mining	76	1.61	0.273
C	Manufacturing	3841	81.5	0.281
D	Industry of electric power, heat, gas and water production and supply	53	1.12	0.375
E	Construction	134	2.84	0.295
F	Wholesale and retail	49	1.04	0.305
G	Transport, storage and postal service	13	0.28	0.183
I	Information transmission, software and information technology services	312	6.62	0.350
K	Real Estate	3	0.06	0.438
L	Leasing and commercial service	39	0.83	0.343
M	Scientific research and technical service	47	1.00	0.292
N	Water conservancy, environment and public facility management	67	1.42	0.143
P	Education	12	0.25	0.075
Q	Health and social work	3	0.06	0.173
R	Culture, sports and entertainment	29	0.62	0.356
S	Diversified industries	10	0.21	0.889
Total		4713	100.00	

Panel C: Full sample distribution across provinces

	Headquarters of firms		
	(1)	**(2)**	**(3)**
Province	***N***	**% of all Obs.**	**Mean_*Mig_Prop***
Beijing	395	8.38	0.470
Tianjin	54	1.15	0.299
Hebei	68	1.44	0.242

(Continues)

TABLE 1 | (Continued)

Panel C: Full sample distribution across provinces			
	Headquarters of firms		
	(1)	(2)	(3)
Province	***N***	**% of all Obs.**	**Mean_*Mig_Prop***
Shanxi	48	1.02	0.114
Inner Mongolia	16	0.34	0.194
Liaoning	70	1.49	0.113
Jilin	29	0.62	0.018
Heilongjiang	31	0.66	0.147
Shanghai	240	5.09	0.502
Jiangsu	647	13.73	0.148
Zhejiang	703	14.92	0.165
Anhui	116	2.46	0.231
Fujian	188	3.99	0.214
Jiangxi	71	1.51	0.132
Shandong	294	6.24	0.114
Henan	149	3.16	0.151
Hubei	94	1.99	0.208
Hunan	158	3.35	0.128
Guangdong	909	19.29	0.493
Guangxi	37	0.79	0.314
Hainan	10	0.21	0.274
Chongqing	37	0.79	0.368
Sichuan	135	2.86	0.189
Guizhou	11	0.23	0.165
Yunnan	60	1.27	0.320
Tibet	12	0.25	0.361
Shaanxi	50	1.06	0.238
Gansu	55	1.17	0.249
Qinghai	14	0.30	0.304
Ningxia	7	0.15	0.000
Xinjiang	5	0.11	0.167

Note: This table reports the distribution of our sample. Panel A reports the sample selection procedure. Panel B reports the number of observations in each industry and the percentage of observations in the whole sample. Panel C reports the corresponding percentages of the full sample by province. Columns (1) and (2) in Panel C report the number of firm headquarters in each province and the percentage in the whole sample, respectively.

5 | Results

5.1 | Descriptive Statistics and Correlation Analysis

Table 1 exhibits the distribution of the sample. Panels B and C of Table 1 present the distribution of the sample by industry and province, respectively. Industries are categorised according to the Guidance on the Industry Category of Listed Companies issued by the China Securities Regulatory Commission (CSRC) in 2012. The top three industries in our sample are manufacturing (3841), followed by information transmission, software and information technology services (312) and construction (134). The industry distribution of the

full sample is consistent with the fact that the manufacturing sector dominates listed firms in China. Column (4) in Panel B presents the mean value of *Mig_Prop* across industries. Sectors such as information technology and cultural services exhibit relatively high *Mig_Prop* (0.350 and 0.356, respectively), indicating a stronger tendency towards cross-regional recruitment. In contrast, traditional and locally anchored sectors like education (0.075) and public utilities (0.143) show markedly lower migrant representation.

Column (1) in Panel C shows the number of firms headquartered in each province, and Column (2) provides the percentage breakdown. The highest number of firm headquarters is found in Guangdong ($n = 909$), whereas Xinjiang has the smallest number of firm headquarters ($n = 5$). Column (3) in Panel C shows the mean value of *Mig_Prop* across provinces. As expected, highly economically developed regions such as Shanghai (50.2%), Guangdong (49.3%) and Beijing (47%) exhibit the highest *Mig_Prop* values, with migrants comprising nearly or more than half of the TMT. This suggests that firms in these regions are more inclined to appoint migrant managers, likely due to greater openness, talent mobility and the strategic benefits of managerial diversity. Other municipalities, such as Chongqing (36.8%) and Tianjin (29.9%), also show relatively high shares of migrant managers. However, provinces such as Ningxia (0.0%), Jilin (1.8%) and Liaoning (11.3%) demonstrate a lower level of migrant managers in the TMT, reflecting more localised managerial structures or limited inflow of external talent.

Table 2 summarises descriptive statistics for the regression variables. The mean of patent applications is 17.73, 15.02 and 6.30 for *Apply*1 (total patents), *Apply 2* (invention plus utility patents) and *Iapply* (invention patents), respectively.[14] In terms of patents granted, the corresponding values are 14.64, 11.88 and 2.55 (before natural logarithm). Additionally, each patent in our sample, on average, receives 9.69 citations per year. These values, in general, suggest a relatively low level of innovation output in Chinese firms compared with US studies. The difference between the maximum and minimum value is quite large, ranging from a minimum of 0 to a maximum of 818.75 for the total patent applications (untabulated). The large differences indicate the variations in the level of corporate innovation across different firms are significant, which potentially facilitates this study. The mean value of *Mig_Prop* is 0.277, indicating that, on average, the percentage of migrant managers in the TMT is 27.8%. Approximately 20% of the migrant managers in the TMT have migrated only once (*Mig_Pure*), while about 8% have experienced multiple migrations (*Mig_Multiple*).

Firms in our sample are relatively large (average *Size* is 21.60), profitable (mean *Roa* of 5.10%), have good growth opportunities (mean *Growth* of 28%) and have higher leverage (mean *Lev* of 0.35). The mean values of these basic firm-level controls are similar to those in previous studies (Wan et al. 2021; Zhou et al. 2021). The mean value of *home CEO* is 0.59, implying that 59% of CEOs are from local provinces, which is consistent with prior literature (Lai et al. 2020; Ren et al. 2021; Yonker 2017). With respect to TMT characteristics, the mean of TMT size (*TMT_size*) is 6.05, and their average age (*TMT_age*) is 46.76, with approximately 85% being male. The mean value of TMT education (*TMT_edu*) is 1.176 (3.241 before taking the natural logarithm), suggesting that the average education level of TMTs is equivalent to a bachelor's degree.

Table 3 shows the Pearson correlation matrix for the variables used in the baseline regression model. *Mig_Prop* is positively and significantly correlated with $Apply1_{t+1}$, $Grant1_{t+1}$ and $Citation_{t+1}$ at the 1% level (correlation coefficients: 0.12, 0.10 and 0.10, respectively). This provides univariate support that migrant TMT is positively associated with corporate innovation. Among the control variables, *Size* and *Lev* are positively and significantly correlated with innovation measures (Hall and Ziedonis 2001; Yuan and Wen 2018). TMT characteristics, such as *TMT_size*, *TMT_age*, *TMT_edu* and *TMT_gender* are significantly and positively correlated with innovation measures. The correlation between CEO hometown identity (*Home CEO*) and innovation measures is negative and significant. The largest variance inflation factor (VIF) is 1.95, which is far less than 10, suggesting that multicollinearity is not a serious concern in the estimations in this study (Marquardt 1970).

5.2 | Baseline Regression Results

We estimate the OLS regressions (Equations 1 and 2) to examine the association between migrant TMT and corporate innovation and report the results in Table 4. As per Equation (1), the independent variable of interest is *Mig_Prop*, with the dependent variables being one-year-ahead innovation outputs (measured as patent applications, patents granted and patent citations). Columns (1–6) of Table 4 present the results for patent applications, measured by $Apply1_{t+1}$, $Apply2_{t+1}$ and $Iapply_{t+1}$, respectively. We find the coefficients of *Mig_Prop* are positive and significant at the 1% level, with values of 0.494, 0.542 and 0.523 in Columns (1), (3) and (5). The findings are also economically significant. For example, a one-standard-deviation increase in *Mig_Prop* in year t is associated with an 18.7% increase in the total number of patent applications in year $t+1$ (Column 1), a 20.8% increase in the number of utility-plus-invention patent applications in year $t+1$ (Column 3), and a 22.1% increase in the number of invention patents in year $t+1$ (Column 5).[15] This suggests that firms that have TMTs with more migrant managers lead to more patent applications and are more likely to engage in highly innovative strategies (i.e., generating more utility and invention patents).

As we pointed out earlier, migrant managers can be either one-time migrants or multiple migrants, considering their migration experiences. Therefore, we replace *Mig_Prop* in Equation (1) with *Mig_Pure* and *Mig_Multiple* in Equation (2) to infer the differential effects of migration experiences, if any, on corporate innovation. The results are reported in Columns (2), (4) and (6) of Table 4. We find the coefficients for migration variables positive and significant. In Column (2), for example, the coefficients of *Mig_Pure* and *Mig_Multiple* are 0.417 ($p < 0.05$) and 0.714 ($p < 0.01$). We find the coefficient on *Mig_Multiple* larger in magnitude than *Mig_Pure* for the other innovation measures as well, despite multiple-time migrants comprising a small fraction of all migrant managers.[16]

TABLE 2 | Descriptive statistics.

Variable	*N*	Mean	SD	0.25	Median	0.75
Mig_Prop_t	4713	0.277	0.289	0.000	0.200	0.444
Mig_Pure_t	4713	0.204	0.238	0.000	0.143	0.333
$Mig\_Multiple_t$	4713	0.073	0.142	0.000	0.000	0.125
$Apply1_{t+1}$	4713	3.052	1.419	2.079	3.091	3.989
$Apply2_{t+1}$	4713	2.900	1.443	1.946	2.944	3.850
$Iapply_{t+1}$	4713	2.106	1.369	1.099	2.079	2.996
$Grant1_{t+1}$	4713	2.900	1.318	1.946	2.890	3.761
$Grant2_{t+1}$	4713	2.708	1.332	1.792	2.708	3.584
$Igrant_{t+1}$	4713	1.365	1.145	0.693	1.099	2.079
$Citation_{t+1}$	3387	1.068	0.601	0.741	1.223	1.522
$Size_t$	4713	21.600	1.273	20.740	21.410	22.140
Roa_t	4713	0.051	0.047	0.025	0.050	0.077
Lev_t	4713	0.351	0.185	0.199	0.334	0.485
$Growth_t$	4713	0.283	0.451	0.046	0.136	0.328
$Tobinq_t$	4713	1.923	0.972	1.297	1.616	2.207
TMT_size_t	4713	1.804	0.347	1.609	1.792	2.079
TMT_age_t	4713	3.841	0.079	3.789	3.845	3.896
TMT_edu_t	4713	1.173	0.214	1.050	1.179	1.299
TMT_gender_t	4713	0.850	0.158	0.750	0.857	1.000
$Bind_t$	4713	0.376	0.054	0.333	0.333	0.429
$Top\ Holding_t$	4713	0.343	0.139	0.239	0.330	0.428
$Firm\ Age_t$	4713	2.627	0.433	2.398	2.708	2.944
$Home\ CEO_t$	4713	0.590	0.492	0.000	1.000	1.000
Rem_t	3486	−0.019	0.170	−0.103	−0.004	0.083
$Risk_t$	3305	0.057	0.050	0.027	0.042	0.069
SOE_t	4713	0.194	0.395	0.000	0.000	0.000
RD_Ratio_{t+1}	4713	0.966	1.149	0.000	0.693	1.609
$Gpat\_App_{t+1}$	4713	0.601	0.919	0.000	0.000	1.099
$IGpat\_App_{t+1}$	4713	0.734	0.981	0.000	0.000	1.386
$Gpat\_grant_{t+1}$	4713	0.267	0.586	0.000	0.000	0.000
$IGpat\_grant_{t+1}$	4713	0.267	0.586	0.000	0.000	0.000

Note: This table reports the summary statistics of the regression variables. All variables are defined in Appendix B.

Because not all patents applied for would be successful, the association between migrant TMT and patents granted is further examined and the results are reported in Columns (7–12) of Table 4. The results are generally consistent with those of patent applications. For example, the coefficients on *Mig_Prop* are significant and positive at the 1% level for all three patent-granted measures, with coefficients being 0.433, 0.504 and 0.364 for $Grant1_{t+1}$, $Grant2_{t+1}$ and $Igrant_{t+1}$, respectively. The results are also economically significant. For example, a one-standard-deviation increase in *Mig_Prop* in year *t* is associated with a 16.8% increase in the total number of patents granted in year $t+1$ according to the result in Column (7), a 19.9% increase in the number of utility plus invention patents granted based on the result in Column (9), and an 18.2% increase in the number of invention patents granted based on the result in Column (11). The coefficients on *Mig_Pure* and *Mig_Multiple* are also positive and significant in Columns (8), (10) and (12), with the magnitude of the coefficients on *Mig_Multiple* being larger than that of *Mig_Pure*.

TABLE 3 | Pearson correlation matrix.

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1.*Mig_Prop*	1.00																						
2.Mig_Pure	***0.87***	1.00																					
3.Mig_Multiple	***0.57***	***0.09***	1.00																				
*4.Apply*1	***0.12***	***0.08***	***0.10***	1.00																			
5.Apply2	***0.13***	***0.09***	***0.10***	***0.96***	1.00																		
6.Iapply	***0.15***	***0.12***	***0.12***	***0.85***	***0.89***	1.00																	
*7.Grant*1	***0.10***	***0.07***	***0.10***	***0.78***	***0.74***	***0.66***	1.00																
8.Grant2	**0.11**	***0.08***	***0.10***	***0.75***	***0.78***	***0.69***	***0.94***	1.00															
9.Igrant	***0.14***	***0.10***	***0.12***	***0.58***	***0.60***	***0.68***	***0.66***	***0.70***	1.00														
10.Citation	***0.10***	***0.07***	***0.08***	***0.42***	***0.45***	***0.42***	***0.38***	***0.41***	***0.42***	1.00													
11.*Size*	−0.00	−0.10	0.01	***0.40***	***0.40***	***0.39***	***0.45***	***0.45***	***0.40***	***0.21***	1.00												
12.Roa	0.02*	0.02	0.02	0.02	−0.01	0.02	−0.02	***−0.05***	−0.10	**0.03**	***−0.16***	1.00											
13.Lev	0.01	0.01	0.01	***0.05***	***0.08***	***0.07***	***0.08***	***0.11***	***0.08***	0.02	***0.37***	***−0.23***	1.00										
14.Growth	***0.07***	***0.06***	**0.03**	−0.01	−0.01	−0.01	***−0.07***	***−0.08***	***−0.04***	**0.04**	***−0.35***	***0.24***	***−0.03***	1.00									
15.Tobinq	0.02*	0.01	**0.03**	***−0.07***	***−0.08***	−0.02	***−0.11***	***−0.13***	−0.01	−0.02	***−0.23***	***0.22***	***−0.15***	***−0.03***	1.00								
16.TMT_size	***−0.08***	***−0.05***	***−0.09***	***0.16***	***0.15***	***0.14***	***0.16***	***0.16***	***0.13***	***0.16***	***0.26***	−0.01	***0.04***	−0.02*	***−0.12***	1.00							
17.TMT_age	***−0.07***	***−0.05***	***−0.06***	***0.06***	***0.07***	***0.06***	***0.12***	***0.12***	***0.10***	***−0.08***	***0.31***	***−0.05***	***0.10***	***−0.19***	***−0.07***	***0.13***	1.00						
18.TMT_edu	***0.20***	***0.13***	***0.19***	***0.12***	***0.11***	***0.15***	***0.11***	***0.10***	***0.16***	***0.08***	***0.20***	−0.01	***0.07***	***−0.04***	***0.08***	−0.00	***−0.04***	1.00					
19.TMT_gender	−0.01	−0.00	−0.02	***0.08***	***0.09***	***0.08***	***0.08***	***0.08***	***0.07***	***0.10***	***0.10***	−0.02	**0.03**	−0.02	***−0.07***	***0.11***	***0.12***	***0.07***	1.00				
20.Bind	***0.04***	**0.03**	***0.04***	***0.04***	**0.03**	***0.04***	***0.05***	***0.04***	***0.05***	−0.00	***0.06***	−0.02	***0.05***	−0.01	**0.03**	***−0.08***	−0.01	***0.05***	***−0.07***	1.00			
21.Top Holding	0.03*	***0.04***	−0.01	***0.04***	0.02	−0.00	***0.06***	**0.03**	0.01	***0.10***	***0.18***	***0.11***	***0.04***	−0.00	***−0.05***	−0.02	**0.03**	0.02	0.01	***0.09***	1.00		
22.Firm Age	***−0.08***	***−0.06***	***−0.06***	**0.04**	**0.03**	***0.05***	***0.09***	***0.09***	***0.06***	***−0.25***	***0.15***	***−0.08***	***0.08***	***−0.22***	***0.04***	−0.01	***0.26***	−0.01	***−0.06***	***0.05***	***−0.07***	1.00	
23.Home CEO	***−0.49***	***−0.40***	***−0.33***	***−0.13***	***−0.15***	***−0.15***	***−0.13***	***−0.14***	***−0.13***	***−0.10***	***−0.13***	***0.06***	***−0.05***	0.01	−0.01	0.02	0.02*	***−0.19***	***0.06***	−0.01	−0.02	***0.03***	1.00

Note: This table shows the Pearson correlation matrix of TMT migration measures, corporate innovation measures and control variables. Bold and italics indicate statistical significance at $p < 0.01$; bold values indicate statistical significance at $p < 0.05$; and * indicates statistical significance at $p < 0.10$. All variables are defined in Appendix B.

