Green innovation and cross-border M&As: Evidence from China

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Abstract:
Using a sample of cross-border mergers and acquisitions (CBMAs) attempted by Chinese listed firms between 2007 and 2021, we explore how green innovation affects emerging market economy (EME) bidders' internationalization via CBMAs. We document that green innovative bidders are more likely to complete CBMA deals successfully, realize higher announcement abnormal returns in the short-run, and achieve better post-merger operating performance in the long term. This better performance is achieved due to lower growth rate of carbon emission, superior environmental performance, reduced environmental compliance costs, and larger government subsidies after CBMA deal completion. Moreover, the positive effect of green innovation on deal completion probability and post-merger operating performance is more pronounced when host economies have greater physical climate risk, while weakened when host economies incur higher economic policy uncertainty. Brought together, these findings suggest that green innovative EME bidders positively respond to stakeholders' concerns about climate change-related risks and environmental issues, thus contributing to the attainment of legitimacy and facilitating their internationalization via CBMAs.

Keywords: green innovation; cross-border mergers and acquisitions (CBMAs); carbon emissions; government subsidies; uncertainty

JEL codes: G32; G34; M14.

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1 Introduction

Climate change and carbon neutrality have attracted wide-ranging discussion in recent years, posing new challenges to firms' internationalization strategies through cross-border mergers and acquisitions (CBMAs). Extant studies indicate that climate-change-related risk (e.g., carbon risk) has already become a material risk for investors and other stakeholders (Krueger et al., 2020; Bolton and Kacperczyk, 2021; Bose et al., 2021; Huang et al., 2021). When making legitimacy assessments of CBMA transactions proposed by bidding firms, stakeholders at home and abroad would naturally pay attention to the bidding firms' capacity to handle climate-change-related challenges. Host market stakeholders' legitimacy concerns have long plagued cross-border bidders during the process of CBMAs (Arouri et al., 2019), and cross-border bidders from emerging market economies (EMEs) are particularly vulnerable to these legitimacy concerns (Hawn, 2020; Gao et al., 2022).

As one of the key capabilities that a firm could develop to maintain competitiveness and sustainability (Chen et al., 2006; Huang and Li, 2017), corporate green innovation aims to save resources, improve energy efficiency, prevent and control pollution and emissions, and achieve optimized manufacturing processes and sustainable development (Metz et al., 2000; Huang and Li, 2017). Compared with general innovation, green innovation is more strongly orientated towards corporate social responsibility (CSR) and environmental concern. Different from general CSR activities which usually defensively address legitimacy concerns from host-economy stakeholders, green innovation provides a more aggressive approach for cross-border bidders to demonstrate their social responsibility and work towards sustainable growth (Chiou et al., 2011). In addition, firms' capability on green innovation is gauged on a more solid and objective ground than general CSR. CSR performance is usually measured by agency's ratings, which are (partly) built upon firms' voluntarily information disclosure, whereas green innovation capability is measured by green patents endorsed by the government. Therefore, we posit that cross-border bidders from EMEs could leverage green innovative capability to effectively respond to the legitimacy concerns over climate-change-related challenges from host market stakeholders.

Although previous studies on M&As or CBMAs have paid attention to the impact of innovation (Zhao, 2009; Bena and Li, 2014; Wu and Chung, 2019; Frésard et al., 2020; Vissa and Thenmozhi, 2022) and CSR performance (Deng et al., 2013; Arouri et al., 2019; Yen and André, 2019; Hawn, 2020; Alexandridis et al., 2022), they have mainly focused on general innovation or general CSR, and largely neglected the particular type of innovation or the specific component of CSR---green innovation. The impact of green innovation on EME firms' internationalization via CBMAs, and in particular, the underlying mechanisms of such impact, remain unexplored. We intend to fill this gap by examining the systematic impact of corporate green innovation on completion probability, announcement wealth effect, and post-merger operating performance. More importantly, we investigate the underlying mechanisms of such impact, through various lenses, including bidding firms' growth rate of carbon emission, environmental performance and compliance cost, and host economies' physical climate risk and economic policy uncertainty.

We select CBMAs attempted by Chinese bidders to construct our sample for empirical analysis for three reasons. First, China is the largest EME in the world and Chinese firms' internationalization via CBMAs has been booming since its national "Going Global" strategy was launched in 2001 (Schweizer et al., 2019). Second, as China has set goals to reach its CO2 (carbon dioxide) emissions peak before 2030 and realize carbon neutrality before 2060 (known as the "dual carbon" goals) (Xinhua, 2020), there is an increasing trend of applied and granted green patents in China.[1] Benefiting from these green innovative technologies, China's carbon

[1] According to a report issued by the China National Intellectual Property Administration, the average annual growth rate of green patent applications in China is 3.7 percent higher than that of general patent applications over the period of 2014 – 2017. The report is available at: https://www.cnipa.gov.cn/20180829161402137643.pdf.

emission intensity in 2020 dropped by 48.4% compared to 2005.[2] In the context of Chinese bidders' internationalization journey via CBMAs, these efforts to tackle climate change and address environmental concerns may help them overcome legitimacy challenges from host-economy stakeholders. Third, like many other EMEs, the institutional environment and government intervention in China plays an important role in guiding corporate investment and activities. In China, local and central governments have the discretion to subsidize firms' investments such as corporate green innovation aiming to increase public interest (Lin et al., 2015). Brought together, China provides an ideal setting to explore in depth the effect of green innovation on CBMAs and its underlying mechanisms.

Using a sample of 668 CBMA attempts by Chinese listed firms between 2007 and 2021, we measure the intensity of green innovation at firm level using the total number of green patents granted within our sample periods (*Number of green patents,* including patents of both invention and utility model), and systematically investigate the completion probability, capital market reactions, and real economic outcome in terms of post-merger operating performance of the CBMAs proposed by Chinese bidders. We find consistent evidence that green innovation capability prior to announcement positively contributes to Chinese bidders' internationalization experience. Specifically, green innovative bidders are more likely to complete a CBMA deal successfully, realize higher announcement abnormal returns, and achieve better post-merger operating performance. Next, we investigate four underlying channels of operating performance, and find that lower growth rate of carbon emission, better environmental performance, reduced environmental compliance costs, and larger patent-related government subsidies in the long-run after CBMA deal completion together contribute to improvement in post-merger operating performance. Furthermore, we document that the positive impact of green innovation on the probability of deal completion and post-merger operating performance

[2] See the transcript of the fifth press conference of the 20th National Congress of the Communist Party of China, available at: http://www.news.cn/politics/cpc20/zb/jzh10698/index.htm.

is more evident when host economies are characterized by elevated physical climate risk. Conversely, this positive impact diminishes when host economies have higher economic policy uncertainty.

We conduct a battery of robustness tests on our baseline findings. First, we replace our key explanatory variable (*Number of green patents*) with two alternative variables, namely scaled number of green patents after addressing the truncation problem (*Green patent index (GPI)*), and discounted number of green patents in the spirit of depreciated R&D expenses (*Number of discounted green patents*). Second, we adopt alternative models to calculate the abnormal returns and alternative measure of post-merger operating performance. Third, we employ the instrumental variable approach and propensity score matching (PSM) method to address potential endogeneity concerns of corporate green innovation. Fourth, we further control for province effect, target economy effect, and a set of variables (e.g., bidder's CSR, host economy's climate risk, host economy's aggregate green innovation) in the baseline specifications, respectively. Fifth, we require firms to have at least one granted green patent to be included in our sample and repeat all the tests with this restricted sample. Our conclusions remain intact with all these robustness checks. Overall, these empirical results are consistent with our central hypothesis that a good green innovation profile can help bidders to alleviate legitimacy concerns from host market stakeholders, and demonstrate their capabilities and commitment to substantially combat climate change issues and realize sustainable development through reduced carbon emissions and environmental compliance costs in the future. Therefore, it is easier for green innovative bidders from EMEs to gain legitimacy and support from stakeholders at home and abroad, hence enjoying a smoother journey of internationalization via CBMAs. Our analysis on the underlying channels of operating performance improvement further strengthens our confidence in the reported findings on the positive impact of green innovation in the context of EME bidders' CBMAs.

Specifically, our paper contributes to three streams of existing literature. First, our paper complements recent studies on green innovation and firm value (Hao et al., 2021; Kim et al., 2021; Truong and Berrone, 2022), which have documented that green innovation exerts positive effects on firm value in the long run. We show that EME bidders' green innovation is an important determinant of their CBMA completion, capital market reactions, and post-merger operating performance. More importantly, we document that firms enjoy benefits of green innovative technologies, achieving lower growth in carbon emissions and improvement of corporate environmental performance, both of which contribute to a better corporate reputation and a reduced environmental compliance cost. In addition, being able to gain a larger amount of government subsidies for innovative activities directly improves merged firms' financial status and alleviates potential financial distress risk. All of these result in a more favorable real economic outcome for merged firms.

Second, our paper contributes to the literature on internationalization through CBMAs, especially those attempted by EME bidders, by explicitly investigating how corporate green innovation could influence their cross-border deals. Previous studies on EME firms' CBMAs have documented that factors such as media coverage of corporate social irresponsibility (Hawn, 2020), opaqueness (Li et al., 2019), and political connections (Schweizer et al., 2019) could affect their CBMAs. Gao et al. (2022) regard green patent development as an assertive green marketing approach and finds that it could help to achieve CBMA completion from a marketing perspective. Our paper argues that firms' green innovation profile, as a demonstration of a firm's capability and commitment to address climate-change- and environment-related challenges, rather than being a marketing tool, casts a material and substantial influence on their internationalization via CBMAs.

Third, our paper contributes to the emerging literature on carbon emissions (risks) (Krueger et al., 2020; Bolton and Kacperczyk, 2021; Bose et al., 2021). Bose et al. (2021)

examine the effect of carbon risk on corporate M&A decisions and find that acquirers with a higher carbon risk are more inclined to buy target firms in overseas countries with lower GDP or weaker environmental, regulatory, or governance standards. Their findings support the existence of shifting carbon emissions across national borders. However, in the channel analysis of our study, we document that green innovative acquirers are likely to decrease long-run carbon emissions after CBMA deal completion, suggesting the potential of carbon reductions through green technologies.

Our paper proceeds as follows: Section 2 reviews the literature and develops hypotheses; Section 3 describes the sample data and outlines the empirical methodology; Section 4 discusses our main empirical results on the effect of green innovation on CBMA outcomes, and on underlying channels of post-merger operating performance improvement; and Section 5 concludes and discusses the implications.

2 Literature review and hypotheses development

2.1 Relationship between green innovation and firm performance

Different scholars have given different definitions and listed varying aspects of green innovation based on their own research needs. For example, Tseng et al. (2013) propose four aspects of green innovation via evaluating 22 linguistic criteria, namely green management innovation, green process innovation, green product innovation, and green technological innovation. Most scholars have divided green innovation into green process innovation and green product/service innovation (Chen et al., 2006; Chen, 2008; Chang, 2011; Cuerva et al., 2014; Huang and Li, 2017; Xie et al., 2019; Takalo et al., 2021). Even for green product innovation, some scholars pay more attention to products with eco−labelling certification (Lin et al., 2014), and others focus more on green (technological) patents (Li et al., 2018a; Ren et al., 2021; Ren et al., 2022). Green innovation in this paper is more related to environmentally sound technologies (ESTs) that aim to protect the environment (by reducing greenhouse gas emissions, lessening pollutants, minimizing waste, increasing energy efficiency, and saving resources) and bring about socio‒economic, cultural, and environmental sustainability, following the definition adopted by the United Nations Framework Convention on Climate Change (UNFCCC) (Metz et al., 2000). Since Takalo et al. (2021) conducted a good systematic literature review on green innovation around the world, we mainly focus on how stakeholders perceive the value of a firm's green innovation.

A firm's stakeholders are the relevant groups that can affect its development or be materially affected by it (Freeman, 1984; Freeman, 1994). Broadly speaking, corporate stakeholders include governments, social communities/non-government organizations (NGOs), media outlets, industrial associations, competitors or industrial peers, consumers, suppliers, investors, lenders (banks), managers, and employees (Qin et al., 2019). Stakeholder theory emphasizes that stakeholder pressures can critically exert an influence by constraining or enabling corporate activities (Mitchell et al., 2016). Moreover, stakeholders' green pressures incentivize corporate green innovative activities (Adomako et al., 2022).

One such green pressure comes from government (regulators). *Porter hypothesis* states that stringent environmental regulations stimulate corporate innovation, eventually leading firms to gain competitive advantages globally (Porter, 1990; Porter, 1991) and this has been supported by empirical evidence (Jaffe and Palmer, 1997). Berrone et al. (2013) confirm that institutional pressures can stimulate green innovation, while Wang et al. (2021) demonstrate that stricter regulation motivates more firms to apply green technology once the technology is available but may stifle a firm to be innovative when facing fierce competition from the perspective of a global game. Some government policies, such as an emissions trading system (Calel and Dechezleprêtre, 2016; Cui et al., 2018; Zhu et al., 2019) and green credit policy (Hong et al., 2021; Hu et al., 2021b), can also spur corporate green innovation. When a firm meets the government's demand for environmental protection and sustainable development via green innovation, it is more likely to obtain environmental legitimacy (Truong and Berrone, 2022) and gain government subsidies (Hu et al., 2021b) or green credit/bank loans (Xing et al., 2021), helping to alleviate its financing constraints (Zhang et al., 2020).

Green innovation incorporates the ideas of environmental protection and sustainability within a firm's product development activities (Chen, 2008) and may also contribute to its environmental performance and sustainability (Huang and Li, 2017). Elsewhere, previous studies indicate that green innovation is part of a firm's efforts to promote its CSR performance (Chang, 2011; Li et al., 2018a; Kim et al., 2021), while Carrión-Flores and Innes (2010) find that green innovation induced by tightened pollution targets drives US toxic emissions to reduce. Dutt and King (2014) show that end–of–pipe (EOP) treatment corresponds with an initial increase in reported waste, followed by continuous reduction. In addition, green innovation has been found to effectively reduce carbon emissions (Zhang et al., 2017; Töbelmann and Wendler, 2020), albeit earlier findings of Chen (2001) indicate that green product innovation and stronger environmental standards might not necessarily contribute positively to environmental protection.

In addition, green innovation can also become a valuable firm resource (Khanra et al., 2021), bringing about many potential benefits including improved production efficiency and lower cost, enhanced quality, new marketing opportunities and potential entry into new markets, price premiums, potentially winning a competitive advantage (Chen et al., 2006; Kesidou and Demirel, 2012; Cheng et al., 2014), boosting reputation and image (Chen, 2008), increased labor productivity (Woo et al., 2014), and gaining support from consumers, social communities, or environmental NGOs. Therefore, a firm with a better green innovation profile is more likely to realize better financial performance and higher firm value (Xie et al., 2016; Tang et al., 2018; Xie et al., 2019; Zhang et al., 2019; Hao et al., 2021; Truong and Berrone, 2022). Kim et al. (2021) observe that green innovation produces a long-term value enhancement effect for multinationals, especially for those in mining & oil and energy sectors. Indeed, more institutional investors and equity analysts tend to follow green innovative firms and push them to disclose more information, thereby lowering the stock price crash risk (Zaman et al., 2021). However, Garel and Petit-Romec (2021) show that green innovation exerts a positive but not significant influence on stock returns during the COVID−19 crisis.

Briefly, only a few studies have explored the relationship between green innovation and M&As, and the effect of green innovation on CBMA still merits further study. With this in mind and based on Gao et al. (2022), we aim to uncover the systematic effect of green innovation on a series of CBMA outcomes in the context of China.

2.2 Relationship between corporate innovation and M&As

A large body of literature has explored the factors influencing corporate innovation,[3] wherein the effect of M&As on corporate innovation has drawn substantial attention from both academia and practitioners. One strand of the literature argues that M&As can promote corporate innovation through a complementary or synergistic effect. Cassiman and Veugelers (2006) point out that a firm's internal research and development (R&D) and external knowledge acquisition are complementary, producing economies of scale and promoting innovative efficiency post-merger. Bena and Li (2014) find that a technological overlap between bidder and target prior to the announcement improves subsequent innovation output via using a quasi−experiment including withdrawn bids that failed due to reasons irrelevant to innovation, thus supporting the synergistic effect. Phillips and Zhdanov (2013) suggest that, in addition to demand and competition, industry M&A activities lead to an increase in a firm's R&D as well, while Sevilir and Tian (2012) show a positive association between a firm's M&A

[3] These factors include firm-level characteristics (e.g., venture capital, ownership structure, corporate governance, analyst coverage, institutional investment, and stock liquidity), market-wide economic forces (e.g., product market competition and import penetration), and country-level characteristics (e.g., a nation's institutions, laws, policies, and financial market development). For more detail, see He and Tian (2018) who conducted an excellent review on corporate innovation based on papers published in the top six accounting and finance journals.

activity and its subsequent innovation outcomes. Another competing view however argues that M&As reduce a firm's R&D and innovation due to decreased competition and increased debt. In addition, Fulghieri and Sevilir (2009) create a model that reduced competition caused by M&As discourages employees to innovate. Meanwhile, M&As increase the bidders' debt, which forces them to decrease R&D investment (Hall and Lerner, 2010). Barden (2012) proposes that M&As bring uncertainty about new job responsibilities and required layoffs for managers, thus increasing managerial resistance and post–integration costs and further leading to a decline in resources required by innovative activities. Seru (2014) also presents that firms acquired in diversifying M&As bring about fewer and less novel innovations compared with target firms whose M&As failed to go through.

Another stream of literature also examines the impact of corporate innovation on M&As. Zhao (2009) discovers that less innovative firms engage more in M&A activities and benefit more from them compared to more innovative firms. Bena and Li (2014) suggest that firms with large patent portfolios and low R&D investments tend to be bidders, while firms with high R&D investments and slow growth in patent output are more likely to be targets. Similarly, Wu and Chung (2019) find that firms with more innovation outputs and R&D expenses are more inclined to be acquired. They also find that the target firm's innovation output leads to higher takeover premium and brings higher announcement abnormal returns as well as better post-merger operating performance to the bidder. Elsewhere, Frésard et al. (2020) show that R&D-intensive firms are less likely while firms with patented innovation are more likely to be targets in vertical M&As.

In recent years, the relationship between green innovation and (green) M&As has also attracted the attention of researchers and scholars. Likewise, a further strand of literature has found that green innovation is significantly promoted after the implementation of green M&As (Huang and Yuan, 2022; Liang et al., 2022; Zhang et al., 2022), exploratory and exploitative international M&As (Wu and Qu, 2021), and technology driven CBMAs (Li, 2022). Meanwhile, some extant studies regard green innovation as a channel in the positive effect of green M&As on export performance (Lu, 2022) and that CBMAs have a positive effect on post-merger CSR performance (Chen et al., 2022). Differently, Gao et al. (2022) regard developing green innovation as an assertive green marketing approach and find that it can increase the completion rates of CBMAs attempted by Chinese bidders.

