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 internationalization via CBMAs. We show that green innovative bidders are more likely to complete CBMA deals successfully and realize higher short- and long-term abnormal returns. Furthermore, acquirers with a better green innovation profile achieve better post-merger operating performance, which could be induced by lower carbon emissions, superior environmental performance, and greater government subsidies in the long run after CBMA deal completion. These findings suggest that green innovative 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; China

JEL codes: G32; G34; M14.

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, as the latter almost always face problems such as the liability of foreignness, newness, and origin (Hawn, 2020), as well as uncertainties (Arouri et al., 2019). Cross-border bidders from emerging market economies (EMEs) are particularly vulnerable to legitimacy judgments made by host market stakeholders due to lack of overseas expansion experience (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 sustainable development (Metz et al., 2000). Compared to general innovation activities, green innovation is more strongly orientated toward corporate social responsibility (CSR) and environmental concern. Therefore, we posit that cross-border bidders from EMEs could leverage green innovative capability to respond to their encountered legitimacy concerns over climate-change-related challenges from host market stakeholders. Although previous studies have investigated the impact of general innovation on M&As or CBMAs (Zhao, 2009; Bena and Li, 2014; Wu and Chung, 2019; Frésard et al., 2020; Vissa and Thenmozhi, 2022), or the impact of green innovation on CBMA completion probability only (Gao et al., 2022), they have mainly emphasized the aspect of competitive advantage brought about by general innovation, without focusing on green innovation and its systematic effect on EME firms' internationalization via CBMAs. We intend to fill this gap by examining the systematic impact of corporate green innovation on completion probability, short- and long-run wealth effect, post-merger operating performance, and the underlying mechanisms of such impact.

We select CBMAs attempted by Chinese bidders to construct our sample for empirical analysis. 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). Studies on Chinese bidders' legitimacy challenges during the process of CBMAs have attracted widespread attention from researchers and scholars in recent years (Wan and Wong, 2009; Li et al., 2019; Schweizer et al., 2019; Gao et al., 2022). Meanwhile, as China has set itself 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/or granted green patents in China.[1] Benefiting from these green innovative technologies, China's carbon emission intensity in 2020 dropped by 48.4% compared to 2005, exceeding the target that it promised the international community it would reach.[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. Furthermore, 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

[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.

[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.

increase public interest (Lin et al., 2015). Ultimately, China provides a good opportunity 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 profiles at firm level using the total number of green patents granted within our sample periods (*Number of green patents*, including two types of invention and utility model), and systematically investigate the completion probability, wealth effect from capital market, and real economic outcome in terms of post-merger operating performance of the CBMAs proposed by Chinese bidders. We find consistent and strong evidence that green innovation prior to the announcement positively contributes to Chinese bidders' internationalization experience. Specifically, green innovative bidders are more likely to complete a CBMA deal successfully and realize higher short- and long-run abnormal returns. Acquiring firms with better green innovation profile also tend to achieve better post-merger operating performance. Next, we further investigate three underlying channels of operating performance, and find that lower carbon emissions, better environmental performance, and larger patent-related government subsidies in the long run after CBMA deal completion together contribute to improvement in post-merger operating performance.

We conduct a battery of robustness tests on our reported 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 windows to calculate the abnormal returns in the short and long run. Third, we employ the instrumental variable approach and matched samples to address potential endogeneity concerns. Our conclusions remain intact following all of these robustness checks. Overall, these empirical results are consistent with our central hypothesis that a green innovation profile can help bidders alleviate legitimacy concerns from host market stakeholders. A firm's green innovation profile demonstrates their capabilities and commitment to substantially reduce carbon emissions and improve environmental performance 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 strengthen our confidence in the reported findings on the impact of corporate 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 CBMA completion, capital market reactions, and post-merger operating performance. More importantly, we document three potential channels through which green innovation could help to improve corporate operating performance in the context of CBMAs. Benefitting from green innovative technologies, firms could reduce carbon emissions and improve corporate environmental performance, both of which could contribute to a better corporate reputation and a reduction in compliance cost, resulting in a favorable real economic outcome for merged firms. In addition, being able to gain a larger amount of government subsidies for innovative activities could directly improve merged firms' financial status and alleviate potential financial distress risk.

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. The most recent paper by Gao et al. (2022) regards 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 corporate green innovation profile, as a demonstration of a firm's capability and commitment to address climate-change- and environment-related risks, rather than being a marketing tool, can have a positive influence on their internationalization via CBMAs. Apart from deal completion probability, we provide systematic evidence on how green innovation could affect other CBMA outcomes (i.e., capital market reactions and real economic impact in terms of post-merger performance).

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 our extended channel analysis, we provide evidence that green innovative acquirers in "two high" industries are likely to decrease long-run carbon emissions after CBMA deal completion, supporting the trend of carbon reductions through green technologies.

Our paper proceeds as follows: Section 2 reviews the prior 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 a series of CBMA outcomes and includes extended analyses 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 put, 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]

[3] These factors include firm-level characteristics (e.g., venture capital, ownership structure, corporate governance,

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 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

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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.

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 through three potential underlying channels.

First, green innovation in nature is conducive to reducing carbon emissions, helping bidders mitigate climate-change-related risks, decrease compliance costs, 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 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 and win the favor of investors, increasing the likelihood of completion and receiving positive market reactions in the short and long run. In addition, green innovation helps to reduce compliance costs (Berrone et al., 2013), thereby promoting the bidder's post-merger operating performance.

Second, green innovation can provide cross-border bidders with a pro-environment image, good reputation, superior environmental performance, and differentiated competitive

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

advantages, 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. 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.

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 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 stated that focusing on other stakeholders' concerns would ultimately benefit shareholders in the long run. Therefore, green innovative bidders tend to realize higher market returns and better post-merger operating performance.

Third, 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 hypotheses.

H1: Green innovative bidders are more likely to complete proposed CBMA transactions successfully, realize higher abnormal returns in the short and long term, and achieve better post-merger operating performance.

H2a: Green innovative bidders are more likely to reduce carbon emissions in the long term.

H2b: Green innovative bidders are more likely to improve environmental performance in the long term.

H2c: Green innovative bidders are more likely to obtain larger government subsidies in the long term.

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),[5] and apply the following screening criteria. 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.

Table 1 presents the sample distribution of CBMA deals attempted by Chinese bidders. In

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[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 because this is the latest year for which required financial data could be extracted.

[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.

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.[7] Most of the deals 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

[7] 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.

Hong Kong (11.53% (9.69%)), Australia (8.23% (9.12%)), Canada (6.89% (7.98%)), and Germany (6.59% (5.98%)).

3.2 Measures of green innovation

Based on the definition outlined in subsection 2.2, we use green patents to measure green innovation. The green patent 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).[8] Compared with patent databases in English (e.g., PATSTAT, Espacenet, and Google Patents),[9] 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.[10] 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),[11] following previous literature (Albino et al., 2014; Cui et al.,

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[8] 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.

[9] 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/.

[10] 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.

[11] 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

2018; Zhang et al., 2019; Zhu et al., 2019; Hong et al., 2021; Hu et al., 2021b; Tang et al., 2021; Zhou et al., 2021; 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 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.[12] 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.[13] Due to the lowest novelty and there being no coverage of IPC

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.

[12] 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.

[13] 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).

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.[14] 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., 2021), 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

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

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., 2021; Xiang et al., 2022).

3.3 Measures of deal completion, and short- and long-run performance

Our first dependent variable of interest is the probability of deal completion (*Completion*), which is a dummy variable, equal to one if an announced deal is recorded as "Completed" in SDC, and zero otherwise. The second dependent variable of our interest is the short-run market reactions to the CBMA announcements, measured by cumulative abnormal returns (CARs). To compute the bidder's CAR, we estimate the market model parameters in the spirit of Deng et al. (2013) and adopt a five-day event window (−2, 2) 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. For robustness, we employ a seven-day event window (−3, 3) as well.

To complete the full picture of gauging the value implications of CBMAs, we also examine long-run stock market reactions and long-run operating performance. The former is proxied by one- and five-year post-merger buy-and-hold abnormal returns (BHARs), and the latter is measured by one-year post-merger return on equity (*ROE (0, 1)*) and the median of five-year post-merger ROEs (*ROE (0, 5)*), respectively. In the spirit of previous work (Loughran and Vijh, 1997; Chakrabarti et al., 2009), long-term BHARs are calculated for one year and five years following the month of effective/completed date (month 0), namely months (0, 12) and (0, 60), respectively, by geometrically compounding the bidder's monthly returns during the period and then subtracting the market benchmark in China. In addition, we further explore other post-merger performances, namely carbon emissions, environmental performance, and government subsidies. Carbon emissions include one-year and the median of five-year post-merger carbon emissions (*CO2 (0, 1)* and *CO2 (0, 5)*), while we mainly focus on Scope 1 carbon emissions because their sources are directly owned or controlled by the bidder and calculate the ratio of absolute carbon emissions to the bidder's total assets. Environmental performance is measured by environmental rating scores (*Environment (0, 1)* and *Environment (0, 5)*), retrieved from Refinitiv (formerly ASSET4) ESG database (i.e., Environment Pillar Scores). Government subsidies refer to patent-related government subsidies received by the bidder within one and five years after deal completion (*Subsidy (0, 1)* and *Subsidy (0, 5)*). The detailed variable definitions can be found in Appendix.

3.4 Control variables

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*) 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*) 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 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*, 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*). Detailed information for all control variables is provided in

Appendix.

3.5 Empirical settings

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. 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 3.3 at a time in the regressions. CLV_i, FLV_i, and DLV_i are control variables specified in subsection 3.4. 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.

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, we check the bidder's annual reports and online financial resources (e.g., *Sina Finance*) for complementary information. Sources of other variables can be found in Appendix. Moreover, all continuous variables used in the regressions are winsorized at the 1% and 99% level.

Next, we start our analyses of how the market reacts to CBMAs initiated by green innovative bidders in the short and long run by using a standard event study method. Eq. (2) and Eq. (3) are used to examine the short-term and long-term market reactions to CBMAs by green innovative bidders, respectively.

$$CAR_i = \alpha_1 + \beta_2 GP_i + \theta_1 CLV_i + \theta_2 FLV_i + \theta_3 DLV_i + Year + Industry + \varepsilon_i \quad \text{Eq. (2)}$$

$$BHAR_i = \alpha_1 + \beta_3 GP_i + \theta_1 CLV_i + \theta_2 FLV_i + \theta_3 DLV_i + Year + Industry + \varepsilon_i$$

Eq. (3)

where CAR_i in Eq. (2) measures the short-term market reactions to the green innovative bidder i during the period beginning two days before and ending two days after the CBMA announcement and $BHAR_i$ in Eq. (3) measures the long-term market reactions to the green innovative bidder *i* during the period of 12 months or 60 months after the month of cross-border deal completion. Other settings in both Eq. (2) and Eq. (3) are the same as those in Eq. (1).

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 mean of 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.

For completeness, we further form two different control samples to explore other long-term performances of CBMAs completed by green innovative bidders. As Zhao (2009) points out, the matching method can alleviate the possible nonlinearity issue due to smaller sample size relative to the population of all firms. In addition, we select control firms following the steps outlined below in the spirit of Bena and Li (2014). First, we require that matching firms were neither bidders in the five-year period before the focal deal announcement year t nor financially troubled firms (e.g., delisted firms or firms with special treatment). Second, bidders and matching firms operated in the same industry in year $t-1$, where industry definitions are based on the first digit of CSRC (2012) industry code. Third, we select the control firm closest in size to the bidding firm in year $t-1$.[15] After the above matching process, we also check the availability of required financial data for both acquiring and matched firms. Lastly, we estimate the following multivariate regression.

$$Perf_i = \alpha_1 + \beta_4 GP_i + \beta_5 GP_i \times Treat_i + \beta_6 Treat_i + \theta_2 FLV_i + Year + Industry + \varepsilon_i \quad \text{Eq. (4)}$$

where $Perf_i$ stands for a battery of long-term post-merger outcome variables as defined in subsection 3.2, namely post-merger operating performance (*ROE (0, 1)* and *ROE (0, 5)*), post-merger carbon emissions (*CO2 (0, 1)* and *CO2 (0, 5)*), post-merger government subsidies (*Subsidy (0, 1)* and *Subsidy (0, 5)*), and post-merger environmental performance (*Environment (0, 1)* and *Environment (0, 5)*). $Treat_i$ is a dummy variable that equals one if firm i is the acquirer that completed a CBMA deal, and zero otherwise. All other variables are as described in previous equations. The coefficient on the interaction term (β_5) is primarily of our interest and we expect β_5 to be significantly negative when the dependent variable is post-merger carbon emissions, while significantly positive when the dependent variable is any of the other three outcome variables.