TABLE 4 | Baseline regression results.

	$Apply1_{t+1}$		$Apply2_{t+1}$		$Iapply_{t+1}$		$Grant1_{t+1}$		$Grant2_{t+1}$		$Igrant_{t+1}$		$Citation_{t+1}$	
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**
Mig_Prop	0.494***		0.542***		0.523***		0.433***		0.504***		0.364***		0.581***	
	(0.149)		(0.151)		(0.145)		(0.143)		(0.144)		(0.126)		(0.157)	
Mig_Pure		0.417**		0.477***		0.483***		0.356**		0.433***		0.302**		0.445**
		(0.169)		(0.177)		(0.170)		(0.162)		(0.167)		(0.146)		(0.183)
Mig_ Multiple		0.714***		0.726***		0.639**		0.654***		0.704***		0.541**		0.983***
		(0.248)		(0.259)		(0.265)		(0.253)		(0.254)		(0.247)		(0.279)
Size	0.611***	0.610***	0.612***	0.611***	0.583***	0.583***	0.569***	0.568***	0.560***	0.559***	0.482***	0.481***	0.602***	0.600***
	(0.036)	(0.036)	(0.039)	(0.039)	(0.038)	(0.038)	(0.035)	(0.035)	(0.037)	(0.037)	(0.035)	(0.035)	(0.042)	(0.041)
Roa	1.450**	1.437**	0.748	0.737	1.267*	1.260*	0.663	0.650	−0.188	−0.201	0.259	0.248	1.402*	1.381*
	(0.712)	(0.715)	(0.761)	(0.763)	(0.691)	(0.692)	(0.671)	(0.674)	(0.712)	(0.715)	(0.559)	(0.561)	(0.799)	(0.799)
Lev	−1.826***	−1.815***	−1.374**	−1.364**	−0.609	−0.603	−1.379**	−1.367**	−0.810	−0.800	−0.523	−0.515	−1.757**	−1.730**
	(0.675)	(0.674)	(0.695)	(0.693)	(0.653)	(0.652)	(0.652)	(0.650)	(0.668)	(0.665)	(0.573)	(0.571)	(0.754)	(0.752)
Growth	0.442***	0.441***	0.452***	0.452***	0.487***	0.487***	0.363***	0.363***	0.353***	0.352***	0.332***	0.332***	0.355***	0.355***
	(0.048)	(0.048)	(0.049)	(0.049)	(0.047)	(0.047)	(0.042)	(0.043)	(0.043)	(0.043)	(0.038)	(0.038)	(0.054)	(0.054)
Tobinq	0.047	0.047	0.053	0.053	0.109***	0.109***	0.022	0.022	0.022	0.022	0.099***	0.098***	0.061	0.062
	(0.034)	(0.034)	(0.036)	(0.037)	(0.037)	(0.037)	(0.031)	(0.031)	(0.034)	(0.034)	(0.032)	(0.032)	(0.038)	(0.038)
TMT_size	0.215**	0.220**	0.186*	0.190*	0.192*	0.195*	0.237**	0.242**	0.193*	0.198*	0.143	0.147*	0.103	0.112
	(0.108)	(0.108)	(0.108)	(0.108)	(0.103)	(0.103)	(0.103)	(0.103)	(0.102)	(0.102)	(0.088)	(0.087)	(0.118)	(0.118)
TMT_age	−0.958**	−0.955**	−0.953*	−0.951*	−0.759*	−0.758*	−0.711	−0.708	−0.681	−0.678	−0.072	−0.069	−0.810	−0.811
	(0.464)	(0.464)	(0.486)	(0.486)	(0.454)	(0.454)	(0.445)	(0.444)	(0.462)	(0.462)	(0.370)	(0.369)	(0.497)	(0.494)
TMT_edu	0.111	0.096	0.055	0.042	0.198	0.190	0.021	0.006	−0.035	−0.048	0.189	0.177	0.135	0.105
	(0.165)	(0.163)	(0.180)	(0.179)	(0.171)	(0.170)	(0.158)	(0.157)	(0.169)	(0.169)	(0.138)	(0.137)	(0.183)	(0.182)
TMT_ gender	0.418*	0.422*	0.463**	0.466**	0.441**	0.443**	0.383*	0.387*	0.457**	0.461**	0.314*	0.317*	0.249	0.257
	(0.218)	(0.218)	(0.218)	(0.218)	(0.203)	(0.203)	(0.208)	(0.208)	(0.208)	(0.208)	(0.166)	(0.165)	(0.256)	(0.257)
Bind	0.080	−0.056	−0.265	−0.269	−0.267	−0.270	0.014	0.009	−0.171	−0.175	0.121	0.117	−0.229	−0.224
	(0.621)	(0.625)	(0.639)	(0.636)	(0.610)	(0.608)	(0.632)	(0.627)	(0.626)	(0.622)	(0.532)	(0.529)	(0.675)	(0.666)

(Continues)

TABLE 4 | (Continued)

	$Apply1_{t+1}$		$Apply2_{t+1}$		$Iapply_{t+1}$		$Grant1_{t+1}$		$Grant2_{t+1}$		$Igrant_{t+1}$		$Citation_{t+1}$	
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**
Top Holding	−0.365	−0.359	−0.617**	−0.612**	−0.672***	−0.668***	−0.063	−0.057	−0.372	−0.366	−0.417*	−0.411*	−0.443	−0.424
	(0.253)	(0.252)	(0.259)	(0.258)	(0.251)	(0.251)	(0.243)	(0.242)	(0.246)	(0.245)	(0.217)	(0.216)	(0.285)	(0.283)
Firm Age	0.076	0.077	0.050	0.051	0.041	0.042	0.045	0.047	0.032	0.033	0.068	0.069	0.028	0.030
	(0.094)	(0.095)	(0.095)	(0.095)	(0.095)	(0.095)	(0.090)	(0.089)	(0.088)	(0.088)	(0.077)	(0.077)	(0.095)	(0.094)
Home CEO	−0.171**	−0.165**	−0.220***	−0.215***	−0.160**	−0.156*	−0.146*	−0.140*	−0.196**	−0.191**	−0.047	−0.042	−0.134	−0.125
	(0.081)	(0.081)	(0.083)	(0.083)	(0.081)	(0.081)	(0.077)	(0.077)	(0.078)	(0.078)	(0.068)	(0.068)	(0.089)	(0.088)
_cons	−8.590***	−8.569***	−8.273***	−8.255***	−9.597***	−9.585***	−8.876***	−8.854***	−8.640***	−8.621***	−10.782***	−10.765***	−7.445***	−7.426***
	(1.783)	(1.773)	(1.931)	(1.923)	(1.848)	(1.843)	(1.692)	(1.679)	(1.805)	(1.794)	(1.539)	(1.526)	(1.964)	(1.943)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4713	4713	4713	4713	4713	4713	4713	4713	4713	4713	4713	4713	3387	3387
Adj_R^2	0.34	0.34	0.33	0.33	0.31	0.31	0.34	0.34	0.33	0.33	0.30	0.30	0.57	0.57

Note: This table presents the OLS regression results of the association between TMT migration and corporate innovation for the period 2008 to 2020. The dependent variables of the regressions are the innovation output measures. $Apply1_{t+1}$, $Apply2_{t+1}$, $Iapply_{t+1}$ refer to the number of total patents applied, utility and invention patents applied and invention patents applied in the following year, respectively. Patents granted, likewise, is proxied by the total number of patents granted ($Grant1_{t+1}$), utility and invention patents granted ($Grant2_{t+1}$) and invention patents granted in the following year ($Igrant_{t+1}$). $Citaition_{t+1}$ is the patent citations in the following year. The key independent variables are the proportion of migrant managers (*Mig_Prop*), pure migrant managers (*Mig_Pure*) and multiple migrant managers (*Mig_Multiple*). Robust standard errors clustered at the firm-level are in brackets. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. All variables are defined in Appendix B.

TABLE 5 | Firm-fixed effects regression.

	$Apply1_{t+1}$	$Apply1_{t+1}$	$Iapply_{t+1}$	$Grant1_{t+1}$	$Grant2_{t+1}$	$Igrant_{t+1}$	$Citation_{t+1}$
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Mig_Prop	0.391***	0.393***	0.245*	0.237**	0.254**	0.150	0.605***
	(0.141)	(0.141)	(0.137)	(0.122)	(0.121)	(0.119)	(0.232)
Size	0.405***	0.414***	0.442***	0.488***	0.464***	0.318***	0.411***
	(0.049)	(0.049)	(0.048)	(0.043)	(0.042)	(0.041)	(0.082)
Roa	1.880***	1.696***	1.725***	1.109***	0.945***	0.000	1.310*
	(0.408)	(0.407)	(0.396)	(0.353)	(0.351)	(0.344)	(0.747)
Lev	0.242	0.469	0.259	1.092***	1.443***	0.546	0.809
	(0.451)	(0.450)	(0.437)	(0.390)	(0.388)	(0.380)	(0.744)
Growth	0.210***	0.223***	0.255***	0.191***	0.183***	0.131***	0.147***
	(0.039)	(0.039)	(0.038)	(0.034)	(0.034)	(0.033)	(0.055)
Tobinq	0.022	0.028	0.021	0.004	0.006	−0.013	−0.016
	(0.020)	(0.020)	(0.020)	(0.018)	(0.018)	(0.017)	(0.030)
TMT_size	0.168**	0.158**	0.162**	0.195***	0.176***	0.047	−0.015
	(0.068)	(0.068)	(0.066)	(0.059)	(0.058)	(0.057)	(0.110)
TMT_age	0.412	0.008	0.002	0.526*	0.177	−0.121	−0.132
	(0.338)	(0.337)	(0.328)	(0.292)	(0.291)	(0.285)	(0.566)
TMT_edu	0.253*	0.214	0.170	0.050	0.058	0.155	0.585**
	(0.145)	(0.144)	(0.140)	(0.125)	(0.124)	(0.122)	(0.231)
TMT_gender	−0.172	−0.154	−0.072	−0.058	0.007	0.104	−0.130
	(0.158)	(0.158)	(0.153)	(0.137)	(0.136)	(0.133)	(0.264)
Bind	−0.322	−0.148	−0.261	−0.304	−0.065	−0.127	0.678
	(0.459)	(0.458)	(0.445)	(0.397)	(0.395)	(0.387)	(0.714)
Top Holding	0.248	0.117	0.016	0.220	0.124	−0.418	−0.670
	(0.360)	(0.360)	(0.349)	(0.312)	(0.310)	(0.303)	(0.597)
Firm Age	0.013	−0.055	−0.158	0.385***	0.397***	0.412***	−0.013
	(0.151)	(0.151)	(0.146)	(0.131)	(0.130)	(0.127)	(0.228)
Home CEO	0.026	0.023	−0.031	0.122**	0.113**	0.195***	0.068
	(0.061)	(0.061)	(0.059)	(0.053)	(0.052)	(0.051)	(0.097)
_cons	−8.537***	−7.215***	−8.285***	−11.561***	−10.213***	−6.762***	−5.649**
	(1.617)	(1.614)	(1.568)	(1.398)	(1.390)	(1.362)	(2.771)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province	No	No	No	No	No	No	No
N	4713	4713	4713	4713	4713	4713	3387
Adj_R^2	0.235	0.244	0.179	0.243	0.255	0.169	0.459

Note: This table presents the fixed-effects regression results of the association between TMT migration and corporate innovation for the period 2008 to 2020. The dependent variables of the regressions are the innovation output measures. $Apply1_{t+1}$, $Apply2_{t+1}$ and $Iapply_{t+1}$ refer to the number of total patents applied, utility and invention patents applied, and invention patents applied in the following year, respectively. Patents granted, likewise, are proxied by the total number of patents granted ($Grant1_{t+1}$), utility and invention patents granted ($Grant2_{t+1}$), and invention patents granted in the following year ($Igrant_{t+1}$). $Citaition_{t+1}$ is the patent citations in the following year. The key independent variables are the proportion of migrant managers (*Mig_Prop*). Robust standard errors clustered at the firm level are in brackets. *, ** and **** * * indicate statistical significance at the 10%, 5% and 1% levels, respectively. All variables are defined in Appendix B.

TABLE 6 | Entropy balancing approach.