2.3 Relationship between green innovation and CBMAs

In this subsection, we develop the hypotheses on the relationship between green innovation and EME bidders' CBMAs. CBMAs are complex and uncertain because their imprints and outcomes make it difficult for host-economy stakeholders to judge their legitimacy (Li et al., 2017). In addition, cross-border bidders from EMEs are particularly difficult to adapt to for host market stakeholders due to their liability of foreignness, liability of newness, and liability of origin (Hawn, 2020). Furthermore, stakeholder theory suggests that corporate activities are affected by stakeholder pressures (Mitchell et al., 2016). To alleviate stakeholders' green pressures and gain legitimacy from host economy, EME bidders' green innovation may be promoted (Adomako et al., 2022) and this helps them to create an ethical relationship with stakeholders (Khojastehpour and Shams, 2020). Therefore, we propose that green innovation would be positively related with CBMA outcomes.

2.3.1 Relationship between green innovation and probability of deal completion

Green innovation in nature is conducive to reducing carbon emissions, helping bidders mitigate climate-change-related risks and achieve legitimacy from host market stakeholders. Across the globe, firms are exposed to increasing climate change risks (Flammer et al., 2021). To deal with this global negative externality (Nordhaus, 2019), more and more economies have committed to, or are considering, carbon neutrality goals.[4] Stakeholders at home and abroad

[4] The list is available at: https://eciu.net/netzerotracker.

are also more concerned about climate change induced by carbon emissions, including investors (Krueger et al., 2020; Bolton and Kacperczyk, 2021) and banks (Huang et al., 2021). Moreover, green innovation can contribute to a reduction in carbon emissions (Zhang et al., 2017; Többelmann and Wendler, 2020), helping to mitigate climate change risks. When a cross-border bidder presents its green innovation prior to the announcement, it signals its strong green innovation capability and long-term commitment to tackle the climate challenges in an assertive approach (Gao et al., 2022). Thus, such a bidder is more likely to be accepted by stakeholders at home and abroad, increasing the likelihood of completion.

In addition, green innovation can provide cross-border bidders with a pro-environment image, good reputation, and superior environmental performance, all of which make it easier for them to gain legitimacy from host market stakeholders. Green innovation assists cross-border bidders in promoting their reputation and image (Chen, 2008), and become superior performers in terms of the environment (Zhang et al., 2017; Többelmann and Wendler, 2020), differentiating them from other bidding firms and strengthening their bargaining power in the global M&A market (Gao et al., 2022). Moreover, green innovation brings an information advantage to cross-border bidders and makes them more transparent to stakeholders as green innovative firms tend to disclose more information due to feeling under pressure from institutional investors and equity analysts, who have taken environmental issues into greater account in recent years (Zaman et al., 2021).

Good reputation together with superior environmental performance and an information advantage make green innovative bidders more favorable to and trusted by stakeholders in foreign markets, reducing the likelihood of deals' being called off by regulators or pressure from local stakeholders. Green innovation is particularly important for EME bidders as it shows their willingness to abide by international conventions and local environmental regulations and reduce information asymmetry between EME bidders and host market stakeholders as the latter are more likely to conduct more legitimacy assessments based on limited information provided by the former (Hawn, 2020). Previous literature indicates that opaqueness reduces the likelihood of CBMA deal completion (Li et al., 2019). Therefore, EME bidders with a better green innovation profile are more likely to gain legitimacy from host market stakeholders and complete CBMA deals successfully.

Putting all together, we propose the following hypothesis:

H1: Green innovative bidders are more likely to complete CBMA deals successfully.

2.3.2 Relationship between green innovation and abnormal stock returns

As we discussed in *H1*, green innovation aims to tackle climate change issues, which have been perceived as a material risk by investors (Krueger et al., 2020; Bolton and Kacperczyk, 2021; Bose et al., 2021; Huang et al., 2021) and influencing corporate stock prices (Jain and Zaman, 2020). Moreover, green innovation helps firms enhance their reputation and image (Chen, 2008), increase information transparency and attract more investors' attention (Zaman et al., 2021). Green innovative activities also show their institutional reactions to meet stakeholders' demands, aiming to enhance their environmental legitimacy (Truong and Berrone, 2022). As a result, improved environmental reputation and legitimacy make it easier for potential investors to access and evaluate information, leading them to reward green innovative firms with higher market value (Truong and Berrone, 2022) and long-term value for shareholders (Kim et al., 2021). In this case, green innovative bidders are more likely to win the favor of investors and receive positive market reactions, gaining higher abnormal stock returns. Therefore, we propose the following hypothesis:

H2: Green innovative bidders are more likely to realize higher abnormal stock returns.

2.3.3 Relationship between green innovation and post-merger operating performance

Extant literature indicates that general innovation is a crucial source of firm value (Bloom and Van Reenen, 2002; Nicholas, 2008; Pástor and Veronesi, 2009) and its subcategory, green innovation, is no exception. In addition, firms with a better green innovation profile are more likely to gain a differentiated competitive advantage (Chen et al., 2006; Peng and Lin, 2008; Kesidou and Demirel, 2012; Cheng et al., 2014; Huang and Li, 2017; Xie et al., 2019), such as in the form of improved production efficiency and lower cost, enhanced quality, new marketing opportunities and potential entry to new markets, and price premiums. Khanra et al. (2021) highlight that green innovation can be a valuable firm resource that contributes to both establishing a competitive advantage and achieving sustainable development. It creates not only new market opportunities by adopting new environmental technologies and processes or eco−designed products (Garel and Petit-Romec, 2021), but also higher market value (Truong and Berrone, 2022) and long-term value for shareholders by avoiding long−tailed environmental effects caused by carbon emissions and other factors (Kim et al., 2021), consistent with Freeman (1984) who states that focusing on other stakeholders' concerns would ultimately benefit shareholders in the long run. In addition, green innovation helps to reduce compliance costs (Berrone et al., 2013). Therefore, green innovative bidders tend to achieve better post-merger operating performance.

Moreover, green innovation also attracts external financial resources (e.g., government subsidies) to cross-border bidders and directly contributes to their post-merger operating performance. China has already started to promote green development, and firms with a better green innovation profile are thus more likely to receive government's financial support, e.g., government subsidies (Li et al., 2018b) or bank loans (Xing et al., 2021), leading to reduced financing constraints (Zhang et al., 2020). Data from the National Bureau of Statistics of China show that fiscal environmental protection expenditure increased from 99.6 billion yuan in 2007 to 553.6 billion yuan in 2021, with a compound annual growth rate of 13%. Therefore, green innovative bidders are more inclined to obtain related financial resources (e.g., patent-related government subsidies) from the Chinese government, increasing their income and leading to better post-merger operating performance.

With all of the above in mind, we propose the following hypothesis:

H3: Green innovative bidders are more likely to achieve better post-merger operating performance.

3 Data and methodology

3.1 Sample construction

We initially extract all M&A attempts made by Chinese firms between 2007 and 2021 from Refinitiv Eikon Deals database (formerly Thomson Reuters SDC M&A database, hereafter SDC), and apply the following screening criteria.[5] First, for each deal, we require that the target firm be outside mainland China (i.e., cross-border deal). Second, the transaction value has to be available and greater than 0 (including both small and significant deals). Third, the percentage acquired has to be available. Following Schweizer et al. (2019), we further remove deals with target locations in tax havens or offshore financial centers.[6] Next, we require that neither the Chinese bidders nor the foreign targets be from the financial industry, following Bena and Li (2014). To obtain required financial information and firm-level characteristics, we require the Chinese bidders to be publicly traded in stock exchanges in mainland China prior to the announcement year. These filters yield 668 CBMA deals announced by 437 Chinese listed firms, including 351 completed CBMA deals implemented by 254 Chinese acquirers.

3.2 Measures of key explanatory variable

Green innovation is the key explanatory variable in this paper. Based on the definition outlined in subsection 2.1, we use green patents to measure green innovation. The green patent

[5] Previous studies indicate that R&D expenses play an important role in M&A activities (Zhao, 2009; Phillips and Zhdanov, 2013; Bena and Li, 2014; Frésard et al., 2020). Our sample begins in 2007 because we require lagged one-year R&D expenses as an important control variable and the data on R&D expenses are available since 2006 when the Chinese listed firms were required to disclose detailed R&D expenses in their annual reports based on new accounting standards (Ren et al., 2022). In addition, in 2007, the construction of ecological civilization was written into the Report to the (17th) National Congress of the Communist Party of China (CPC, the dominant ruling party in China) and became an explicit goal of the CPC for the first time (Available at: https://www.mee.gov.cn/home/ztbd/rdzl/stwm/201210/t20121024_240281.shtml). Our sample ends in 2021 due to the availability of required financial data. Appendix A2 reports the sample selection criteria and the number of CBMA deals.
[6] The following tax havens or offshore financial centers were excluded from our sample: American Samoa, Bermuda, British Virgin Islands, Cayman Islands, Mauritius, Panama, and Samoa.

data are obtained in three steps. First, we extract all patent data (both green and non-green) for each sample bidder from the State Intellectual Property Office of China (hereafter, SIPO database), following previous literature (Ren et al., 2022).[7] Compared with patent databases in English (e.g., PATSTAT, Espacenet, and Google Patents),[8] SIPO database has a better coverage of and more comprehensive information on Chinese firms' patents (He et al., 2018). In addition, there are other platforms offering patent searches in China, such as Baiten, incoPat, SooPat, patsnap (Zhihuiya), Tianyancha, and Qichacha.[9] All of them provide the following basic information for each patent: title, type, application number, applicant(s), filing/application date, announcement (publication) number, announcement (publication) date, grant date, and main International Patent Classification (IPC) code.

Second, we require that all of the extracted patents had eventually been granted within our sample period (from 2007 to 2021), following Kim et al. (2021), and distinguish green patents from non-green patents based on the IPC Green Inventory provided by the World Intellectual Property Organization (WIPO),[10] following previous literature (Albino et al., 2014; Cui et al., 2018; Zhang et al., 2019; Zhu et al., 2019; Hong et al., 2021; Hu et al., 2021b; Tang et al., 2021; Zhou et al., 2021b; Chen et al., 2022; Ren et al., 2022; Xia et al., 2022; Xiang et al., 2022). The IPC Green Inventory is related to ESTs, as listed by UNFCCC, and now widely distributed in

[7] We applied the bidding listed firms' current and historical company names (in Chinese) to search for their patents. The SIPO database is available at: http://cpquery.cnipa.gov.cn/. He et al. (2018) constructed a Chinese Patent Database matching SIPO patents to listed firms and their subsidiaries in China from 1990 to 2010 (see Chinese Patent Data Project (CPDP) for more details), and Zhang et al. (2019) used the CPDP database in their research.
[8] See PATSTAT at https://www.epo.org/searching−for−patents/business/patstat.html, Espacenet at https://worldwide.espacenet.com/patent/, and Google Patents at https://patents.google.com/.
[9] Previous studies have used one of these databases, e.g., Li et al. (2018a) and Ren et al. (2021) adopted Baiten (https://www.baiten.cn/), while Han et al. (2022) and Li et al. (2021) employed incoPat (https://www.incopat.com/). SooPat can be accessed at http://www.soopat.com/; patsnap can be accessed at https://www.zhihuiya.com/; Tianyancha can be accessed at http://www.tianyancha.com/; and Qichacha can be accessed at https://www.qcc.com/. For the sake of cybersecurity, some websites can only be visited in China.
[10] The IPC Green Inventory is available at: https://www.wipo.int/classifications/ipc/green−inventory/home. We note that some papers (e.g., Cohen et al. (2020) and Gao and Li (2021)) identify green patents following the guidelines created by the Organization for Economic Co−operation and Development (OECD) (available at: https://www.oecd.org/environment/indicators−modelling−outlooks/green−patents.htm, or see Haščič and Migotto (2015) for more details). Their identification relies on the Cooperative Patent Classification (CPC), or the IPC code provided by the USPTO (available at: https://www.uspto.gov/), while SIPO only provides the IPC code. incoPat provides both IPC and CPC codes for Chinese firms' patents but the coverage of CPC codes is very limited. Therefore, we finally decided to use the IPC code to identify green patents.

various technical fields of IPC. It covers seven topics in total, namely (1) alternative energy production, (2) transportation, (3) energy conservation, (4) waste management, (5) agriculture/forestry, (6) administrative, regulatory, or design aspects, and (7) nuclear power generation.

Third, we match the main IPC code in the SIPO database with the code list in the IPC Green Inventory for each patent, then generate an indicator that equals one if the codes can be matched, and zero otherwise. To get the firm-year green patent data, we sum each green patent across all technology classes for each firm in each year. Notably, we base patent counts and other patent-related measures on patent application year instead of grant year in that the application years are closer and better aligned with the time of the actual (green) innovative activities than the grant years (Griliches et al., 1986; Hall et al., 2001; Hall et al., 2005; Zhao, 2009; Carrión-Flores and Innes, 2010; Bhattacharya et al., 2017; Mishra, 2017). Different from patents in the US, patents in China are classified into three types, namely invention, utility model, and (external) design patents.[11] The average lag between patent applications and grants is about three years, six months to one year, and six months for invention, utility model, and design patents, respectively.[12] Due to the lowest novelty and there being no coverage of IPC codes provided by the SIPO database, design patents cannot be identified as green patents.

Based on the green patent counts, we generate four variables. First, in the spirit of Chen et al. (2022), we generate a dummy variable (*GP dummy*) that equals one if Chinese bidders have had at least one green patent that had been applied for within five years prior to the announcement year and eventually granted within our sample period, and zero otherwise.[13]

[11] According to China's patent law, (1) an invention patent refers to any new technical solution relating to a product, a process, or improvement thereof; (2) a utility model patent refers to any new technical solution relating to the shape, the structure, or their combination, of a product, which is fit for practical use; and (3) design patent refers to any new design relating to the shape, pattern, color, or their combination, of a product which creates an aesthetic feeling and is fit for industrial application. For example, a waterproof LED display screen (Application number: CN201910206285.7) is the invention patent; a display screen module (Application number: CN202122474364.1) is the utility model patent; while a LED display screen box (Application number: CN202130025499.2) is the design patent. Also see He et al. (2018) for more details.

[12] Available at: https://www.cnipa.gov.cn/art/2018/11/28/art_707_179.html. In the US, it is about two years (Hall et al., 2001; Hall et al., 2005; Zhao, 2009; Carrión-Flores and Innes, 2010).

[13] We trace back the past five years in the spirit of Bena and Li (2014). Among 668 observations, 337 have available GP data,

Second, for those bidders with *GP dummy* equal to one, we create a continuous variable related to the intensity of green patents in the spirit of previous studies (Kim et al., 2020; Hu et al., 2021b; Kim et al., 2021; Zhou et al., 2021b), i.e., *Ln (1+GP (sum))*, which equals the natural logarithm of one plus the aggregated number of green patents that were applied within five years prior to the announcement year and eventually granted within our sample periods. For those bidders with *GP dummy* equal to zero, we replace the variable value with zero. Third, we construct a green patent index (GPI) in the spirit of Bena and Li (2014). One of the steps to build GPI is to adjust the number of green patents using a "weight factor" (i.e., by scaling the number of green patents with the median value of green patents in a given year and technology class). This adjustment is in the spirit of prior literature (Hall et al., 2001; Hall et al., 2005; Kim et al., 2021) and can help to address the truncation problem commonly encountered in innovation studies. Fourth, we generate a discounted GP−counts-related variable in the spirit of Frésard et al. (2020). According to patent law, the legal protection of a patent has a specific term and starts from the filing date. Prior to the announcement year, the closer the filing date is to the announcement year, the stronger the legal protection and patent effect, and vice versa. Therefore, the discounted effect of a green patent is similar to the depreciated R&D expenses used by Frésard et al. (2020). The specific definitions of all four variables are described in Appendix. For each variable, we distinguish between green invention− and green utility model-related variables in the spirit of extant literature (Zhang et al., 2019; Zhu et al., 2019; Tang et al., 2021; Zhou et al., 2021b; Xiang et al., 2022).

All bidders' stock trading and financial data are retrieved from China Stock Market and Accounting Research (CSMAR) database, GP-related data are extracted from SIPO database, and deal-related information is obtained from SDC database. For values missing in the CSMAR,

of which 224 have available GP data in year $t-1$ or earlier, 53 have available GP data in year $t-2$ or earlier but not in year $t-1$, 21 have available GP data in year $t-3$ or earlier but not from year $t-2$ to year $t-1$, 23 have available GP data in year $t-4$ or earlier but not from year $t-3$ to year $t-1$, 16 have available GP data in year $t-5$ but not from year $t-4$ to year $t-1$.

we check the bidder's annual reports and online financial resources (e.g., *Sina Finance*) for complementary information. Cultural data are extracted from Geert Hofstede's website and Worldwide Governance Indicators are provided by World Bank. All continuous variables used in the regressions are winsorized at the 1% and 99% level. And detailed information of all variables and data sources can be found in Appendix Table A1.

3.3 Descriptive statistics

Table 1 presents the sample distribution of CBMA deals attempted by Chinese bidders. In Panel A, an increasing trend is shown in the number of announced deals before 2016, surging from 13 (1.95%) in 2007 to 105 (15.72%) in 2016, and then the number decreases continuously to 30 (4.49%) in 2020 until it rebounds slightly in 2021. The pattern for number of completed deals is similar to that of announced deals. The average deal values are US$169.71 million and US$213.03 million for announced and completed deals, respectively, and the highest values for both were recorded in 2020. In addition, the completion rate in our sample fluctuates around a 52.54% average during the period of 2007 to 2021.

− insert Table 1 about here −

Panel B of Table 1 presents that a majority (70.48% for announced deals and 78.74% for completed deals) of Chinese bidders initiated or completed only one CBMA deal during the sample period. Meanwhile, 18.54% (12.60%) and 5.95% (3.94%) of Chinese CBMA bidders announced (completed) two and three cross-border deals, respectively. Only a small portion (5.03% for announced deals and 4.72% for completed deals) of Chinese CBMA bidders/acquirers are active bidders/acquirers (with more than three attempts made or completed during the sample period) in the global corporate control market, accounting for 17.96% (16.24%) of CBMA deals attempted (completed) by Chinese bidders.

Panel C of Table 1 displays the sample distribution by bidders' industry.[14] Most of the deals

[14] We use the industry categories classified by the China Securities Regulatory Commission (CSRC) in 2012. Available at: http://www.csrc.gov.cn/pub/newsite/flb/flfg/bmgf/zh/gfxwjtj/201310/t20131016_236281.html.

were attempted (completed) by bidders in the manufacturing industry, accounting for 71.86% (71.23%) of sample deals. Meanwhile, the average deal values in the industry of transportation, warehousing, and postal services are the highest for both announced and completed deals, with values of US$864.61 million and US$1,274.17 million, respectively. Panel D reports the geographic distributions of the target firms. For announced (completed) deals, the US is the most popular host economy, accounting for 16.62% (14.81%) of sample deals, followed by Hong Kong (11.53% (9.69%)), Australia (8.23% (9.12%)), Canada (6.89% (7.98%)), and Germany (6.59% (5.98%)).