For robustness, we keep the former two steps and compute the propensity score for each firm in the third step by estimating the logit regression in which the independent variables are firm size, B/M ratio, and leverage, in the spirit of Bena and Li (2014) and Deng et al. (2013), and then we choose the control firm with the propensity score closest to the bidding firm.

[15] In the spirit of Fee and Thomas (2004), "closest in size" here means that the total assets of matching firms are between 90% and 110% of the bidding firms' total assets.

3.6 Summary statistics

Panel A of Table 2 presents the summary statistics for CBMAs attempted by Chinese bidders between 2007 and 2021. It shows that the average completion rate is 52.5%; the average GDP growth for the target economies is 2.5% (2.4%) in the sample of announced (completed) deals; 8.1% (9.7%) of the sample bidders are listed overseas, 11.2% (12.8%) are SOEs, 39.4% (55.6%) employed at least one financial or legal advisor in initiating cross-border deals; 26.9% (31.3%) of the announced (completed) deals sample were paid fully in cash and 1.3% (2%) were tender offers; 29% (29.3%) of the sample target firms operate in a high-tech industry; and 47% (49.9%) 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 *GDP growth*, *Leverage*, and *Ln (1+Listed age)*.

− insert Table 2 about here −

Panel B1 of Table 2 displays the differences in summary statistics for acquiring and matched firms using industry-, year-, and firm size-matching. It is clear that there is no significant difference in firm size for acquiring and matched firms. However, acquiring firms' ROE (ROA) is significantly greater than that of matched firms, while carbon emissions, B/M ratio, CGI, free cash flow, leverage, and listed age for acquiring firms are significantly smaller than those for matched firms. Panel B2 of Table 2 displays the differences in summary statistics for acquiring and matched firms using industry, year, firm size, B/M ratio, and leverage matching. Again, acquiring and matched firms show no significant differences in firm size, B/M ratio, and leverage. Long-term carbon emissions, CGI, and free cash flow for acquiring firms are still significantly less than those for matched firms, while environmental score and GP variables for acquiring firms are significantly larger than those for matched firms. Overall, the significant differences in ROE, carbon emissions, and environmental score meet our expectations, and we will further conduct multivariate analyses by controlling for other factors.

Panel C of Table 2 presents the univariate tests for short- and long-run abnormal returns. We only find that long-run abnormal returns, i.e., BHAR (0, 60), for bidders with green innovation are significantly higher than those for bidders without green innovation, which is consistent with our previous prediction. We will further explore the effect of green innovation using its intensity variables in our multivariate analyses.

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 Empirical results

4.1 Green innovation and probability of deal completion

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 the 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 6.56 percent (after addressing the endogeneity problem, the number more than doubles to 13.69 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. We also use the matched sample to regress whether the firm completes a CBMA deal (*Treat* dummy) on green innovation, controlling for firm-level variables, year- and industry-effect. The un-tabulated results show that the positive effect of green innovation persists.

− insert Table 4 about here −

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. According to the second-stage regression results, green innovative bidders are still prone to have higher probability of CBMA deal completion. 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 Hypothesis 1.

4.2 Green innovation and short-term abnormal returns

Panel A of Table 5 presents the baseline estimates from multivariate regressions using the CAR (–2, 2) as the dependent variable and green innovation as a key independent variable, and the controls are as discussed in Eq. (2). Overall, green innovation is positively correlated with CAR (–2, 2). 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 the 1% or 5% or 10% level. Next, we estimate the regressions using CAR (–3, 3) as the dependent variable and the other settings are as specified in Eq. (2). The un-tabulated results are consistent with those in Table 5. Therefore, green innovative bidders can obtain superior short-term abnormal returns, supporting our previous prediction.

− insert Table 5 about here −

4.3 Green innovation and long-term abnormal returns

Panel A of Table 6 reports the baseline regression results of long-term abnormal returns 12 months and 60 months after the month of CBMA deal completion. The dependent variables are BHAR (0, 12) in columns (1) – (3) and BHAR (0, 60) in columns (4) – (6), respectively, the key independent variable is green innovation, and the other settings are provided in Eq. (3). We note that the coefficient estimates on *invention*-related green innovation become significantly positive when we change from 12-month to 60-month post-merger abnormal returns, while the coefficients on overall green innovation stay insignificant and the coefficient estimates on *utility model*-related green innovation become significantly negative. After conducting 2SLS regressions in Panel B of Table 6, the coefficients on both overall and *invention*-related green innovation become significantly positive, while the negative coefficients on *utility model*-related green innovation become insignificant. In general, green innovative bidders can also realize higher long-term post-merger abnormal returns, which confirms our prior expectation.

− insert Table 6 about here −

4.4 Green innovation and post-merger operating performance

As we discussed in subsection 3.5, we use two different control samples to compare the operating performance of acquiring firms during the one-year and five-year period after CBMA deal completion with the performance of non-acquiring firms. The dependent variables are ROE (0, 1) in columns (1) – (3) and ROE (0, 5) in columns (4) – (6) of Table 7, the variable of our interest is the interaction terms between green innovation and *Treat* dummy, and the other settings are depicted in Eq. (4). Panel A of Table 7 reports the regression results of long-term post-merger operating performance using the *Industry-, Year-, and Size-Matched* sample. We find that the coefficients on the interaction terms including overall and *utility model*-related green innovation become significantly positive when we change the dependent variable from

ROE (0, 1) to *ROE (0, 5)* except for the coefficient on the interaction term between *Treat* dummy and *Ln (1+Dis. GP (sum))*, while the coefficients on the interaction terms including *invention*-related green innovation stay insignificant all of the time. Panel B of Table 7 reports the regression results using the *Industry-, Year-, Size-, B/M ratio-, and Leverage-Matched* sample. Only the coefficients on the interaction terms including *utility model*-related green innovation become significantly positive when we change the dependent variable from *ROE (0, 1)* to *ROE (0, 5)*. Overall, compared with non-acquiring firms, acquiring firms with green innovation tend to achieve better long-term post-merger operating performance.

− insert Table 7 about here −

We note that for acquiring firms (i.e., *Treat* dummy equals zero), green innovation is significantly and negatively related with long-term post-merger operating performance, especially the median performance five years after CBMA deal completion. This is possible because green innovation may be expensive and with uncertain or low financial returns (Berrone et al., 2013; Hu et al., 2021a), and even burden firms with larger operating costs (Hao et al., 2021). Meanwhile, green innovative bidders are likely to obtain synergies (e.g., from new market opportunities brought about by green innovation) (Kesidou and Demirel, 2012; Garel and Petit-Romec, 2021; Gao et al., 2022) at home and abroad, helping them create better post-merger operating performance. In addition, green innovative bidders can receive more external financial resources, e.g., government subsidies (we will verify this point in the following subsection 4.5).

4.5 Underlying mechanism analysis

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. (4), namely carbon emissions, environmental performance, and government subsidies.

First, we replace *ROE (0, 1)* and *ROE (0, 5)* in Table 7 with *CO2 (0, 1)* and *CO2 (0, 5)*, respectively, and re-run the estimation of Eq. (4). Panel A of Table 8 reports the regression results using the *Industry-, Year-, and Size-Matched* sample. We find that the coefficients on the interaction terms between *Treat* dummy and green innovation are significantly negative except for regressing *CO2 (0, 5)* on the interaction terms between *Treat* dummy and *invention-*related green innovation. When using the *Industry-, Year-, Size-, B/M ratio-,* and *Leverage-Matched* sample in Panel B of Table 8, the coefficients on the interaction terms become significantly negative after the dependent variable shifts from *CO2 (0, 1)* to *CO2 (0, 5)*. 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; Többelmann and Wendler, 2020).

− insert Table 8 about here −

Similarly, we observe that the coefficients on green innovation are significantly positive for non-acquiring firms. One possible explanation is that non-acquiring firms with green innovation are in essence those firms operating in industries with high energy consumption and high pollution ("Two high" for short)[17]. They are pressured to innovate green technologies to gain local legitimacy and mitigate the potential regulatory risks (Berrone et al., 2013), intentionally or unintentionally ignoring the substantial reduction in emissions. Due to more stakeholder concerns at home and abroad, acquiring firms will pay more attention to the substantial reduction in emissions. Extant studies have also confirmed that green innovation is mainly contributed by firms operating in "Two high" industries (e.g., oil, gas, and energy sector)

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[16] We also replace Scope 1 carbon emissions with Scope 2 and Scope 3 carbon emissions, respectively. Unfortunately, when the dependent variable is measured by Scope 2 carbon emissions (GHG emissions from consumption of purchased electricity, heat or steam by the firm), the results are not always consistent. But when the dependent variable is measured by 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 still hold only if using the median value of five-year data. For brevity, these results are available upon request.

[17] We follow Zhang et al. (2021) to define "Two high" industries, including: coal, cement, thermal power, iron and steel, electrolytic aluminum, building materials, mining, chemical, metallurgy, petrochemical, light industry (brewing, papermaking, fermentation), pharmaceuticals, textiles, and tannery. More details (in Chinese) are available at: http://www.gov.cn/gzdt/2008−07/07/content_1038083.htm.

(Cohen et al., 2020; Ren et al., 2022). We further check the distribution of green innovation by industry in our sample and find that the bidding firms to produce the largest number of green patents on average are those operating in the following industries: (1) water conservancy, environment, and public facilities management; (2) mining; (3) construction; and (4) electricity, heat, gas, and water production and supply. Most of these could be closely related to "Two high" industries. Then, we use the "Two high" subsample to re-estimate Eq. (4). The results are reported in Panels C and D of Table 8, respectively, and show that the coefficients on green innovation are still positive but their magnitudes become greater, confirming our predictions.

Second, we replace *ROE (0, 1)* and *ROE (0, 5)* in Table 7 with *Environment (0, 1)* and *Environment (0, 5)*, respectively, and re-run the estimation of Eq. (4). Panels A and B of Table 9 report the regression results using the *Industry-, Year-, and Size-Matched* sample and the *Industry-, Year-, Size-, B/M ratio-, and Leverage-Matched* sample, respectively. According to the coefficients on the interaction terms, green innovation brings a higher environmental score to green innovative acquirers in the long run, which is in accordance with Huang and Li (2017).

− insert Table 9 about here −

Third, we replace *ROE (0, 1)* and *ROE (0, 5)* in Table 7 with *Subsidy (0, 1)* and *Subsidy (0, 5)*, respectively, and re-run the estimation of Eq. (4). Panels A and B of Table 10 report the regression results using the *Industry-, Year-, and Size-Matched* sample and the *Industry-, Year-, Size-, B/M ratio-, and Leverage-Matched* sample, respectively. We find that the coefficients on the interaction terms are significantly positive, indicating that, compared with non-acquiring firms, 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 −

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 and realize superior short- and long-term abnormal returns. Furthermore, green innovative bidders also tend to achieve better post-merger operating performance. We then use two different matched samples and find that acquiring firms with a better green innovation profile will realize lower carbon emissions, superior environmental performance, and greater patent-related government subsidies in the long term after CBMA deal completion, which are three potential channels for the improvement in post-merger operating performance.

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. Previous studies have found that media coverage of corporate irresponsible actions (Hawn, 2020) and opaqueness (Li et al., 2019) will lower the likelihood of deal completion of EME bidder's CBMAs, while political connections will bring both benefits and disadvantages to Chinese cross-border bidders (Schweizer et al., 2019). In addition to raising the probability of deal completion (Gao et al., 2022), we further find that green innovation will help Chinese bidders realize higher short- and long-term abnormal returns and achieve better post-merger operating performance. Therefore, 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 more stakeholders introduced by initiating CBMAs can motivate green innovative acquirers to reduce carbon emissions owned or controlled by themselves in the long run. Our study supports the international voice for carbon reductions through green technologies, which is strikingly different from Bose et al. (2021), who find that acquirers with higher carbon emissions are more likely to buy foreign targets in countries with lower GDP or weaker environmental, regulatory, or governance standards, and the subsequent announcement returns are greater. Their research supports shifting carbon emissions across borders, which is unethical.

Third, our findings may provide practical implications to policymakers or 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 after CBMA deal completion in the long term, which is a potential channel through which post-merger operating performance can be boosted. As green innovation can be costly and risky (Berrone et al., 2013; Hao et al., 2021; Hu et al., 2021a), policymakers should encourage corporate green innovative activities and substantially promote firms' internationalization via CBMAs. In addition, regulators should continuously strengthen their environmental protection supervision of firms in "Two high" industries, and urge them to take substantial emissions reduction actions, rather than just applying for green patents to cover up their inaction.