Panel A: Covariate balance

	Weight variables before entropy balancing						Weight variables after entropy balancing					
	Treated			Control			Treated			Control		
Covariates	Mean	Variance	Skewness	Mean	Variance	Skewness	Mean	Variance	Skewness	Mean	Variance	Skewness
Size	21.630	1.718	1.160	21.580	1.355	1.037	21.630	1.718	1.160	21.630	1.717	1.161
Roa	0.050	0.003	−0.857	0.049	0.003	−0.760	0.050	0.003	−0.857	0.050	0.003	−0.857
Lev	0.361	0.040	0.342	0.365	0.036	0.359	0.361	0.035	0.342	0.361	0.035	0.342
Growth	0.305	0.235	2.818	0.258	0.180	2.955	0.305	0.234	2.818	0.305	0.234	2.817
Tobinq	1.982	1.031	2.222	1.929	1.000	2.275	1.982	1.031	2.222	1.982	1.030	2.222
TMT_size	1.724	0.121	0.162	1.826	0.110	−0.066	1.724	0.121	0.162	1.724	0.121	1.162
TMT_age	3.836	0.006	−0.167	3.846	0.006	−0.194	3.836	0.006	−0.167	3.835	0.006	−0.155
TMT_edu	1.227	0.040	−0.220	1.160	0.046	−0.092	1.227	0.040	−0.220	1.227	0.040	−0.218
TMT_gender	0.853	0.026	−0.928	0.843	0.025	−0.912	0.853	0.026	−0.928	0.853	0.026	−0.927
Bind	0.379	0.003	1.041	0.376	0.003	1.239	0.379	0.003	1.041	0.379	0.003	1.043
Top Holding	0.341	0.020	0.467	0.336	0.019	0.411	0.341	0.020	0.467	0.341	0.020	0.467
Firm Age	2.593	0.200	−0.920	2.671	0.175	−1.066	2.593	0.200	−0.920	2.593	0.200	−0.919
Home CEO	0.175	0.144	1.713	0.752	0.187	−1.164	0.175	0.144	1.713	0.176	0.145	1.698

Panel B: Entropy-balanced regression

	$Apply1_{t+1}$	$Apply1_{t+1}$	$Iapply_{t+1}$	$Grant1_{t+1}$	$Grant2_{t+1}$	$Igrant_{t+1}$	$Citation_{t+1}$
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mig_Prop	0.436***	0.480***	0.624***	0.296**	0.348**	0.436***	0.406**
	(0.162)	(0.163)	(0.156)	(0.149)	(0.148)	(0.122)	(0.167)
Size	0.637***	0.645***	0.620***	0.580***	0.584***	0.491***	0.664***
	(0.041)	(0.041)	(0.042)	(0.038)	(0.037)	(0.037)	(0.056)
Roa	1.928**	1.338	1.448*	1.436*	0.684	0.376	0.895
	(0.924)	(0.941)	(0.805)	(0.817)	(0.800)	(0.630)	(0.863)
Lev	−3.358***	−2.856***	−1.831**	−2.330**	−1.855**	−1.045	−2.844***

(Continues)

TABLE 6 | (Continued)

Panel B: Entropy-balanced regression

	$Apply1_{t+1}$	$Apply1_{t+1}$	$Iapply_{t+1}$	$Grant1_{t+1}$	$Grant2_{t+1}$	$Igrant_{t+1}$	$Citation_{t+1}$
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
	(1.119)	(1.093)	(0.786)	(0.909)	(0.918)	(0.664)	(0.926)
Growth	0.458***	0.459***	0.475***	0.391***	0.391***	0.295***	0.348***
	(0.064)	(0.066)	(0.064)	(0.055)	(0.056)	(0.045)	(0.078)
Tobinq	−0.024	−0.014	0.077	−0.067	−0.059	0.089**	0.054
	(0.055)	(0.057)	(0.049)	(0.049)	(0.051)	(0.043)	(0.059)
TMT_size	0.315**	0.287**	0.319**	0.284**	0.230*	0.236**	0.178
	(0.138)	(0.138)	(0.143)	(0.121)	(0.120)	(0.112)	(0.149)
TMT_age	−0.683	−0.607	−0.256	−0.425	−0.162	0.404	0.388
	(0.663)	(0.665)	(0.654)	(0.599)	(0.599)	(0.495)	(0.718)
TMT_edu	0.256	0.241	0.278	0.111	0.091	0.287*	0.209
	(0.202)	(0.209)	(0.202)	(0.188)	(0.191)	(0.159)	(0.211)
TMT_gender	1.027***	1.083***	0.907***	0.906***	0.979***	0.548***	0.842**
	(0.271)	(0.277)	(0.259)	(0.242)	(0.251)	(0.198)	(0.340)
Bind	0.413	0.072	−0.429	0.777	0.307	0.017	−0.334
	(0.783)	(0.784)	(0.751)	(0.740)	(0.748)	(0.621)	(0.892)
Top Holding	−0.213	−0.477	−0.592*	0.150	−0.131	−0.435	−0.247
	(0.315)	(0.318)	(0.327)	(0.290)	(0.294)	(0.265)	(0.396)
Firm Age	−0.032	−0.065	−0.027	0.011	−0.003	0.046	−0.076
	(0.111)	(0.115)	(0.106)	(0.100)	(0.099)	(0.088)	(0.114)
Home CEO	−0.211**	−0.277***	−0.197**	−0.175**	−0.235***	−0.055	−0.242**
	(0.093)	(0.095)	(0.092)	(0.082)	(0.084)	(0.070)	(0.095)
_cons	−11.152***	−11.321***	−12.903***	−11.061***	−12.012***	−13.129***	−13.465***
	(2.414)	(2.449)	(2.461)	(2.177)	(2.194)	(1.847)	(2.696)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes

(Continues)

TABLE 6 | (Continued)

Panel B: Entropy-balanced regression

Variables	$Apply1_{t+1}$	$Apply1_{t+1}$	$Iapply_{t+1}$	$Grant1_{t+1}$	$Grant2_{t+1}$	$Igrant_{t+1}$	$Citation_{t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4713	4713	4713	4713	4713	4713	3387
Adj_R^2	0.422	0.422	0.386	0.430	0.425	0.348	0.634

Note: This table reports the entropy balance test results. Panel A shows the covariate balance with and without weighting. Panel B shows the entropy-balanced regression estimates. The dependent variables of the regressions are the innovation output measures. $Apply1_{t+1}$, $Apply2_{t+1}$, $Iapply_{t+1}$ refer to the number of total patents applied, utility and invention patents applied and invention patents applied in the following year, respectively. Patents granted, likewise, is proxied by the total number of patents granted ($Grant1_{t+1}$), utility and invention patents granted ($Grant2_{t+1}$) and invention patents granted in the following year ($Igrant_{t+1}$). $Citaition_{t+1}$ is the patent citations in the following year. The independent variable is the proportion of migrant managers (*Mig_Prop*). Robust standard errors clustered at the firm-level are in brackets. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. All variables are defined in Appendix B.

Finally, we also consider innovation quality as proxied by patent citations. The coefficient on *Mig_Prop is* 0.581 ($p < 0.01$) (Column 13). In terms of economic significance, a one-standard-deviation increase in *Mig_Prop* in year *t* is associated with a 23.6% increase in the patent citations. For the citation measure, too, the coefficients on *Mig_Pure* and *Mig_Multiple* are positive and significant (Column 14), and the magnitude of the coefficient on *Mig_Multiple* is larger than that of *Mig_Pure*. Overall, the regression results in Table 4 suggest that migrant TMT has a positive and significant effect on both the quantity and quality of innovation outputs, which rejects our Hypothesis 1.

With respect to the firm-related control variables, we find that larger firms are associated with higher innovation outputs, as the coefficient estimates on *Size* are positive and significant at the 1% level. Likewise, firms with higher growth opportunities (*Growth*) are more innovative. TMT size (*TMT_size*) and TMT gender (*TMT_gender*) are significantly and positively associated with corporate innovation, suggesting that a firm with a larger and male-dominated TMT is associated with innovation. Conversely, the coefficients on *Lev* and *TMT_age* are significantly negative, suggesting that leverage and age are two constraints on firm innovation. The coefficient of CEO hometown identity (*Home CEO*) is significant and negative, implying that CEO hometown identity leads to fewer innovation outputs. Different from the findings in Ren et al. (2021) that a firm with a hometown CEO tends to innovate more, the finding in this study is consistent with Yonker (2017) and Jiang et al. (2019), who suggest that hometown bias can cause suboptimal decisions, leading to fewer innovative outputs.

5.3 | Endogeneity Tests

The regression results so far indicate a positive association between migrant TMT and corporate innovation. However, the results might be subject to endogeneity concerns. First, it is possible for omitted variables to bias the regression results if migration and firm innovation decisions are jointly determined by other unobservable factors. Second, the results are likely to suffer from problems of reverse causality. Innovative firms may prefer to hire talented managers from all over the nation, which would lead to more migrant managers in the TMT. However, by using one-year-ahead innovation measures in all our regression specifications, we have alleviated this concern. Other potential endogeneity issues are addressed in several ways, including firm-fixed effects regression, the entropy matching approach, and instrumental variable regression.

5.3.1 | Firm-Fixed Effect Result

The firm-fixed effect regression model is used to rule out endogeneity concerns arising from time-invariant firm characteristics and further strengthen the results against omitted variable bias. We report the fixed-effect regression results in Table 5. The coefficients on migrant TMT remain positive across various innovation measures. For example, in Column (1), the coefficient on *Mig_Prop* is 0.391, positive and statistically significant at the 1% level. In general, the findings are consistent with the baseline findings in Table 4.

5.3.2 | Entropy Balancing Test

In recent studies, entropy balance matching has been shown to be more effective than propensity score matching, as it relies on less restrictive assumptions, avoids sample reduction and achieves balance for multiple moments of the covariate distribution (e.g., Hainmueller 2012; McMullin and Schonberger 2020). To better address the endogeneity issues arising from variation in observable firm characteristics, the baseline regression model is re-run using the entropy-balanced sample, and the results are presented in Table 6. This method ensures proper covariate balance between treated (Migrant TMT) and control (Non-migrant TMT) samples. For the entropy balancing test, we code migrant TMT (*Mig_TMT*) as 1 if at least 50% of the TMT managers are migrants and zero otherwise. By using entropy balancing, observations in the control group are allocated a weight so that the mean, variance and skewness of the distribution for each matched variable are very similar to their counterparts in the treated sample, resulting in no significant differences between the treated and control groups. The matching process used is based on 13 different covariates, and the differences in covariates after entropy balancing suggest that proper entropy balancing is achieved (Panel A of Table 6). Entropy-balanced regression is then run, and the results are reported in Panel B of Table 6. The coefficients on *Mig_Prop* are significant and positive for all patent output measures, consistent with the main findings that migrant TMT is associated with more patents applied, more patents granted and more citations.[17]

5.3.3 | Instrumental Variable Analysis

Instrumental variable regressions are also used to further mitigate potential endogeneity concerns. Two instrumental variables are used in this study. First, similar to the approach adopted by prior literature (Hochberg and Lindsey 2010; Kang et al. 2018; Ren et al. 2021), the average value of the proportion of migrant managers (*Mig_Prop*) in the same province is used by excluding the focal firm as an instrument. Firms from the same province operate in a similar environment, so they are likely to be equally receptive to hiring migrant managers. Therefore, *Mig_Prop* would be correlated across firms in the same province, making the *relevance* condition of the instrumental variable satisfied. However, it is unlikely that corporate innovation is directly influenced by the hiring of migrant managers by other firms, thereby satisfying the *exclusion* criteria as well. Panel A of Table 7 presents the results. The coefficient for the first-stage variable, *Average_TMT_Prov* (0.615, $p < 0.01$), is positive and highly significant, implying that the proportion of migrant managers is highly related across firms in the same province. The coefficients on *Mig_Prop* in the second stage are, in general, positive and significant for innovation outputs.

In addition, the validity of the instrumental variables is also tested. The *K-Paap rk LM* statistic (389.15) for the under-identification test is significant at the 1% level, suggesting that the chosen instrument satisfies the identification criteria. In terms of the weak instrumental variable test, the *Cragg–Donald Wald F* statistic and the *K–Paap Wald rk F* statistic are much greater than the *Stock–Yogo* (2005) critical value; hence, the instrument in this study also passes the weak instrument test. These results indicate that this model is well specified and adequately defined (Wouterse 2016).

Second, prior literature has shown that weather conditions can be used as a suitable instrument. For example, Lai et al. (2020) use the percentage of clear days in the firm's headquarters locations as an instrument to examine the association between local CEOs and myopic decisions. Motivated by these studies, we use annual temperature differences in the regions where firms are headquartered as the second instrument. As firms in regions with more desirable weather can more easily attract talented managers from across the country (Lai et al. 2020), it is anticipated that regions with lower annual temperature differences have more pleasant weather and are therefore more attractive to migrant managers. Furthermore, weather conditions, as exogenous factors, are less likely to directly influence corporate innovation (Lai et al. 2020), thereby satisfying the exclusion criteria.

Weather condition data is collected from the China Meteorological Data Sharing Service System (CMDSSS), which records daily minimum, maximum and average temperatures, sunshine duration, precipitation, wind speed and relative humidity for 820 weather stations in China.[18] To calculate the temperature difference, first, the daily provincial-level average temperatures are calculated using the daily minimum and maximum temperature data from the CMDSSS and then annualised. Then, a relative temperature difference variable, *Temp_Diff*, is created. *Temp_Diff* is calculated as the annual provincial temperature difference minus the annual country-level temperature difference excluding the focal province, multiplied by −1 so that higher values imply more pleasant weather.[19] A positive and significant coefficient on *Temp_Diff* is expected in the first-stage regression.

The result is reported in Panel B of Table 7. The coefficient on the first-stage variable *Temp_Diff* is positive and significant (coefficient, 0.239, $p < 0.01$), consistent with the prediction that managers are more likely to migrate to regions with lower temperature differences. Importantly, the coefficient on the predicted value of *Mig_Prop* is also positive and significant in the second stage for various innovation measures. For example, the coefficient on *Mig_Prop* is 2.500 ($p < 0.01$) for $Apply1_{t+1}$ (Column 2). The *K-Paap rk LM* statistic (138.966) for the under-identification test is significant at the 1% level, suggesting that the chosen instrument (*Temp_Diff*) satisfies the identification criteria. In terms of the weak instrumental variable test, the *Cragg–Donald Wald F* statistic and *K-Paap Wald rk F* statistic are much greater than the *Stock–Yogo* (2005) critical value; hence, the instrument in this study also passes the weak instrument test. In conclusion, the results of the instrumental variable regression suggest that migrant TMT is positively associated with corporate innovation.

While the average proportion of migrant managers in the same province is unlikely to have a direct effect on a firm's innovation, we acknowledge the possibility that it may be correlated with unobserved province-level shocks, such as regional innovation policies or development strategies that could simultaneously affect both managerial mobility and innovation outcomes. These unobserved factors may, in turn, influence the likelihood of other firms appointing migrant CEOs, thereby indirectly affecting the focal firm. To address this concern, we include province and

TABLE 7 | 2SLS regression results.