Panel A (B) of Table 2 presents the summary statistics for CBMAs attempted (completed) by Chinese bidders. It shows that the average completion rate is 52.5%; the average GDP growth for the target economies is 2.4% (2.7%) in the sample of announced (completed) deals; 8.1% (8.6%) of the sample bidders are listed overseas, 11.4% (12.6%) are SOEs, 39.4% (53.3%) employed at least one financial or legal advisor in initiating cross-border deals; 26.9% (32.1%) of the announced (completed) deals sample were paid fully in cash and 1.3% (2%) were tender offers; 29% (30.1%) of the sample target firms operate in a high-tech industry; and 47% (51.7%) of the announced (completed) deals sample are with the bidding and target firms operating in the same industry. It is also noted that the mean value of many variables for the completed deals sample is greater than that for the announced deals sample, except for *Leverage* and *Ln (1+Listed age)*.

− insert Table 2 about here −

Table 3 shows the correlation matrices and all correlations among our test variables are smaller than 0.75 except for those among GP variables, while the variance inflation factors (VIFs) are far less than 10 in our multivariate analyses, confirming that multicollinearity is not a concern. We also note that all GP variables are significantly and positively correlated with *Completion*, consistent with our prior prediction. We will further examine the effect of green innovation on completion probability in multivariate analyses.

− insert Table 3 about here −

4 Baseline empirical results

4.1 Green innovation and probability of deal completion

To examine how a bidder's green innovation can affect the completion probability of its CBMA deals, we estimate the following probit regressions.

$$Pr(Completion_i) = \alpha_1 + \beta_1 GP_i + \theta_1 CLV_i + \theta_2 FLV_i + \theta_3 DLV_i + Year + Industry + \varepsilon_i \quad \text{Eq. (1)}$$

where i indexes a deal. $Completion_i$ is the completion probability of the cross-border deals, which is a dummy variable equals one if an announced deal is recorded as "Completed" in SDC, and zero otherwise. GP_i is the key explanatory variable, capturing the bidder's intensity of green patents prior to its deal announcement. We use each of the GP intensity-related variables described in subsection 3.2 at a time in the regressions. We include an array of country-, firm-, and deal-level variables that could potentially affect the probability of deal completion, as well as the short- and long-term performance of a Chinese bidder carrying out a CBMA deal. Country-level variables (CLV_i) include *Cultural distance*, *Institutional distance*, and *GDP growth* based on prior studies (Li et al., 2019; Schweizer et al., 2019). Firm- and deal-level characteristics are also controlled in the spirit of previous literature (Deng et al., 2013; Li et al., 2019; Schweizer et al., 2019). Firm-level variables (FLV_i) include *B/M ratio*, corporate governance index (*Ln (1+CGI)*), *Firm size*, free cash flow (*Ln (1+FCF)*), *Leverage*, listed age (*Ln (1+Listed age)*), *Listed overseas*, profitability (*ROA*), and *SOE*. Existing research also shows that corporate general innovations and R&D expenditures can affect a firm's M&A activities (Zhao, 2009; Phillips and Zhdanov, 2013; Bena and Li, 2014; Frésard et al., 2020). Therefore, we further control for the bidder's number of general patents (*Ln (1+Patents (sum))*) and R&D expenses (*R&D/Total assets*). Deal-level variables (DLV_i) include payment methods

(*All cash deal*), whether the bidder employs any financial or legal advisors (*Financial/Legal advisor*), whether the target firm operates in a high-tech industry (*High-tech target firm*), *Past CBMA experience*, whether the target firm is publicly traded (*Public target*), relative deal size (*Ln (1+Relative deal size)*), whether the bidding and target firms operate in the same industry (*Same industry*), and whether the deal is a tender offer (*Tender offer*). We also include year and industry effects to control for potential factors related to certain years and industries that might affect CBMA attempts by Chinese bidders.

Panel A of Table 4 reports the baseline regression results of the probability of CBMA deal completion. The dependent variables of columns (1) – (3), (4) – (6), and (7) – (9) are based on the number of GP, GPI, and the number of discounted GP, respectively. The probit regressions show that the estimated coefficient on green innovation is positive and statistically significant at 1% level, indicating that green innovative bidders are more likely to complete a CBMA deal. Specifically, in column (1), one unit increase in *Ln (1+GP (sum))* will promote the probability of CBMA deal completion by 6.33 percent (after addressing the endogeneity problem, the number more than doubles to 13.67 percent). Previous studies argue that non-linear models (e.g., the probit model) yield biased estimates when the number of fixed effects is large and the group size is small (Kalbfleisch and Sprott, 1970; Hsiao, 1992). Therefore, we follow Li et al. (2019) to replace probit model with logit model, and the un-tabulated results still hold.

− insert Table 4 about here −

To a certain extent, using five-year lagged green patents and CBMA announcement abnormal returns in the above model specifications can alleviate the potential endogeneity problem caused by reverse causality in the spirit of Deng et al. (2013). However, it remains probably that we would ignore unobservable factors affecting green innovation and CBMA outcomes, e.g., the bidding firm’s unpatented green technologies (Hao et al., 2021), leading to omitted variable problem. To address this kind of endogeneity issue, we use two-stage least squares (2SLS) regressions in which we adopt the Province-year GP variables in our sample as instrumental variables (IVs) in the spirit of Hao et al. (2021). The higher the annual average GP level of a province in which the bidder's headquarters is located, the more likely the bidder is to produce more green innovations in the face of local pressure (e.g., market competition, regulation, and customer expectations). Thus, the relevance requirement of IV is satisfied. Meanwhile, the annual mean of past GP in the province is unlikely to affect the firm's CBMA performance significantly and directly since M&As are largely unpredictable events (Deng et al., 2013), thereby meeting the exclusion condition of IVs.

Panel B of Table 4 presents the estimated results using two-stage probit least squares (2SPLS) regressions. Columns (1), (3), and (5) show the results of first-stage regressions, only controlling for firm-level variables, year- and industry-effect. Columns (2), (4), and (6) show the results of second-stage regressions with all controls as described in Eq. (1). As expected, the IV in the first-stage regressions has positive and significant coefficients. The *p*-values for the Cragg and Donald (1993) IV relevance test are less than 0.001, rejecting the null hypothesis of weak IV. Therefore, this result substantiates the relevance of our IV. According to the second-stage regression results, green innovative bidders are still prone to have higher probability of CBMA deal completion. Since we employ a single IV to instrument the sole endogenous explanatory variable, the chances of encountering overidentification problems are relatively low. We further note that the magnitude of coefficients on GP variables in Panel B is generally much larger than that in Panel A, meaning higher probability of CBMA deal completion. Brought together, green innovation helps Chinese bidders increase the probability of CBMA deal completion, consistent with *H1*.

4.2 Green innovation and abnormal stock returns

Next, we start our analyses of how capital market reacts to CBMAs initiated by green innovative bidders by using a standard event study method. Eq. (2) are used to examine the market reactions to CBMAs by green innovative bidders.

$$CAR_i = \alpha_1 + \beta_2 GP_i + \theta_1 CLV_i + \theta_2 FLV_i + \theta_3 DLV_i + Year + Industry + \varepsilon_i$$

Eq. (2)

where CAR_i in Eq. (2) measures market reactions to green innovative bidder *i* during the period beginning three days before and ending three days after CBMA announcement. Other settings in Eq. (2) are the same as those in Eq. (1). We use cumulative abnormal returns (CARs) to measure market reactions to CBMA announcements. And to compute the bidder's CAR, we estimate the market model parameters in the spirit of Deng et al. (2013) and adopt a seven-day event window (−3, 3) around the announcement date (day 0), using daily returns over an estimation period from 210 days to 11 days before day 0. Following Fee and Thomas (2004), we also require that a bidder had at least 100 trading days over the estimation window.

Panel A of Table 5 presents the baseline estimates from multivariate regressions using the *CAR (–3, 3)* as the dependent variable and green innovation as a key independent variable, and the controls are as discussed in Eq. (2). Overall, the coefficients on *invention*-related green innovation are positive and significant at 1% or 5% level, indicating that green innovation represented by green *invention* patents is positively correlated with *CAR (–3, 3)*. In Panel B of Table 5, we report the results from the 2SLS regressions. The coefficient estimates on the predicted variable for green innovation are positive and significant at 5% or 10% level.

For robustness, we employ Fama-French three-factor and five-factor model to calculate CARs in the spirit of Liu et al. (2019), respectively, and apply the same seven-day event window (−3, 3). We replace *CAR (–3, 3)* with newly-computed CARs (*CAR (–3, 3)_FF3* and *CAR (–3, 3)_FF5*) as the dependent variable and the other settings are as specified in Eq. (2). The un-tabulated results are consistent with those in Panel A of Table 5. We also employ buy−and−hold abnormal returns (BHARs) to measure market reactions after CBMA announcement. In the spirit of previous work (Loughran and Vijh, 1997; Chakrabarti et al., 2009), BHARs are calculated for 60, 90, and 120 days following the announcement date (day 0), respectively, by geometrically compounding the bidder's daily returns during the period and then subtracting the market benchmark in China. We replace *CAR (–3, 3)* with newly-computed BHARs (*BHAR (0, 60)*, *BHAR (0, 90)*, and *BHAR (0, 120)*), remaining other settings the same with those in Eq. (2), and the un-tabulated results are similar with those in Panel A of Table 5. Therefore, green innovative bidders (especially those with green invention patents) can obtain superior announcement abnormal returns, supporting *H2*.

− insert Table 5 about here −

4.3 Green innovation and post-merger operating performance

To complete the full picture of gauging the value implications of CBMAs, we also examine the effect of green innovation on post-merger operating performance via estimating Eq. (3).

$$PostPerf_i = \alpha_1 + \beta_2 GP_i + \theta_1 CLV_i + \theta_2 FLV_i + \theta_3 DLV_i + Year + Industry + \varepsilon_i \qquad \text{Eq. (3)}$$

where $PostPerf_i$ is the changes in operating performance of merging firms induced by the deal i, measured by changes in return on equity (ΔROE). Other settings in Eq. (3) are the same as those in Eq. (1). In the spirit of Fee and Thomas (2004), ΔROE is the difference between the combined firm's operating performance in the third year after deal completion and the bidder's operating performance for one year prior to CBMA announcement year. We employ ROE to measure operating performance following Schweizer et al. (2019), and require that by the end of 2022, acquirers have available ROE data in the following three years of deal completion.[15] For robustness, we also employ return on invested capital (ROIC) to measure operating performance ($\Delta ROIC$) following O'Shaughnessy and Flanagan (1998).

Table 6 reports the OLS regression results of post-merger changes in acquirer's operating

[15] This requirement will make post-merger operating performance comparable. Among all 351 completed deals in our sample, 49 completed deals are dropped due to missing post-merger ROE data, and both announcement year and completion year range from 2007 to 2019. We further check that if announcement year is from 2007 to 2019, the regression results of both deal completion probability and announcement abnormal returns do not change.

performance based on completed CBMA deals. We regress ΔROE on green innovation and the results in Panel A present that the coefficients on green innovation are positive except for *utility model*-related green innovation, but only significant for *invention*-related green innovation in columns (5) and (8). After replacing ΔROE with $\Delta ROIC$, all coefficients on *invention*-related green innovation are positive and significant at 5% or 10% level. The un-tabulated results are available upon request. We further adopt the similar 2SLS regressions as depicted in subsection 4.1 and display the results in Panel B. The coefficients on all predicted variables for green innovation are positive and significant at 1% level. The above results indicate that green innovation helps acquirers to achieve better post-merger operating performance, supporting *H3*.

− insert Table 6 about here −

4.4 Robustness tests

4.4.1 Additional fixed effects

One might argue that Chinese bidder's CBMA could be influenced by the uneven economic and social developments and policies within the province where its headquarters is situated. Therefore, we further incorporate this province-level effect into the baseline specifications following Yang et al. (2019). The un-tabulated results show that our conclusions are consistent. One might also argue that other unobservable factors could affect Chinese bidder's CBMA in addition to previously stated country-specific characteristics. Therefore, we further control target economy effect. Again, the results are available upon request and our conclusions do not change.

4.4.2 Additional control variables

Previous literature has demonstrated that bidder's corporate social responsibility (CSR) (Hawn, 2020; Gao et al., 2022) and target economy's climate risk (Li et al., 2023) can affect CBMA outcomes. To avoid potential omitted variable issues, we further control *Bidder's CSR* and *Target economy's climate risk* in the baseline regressions, respectively. The un-tabulated results present that green innovation, especially *invention*-related green innovation, still exerts positive and significant effect on deal completion probability, announcement abnormal returns, and post-merger operating performance. Due to difficulty in obtaining target firms' green patents data, we instead control target economy's green innovative capabilities, measured by the logarithm of one plus the number of environmental patents provided by WIPO (*Target economy's GP*). Again, the positive and significant effect of (*invention*-related) green innovation still holds across all three baseline regressions.

4.4.3 Subsample tests

We notice that the proportion of green innovative bidders in our sample (50.45%) is only slightly greater than that of non-green innovative bidders (49.55%). To ensure our results are not driven by non-green innovative bidders, we follow Rahman et al. (2023) to conduct the subsample analysis. The un-tabulated results indicate that (*invention*-related) green innovation is still positively and significantly associated with deal completion probability, announcement abnormal returns, and post-merger operating performance, respectively. Moreover, the magnitudes of the coefficients on green innovation are marginally larger. Therefore, these results confirm that our previous findings are not biased by non-green innovative bidders.

4.4.4 Address potential endogeneity issues

In addition to previous 2SLS regressions in subsection 4.1 to 4.3, we further adopt propensity score matching (PSM) and Heckman two-stage regressions to address other potential endogeneity issues.

First, the probit regressions of deal completion probability might suffer from selection bias that other firm-specific characteristics than green innovation could bring about the positive relationship. We use PSM to address this concern and apply logit regressions of *GP dummy* on firm-level variables as described in Eq. (1) to calculate propensity score, together with one−to−one nearest neighbor matching method without replacement. We use the matched sample to re-estimate Eq. (1) and the un-tabulated results show that the coefficients on green innovation are still positive except for 3 of them losing significance. We apply the similar PSM method to the OLS regressions of post-merger operating performance using completed deals only. The un-tabulated results still display a positive relationship but without keeping significance.

Second, we use an alternative matched sample to re-run the OLS regressions of post-merger operating performance in the spirit of Bena and Li (2014). The argument is that better post-merger operating performance in Table 6 could be driven by the inherent effect of green innovation instead of green innovative bidder's CBMA activities. We start with all 58 withdrawn deals in our sample and do not find any withdrawal reason related to green innovation. Then we match each withdrawn deal with a successfully completed deal based on green innovation (*Ln (1+GP (sum))*) and firm characteristics as depicted in Eq. (3) using the similar PSM. We end up with 49 withdrawn deals and 49 completed deals. The un-tabulated results show that there still exists a positive association between green innovation and operating performance after the deal closes.

Third, the OLS regressions of post-merger operating performance only include completed deals, resulting in nearly 47.5% sample loss. The selection of completed deals could not be random and there might be a selection bias in our results. We perform a Heckman two-stage model to correct this issue. In the first stage, we run the probit regression of deal completion probability as described in Eq. (1), and then obtain the inverse Mills ratio (IMR). In the second stage, we introduce IMR as a control variable into the OLS regressions as described in Eq. (3). The un-tabulated results indicate that the coefficients on green innovation are still positive and significant, and green innovative bidders can achieve better post-merger operating performance.

4.5 Further analyses

In this subsection we provide further analysis by investigating the impact of green innovation on other long-term post-merger performances based on the settings of Eq. (3), namely carbon emissions, environmental performance, environmental compliance costs, and patent-related government subsidies.

4.5.1 Green innovation and post-merger carbon emissions

According to the nature of green innovation, we expect that green innovative acquirers tend to realize lower absolute carbon emissions or growth rate. We focus on the growth rate of Scope 2 carbon emissions, which originate from consumption of purchased electricity, heat, or steam by the acquiring firm, and calculate the average growth rate of Scope 2 carbon emissions three years after deal completion (*CO2 growth rate*). Then we replace $PostPerf_i$ with *CO2 growth rate* and re-run the Eq. (3). The results are presented in Table 7, showing a negative and significant relationship between green innovation and post-merger carbon emissions' growth rate (columns (1), (4), and (7)). These results indicate that green innovative acquirers can realize lower carbon emissions compared with non-acquiring firms in the long run,[16] consistent with the findings of prior studies (Zhang et al., 2017; Töbelmann and Wendler, 2020).

− insert Table 7 about here −

4.5.2 Green innovation and post-merger environmental performance

Next, we replace $PostPerf_i$ with Environmental performance (*Env score*), which is measured by the median value of environmental pillar scores three years after deal completion, then divided by 100. We re-run the estimation of Eq. (3) and report the regression results in Table 8. Based on the coefficients on GP-related variables, which are positive and significant at 1% level except for column (6), green innovation brings a higher environmental score to green innovative acquirers in the long run, which is in accordance with Huang and Li (2017).

[16] We also replace Scope 2 carbon emissions with Scope 1 and Scope 3 carbon emissions, respectively. Unfortunately, when the dependent variable is measured by Scope 1 carbon emissions (carbon emissions from sources that are owned or controlled by the firm) or Scope 3 carbon emissions (including upstream and downstream emissions, the former are GHG emissions from other upstream activities not covered in Scope 2, the latter are associated with the use of sold goods and services), the results are not consistent. For brevity, these results are available upon request.

− insert Table 8 about here –

4.5.3 Green innovation and post-merger environmental compliance costs

As we argued earlier that green innovation is a valuable firm resource (Khanra et al., 2021), bringing about a competitive advantage of low costs (Chen et al., 2006), one of which is low environmental compliance costs (Tian et al., 2023). Lower environmental compliance costs induced by green innovation can contribute to better operating performance. To verify this idea, we measure environmental compliance costs (ECC) by aggregating the annual expenses related to environmental protection and sustainable development reported by the firm in the spirit of Tian et al. (2023) and compute the logarithm of one plus median value of ECCs three years after deal completion (*Ln (1+ECC)*). We replace $PostPerf_i$ with *Ln (1+ECC)* and display the re-estimated results of Eq. (3) in Table 9. The coefficients on green innovation are negative and significant except for columns (2), (5), and (8), indicating that acquirers with green innovation will realize lower environmental compliance costs after deal completion.

4.5.4 Green innovation and post-merger patent-related government subsidies

In this subsection, we replace $PostPerf_i$ with patent-related government subsidies (Δ*Patent subsidies*), which is the difference between the patent-related government subsidies received by the firm in the third year after deal completion and those for one year prior to CBMA announcement and re-run the estimation of Eq. (3). Table 10 report the regression results and we find that the coefficients on green innovation are significantly positive, especially for *invention*-related green innovation, indicating that acquiring firms with green innovation are more likely to receive larger patent-related government subsidies in the long run, which is consistent with Li et al. (2018b).