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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		
	No.	Percent (%)	Deal value	No.	Percent (%)	Deal value
Argentina	2	0.30	491.50	2	0.57	491.50
Australia	55	8.23	130.23	32	9.12	166.19
Austria	1	0.15	56.96	1	0.28	56.96
Belgium	3	0.45	56.70	1	0.28	33.32
Bolivia	2	0.30	7.14	2	0.57	7.14
Brazil	7	1.05	104.25	4	1.14	160.90
Cambodia	1	0.15	4.88	–	–	–
Canada	46	6.89	155.17	28	7.98	182.93
Chile	1	0.15	14.28	1	0.28	14.28
Congo (DRC)	2	0.30	1454.37	2	0.57	1454.37
Congo (RC)	1	0.15	550.00	–	–	–
Croatia	3	0.45	23.23	3	0.85	23.23
Czech Republic	2	0.30	10.83	1	0.28	17.96
Denmark	6	0.90	197.93	3	0.85	31.27
Egypt	1	0.15	57.00	1	0.28	57.00
Finland	7	1.05	39.87	4	1.14	23.17
France	20	2.99	111.21	13	3.70	163.12
Gabon	2	0.30	62.80	1	0.28	38.15
Germany	44	6.59	83.72	21	5.98	119.38
Greece	1	0.15	7.12	–	–	–
Hong Kong	77	11.53	279.46	34	9.69	418.68
Hungary	4	0.60	474.55	3	0.85	631.15
India	3	0.45	364.83	2	0.57	546.60
Indonesia	5	0.75	28.79	3	0.85	44.52
Iraq	1	0.15	108.15	–	–	–
Ireland	1	0.15	0.19	–	–	–
Israel	13	1.95	382.87	3	0.85	1004.38
Italy	33	4.94	63.69	19	5.41	69.16
Jamaica	1	0.15	9.00	–	–	–
Japan	25	3.74	23.71	14	3.99	29.58
Kazakhstan	6	0.90	157.81	3	0.85	284.72
Kyrgyzstan	1	0.15	3.51	–	–	–
Laos	1	0.15	27.98	–	–	–
Luxembourg	5	0.75	325.32	5	1.42	325.32
Malawi	1	0.15	10.00	1	0.28	10.00
Malaysia	6	0.90	98.81	3	0.85	24.19
Mali	1	0.15	130.00	–	–	–
Malta	1	0.15	26.73	1	0.28	26.73

Target economies	Announced deals			Completed deals		
	No.	Percent (%)	Deal value	No.	Percent (%)	Deal value
Mauritania	2	0.30	22.82	1	0.28	36.90
Mexico	2	0.30	85.90	2	0.57	85.90
Mongolia	3	0.45	657.88	–	–	–
Mozambique	1	0.15	3775.37	1	0.28	3775.37
Myanmar	1	0.15	4.00	–	–	–
Netherlands	8	1.20	52.58	4	1.14	89.84
New Zealand	8	1.20	20.37	5	1.42	21.58
Norway	1	0.15	7.68	1	0.28	7.68
Oman	1	0.15	0.36	–	–	–
Pakistan	3	0.45	607.20	–	–	–
Poland	3	0.45	34.50	3	0.85	34.50
Russia	4	0.60	82.32	2	0.57	141.26
Saudi Arabia	1	0.15	562.00	–	–	–
Serbia	4	0.60	469.42	1	0.28	28.71
Singapore	18	2.69	187.38	12	3.42	198.80
Slovakia	1	0.15	399.76	1	0.28	399.76
Slovenia	1	0.15	11.06	–	–	–
South Africa	3	0.45	339.28	–	–	–
South Korea	15	2.25	19.03	6	1.71	27.35
Spain	9	1.35	50.33	7	1.99	63.43
Sri Lanka	1	0.15	30.00	–	–	–
Sweden	4	0.60	5.44	1	0.28	7.55
Switzerland	9	1.35	34.51	6	1.71	40.13
Taiwan	14	2.10	23.26	7	1.99	17.31
Tajikistan	5	0.75	151.98	2	0.57	327.27
Tanzania	2	0.30	57.62	1	0.28	115.11
Thailand	6	0.90	13.52	1	0.28	4.17
Trinidad and Tobago	1	0.15	96.50	–	–	–
Turkey	2	0.30	83.97	2	0.57	83.97
Uganda	1	0.15	0.84	–	–	–
United Arab Emirates	3	0.45	426.02	3	0.85	426.02
United Kingdom	22	3.29	115.01	14	3.99	137.92
United States	111	16.62	246.12	52	14.81	324.42
Uruguay	1	0.15	33.47	1	0.28	33.47
Vietnam	3	0.45	1.89	2	0.57	2.37
Zambia	2	0.30	150.00	2	0.57	150.00
Total	668	100.00	169.71	351	100.00	213.03

Table 2

Summary statistics

Panel A presents the summary statistics for full announced and completed CBMA deals between 2007 and 2021 attempted by Chinese bidders. Panel B displays the difference tests for acquiring firms and matched firms. Panel B1 is based on the *Industry-, Year-, and Size-Matched* sample, and Panel B2 is based on the *Industry-, Year-, Size-, B/M ratio-, and Leverage-Matched* sample. Panel C reports the univariate tests for cumulative abnormal returns (CARs) and buy-and-hold abnormal returns (BHARs). 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). 5-day and 7-day event windows are employed, respectively. BHAR is calculated for 12 and 60 months following the month of CBMA deal completion, respectively, by geometrically compounding the bidder's monthly returns during the period and then subtracting the market benchmark in China. Bidders are grouped based on the *GP dummy* 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. 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 full sample

Variables	Announced deals						Completed deals					
	N	Mean	S.D.	Min	Median	Max	N	Mean	S.D.	Min	Median	Max
Completion	668	0.525	0.500	0.000	1.000	1.000						
CAR (−2, 2)	574	0.010	0.070	−0.173	0.004	0.275						
BHAR (0, 12)							324	0.074	0.478	−0.565	−0.047	2.265
BHAR (0, 60)							144	−0.002	1.067	−1.275	−0.214	5.234
Ln (1+GP (sum))	668	1.048	1.421	0.000	0.693	6.089	351	1.209	1.536	0.000	0.693	6.089
Ln (1+GP (invention))	668	0.672	1.170	0.000	0.000	5.421	351	0.797	1.292	0.000	0.000	5.421
Ln (1+GP (utility model))	668	0.801	1.214	0.000	0.000	5.283	351	0.937	1.300	0.000	0.000	5.283
Ln (1+GPI (sum))	668	0.871	1.232	0.000	0.288	5.301	351	1.005	1.324	0.000	0.405	5.301
Ln (1+GPI (invention))	668	0.573	1.019	0.000	0.000	4.552	351	0.682	1.127	0.000	0.000	4.552
Ln (1+GPI (utility model))	668	0.711	1.093	0.000	0.000	4.899	351	0.827	1.166	0.000	0.000	4.899
Ln (1+Dis. GP (sum))	668	0.899	1.296	0.000	0.182	5.923	351	1.053	1.415	0.000	0.336	5.923
Ln (1+Dis. GP (invention))	668	0.562	1.044	0.000	0.000	5.162	351	0.680	1.168	0.000	0.000	5.162
Ln (1+Dis. GP (utility model))	668	0.680	1.096	0.000	0.000	5.034	351	0.802	1.188	0.000	0.000	5.034
Cultural distance	668	3.502	1.915	0.455	3.219	6.413	351	3.551	1.872	0.455	3.219	6.413
Institutional distance	668	2.921	1.292	0.115	3.152	5.199	351	2.988	1.288	0.115	3.171	5.199
GDP growth	668	0.025	0.079	−0.173	0.040	0.220	351	0.024	0.082	−0.173	0.040	0.220
B/M ratio	668	0.393	0.294	0.054	0.312	1.528	351	0.394	0.300	0.054	0.307	1.528
Ln (1+CGI)	668	1.465	0.290	0.693	1.474	2.079	351	1.468	0.285	0.693	1.534	2.079
Firm size	668	22.524	1.529	20.045	22.237	27.955	351	22.659	1.576	20.045	22.418	27.955
Ln (1+FCF)	668	1.906	19.603	−23.967	17.101	24.477	351	2.320	19.768	−23.967	17.575	24.477
Leverage	668	0.414	0.195	0.040	0.423	0.868	351	0.411	0.186	0.040	0.426	0.868
Ln (1+Listed age)	668	1.881	0.911	0.000	1.946	3.296	351	1.863	0.926	0.000	1.946	3.296
Listed overseas	668	0.081	0.273	0.000	0.000	1.000	351	0.097	0.296	0.000	0.000	1.000
ROA	668	0.054	0.047	−0.088	0.047	0.210	351	0.059	0.048	−0.088	0.052	0.210
SOE	668	0.112	0.316	0.000	0.000	1.000	351	0.128	0.335	0.000	0.000	1.000
Ln (1+Patents (sum))	668	3.387	2.082	0.000	3.466	9.304	351	3.567	2.163	0.000	3.526	9.304
R&D/Total assets	668	0.018	0.018	0.000	0.015	0.101	351	0.020	0.021	0.000	0.016	0.101
All cash deal	668	0.269	0.444	0.000	0.000	1.000	351	0.313	0.465	0.000	0.000	1.000

(*Panel A continued*)

Variables	Announced deals						Completed deals					
	N	Mean	S.D.	Min	Median	Max	N	Mean	S.D.	Min	Median	Max
Financial/Legal advisor	668	0.394	0.489	0.000	0.000	1.000	351	0.556	0.498	0.000	1.000	1.000
High-tech target firm	668	0.290	0.454	0.000	0.000	1.000	351	0.293	0.456	0.000	0.000	1.000
Past CBMA experience	668	0.284	0.543	0.000	0.000	2.398	351	0.318	0.572	0.000	0.000	2.398
Ln (1+Relative deal size)	668	0.061	0.144	0.000	0.012	0.897	351	0.068	0.149	0.000	0.018	0.897
Same industry	668	0.470	0.499	0.000	0.000	1.000	351	0.499	0.501	0.000	0.000	1.000
Tender offer	668	0.013	0.115	0.000	0.000	1.000	351	0.020	0.140	0.000	0.000	1.000

Panel B: Summary statistics for acquiring firms and matched firms

Panel B1: Industry-, Year-, and Size-Matched sample

Variables	Acquiring firms (A)			Matched firms (M)			Test of difference (A−M)	
	N1	Mean	Median	N0	Mean	Median	Mean	Median
ROE (0, 1)	263	0.068	0.069	263	0.059	0.062	0.009	0.007*
ROE (0, 5)	263	0.046	0.071	263	0.062	0.060	−0.016	0.011
CO2 (0, 1)	135	0.095	0.026	115	0.385	0.041	−0.290***	−0.015***
CO2 (0, 5)	174	0.086	0.023	141	0.389	0.026	−0.303***	−0.003**
fGHG14	135	1.036	0.284	115	4.543	0.399	−3.507***	−0.115**
f5GHG14_med	174	0.938	0.285	141	4.150	0.369	−3.212***	−0.084*
Subsidy (0, 1)	240	3.852	0.000	230	3.504	0.000	0.348	0.000
Subsidy (0, 5)	240	3.597	0.000	230	3.090	0.000	0.507	0.000
Environment (0, 1)	60	0.316	0.281	38	0.306	0.276	0.010	0.005
Environment (0, 5)	105	0.305	0.302	76	0.280	0.243	0.025	0.059
Ln (1+GP (sum))	263	0.855	0.000	263	0.708	0.000	0.147	0.000
Ln (1+GP (invention))	263	0.505	0.000	263	0.399	0.000	0.106	0.000*
Ln (1+GP (utility model))	263	0.653	0.000	263	0.547	0.000	0.106	0.000
Ln (1+GPI (sum))	263	0.741	0.000	263	0.601	0.000	0.140	0.000
Ln (1+GPI (invention))	263	0.446	0.000	263	0.349	0.000	0.097	0.000*
Ln (1+GPI (utility model))	263	0.597	0.000	263	0.496	0.000	0.101	0.000
Ln (1+Dis. GP (sum))	263	0.727	0.000	263	0.597	0.000	0.130	0.000
Ln (1+Dis. GP (invention))	263	0.412	0.000	263	0.336	0.000	0.076	0.000*
Ln (1+Dis. GP (utility model))	263	0.553	0.000	263	0.450	0.000	0.103	0.000
B/M ratio	263	0.312	0.233	263	0.394	0.315	−0.082***	−0.082***
Ln (1+CGI)	263	1.294	1.386	263	1.405	1.386	−0.111***	0.000***
Firm size	263	22.138	21.964	263	22.242	22.070	−0.104	−0.106
Ln (1+FCF)	263	−3.722	−17.959	263	−0.144	13.651	−3.578**	−31.610
Leverage	263	0.362	0.369	263	0.413	0.413	−0.051***	−0.044***
Ln (1+Listed age)	263	1.654	1.792	263	1.925	2.079	−0.271***	−0.287***
Listed overseas	263	0.049	0.000	263	0.034	0.000	0.015	0.000
ROA	263	0.050	0.041	263	0.039	0.032	0.011**	0.009**
SOE	263	0.080	0.000	263	0.091	0.000	−0.011	0.000
Ln (1+Patents (sum))	263	2.970	2.890	263	2.785	2.996	0.185	−0.106
R&D/Total assets	263	0.025	0.014	263	0.023	0.017	0.002	−0.003