	First-stage	Second stage						
	Mig_Prop	$Apply1_{t+1}$	$Apply2_{t+1}$	$Iapply_{t+1}$	$Grant1_{t+1}$	$Grant2_{t+1}$	$Igrant_{t+1}$	$Citation_{t+1}$
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: The provincial level of the proportion of migrant managers in the TMT excluding the focal firm as the instrument								
Average_Mig_Prov	0.615***							
	(0.054)							
Mig_prop		0.743*	0.604	0.840**	0.800**	0.684*	0.897***	0.858**
		(0.387)	(0.403)	(0.393)	(0.375)	(0.381)	(0.324)	(0.424)
Size	−0.008	0.586***	0.588***	0.567***	0.548***	0.539***	0.476***	0.587***
	(0.007)	(0.038)	(0.041)	(0.040)	(0.038)	(0.039)	(0.036)	(0.046)
Roa	0.048	1.529***	1.033*	1.335**	0.716	0.158	0.300	2.312***
	(0.043)	(0.547)	(0.575)	(0.527)	(0.522)	(0.536)	(0.430)	(0.817)
Lev	0.007	−1.723**	−1.511**	−0.819	−1.432**	−1.095	−0.705	−1.740**
	(0.120)	(0.671)	(0.691)	(0.654)	(0.671)	(0.692)	(0.582)	(0.842)
Growth	0.005	0.289***	0.295***	0.324***	0.233***	0.211***	0.223***	0.215***
	(0.007)	(0.048)	(0.047)	(0.048)	(0.046)	(0.050)	(0.042)	(0.049)
Tobinq	−0.004	0.011	0.010	0.073*	−0.008	−0.018	0.073**	0.018
	(0.006)	(0.038)	(0.042)	(0.041)	(0.034)	(0.038)	(0.034)	(0.041)
TMT_size	−0.038**	0.277***	0.247**	0.230**	0.294***	0.250**	0.173**	0.173
	(0.019)	(0.103)	(0.103)	(0.100)	(0.099)	(0.098)	(0.087)	(0.107)
TMT_age	0.012	−1.246***	−1.267***	−0.977**	−0.970**	−0.969**	−0.164	−0.976
	(0.091)	(0.457)	(0.475)	(0.446)	(0.441)	(0.456)	(0.365)	(0.469)
TMT_edu	0.076**	−0.005	−0.049	0.104	−0.101	−0.130	0.140	−0.023
	(0.032)	(0.162)	(0.175)	(0.173)	(0.154)	(0.163)	(0.138)	(0.185)
TMT_gender	0.070*	0.425**	0.504**	0.462**	0.343*	0.449**	0.244	0.172
	(0.042)	(0.217)	(0.221)	(0.209)	(0.204)	(0.208)	(0.167)	(0.239)
Bind	0.046	0.345	0.152	0.060	0.358	0.186	0.298	0.306
	(0.118)	(0.639)	(0.648)	(0.633)	(0.642)	(0.633)	(0.545)	(0.683)
Top Holding	0.023	−0.334	−0.569**	−0.637**	−0.062	−0.346	−0.413*	−0.403
	(0.056)	(0.257)	(0.263)	(0.260)	(0.247)	(0.251)	(0.226)	(0.296)
Firm Age	−0.029	0.040	0.018	0.013	0.002	−0.006	0.034	−0.012
	(0.022)	(0.096)	(0.097)	(0.097)	(0.091)	(0.090)	(0.079)	(0.088)
Home CEO	−0.225***	−0.057	−0.138	−0.042	−0.011	−0.087	0.074	−0.025
	(0.016)	(0.129)	(0.136)	(0.135)	(0.125)	(0.128)	(0.110)	(0.144)
_cons	0.518	−7.036***	−6.633***	−8.472***	−7.554***	−7.152***	−10.380***	−10.882***
	(0.353)	(1.851)	(1.981)	(1.862)	(1.801)	(1.904)	(1.582)	(2.067)
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5842	4713	4713	4713	4713	4713	4713	3387
Adj_R^2	0.380	0.302	0.298	0.267	0.297	0.292	0.251	0.548
K-Paap-LM *stat.*	389.15							
	0.000							

(Continues)

TABLE 7 | (Continued)

	First-stage	Second stage						
	Mig_Prop	$Apply1_{t+1}$	$Apply2_{t+1}$	$Iapply_{t+1}$	$Grant1_{t+1}$	$Grant2_{t+1}$	$Igrant_{t+1}$	$Citation_{t+1}$
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cragg–Donald Wald *F*	792.014							
K-Paap Wald *F stat.*	125.001							
Stock-Yogo critical value at 10%	16.38							
Panel B: The provincial average temperature difference as the instrument								
Diff_Temp	0.239***							
	(0.037)							
Mig_prop		2.500***	2.229***	1.570**	2.188***	1.995***	1.035*	1.833**
		(0.688)	(0.710)	(0.668)	(0.670)	(0.681)	(0.559)	(0.723)
Size	−0.010	0.623***	0.624***	0.592***	0.575***	0.566***	0.488***	0.573***
	(0.008)	(0.041)	(0.043)	(0.041)	(0.041)	(0.041)	(0.037)	(0.043)
Roa	0.220*	1.177	0.511	1.198	0.438	−0.326	0.237	1.288*
	(0.118)	(0.820)	(0.853)	(0.751)	(0.786)	(0.811)	(0.631)	(0.676)
Lev	0.005	−2.387***	−2.089**	−1.271*	−1.789**	−1.415*	−0.893	−2.048**
	(0.137)	(0.817)	(0.823)	(0.728)	(0.785)	(0.795)	(0.628)	(0.823)
Growth	0.009	0.486***	0.505***	0.541***	0.393***	0.392***	0.395***	0.376***
	(0.010)	(0.064)	(0.064)	(0.059)	(0.058)	(0.058)	(0.048)	(0.067)
Tobinq	−0.005	0.043	0.044	0.086**	0.018	0.011	0.082**	0.041
	(0.007)	(0.040)	(0.041)	(0.041)	(0.037)	(0.038)	(0.035)	(0.040)
TMT_size	−0.056***	0.399***	0.354***	0.284***	0.398***	0.333***	0.209**	0.225**
	(0.019)	(0.117)	(0.117)	(0.108)	(0.111)	(0.109)	(0.095)	(0.111)
TMT_age	0.057	−1.183**	−1.196**	−0.979**	−0.911*	−0.884*	−0.092	−0.918*
	(0.095)	(0.500)	(0.506)	(0.458)	(0.476)	(0.482)	(0.378)	(0.481)
TMT_edu	0.162***	−0.300	−0.324	−0.038	−0.311	−0.348*	0.100	−0.226**
	(0.037)	(0.211)	(0.213)	(0.205)	(0.202)	(0.201)	(0.167)	(0.205)
TMT_Gender	0.037	0.323	0.407*	0.424*	0.239	0.360	0.244	0.102
	(0.046)	(0.244)	(0.243)	(0.217)	(0.228)	(0.227)	(0.172)	(0.205)
Bind	0.125	0.001	−0.134	0.004	0.077	−0.063	0.324	0.097
	(0.124)	(0.700)	(0.691)	(0.638)	(0.678)	(0.662)	(0.546)	(0.655)
Top Holding	0.035	−0.454	−0.679**	−0.687***	−0.148	−0.424	−0.425*	−0.543*
	(0.060)	(0.281)	(0.280)	(0.263)	(0.265)	(0.263)	(0.228)	(0.286)
Firm Age	−0.039	0.083	0.063	0.035	0.027	0.022	0.037	0.018
	(0.024)	(0.109)	(0.108)	(0.101)	(0.104)	(0.101)	(0.085)	(0.102)
Home CEO	−0.277***	0.449**	0.329	0.160	0.396**	0.296	0.107	0.268
	(0.016)	(0.209)	(0.217)	(0.205)	(0.200)	(0.205)	(0.169)	(0.227)
_cons	−7.392***	−9.498***	−9.111***	−9.553***	−8.415***	−8.043***	−11.182***	−11.301***
	(1.268)	(2.104)	(2.207)	(2.022)	(2.007)	(2.091)	(1.712)	(2.207)
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

(Continues)

TABLE 7 | (Continued)

	First-stage	Second stage						
	Mig_Prop	$Apply1_{t+1}$	$Apply2_{t+1}$	$Iapply_{t+1}$	$Grant1_{t+1}$	$Grant2_{t+1}$	$Igrant_{t+1}$	$Citation_{t+1}$
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
N	5515	4419	4419	4419	4419	4419	4419	3369
Adj_R^2	0.318	0.194	0.219	0.243	0.201	0.215	0.244	0.512
K-Paap-LM *stat*.	138.966							
	0.000							
Cragg–Donald Wald *F*	792.014							
K-Paap Wald F *stat*.	125.001							
Stock-Yogo critical value at 10%	16.38							

Note: This table reports the estimated results from the two-stage least squares (2SLS) instrumental variables regressions. The first instrumental variable, *Average_Mig_Prov*, in Panel A, is the average value of *Mig_Prop* of all other firms excluding the focal firm in the same province in year *t*. Panel B reports the result of the second instrumental variable, temperature differences (*Diff_Temp*). The dependent variables of the regressions are the innovation output measures. $Apply1_{t+1}$, $Apply2_{t+1}$, $Iapply_{t+1}$ refer to the number of total patents applied, utility and invention patents applied and invention patents applied in the following year, respectively. Patents granted, likewise, is proxied by the total number of patents granted ($Grant1_{t+1}$), utility and invention patents granted ($Grant2_{t+1}$) and invention patents granted in the following year ($Igrant_{t+1}$). $Citaition_{t+1}$ is the patent citations in the following year. Robust standard errors clustered at the firm-level are in brackets. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. All variables are defined in Appendix B.

year fixed effects to absorb time-invariant provincial characteristics and common temporal shocks, as well as province-level controls to capture evolving regional factors. Although we cannot fully rule out the possibility of simultaneous province-level shocks influencing both variables, such risks are substantially reduced after these controls. It is also possible that temperature differences may influence local industrial policies, which in turn affect corporate innovation. For example, regions with more favourable climates may attract more talent and firms, prompting local governments to implement pro-innovation industrial policies, such as R&D subsidies or technology zones. This could represent a potential violation of the exclusion restriction, as *Temp_Diff* may affect innovation through policy channels beyond talent mobility. While we attempt to mitigate this concern by including province and year fixed effects and controlling for key regional economic indicators, we acknowledge that there may remain some potential threats to the exclusion restriction for each instrument.

5.4 | Mediation Tests

As discussed earlier, migrants may possess inherent risk preferences that align with innovative activities. At the same time, they face fewer constraints from local social networks, which provide greater autonomy in decision-making and encourage riskier decisions. Therefore, risk-taking can serve as a mediating mechanism through which migrant TMT influence corporate innovation.

In addition, based on cognitive adaptation theory, the experience of adapting to new cultural and institutional environments fosters enhanced cognitive flexibility and integrative thinking. These traits help managers better identify and commit to projects with long-term strategic goals. Accordingly, we propose a long-term horizon as a second mediating mechanism. It captures how migrant TMTs' adaptive cognition influences their innovation-related decisions by prioritising future-oriented strategies.

In sum, managerial risk-taking and long-term horizons capture key psychological and sociological mechanisms linking migrant TMT to corporate innovation. Specifically, risk-taking reflects migrants' greater risk tolerance and independence shaped by their marginal position, while a long-term horizon reflects their cognitive flexibility developed through cross-cultural adaptation. Including these mediators in the empirical model allows us to better explain how migrant characteristics translate into innovative decisions.

In this section, we follow the mediation test approach of Baron and Kenny (1986) to examine two potential channels: the long-term orientation of migrant TMT and the willingness to take risks. More particularly, we run the following two regressions:

$$Mediators = \alpha_0 + \beta_1 Mig\_Prop_{i,t} + \sum Controls_t + IndustryFE + YearFE + ProvinceFE \tag{3.1}$$

$$Innovation_{i,t+1} = \alpha_0 + \beta_1 Mig\_Prop_{i,t} + \beta_2 Mediators_{i,t} + \sum Controls_t + IndustryFE + YearFE + ProvinceFE \tag{3.2}$$

Where *Mediators* are the two mediating variables, and control variables are defined as before. Following prior literature (Bushee 1998), when a migrant TMT is more likely to hold long-term visions, it would engage less in real earnings management (*Rem*), and hence *Rem* is used as the first mediating variable. The risk-taking attitude (*Risk*) of migrant TMT is used as the second mediating variable, proxied by earnings volatility. The total effect can be broken down into direct and

TABLE 8 | Mediation test results.

	Rem	*Apply1* $_{t+1}$	*Apply2* $_{t+1}$	*Iapply* $_{t+1}$	*Grant1*$_{t+1}$	*Grant2* $_{t+1}$	*Igrant* $_{t+1}$	*Citation*$_{t+1}$
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Panel A: Mediating effect of real earnings management								
Mig_Prop	−0.047**	0.444***	0.508***	0.504***	0.424***	0.489***	0.316**	0.519***
	(0.020)	(0.165)	(0.166)	(0.159)	(0.161)	(0.161)	(0.132)	(0.178)
Rem		−0.734***	−0.502**	−0.463**	−0.801***	−0.514**	−0.559***	−0.502**
		(0.236)	(0.241)	(0.221)	(0.231)	(0.233)	(0.188)	(0.250)
Home_CEO	−0.002	−0.170*	−0.209**	−0.179**	−0.152*	−0.205**	−0.099	−0.137
	(0.011)	(0.088)	(0.090)	(0.090)	(0.084)	(0.085)	(0.076)	(0.099)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
_cons	0.098	−9.120***	−8.578***	−10.410***	−9.079***	−8.578***	−11.902***	−6.848***
	(0.240)	(2.014)	(2.204)	(2.145)	(1.979)	(2.102)	(1.795)	(2.238)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4435	3486	3486	3486	3486	3486	3486	2428
Adj_R^2	0.188	0.373	0.366	0.329	0.355	0.348	0.320	0.611
Direct effect		0.444***	0.508***	0.504***	0.424***	0.489***	0.316***	0.519***
Indirect effect		0.036***	0.025**	0.023***	0.040***	0.025***	0.028***	0.020**
Panel B: Mediating effect of risk-taking								
Mig_Prop	0.014**	0.364**	0.424**	0.391**	0.364**	0.432***	0.252**	0.436**
	(0.007)	(0.163)	(0.165)	(0.156)	(0.163)	(0.151)	(0.126)	(0.165)
Risk		0.831	1.502**	1.537**	0.831	0.924	0.562	1.290*
		(0.625)	(0.631)	(0.669)	(0.625)	(0.581)	(0.549)	(0.654)
Home CEO	0.005*	−0.261***	−0.302***	−0.248***	−0.261***	−0.216**	−0.106	−0.183**
	(0.003)	(0.093)	(0.095)	(0.094)	(0.093)	(0.087)	(0.078)	(0 0.099)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
_cons	0.256***	−9.362***	−9.193***	−10.645***	−9.413***	−9.369***	−10.172***	−9.704***
	(0.075)	(2.027)	(2.141)	(2.075)	(1.932)	(2.005)	(1.736)	(2.455)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3648	3305	3305	3305	3305	3305	3305	3002
Adj_R^2	0.149	0.346	0.347	0.338	0.346	0.360	0.313	0.513
Direct effect		0.364***	0.424***	0.391***	0.364***	0.432***	0.252***	0.436***
Indirect effect		0.010	0.019**	0.020**	0.003	0.012*	0.007	0.014*

Note: This table reports the mediation test results. Panel A reports the result of the mediating effect of real earnings management (*Rem*). Panel B reports the result of the mediating effect of risk-taking (*Risk*). The dependent variables of the regressions are the innovation output measures. $Apply1_{t+1}$, $Apply2_{t+1}$, $Iapply_{t+1}$ refer to the number of total patents applied, utility and invention patents applied and invention patents applied in the following year, respectively. Patents granted, likewise, is proxied by the total number of patents granted ($Grant1_{t+1}$), utility and invention patents granted ($Grant2_{t+1}$), and invention patents granted in the following year ($Igrant_{t+1}$). $Citaition_{t+1}$ is the patent citations in the following year. Control Variables are the same as in the baseline regression table. Robust standard errors clustered at the firm level are in brackets. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively. All variables are defined in Appendix B.

indirect effects, which are calculated based on the bootstrap approach. The results are reported in Table 8. Panel A of Table 8 reports the results of the mediation effect of *Rem*, and Panel B for *Risk*.