− insert Table 10 about here –

4.5.5 Effect of 2012 policy

China has implemented the “Administrative Measures for the Priority Examination of

Invention Patent Applications" since August 1, 2012 ("the 2012 policy"),[17] which will prioritize the examination of important patent applications related to energy conservation, environmental protection, low-carbon technology, resource conservation, and other patents that are conducive to green development. Additionally, it prioritizes patent applications that are of significant national or public interest. We expect that Chinese bidders would be more motivated to involve in green innovative activities and subsequent green patents applications after 2012. Therefore, the positive effect of green innovation on post-merger operating performance will be more pronounced after 2012. We conduct subgroups analysis and the results reported in Table 11 confirm our expectation, especially for *invention*-related green innovation.

4.5.6 Moderating effect of physical climate risk and economic policy uncertainty

Physical climate risk can influence corporate activities and performance (Ortiz-Bobea et al., 2020; Addoum et al., 2023). Uncertainty has become increasingly common in recent years and can originate from various sources (Jia and Li, 2020), and existing studies suggest that it would affect CBMAs (Lee, 2018; Arouri et al., 2019; Cao et al., 2019). In this subsection, we explore the moderating effect of physical climate risk and economic policy uncertainty on the relationship between green innovation and CBMA outcomes (i.e., deal completion probability and post-merger operating performance).

We employ the heatwave days a host country experiences in a year to proxy the exposure to physical climate risk of host economy. Stakeholders in such target country are more likely to welcome and accept foreign firms with the capabilities to combat climate change issues, e.g., green innovative bidders. Therefore, we expect that the positive effect of green innovation on deal completion probability and post-merger operating performance will be more pronounced for bidders entering target country with higher physical climate risk. We measure *Physical*

[17] This policy had been replaced by the "Administrative Measures for the Priority Examination of Patents" implemented since August 1, 2017. Available at: https://www.gov.cn/xinwen/2017−08/02/content_5215464.htm.

climate risk using the *Heat Index 35* developed by the World Bank and report the results in Panel A of Table 12. The coefficients on interaction terms between GP-related variables and *Physical climate risk* are positive and significant except for those in columns (3) and (6) of Panel A1 losing significance, still confirming our previous expectations.

Second, economic policy uncertainty (EPU) has attracted a lot of attentions from scholars since the work of Baker et al. (2016). EPU complicates decision-making by destabilizing the macroeconomic environment (Baker et al., 2016) and can hinder firms in establishing and maintaining strong connections with their economic stakeholders (Lins et al., 2017). Current study finds that corporate innovative activities will suffer a significant decline in a country with higher EPU (Bhattacharya et al., 2017). We expect that when a target country experiences higher EPU, whether the CBMA bidders with green innovation are favoured by target country stakeholders is questioned. These bidders' operations and investments would be obstructed in the target country to a certain extent. Therefore, the positive effect of green innovation on deal completion probability and post-merger operating performance will be weakened for bidders entering target country with higher EPU. We measure EPU by adopting the index developed by Baker et al. (2016), and compute the average of monthly EPU in a year to get the annual EPU following Jia and Li (2020), then we use the logarithm of annual EPU (*Ln (EPU)*) in our regressions. The results are presented in Panel B of Table 12 and the coefficients on interaction terms between GP-related variables and EPU are negative and especially significant for *invention*-related green innovation, which are consistent with our prior prediction.

5 Conclusion

This paper has empirically examined the systematic effect of corporate green innovation on Chinese bidders' subsequent CBMA deals. Using a sample of 668 CBMA attempts by Chinese listed firms over the 2007−2021 period, we uncover that green innovation prior to the announcement positively contributes to Chinese bidders' internationalization through CBMAs.

Specifically, green innovative bidders tend to complete CBMA deals successfully, realize superior announcement abnormal returns, and achieve better post-merger operating performance. These results remain intact after a battery of robustness tests, including (1) additional control of province and target economy fixed effects, (2) additional control of bidder's CSR, target economy's climate risk and green innovation, (3) subsample tests, and (4) solution of potential endogeneity issues. Further analyses indicate that the positive effect of green innovation on post-merger operating performance could originate from lower carbon emissions' growth rate, better environmental performance, reduced environmental compliance costs, and larger patent-related government subsidies after deal completion. Moreover, the positive effect of green innovation on deal completion probability and post-merger operating performance will be more pronounced when bidders enter target economies with higher physical climate risk, while weakened when they enter target economies with higher EPU.

These findings of our paper suggest the following implications. First, our paper has illuminated the role of green innovation in the success of CBMAs attempted by EME bidders. The implication for prospective bidders from EMEs is that they are strongly encouraged to improve their green innovation capabilities to enhance their competitive advantages and alleviate legitimacy concerns in internationalization via CBMAs.

Second, our findings appear positive in relation to global actions being taken to combat climate change and achieve carbon neutrality. Specifically, we have provided evidence that green innovative acquirers tend to reduce carbon emissions' growth rate after CBMAs, and the effort on green innovation makes these acquirers more favorable especially in host economies with higher physical climate risk.

Third, our findings may provide practical implications to policymakers and regulators. Our paper echoes Boateng et al. (2021) who argue that EME governments' direct financial incentives facilitate firms' internationalization and help them create value. We find that green innovative acquirers are prone to gain larger patent-related government subsidies. As green innovation can be costly and risky (Berrone et al., 2013; Hao et al., 2021; Hu et al., 2021a), our study provides reference for policymakers in forming policies encouraging firms' investment in green innovative activities.

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Table 1

Sample description

This table shows the distribution of cross-border mergers and acquisitions (CBMAs) attempted by Chinese bidders during 2007−2021. Panel A reports the distribution of announced and completed CBMA deals attempted by Chinese bidders by announcement year. Panel B presents the frequency of announced and completed CBMA deals by Chinese bidders. Panel C reports the distribution by Chinese bidders' industries based on first one-digit of 2012 China Securities Regulatory Commission (CSRC) Industry Codes. Panel D reports the distribution by target economies of Chinese CBMAs. The unit of average deal value is million US dollars ($M).

Panel A: Sample distribution by announcement year

Announcement year	Announced deals			Completed deals			Completion rate (%)
	No.	Percent (%)	Deal value ($M)	No.	Percent (%)	Deal value ($M)	
2007	13	1.95	43.84	5	1.42	57.77	38.46
2008	14	2.10	45.45	6	1.71	65.70	42.86
2009	23	3.44	239.85	15	4.27	332.24	65.22
2010	23	3.44	129.11	14	3.99	162.73	60.87
2011	32	4.79	43.69	17	4.84	55.83	53.13
2012	40	5.99	84.68	18	5.13	77.66	45.00
2013	42	6.29	163.11	18	5.13	353.60	42.86
2014	33	4.94	167.62	19	5.41	212.39	57.58
2015	92	13.77	180.54	56	15.95	136.00	60.87
2016	105	15.72	239.35	54	15.38	306.45	51.43
2017	71	10.63	136.70	34	9.69	150.08	47.89
2018	70	10.48	232.21	38	10.83	313.10	54.29
2019	48	7.19	96.34	25	7.12	141.41	52.08
2020	30	4.49	304.15	14	3.99	466.78	46.67
2021	32	4.79	158.08	18	5.13	158.09	56.25
Total	668	100.00	169.71	351	100.00	213.03	52.54

Panel B: Frequency of bidders' attempts

Frequency	Announced deals		Completed deals	
	No.	Percent (%)	No.	Percent (%)
1	308	70.48	200	78.74
2	81	18.54	32	12.60
3	26	5.95	10	3.94
4	10	2.29	9	3.54
5	6	1.37	1	0.39
6	3	0.69	1	0.39
7	1	0.23		0.00
10	1	0.23	1	0.39
15	1	0.23		0.00
Total	437	100.00	254	100.00

Panel C: Sample distribution by bidders' industry

CSRC2012 (first digit code)	Announced deals			Completed deals		
	No.	Percent (%)	Deal value	No.	Percent (%)	Deal value
Agriculture, Forestry, Animal Husbandry, and Fishery (A)	10	1.50	72.66	7	1.99	29.23
Mining (B)	63	9.43	431.91	38	10.83	504.75
Manufacturing (C)	480	71.86	132.77	250	71.23	170.85
Electricity, Heat, Gas, and Water Production and Supply (D)	7	1.05	508.20	2	0.57	346.59
Construction (E)	15	2.25	49.53	9	2.56	53.72
Wholesale and Retail Trade (F)	21	3.14	246.79	8	2.28	288.96
Transportation, Warehousing, and Postal Services (G)	9	1.35	864.61	6	1.71	1274.17
Information Transmission, Software, and IT Services (I)	28	4.19	103.28	15	4.27	59.49
Real Estate (K)	1	0.15	40.49	–	–	–
Leasing and Business Services (L)	6	0.90	84.49	1	0.28	179.95
Scientific Research and Technical Services (M)	12	1.80	37.14	5	1.42	47.40
Water Conservancy, Environment, and Public Facilities Management (N)	6	0.90	11.16	4	1.14	9.86
Education (P)	1	0.15	11.15	–	–	–
Health and Social Work (Q)	2	0.30	20.71	2	0.57	20.71
Culture, Sports, and Entertainment (R)	6	0.90	67.31	3	0.85	40.25
Comprehensive (S)	1	0.15	30.86	1	0.28	30.86
Total	668	100.00	169.71	351	100.00	213.03

Panel D: Sample distribution by target economies

Target economies	Announced deals			Completed deals			Target economies	Announced deals			Completed deals		
	No.	Percent (%)	Deal value	No.	Percent (%)	Deal value		No.	Percent (%)	Deal value	No.	Percent (%)	Deal value
Argentina	2	0.30	491.50	2	0.57	491.50	Mauritania	2	0.30	22.82	1	0.28	36.90
Australia	55	8.23	130.23	32	9.12	166.19	Mexico	2	0.30	85.90	2	0.57	85.90
Austria	1	0.15	56.96	1	0.28	56.96	Mongolia	3	0.45	657.88	–	–	–
Belgium	3	0.45	56.70	1	0.28	33.32	Mozambique	1	0.15	3775.37	1	0.28	3775.37
Bolivia	2	0.30	7.14	2	0.57	7.14	Myanmar	1	0.15	4.00	–	–	–
Brazil	7	1.05	104.25	4	1.14	160.90	Netherlands	8	1.20	52.58	4	1.14	89.84
Cambodia	1	0.15	4.88	–	–	–	New Zealand	8	1.20	20.37	5	1.42	21.58
Canada	46	6.89	155.17	28	7.98	182.93	Norway	1	0.15	7.68	1	0.28	7.68
Chile	1	0.15	14.28	1	0.28	14.28	Oman	1	0.15	0.36	–	–	–
Congo (DRC)	2	0.30	1454.37	2	0.57	1454.37	Pakistan	3	0.45	607.20	–	–	–
Congo (RC)	1	0.15	550.00	–	–	–	Poland	3	0.45	34.50	3	0.85	34.50
Croatia	3	0.45	23.23	3	0.85	23.23	Russia	4	0.60	82.32	2	0.57	141.26
Czech Republic	2	0.30	10.83	1	0.28	17.96	Saudi Arabia	1	0.15	562.00	–	–	–
Denmark	6	0.90	197.93	3	0.85	31.27	Serbia	4	0.60	469.42	1	0.28	28.71
Egypt	1	0.15	57.00	1	0.28	57.00	Singapore	18	2.69	187.38	12	3.42	198.80
Finland	7	1.05	39.87	4	1.14	23.17	Slovakia	1	0.15	399.76	1	0.28	399.76
France	20	2.99	111.21	13	3.70	163.12	Slovenia	1	0.15	11.06	–	–	–
Gabon	2	0.30	62.80	1	0.28	38.15	South Africa	3	0.45	339.28	–	–	–
Germany	44	6.59	83.72	21	5.98	119.38	South Korea	15	2.25	19.03	6	1.71	27.35
Greece	1	0.15	7.12	–	–	–	Spain	9	1.35	50.33	7	1.99	63.43
Hong Kong	77	11.53	279.46	34	9.69	418.68	Sri Lanka	1	0.15	30.00	–	–	–
Hungary	4	0.60	474.55	3	0.85	631.15	Sweden	4	0.60	5.44	1	0.28	7.55
India	3	0.45	364.83	2	0.57	546.60	Switzerland	9	1.35	34.51	6	1.71	40.13
Indonesia	5	0.75	28.79	3	0.85	44.52	Taiwan	14	2.10	23.26	7	1.99	17.31
Iraq	1	0.15	108.15	–	–	–	Tajikistan	5	0.75	151.98	2	0.57	327.27
Ireland	1	0.15	0.19	–	–	–	Tanzania	2	0.30	57.62	1	0.28	115.11
Israel	13	1.95	382.87	3	0.85	1004.38	Thailand	6	0.90	13.52	1	0.28	4.17
Italy	33	4.94	63.69	19	5.41	69.16	Trinidad and Tobago	1	0.15	96.50	–	–	–
Jamaica	1	0.15	9.00	–	–	–	Turkey	2	0.30	83.97	2	0.57	83.97
Japan	25	3.74	23.71	14	3.99	29.58	Uganda	1	0.15	0.84	–	–	–
Kazakhstan	6	0.90	157.81	3	0.85	284.72	United Arab Emirates	3	0.45	426.02	3	0.85	426.02
Kyrgyzstan	1	0.15	3.51	–	–	–	United Kingdom	22	3.29	115.01	14	3.99	137.92
Laos	1	0.15	27.98	–	–	–	United States	111	16.62	246.12	52	14.81	324.42
Luxembourg	5	0.75	325.32	5	1.42	325.32	Uruguay	1	0.15	33.47	1	0.28	33.47
Malawi	1	0.15	10.00	1	0.28	10.00	Vietnam	3	0.45	1.89	2	0.57	2.37
Malaysia	6	0.90	98.81	3	0.85	24.19	Zambia	2	0.30	150.00	2	0.57	150.00
Mali	1	0.15	130.00	–	–	–	Total	668	100.00	169.71	351	100.00	213.03
Malta	1	0.15	26.73	1	0.28	26.73							

Table 2

Summary statistics

Panel A presents the summary statistics for full announced CBMA deals between 2007 and 2021 attempted by Chinese bidders. Panel B displays the summary statistics for completed CBMA deals with available three-year financial data after deal completion. All variables are defined in Appendix, and all continuous ones are winsorized at the 1st and 99th percentiles. *, **, and *** denote significance at 10%, 5%, and 1%.

Panel A: Summary statistics for regressions of deal completion probability

Variables	N	Mean	S.D.	Min	Median	Max
Completion	668	0.525	0.500	0.000	1.000	1.000
CAR (−3, 3)	662	0.008	0.128	−0.412	0.006	0.424
Ln (1+GP (sum))	668	1.048	1.421	0.000	0.693	6.089
Ln (1+GP (invention))	668	0.672	1.170	0.000	0.000	5.421
Ln (1+GP (utility model))	668	0.801	1.214	0.000	0.000	5.283
Ln (1+GP Index (sum))	668	0.871	1.232	0.000	0.288	5.301
Ln (1+GP Index (invention))	668	0.573	1.019	0.000	0.000	4.552
Ln (1+GP Index (utility model))	668	0.711	1.093	0.000	0.000	4.899
Ln (1+Dis. GP (sum))	668	0.899	1.296	0.000	0.182	5.923
Ln (1+Dis. GP (invention))	668	0.562	1.044	0.000	0.000	5.162
Ln (1+Dis. GP (utility model))	668	0.680	1.096	0.000	0.000	5.034
Cultural distance	668	3.502	1.915	0.455	3.219	6.413
Institutional distance	668	2.921	1.292	0.115	3.152	5.199
GDP growth	668	0.024	0.080	−0.172	0.038	0.223
B/M ratio	668	0.393	0.294	0.054	0.312	1.528
Ln (1+CG index)	668	1.465	0.290	0.693	1.474	2.079
Firm size	668	22.524	1.529	20.045	22.237	27.955
Ln (1+Free cash flow)	668	1.905	19.603	−23.967	17.101	24.477
Leverage	668	0.414	0.195	0.040	0.423	0.868
Ln (1+Listed age)	668	1.881	0.911	0.000	1.946	3.296
Listed overseas	668	0.081	0.273	0.000	0.000	1.000
ROA	668	0.054	0.047	−0.088	0.047	0.210
SOE bidder	668	0.114	0.318	0.000	0.000	1.000
Ln (1+Patents (total))	668	3.387	2.082	0.000	3.466	9.304
R&D/Total assets	668	0.018	0.018	0.000	0.015	0.101
All cash deal	668	0.269	0.444	0.000	0.000	1.000
Financial/Legal advisor	668	0.394	0.489	0.000	0.000	1.000
High-tech target firm	668	0.290	0.454	0.000	0.000	1.000
Past CBMA experience	668	0.284	0.543	0.000	0.000	2.398
Public target	668	0.193	0.395	0.000	0.000	1.000
Ln (1+Relative deal size)	668	0.061	0.144	0.000	0.012	0.897
Same industry	668	0.470	0.499	0.000	0.000	1.000
Tender offer	668	0.013	0.115	0.000	0.000	1.000

Panel B: Summary statistics for regressions of post-merger operating performance

Variables	N	Mean	S.D.	Min	Median	Max
ΔROE	302	−0.036	0.210	−1.066	−0.019	1.064
Ln (1+GP (sum))	302	1.162	1.483	0.000	0.693	6.089
Ln (1+GP (invention))	302	0.752	1.209	0.000	0.000	5.421
Ln (1+GP (utility model))	302	0.910	1.268	0.000	0.000	5.283
Ln (1+GP Index (sum))	302	0.963	1.274	0.000	0.336	5.301
Ln (1+GP Index (invention))	302	0.646	1.067	0.000	0.000	4.552
Ln (1+GP Index (utility model))	302	0.803	1.136	0.000	0.000	4.899
Ln (1+Dis. GP (sum))	302	1.014	1.359	0.000	0.336	5.923
Ln (1+Dis. GP (invention))	302	0.642	1.087	0.000	0.000	5.162
Ln (1+Dis. GP (utility model))	302	0.776	1.150	0.000	0.000	5.034
Cultural distance	302	3.598	1.890	0.455	3.219	6.413
Institutional distance	302	3.083	1.288	0.115	3.278	5.199
GDP growth	302	0.027	0.083	−0.172	0.041	0.223
B/M ratio	302	0.371	0.279	0.054	0.295	1.528
Ln (1+CG index)	302	1.478	0.284	0.693	1.609	2.079
Firm size	302	22.512	1.541	20.045	22.265	27.955
Ln (1+Free cash flow)	302	2.480	19.583	−23.967	17.567	24.477
Leverage	302	0.408	0.191	0.040	0.426	0.868
Ln (1+Listed age)	302	1.826	0.893	0.000	1.946	3.219
Listed overseas	302	0.086	0.281	0.000	0.000	1.000
ROA	302	0.060	0.047	−0.088	0.052	0.210
SOE bidder	302	0.126	0.332	0.000	0.000	1.000
Ln (1+Patents (total))	302	3.515	2.152	0.000	3.466	9.304
R&D/Total assets	302	0.020	0.020	0.000	0.016	0.101
All cash deal	302	0.321	0.468	0.000	0.000	1.000
Financial/Legal advisor	302	0.533	0.500	0.000	1.000	1.000
High-tech target firm	302	0.301	0.460	0.000	0.000	1.000
Past CBMA experience	302	0.278	0.519	0.000	0.000	2.398
Public target	302	0.238	0.427	0.000	0.000	1.000
Ln (1+Relative deal size)	302	0.068	0.153	0.000	0.016	0.897
Same industry	302	0.517	0.501	0.000	1.000	1.000
Tender offer	302	0.020	0.140	0.000	0.000	1.000

Table 3

Correlation matrices (Pearson)

All variables are defined in Appendix, and all continuous ones are winsorized at the 1^{st} and 99^{th} percentiles. *, **, and *** denote significance at 10%, 5%, and 1%.

	Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
1	*Completion*	1.000																
2	*CAR (−3, 3)*	0.076*	1.000															
3	Δ*ROE*	0.046	0.062	1.000														
4	*Ln (1+GP (sum))*	0.119***	−0.003	0.065	1.000													
5	*Ln (1+GP (invention))*	0.112***	0.025	0.074	0.932***	1.000												
6	*Ln (1+GP (utility model))*	0.118***	−0.017	0.034	0.954***	0.824***	1.000											
7	*Ln (1+GP Index (sum))*	0.114***	−0.002	0.067	0.994***	0.934***	0.951***	1.000										
8	*Ln (1+GP Index (invention))*	0.113***	0.026	0.079	0.922***	0.993***	0.814***	0.929***	1.000									
9	*Ln (1+GP Index (utility model))*	0.112***	−0.016	0.038	0.947***	0.822***	0.995***	0.951***	0.814***	1.000								
10	*Ln (1+Dis. GP (sum))*	0.125***	0.003	0.067	0.992***	0.933***	0.953***	0.988***	0.924***	0.947***	1.000							
11	*Ln (1+Dis. GP (invention))*	0.119***	0.028	0.077	0.915***	0.990***	0.815***	0.920***	0.984***	0.814***	0.930***	1.000						
12	*Ln (1+Dis. GP (utility model))*	0.118***	−0.012	0.036	0.940***	0.821***	0.990***	0.938***	0.810***	0.986***	0.953***	0.819***	1.000					
13	*Cultural distance*	0.027	−0.047	0.030	0.002	0.001	−0.011	−0.006	0.001	−0.017	−0.000	−0.004	−0.010	1.000				
14	*Institutional distance*	0.055	−0.041	−0.038	−0.034	−0.030	−0.024	−0.028	−0.024	−0.024	−0.028	−0.025	−0.025	0.302***	1.000			
15	*GDP growth*	−0.007	0.018	−0.029	−0.034	−0.009	−0.059	−0.033	−0.002	−0.057	−0.034	−0.010	−0.060	−0.067*	−0.035	1.000		
16	*B/M ratio*	0.004	0.072*	0.033	0.304***	0.309***	0.308***	0.319***	0.310***	0.316***	0.306***	0.307***	0.303***	−0.148***	−0.103***	0.126***	1.000	
17	*Ln (1+CG index)*	0.010	0.026	−0.032	0.082**	0.077**	0.101***	0.086**	0.071*	0.111***	0.099**	0.089**	0.121***	−0.039	0.003	0.011	0.106***	1.000
18	*Firm size*	0.093**	−0.003	−0.000	0.570***	0.605***	0.529***	0.587***	0.604***	0.538***	0.575***	0.609***	0.529***	−0.059	−0.032	0.070*	0.556***	0.126***
19	*Ln (1+Free cash flow)*	0.022	0.038	−0.035	0.063	0.065*	0.071*	0.068*	0.059	0.075*	0.062	0.068*	0.070*	0.010	−0.049	0.050	0.232***	0.100***
20	*Leverage*	−0.017	−0.006	−0.049	0.255***	0.239***	0.236***	0.265***	0.245***	0.241***	0.249***	0.231***	0.225***	−0.143***	−0.056	0.031	0.183***	0.056
21	*Ln (1+Listed age)*	−0.021	0.054	0.001	0.091**	0.092**	0.074*	0.099**	0.093**	0.078**	0.074*	0.071*	0.058	−0.085**	−0.081**	0.028	0.328***	0.016
22	*Listed overseas*	0.062	−0.011	0.028	0.303***	0.340***	0.239***	0.320***	0.352***	0.249***	0.296***	0.331***	0.234***	0.093**	0.072*	−0.071*	0.239***	0.050
23	*ROA*	0.113***	−0.015	−0.157***	−0.038	−0.049	−0.021	−0.037	−0.044	−0.020	−0.029	−0.042	−0.012	0.157***	0.069*	0.080**	−0.155***	−0.039
24	*SOE bidder*	0.057	−0.010	0.111**	0.152***	0.188***	0.107***	0.159***	0.190***	0.112***	0.160***	0.196***	0.109***	−0.086**	0.051	−0.079**	0.199***	0.049
25	*Ln (1+Patents (total))*	0.091**	0.012	−0.005	0.735***	0.671***	0.706***	0.729***	0.666***	0.700***	0.729***	0.664***	0.693***	−0.019	−0.038	−0.030	0.234***	0.087**
26	*R&D/Total assets*	0.097**	−0.047	0.046	0.137***	0.124***	0.108***	0.117***	0.128***	0.093**	0.139***	0.123***	0.110***	0.026	0.008	−0.146***	−0.182***	−0.055
27	*All cash deal*	0.104***	0.028	−0.003	0.073*	0.087**	0.064*	0.075*	0.087**	0.062	0.070*	0.085**	0.058	−0.028	0.131***	0.096**	0.112***	0.003
28	*Financial/Legal advisor*	0.349***	0.106***	0.006	0.091**	0.097**	0.076**	0.090**	0.097**	0.076**	0.097**	0.107***	0.080**	0.018	0.113***	−0.128***	0.100***	0.036
29	*High-tech target firm*	0.007	−0.032	0.015	−0.078**	−0.074*	−0.083**	−0.093**	−0.083**	−0.094**	−0.078**	−0.072*	−0.085**	0.016	0.036	−0.019	−0.202***	−0.100***
30	*Past CBMA experience*	0.066*	−0.020	0.039	0.366***	0.414***	0.302***	0.380***	0.410***	0.310***	0.364***	0.411***	0.298***	0.074*	−0.040	−0.019	0.262***	−0.040
31	*Public target*	0.154***	0.014	0.046	0.130***	0.160***	0.116***	0.134***	0.164***	0.112***	0.131***	0.160***	0.115***	0.088**	0.182***	0.057	0.136***	−0.016
32	*Ln (1+Relative deal size)*	0.052	0.191***	−0.004	−0.072*	−0.058	−0.075*	−0.072*	−0.061	−0.080**	−0.070*	−0.051	−0.078**	−0.090**	0.006	0.014	0.056	0.037
33	*Same industry*	0.060	0.045	0.120**	0.022	0.030	0.017	0.029	0.034	0.020	0.032	0.040	0.019	0.016	−0.070*	0.026	0.020	−0.010
34	*Tender offer*	0.059	−0.034	−0.034	0.043	0.045	0.028	0.048	0.050	0.030	0.038	0.045	0.010	0.014	0.078**	0.081**	0.062	−0.004

(*Panel A continued*)

	Variables	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)	(31)	(32)	(33)	(34)
18	*Firm size*	1.000																
19	*Ln (1+Free cash flow)*	0.138***	1.000															
20	*Leverage*	0.469***	0.072*	1.000														
21	*Ln (1+Listed age)*	0.396***	0.189***	0.402***	1.000													
22	*Listed overseas*	0.459***	0.055	0.122***	0.009	1.000												
23	*ROA*	−0.023	0.078**	−0.347***	−0.181***	0.022	1.000											
24	*SOE bidder*	0.226***	0.065*	0.099**	0.192***	0.188***	−0.074*	1.000										
25	*Ln (1+Patents (total))*	0.403***	0.111***	0.153***	0.015	0.199***	0.053	0.080**	1.000									
26	*R&D/Total assets*	−0.164***	−0.028	−0.172***	−0.177***	−0.037	0.155***	−0.057	0.321***	1.000								
27	*All cash deal*	0.139***	−0.008	0.037	0.034	0.129***	−0.043	0.059	0.046	−0.073*	1.000							
28	*Financial/Legal advisor*	0.250***	0.027	0.124***	0.076**	0.188***	−0.020	0.126***	0.081**	−0.026	0.146***	1.000						
29	*High-tech target firm*	−0.209***	−0.011	−0.234***	−0.131***	−0.105***	0.087**	−0.022	0.006	0.337***	−0.024	−0.077**	1.000					
30	*Past CBMA experience*	0.524***	0.082**	0.180***	0.250***	0.397***	−0.030	0.219***	0.251***	−0.123***	0.129***	0.112***	−0.141***	1.000				
31	*Public target*	0.253***	0.002	0.073*	0.107***	0.272***	0.009	0.040	0.068*	−0.077**	0.412***	0.180***	0.030	0.239***	1.000			
32	*Ln (1+Relative deal size)*	−0.030	0.027	0.116***	0.195***	−0.006	−0.201***	0.078**	−0.121***	−0.147***	0.131***	0.288***	0.024	−0.015	0.048	1.000		
33	*Same industry*	0.060	0.035	−0.063	−0.039	0.095**	0.096**	0.040	0.042	0.035	0.036	0.002	0.137***	0.083**	0.033	−0.013	1.000	
34	*Tender offer*	0.074*	−0.028	−0.002	−0.011	0.156***	0.009	0.040	0.019	−0.065*	0.192***	0.145***	−0.046	0.128***	0.239***	−0.001	0.020	1.000

Table 4

Probability of deal completion

This table reports the probit regression results of completion probability based on announced deals. Panel A presents the baseline regression results. The dependent variable is *Completion*, a dummy variable that equals one if an announced deal is recorded as "Completed" in SDC, and zero otherwise. The key independent variable is green innovation, measured by three groups of green patents (GPs) variables, i.e., number of green patents (columns (1) – (3) in Panel A), green patent index (GPI) (columns (4) – (6) in Panel A), and number of discounted green patents (columns (7) – (9) in Panel A). Each group of green patent variables include three variables, one for overall green patents (columns (1), (4), and (7) in Panel A), the other two for subcategories of overall green patents, i.e., green invention patents (columns (2), (5), and (8) in Panel A) and green utility model patents (columns (3), (6), and (9) in Panel A). Panel B presents the two-stage probit least squares (2SPLS) regression results. The first stage regresses each GP variable of each group on the instrumental variable (IV), i.e., the Province-year corresponding GP variable, only controlling for Firm-level variables. The second stage regresses Completion on each predicted GP variable from the corresponding first stage, meanwhile, including all control variables. The 2SPLS regression results for each group of GP variables are displayed in Panel B1, B2, and B3, respectively. All variables are defined in Appendix, and all continuous ones are winsorized at the 1st and 99th percentiles. *z*-statistics (in parentheses) for probit regressions and *t*-statistics (in parentheses) for ordinary least squares (OLS) regressions are based on standard errors clustered by bidders' industry, which is defined based on the first one-digit CSRC industry classification of 2012. Year and Industry effects are included in all regressions. *, **, and *** denote significance at 10%, 5%, and 1%. The coefficients on the constant and controls are suppressed for brevity in Panel B and available upon request.

Panel A: Baseline regressions

Variables	(1) Completion	(2) Completion	(3) Completion	(4) Completion	(5) Completion	(6) Completion	(7) Completion	(8) Completion	(9) Completion
Ln (1+GP (sum))	0.194***								
	(8.13)								
Ln (1+GP (invention))		0.174***							
		(8.13)							
Ln (1+GP (utility model))			0.221***						
			(6.44)						
Ln (1+GP Index (sum))				0.215***					
				(9.01)					
Ln (1+GP Index (invention))					0.191***				
					(5.98)				
Ln (1+GP Index (utility model))						0.235***			
						(6.72)			
Ln (1+Dis. GP (sum))							0.228***		
							(7.87)		
Ln (1+Dis. GP (invention))								0.212***	
								(7.24)	
Ln (1+Dis. GP (utility model))									0.237***
									(5.78)
Cultural distance	−0.021	−0.020	−0.019	−0.019	−0.019	−0.018	−0.021	−0.020	−0.019
	(−0.82)	(−0.74)	(−0.75)	(−0.78)	(−0.72)	(−0.71)	(−0.83)	(−0.74)	(−0.74)
Institutional distance	0.020	0.020	0.016	0.018	0.020	0.016	0.020	0.021	0.017
	(0.57)	(0.59)	(0.46)	(0.53)	(0.59)	(0.45)	(0.58)	(0.61)	(0.49)
GDP growth	1.394	1.303	1.540*	1.408	1.280	1.540*	1.386	1.296	1.527*
	(1.59)	(1.50)	(1.68)	(1.58)	(1.47)	(1.68)	(1.57)	(1.48)	(1.67)
B/M ratio	0.140	0.154	0.083	0.129	0.145	0.080	0.133	0.154	0.094
	(0.69)	(0.73)	(0.40)	(0.63)	(0.68)	(0.39)	(0.66)	(0.72)	(0.45)

Panel A (*Continued*)

Ln (1+CG index)	−0.029	−0.027	−0.039	−0.029	−0.021	−0.045	−0.039	−0.028	−0.056
	(−0.36)	(−0.35)	(−0.41)	(−0.37)	(−0.27)	(−0.48)	(−0.45)	(−0.35)	(−0.56)
Firm size	−0.080*	−0.078*	−0.076	−0.079*	−0.074*	−0.074	−0.088*	−0.088**	−0.077
	(−1.74)	(−1.84)	(−1.51)	(−1.82)	(−1.89)	(−1.48)	(−1.87)	(−2.04)	(−1.49)
Ln (1+Free cash flow)	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.68)	(0.56)	(0.59)	(0.64)	(0.58)	(0.58)	(0.69)	(0.52)	(0.59)
Leverage	−0.067	−0.013	−0.070	−0.071	−0.029	−0.074	−0.055	−0.001	−0.048
	(−0.27)	(−0.06)	(−0.27)	(−0.29)	(−0.12)	(−0.28)	(−0.21)	(−0.00)	(−0.18)
Ln (1+Listed age)	−0.035	−0.029	−0.029	−0.035	−0.031	−0.031	−0.024	−0.018	−0.025
	(−0.83)	(−0.69)	(−0.72)	(−0.85)	(−0.70)	(−0.76)	(−0.60)	(−0.44)	(−0.63)
Listed overseas	−0.353**	−0.360***	−0.297**	−0.363**	−0.373**	−0.306**	−0.330**	−0.341***	−0.288**
	(−2.25)	(−2.64)	(−2.18)	(−2.20)	(−2.48)	(−2.24)	(−2.28)	(−2.70)	(−2.40)
ROA	3.420***	3.463***	3.235***	3.375***	3.418***	3.211***	3.416***	3.496***	3.220***
	(6.60)	(6.48)	(6.56)	(6.55)	(6.29)	(6.50)	(6.83)	(6.72)	(6.54)
SOE bidder	0.036	0.032	0.067	0.041	0.034	0.069	0.026	0.023	0.062
	(0.26)	(0.22)	(0.52)	(0.30)	(0.24)	(0.54)	(0.19)	(0.16)	(0.49)
Ln (1+Patents (total))	−0.073***	−0.040*	−0.070**	−0.068***	−0.036*	−0.066**	−0.077***	−0.042**	−0.065**
	(−2.74)	(−1.81)	(−2.48)	(−2.59)	(−1.71)	(−2.33)	(−2.93)	(−2.00)	(−2.34)
R&D/Total assets	9.333***	8.659***	9.824***	9.394***	8.565***	9.874***	9.045***	8.449***	9.611***
	(3.91)	(3.69)	(3.81)	(3.83)	(3.63)	(3.84)	(3.72)	(3.54)	(3.75)
All cash deal	0.133*	0.134*	0.136*	0.136*	0.136*	0.140*	0.142*	0.142*	0.143*
	(1.72)	(1.75)	(1.79)	(1.78)	(1.77)	(1.83)	(1.81)	(1.82)	(1.85)
Financial/Legal advisor	1.112***	1.100***	1.112***	1.112***	1.097***	1.108***	1.116***	1.102***	1.107***
	(8.22)	(8.48)	(8.02)	(8.22)	(8.69)	(7.97)	(8.25)	(8.55)	(7.97)
High-tech target firm	0.011	0.015	0.011	0.016	0.018	0.012	0.015	0.015	0.016
	(0.18)	(0.23)	(0.18)	(0.26)	(0.29)	(0.20)	(0.24)	(0.24)	(0.26)
Past CBMA experience	0.102	0.091	0.117	0.097	0.094	0.112	0.099	0.088	0.116
	(1.47)	(1.27)	(1.49)	(1.38)	(1.25)	(1.43)	(1.48)	(1.26)	(1.48)
Public target	0.323***	0.320***	0.318***	0.327***	0.321***	0.326***	0.317***	0.317***	0.312***
	(3.49)	(3.45)	(3.46)	(3.55)	(3.46)	(3.55)	(3.36)	(3.37)	(3.33)
Ln (1+Relative deal size)	−0.346	−0.359	−0.340	−0.345	−0.352	−0.325	−0.365	−0.384	−0.340
	(−0.67)	(−0.73)	(−0.66)	(−0.68)	(−0.72)	(−0.63)	(−0.70)	(−0.79)	(−0.65)
Same industry	0.122*	0.117	0.118	0.118*	0.116	0.118	0.117*	0.117	0.116
	(1.71)	(1.64)	(1.63)	(1.67)	(1.62)	(1.64)	(1.65)	(1.62)	(1.61)
Tender offer	−0.428	−0.392	−0.435	−0.435	−0.396	−0.439	−0.421	−0.395	−0.396
	(−0.66)	(−0.60)	(−0.67)	(−0.67)	(−0.61)	(−0.68)	(−0.65)	(−0.61)	(−0.62)
Constant	1.642	1.470	1.597	1.634	1.391	1.567	1.858	1.680	1.622
	(1.11)	(1.05)	(1.01)	(1.14)	(1.06)	(1.00)	(1.23)	(1.20)	(1.01)
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	668	668	668	668	668	668	668	668	668
Pseudo R^2	0.169	0.166	0.170	0.168	0.165	0.169	0.171	0.166	0.170

Panel B: 2SPLS

Panel B1: Number of green patents

Variables	(1) 1st stage Ln (1+GP (sum))	(2) 2nd stage Completion	(3) 1st stage Ln (1+GP (invention))	(4) 2nd stage Completion	(5) 1st stage Ln (1+GP (utility model))	(6) 2nd stage Completion
Province-year Ln (1+GP (sum))	0.432***					
	(6.11)					
Province-year Ln (1+GP (invention))			0.516***			
			(5.53)			
Province-year Ln (1+GP (utility model))					0.472***	
					(11.06)	
Predicted Ln (1+GP (sum))		0.417***				
		(4.64)				
Predicted Ln (1+GP (invention))				0.405***		
				(3.82)		
Predicted Ln (1+GP (utility model))						0.450***
						(4.83)
Firm-level controls and constant	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	No	Yes	No	Yes	No	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	668	668	668	668	668	668
Adjusted R^2	0.712		0.692		0.665	
Pseudo R^2		0.166		0.166		0.166
First-stage Cragg and Donald test	*p*-value < 0.001		*p*-value < 0.001		*p*-value < 0.001	
Overidentification test	Equation exactly identified		Equation exactly identified		Equation exactly identified	