Panel B2: Industry-, Year-, Size-, B/M ratio-, and Leverage-Matched sample

Variables	Acquiring firms (A)			Matched firms (M)			Test of difference (A−M)	
	N1	Mean	Median	N0	Mean	Median	Mean	Median
ROE (0, 1)	287	0.053	0.068	287	0.027	0.064	0.026	0.004
ROE (0, 5)	287	0.038	0.069	287	0.058	0.058	−0.020	0.011
CO2 (0, 1)	151	0.181	0.033	125	0.315	0.025	−0.134	0.008
CO2 (0, 5)	196	0.173	0.026	162	0.315	0.024	−0.142*	0.002
fGHG14	151	2.434	0.308	125	4.066	0.269	−1.632	0.039
f5GHG14_med	196	2.297	0.310	162	3.985	0.294	−1.688	0.016
Subsidy (0, 1)	264	3.349	0.000	255	2.986	0.000	0.363	0.000
Subsidy (0, 5)	264	3.274	0.000	255	2.981	0.000	0.293	0.000
Environment (0, 1)	78	0.304	0.265	46	0.293	0.270	0.011	−0.005
Environment (0, 5)	122	0.310	0.291	89	0.252	0.217	0.058*	0.074*
Ln (1+GP (sum))	287	0.924	0.000	287	0.706	0.000	0.218**	0.000
Ln (1+GP (invention))	287	0.568	0.000	287	0.389	0.000	0.179**	0.000
Ln (1+GP (utility model))	287	0.699	0.000	287	0.533	0.000	0.166**	0.000
Ln (1+GPI (sum))	287	0.771	0.000	287	0.591	0.000	0.180**	0.000
Ln (1+GPI (invention))	287	0.493	0.000	287	0.342	0.000	0.151**	0.000
Ln (1+GPI (utility model))	287	0.626	0.000	287	0.476	0.000	0.150*	0.000
Ln (1+Dis. GP (sum))	287	0.802	0.000	287	0.581	0.000	0.221**	0.000*
Ln (1+Dis. GP (invention))	287	0.480	0.000	287	0.311	0.000	0.169**	0.000
Ln (1+Dis. GP (utility model))	287	0.601	0.000	287	0.435	0.000	0.166**	0.000
B/M ratio	287	0.317	0.233	287	0.326	0.269	−0.009	−0.036
Ln (1+CGI)	287	1.295	1.386	287	1.392	1.386	−0.097***	0.000***
Firm size	287	22.303	22.036	287	22.148	21.938	0.155	0.098
Ln (1+FCF)	287	−5.330	−18.663	287	−0.836	−15.834	−4.494***	−2.829**
Leverage	287	0.360	0.369	287	0.346	0.311	0.014	0.058
Ln (1+Listed age)	287	1.584	1.609	287	1.736	1.946	−0.152*	−0.337*
Listed overseas	287	0.073	0.000	287	0.031	0.000	0.042	0.000
ROA	287	0.046	0.038	287	0.050	0.046	−0.004	−0.008
SOE	287	0.073	0.000	287	0.084	0.000	−0.011	0.000
Ln (1+Patents (sum))	287	2.945	2.890	287	2.644	2.833	0.301	0.057
R&D/Total assets	287	0.022	0.013	287	0.026	0.017	−0.004	−0.004

Panel C: Univariate tests

Variables	Mean	Median	Mean	Median	Mean	Median	Mean	Median
	Full sample (N=574)		GP dummy=1 (N1=302)		GP dummy=0 (N0=272)		Test of difference(N1−N0)	
CAR (−2, 2)	0.010***	0.004**	0.009**	0.004*	0.010**	0.006*	−0.001	−0.002
p−value	0.001	0.010	0.013	0.066	0.027	0.076	0.856	0.806
CAR (−3, 3)	0.008**	0.003*	0.009**	0.003	0.006	0.003	0.003	0.000
p−value	0.019	0.096	0.030	0.127	0.239	0.408	0.613	0.688

Variables	Mean	Median	Mean	Median	Mean	Median	Mean	Median
	Full sample (N=324)		GP dummy=1 (N1=173)		GP dummy=0 (N0=151)		Test of difference(N1−N0)	
BHAR (0, 12)	0.074***	−0.047	0.071**	−0.036	0.077*	−0.061	−0.006	0.025
p−value	0.006	0.873	0.044	0.932	0.058	0.880	0.911	0.865
	Full sample (N=144)		GP dummy=1 (N1=81)		GP dummy=0 (N0=63)		Test of difference(N1−N0)	
BHAR (0, 60)	−0.002	−0.214**	0.177	−0.069	−0.232**	−0.348***	0.409**	0.279*
p−value	0.982	0.013	0.201	0.733	0.017	0.001	0.022	0.050

Table 3

Correlation matrices

Panel A presents the Pearson's correlation coefficients for full sample. Panel B reports the correlation coefficients for the *Industry-, Year-, and Size-Matched* sample and the *Industry-, Year-, Size-, B/M ratio-, and Leverage-Matched* sample, respectively. 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: Correlation coefficients for sample bidders

	Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
1	*Completion*	1.000															
2	*Ln (1+GP (sum))*	0.119***	1.000														
3	*Ln (1+GP (invention))*	0.112***	0.932***	1.000													
4	*Ln (1+GP (utility model))*	0.118***	0.954***	0.824***	1.000												
5	*Ln (1+GPI (sum))*	0.114***	0.994***	0.934***	0.951***	1.000											
6	*Ln (1+GPI (invention))*	0.113***	0.922***	0.993***	0.814***	0.929***	1.000										
7	*Ln (1+GPI (utility model))*	0.112***	0.947***	0.822***	0.995***	0.951***	0.814***	1.000									
8	*Ln (1+Dis. GP (sum))*	0.125***	0.992***	0.933***	0.953***	0.988***	0.924***	0.947***	1.000								
9	*Ln (1+Dis. GP (invention))*	0.119***	0.915***	0.990***	0.815***	0.920***	0.984***	0.814***	0.930***	1.000							
10	*Ln (1+Dis. GP (utility model))*	0.118***	0.940***	0.821***	0.990***	0.938***	0.810***	0.986***	0.953***	0.819***	1.000						
11	*Cultural distance*	0.027	0.002	0.001	−0.011	−0.006	0.001	−0.017	−0.000	−0.004	−0.010	1.000					
12	*Institutional distance*	0.055	−0.034	−0.030	−0.024	−0.028	−0.024	−0.024	−0.028	−0.025	−0.025	0.302***	1.000				
13	*GDP growth*	−0.006	−0.031	−0.004	−0.056	−0.029	0.002	−0.054	−0.031	−0.006	−0.057	−0.071*	−0.040	1.000			
14	*B/M ratio*	0.004	0.304***	0.309***	0.308***	0.319***	0.310***	0.316***	0.306***	0.307***	0.303***	−0.148***	−0.103***	0.124***	1.000		
15	*Ln (1+CGI)*	0.010	0.082**	0.077**	0.101***	0.086**	0.071*	0.111***	0.099**	0.089**	0.121***	−0.039	0.003	0.009	0.106***	1.000	
16	*Firm size*	0.093**	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***	1.000
17	*Ln (1+FCF)*	0.022	0.063	0.065*	0.071*	0.068*	0.059	0.075*	0.062	0.068*	0.070*	0.010	−0.049	0.046	0.231***	0.100***	0.138***
18	*Leverage*	−0.017	0.255***	0.239***	0.236***	0.265***	0.246***	0.241***	0.250***	0.231***	0.225***	−0.143***	−0.056	0.037	0.182***	0.056	0.469***
19	*Ln (1+Listed age)*	−0.021	0.091**	0.092**	0.074*	0.099**	0.093**	0.078**	0.074*	0.071*	0.058	−0.085**	−0.081**	0.030	0.328***	0.016	0.396***
20	*Listed overseas*	0.062	0.303***	0.340***	0.239***	0.320***	0.352***	0.249***	0.296***	0.331***	0.234***	0.093**	0.072*	−0.074*	0.239***	0.050	0.459***
21	*ROA*	0.112***	−0.039	−0.049	−0.022	−0.037	−0.045	−0.021	−0.029	−0.043	−0.012	0.157***	0.069*	0.080**	−0.155***	−0.039	−0.024
22	*SOE*	0.053	0.157***	0.191***	0.111***	0.164***	0.194***	0.116***	0.164***	0.199***	0.112***	−0.094**	0.043	−0.068*	0.203***	0.043	0.231***
23	*Ln (1+Patents (sum))*	0.091**	0.735***	0.671***	0.706***	0.729***	0.666***	0.700***	0.729***	0.664***	0.693***	−0.019	−0.038	−0.031	0.234***	0.087**	0.403***
24	*R&D/Total assets*	0.097**	0.137***	0.124***	0.108***	0.117***	0.129***	0.093**	0.139***	0.123***	0.110***	0.026	0.008	−0.148***	−0.182***	−0.055	−0.164***
25	*All cash deal*	0.104***	0.073*	0.087**	0.064*	0.075*	0.087**	0.062	0.070*	0.085**	0.058	−0.028	0.131***	0.099**	0.112***	0.003	0.139***
26	*Financial/Legal advisor*	0.349***	0.091**	0.097**	0.076**	0.090**	0.097**	0.076**	0.097**	0.107***	0.080**	0.018	0.113***	−0.129***	0.100***	0.036	0.250***
27	*High-tech target firm*	0.007	−0.078**	−0.074*	−0.083**	−0.093**	−0.083**	−0.094**	−0.078**	−0.072*	−0.085**	0.016	0.036	−0.017	−0.203***	−0.100***	−0.209***
28	*Past CBMA experience*	0.066*	0.366***	0.414***	0.302***	0.380***	0.410***	0.310***	0.364***	0.411***	0.298***	0.074*	−0.040	−0.017	0.262***	−0.040	0.524***
29	*Ln (1+Relative deal size)*	0.052	−0.072*	−0.058	−0.075*	−0.072*	−0.061	−0.080**	−0.070*	−0.051	−0.078**	−0.090**	0.006	0.016	0.056	0.037	−0.030
30	*Same industry*	0.060	0.022	0.030	0.017	0.029	0.034	0.020	0.032	0.040	0.019	0.016	−0.070*	0.019	0.020	−0.010	0.060
31	*Tender offer*	0.059	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	0.074*

(*Panel A continued*)

	Variables	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)	(31)
17	*Ln (1+FCF)*	1.000														
18	*Leverage*	0.071*	1.000													
19	*Ln (1+Listed age)*	0.189***	0.402***	1.000												
20	*Listed overseas*	0.055	0.122***	0.009	1.000											
21	*ROA*	0.079**	−0.347***	−0.181***	0.021	1.000										
22	*SOE*	0.062	0.102***	0.197***	0.190***	−0.076**	1.000									
23	*Ln (1+Patents (sum))*	0.111***	0.153***	0.015	0.199***	0.053	0.079**	1.000								
24	*R&D/Total assets*	−0.028	−0.172***	−0.177***	−0.037	0.155***	−0.069*	0.321***	1.000							
25	*All cash deal*	−0.008	0.037	0.034	0.129***	−0.043	0.062	0.046	−0.073*	1.000						
26	*Financial/Legal advisor*	0.027	0.124***	0.076**	0.188***	−0.020	0.131***	0.081**	−0.026	0.146***	1.000					
27	*High-tech target firm*	−0.011	−0.233***	−0.131***	−0.105***	0.087**	−0.029	0.006	0.337***	−0.024	−0.077**	1.000				
28	*Past CBMA experience*	0.082**	0.180***	0.250***	0.397***	−0.030	0.223***	0.251***	−0.123***	0.129***	0.112***	−0.141***	1.000			
29	*Ln (1+Relative deal size)*	0.027	0.116***	0.195***	−0.006	−0.201***	0.081**	−0.121***	−0.147***	0.131***	0.288***	0.024	−0.015	1.000		
30	*Same industry*	0.035	−0.062	−0.039	0.095**	0.095**	0.045	0.042	0.035	0.036	0.002	0.137***	0.083**	−0.013	1.000	
31	*Tender offer*	−0.028	−0.002	−0.011	0.156***	0.008	0.041	0.019	−0.065*	0.192***	0.145***	−0.046	0.128***	−0.001	0.020	1.000

Panel B: Correlation coefficients for two different matched samples
Panel B1: Industry-, Year-, and Size-Matched sample

	Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
1	*ROE (0, 1)*	1.000										
2	*ROE (0, 5)*	0.540***	1.000									
3	*Ln (1+GP (sum))*	−0.029	0.003	1.000								
4	*Ln (1+GP (invention))*	−0.039	−0.016	0.914***	1.000							
5	*Ln (1+GP (utility model))*	−0.000	0.029	0.944***	0.781***	1.000						
6	*Ln (1+GPI (sum))*	−0.012	0.008	0.993***	0.908***	0.945***	1.000					
7	*Ln (1+GPI (invention))*	−0.032	−0.011	0.911***	0.994***	0.786***	0.913***	1.000				
8	*Ln (1+GPI (utility model))*	0.008	0.034	0.938***	0.779***	0.994***	0.946***	0.788***	1.000			
9	*Ln (1+Dis. GP (sum))*	−0.033	0.007	0.990***	0.919***	0.941***	0.985***	0.918***	0.935***	1.000		
10	*Ln (1+Dis. GP (invention))*	−0.040	−0.000	0.895***	0.988***	0.768***	0.890***	0.985***	0.767***	0.913***	1.000	
11	*Ln (1+Dis. GP (utility model))*	−0.002	0.026	0.931***	0.781***	0.989***	0.934***	0.788***	0.984***	0.943***	0.773***	1.000
12	*B/M ratio*	−0.002	0.046	0.145***	0.128***	0.160***	0.160***	0.139***	0.167***	0.140***	0.126***	0.155***
13	*Ln (1+CGI)*	0.057	0.042	−0.030	−0.049	−0.012	−0.030	−0.043	−0.008	−0.028	−0.046	−0.012
14	*Firm size*	0.090**	0.156***	0.373***	0.388***	0.348***	0.391***	0.403***	0.363***	0.375***	0.394***	0.351***
15	*Ln (1+FCF)*	0.101**	0.071	0.016	0.026	0.012	0.016	0.028	0.012	0.007	0.016	0.010
16	*Leverage*	−0.039	0.027	0.250***	0.223***	0.257***	0.257***	0.236***	0.260***	0.252***	0.220***	0.266***
17	*Ln (1+Listed age)*	−0.028	−0.006	0.090**	0.089**	0.074*	0.100**	0.089**	0.088**	0.071	0.076*	0.056
18	*Listed overseas*	0.042	0.024	0.269***	0.288***	0.265***	0.285***	0.310***	0.278***	0.278***	0.302***	0.273***
19	*ROA*	0.353***	0.281***	−0.031	−0.020	−0.039	−0.036	−0.024	−0.039	−0.025	−0.011	−0.041
20	*SOE*	−0.013	0.045	0.024	0.034	−0.003	0.029	0.041	0.004	0.028	0.040	0.003
21	*Ln (1+Patents (sum))*	0.057	0.095**	0.665***	0.588***	0.635***	0.663***	0.586***	0.634***	0.642***	0.572***	0.609***
22	*R&D/Total assets*	0.031	0.055	0.377***	0.385***	0.330***	0.355***	0.362***	0.323***	0.374***	0.381***	0.318***

(*Panel B1 continued*)

	Variables	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
12	*B/M ratio*	1.000										
13	*Ln (1+CGI)*	0.156***	1.000									
14	*Firm size*	0.495***	0.085*	1.000								
15	*Ln (1+FCF)*	0.198***	0.116***	0.098**	1.000							
16	*Leverage*	0.221***	0.084*	0.508***	0.104**	1.000						
17	*Ln (1+Listed age)*	0.315***	0.133***	0.429***	0.205***	0.354***	1.000					
18	*Listed overseas*	0.255***	0.067	0.424***	−0.047	0.191***	0.021	1.000				
19	*ROA*	−0.170***	0.033	−0.045	0.136***	−0.343***	−0.149***	−0.057	1.000			
20	*SOE*	0.132***	0.103**	0.145***	0.000	0.033	0.173***	0.106**	0.010	1.000		
21	*Ln (1+Patents (sum))*	0.100**	−0.043	0.288***	0.029	0.157***	0.054	0.230***	0.012	0.017	1.000	
22	*R&D/Total assets*	−0.006	0.000	0.044	0.170***	−0.018	0.171***	0.061	0.083*	−0.045	0.418***	1.000

Panel B2: Industry-, Year-, Size-, B/M ratio-, and Leverage-Matched sample

	Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
1	*ROE (0, 1)*	1.000										
2	*ROE (0, 5)*	0.441***	1.000									
3	*Ln (1+GP (sum))*	0.013	0.028	1.000								
4	*Ln (1+GP (invention))*	−0.002	−0.000	0.907***	1.000							
5	*Ln (1+GP (utility model))*	0.025	0.065	0.945***	0.772***	1.000						
6	*Ln (1+GPI (sum))*	0.015	0.027	0.993***	0.901***	0.939***	1.000					
7	*Ln (1+GPI (invention))*	−0.006	0.004	0.906***	0.992***	0.774***	0.905***	1.000				
8	*Ln (1+GPI (utility model))*	0.024	0.062	0.935***	0.762***	0.993***	0.937***	0.766***	1.000			
9	*Ln (1+Dis. GP (sum))*	0.020	0.038	0.990***	0.913***	0.936***	0.984***	0.913***	0.927***	1.000		
10	*Ln (1+Dis. GP (invention))*	0.005	0.011	0.883***	0.987***	0.748***	0.879***	0.979***	0.741***	0.904***	1.000	
11	*Ln (1+Dis. GP (utility model))*	0.034	0.069*	0.932***	0.778***	0.989***	0.928***	0.780***	0.983***	0.942***	0.763***	1.000
12	*B/M ratio*	0.063	0.063	0.159***	0.138***	0.182***	0.166***	0.143***	0.184***	0.158***	0.131***	0.184***
13	*Ln (1+CGI)*	0.001	0.062	0.051	0.066	0.054	0.053	0.072*	0.056	0.065	0.079*	0.061
14	*Firm size*	0.104**	0.123***	0.389***	0.396***	0.361***	0.400***	0.398***	0.368***	0.398***	0.407***	0.372***
15	*Ln (1+FCF)*	0.023	0.106**	−0.009	−0.005	0.013	−0.003	0.011	0.015	−0.013	−0.013	0.008
16	*Leverage*	−0.058	0.026	0.206***	0.148***	0.233***	0.215***	0.154***	0.240***	0.203***	0.142***	0.234***
17	*Ln (1+Listed age)*	−0.064	−0.053	−0.006	−0.031	0.028	−0.001	−0.030	0.034	−0.033	−0.056	0.005
18	*Listed overseas*	0.041	0.030	0.222***	0.236***	0.178***	0.244***	0.254***	0.191***	0.238***	0.258***	0.185***
19	*ROA*	0.238***	0.326***	−0.012	0.016	−0.019	−0.018	0.018	−0.025	0.001	0.019	−0.008
20	*SOE*	0.030	0.025	0.032	0.058	−0.000	0.039	0.062	0.006	0.030	0.055	0.000
21	*Ln (1+Patents (sum))*	0.026	0.082*	0.670***	0.570***	0.652***	0.658***	0.572***	0.643***	0.640***	0.542***	0.621***
22	*R&D/Total assets*	−0.042	0.006	0.260***	0.245***	0.242***	0.239***	0.245***	0.226***	0.228***	0.210***	0.205***

(*Panel B2 continued*)

	Variables	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
12	*B/M ratio*	1.000										
13	*Ln (1+CGI)*	0.211***	1.000									
14	*Firm size*	0.523***	0.162***	1.000								
15	*Ln (1+FCF)*	0.269***	0.159***	0.064	1.000							
16	*Leverage*	0.268***	0.100**	0.478***	0.043	1.000						
17	*Ln (1+Listed age)*	0.314***	0.058	0.270***	0.228***	0.419***	1.000					
18	*Listed overseas*	0.172***	0.054	0.411***	−0.024	0.085**	−0.075*	1.000				
19	*ROA*	−0.104**	0.055	0.019	0.139***	−0.301***	−0.184***	−0.030	1.000			
20	*SOE*	0.071*	0.081*	0.145***	−0.037	0.039	0.158***	0.077*	−0.047	1.000		
21	*Ln (1+Patents (sum))*	0.133***	0.006	0.220***	0.040	0.153***	0.074*	0.099**	0.067	0.024	1.000	
22	*R&D/Total assets*	0.024	0.053	−0.034	0.213***	0.012	0.225***	−0.005	0.026	0.033	0.437***	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)), 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)). 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 mean of 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. *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. 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%. The coefficients on the constant and controls are suppressed for brevity in Panel B and available upon request.

Panel A: Baseline regressions

Variables	(1) Probit Completion	(2) Probit Completion	(3) Probit Completion	(4) Probit Completion	(5) Probit Completion	(6) Probit Completion	(7) Probit Completion	(8) Probit Completion	(9) Probit Completion
Ln (1+GP (sum))	0.200***								
	(9.32)								
Ln (1+GP (invention))		0.183***							
		(7.76)							
Ln (1+GP (utility model))			0.229***						
			(7.27)						
Ln (1+GPI (sum))				0.220***					
				(10.52)					
Ln (1+GPI (invention))					0.201***				
					(5.67)				
Ln (1+GPI (utility model))						0.242***			
						(7.56)			
Ln (1+Dis. GP (sum))							0.237***		
							(8.90)		
Ln (1+Dis. GP (invention))								0.223***	
								(7.09)	
Ln (1+Dis. GP (utility model))									0.248***
									(6.44)
Cultural distance	−0.019	−0.018	−0.017	−0.018	−0.018	−0.016	−0.020	−0.019	−0.018
	(−0.83)	(−0.76)	(−0.74)	(−0.78)	(−0.73)	(−0.69)	(−0.84)	(−0.76)	(−0.75)
Institutional distance	0.038	0.038	0.034	0.036	0.038	0.034	0.038	0.039	0.035
	(1.22)	(1.22)	(1.06)	(1.18)	(1.23)	(1.06)	(1.22)	(1.23)	(1.09)
GDP growth	1.658*	1.556*	1.815*	1.673*	1.537	1.818*	1.646*	1.547	1.796*
	(1.73)	(1.65)	(1.83)	(1.73)	(1.61)	(1.84)	(1.71)	(1.62)	(1.82)
B/M ratio	0.167	0.182	0.108	0.157	0.173	0.106	0.161	0.182	0.118
	(1.02)	(1.07)	(0.64)	(0.95)	(1.01)	(0.64)	(0.99)	(1.06)	(0.69)

(*Panel A continued*)

Ln (1+CGI)	−0.041	−0.040	−0.050	−0.041	−0.034	−0.057	−0.051	−0.042	−0.068
	(−0.41)	(−0.41)	(−0.44)	(−0.42)	(−0.34)	(−0.50)	(−0.48)	(−0.41)	(−0.57)
Firm size	−0.074	−0.074	−0.071	−0.074	−0.071	−0.069	−0.084	−0.085*	−0.074
	(−1.43)	(−1.52)	(−1.26)	(−1.48)	(−1.57)	(−1.22)	(−1.58)	(−1.71)	(−1.27)
Ln (1+FCF)	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.65)	(0.54)	(0.57)	(0.61)	(0.56)	(0.55)	(0.66)	(0.49)	(0.57)
Leverage	−0.013	0.042	−0.015	−0.017	0.026	−0.019	−0.001	0.055	0.006
	(−0.04)	(0.16)	(−0.05)	(−0.06)	(0.10)	(−0.07)	(−0.00)	(0.20)	(0.02)
Ln (1+Listed age)	−0.024	−0.018	−0.018	−0.024	−0.019	−0.020	−0.013	−0.005	−0.014
	(−0.54)	(−0.39)	(−0.43)	(−0.55)	(−0.40)	(−0.47)	(−0.30)	(−0.13)	(−0.33)
Listed overseas	−0.312*	−0.321**	−0.253	−0.321*	−0.334**	−0.262*	−0.289*	−0.302**	−0.244*
	(−1.73)	(−2.05)	(−1.61)	(−1.71)	(−1.97)	(−1.66)	(−1.73)	(−2.06)	(−1.75)
ROA	3.552***	3.601***	3.360***	3.508***	3.557***	3.335***	3.550***	3.635***	3.343***
	(7.33)	(6.98)	(7.37)	(7.30)	(6.81)	(7.32)	(7.56)	(7.26)	(7.28)
SOE	−0.050	−0.053	−0.017	−0.044	−0.051	−0.015	−0.061	−0.063	−0.021
	(−0.36)	(−0.36)	(−0.13)	(−0.31)	(−0.35)	(−0.11)	(−0.44)	(−0.43)	(−0.16)
Ln (1+Patents (sum))	−0.080***	−0.046**	−0.077***	−0.074***	−0.042*	−0.072***	−0.084***	−0.049**	−0.073***
	(−3.08)	(−2.06)	(−2.82)	(−2.88)	(−1.95)	(−2.64)	(−3.32)	(−2.27)	(−2.71)
R&D/Total assets	9.407***	8.703***	9.909***	9.465***	8.606***	9.953***	9.106***	8.480***	9.690***
	(3.79)	(3.53)	(3.71)	(3.71)	(3.46)	(3.74)	(3.58)	(3.37)	(3.64)
All cash deal	0.232***	0.233***	0.234***	0.237***	0.235***	0.239***	0.240***	0.240***	0.238***
	(4.43)	(4.45)	(4.54)	(4.57)	(4.48)	(4.62)	(4.56)	(4.60)	(4.59)
Financial/Legal advisor	1.137***	1.125***	1.137***	1.137***	1.122***	1.133***	1.142***	1.127***	1.133***
	(8.26)	(8.54)	(8.07)	(8.26)	(8.75)	(8.01)	(8.29)	(8.62)	(8.02)
High-tech target firm	0.058	0.061	0.057	0.064	0.065	0.059	0.061	0.061	0.061
	(1.16)	(1.19)	(1.15)	(1.27)	(1.24)	(1.18)	(1.24)	(1.21)	(1.23)
Past CBMA experience	0.120*	0.109	0.136*	0.116*	0.112	0.132*	0.117*	0.106	0.135*
	(1.83)	(1.62)	(1.81)	(1.75)	(1.59)	(1.76)	(1.86)	(1.62)	(1.79)
Ln (1+Relative deal size)	−0.367	−0.381	−0.363	−0.366	−0.374	−0.347	−0.388	−0.408	−0.364
	(−0.71)	(−0.77)	(−0.70)	(−0.72)	(−0.76)	(−0.67)	(−0.75)	(−0.84)	(−0.69)
Same industry	0.113	0.109	0.110	0.109	0.107	0.110	0.108	0.108	0.108
	(1.57)	(1.50)	(1.50)	(1.52)	(1.48)	(1.51)	(1.51)	(1.48)	(1.48)
Tender offer	−0.319	−0.284	−0.330	−0.324	−0.287	−0.330	−0.317	−0.289	−0.293
	(−0.46)	(−0.41)	(−0.48)	(−0.47)	(−0.42)	(−0.49)	(−0.46)	(−0.42)	(−0.43)
Constant	1.488	1.343	1.459	1.477	1.268	1.415	1.729	1.570	1.505
	(0.93)	(0.89)	(0.86)	(0.95)	(0.89)	(0.84)	(1.06)	(1.03)	(0.87)
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	0.165	0.161	0.166	0.164	0.161	0.165	0.166	0.162	0.166