We expect a migrant TMT to be less likely to engage in real earnings management compared to their non-migrant TMT counterparts. In Panel A of Table 8, we find that *Mig_Prop* is associated with lower *Rem*, and the significant indirect effect indicates that *Rem* plays a mediating role in influencing the association between migrant TMT and corporate innovation. In the first stage, the coefficient on *Mig_Prop* (−0.047) in Column (1) is significant and negative at the 5% level, suggesting that migrant TMT engages less in real earnings management. In the second stage, the coefficients on *Mig_Prop* measures are positive, whereas the coefficients on *Rem* are negative from Columns (2) to (8). For example, in Column (2), the coefficients on *Mig_Prop* and *Rem* are 0.444 ($p < 0.01$) and −0.734 ($p < 0.01$), respectively. Also, the bootstrap test results for the indirect effect are significant for all specifications, suggesting that migrant TMT engaging less in real earnings management would lead to more patent applications. Similar results can be found for patents granted in Columns (5–7) and patent citations in Column (8). Overall, the results support the prediction that a long-term time horizon (proxied by *Rem*) is one channel influencing the association between migrant TMT and corporate innovation.

Panel B of Table 8 reports the mediating test result of risk-taking on the association between migrant TMT and corporate innovation. Firm risk-taking behaviour is measured using earnings volatility, i.e., the forward-looking rolling standard deviation of *Ebitda/Sales* over a three-year period (year $t+1$ to $t+3$). This firm risk-taking measurement is commonly used in accounting and finance studies (e.g., Kim et al. 2017; Ren et al. 2021). In the first stage, the coefficient on *Mig_Prop* (0.014) in Column (1) is positive and significant at the 5% level, suggesting that migrant TMT is more likely to take risks. In the second stage, the coefficients on *Mig_Prop* (0.424) and *Risk* (1.502) are both positive at the 5% level in Column (3). In addition, the significant indirect effect using bootstrapping (0.019, $p < 0.05$) also suggests that a firm with a migrant TMT is likely to take risky decisions, resulting in more patents applied for. However, the mediating effect of risk-taking on patents granted and patent citations is much weaker. The positive indirect effect of *Mig_Prop* can only be found for $Grant2_{t+1}$ and $Citation_{t+1}$ at the 10% level.

5.5 | Moderating Tests

In this section, we report the moderation test results for *state ownership* and *cultural diversity* on the association between migrant TMT and corporate innovation.

5.5.1 | The Effect of State Ownership (SOE)

SOEs and non-SOEs differ significantly in terms of business and investment strategies, industry regulations, resource allocations, financing constraints, political connections and corporate social responsibility (Chen et al. 2010; Shleifer and Vishny 1994). In China, top managers in SOEs are often appointed directly by the Chinese government, making top managers in the migrant TMTs more independent from each other, which could lead to a more innovative environment in the migrant TMT. Also, SOEs are better connected with the government; thus, they have easier access to financing channels and tend to have less management myopia (Lin et al. 2023). Therefore, a migrant TMT in an SOE with a more innovative environment and easier access to financing channels would lead to more innovative outputs. In contrast, non-SOEs are more likely to be faced with financial constraints (Guariglia et al. 2011), and the appointment of top managers in non-SOEs is often influenced by kinship, emotional relationships and management hierarchy (Yin et al. 2022). Corporate decisions made by a migrant TMT in non-SOEs are more likely to be impacted by these social connections, thereby resulting in fewer innovation outputs, among others. We create a dummy variable, SOE, coded 1 if a firm is defined as state-owned, and 0 otherwise. Table 9 reports the result. The coefficients on the interactive variable *Mig_Prop*×*SOE* are positive and significant. For example, the coefficient is 0.563 ($p < 0.01$) when the dependent variable is $Apply1_{t+1}$ (Column 1). This suggests that the positive association between migrant TMT and corporate innovation is more pronounced in SOEs.

5.5.2 | Migration Effect Versus Cultural Effect

Our findings thus far indicate a positive association between migrant TMT and corporate innovation. However, this relationship may be driven more by cultural adaptability than by the migration experience itself. To address this concern, we conduct a subsample analysis focusing on cities with varying levels of multicultural environments to control the confounding effects of cultural influences. For example, cities such as Guangzhou and Shanghai are characterised by high cultural diversity, with local populations accustomed to interactions across linguistic and cultural boundaries. In these environments, migrant executives may integrate more readily, potentially enhancing their innovative contributions. Conversely, in culturally homogeneous cities with limited exposure to diverse perspectives, migrant TMT members face greater adjustment challenges that may distinctly affect their innovation output.

Specifically, following Lei et al. (2022), we measure city-level cultural diversity using dialect data. *Diversity* is the dialect differentiation index, which ranges from 0 to 1, with higher values indicating greater dialect diversity.[20] We then divide the sample at the median level of dialect diversity. We construct a binary variable, *Diversity_High*, which equals 1 if a city's dialect diversity exceeds the median and 0 otherwise.

The results, presented in Table 10, suggest that the positive relationship between migrant TMT and corporate innovation remains consistently positive and statistically significant in both subsamples. For instance, the coefficient of *Mig_Prop* on $Apply1_{t+1}$ is 0.564 ($p < 0.01$) when *Diversity_High* = 1, compared to 0.444 ($p < 0.05$) when *Diversity_High* = 0. This suggests that migrant TMT exerts a positive impact on innovation irrespective of whether the city environment is characterised by high or low cultural diversity. In other words, the migration

TABLE 9 | Migrant TMT, SOE and corporate innovation.

Variables	$Apply1_{t+1}$ (1)	$Apply2_{t+1}$ (2)	$Iapply_{t+1}$ (3)	$Grant1_{t+1}$ (4)	$Grant2_{t+1}$ (5)	$IGrant_{t+1}$ (6)	$Citation_{t+1}$ (7)
Mig_Prop	0.332**	0.354**	0.397***	0.265*	0.288**	0.233**	0.417***
	(0.148)	(0.150)	(0.142)	(0.143)	(0.143)	(0.118)	(0.154)
Mig_Prop×SOE	0.788**	0.998***	1.036***	0.781**	1.044***	1.002***	0.756*
	(0.324)	(0.358)	(0.351)	(0.314)	(0.340)	(0.305)	(0.458)
SOE	−0.030	−0.113	−0.091	−0.128	−0.229	−0.095	−0.187
	(0.153)	(0.173)	(0.166)	(0.144)	(0.164)	(0.134)	(0.190)
Home CEO	−0.175**	−0.225***	−0.164**	−0.152**	−0.203***	−0.050	−0.134
	(0.079)	(0.081)	(0.079)	(0.077)	(0.077)	(0.065)	(0.088)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
_cons	−8.165***	−8.026***	−9.105***	−8.860***	−8.843***	−10.304***	−7.586***
	(1.901)	(2.006)	(1.874)	(1.819)	(1.887)	(1.577)	(2.042)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4713	4713	4713	4713	4713	4713	3387
Adj_R^2	0.341	0.337	0.315	0.340	0.339	0.303	0.581

Note: This table presents results from the regression of the moderating role of ownership structure on the association between migrant TMT and corporate innovation. SOE is the dummy variable of state ownership. The dependent variables of the regressions are the innovation output measures. $Apply1_{t+1}$, $Apply2_{t+1}$ *and* $Iapply_{t+1}$ refer to the number of total patents applied, utility and invention patents applied and invention patents applied in the following year, respectively. Patents granted, likewise, is proxied by the total number of patents granted ($Grant1_{t+1}$), utility and invention patents granted ($Grant2_{t+1}$), and invention patents granted in the following year ($Igrant_{t+1}$). $Citaition_{t+1}$ is the patent citations in the following year. Control variables are the same as the baseline regression table. Robust standard errors clustered at the firm-level are in brackets. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively. All variables are defined in Appendix B.

effect does not simply arise from migrants' enhanced ability to adapt to culturally diverse environments. Instead, this finding provides strong evidence that the innovation effect we identify is robustly driven by migration itself, rather than primarily reflecting cultural adaptability or the cultural diversity inherent to certain cities.

5.6 | Additional Analysis

5.6.1 | Sensitivity Analysis of the Migration Measure

To address concerns regarding the limitations of measuring migration by comparing a manager's birthplace with the location of the firm's headquarters, we conduct a sensitivity analysis using an alternative definition of the migration measure.

As noted earlier, birthplace may not fully reflect a manager's actual migration experience. For example, it does not capture how many years a manager has lived or worked in the province where the firm is located. To address these limitations and test the sensitivity of the migration measure, we redefine a manager as a migrant if the province of their undergraduate university differs from the province of the firm's headquarters. University location reflects a period during which individuals may develop a sense of attachment to the region. Based on this alternative definition, we construct the variable *Uni_Mig_Prop*, which captures the proportion of migrant managers in the TMT using the university-based criterion.

The results, presented in Table 11, show that our baseline findings remain robust under the redefined migration measure. For example, the coefficients on *Mig_Uni_Prop* are positive and statistically significant at $p < 0.05$ or better across all the innovation measures.

5.6.2 | Alternative Explanations: Additional Controls

While our findings suggest that the long-term horizon and risk-taking preferences of migrant TMTs contribute to higher levels of corporate innovation, we acknowledge that other factors may also influence these outcomes. For instance, firms with superior resources may be better positioned to attract talented migrant managers (Dokko and Jiang 2017), implying that it could be the firm's existing advantages, rather than managerial characteristics, that drive innovation.

Another important factor is regional economic development. Firms located in more developed areas often benefit from superior innovation infrastructure and greater access to knowledge spillovers, both of which can significantly enhance innovation performance (Shi et al. 2020). Industry structure also plays a critical role; for example, competition within an industry can

TABLE 10 | Migration effect versus cultural effect: Subsample based on cultural diversity.

	Diver_High = 1	Diver_High = 0	Diver_High = 1	Diver_High = 0	Diver_High = 1	Diver_High = 0
	$Apply1_{t+1}$	$Apply1_{t+1}$	$Apply2_{t+1}$	$Apply2_{t+1}$	$Iapply_{t+1}$	$Iapply_{t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Patent applications						
Mig_Prop	0.564***	0.444**	0.606***	0.428**	0.691***	0.536***
	(0.198)	(0.177)	(0.196)	(0.181)	(0.189)	(0.178)
Home CEO	−0.133	−0.099	−0.168	−0.137	−0.123	−0.093
	(0.119)	(0.103)	(0.118)	(0.106)	(0.117)	(0.107)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
_cons	−7.074***	−8.047***	−6.139**	−8.530***	−9.599***	−11.238***
	(2.506)	(2.501)	(2.663)	(2.644)	(2.281)	(2.162)
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
N	2425	2322	2425	2322	2425	2322
Adj_R^2	0.29	0.34	0.29	0.34	0.27	0.29
Panel B: Patents granted						
Mig_Prop	0.551***	0.344**	0.603***	0.350**	0.575***	0.364**
	(0.196)	(0.173)	(0.191)	(0.173)	(0.165)	(0.159)
Home CEO	−0.100	−0.071	−0.131	−0.109	−0.080	−0.009
	(0.116)	(0.101)	(0.113)	(0.101)	(0.095)	(0.090)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
_cons	−7.074***	−8.047***	−6.139**	−8.530***	−9.599***	−11.238***
	(2.506)	(2.501)	(2.663)	(2.644)	(2.281)	(2.162)
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
N	2425	2322	2425	2322	2425	2322
Adj_R^2	0.27	0.36	0.27	0.36	0.26	0.28

Panel C: Patent citations

	Diver_High = 1	Diver_High = 0
	Citation	Citation
	(1)	(2)
Mig_Prop	0.450**	0.435**
	(0.229)	(0.216)
Home CEO	−0.229	−0.013
	(0.142)	(0.128)
Other Controls	Yes	Yes
_cons	−4.754	−8.597***

(Continues)

TABLE 10 | (Continued)

Panel C: Patent citations		
	Diver_High = 1	Diver_High = 0
	Citation	Citation
	(1)	(2)
	(3.133)	(3.251)
Year	Yes	Yes
Industry	Yes	Yes
N	1418	1330
Adj_R^2	0.42	0.51

Note: This table presents results from the regression of subsamples based on cultural diversity. *Diver_High* equals 1 if a city's dialect diversity exceeds the median, and 0 otherwise. The dependent variable of the regressions is the innovation output measures. $Apply1_{t+1}$, $Apply2_{t+1}$, $Iapply_{t+1}$ refer to the number of total patents applied, utility and invention patents applied and invention patents applied in the following year, respectively. Patents granted, likewise, is proxied by the total number of patents granted ($Grant1_{t+1}$), utility and invention patents granted ($Grant2_{t+1}$) and invention patents granted in the following year ($Igrant_{t+1}$). $Citaition_{t+1}$ is the patent citations in the following year. Control variables are the same as the baseline regression table. Robust standard errors clustered at the firm-level are in brackets. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively. All variables are defined in Appendix B.

TABLE 11 | Sensitivity analysis of the migration measure.

	$Apply1_{t+1}$	$Apply2_{t+1}$	$Iapply_{t+1}$	$Grant1_{t+1}$	$Grant2_{t+1}$	$IGrant_{t+1}$	$Citation_{t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mig_Uni_Prop	0.433***	0.483***	0.465***	0.443***	0.498***	0.294**	0.447**
	(0.158)	(0.163)	(0.161)	(0.149)	(0.153)	(0.133)	(0.214)
Home_CEO	−0.153*	−0.197**	−0.180**	−0.073	−0.113	−0.057	−0.127
	(0.083)	(0.087)	(0.089)	(0.077)	(0.078)	(0.075)	(0.103)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
_cons	−8.035***	−7.191***	−8.396***	−8.520***	−7.665***	−9.660***	−7.552***
	(1.913)	(2.076)	(2.025)	(1.870)	(2.006)	(1.727)	(2.479)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3832	3832	3832	3832	3832	3832	2249
Adj_R^2	0.32	0.32	0.30	0.32	0.31	0.28	0.45

Note: This table presents the sensitivity analysis of the migration measure. The dependent variables of the regressions are the innovation output measures. $Apply1_{t+1}$, $Apply2_{t+1}$, $Iapply_{t+1}$ refer to the number of total patents applied, utility and invention patents applied and invention patents applied in the following year, respectively. Patents granted, likewise, are proxied by the total number of patents granted ($Grant1_{t+1}$), utility and invention patents granted ($Grant2_{t+1}$) and invention patents granted in the following year ($Igrant_{t+1}$). $Citaition_{t+1}$ is the patent citations in the following year. The key independent variable is the proportion of migrant managers in the TMT, defined as the difference between the province of a manager's university and the province of the firm's headquarters (*Mig_Uni_Prop*). Robust standard errors clustered at the firm level are in brackets. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. All variables are defined in Appendix B.

shape firms' innovation incentives, as highly competitive environments may necessitate distinct innovation strategies that are independent of managerial backgrounds (Aghion et al. 2005; Bloom et al. 2016; Thakor and Lo 2017).

To control for these alternative explanations and better isolate the unique contribution of managerial migration, we incorporate a set of contextual control variables into our baseline model. Specifically, we control for government subsidies (*Subsidy*), regional economic development, proxied by provincial GDP per capita (*GDP_Capita*) and the proportion of urban population (*Urban*), and industry competition, measured by the Herfindahl–Hirschman Index (*Hhi*).

The results are reported in Table 12. After controlling for these variables, our main findings remain robust, supporting the conclusion that it is the presence of the migrant managers in the TMT, rather than other contextual factors, that primarily drives corporate innovation. Notably, *Subsidy* is positively and significantly associated with innovation, consistent with Howell (2017), who finds that government support can stimulate innovation activities. In addition, industry competition (*Hhi*) is negatively related

TABLE 12 | Additional controls.