Panel B2: Green patent index (GPI)

Variables	(1) 1st stage Ln (1+GPI (sum))	(2) 2nd stage Completion	(3) 1st stage Ln (1+GPI (invention))	(4) 2nd stage Completion	(5) 1st stage Ln (1+GPI (utility model))	(6) 2nd stage Completion
Province-year Ln (1+GPI (sum))	0.422***					
	(6.27)					
Province-year Ln (1+GPI (invention))			0.530***			
			(5.91)			
Province-year Ln (1+GPI (utility model))					0.467***	
					(11.16)	
Predicted Ln (1+GPI (sum))		0.446***				
		(3.80)				
Predicted Ln (1+GPI (invention))				0.430***		
				(4.15)		
Predicted Ln (1+GPI (utility model))						0.458***
						(4.16)
Firm-level controls and constant	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	No	Yes	No	Yes	No	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	668	668	668	668	668	668
Adjusted R^2	0.716		0.695		0.668	
Pseudo R^2		0.165		0.166		0.165
First-stage Cragg and Donald test	*p*-value < 0.001		*p*-value < 0.001		*p*-value < 0.001	
Overidentification test	Equation exactly identified		Equation exactly identified		Equation exactly identified	

Panel B3: Number of discounted green patents

Variables	(1) 1st stage Ln (1+Dis. GP (sum))	(2) 2nd stage Completion	(3) 1st stage Ln (1+Dis. GP (invention))	(4) 2nd stage Completion	(5) 1st stage Ln (1+Dis. GP (utility model))	(6) 2nd stage Completion
Province-year Ln (1+Dis. GP (sum))	0.418***					
	(5.03)					
Province-year Ln (1+Dis. GP (invention))			0.494***			
			(4.41)			
Province-year Ln (1+Dis. GP (utility model))					0.485***	
					(12.50)	
Predicted Ln (1+Dis. GP (sum))		0.507***				
		(4.67)				
Predicted Ln (1+Dis. GP (invention))				0.504***		
				(4.38)		
Predicted Ln (1+Dis. GP (utility model))						0.485***
						(4.43)
Firm-level controls and constant	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	No	Yes	No	Yes	No	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	668	668	668	668	668	668
Adjusted R^2	0.713		0.692		0.660	
Pseudo R^2		0.167		0.167		0.166
First-stage Cragg and Donald test	p-value < 0.001		p-value < 0.001		p-value < 0.001	
Overidentification test	Equation exactly identified		Equation exactly identified		Equation exactly identified	

Table 5

Announcement abnormal returns

This table reports the ordinary least squares (OLS) regression results of short-term market reactions based on announced deals. The dependent variable is cumulative abnormal return (CAR) using seven-day event window, i.e., CAR (−3, 3). CAR is computed using the market model and the model parameters are estimated using an estimation period from 210 days to 11 days before the announcement date. At least 100 trading days over the estimation window are required for a bidder in the sample (Fee and Thomas, 2004). The key independent variable is green innovation, measured by three groups of green patents (GPs) variables, i.e., number of green patents (columns (1) – (3) in Panel A), green patent index (GPI) (columns (4) – (6) in Panel A), and number of discounted green patents (columns (7) – (9) in Panel A). Each group of green patent variables include three variables, one for overall green patents (columns (1), (4), and (7) in Panel A), the other two for subcategories of overall green patents, i.e., green invention patents (columns (2), (5), and (8) in Panel A) and green utility model patents (columns (3), (6), and (9) in Panel A). Panel B presents the two-stage least squares (2SLS) regression results. The first stage regresses each GP variable of each group on the instrumental variable (IV), i.e., the Province-year corresponding GP variable, only controlling for Firm-level variables. The second stage regresses CAR (−3, 3) on each predicted GP variable from the corresponding first stage, meanwhile, including all control variables. The 2SLS regression results for each group of GP variables are displayed in Panel B1, B2, and B3, respectively. All variables are defined in Appendix, and all continuous ones are winsorized at the 1st and 99th percentiles. *t*-statistics (in parentheses) for OLS regressions are based on standard errors clustered by bidders' industry, which is defined based on the first one-digit CSRC industry classification of 2012. Year and Industry effects are included in all regressions. *, **, and *** denote significance at 10%, 5%, and 1%. The coefficients on the constant and controls are suppressed for brevity and available upon request.

Panel A: Baseline regressions

Variables	(1) CAR (−3, 3)	(2) CAR (−3, 3)	(3) CAR (−3, 3)	(4) CAR (−3, 3)	(5) CAR (−3, 3)	(6) CAR (−3, 3)	(7) CAR (−3, 3)	(8) CAR (−3, 3)	(9) CAR (−3, 3)
Ln (1+GP (sum))	−0.003								
	(−1.14)								
Ln (1+GP (invention))		0.008^{***}							
		(3.04)							
Ln (1+GP (utility model))			-0.009^{*}						
			(−1.93)						
Ln (1+GP Index (sum))				−0.004					
				(−1.24)					
Ln (1+GP Index (invention))					0.010^{**}				
					(2.52)				
Ln (1+GP Index (utility model))						-0.010^{*}			
						(−1.86)			
Ln (1+Dis. GP (sum))							−0.002		
							(−0.62)		
Ln (1+Dis. GP (invention))								0.010^{***}	
								(3.54)	
Ln (1+Dis. GP (utility model))									−0.008
									(−1.52)
Controls and constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	662	662	662	662	662	662	662	662	662
Adjusted R^2	0.036	0.038	0.038	0.036	0.038	0.038	0.036	0.038	0.037

Panel B: 2SLS

Panel B1: Number of green patents

Variables	(1) 1st stage Ln (1+GP (sum))	(2) 2nd stage CAR (−3, 3)	(3) 1st stage Ln (1+GP (invention))	(4) 2nd stage CAR (−3, 3)	(5) 1st stage Ln (1+GP (utility model))	(6) 2nd stage CAR (−3, 3)
Province-year Ln (1+GP (sum))	0.431***					
	(6.06)					
Province-year Ln (1+GP (invention))			0.516***			
			(5.49)			
Province-year Ln (1+GP (utility model))					0.473***	
					(11.06)	
Predicted Ln (1+GP (sum))		0.021**				
		(2.60)				
Predicted Ln (1+GP (invention))				0.029*		
				(1.97)		
Predicted Ln (1+GP (utility model))						0.003
						(0.53)
Firm-level controls and constant	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	No	Yes	No	Yes	No	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	662	662	662	662	662	662
Adjusted R^2	0.714	0.038	0.692	0.041	0.669	0.036
First-stage Cragg and Donald test	*p*-value < 0.001		*p*-value < 0.001		*p*-value < 0.001	
Overidentification test	Equation exactly identified		Equation exactly identified		Equation exactly identified	

Panel B2: Green patent index (GPI)

Variables	(1) 1st stage Ln (1+GPI (sum))	(2) 2nd stage CAR (−3, 3)	(3) 1st stage Ln (1+GPI (invention))	(4) 2nd stage CAR (−3, 3)	(5) 1st stage Ln (1+GPI (utility model))	(6) 2nd stage CAR (−3, 3)
Province-year Ln (1+GPI (sum))	0.422***					
	(6.24)					
Province-year Ln (1+GPI (invention))			0.530***			
			(5.89)			
Province-year Ln (1+GPI (utility model))					0.468***	
					(11.29)	
Predicted Ln (1+GPI (sum))		0.021*				
		(2.04)				
Predicted Ln (1+GPI (invention))				0.031*		
				(2.02)		
Predicted Ln (1+GPI (utility model))						0.002
						(0.26)
Firm-level controls and constant	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	No	Yes	No	Yes	No	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	662	662	662	662	662	662
Adjusted R^2	0.718	0.038	0.696	0.041	0.673	0.036
First-stage Cragg and Donald test	*p*-value < 0.001		*p*-value < 0.001		*p*-value < 0.001	
Overidentification test	Equation exactly identified		Equation exactly identified		Equation exactly identified	

Panel B3: Number of discounted green patents

Variables	(1) 1st stage Ln (1+Dis. GP (sum))	(2) 2nd stage CAR (−3, 3)	(3) 1st stage Ln (1+Dis. GP (invention))	(4) 2nd stage CAR (−3, 3)	(5) 1st stage Ln (1+Dis. GP (utility model))	(6) 2nd stage CAR (−3, 3)
Province-year Ln (1+Dis. GP (sum))	0.418***					
	(5.00)					
Province-year Ln (1+Dis. GP (invention))			0.494***			
			(4.38)			
Province-year Ln (1+Dis. GP (utility model))					0.485***	
					(12.50)	
Predicted Ln (1+Dis. GP (sum))		0.023**				
		(2.72)				
Predicted Ln (1+Dis. GP (invention))				0.032*		
				(1.77)		
Predicted Ln (1+Dis. GP (utility model))						0.004
						(0.57)
Firm-level controls and constant	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	No	Yes	No	Yes	No	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	662	662	662	662	662	662
Adjusted R^2	0.715	0.038	0.693	0.040	0.664	0.036
First-stage Cragg and Donald test	*p*-value < 0.001		*p*-value < 0.001		*p*-value < 0.001	
Overidentification test	Equation exactly identified		Equation exactly identified		Equation exactly identified	

Table 6

Post-merger operating performance

This table reports the ordinary least squares (OLS) regression results of post-merger operating performance based on completed deals. The dependent variable is ΔROE, which is the difference between the combined firm's operating performance for three years after deal completion and the bidder's operating performance for one year prior to CBMA announcement. The key independent variable is green innovation, measured by three groups of green patents (GPs) variables, i.e., number of green patents (columns (1) – (3) in Panel A), green patent index (GPI) (columns (4) – (6) in Panel A), and number of discounted green patents (columns (7) – (9) in Panel A). Each group of green patent variables include three variables, one for overall green patents (columns (1), (4), and (7) in Panel A), the other two for subcategories of overall green patents, i.e., green invention patents (columns (2), (5), and (8) in Panel A) and green utility model patents (columns (3), (6), and (9) in Panel A). Panel B presents the two-stage least squares (2SLS) regression results. The first stage regresses each GP variable of each group on the instrumental variable (IV), i.e., the Province-year corresponding GP variable, only controlling for Firm-level variables. The second stage regresses ΔROE on each predicted GP variable from the corresponding first stage, meanwhile, including all control variables. The 2SLS regression results for each group of GP variables are displayed in Panel B1, B2, and B3, respectively. All variables are defined in Appendix, and all continuous ones are winsorized at the 1st and 99th percentiles. *t*-statistics (in parentheses) for OLS regressions are based on standard errors clustered by bidders' industry, which is defined based on the first one-digit CSRC industry classification of 2012. Year and Industry effects are included in all regressions. *, **, and *** denote significance at 10%, 5%, and 1%. The coefficients on the constant and controls are suppressed for brevity and available upon request.

Panel A: Baseline regressions

Variables	(1) ΔROE	(2) ΔROE	(3) ΔROE	(4) ΔROE	(5) ΔROE	(6) ΔROE	(7) ΔROE	(8) ΔROE	(9) ΔROE
Ln (1+GP (sum))	0.010								
	(1.42)								
Ln (1+GP (invention))		0.010							
		(1.45)							
Ln (1+GP (utility model))			−0.002						
			(−0.35)						
Ln (1+GP Index (sum))				0.013					
				(1.43)					
Ln (1+GP Index (invention))					0.016**				
					(2.38)				
Ln (1+GP Index (utility model))						0.001			
						(0.08)			
Ln (1+Dis. GP (sum))							0.010		
							(1.60)		
Ln (1+Dis. GP (invention))								0.012**	
								(2.19)	
Ln (1+Dis. GP (utility model))									−0.003
									(−0.48)
Controls and constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	302	302	302	302	302	302	302	302	302
Adjusted R^2	0.057	0.056	0.055	0.057	0.057	0.055	0.057	0.056	0.055

Panel B: 2SLS

Panel B1: Number of green patents

Variables	(1) 1st stage Ln (1+GP (sum))	(2) 2nd stage ΔROE	(3) 1st stage Ln (1+GP (invention))	(4) 2nd stage ΔROE	(5) 1st stage Ln (1+GP (utility model))	(6) 2nd stage ΔROE
Province-year Ln (1+GP (sum))	0.446***					
	(8.25)					
Province-year Ln (1+GP (invention))			0.495***			
			(8.70)			
Province-year Ln (1+GP (utility model))					0.462***	
					(15.26)	
Predicted Ln (1+GP (sum))		0.061***				
		(9.10)				
Predicted Ln (1+GP (invention))				0.070***		
				(8.16)		
Predicted Ln (1+GP (utility model))						0.061***
						(9.12)
Firm-level controls and constant	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	No	Yes	No	Yes	No	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	302	302	302	302	302	302
Adjusted R^2	0.712	0.064	0.702	0.065	0.659	0.062
First-stage Cragg and Donald test	*p*-value < 0.001		*p*-value < 0.001		*p*-value < 0.001	
Overidentification test	Equation exactly identified		Equation exactly identified		Equation exactly identified	

Panel B2: Green patent index (GPI)

Variables	(1) 1st stage Ln (1+GPI (sum))	(2) 2nd stage ΔROE	(3) 1st stage Ln (1+GPI (invention))	(4) 2nd stage ΔROE	(5) 1st stage Ln (1+GPI (utility model))	(6) 2nd stage ΔROE
Province-year Ln (1+GPI (sum))	0.414***					
	(8.91)					
Province-year Ln (1+GPI (invention))			0.484***			
			(9.85)			
Province-year Ln (1+GPI (utility model))					0.447***	
					(15.49)	
Predicted Ln (1+GPI (sum))		0.089***				
		(10.57)				
Predicted Ln (1+GPI (invention))				0.084***		
				(7.66)		
Predicted Ln (1+GPI (utility model))						0.080***
						(10.80)
Firm-level controls and constant	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	No	Yes	No	Yes	No	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	302	302	302	302	302	302
Adjusted R^2	0.712	0.068	0.709	0.066	0.658	0.064
First-stage Cragg and Donald test	*p*-value < 0.001		*p*-value < 0.001		*p*-value < 0.001	
Overidentification test	Equation exactly identified		Equation exactly identified		Equation exactly identified	

Panel B3: Number of discounted green patents

Variables	(1) 1st stage Ln (1+Dis. GP (sum))	(2) 2nd stage ΔROE	(3) 1st stage Ln (1+Dis. GP (invention))	(4) 2nd stage ΔROE	(5) 1st stage Ln (1+Dis. GP (utility model))	(6) 2nd stage ΔROE
Province-year Ln (1+Dis. GP (sum))	0.453***					
	(7.76)					
Province-year Ln (1+Dis. GP (invention))			0.511***			
			(8.78)			
Province-year Ln (1+Dis. GP (utility model))					0.503***	
					(16.21)	
Predicted Ln (1+Dis. GP (sum))		0.070***				
		(8.90)				
Predicted Ln (1+Dis. GP (invention))				0.073***		
				(7.00)		
Predicted Ln (1+Dis. GP (utility model))						0.069***
						(11.58)
Firm-level controls and constant	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	No	Yes	No	Yes	No	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	302	302	302	302	302	302
Adjusted R^2	0.718	0.065	0.718	0.064	0.650	0.064
First-stage Cragg and Donald test	p-value < 0.001		p-value < 0.001		p-value < 0.001	
Overidentification test	Equation exactly identified		Equation exactly identified		Equation exactly identified	

Table 7

Post-merger carbon emissions' growth rate

This table reports the ordinary least squares (OLS) regression results of post-merger carbon emission' growth rate based on completed deals. The dependent variable is *CO2 growth rate*, which is the average growth rate of Scope 2 carbon emissions three years after deal completion. The key independent variable is green innovation, measured by three groups of green patents (GPs) variables, i.e., number of green patents (columns (1) – (3)), green patent index (GPI) (columns (4) – (6)), and number of discounted green patents (columns (7) – (9)). Each group of green patent variables include three variables, one for overall green patents (columns (1), (4), and (7)), the other two for subcategories of overall green patents, i.e., green invention patents (columns (2), (5), and (8)) and green utility model patents (columns (3), (6), and (9)). All variables are defined in Appendix, and all continuous ones are winsorized at the 1st and 99th percentiles. *t*-statistics (in parentheses) for OLS regressions are based on standard errors clustered by bidders' industry, which is defined based on the first one-digit CSRC industry classification of 2012. Year and Industry effects are included in all regressions. *, **, and *** denote significance at 10%, 5%, and 1%. The coefficients on the constant and controls are suppressed for brevity and available upon request.

Variables	(1) CO2 growth rate	(2) CO2 growth rate	(3) CO2 growth rate	(4) CO2 growth rate	(5) CO2 growth rate	(6) CO2 growth rate	(7) CO2 growth rate	(8) CO2 growth rate	(9) CO2 growth rate
Ln (1+GP (sum))	−0.093**								
	(−2.57)								
Ln (1+GP (invention))		−0.024							
		(−0.32)							
Ln (1+GP (utility model))			−0.079**						
			(−2.39)						
Ln (1+GP Index (sum))				−0.108*					
				(−2.09)					
Ln (1+GP Index (invention))					−0.040				
					(−0.42)				
Ln (1+GP Index (utility model))						−0.080			
						(−1.70)			
Ln (1+Dis. GP (sum))							−0.082*		
							(−1.91)		
Ln (1+Dis. GP (invention))								−0.030	
								(−0.34)	
Ln (1+Dis. GP (utility model))									−0.059
									(−1.62)
Controls and constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	117	117	117	117	117	117	117	117	117
Adjusted R^2	0.459	0.444	0.455	0.457	0.445	0.454	0.455	0.445	0.450

Table 8

Post-merger environmental performance

This table reports the ordinary least squares (OLS) regression results of post-merger environmental performance (*Env score*) based on completed deals. The dependent variable is *Env score*, which is measured by the median value of environmental pillar scores three years after deal completion. The key independent variable is green innovation, measured by three groups of green patents (GPs) variables, i.e., number of green patents (columns (1) – (3)), green patent index (GPI) (columns (4) – (6)), and number of discounted green patents (columns (7) – (9)). Each group of green patent variables include three variables, one for overall green patents (columns (1), (4), and (7)), the other two for subcategories of overall green patents, i.e., green invention patents (columns (2), (5), and (8)) and green utility model patents (columns (3), (6), and (9)). All variables are defined in Appendix, and all continuous ones are winsorized at the 1st and 99th percentiles. *t*-statistics (in parentheses) for OLS regressions are based on standard errors clustered by bidders' industry, which is defined based on the first one-digit CSRC industry classification of 2012. Year and Industry effects are included in all regressions. *, **, and *** denote significance at 10%, 5%, and 1%. The coefficients on the constant and controls are suppressed for brevity and available upon request.