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))	0.431***					
	(6.11)					
Province-year Ln (1+GP (invention))			0.513***			
			(5.42)			
Province-year Ln (1+GP (utility model))					0.473***	
					(11.57)	
Predicted Ln (1+GP (sum))		0.415***				
		(4.72)				
Predicted Ln (1+GP (invention))				0.407***		
				(3.86)		
Predicted Ln (1+GP (utility model))						0.444***
						(5.00)
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		0.693		0.665	
Pseudo R^2		0.161		0.161		0.161

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***					
	(6.24)					
Province-year Ln (1+GPI (invention))			0.527***			
			(5.76)			
Province-year Ln (1+GPI (utility model))					0.468***	
					(11.70)	
Predicted Ln (1+GPI (sum))		0.442***				
		(3.81)				
Predicted Ln (1+GPI (invention))				0.434***		
				(4.29)		
Predicted Ln (1+GPI (utility model))						0.448***
						(4.22)
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		0.696		0.669	
Pseudo R^2		0.160		0.161		0.160

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))	0.416***					
	(5.02)					
Province-year Ln (1+Dis. GP (invention))			0.490***			
			(4.32)			
Province-year Ln (1+Dis. GP (utility model))					0.485***	
					(13.26)	
Predicted Ln (1+Dis. GP (sum))		0.506***				
		(4.83)				
Predicted Ln (1+Dis. GP (invention))				0.509***		
				(4.45)		
Predicted Ln (1+Dis. GP (utility model))						0.480***
						(4.68)
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	0.714		0.693		0.661	
Pseudo R^2		0.162		0.162		0.161

Table 5

Short-term 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 five-day event window, i.e., CAR (−2, 2). 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)), 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)). 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 mean of corresponding GP variable, only controlling for Firm-level variables. The second stage regresses CAR (−2, 2) 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. *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. 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%. The coefficients on the constant and controls are suppressed for brevity and available upon request.

Panel A: Baseline regressions

Variables	(1) CAR (−2, 2)	(2) CAR (−2, 2)	(3) CAR (−2, 2)	(4) CAR (−2, 2)	(5) CAR (−2, 2)	(6) CAR (−2, 2)	(7) CAR (−2, 2)	(8) CAR (−2, 2)	(9) CAR (−2, 2)
Ln (1+GP (sum))	0.000								
	(0.17)								
Ln (1+GP (invention))		0.003							
		(1.16)							
Ln (1+GP (utility model))			0.000						
			(0.12)						
Ln (1+GPI (sum))				0.001					
				(0.19)					
Ln (1+GPI (invention))					0.004				
					(1.33)				
Ln (1+GPI (utility model))						−0.001			
						(−0.17)			
Ln (1+Dis. GP (sum))							0.001		
							(0.36)		
Ln (1+Dis. GP (invention))								0.004	
								(1.48)	
Ln (1+Dis. GP (utility model))									0.001
									(0.17)
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	574	574	574	574	574	574	574	574	574
Adjusted R^2	0.006	0.008	0.006	0.006	0.008	0.006	0.006	0.008	0.006

Panel B: 2SLS

Panel B1: Number of green patents

Variables	(1) 1st stage Ln (1+GP (sum))	(2) 2nd stage CAR (−2, 2)	(3) 1st stage Ln (1+GP (invention))	(4) 2nd stage CAR (−2, 2)	(5) 1st stage Ln (1+GP (utility model))	(6) 2nd stage CAR (−2, 2)
Province-year Ln (1+GP (sum))	0.437*** (4.95)					
Province-year Ln (1+GP (invention))			0.531*** (4.50)			
Province-year Ln (1+GP (utility model))					0.470*** (7.77)	
Predicted Ln (1+GP (sum))		0.011*** (4.52)				
Predicted Ln (1+GP (invention))				0.011*** (3.60)		
Predicted Ln (1+GP (utility model))						0.008** (2.63)
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	574	574	574	574	574	574
Adjusted R^2	0.726	0.009	0.701	0.009	0.692	0.008

Panel B2: Green patent index (GPI)

Variables	(1) 1st stage Ln (1+GPI (sum))	(2) 2nd stage CAR (−2, 2)	(3) 1st stage Ln (1+GPI (invention))	(4) 2nd stage CAR (−2, 2)	(5) 1st stage Ln (1+GPI (utility model))	(6) 2nd stage CAR (−2, 2)
Province-year Ln (1+GPI (sum))	0.428*** (5.05)					
Province-year Ln (1+GPI (invention))			0.546*** (4.81)			
Province-year Ln (1+GPI (utility model))					0.462*** (7.87)	
Predicted Ln (1+GPI (sum))		0.012*** (3.34)				
Predicted Ln (1+GPI (invention))				0.010** (2.96)		
Predicted Ln (1+GPI (utility model))						0.008** (2.23)
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	574	574	574	574	574	574
Adjusted R^2	0.730	0.008	0.706	0.008	0.698	0.007

Panel B3: Number of discounted green patents

Variables	(1) 1st stage Ln (1+Dis. GP (sum))	(2) 2nd stage CAR (−2, 2)	(3) 1st stage Ln (1+Dis. GP (invention))	(4) 2nd stage CAR (−2, 2)	(5) 1st stage Ln (1+Dis. GP (utility model))	(6) 2nd stage CAR (−2, 2)
Province-year Ln (1+Dis. GP (sum))	0.425***					
	(4.14)					
Province-year Ln (1+Dis. GP (invention))			0.506***			
			(3.64)			
Province-year Ln (1+Dis. GP (utility model))					0.486***	
					(8.68)	
Predicted Ln (1+Dis. GP (sum))		0.012***				
		(4.01)				
Predicted Ln (1+Dis. GP (invention))				0.014***		
				(3.57)		
Predicted Ln (1+Dis. GP (utility model))						0.006*
						(1.83)
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	574	574	574	574	574	574
Adjusted R^2	0.729	0.009	0.701	0.009	0.689	0.007

Table 6

Long-term abnormal returns

This table reports the ordinary least squares (OLS) regression results of long-term market reactions based on completed deals. The dependent variable is buy-and-hold abnormal returns (BHARs). BHAR is calculated for 12 and 60 months following the month of CBMA deal completion, i.e., BHAR (0, 12) and BHAR (0, 60), by geometrically compounding the bidder's monthly returns during the period and then subtracting the market benchmark in China. The key independent variable is green innovation, measured by three groups of green patents (GPs) variables, i.e., number of green patents (Panel A1), green patent index (GPI) (Panel A2), and number of discounted green patents (Panel A3). Each group of green patent variables include three variables, one for overall green patents (columns (1) and (4)), the other two for subcategories of overall green patents, i.e., green invention patents (columns (2) and (5)) and green utility model patents (columns (3) and (6)). 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 mean of corresponding GP variable, only controlling for Firm-level variables. The second stage regresses BHAR (0, 12) or BHAR (0, 60) 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. *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. 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%. The coefficients on the constant and controls are suppressed for brevity and available upon request.

Panel A: Baseline regressions

Panel A1: Number of green patents

Variables	(1) BHAR (0, 12)	(2) BHAR (0, 12)	(3) BHAR (0, 12)	(4) BHAR (0, 60)	(5) BHAR (0, 60)	(6) BHAR (0, 60)
Ln (1+GP (sum))	−0.020			0.039		
	(−0.81)			(1.01)		
Ln (1+GP (invention))		0.014			0.208***	
		(0.64)			(5.31)	
Ln (1+GP (utility model))			−0.046			−0.084**
			(−1.25)			(−2.96)
Controls and constant	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	324	324	324	144	144	144
Adjusted R^2	0.137	0.136	0.142	0.098	0.113	0.101

Panel A2: Green patent index (GPI)

Variables	(1) BHAR (0, 12)	(2) BHAR (0, 12)	(3) BHAR (0, 12)	(4) BHAR (0, 60)	(5) BHAR (0, 60)	(6) BHAR (0, 60)
Ln (1+GPI (sum))	−0.025			0.011		
	(−0.80)			(0.26)		
Ln (1+GPI (invention))		0.020			0.218***	
		(0.94)			(4.55)	
Ln (1+GPI (utility model))			−0.057			−0.067
			(−1.40)			(−1.73)
Controls and constant	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	324	324	324	144	144	144
Adjusted R^2	0.137	0.136	0.143	0.097	0.110	0.099

Panel A3: Number of discounted green patents

Variables	(1) BHAR (0, 12)	(2) BHAR (0, 12)	(3) BHAR (0, 12)	(4) BHAR (0, 60)	(5) BHAR (0, 60)	(6) BHAR (0, 60)
Ln (1+Dis. GP (sum))	−0.018			−0.033		
	(−0.60)			(−0.99)		
Ln (1+Dis. GP (invention))		0.021			0.151**	
		(0.83)			(2.71)	
Ln (1+Dis. GP (utility model))			−0.042			−0.114***
			(−1.15)			(−3.80)
Controls and constant	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	324	324	324	144	144	144
Adjusted R^2	0.136	0.136	0.140	0.097	0.103	0.103

Panel B: 2SLS

Panel B1: Number of green patents

Variables	(1) 1st stage Ln (1+GP (sum))	(2) 2nd stage BHAR (0, 12)	(3) 1st stage Ln (1+GP (invention))	(4) 2nd stage BHAR (0, 12)	(5) 1st stage Ln (1+GP (utility model))	(6) 2nd stage BHAR (0, 12)	(7) 1st stage Ln (1+GP (sum))	(8) 2nd stage BHAR (0, 60)	(9) 1st stage Ln (1+GP (invention))	(10) 2nd stage BHAR (0, 60)	(11) 1st stage Ln (1+GP (utility model))	(12) 2nd stage BHAR (0, 60)
Province-year Ln (1+GP (sum))	0.455***						0.310**					
	(5.23)						(2.84)					
Province-year Ln (1+GP (invention))			0.523***						0.292**			
			(4.80)						(2.47)			
Province-year Ln (1+GP (utility model))					0.467***						0.406***	
					(9.79)						(5.01)	
Predicted Ln (1+GP (sum))		0.069						0.214**				
		(1.54)						(2.56)				
Predicted Ln (1+GP (invention))				0.117*						0.808***		
				(1.95)						(7.07)		
Predicted Ln (1+GP (utility model))						−0.023						−0.093
						(−0.60)						(−1.31)
Firm-level controls and constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	324	324	324	324	324	324	144	144	144	144	144	144
Adjusted R^2	0.734	0.138	0.732	0.143	0.678	0.136	0.765	0.099	0.744	0.115	0.714	0.098