Variables	$Apply1_{t+1}$ (1)	$Apply2_{t+1}$ (2)	$Iapply_{t+1}$ (3)	$Grant1_{t+1}$ (4)	$Grant2_{t+1}$ (5)	$IGrant_{t+1}$ (6)	$Citation_{t+1}$ (7)
Mig_Prop	0.367***	0.377***	0.409***	0.322**	0.339**	0.268**	0.332*
	(0.142)	(0.142)	(0.135)	(0.137)	(0.136)	(0.111)	(0.173)
Subsidy	9.256***	10.887***	12.647***	7.954***	9.636***	10.437***	10.036***
	(1.473)	(1.525)	(1.607)	(1.401)	(1.414)	(1.375)	(1.737)
GDP_Capita	−0.184	−0.123	0.092	0.019	0.084	0.288	−0.311
	(0.362)	(0.344)	(0.323)	(0.321)	(0.310)	(0.249)	(0.581)
Hhi	−1.127*	−2.671***	−3.229***	−0.591	−2.260***	−2.723***	−1.087
	(0.584)	(0.641)	(0.613)	(0.561)	(0.613)	(0.497)	(0.677)
Urban	1.608	3.077**	3.614**	0.087	1.570	2.248	8.527***
	(1.551)	(1.564)	(1.543)	(1.407)	(1.432)	(1.427)	(2.336)
Home CEO	−0.175**	−0.226***	−0.168**	−0.150**	−0.203***	−0.053	−0.127
	(0.079)	(0.080)	(0.077)	(0.076)	(0.075)	(0.064)	(0.099)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
_cons	−8.731**	−9.945**	−13.868***	−9.991***	−11.338***	−16.099***	−13.456**
	(4.341)	(4.236)	(3.995)	(3.777)	(3.699)	(2.988)	(6.321)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4702	4702	4702	4702	4702	4702	2721
Adj_R^2	0.35	0.36	0.35	0.35	0.36	0.33	0.49

Note: This table presents the regression including additional controls. *Subsidy* is government subsidies, *GDP_Capita* is the regional economic development and *Hhi* is industry competition, measured by the Herfindahl–Hirschman Index. The dependent variables of the regressions are the innovation output measures. $Apply1_{t+1}$, $Apply2_{t+1}$, $Iapply_{t+1}$ refer to the number of total patents applied, utility and invention patents applied and invention patents applied in the following year, respectively. Patents granted, likewise, is proxied by the total number of patents granted ($Grant1_{t+1}$), utility and invention patents granted ($Grant2_{t+1}$) and invention patents granted in the following year ($Igrant_{t+1}$). $Citaition_{t+1}$ is the patent citations in the following year. Robust standard errors clustered at the firm-level are in brackets. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively. All variables are defined in Appendix B.

to innovation, suggesting that firms operating in less concentrated (i.e., more competitive) industries tend to be more innovative.

5.6.3 | Migrant TMT and R&D Investment

In all the regressions, we have used output-based innovation measures. However, prior studies also consider input-based measures such as R&D investment because they consider the amount of resources allocated to innovative projects (Huang et al. 2021). We, therefore, test whether migrant TMT is associated with the inputs of innovation, measured by R&D expenses divided by total assets. The results, as reported in Table 13, are similar to those in the baseline model. The coefficient on *Mig_Prop* (0.012) is significant and positive at the 1% level. The result is also economically significant. For instance, the coefficient of 0.012 implies that a one-standard-deviation increase in *Mig_Prop* is associated with a 12.4% [(0.012 × 0.289/0.028)] increase in R&D intensity. The findings supplement the baseline results that a migrant TMT can increase not only innovative outputs but also input investments.

5.6.4 | Sub-Sample Analysis Excluding Beijing, Shanghai, Guangzhou and Shenzhen

To address the possibility that our results can be driven by a few large cities such as Beijing and Shanghai, we delete firms with headquarters in the four largest cities (Beijing, Shanghai, Shenzhen and Guangzhou) and rerun the baseline regressions. We report the results in Table 14. We find that the coefficients on *Mig_Prop* remain positive and significant for all the regression specifications. For example, the coefficient on *Mig_Prop* for $Citation_{t+1}$ is 0.461 ($p < 0.05$). The results indicate that the findings of our baseline model are robust after excluding the effects of the four largest cities.

5.6.5 | Alternative Measurement of Migrant TMT

We also use an alternative measure of migrant TMT by creating a dummy variable to measure migrant TMT. We define *Mig_Dum* as coded 1 when a firm has at least one migrant manager in the TMT and zero otherwise. The coefficients on *Mig_Dum*

remain significant and positive at the 1% level for all innovation measures (results untabulated). For example, the coefficient on *Mig_Dum* is 0.338 ($p<0.01$) when innovation is proxied by $Citation_{t+1}$.

TABLE 13 | Migrant TMT and R&D investment.

Variables	RD_Ratio_{t+1} (1)
Mig_Prop	0.012***
	(0.002)
Home CEO	−0.002*
	(0.001)
Other controls	Yes
_cons	0.053*
	(0.031)
Year	Yes
Industry	Yes
Province	Yes
N	4713
Adj_R^2	0.295

Note: This table reports the association between R&D investment (RD_Ratio_{t+1}). Control Variables are the same as in the baseline regression table. Robust standard errors clustered at the firm level are in brackets. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively. All variables are defined in Appendix B.

6 | Conclusions

Using a sample of Chinese A-share listed firms from 2008 to 2020, we examine the association between migrant TMT and corporate innovation. The results show that firms with a larger proportion of migrant managers in the TMT have greater innovation outputs in terms of patent applications, patent grants and patent citations. The findings are robust to a set of endogeneity tests. Further, the mediating effect of migrant TMT and corporate innovation is explored, and it is found that migrant TMTs have a longer time horizon and are more willing to take risks, would be more innovative and thereby cause more innovation outputs. Furthermore, it is found that the positive association between migrant TMT and corporate innovation is more pronounced in SOEs. Finally, subsample analyses show that the positive effect of migrant TMTs on innovation holds in both high- and low-cultural-diversity regions, suggesting that the observed effect is not primarily driven by cultural adaptability but reflects a robust migration-driven mechanism.

Given the importance of migration and teamwork, these results have important implications for the appointment of TMT and contracting practices. More specifically, given the positive effects of migrant TMT on corporate innovation, when a firm is implementing an innovation-driven development strategy, it would be better if the board of directors considered the proportion of migrant managers in the TMT when appointing TMT managers. Overall, these findings shed light on whether and how migrant managers working in a TMT relate to corporate decisions. The results enrich the migration literature by showing that migration impacts corporate practices beyond individual behaviour, which highlights the value of migrant managers working as a team. The results have important

TABLE 14 | Migrant TMT and corporate innovation: Subsample analysis excluding Beijing, Shanghai, Guangzhou and Shenzhen.

Variables	$Apply1_{t+1}$ (1)	$Apply2_{t+1}$ (2)	$Iapply_{t+1}$ (3)	$Grant1_{t+1}$ (4)	$Grant2_{t+1}$ (5)	$Igrant_{t+1}$ (6)	$Citation_{t+1}$ (7)
Mig_Prop	0.424**	0.458***	0.422**	0.376**	0.424**	0.300**	0.461**
	(0.174)	(0.173)	(0.170)	(0.171)	(0.166)	(0.145)	(0.182)
Home CEO	−0.261***	−0.308***	−0.276***	−0.217**	−0.267***	−0.121	−0.225**
	(0.090)	(0.090)	(0.090)	(0.087)	(0.086)	(0.076)	(0.098)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
_cons	−8.704***	−8.125***	−9.270***	−8.028***	−7.534***	−10.383***	−7.128***
	(1.983)	(2.161)	(2.068)	(1.892)	(2.024)	(1.677)	(2.259)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3752	3752	3752	3752	3752	3752	2661
Adj_R^2	0.34	0.33	0.31	0.331	0.331	0.300	0.574

Note: This table reports the estimated results using subsample excluding Beijing, Shanghai, Guangzhou and Shenzhen. The dependent variables of the regressions are the innovation output measures. $Apply1_{t+1}$, $Apply2_{t+1}$, $Iapply_{t+1}$ refer to the number of total patents applied, utility and invention patents applied, and invention patents applied in the following year, respectively. Patents granted, likewise, are proxied by the total number of patents granted ($Grant1_{t+1}$), utility and invention patents granted ($Grant2_{t+1}$) and invention patents granted in the following year ($Igrant_{t+1}$). $Citaition_{t+1}$ is the patent citations in the following year. Control variables are the same as the baseline regression table. Robust standard errors clustered at the firm level are in brackets. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively. All variables are defined in Appendix B.

implications for corporate decision-making in firm innovation and beyond.

The findings provide important evidence on the benefits of migrant TMT on corporate innovation in the Chinese context. However, caution is warranted when extending these insights to other national settings. The internal migration opportunity is not equally available across countries, especially in terms of institutional complexity and the composition of the talent pool. In particular, China's unique administrative and policy environment, such as the *hukou* system, shapes migration dynamics in ways that may not apply elsewhere. However, several behavioural mechanisms, such as migrants' heightened risk tolerance and adaptability, are not unique to the Chinese context and may be generalisable across different settings. These broadly applicable features offer a valuable basis for extending the theoretical insights beyond the specific institutional environment examined.

Acknowledgements

We appreciate constructive comments from the Associate Editor and an anonymous reviewer. We acknowledge the comments from the conference participants at the 2022 Auckland Region Accounting (ARA) Conference and the 2024 AFAANZ Conference. The authors would also like to thank the Chinese Scholarship Council (CSC) for financial support. Open access publishing facilitated by Massey University, as part of the Wiley - Massey University agreement via the Council of Australian University Librarians.

Data Availability Statement

Author elects to not share data.

Endnotes

[1] Corporate innovation plays a critical role in promoting long-term economic development at both national and firm levels (Aghion et al. 2005; Porter 1992). Among the various drivers of corporate innovation, increasing attention has been paid to the role of TMTs, as they make key strategic decisions and allocate resources that shape firms' innovation (Chemmanur et al. 2019). Innovation represents an ideal outcome to examine in relation to migrant TMTs because it directly benefits from the cognitive diversity and varied regional experiences these executives bring. While other firm consequences could be studied, innovation uniquely captures how knowledge transfer across regional boundaries translates into a tangible competitive advantage. Given China's significant regional heterogeneity in institutional settings, market development, and cultural norms (Lei et al. 2022), examining how migrant TMTs influence innovation provides rich insights into how geographic relocation shapes strategic decision-making and resource allocation in ways that other performance measures might not reveal as clearly.

[2] Since the migrant manager is a member of the TMT, and the TMT can be split into homogenous subgroups; one could argue that the underlying construct of our paper is related to TMT faultline literature. The TMT faultlines are hypothetical dividing lines that split a team into homogenous subgroups based on team members' alignment along their multiple characteristics (Lau and Murnighan 1998; Thatcher et al. 2003). Subsequent studies further distinguished faultlines into bio-demographic faultlines represented by physical characteristics, such as age, gender or ethnicity, and task-related fault lines characterised by position, tenure, education, professional or functional background (Bezrukova et al. 2009; Hutzschenreuter and Horstkotte 2013; Ndofor et al. 2015). Ma et al. (2021) document an inverted *U*-shaped relationship between task-related faultline and green technology innovation for a sample of Chinese firms. Although we use the upper echelons theory, we discuss the characteristics of migrant managers, relying primarily on the self-selection theory from the migration literature. Consequently, our arguments in Section 3 draw both both the migration and upper echelons theories. As a result, our paper is distinct from the literature on the TMT faultlines.

[3] China National Medium- and Long-term S&T Strategic Plan (outline): http://www.gov.cn/jrzg/2006-02/09/content_183787_7.htm (In Chinese).

[4] Notice of the Ministry of Finance, the State Administration of Taxation and the Ministry of Science and Technology on Improving the Policies for the Weighted Pre-tax Deduction of Research and Development Expenses: http://lawinfochina.com/display.aspx?id=20643&lib=law.

[5] 'Research and development expenditure (% of GDP)' by the World Bank, https://data.worldbank.org/indicator/GB.XPD.RSDV.GD.ZS?locations=CN.

[6] The process of imprinting occurs when a focal entity develops characteristics that reflect prominent features of its environment during a brief period of susceptibility, and these characteristics persist even when the environment significantly changes over time (Marquis and Tilcsik 2013).

[7] According to Abrams and Hogg (1988), social identity is the belief that one belongs to a particular social group, based on comparisons between members of the selected group and other groups (Stets and Burke 2000). Those in a group are like-minded individuals, sharing similar beliefs, identifying with one another, having similar opinions, and behaving similarly (Stets and Burke 2000).

[8] Individuals who integrate into groups are likely to lose their ability to think for themselves, and instead, tend to conform to in-group thoughts, which ultimately leads to biased decision-making. Favouritism in-group ignores or fails to adequately consider the costs of favoured decisions and suggestions from specialists outside the group. Tajfel and Turner (1986) describe bias as emphasising in-group membership at the expense of outgroup members.

[9] We do so because the first 6 digits of ID may not always accurately reflect the actual place of birth. The State Council of China introduced "The People's Republic of China Identity Card Trial Regulations" in April 1984, marking China's initial set of regulations governing residents' identification cards. This means a manager who was born after the promulgation of this regulation had the option to obtain his/her ID in the place of study or employment, potentially resulting in the first six digits of their ID not accurately indicating their actual birthplace.

[10] While we define migrant managers based on the geographic difference between their place of origin and the location of the firm, we acknowledge that this approach has certain limitations. Specifically, using birthplace as a proxy for migration status may not fully capture the complexities of individual migration experiences. However, this method is widely adopted in the existing literature as a practical and consistent approach to identifying migrant managers (e.g., Gao et al. 2021; Guo et al. 2023), given the challenges of obtaining more precise personal migration histories in large-scale studies. Despite its limitations, birthplace remains a reasonable proxy for regional socialisation and cultural adaptation, which are critical for understanding managerial behaviour and decision-making in different institutional contexts. Nevertheless, we caution that this measure should be interpreted carefully, as it may not fully capture managers who have developed their careers in regions different from their place of birth. Future research could improve upon this approach by using more precise data, such as long-term residence history or self-reported migration experiences, to better capture the true nature of managerial migration.

[11] We obtained managers' migration movements from their public profiles. Although tracking a manager's entire migration journey

through public profiles can be challenging and may lead to potential underestimations, it provides a fundamental understanding of their migration history.

[12] Input-based measures such as R&D expenditure have often been used as the most common measurement for a firm's innovation activities. However, limitations also exist in the use of input-based measurement. First, R&D expenditures cannot capture a firm's innovation strategies and innovation performance (Manso 2011) as it only reflects one particular observable quantitative input (Aghion et al. 2013). As stressed by Aghion et al. (2013), the innovation output depends more on the productivity of R&D expenses than on the amount of R&D. Therefore, the increase in the amount of R&D expenses cannot necessarily guarantee more innovation outputs (Gao et al. 2018; Lanjouw and Schankerman 2004). Second, R&D expenses are more sensitive to accounting standards than innovation outputs, as whether they should be capitalised or expensed is quite specific (Acharya and Subramanian 2009). Thus, R&D expenditures used in research do not necessarily reflect the firm's actual R&D expenses.

[13] As per the Patent Law of the People's Republic of China, patents in China are divided into three types: invention, utility model and design patents. Among these three types of patents, invention and utility model patents include both substantial and format elements, while design patents only include format elements. To mitigate the concern that the number of patents applied for or granted captures mainly the quantity of patents, we also use the number of inventions plus utility model patents (*Apply2*) and invention patents (*Iapply*), considering these two kinds of patents are of higher quality and more innovative than others, with invention patents having the highest quality among these three types.