Variables	(1) Env score	(2) Env score	(3) Env score	(4) Env score	(5) Env score	(6) Env score	(7) Env score	(8) Env score	(9) Env score
Ln (1+GP (sum))	0.031***								
	(19.83)								
Ln (1+GP (invention))		0.074***							
		(7.77)							
Ln (1+GP (utility model))			0.013**						
			(2.97)						
Ln (1+GP Index (sum))				0.030***					
				(10.03)					
Ln (1+GP Index (invention))					0.066***				
					(7.56)				
Ln (1+GP Index (utility model))						0.012			
						(1.47)			
Ln (1+Dis. GP (sum))							0.031***		
							(7.49)		
Ln (1+Dis. GP (invention))								0.073***	
								(6.09)	
Ln (1+Dis. GP (utility model))									0.019***
									(5.23)
Controls and constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	96	96	96	96	96	96	96	96	96
Adjusted R^2	0.320	0.355	0.312	0.317	0.336	0.311	0.319	0.346	0.314

Table 9

Post-merger environmental compliance costs

This table reports the ordinary least squares (OLS) regression results of post-merger environmental compliance costs (ECC) based on completed deals. The dependent variable is Ln (1+*ECC)*, which is the logarithm of one plus median value of ECCs three years after deal completion. The key independent variable is green innovation, measured by three groups of green patents (GPs) variables, i.e., number of green patents (columns (1) – (3)), green patent index (GPI) (columns (4) – (6)), and number of discounted green patents (columns (7) – (9)). Each group of green patent variables include three variables, one for overall green patents (columns (1), (4), and (7)), the other two for subcategories of overall green patents, i.e., green invention patents (columns (2), (5), and (8)) and green utility model patents (columns (3), (6), and (9)). All variables are defined in Appendix, and all continuous ones are winsorized at the 1st and 99th percentiles. *t*-statistics (in parentheses) for OLS regressions are based on standard errors clustered by bidders' industry, which is defined based on the first one-digit CSRC industry classification of 2012. Year and Industry effects are included in all regressions. *, **, and *** denote significance at 10%, 5%, and 1%. The coefficients on the constant and controls are suppressed for brevity and available upon request.

Variables	(1) Ln (1+ECC)	(2) Ln (1+ECC)	(3) Ln (1+ECC)	(4) Ln (1+ECC)	(5) Ln (1+ECC)	(6) Ln (1+ECC)	(7) Ln (1+ECC)	(8) Ln (1+ECC)	(9) Ln (1+ECC)
Ln (1+GP (sum))	−0.250*								
	(−2.05)								
Ln (1+GP (invention))		−0.117							
		(−0.58)							
Ln (1+GP (utility model))			−0.413*						
			(−2.13)						
Ln (1+GP Index (sum))				−0.394**					
				(−2.91)					
Ln (1+GP Index (invention))					−0.340				
					(−1.33)				
Ln (1+GP Index (utility model))						−0.442**			
						(−2.67)			
Ln (1+Dis. GP (sum))							−0.390***		
							(−3.30)		
Ln (1+Dis. GP (invention))								−0.256	
								(−0.78)	
Ln (1+Dis. GP (utility model))									−0.450**
									(−2.32)
Controls and constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	302	302	302	302	302	302	302	302	302
Adjusted R^2	0.323	0.322	0.324	0.323	0.323	0.324	0.324	0.323	0.324

Table 10

Post-merger patent-related government subsidies

This table reports the ordinary least squares (OLS) regression results of post-merger patent-related government subsidies based on completed deals. The dependent variable is Δ*Patent subsidies*, which is the logarithm of one plus the difference between patent-related government subsidies received by the firm in the third year after deal completion and those for one year prior to CBMA announcement. The key independent variable is green innovation, measured by three groups of green patents (GPs) variables, i.e., number of green patents (columns (1) – (3)), green patent index (GPI) (columns (4) – (6)), and number of discounted green patents (columns (7) – (9)). Each group of green patent variables include three variables, one for overall green patents (columns (1), (4), and (7)), the other two for subcategories of overall green patents, i.e., green invention patents (columns (2), (5), and (8)) and green utility model patents (columns (3), (6), and (9)). All variables are defined in Appendix, and all continuous ones are winsorized at the 1st and 99th percentiles. *t*-statistics (in parentheses) for OLS regressions are based on standard errors clustered by bidders' industry, which is defined based on the first one-digit CSRC industry classification of 2012. Year and Industry effects are included in all regressions. *, **, and *** denote significance at 10%, 5%, and 1%. The coefficients on the constant and controls are suppressed for brevity and available upon request.

Variables	(1) ΔPatent subsidies	(2) ΔPatent subsidies	(3) ΔPatent subsidies	(4) ΔPatent subsidies	(5) ΔPatent subsidies	(6) ΔPatent subsidies	(7) ΔPatent subsidies	(8) ΔPatent subsidies	(9) ΔPatent subsidies
Ln (1+GP (sum))	1.428**								
	(2.61)								
Ln (1+GP (invention))		1.124**							
		(2.99)							
Ln (1+GP (utility model))			1.129						
			(1.56)						
Ln (1+GP Index (sum))				1.544**					
				(2.39)					
Ln (1+GP Index (invention))					1.592***				
					(4.03)				
Ln (1+GP Index (utility model))						1.192			
						(1.45)			
Ln (1+Dis. GP (sum))							1.787**		
							(2.65)		
Ln (1+Dis. GP (invention))								1.397***	
								(3.07)	
Ln (1+Dis. GP (utility model))									1.436
									(1.58)
Controls and constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	225	225	225	225	225	225	225	225	225
Adjusted R^2	0.010	−0.006	−0.003	0.005	0.000	−0.004	0.018	−0.004	0.002

Table 11

The effect of 2012 policy

This table reports the ordinary least squares (OLS) regression results of subgroups analysis based on the 2012 policy. This policy was implemented since August 1, 2012, and the government would prioritize the examination of important patent applications related to green development. Subgroup of announced deals after 2012 is displayed in columns (1), (3), and (5), while subgroup of announced deals before 2012 (including 2012) is displayed in columns (2), (4), and (6). The dependent variable is ΔROE, which is the difference between the combined firm's operating performance for three years after deal completion and the bidder's operating performance for one year prior to CBMA announcement. The key independent variable is green innovation, measured by three groups of green patents (GPs) variables, i.e., number of green patents (Panel A), green patent index (GPI) (Panel B), and number of discounted green patents (Panel C). Each group of green patent variables include three variables, one for overall green patents (columns (1) and (2)), the other two for subcategories of overall green patents, i.e., green invention patents (columns (3) and (4)) and green utility model patents (columns (5) and (6)). All variables are defined in Appendix, and all continuous ones are winsorized at the 1st and 99th percentiles. *t*-statistics (in parentheses) for OLS regressions are based on standard errors clustered by bidders' industry, which is defined based on the first one-digit CSRC industry classification of 2012. Year and Industry effects are included in all regressions. *, **, and *** denote significance at 10%, 5%, and 1%. The coefficients on the constant and controls are suppressed for brevity and available upon request.

Panel A: Number of green patents						
	(1) After 2012 ΔROE	(2) Before 2012 ΔROE	(3) After 2012 ΔROE	(4) Before 2012 ΔROE	(5) After 2012 ΔROE	(6) Before 2012 ΔROE
Ln (1+GP (sum))	0.018*	−0.007				
	(1.95)	(−0.64)				
Ln (1+GP (invention))			0.021*	−0.030		
			(1.92)	(−1.79)		
Ln (1+GP (utility model))					0.003	0.012
					(0.44)	(1.74)
Controls and constant	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	228	74	228	74	228	74
Adjusted R^2	0.061	0.509	0.061	0.526	0.056	0.510
Difference	0.025*		0.051***		−0.009	
p-value	0.0513		0.0000		0.7930	
Panel B: Green patent index (GPI)						
Variables	(1) After 2012 ΔROE	(2) Before 2012 ΔROE	(3) After 2012 ΔROE	(4) Before 2012 ΔROE	(5) After 2012 ΔROE	(6) Before 2012 ΔROE
Ln (1+GP Index (sum))	0.021	0.004				
	(1.60)	(0.34)				
Ln (1+GP Index (invention))			0.027**	−0.023		
			(2.36)	(−1.36)		
Ln (1+GP Index (utility model))					0.004	0.031***
					(0.44)	(3.90)
Controls and constant	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	228	74	228	74	228	74
Adjusted R^2	0.060	0.508	0.062	0.516	0.056	0.521
Difference	0.017		0.050***		−0.027	
p-value	0.1773		0.0001		0.6841	
Panel C: Number of discounted green patents						
Variables	(1) After 2012 ΔROE	(2) Before 2012 ΔROE	(3) After 2012 ΔROE	(4) Before 2012 ΔROE	(5) After 2012 ΔROE	(6) Before 2012 ΔROE
Ln (1+Dis. GP (sum))	0.021*	−0.011				
	(2.08)	(−1.32)				
Ln (1+Dis. GP (invention))			0.026**	−0.037*		
			(2.45)	(−2.13)		
Ln (1+Dis. GP (utility model))					0.004	0.009
					(0.57)	(1.25)
Controls and constant	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	228	74	228	74	228	74
Adjusted R^2	0.061	0.511	0.061	0.530	0.056	0.509
Difference	0.032**		0.063***		−0.005	
p-value	0.0366		0.0000		0.5923	

Table 12

Moderating effect of uncertainty

This table reports the ordinary least squares (OLS) regression results for baseline modules (Eq. (1) and Eq. (3)) with moderating effects of uncertainty. In Panel A1 and B1, the dependent variable is *Completion*, a dummy variable that equals one if an announced deal is recorded as "Completed" in SDC, and zero otherwise. In Panel A2 and B2, the dependent variable is Δ*ROE*, which is the difference between the combined firm's operating performance for three years after deal completion and the bidder's operating performance for one year prior to CBMA announcement. The key independent variable is green innovation, measured by three groups of green patents (GPs) variables, i.e., number of green patents (columns (1) – (3)), green patent index (GPI) (columns (4) – (6)), and number of discounted green patents (columns (7) – (9)). Each group of green patent variables include three variables, one for overall green patents (columns (1), (4), and (7)), the other two for subcategories of overall green patents, i.e., green invention patents (columns (2), (5), and (8)) and green utility model patents (columns (3), (6), and (9)). The moderators include *Physical climate risk* and economic policy uncertainty (*Ln (EPU)*). All variables are defined in Appendix, and all continuous ones are winsorized at the 1st and 99th percentiles. *t*-statistics (in parentheses) for OLS regressions are based on standard errors clustered by bidders' industry, which is defined based on the first one-digit CSRC industry classification of 2012. Year and Industry effects are included in all regressions. *, **, and *** denote significance at 10%, 5%, and 1%. The coefficients on the constant and controls are suppressed for brevity and available upon request.

Panel A: Moderating effect of Physical climate risk

Panel A1: Probability of deal completion

Variables	(1) Completion	(2) Completion	(3) Completion	(4) Completion	(5) Completion	(6) Completion	(7) Completion	(8) Completion	(9) Completion
Ln (1+GP (sum))	0.183***								
	(5.83)								
Ln (1+GP (sum)) × Physical climate risk	0.006*								
	(1.79)								
Ln (1+GP (invention))		0.141***							
		(5.57)							
Ln (1+GP (invention)) × Physical climate risk		0.006***							
		(3.75)							
Ln (1+GP (utility model))			0.213***						
			(5.30)						
Ln (1+GP (utility model)) × Physical climate risk			0.007						
			(1.60)						
Ln (1+GP Index (sum))				0.198***					
				(5.74)					
Ln (1+GP Index (sum)) × Physical climate risk				0.007*					
				(1.74)					
Ln (1+GP Index (invention))					0.149***				
					(4.48)				
Ln (1+GP Index (invention)) × Physical climate risk					0.006***				
					(4.10)				
Ln (1+GP Index (utility model))						0.229***			
						(5.52)			
Ln (1+GP Index (utility model)) × Physical climate risk						0.008			
						(1.59)			

Panel A1 (Continued)

Variables	(1) Completion	(2) Completion	(3) Completion	(4) Completion	(5) Completion	(6) Completion	(7) Completion	(8) Completion	(9) Completion
Ln (1+Dis. GP (sum))							0.203***		
							(5.34)		
Ln (1+Dis. GP (sum)) × Physical climate risk							0.005*		
							(1.93)		
Ln (1+Dis. GP (invention))								0.150***	
								(3.69)	
Ln (1+Dis. GP (invention)) × Physical climate risk								0.006***	
								(4.18)	
Ln (1+Dis. GP (utility model))									0.225***
									(4.73)
Ln (1+Dis. GP (utility model)) × Physical climate risk									0.006*
									(1.72)
Physical climate risk	−0.024***	−0.016***	−0.025***	−0.024***	−0.015**	−0.025***	−0.021***	−0.015**	−0.022***
	(−3.01)	(−2.77)	(−2.90)	(−2.97)	(−2.40)	(−2.88)	(−3.34)	(−2.42)	(−3.32)
Controls and constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	577	577	577	577	577	577	577	577	577
Pseudo R^2	0.198	0.192	0.199	0.197	0.191	0.199	0.197	0.191	0.197

Panel A2: Post-merger operating performance

Variables	(1) ΔROE	(2) ΔROE	(3) ΔROE	(4) ΔROE	(5) ΔROE	(6) ΔROE	(7) ΔROE	(8) ΔROE	(9) ΔROE
Ln (1+GP (sum))	0.0173*								
	(1.91)								
Ln (1+GP (sum)) × Physical climate risk	0.0003***								
	(3.53)								
Ln (1+GP (invention))		0.0153*							
		(1.78)							
Ln (1+GP (invention)) × Physical climate risk		0.0002***							
		(4.65)							
Ln (1+GP (utility model))			0.0072						
			(0.91)						
Ln (1+GP (utility model)) × Physical climate risk			0.0003***						
			(3.69)						
Ln (1+GP Index (sum))				0.0199					
				(1.73)					
Ln (1+GP Index (sum)) × Physical climate risk				0.0003***					
				(3.58)					
Ln (1+GP Index (invention))					0.0213**				
					(2.68)				
Ln (1+GP Index (invention)) × Physical climate risk					0.0003***				
					(4.48)				
Ln (1+GP Index (utility model))						0.0089			
						(0.98)			
Ln (1+GP Index (utility model)) × Physical climate risk						0.0004***			
						(3.79)			
Ln (1+Dis. GP (sum))							0.0190*		
							(2.05)		
Ln (1+Dis. GP (sum)) × Physical climate risk							0.0002***		
							(3.36)		
Ln (1+Dis. GP (invention))								0.0186***	
								(3.07)	
Ln (1+Dis. GP (invention)) × Physical climate risk								0.0002***	
								(4.47)	
Ln (1+Dis. GP (utility model))									0.0079
									(0.99)
Ln (1+Dis. GP (utility model)) × Physical climate risk									0.0003***
									(3.72)
Physical climate risk	−0.0014***	−0.0010**	−0.0015***	−0.0014***	−0.0010**	−0.0014***	−0.0012***	−0.0010**	−0.0013***
	(−4.31)	(−2.71)	(−3.46)	(−4.21)	(−2.48)	(−3.45)	(−3.70)	(−2.41)	(−3.03)
Controls and constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	269	269	269	269	269	269	269	269	269
Adjusted R^2	0.064	0.062	0.059	0.064	0.063	0.059	0.064	0.062	0.059

Panel B: Moderating effect of economic policy uncertainty

Panel B1: Probability of deal completion

Variables	(1) Completion	(2) Completion	(3) Completion	(4) Completion	(5) Completion	(6) Completion	(7) Completion	(8) Completion	(9) Completion
Ln (1+GP (sum))	1.388***								
	(3.10)								
Ln (1+GP (sum)) × Ln (EPU)	−0.246***								
	(−2.78)								
Ln (1+GP (invention))		1.260***							
		(2.68)							
Ln (1+GP (invention)) × Ln (EPU)		−0.229**							
		(−2.46)							
Ln (1+GP (utility model))			1.579***						
			(4.34)						
Ln (1+GP (utility model)) × Ln (EPU)			−0.280***						
			(−4.06)						
Ln (1+GP Index (sum))				1.529***					
				(3.16)					
Ln (1+GP Index (sum)) × Ln (EPU)				−0.268***					
				(−2.77)					
Ln (1+GP Index (invention))					1.286**				
					(2.53)				
Ln (1+GP Index (invention)) × Ln (EPU)					−0.231**				
					(−2.32)				
Ln (1+GP Index (utility model))						1.817***			
						(4.64)			
Ln (1+GP Index (utility model)) × Ln (EPU)						−0.327***			
						(−4.35)			
Ln (1+Dis. GP (sum))							1.468***		
							(3.25)		
Ln (1+Dis. GP (sum)) × Ln (EPU)							−0.257***		
							(−2.94)		
Ln (1+Dis. GP (invention))								1.381***	
								(2.79)	
Ln (1+Dis. GP (invention)) × Ln (EPU)								−0.248***	
								(−2.67)	
Ln (1+Dis. GP (utility model))									1.912***
									(4.69)
Ln (1+Dis. GP (utility model)) × Ln (EPU)									−0.345***
									(−4.47)
Ln (EPU)	0.307**	0.195	0.257	0.267**	0.171	0.257	0.265*	0.173	0.258
	(2.35)	(1.28)	(1.50)	(1.97)	(1.11)	(1.47)	(1.79)	(1.06)	(1.44)
Controls and constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	429	429	429	429	429	429	429	429	429
Pseudo R^2	0.217	0.211	0.217	0.216	0.210	0.217	0.216	0.210	0.218

Panel A2: Post-merger operating performance

Variables	(1) ΔROE	(2) ΔROE	(3) ΔROE	(4) ΔROE	(5) ΔROE	(6) ΔROE	(7) ΔROE	(8) ΔROE	(9) ΔROE
Ln (1+GP (sum))	0.074**								
	(2.30)								
Ln (1+GP (sum)) × Ln (EPU)	−0.009								
	(−1.22)								
Ln (1+GP (invention))		0.099***							
		(5.68)							
Ln (1+GP (invention)) × Ln (EPU)		−0.015**							
		(−2.83)							
Ln (1+GP (utility model))			0.104*						
			(1.82)						
Ln (1+GP (utility model)) × Ln (EPU)			−0.016						
			(−1.27)						
Ln (1+GP Index (sum))				0.080**					
				(2.22)					
Ln (1+GP Index (sum)) × Ln (EPU)				−0.009					
				(−1.10)					
Ln (1+GP Index (invention))					0.133***				
					(5.95)				
Ln (1+GP Index (invention)) × Ln (EPU)					−0.020***				
					(−3.05)				
Ln (1+GP Index (utility model))						0.116*			
						(1.89)			
Ln (1+GP Index (utility model)) × Ln (EPU)						−0.017			
						(−1.30)			
Ln (1+Dis. GP (sum))							0.089**		
							(2.69)		
Ln (1+Dis. GP (sum)) × Ln (EPU)							−0.011		
							(−1.46)		
Ln (1+Dis. GP (invention))								0.107***	
								(8.03)	
Ln (1+Dis. GP (invention)) × Ln (EPU)								−0.015***	
								(−3.38)	
Ln (1+Dis. GP (utility model))									0.139**
									(2.34)
Ln (1+Dis. GP (utility model)) × Ln (EPU)									−0.022
									(−1.73)
Ln (EPU)	0.055***	0.054***	0.054***	0.053***	0.056***	0.053***	0.056***	0.053***	0.056***
	(7.56)	(4.50)	(7.06)	(7.67)	(4.64)	(7.38)	(7.57)	(4.27)	(6.87)
Controls and constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	204	204	204	204	204	204	204	204	204
Adjusted R^2	0.035	0.030	0.032	0.035	0.032	0.033	0.037	0.031	0.033