Panel B2: Green patent index (GPI)

Variables	(1) 1st stage Ln (1+GPI (sum))	(2) 2nd stage BHAR (0, 12)	(3) 1st stage Ln (1+GPI (invention))	(4) 2nd stage BHAR (0, 12)	(5) 1st stage Ln (1+GPI (utility model))	(6) 2nd stage BHAR (0, 12)	(7) 1st stage Ln (1+GPI (sum))	(8) 2nd stage BHAR (0, 60)	(9) 1st stage Ln (1+GPI (invention))	(10) 2nd stage BHAR (0, 60)	(11) 1st stage Ln (1+GPI (utility model))	(12) 2nd stage BHAR (0, 60)
Province-year Ln (1+GPI (sum))	0.366***						0.243**					
	(5.61)						(2.66)					
Province-year Ln (1+GPI (invention))			0.465***						0.260**			
			(5.41)						(2.85)			
Province-year Ln (1+GPI (utility model))					0.398***						0.346***	
					(10.60)						(5.03)	
Predicted Ln (1+GPI (sum))		0.086						0.273**				
		(1.54)						(2.56)				
Predicted Ln (1+GPI (invention))				0.131*						0.908***		
				(1.95)						(7.07)		
Predicted Ln (1+GPI (utility model))						−0.027						−0.109
						(−0.60)						(−1.31)
Firm-level controls and constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	324	324	324	324	324	324	144	144	144	144	144	144
Adjusted R^2	0.734	0.138	0.735	0.143	0.675	0.136	0.770	0.099	0.769	0.115	0.716	0.098

Panel B3: Number of discounted green patents

Variables	(1) 1st stage Ln (1+Dis. GP (sum))	(2) 2nd stage BHAR (0, 12)	(3) 1st stage Ln (1+Dis. GP (invention))	(4) 2nd stage BHAR (0, 12)	(5) 1st stage Ln (1+Dis. GP (utility model))	(6) 2nd stage BHAR (0, 12)	(7) 1st stage Ln (1+Dis. GP (sum))	(8) 2nd stage BHAR (0, 60)	(9) 1st stage Ln (1+Dis. GP (invention))	(10) 2nd stage BHAR (0, 60)	(11) 1st stage Ln (1+Dis. GP (utility model))	(12) 2nd stage BHAR (0, 60)
Province-year Ln (1+Dis. GP (sum))	0.391***						0.289**					
	(4.57)						(3.04)					
Province-year Ln (1+Dis. GP (invention))			0.442***						0.272**			
			(4.14)						(3.03)			
Province-year Ln (1+Dis. GP (utility model))					0.424***						0.379***	
					(12.38)						(5.61)	
Predicted Ln (1+Dis. GP (sum))		0.080						0.230**				
		(1.54)						(2.56)				
Predicted Ln (1+Dis. GP (invention))				0.138*						0.869***		
				(1.95)						(7.07)		
Predicted Ln (1+Dis. GP (utility model))						−0.025						−0.100
						(−0.60)						(−1.31)
Firm-level controls and constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	324	324	324	324	324	324	144	144	144	144	144	144
Adjusted R^2	0.739	0.138	0.741	0.143	0.667	0.136	0.767	0.099	0.758	0.115	0.703	0.098

Table 7

Post-merger operating performance

This table reports the ordinary least squares (OLS) regression results of post-merger operating performance measured by return on equity (ROE). Panel A reports the OLS regression results based on the *Industry-, Year-, and Size-Matched* sample. Panel B reports the OLS regression results based on the *Industry-, Year-, Size-, B/M ratio-, and Leverage-Matched* sample. The dependent variables are *ROE (0, 1)* and *ROE (0, 5)*, respectively. The key independent variable is green innovation, measured by three groups of green patents (GPs) variables, i.e., number of green patents (Panel A1 and B1), green patent index (GPI) (Panel A2 and B2), and number of discounted green patents (Panel A3 and B3). Each group of green patent variables include three variables, one for overall green patents (columns (1) and (4)), the other two for subcategories of overall green patents, i.e., green invention patents (columns (2) and (5)) and green utility model patents (columns (3) and (6)). The interaction term is between green innovation and *Treat* dummy that equals one if a firm completed a CBMA deal, and zero otherwise. *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. 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%. The coefficients on the constant and controls are suppressed for brevity and available upon request.

Panel A: Industry-, Year-, and Size-Matched sample

Panel A1: Number of green patents

Variables	(1) ROE (0, 1)	(2) ROE (0, 1)	(3) ROE (0, 1)	(4) ROE (0, 5)	(5) ROE (0, 5)	(6) ROE (0, 5)
Ln (1+GP (sum))	−0.017***			−0.022***		
	(−5.46)			(−8.08)		
Treat × Ln (1+GP (sum))	0.005			0.009*		
	(0.72)			(1.96)		
Ln (1+GP (invention))		−0.020***			−0.025***	
		(−11.90)			(−17.13)	
Treat × Ln (1+GP (invention))		0.003			−0.000	
		(0.61)			(−0.12)	
Ln (1+GP (utility model))			−0.010			−0.019***
			(−1.51)			(−3.53)
Treat × Ln (1+GP (utility model))			0.002			0.018***
			(0.20)			(4.83)
Treat	−0.001	0.001	0.001	−0.028***	−0.022***	−0.032***
	(−0.17)	(0.16)	(0.12)	(−4.32)	(−3.87)	(−7.23)
Firm-level controls and constant	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	526	526	526	526	526	526
Adjusted R^2	0.166	0.168	0.155	0.118	0.123	0.111

Panel A2: Green patent index (GPI)

Variables	(1) ROE (0, 1)	(2) ROE (0, 1)	(3) ROE (0, 1)	(4) ROE (0, 5)	(5) ROE (0, 5)	(6) ROE (0, 5)
Ln (1+GPI (sum))	−0.015***			−0.023***		
	(−3.57)			(−6.90)		
Treat × Ln (1+GPI (sum))	0.004			0.009*		
	(0.46)			(1.84)		
Ln (1+GPI (invention))		−0.021***			−0.027***	
		(−11.99)			(−17.12)	
Treat × Ln (1+GPI (invention))		0.001			−0.001	
		(0.31)			(−0.13)	
Ln (1+GPI (utility model))			−0.008			−0.019**
			(−1.11)			(−2.93)
Treat × Ln (1+GPI (utility model))			0.000			0.018***
			(0.01)			(4.25)
Treat	−0.000	0.002	0.002	−0.027***	−0.021***	−0.032***
	(−0.01)	(0.29)	(0.23)	(−4.27)	(−4.07)	(−6.74)
Firm-level controls and constant	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	526	526	526	526	526	526
Adjusted R^2	0.160	0.166	0.154	0.115	0.122	0.109

Panel A3: Number of discounted green patents

Variables	(1) ROE (0, 1)	(2) ROE (0, 1)	(3) ROE (0, 1)	(4) ROE (0, 5)	(5) ROE (0, 5)	(6) ROE (0, 5)
Ln (1+Dis. GP (sum))	−0.019***			−0.022***		
	(−5.48)			(−7.22)		
Treat × Ln (1+Dis. GP (sum))	0.005			0.008		
	(0.67)			(1.70)		
Ln (1+Dis. GP (invention))		−0.023***			−0.025***	
		(−9.23)			(−13.68)	
Treat × Ln (1+Dis. GP (invention))		0.002			−0.002	
		(0.35)			(−0.33)	
Ln (1+Dis. GP (utility model))			−0.010			−0.021***
			(−1.46)			(−3.64)
Treat × Ln (1+Dis. GP (utility model))			0.001			0.018***
			(0.11)			(4.50)
Treat	−0.001	0.001	0.001	−0.027***	−0.022***	−0.031***
	(−0.13)	(0.16)	(0.21)	(−4.25)	(−3.91)	(−6.84)
Firm-level controls and constant	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	526	526	526	526	526	526
Adjusted R^2	0.168	0.170	0.155	0.116	0.119	0.110

Panel B: Industry-, Year-, Size-, B/M ratio-, and Leverage-Matched sample

Panel B1: Number of green patents

Variables	(1) ROE (0, 1)	(2) ROE (0, 1)	(3) ROE (0, 1)	(4) ROE (0, 5)	(5) ROE (0, 5)	(6) ROE (0, 5)
Ln (1+GP (sum))	−0.011*			−0.013**		
	(−1.82)			(−2.95)		
Treat × Ln (1+GP (sum))	0.005			0.004		
	(0.67)			(0.79)		
Ln (1+GP (invention))		−0.021***			−0.015***	
		(−6.70)			(−4.29)	
Treat × Ln (1+GP (invention))		0.001			−0.008	
		(0.17)			(−1.24)	
Ln (1+GP (utility model))			−0.008			−0.009
			(−1.02)			(−1.37)
Treat × Ln (1+GP (utility model))			0.010			0.017***
			(1.33)			(3.00)
Treat	0.021	0.025	0.019	−0.024**	−0.016*	−0.031***
	(1.12)	(1.64)	(1.04)	(−2.49)	(−2.00)	(−3.52)
Firm-level controls and constant	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	574	574	574	574	574	574
Adjusted R^2	0.066	0.069	0.066	0.136	0.142	0.136

Panel B2: Green patent index (GPI)

Variables	(1) ROE (0, 1)	(2) ROE (0, 1)	(3) ROE (0, 1)	(4) ROE (0, 5)	(5) ROE (0, 5)	(6) ROE (0, 5)
Ln (1+GPI (sum))	−0.011			−0.013**		
	(−1.55)			(−2.36)		
Treat × Ln (1+GPI (sum))	0.004			0.002		
	(0.55)			(0.27)		
Ln (1+GPI (invention))		−0.031***			−0.016***	
		(−10.22)			(−3.83)	
Treat × Ln (1+GPI (invention))		0.006			−0.012	
		(1.19)			(−1.65)	
Ln (1+GPI (utility model))			−0.009			−0.010
			(−1.18)			(−1.40)
Treat × Ln (1+GPI (utility model))			0.012			0.019**
			(1.54)			(2.91)
Treat	0.022	0.023	0.019	−0.022**	−0.015*	−0.031***
	(1.15)	(1.56)	(1.05)	(−2.24)	(−1.87)	(−3.47)
Firm-level controls and constant	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	574	574	574	574	574	574
Adjusted R^2	0.066	0.070	0.066	0.136	0.142	0.136

Panel B3: Number of discounted green patents

Variables	(1) ROE (0, 1)	(2) ROE (0, 1)	(3) ROE (0, 1)	(4) ROE (0, 5)	(5) ROE (0, 5)	(6) ROE (0, 5)
Ln (1+Dis. GP (sum))	−0.009			−0.011**		
	(−1.28)			(−2.19)		
Treat × Ln (1+Dis. GP (sum))	0.000			0.003		
	(0.02)			(0.52)		
Ln (1+Dis. GP (invention))		−0.015**			−0.014**	
		(−2.91)			(−2.85)	
Treat × Ln (1+Dis. GP (invention))		−0.010			−0.009	
		(−1.59)			(−1.20)	
Ln (1+Dis. GP (utility model))			−0.005			−0.008
			(−0.59)			(−1.13)
Treat × Ln (1+Dis. GP (utility model))			0.005			0.015**
			(0.66)			(2.55)
Treat	0.025	0.030*	0.022	−0.023**	−0.017*	−0.028***
	(1.32)	(1.84)	(1.24)	(−2.42)	(−2.06)	(−3.38)
Firm-level controls and constant	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	574	574	574	574	574	574
Adjusted R^2	0.066	0.069	0.065	0.135	0.140	0.135

Table 8

Post-merger carbon emissions

This table reports the ordinary least squares (OLS) regression results of post-merger carbon emissions (Scope 1). Panel A (C) reports the OLS regression results based on the *Industry-, Year-, and Size-Matched* sample (and "Two high" industries). Panel B (D) reports the OLS regression results based on the *Industry-, Year-, Size-, B/M ratio-, and Leverage-Matched* sample (and "Two high" industries). "Two high" means high energy consumptions and high pollutions. The dependent variables are *CO2 (0, 1)* and *CO2 (0, 5)*, respectively. The key independent variable is green innovation, measured by three groups of green patents (GPs) variables, i.e., number of green patents (Panel A1 and B1), green patent index (GPI) (Panel A2 and B2), and number of discounted green patents (Panel A3 and B3). Each group of green patent variables include three variables, one for overall green patents (columns (1) and (4)), the other two for subcategories of overall green patents, i.e., green invention patents (columns (2) and (5)) and green utility model patents (columns (3) and (6)). The interaction term is between green innovation and *Treat* dummy that equals one if a firm completed a CBMA deal, and zero otherwise. *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. 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%. The coefficients on the constant and controls are suppressed for brevity and available upon request.