[14] The number of patent applications used here are the actual number of patents before taking the natural logarithm.

[15] Define $Apply1_{t+1}$ as the y variable and Mig_Prop_t as the x variable of interest; then the coefficient on Mig_Prop_t of 0.494 represents $\mathrm{dln}(1+y)/\mathrm{d}x$. To find the change in y ($\mathrm{d}y$), we derive it as $\mathrm{d}y=[\mathrm{dln}(1+y)/\mathrm{d}x]*\mathrm{d}x*(1+y)$. As the standard deviation of x is 0.286 and the unconditional mean of y is 3.052, we obtain $\mathrm{d}y=[\mathrm{dln}\,(1+y)/\mathrm{d}x]*\mathrm{d}x*(1+y)=0.494*0.286*(1+3.052)=0.572$. This represents an 18.7% (0.572/3.052) increase in the mean of $Apply1_{t+1}$.

[16] One potential confounding effect that could affect the result is our failure to distinguish the first-generation versus second-generation effects. Our arguments are more aligned with the first-generation migrants who have been confronted with more challenges and hence had to take more risks compared to their successor generations. However, if the second generation with parents from other cities plays a dominant role in this association, then confounding factors like the innate genes or the resources from the parents might enable the second-generation migrant to outperform their peers. But as noted in footnote 9, tracking a manager's entire migration journey through public profiles can be challenging. Importantly, we would like the readers to note that such second-generation migrant TMT members are likely to be fewer in our sample, given the age profile.

[17] Untabulated results using *Mig_Pure* and *Mig_Multiple* are generally consistent with *Mig_Prop* for the other analyses as well (results are available upon request).

[18] CMDSSS was developed and is currently managed by the Climatic Data Center, National Meteorological Information Center, China Meteorological Administration. See http://data.cma.cn/for details.

[19] For example, in 2015, the annual temperature difference of Guangdong was 20.81, while the average annual temperature difference of other provinces, excluding Guangdong, was 32.55. *Temp_Diff*, therefore, is 11.74, calculated as (20.81–32.55)*(−1). In comparison, the average annual temperature difference in Ningxia was 31.74, while the average annual temperature difference excluding Ningxia was 32.02. *Temp_Diff*, therefore, is 0.28. Following the notion that migrant managers would be attracted to regions with more pleasant weather, we expect Guangdong to be more attractive than Ningxia in 2015.

[20] Following Lei et al. (2022), we also measure dialect diversity using the number of distinct sub-Chinese dialects spoken within a city, and the untabulated results remain consistent.

References

Abrams, D., and M. A. Hogg. 1988. "Comments on the Motivational Status of Self-Esteem in Social Identity and Intergroup Discrimination." *European Journal of Social Psychology* 18, no. 4: 317–334.

Acharya, V. V., and K. V. Subramanian. 2009. "Bankruptcy Codes and Innovation." *Review of Financial Studies* 22, no. 12: 4949–4988.

Adhikari, B. K., and A. Agrawal. 2016. "Religion, Gambling Attitudes and Corporate Innovation." *Journal of Corporate Finance* 37: 229–248.

Aghion, P., N. Bloom, R. Blundell, R. Griffith, and P. Howitt. 2005. "Competition and Innovation: An Inverted-U Relationship." *Quarterly Journal of Economics* 120, no. 2: 701–728.

Aghion, P., J. Van Reenen, and L. Zingales. 2013. "Innovation and Institutional Ownership." *American Economic Review* 103, no. 1: 277–304.

Amendola, A., C. Barra, and R. Zotti. 2020. "Does Graduate Human Capital Production Increase Local Economic Development? An Instrumental Variable Approach." *Journal of Regional Science* 60, no. 5: 959–994.

An, L., Y. Qin, J. Wu, and W. You. 2024. "The Local Labor Market Effect of Relaxing Internal Migration Restrictions: Evidence From China." *Journal of Labor Economics* 42, no. 1: 161–200.

Baron, R. M., and D. A. Kenny. 1986. "The Moderator–Mediator Variable Distinction in Social Psychological Research: Conceptual, Strategic, and Statistical Considerations." *Journal of Personality and Social Psychology* 51, no. 6: 1173–1182.

Beladi, H., Q. Hou, and M. Hu. 2022. "The Party School Education and Corporate Innovation: Evidence From SOEs in China." *Journal of Corporate Finance* 72: 102143.

Bernile, G., V. Bhagwat, and P. R. Rau. 2017. "What Doesn't Kill You Will Only Make You More Risk-Loving: Early-Life Disasters and CEO Behavior." *Journal of Finance* 72, no. 1: 167–206.

Berry, J. W. 2005. "Acculturation: Living Successfully in Two Cultures." *International Journal of Intercultural Relations* 29, no. 6: 697–712.

Bezrukova, K., K. A. Jehn, E. L. Zanutto, and S. M. B. Thatcher. 2009. "Do Workgroup Faultlines Help or Hurt? A Moderated Model of Faultlines, Team Identification, and Group Performance." *Organization Science* 20, no. 1: 35–50.

Bhattacharya, S., and J. R. Ritter. 1983. "Innovation and Communication: Signalling With Partial Disclosure." *Review of Economic Studies* 50, no. 2: 331–346.

Bian, W., Y. Ji, and H. Zhang. 2019. "Does Dialect Similarity Add Value to Banks? Evidence From China." *Journal of Banking and Finance* 101: 226–241.

Bloom, N., M. Draca, and J. Van Reenen. 2016. "Trade Induced Technical Change? The Impact of Chinese Imports on Innovation, IT and Productivity." *Review of Economic Studies* 83, no. 1: 87–117.

Borjas, G. J. 1985. "Assimilation, Changes in Cohort Quality, and the Earnings of Immigrants." *Journal of Labor Economics* 3, no. 4: 463–489.

Bosetti, V., C. Cattaneo, and E. Verdolini. 2015. "Migration of Skilled Workers and Innovation: A European Perspective." *Journal of International Economics* 96, no. 2: 311–322.

Brown, J. R., and G. Martinsson. 2019. "Does Transparency Stifle or Facilitate Innovation?" *Management Science* 65, no. 4: 1600–1623.

Bushee, B. J. 1998. "The Influence of Institutional Investors on Myopic R&D Investment Behaviour." *Accounting Review* 73, no. 3: 305–333.

Cai, S., and K. F. Zimmermann. 2024. "Social Identity and Labor Market Outcomes of Internal Migrant Workers." *European Economic Review* 163: 104676.

Chan, K. W. 2009. "The Chinese Hukou System at 50." *Eurasian Geography and Economics* 50, no. 2: 197–221.

Chan, K. W. 2010. "The Global Financial Crisis and Migrant Workers in China: 'There Is no Future as a Labourer; Returning to the Village Has no Meaning'." *International Journal of Urban and Regional Research* 34, no. 3: 659–677.

Chemmanur, T. J., L. Kong, K. Krishnan, and Q. Yu. 2019. "Top Management Human Capital, Inventor Mobility, and Corporate Innovation." *Journal of Financial and Quantitative Analysis* 54, no. 6: 2383–2422.

Chen, C., M. Burton, E. Greenberger, and J. Dmitrieva. 1999. "Population Migration and the Variation of Dopamine D4 Receptor (DRD4) Allele Frequencies Around the Globe." *Evolution and Human Behavior* 20, no. 5: 309–324.

Chen, H., J. Z. Chen, G. J. Lobo, and Y. Wang. 2010. "Association Between Borrower and Lender State Ownership and Accounting Conservatism." *Journal of Accounting Research* 48, no. 5: 973–1014.

Chen, S., S. X. Ying, H. Wu, and J. You. 2021. "Carrying on the Family's Legacy: Male Heirs and Firm Innovation." *Journal of Corporate Finance* 69: 101976.

Chircop, J., D. W. Collins, L. H. Hass, and N. N. Q. Nguyen. 2020. "Accounting Comparability and Corporate Innovative Efficiency." *Accounting Review* 95, no. 4: 127–151.

Chiswick, B. 1978. "The Effect of Americanization on the Earnings of Foreign-Born Men." *Journal of Political Economy* 86, no. 5: 897–922.

Chiswick, B. 1999. "Are Immigrants Favorably Self-Selected?" *American Economic Review* 89, no. 2: 181–185.

Cui, H., L. Dai, and Y. Zhang. 2021. "Organization Capital and Corporate Innovation: Evidence From China." *Finance Research Letters* 43: 101956.

Dokko, G., and W. Jiang. 2017. *Managing Talent Across Organizations*, 115–133. Oxford Handbook of Talent Management.

Du, H., S. M. Li, and P. Hao. 2018. "'Anyway, You Are an Outsider': Temporary Migrants in Urban China." *Urban Studies* 55, no. 14: 3185–3201.

Du, X., W. Jian, Y. Du, W. Feng, and Q. Zeng. 2014. "Religion, the Nature of Ultimate Owner, and Corporate Philanthropic Giving: Evidence From China." *Journal of Business Ethics* 123, no. 2: 235–256.

Duleep, H. O. 2015. "The Adjustment of Immigrants in the Labor Market." In *Handbook of the Economics of International Migration*, vol. 1, 105–182. North-Holland.

Duleep, H., X. Liu, and M. Regets. 2022. "How the Earnings Growth of US Immigrants Was Underestimated." *Journal of Population Economics* 35, no. 2: 381–407.

Dustmann, C., U. Schönberg, and J. Stuhler. 2016. "The Impact of Immigration: Why Do Studies Reach Such Different Results?" *Journal of Economic Perspectives* 30, no. 4: 31–56.

Falck, O., S. Heblich, A. Lameli, and J. Südekum. 2012. "Dialects, Cultural Identity, and Economic Exchange." *Journal of Urban Economics* 72, no. 2–3: 225–239.

Gagliardi, L. 2015. "Does Skilled Migration Foster Innovative Performance? Evidence From British Local Areas." *Papers in Regional Science* 94, no. 4: 773–795.

Galasso, A., and T. S. Simcoe. 2011. "CEO Overconfidence and Innovation." *Management Science* 57, no. 8: 1469–1484.

Gao, H., P. H. Hsu, and K. Li. 2018. "Innovation Strategy of Private Firms." *Journal of Financial and Quantitative Analysis* 53, no. 1: 1–32.

Gao, J., H. Wu, J. You, and M. Smith. 2021. "Migrant Entrepreneurs and Firm Innovation." *Accounting and Finance* 61, no. 5: 6069–6112.

Guariglia, A., X. Liu, and L. Song. 2011. "Internal Finance and Growth: Microeconometric Evidence on Chinese Firms." *Journal of Development Economics* 96, no. 1: 79–94.

Guo, L., D. Peng, Y. Rao, and Z. Zhuang. 2023. "Visiting Monks: Are Nonlocal CEOs Paid More?" *International Review of Financial Analysis* 85: 102465.

Hainmueller, J. 2012. "Entropy Balancing for Causal Effects: A Multivariate Reweighting Method to Produce Balanced Samples in Observational Studies." *Political Analysis* 20, no. 1: 25–46.

Hall, B., A. Jaffe, and M. Trajtenberg. 2001. *The NBER Patent Citations Data File: Lessons, Insights and Methodological Tools*. NBER Working Paper 8498.

Hall, B. H., and R. H. Ziedonis. 2001. "The Patent Paradox Revisited: An Empirical Study of Patenting in the US Semiconductor Industry, 1979-1995." *Rand Journal of Economics* 32, no. 1: 101–128.

Hamilton, B. H., N. W. Papageorge, and N. Pande. 2019. "The Right Stuff? Personality and Entrepreneurship." *Quantitative Economics* 10, no. 2: 643–691.

Hanlon, M., K. Yeung, and L. Zuo. 2022. "Behavioral Economics of Accounting: A Review of Archival Research on Individual Decision Makers." *Contemporary Accounting Research* 39, no. 2: 1150–1214.

Hart, D. M., and Z. J. Acs. 2011. "High-Tech Immigrant Entrepreneurship in the United States." *Economic Development Quarterly* 25, no. 2: 116–129.

He, W., C. K. Li, and Y. Si. 2024. "Is Auditors' Migration Status Associated With Their Performance?" *European Accounting Review*, https://doi.org/10.1080/09638180.2024.2384379

Healy, P. M., and K. G. Palepu. 2001. "Information Asymmetry, Corporate Disclosure, and the Capital Markets: A Review of the Empirical Disclosure Literature." *Journal of Accounting and Economics* 31, no. 1–3: 405–440.

Hirshleifer, D., A. Low, and S. H. Teoh. 2012. "Are overconfident CEOs better innovators?" *Journal of Finance* 67, no. 4: 1457–1498.

Hochberg, Y. V., and L. Lindsey. 2010. "Incentives, Targeting, and Firm Performance: An Analysis of Non-Executive Stock Options." *Review of Financial Studies* 23, no. 11: 4148–4186.

Hogg, M. A., D. Van Knippenberg, and D. E. Rast III. 2012. "The Social Identity Theory of Leadership: Theoretical Origins, Research Findings, and Conceptual Developments." *European Review of Social Psychology* 23, no. 1: 258–304.

Holmstrom, B. 1989. "Agency Costs and Innovation." *Journal of Economic Behavior & Organization* 12, no. 3: 305–327.

Howell, S. T. 2017. "Financing Innovation: Evidence From R&D Grants." *American Economic Review* 107, no. 4: 1136–1164.

Huang, B., E. Yang, and Y. Zhang. 2023. "Board Surname Sharing and Investment Efficiency: Evidence From Chinese State-Owned Enterprises." *Corporate Governance: An International Review* 31, no. 4: 597–624.

Huang, H., A. Habib, L. Sun, Y. Liu, and H. Guo. 2021. "Financial Reporting and Corporate Innovation: A Review of the International Literature." *Accounting and Finance* 61, no. 4: 5439–5499.

Huang, M., M. Li, and X. Li. 2023. "Do Non-Local CEOs Affect Environmental, Social and Governance Performance?" *Management Decision* 61, no. 8: 2354–2373.

Hutzschenreuter, T., and J. Horstkotte. 2013. "Performance Effects of Top Management Team Demographic Faultlines in the Process of Product Diversification." *Strategic Management Journal* 34, no. 6: 704–726.

Hu, D., L. Qiu, M. She, and Y. Wang. 2021. "Sustaining the Sustainable Development: How do Firms Turn Government Green Subsidies into Financial Performance Through Green Innovation?" *Business Strategy and the Environment* 30, no. 5: 2271–2292.

Jia, N. 2019. "The Impact of Accounting Restatements on Corporate Innovation Strategy." *Journal of Accounting and Public Policy* 38, no. 3: 219–237.

Jiang, F., Y. Qian, and S. E. Yonker. 2019. "Hometown Biased Acquisitions." *Journal of Financial and Quantitative Analysis* 54, no. 5: 2017–2051.

Kang, J. K., W. L. Liu, A. Low, and L. Zhang. 2018. "Friendly Boards and Innovation." *Journal of Empirical Finance* 45: 1–25.

Kim, K., S. Patro, and R. Pereira. 2017. "Option Incentives, Leverage, and Risk-Taking." *Journal of Corporate Finance* 43: 1–18.

Kong, D., Y. Zhao, and S. Liu. 2021. "Trust and Innovation: Evidence From Ceos' Early-Life Experience." *Journal of Corporate Finance* 69: 101984.

Kopi, M., and W. Clark. 2015. "Internal Migration and Human Capital Theory: To What Extent Is It Selective?" *Economics Letters* 136: 31–34.