Appendix Table A1: Variable definitions

Panel A1: Variable definitions

Variables	Definition
Dependent variables	
Completion	Dummy variable that equals one if an announced deal is recorded as "Completed" in SDC, and zero otherwise. (*Data Source*: Refinitiv Eikon (SDC))
CAR (−3, 3)	Cumulative abnormal returns (CARs) are calculated using the market model in the spirit of Deng et al. (2013), with an estimation period from 210 days to 11 days before the announcement day (day 0). At least 100 trading days over the estimation window are required for a bidder in the sample (Fee and Thomas, 2004). We employ a seven-day event window (−3, 3) around day 0. (*Data Source*: CSMAR)
△ROE	The difference between the combined firm's return on equity (ROE) in the third year after deal completion and the bidder's ROE for one year prior to CBMA announcement year, in the spirit of Fee and Thomas (2004) and Schweizer et al. (2019). (*Data Source*: CSMAR)
Green patent variables	
GP dummy	Dummy variable that equals one if a bidder has at least one green patent (GP) that was applied within five years prior to the announcement year and eventually granted within our sample periods, and zero otherwise; in the spirit of Chen et al. (2022). (*Data Source*: CSMAR)
Ln (1+GP (sum))	Natural logarithm of one plus the aggregated number of green patents that were applied within five years prior to the announcement year and eventually granted within our sample periods, in the spirit of previous literature (Kim et al., 2020; Hu et al., 2021b; Kim et al., 2021; Zhou et al., 2021b). (*Data Source*: SIPO and WIPO)
Ln (1+GP (invention))	Natural logarithm of one plus the aggregated number of green *invention* patents that were applied within five years prior to the announcement year and eventually granted within our sample periods. (*Data Source*: SIPO and WIPO)
Ln (1+GP (utility model))	Natural logarithm of one plus the aggregated number of green *utility model* patents that were applied within five years prior to the announcement year and eventually granted within our sample periods. (*Data Source*: SIPO and WIPO)
Ln (1+GPI (sum))	Green patent index (GPI) is constructed in three steps in the spirit of Bena and Li (2014). First, for each technology class *k* in the IPC Green Inventory and green patent application year *t*, we calculate the median value of the number of applied and eventually granted green patents in technology class *k* with application year *t* across all Chinese bidders with *GP dummy* equal to one in our sample. Second, we scale the number of applied and eventually granted green patents to the Chinese bidder in technology class *k* with application year *t* by the corresponding (class− and application year-specific) median value from the first step. Third, for each Chinese bidder, we aggregate the scaled number of applied and eventually granted patents from the second step across all technology classes and across application years from year *t−5* to year *t−1*. We apply the natural logarithm of one plus GPI in the empirical analyses. A complete IPC classification code is made up of the combined symbols standing for the section (1st level), class (2nd level), subclass (3rd level), and main group (4th level) or subgroup (lower level). For example, in "C02F 1/14" (Treatment of water, wastewater, or sewage using solar energy), "C" is the section of "Chemistry; Metallurgy"; "C02" is the class of "Treatment of water, wastewater, sewage or sludge"; "C02F" is the subclass symbol; "C02F 1/00" is the main group symbol, and "C02F 1/14" is the subgroup symbol. (See WIPO's "Guide to the International Patent Classification" for more details.) In their Internet Appendix, Bena and Li (2014) employ the second level of IPC classification to define the technology class, i.e., the first three-digit IPC code, similar to the three-digit CPC code used by Gao and Li (2021). Therefore, we define a technology class as a 3-digit main IPC code as well. (*Data Source*: SIPO and WIPO)
Ln (1+GPI (invention))	Natural logarithm of one plus green *invention* patent index. (*Data Source*: SIPO and WIPO)
Ln (1+GPI (utility model))	Natural logarithm of one plus green *utility model* patent index. (*Data Source*: SIPO and WIPO)
Ln (1+Dis. GP (sum))	Discounted number of green patent (GP) is computed as (number of GP in year *t−1* + 0.8*number of GP in year *t−2* + 0.6*number of GP in year *t−3* + 0.4*number of GP in year *t−4* + 0.2*number of GP in year *t−5*) in the spirit of Frésard et al. (2020). Number of GP in year *t−1* means the number of green patents that were applied in year *t−1* and eventually granted within our sample periods, and so forth. Then we take the natural logarithm of one plus the discounted GP in the empirical analyses. (*Data Source*: SIPO and WIPO)
Ln (1+Dis. GP (invention))	Natural logarithm of one plus discounted number of green *invention* patents. (*Data Source*: SIPO and WIPO)
Ln (1+Dis. GP (utility model))	Natural logarithm of one plus discounted number of green *utility model* patents. (*Data Source*: SIPO and WIPO)

Panel A1 (Continued)

Variables	Definition
Country-specific variables	
Distances	*Distances* in this paper include *Cultural distance* and *Institutional distance*. Both affect the selection of target locations and are associated with foreign entry strategy in CBMAs (Xu and Shenkar, 2002). *Cultural distance* is computed as the cultural difference between the host economies and China following Kogut and Singh (1988). The national culture data is from Geert Hofstede's website. (*Data Source*: Geert Hofstede's website) *Institutional distance* measures the difference/similarity in institutional development and quality between the host economies and China in year *t−1* following Chan et al. (2008). The data is extracted from the Worldwide Governance Indicators (WGI) developed by the World Bank. (*Data Source*: World Bank: WGI)
GDP growth	Growth rate of target economy's gross domestic product (GDP) in year *t–1*. (*Data Source*: CSMAR)
Firm-specific variables	
B/M ratio	Market−to−book ratio, calculated as the bidder's market value of equity over its book value of equity in year *t–1*. (*Data Source*: CSMAR)
Firm size	Natural logarithm of one plus the bidder's total assets in year *t–1*. (*Data Source*: Refinitiv Eikon (SDC))
Ln (1+FCF)	Natural logarithm of one plus the bidder's free cash flow in year *t–1*. (*Data Source*: CSMAR)
Leverage	Bidder's book value of total liabilities over its book value of total assets in year *t–1*. (*Data Source*: CSMAR)
Ln (1+Listed age)	Natural logarithm of one plus the number of years between the bidder's IPO (initial public offerings) year and year *t–1*. (*Data Source*: CSMAR)
Listed overseas	Dummy variable that equals one if the bidder is cross listed overseas in year *t–1*, and zero otherwise. (*Data Source*: CSMAR)
ROA	Return on total assets (ROA), calculated as bidder's net profit over its total assets in year *t–1*. (*Data Source*: CSMAR)
SOE	Dummy variable that equals one if the equity nature of public bidder's actual controller is recorded as SOE in year *t−1* in the database. (*Data Source*: CSMAR)
Ln (1+Patents (sum))	Natural logarithm of one plus the aggregated number of general patents that were applied within five years prior to the announcement year and eventually granted within our sample periods, in the spirit of Kim et al. (2021). (*Data Source*: SIPO)
R&D/Total assets	Bidder's research and development (R&D) expenses over its total assets in year *t–1* following Bena and Li (2014). (*Data Source*: CSMAR)
Deal-specific variables	
All cash deal	Dummy variable that equals one if the CBMA deal is paid in all cash, and zero otherwise. (*Data Source*: Refinitiv Eikon (SDC))
Financial/Legal advisor	Dummy variable that equals one if the bidder employs at least one financial or legal advisor in a CBMA deal, and zero otherwise. (*Data Source*: Refinitiv Eikon (SDC))
High-tech target firm	Dummy variable that equals one if the target firm operates in high-tech industry, and zero otherwise. (*Data Source*: Refinitiv Eikon (SDC))
Past CBMA experience	Natural logarithm of one plus the accumulated number of completed CBMA deals by firm *i* prior to the focal deal announcement, in the spirit of Dikova et al. (2010). (*Data Source*: Refinitiv Eikon (SDC))
Public target	Dummy variable that equals one if the target firm is publicly traded (coded as "Public" in SDC), and zero otherwise. (*Data Source*: Refinitiv Eikon (SDC))
Ln (1+Relative deal size)	Natural logarithm of one plus relative deal size ratio, calculated as deal value over market value of the bidder's equity in year *t–1*. (*Data Source*: Refinitiv Eikon (SDC) and CSMAR)
Same industry	Dummy variable that equals one if the bidding and target firms operate in the same industry, and zero otherwise. (*Data Source*: Refinitiv Eikon (SDC))
Tender offer	Dummy variable that equals one if the deal is a tender offer, and zero otherwise. (*Data Source*: Refinitiv Eikon (SDC))
Additional variables	
BHAR (0, 60) *BHAR (0, 90)* *BHAR (0, 120)*	In the spirit of Chakrabarti et al. (2009) and Loughran and Vijh (1997), buy−and−hold abnormal returns (BHARs) are computed by geometrically compounding the bidder's daily returns during the period of 60, 90, and 120 days after the announcement date (day 0), respectively, then subtracting the market returns calculated in an analogous way. (*Data Source*: CSMAR)
Bidder's CSR	Raw CSR rating score divided by 100 following Zhou et al. (2021a). CSR data is available from 2010 and stopped updating in 2018. We require one-year lagged CSR measure in multivariate analysis and replace missing values with the average value of lagged three-year data. (*Data Source*: Hexun)

Panel A1 (Continued)

Variables	Definition
CAR (−3, 3)_FF3	Cumulative abnormal returns (CARs) are calculated using the Fama-French three-factor (FF3) model in the spirit of Liu et al. (2019), with an estimation period from 210 days to 11 days before the announcement day (day 0). At least 100 trading days over the estimation window are required for a bidder in the sample (Fee and Thomas, 2004). We employ a seven-day event window (−3, 3) around day 0. (*Data Source*: CSMAR) The regression estimated is: $$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + e_{it}$$ where R_{it} is the return on bidder i for day t, R_{Ft} represents the risk−free return, R_{Mt} stands for the return on the value−weight (VW) market portfolio, $(R_{Mt} - R_{Ft})$ is the excess market return, SMB_t denotes the return on a diversified portfolio consisting of small stocks minus the return on a diversified portfolio of large stocks, HML_t represents the difference between the returns on diversified portfolios of high and low B/M (book−to−market) stocks, and e_{it} is a residual term with a zero mean. The values of $(R_{Mt} - R_{Ft})$, SMB_t, and HML_t are extracted from CSMAR database.
CAR (−3, 3)_FF5	Cumulative abnormal returns (CARs) are calculated using the Fama-French five-factor (FF5) model in the spirit of Fama and French (2015), with an estimation period from 210 days to 11 days before the announcement day (day 0). At least 100 trading days over the estimation window are required for a bidder in the sample (Fee and Thomas, 2004). We employ a seven-day event window (−3, 3) around day 0. (*Data Source*: CSMAR) The regression estimated is: $$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + e_{it}$$ where RMW_t denotes the difference in returns between diversified portfolios comprised of stocks with strong and weak profitability, and CMA_t represents the difference in returns between diversified portfolios of stocks from low and high investment firms. The values of $(R_{Mt} - R_{Ft})$, SMB_t, HML_t, RMW_t, and CMA_t are extracted from CSMAR database.
CO2 growth rate	Average growth rate of Scope 2 carbon emissions three years after deal completion. Scope 2 carbon emissions are from consumption of purchased electricity, heat, or steam by the company (categorized by the Greenhouse Gas Protocol). (*Data Source*: S&P Capital IQ / Trucost)
Env score	Median value of environmental pillar scores three years after deal completion, then divided by 100. (*Data Source*: Refinitiv ESG)
Instrumental variables (IVs)	*Province-year Ln (1+GP (sum))*: Province-year mean of Ln (1+GP (sum)). *Province-year Ln (1+GP (invention))*: Province-year mean of Ln (1+GP (invention)). *Province-year Ln (1+GP (utility model))*: Province-year mean of Ln (1+GP (utility model)). *Province-year Ln (1+GPI (sum))*: Province-year mean of Ln (1+GPI (sum)). *Province-year Ln (1+GPI (invention))*: Province-year mean of Ln (1+GPI (invention)). *Province-year Ln (1+GPI (utility model))*: Province-year mean of Ln (1+GPI (utility model)). *Province-year Ln (1+Dis. GP (sum))*: Province-year mean of Ln (1+Dis. GP (sum)). *Province-year Ln (1+Dis. GP (invention))*: Province-year mean of Ln (1+Dis. GP (invention)). *Province-year Ln (1+Dis. GP (utility model))*: Province-year mean of Ln (1+Dis. GP (utility model)).
Ln (1+ECC)	Median value of environmental compliance costs (ECCs) three years after deal completion. ECC is constructed in the spirit of Tian et al. (2023). Specifically, environmental compliance costs are related to environment and sustainable development reported in firms' Social Responsibility Reports. For missing values, we extract relevant data from firms' annual reports, which are recorded (1) under "administrative expenses" as "pollution discharge fee", "environmental protection fee", "greening fee", "cleaner production fee", "garbage treatment fee", and "environmental protection expenditure" (The *Environmental Protection Tax Law of the People's Republic of China* came into effect on January 1, 2018, therefore, part of fees were transferred to tax, e.g., "pollution discharge fee" to "environmental protection tax", which are recorded under "business tax and surcharges" as "environmental protection tax", "environment tax", "green fund tax", and "carbon emissions tax"), or (2) under "other cash paid related to operating activities" as "pollution discharge fee", "environmental protection fee", "greening fee", "cleaner production fee", "garbage treatment fee", and "environmental protection expenditure". If both methods provide relevant data, we use the mean value to replace the missing values. If neither provide relevant data, we replace missing values with zero. Then we apply the logarithm of one plus median ECC in multivariate regressions. These relevant data in firms' annual reports and Social Responsibility Reports are available in CSMAR database. (*Data Source*: CSMAR)
Ln (EPU)	Logarithm of annual economic policy uncertainty (EPU) index. Following previous literature (Jia and Li, 2020), annual EPU index is the mean of monthly EPU in a year developed by Baker et al. (2016), covering the following target economies in our sample: Australia, Brazil, Canada, Chile, France, Germany, Greece, India, Ireland, Italy, Japan, Mexico, Netherlands, Russia, Singapore, South Korea, Spain, Sweden, United Kingdom, United States. (*Data Source*: Economic Policy Uncertainty Index)

Panel A1 (Continued)

Variables	Definition
∆Patent subsidies	Logarithm of one plus the difference between patent-related government subsidies received by a firm in the third year after deal completion and one year prior to CBMA announcement. (*Data Source*: CSMAR)
Physical climate risk	Measured by Heat Index 35, which is total count of days per year where the daily mean Heat Index rose above 35°C. A Heat Index is a measure of how hot it feels once humidity is factored in with air temperature. Hong Kong and Taiwan are not covered and not every target economy has consecutive data across all years. (*Data Source*: World Bank / Sovereign ESG Data Portal)
△ROIC	The difference between the combined firm's return on invested capital (ROIC) in the third year after deal completion and the bidder's ROIC for one year prior to CBMA announcement year, in the spirit of O'Shaughnessy and Flanagan (1998). (*Data Source*: CSMAR)
Target economy's climate risk	Measured by Global Climate Risk Index (CRI) constructed by Germanwatch following Li et al. (2023). The larger the CRI, the lower the target economy's climate risk. We take the negative value in the regressions, therefore, the larger the value, the higher the climate risk. We also generate a dummy variable (*Climate risk>China*) that equals one if the target economy's climate risk is higher than China's. The CRI data is as of 2019 and does not cover the following target economies in our sample: Egypt, Mali, and Zambia. In addition, not every target economy has consecutive data across all years. (*Data Source*: Germanwatch)
Target economy's GP	Logarithm of one plus the number of environmental patents in a target economy. We also create a dummy variable (*GP>China*) that equals one if the target economy's number of environmental patents is greater than China's. The following target economies are not covered in our sample: Cambodia, Congo (DRC), Gabon, Iraq, Malawi, Mauritania, Mozambique, Myanmar, Sri Lanka, Taiwan, Tanzania, and Uganda. And we replace missing values with zero. (*Data Source*: WIPO IP Statistics Data Center)

Panel A2: Construction of Corporate Governance Index (CGI)

Governance mechanism	Definitions (*Data Source*: CSMAR)
Board independence	Dummy, one if the number of independent directors on the Board of bidder *i* in fiscal year *t−1* is greater than the mean value of the sample in fiscal year *t−1* and zero otherwise.
Board meeting	Dummy, one if the number of the Board meeting of bidder *i* in fiscal year *t−1* is less than the mean value of the sample in fiscal year *t−1* and zero otherwise.
Board size	Dummy, one if the number of directors on the board of directors (the Board) of bidder *i* in fiscal year *t−1* is less than the mean value of the sample in fiscal year *t−1* and zero otherwise.
Chairman age	Dummy, one if the age of the Board chairman of of bidder *i* in fiscal year *t−1* is less than the mean value of the sample in fiscal year *t−1* and zero otherwise.
Chairman tenure	Dummy, one if the tenure (number of years that the chairman has been in office) of the chairman of bidder *i* in fiscal year *t−1* is less than the mean value of the sample in fiscal year *t−1* and zero otherwise.
Foreign auditor	Dummy, one if bidder *i* in fiscal year *t−1* hires a foreign auditor (including "big4" and other auditors outside mainland China) and zero otherwise.
Ownership concentration	Dummy, one if the proportion of shares held by the corporate largest shareholder of bidder *i* in fiscal year *t−1* is greater than the mean value of the sample in fiscal year *t−1* and zero otherwise.
State-owned shares	Dummy, one if the proportion of state−owned shares of bidder *i* in fiscal year *t−1* is no greater than 5% and zero otherwise.
Supervisory board size	Dummy, one if the number of supervisors on the board of supervisors of bidder *i* in fiscal year *t−1* is greater than the mean value of the sample in fiscal year *t−1* and zero otherwise.

Appendix Table A2: Sample selection criteria

Selection criteria	Deal number
(1) All M&A attempts made by Chinese firms between 2007 and 2021	72,599
(2) The target firm is outside mainland China (i.e., cross-border deal)	5,512
(3) The deal value is available and greater than zero	3,438
(4) The percentage acquired has to be available	3,095
(5) Excluded deals with target locations in tax heavens or offshore financial centers	3,054
(6) Neither the Chinese bidders nor the foreign targets are from the financial industry	1,703
(7) Chinese bidders are publicly traded in stock exchanges in mainland China before the announcement year	668