Kuziemko, I., and J. Ferrie. 2014. "The Role of Immigrant Children in Their Parents' Assimilation in the United States, 1850–2010." In *Human Capital in History: The American Record*, 97–120. University of Chicago Press.

Lai, S., Z. Li, and Y. G. Yang. 2020. "East, West, Home's Best: Do Local CEOs Behave Less Myopically?" *Accounting Review* 95, no. 2: 227–255.

Lanjouw, J. O., and M. Schankerman. 2004. "Patent Quality and Research Productivity: Measuring Innovation With Multiple Indicators." *Economic Journal* 114, no. 495: 441–465.

Lau, D. C., and J. K. Murnighan. 1998. "Demographic Diversity and Faultlines: The Compositional Dynamics of Organizational Groups." *Academy of Management Review* 23, no. 2: 325–340.

Lei, G., W. Wang, J. Yu, and K. C. Chan. 2022. "Cultural Diversity and Corporate Tax Avoidance: Evidence From Chinese Private Enterprises." *Journal of Business Ethics* 176, no. 2: 1–379.

Leung, A. K. Y., W. W. Maddux, A. D. Galinsky, and C. Y. Chiu. 2008. "Multicultural Experience Enhances Creativity: The When and How." *American Psychologist* 63, no. 3: 169–181.

Lewis, E., and G. Peri. 2015. "Immigration and the Economy of Cities and Regions." In *Handbook of Regional and Urban Economics*, vol. 5, 625–685. Elsevier.

Lin, N., A. Li, J. Ke, and J. Yuan. 2023. "The Governance Role of Corporate Party Organization on Innovation." *International Review of Economics and Finance* 84: 657–670.

Lissoni, F., and E. Miguelez. 2024. "Migration and Innovation: Learning From Patent and Inventor Data." *Journal of Economic Perspectives* 38, no. 1: 27–54.

Liu, F. C., D. F. Simon, Y. T. Sun, and C. Cao. 2011. "China's Innovation Policies: Evolution, Institutional Structure, and Trajectory." *Research Policy* 40, no. 7: 917–931.

Luo, D., Z. Wu, J. Zhuo, and J. He. 2022. "Market Misvaluation and Corporate Innovation: "Catering" or "Risk Aversion"? —Empirical Evidence From China Capital Market." *China Journal of Accounting Research* 15, no. 3: 100249.

Ma, Y., Q. Zhang, and Q. Yin. 2021. "Top Management Team Faultlines, Green Technology Innovation and Firm Financial Performance." *Journal of Environmental Management* 285: 112095.

Manso, G. 2011. "Motivating Innovation." *Journal of Finance* 66, no. 5: 1823–1860.

Marquardt, D. W. 1970. "Generalized Inverses, Ridge Regression, Biased Linear Estimation, and Nonlinear Estimation." *Technometrics* 12, no. 3: 591–612.

Marquis, C., and A. Tilcsik. 2013. "Imprinting: Toward a Multilevel Theory." *Academy of Management Annals* 7, no. 1: 195–245.

Matthews, L. J., and P. M. Butler. 2011. "Novelty-Seeking DRD4 Polymorphisms Are Associated With Human Migration Distance Out-Of-Africa After Controlling for Neutral Population Gene Structure." *American Journal of Physical Anthropology* 145, no. 3: 382–389.

McAuliffe, M., and B. Khadria. 2020. "Report Overview: Providing Perspective on Migration and Mobility in Increasingly Uncertain Times." *World Migration Report* 2020, no. 1: e00011.

McGrath, R. G., I. C. MacMillan, and S. Scheinberg. 1992. "Elitists, Risk-Takers, and Rugged Individualists? An Exploratory Analysis of Cultural Differences Between Entrepreneurs and Non-Entrepreneurs." *Journal of Business Venturing* 7, no. 2: 115–135.

McMullin, J. L., and B. Schonberger. 2020. "Entropy-Balanced Accruals." *Review of Accounting Studies* 25, no. 1: 84–119.

Ndofor, H. A., D. G. Sirmon, and X. He. 2015. "Utilizing the Firm's Resources: How TMT Heterogeneity and Resulting Faultlines Affect TMT Tasks." *Strategic Management Journal* 36, no. 11: 1656–1674.

Nguyen, L., L. Vu, and X. Yin. 2020. "The Undesirable Effect of Audit Quality: Evidence From Firm Innovation." *British Accounting Review* 52, no. 6: 100938.

Pinate, A. C., A. Faggian, C. Di Berardino, and C. Castaldi. 2023. "The Heterogenous Relationship Between Migration and Innovation: Evidence From Italy." *Industry and Innovation* 30, no. 3: 336–360.

Porter, M. E. 1992. "Capital Choices: Changing the Way America Invests in Industry." *Journal of Applied Corporate Finance* 5, no. 2: 4–16.

Ren, S., Y. Cheng, Y. Hu, and C. Yin. 2021. "Feeling Right at Home: Hometown CEOs and Firm Innovation." *Journal of Corporate Finance* 66: 101815.

Shane, S. 1993. "Cultural Influences on National Rates of Innovation." *Journal of Business Venturing* 8, no. 1: 59–73.

Shi, X., D. Bu, and C. Zhang. 2020. "Official Rotation and Corporate Innovation: Evidence From the Governor Rotation." *China Journal of Accounting Research* 13, no. 4: 361–385.

Shleifer, A., and R. W. Vishny. 1994. "Politicians and Firms." *Quarterly Journal of Economics* 109, no. 4: 995–1025.

Stets, J. E., and P. J. Burke. 2000. "Identity Theory and Social Identity Theory." *Social Psychology Quarterly* 63, no. 3: 224–237.

Tajfel, H. 1982. "Experimental Studies of Intergroup Behaviour." In *Cognitive Analysis of Social Behavior*, 227–246. Springer.

Tajfel, H., and J. C. Turner. 1986. "The Social Identity Theory of Intergroup Behavior." In *Psychology of Intergroup Relations*, edited by S. Worchel and W. G. Austin, 7–24. Nelson Hall.

Talhelm, T., X. Zhang, S. Oishi, et al. 2014. "Large-Scale Psychological Differences Within China Explained by Rice Versus Wheat Agriculture." *Science* 344, no. 6184: 603–608.

Tang, X., J. Shi, J. Han, A. Shu, and F. Xiao. 2021. "Culturally Diverse Board and Corporate Innovation." *Accounting and Finance* 61, no. 4: 5655–5679.

Thakor, R. T., and A. W. Lo. 2017. *Optimal Financing for R&D-Intensive Firms (No. w23831)*. National Bureau of Economic Research.

Thatcher, S. M. B., K. A. Jehn, and E. Zanutto. 2003. "Cracks in Diversity Research: The Effects of Diversity Faultlines on Conflict and Performance." *Group Decision and Negotiation* 12, no. 3: 217–241.

Tian, M., P. Deng, Y. Zhang, and M. P. Salmador. 2018. "How Does Culture Influence Innovation? A Systematic Literature Review." *Management Decision* 56, no. 5: 1088–1107.

United Nations, Department of Economic and Social Affairs, Population Division. 2016. International Migration Report 2015: Highlights (ST/ESA/SER.A/375).

Wan, Q., X. Cheng, K. C. Chan, and S. Gao. 2021. "Born to Innovate? The Birth-Order Effect of CEOs on Corporate Innovation." *Journal of Business Finance & Accounting* 48, no. 9–10: 1846–1888.

Wang, W. W., and C. C. Fan. 2012. "Migrant Workers' Integration in Urban China: Experiences in Employment, Social Adaptation, and Self-Identity." *Eurasian Geography and Economics* 53, no. 6: 731–749.

West, M. A., and N. R. Anderson. 1996. "Innovation in Top Management Teams." *Journal of Applied Psychology* 81, no. 6: 680–693.

Wouterse, F. 2016. "Can Human Capital Variables Be Technology Changing? An Empirical Test for Rural Households in Burkina Faso." *Journal of Productivity Analysis* 45, no. 2: 157–172.

Wu, Y., and C. E. Eesley. 2022. "Regional Migration, Entrepreneurship and University Alumni." *Regional Studies* 56, no. 6: 1015–1032.

Xu, Q., L. Deng, S. Li, and W. Huang. 2021. "Do Hometown Connections Affect Corporate Governance? Evidence From Chinese Listed Companies." *International Review of Economics and Finance* 73: 290–302.

Yin, H., X. Jin, X. Quan, and J. Yu. 2022. "Does Social Network Improve Corporate Financing Efficiency? Evidence From China." *Pacific-Basin Finance Journal* 74: 101802.

Yonker, S. E. 2017. "Geography and the Market for CEOs." *Management Science* 63, no. 3: 609–630.

Yuan, R., and W. Wen. 2018. "Managerial Foreign Experience and Corporate Innovation." *Journal of Corporate Finance* 48: 752–770.

Zhang, D. 2019. "Top Management Team Characteristics and Financial Reporting Quality." *Accounting Review* 94, no. 5: 349–375.

Zhong, R. I. 2018. "Transparency and Firm Innovation." *Journal of Accounting and Economics* 66, no. 1: 67–93.

Zhou, D., M. Bai, X. Liang, and Y. Qin. 2021. "The Early-Life Political Event Experience of the Chair of the Board and the Firm's Innovation Decision." *Australian Accounting Review* 31, no. 3: 186–212.

Appendix A

Some Representative Examples of Tracking Migration Status of TMT Members

In April 1984, the State Council of China introduced "The People's Republic of China Identity Card Trial Regulations", marking China's initial set of regulations governing residents' identification cards. Consequently, it is possible for managers to obtain an ID in the place where they attended university or began their career, even if they were born elsewhere. In this case, the birthplace information obtained from the ID Number may not represent the actual place where the manager was born. We provide three illustrative examples below.

Qiting Lu was the CEO of Shanghai Kangda Chemical New Material Group Co. Ltd. (SZ: 002669). The prospectus for this firm indicates that the first 6 digits of Qiting Lu's ID are 230,107, signifying the unique code of Harbin city, Heilongjiang Province. However, further information derived from newspapers and journals paints a different picture of Qiting Lu's background. It becomes evident that Qiting Lu was actually born in Shanghai in 1940, and spent his early years there, completing his high school education in the city. Subsequently, in 1963, he received his bachelor's degree from Peking University and then began his professional career at the Heilongjiang Chemical Engineering Research Institute in Harbin, Heilongjiang. According to the 1984 regulation on identification card, Mr. Lu obtained his ID in the place where he lived at the time of ID application, that is, Heilongjiang province. In 1988, he returned to his hometown of Shanghai to start his own business and has been living there since then. Given that the firm is headquartered in Shanghai, Qiting Lu is recognised as a *local CEO with external experiences*, instead of a migrant CEO. The news in Chinese can be found at http://www.pdtimes.com.cn/html/2012-05/10/content_9_4.htm.

Another example is associated with the mangers' early life experiences. Li Huang is the president of the board and CEO of Wuhan Guide Infrared Co. Ltd. (SZ: 002414). His ID, which begins with 420,106, indicates his connection to Wuhan City in Hubei Province. However, according to information obtained from newspaper, it has been revealed that Li Huang was originally born in Xi'an, Shaanxi. At the age of 6, he relocated to Wuhan, Hubei with his parents due to their job changes to Wuhan. The fact that he lived in Wuhan, Hubei for the formative years of his childhood, there is a strong argument for regarding him as a local of Hubei Province, as the environment and culture he grew up was the same as those of the locals of Wuhan. In this case, we define Li Huang as a local manager, instead of a migrant. The news is available at http://www.hubeitoday.com.cn/post/34/27991.

However, it is hard to track each manager's entire life by searching relevant news. We also looked into public profiles to determine whether they are locals or migrants. For example, Peizhu Sun was the Vice President of Shandong Meichen Technology & Environment Co. Ltd. (SZ 300237). His ID starts with 220,222: the code of Jilin Province. Looking at his public profile, we find that his place of origin is also in Jilin Province. Also, he was studying in Jilin University, and then worked in Jilin Province for several years. Therefore, it is reasonable to predict that he was born and raised in Jilin Province and is a migrant to Shandong.

Appendix B

Variable Definitions

Variables	Definitions	Data source
Independent variables		
Mig_Prop	The percentage of migrant managers in a TMT calculated as the number of migrant managers in TMT/total TMT size	CSMAR + Manual collection
Mig_Pure	The percentage of pure migrants in the TMT. Pure migrants are managers who migrated once, moving directly from their hometown to their current workplace, as indicated in their public profiles	Decomposition of *Mig_Prop*
Mig_Multiple	The percentage of multiple-time migrants in the TMT. Multiple-time migrants are managers who have migrated more than once, involving relocations to several different provinces before arriving at their current workplace	Decomposition of *Mig_Prop*
Dependent variables		
*Apply*1	Natural logarithm of 1 plus the number of patent applications	CNRDS
Apply2	Natural logarithm of 1 plus the number of invention and utility model patents applied for	CNRDS
Iapply	Natural logarithm of 1 plus the number of invention patents applied for	CNRDS
*Grant*1	Natural logarithm of 1 plus the number of patents granted	CNRDS
Grant2	Natural logarithm of 1 plus the number of invention and utility patents granted	CNRDS
Igrant	Natural logarithm of 1 plus the number of invention patents granted	CNRDS
Citation	Natural logarithm of 1 plus weighted citations which is scaled by the average citations of all patents applied for in the same year and in the same technology class	CSMAR
Control variables		
Size	Natural logarithm of firm's total assets	CSMAR
Roa	Firm profitability, calculated as income before extraordinary items (net income) divided by total assets	CSMAR
Lev	Total debt over total assets	CSMAR
Growth	The growth of a firm's total assets	CSMAR
Tobinq	The company's market value, measured by the ratio of the sum of market values of equity and net liabilities to total assets at the end of period; the market value of unlisted shares is substituted for net assets	CSMAR
TMT_size	Size of top management team, calculated as the natural logarithm of top managers in the TMT	CSMAR
TMT_age	Natural logarithm of the average age of TMT	CSMAR
TMT_edu	The average education level of TMT, where Secondary = 1, College = 2, Bachelor = 3, Master = 4, PhD = 5	CSMAR
TMT_gender	The percentage of male members in the TMT	CSMAR
Bind	Independence of the board, measured as the ratio of the number of independent directors to the total number of directors on the board	CSMAR
Top holding	The percentage of total shares held by the largest shareholder	CSMAR
Firm Age	Number of years since a firm was founded	CSMAR
Home CEO	CEO hometown identity. A dummy variable takes the value of 1 when the firm's headquarters is in the same province as the CEO's hometown, and 0 otherwise	CSMAR + Manual collection
Others		

Variables	Definitions	Data source
Rem	Real earnings management, calculated as Rem = (−1) *abnormal operating cash flow + abnormal production cost + (−1) *abnormal discretionary expenses	CSMAR
Risk	Earnings volatility. The forward-looking rolling standard deviation of EBITDA/Sales over each consecutive 3-year period	CSMAR
SOE	A dummy variable that takes 1 if the firm is state-owned and 0 otherwise	CSMAR
RD_Ratio	R&D expenses to total assets. Missing R&D expenses are replaced with 0	CNRDS
Gpat_app	Natural logarithm of 1 plus the number of green patents applied for	CNRDS
IGpat_app	Natural logarithm of 1 plus the number of green invention patents applied for	CNRDS
Gpat_grant	Natural logarithm of 1 plus the number of green patents granted	CNRDS
IGpat_grant	Natural logarithm of 1 plus the number of green invention patents granted	CNRDS