Panel A: Industry-, Year-, and Size-Matched sample

Panel A1: Number of green patents

Variables	(1) CO2 (0, 1)	(2) CO2 (0, 1)	(3) CO2 (0, 1)	(4) CO2 (0, 5)	(5) CO2 (0, 5)	(6) CO2 (0, 5)
Ln (1+GP (sum))	0.131***			0.107***		
	(5.35)			(3.52)		
Treat × Ln (1+GP (sum))	−0.069**			−0.056**		
	(−2.59)			(−2.25)		
Ln (1+GP (invention))		0.104***			0.047	
		(4.60)			(1.68)	
Treat × Ln (1+GP (invention))		−0.078**			−0.049	
		(−2.49)			(−1.37)	
Ln (1+GP (utility model))			0.178***			0.157***
			(6.34)			(4.50)
Treat × Ln (1+GP (utility model))			−0.075**			−0.063**
			(−2.77)			(−2.28)
Treat	−0.014	−0.031	−0.028	−0.036	−0.055	−0.046
	(−0.22)	(−0.50)	(−0.52)	(−0.55)	(−0.81)	(−0.82)
Firm-level controls and constant	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	250	250	250	315	315	315
Adjusted R^2	0.285	0.274	0.297	0.236	0.226	0.246

Panel A2: Green patent index (GPI)

Variables	(1) CO2 (0, 1)	(2) CO2 (0, 1)	(3) CO2 (0, 1)	(4) CO2 (0, 5)	(5) CO2 (0, 5)	(6) CO2 (0, 5)
Ln (1+GPI (sum))	0.170***			0.146***		
	(5.78)			(3.98)		
Treat × Ln (1+GPI (sum))	−0.090**			−0.078**		
	(−2.97)			(−2.66)		
Ln (1+GPI (invention))		0.145***			0.079**	
		(5.20)			(2.28)	
Treat × Ln (1+GPI (invention))		−0.109**			−0.073	
		(−3.02)			(−1.77)	
Ln (1+GPI (utility model))			0.188***			0.173***
			(6.14)			(4.54)
Treat × Ln (1+GPI (utility model))			−0.072**			−0.065*
			(−2.48)			(−2.19)
Treat	−0.007	−0.021	−0.033	−0.030	−0.049	−0.049
	(−0.10)	(−0.33)	(−0.63)	(−0.46)	(−0.71)	(−0.88)
Firm-level controls and constant	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	250	250	250	315	315	315
Adjusted R^2	0.291	0.279	0.297	0.241	0.228	0.248

Panel A3: Number of discounted green patents

Variables	(1) CO2 (0, 1)	(2) CO2 (0, 1)	(3) CO2 (0, 1)	(4) CO2 (0, 5)	(5) CO2 (0, 5)	(6) CO2 (0, 5)
Ln (1+Dis. GP (sum))	0.146***			0.116***		
	(6.56)			(4.12)		
Treat × Ln (1+Dis. GP (sum))	−0.081**			−0.062**		
	(−2.96)			(−2.29)		
Ln (1+Dis. GP (invention))		0.109***			0.044*	
		(5.42)			(1.92)	
Treat × Ln (1+Dis. GP (invention))		−0.087**			−0.057	
		(−2.74)			(−1.53)	
Ln (1+Dis. GP (utility model))			0.205***			0.178***
			(6.90)			(4.90)
Treat × Ln (1+Dis. GP (utility model))			−0.098**			−0.078**
			(−3.11)			(−2.39)
Treat	−0.011	−0.031	−0.021	−0.037	−0.055	−0.043
	(−0.19)	(−0.52)	(−0.40)	(−0.57)	(−0.84)	(−0.76)
Firm-level controls and constant	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	250	250	250	315	315	315
Adjusted R^2	0.286	0.274	0.298	0.236	0.226	0.246

Panel B: Industry-, Year-, Size-, B/M ratio-, and Leverage-Matched sample

Panel B1: Number of green patents

Variables	(1) CO2 (0, 1)	(2) CO2 (0, 1)	(3) CO2 (0, 1)	(4) CO2 (0, 5)	(5) CO2 (0, 5)	(6) CO2 (0, 5)
Ln (1+GP (sum))	0.130*			0.180*		
	(1.91)			(1.86)		
Treat × Ln (1+GP (sum))	−0.055			−0.094*		
	(−1.04)			(−2.07)		
Ln (1+GP (invention))		0.093**			0.149**	
		(2.83)			(2.80)	
Treat × Ln (1+GP (invention))		−0.111			−0.158**	
		(−1.42)			(−2.29)	
Ln (1+GP (utility model))			0.209			0.282*
			(1.65)			(1.87)
Treat × Ln (1+GP (utility model))			−0.043			−0.093***
			(−0.92)			(−3.00)
Treat	−0.095	−0.084	−0.116	−0.058	−0.053	−0.082
	(−1.67)	(−1.47)	(−1.66)	(−1.45)	(−1.37)	(−1.43)
Firm-level controls and constant	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	276	276	276	358	358	358
Adjusted R^2	0.283	0.275	0.309	0.203	0.192	0.232

Panel B2: Green patent index (GPI)

Variables	(1) CO2 (0, 1)	(2) CO2 (0, 1)	(3) CO2 (0, 1)	(4) CO2 (0, 5)	(5) CO2 (0, 5)	(6) CO2 (0, 5)
Ln (1+GPI (sum))	0.162**			0.212**		
	(2.42)			(2.21)		
Treat × Ln (1+GPI (sum))	−0.066			−0.105*		
	(−1.07)			(−2.09)		
Ln (1+GPI (invention))		0.116**			0.177**	
		(2.22)			(2.25)	
Treat × Ln (1+GPI (invention))		−0.120			−0.163**	
		(−1.34)			(−2.26)	
Ln (1+GPI (utility model))			0.263*			0.330*
			(1.92)			(2.02)
Treat × Ln (1+GPI (utility model))			−0.050			−0.092**
			(−1.00)			(−2.73)
Treat	−0.093	−0.087	−0.113	−0.061	−0.061	−0.087
	(−1.66)	(−1.52)	(−1.59)	(−1.53)	(−1.49)	(−1.45)
Firm-level controls and constant	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	276	276	276	358	358	358
Adjusted R^2	0.287	0.275	0.325	0.205	0.192	0.245

Panel B3: Number of discounted green patents

Variables	(1) CO2 (0, 1)	(2) CO2 (0, 1)	(3) CO2 (0, 1)	(4) CO2 (0, 5)	(5) CO2 (0, 5)	(6) CO2 (0, 5)
Ln (1+Dis. GP (sum))	0.145			0.224*		
	(1.66)			(1.93)		
Treat × Ln (1+Dis. GP (sum))	−0.066			−0.122*		
	(−0.93)			(−2.11)		
Ln (1+Dis. GP (invention))		0.108*			0.200**	
		(2.11)			(2.88)	
Treat × Ln (1+Dis. GP (invention))		−0.130			−0.203**	
		(−1.23)			(−2.27)	
Ln (1+Dis. GP (utility model))			0.247			0.345*
			(1.69)			(1.98)
Treat × Ln (1+Dis. GP (utility model))			−0.068			−0.133***
			(−1.13)			(−3.24)
Treat	−0.099*	−0.087	−0.111	−0.056	−0.050	−0.076
	(−1.92)	(−1.74)	(−1.63)	(−1.48)	(−1.42)	(−1.40)
Firm-level controls and constant	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	276	276	276	358	358	358
Adjusted R^2	0.284	0.275	0.314	0.210	0.196	0.243

Panel C: Industry-, Year-, and Size-Matched sample ("Two high" industries)

Panel C1: Number of green patents

Variables	(1) CO2 (0, 1)	(2) CO2 (0, 1)	(3) CO2 (0, 1)	(4) CO2 (0, 5)	(5) CO2 (0, 5)	(6) CO2 (0, 5)
Ln (1+GP (sum))	0.471*			0.495**		
	(12.17)			(15.80)		
Treat × Ln (1+GP (sum))	−0.297*			−0.366**		
	(−7.98)			(−28.41)		
Ln (1+GP (invention))		0.529***			0.451***	
		(222.92)			(64.47)	
Treat × Ln (1+GP (invention))		−0.386			−0.396*	
		(−5.12)			(−8.77)	
Ln (1+GP (utility model))			0.562*			0.601***
			(8.24)			(94.01)
Treat × Ln (1+GP (utility model))			−0.306*			−0.401**
			(−8.02)			(−26.56)
Treat	0.101	0.101	0.049**	0.014	−0.042	−0.013*
	(5.09)	(0.85)	(26.84)	(0.90)	(−0.31)	(−10.77)
Firm-level controls and constant	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	103	103	103	123	123	123
Adjusted R^2	0.587	0.545	0.620	0.555	0.493	0.588

Panel C2: Green patent index (GPI)

Variables	(1) CO2 (0, 1)	(2) CO2 (0, 1)	(3) CO2 (0, 1)	(4) CO2 (0, 5)	(5) CO2 (0, 5)	(6) CO2 (0, 5)
Ln (1+GPI (sum))	0.533*			0.558**		
	(11.35)			(19.88)		
Treat × Ln (1+GPI (sum))	−0.326*			−0.406**		
	(−8.68)			(−24.32)		
Ln (1+GPI (invention))		0.620**			0.520**	
		(60.24)			(30.02)	
Treat × Ln (1+GPI (invention))		−0.457			−0.462*	
		(−4.62)			(−7.58)	
Ln (1+GPI (utility model))			0.596*			0.640***
			(6.60)			(67.76)
Treat × Ln (1+GPI (utility model))			−0.291*			−0.401**
			(−7.27)			(−25.65)
Treat	0.092*	0.118	0.028	0.004	−0.030	−0.033
	(9.84)	(0.94)	(1.52)	(0.35)	(−0.22)	(−2.41)
Firm-level controls and constant	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	103	103	103	123	123	123
Adjusted R^2	0.598	0.559	0.624	0.564	0.501	0.593

Panel C3: Number of discounted green patents

Variables	(1) CO2 (0, 1)	(2) CO2 (0, 1)	(3) CO2 (0, 1)	(4) CO2 (0, 5)	(5) CO2 (0, 5)	(6) CO2 (0, 5)
Ln (1+Dis. GP (sum))	0.562*			0.589**		
	(9.07)			(38.52)		
Treat × Ln (1+Dis. GP (sum))	−0.378*			−0.461**		
	(−8.82)			(−23.99)		
Ln (1+Dis. GP (invention))		0.708***			0.625***	
		(100.47)			(285.31)	
Treat × Ln (1+Dis. GP (invention))		−0.575			−0.591**	
		(−6.17)			(−14.03)	
Ln (1+Dis. GP (utility model))			0.647			0.694**
			(6.14)			(33.80)
Treat × Ln (1+Dis. GP (utility model))			−0.361*			−0.477**
			(−7.58)			(−21.02)
Treat	0.104*	0.109	0.050	0.021	−0.028	−0.017
	(9.24)	(0.81)	(3.52)	(1.63)	(−0.20)	(−1.48)
Firm-level controls and constant	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	103	103	103	123	123	123
Adjusted R^2	0.604	0.562	0.627	0.569	0.508	0.595

Panel D: Industry-, Year-, Size-, B/M ratio-, and Leverage-Matched sample ("Two high" industries)

Panel D1: Number of green patents

Variables	(1) CO2 (0, 1)	(2) CO2 (0, 1)	(3) CO2 (0, 1)	(4) CO2 (0, 5)	(5) CO2 (0, 5)	(6) CO2 (0, 5)
Ln (1+GP (sum))	0.438			0.483		
	(2.56)			(1.61)		
Treat × Ln (1+GP (sum))	−0.228			−0.197		
	(−1.16)			(−0.86)		
Ln (1+GP (invention))		0.424			0.494	
		(2.42)			(1.64)	
Treat × Ln (1+GP (invention))		−0.408			−0.387	
		(−1.35)			(−1.09)	
Ln (1+GP (utility model))			0.683*			0.725
			(3.53)			(1.92)
Treat × Ln (1+GP (utility model))			−0.105			−0.062
			(−1.06)			(−0.64)
Treat	−0.153	−0.144	−0.266	−0.158*	−0.138	−0.253
	(−2.84)	(−2.85)	(−2.04)	(−3.07)	(−2.25)	(−2.22)
Firm-level controls and constant	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	122	122	122	152	152	152
Adjusted R^2	0.468	0.440	0.573	0.386	0.348	0.493

Panel D2: Green patent index (GPI)

Variables	(1) CO2 (0, 1)	(2) CO2 (0, 1)	(3) CO2 (0, 1)	(4) CO2 (0, 5)	(5) CO2 (0, 5)	(6) CO2 (0, 5)
Ln (1+GPI (sum))	0.508*			0.547		
	(3.44)			(1.93)		
Treat × Ln (1+GPI (sum))	−0.265			−0.225		
	(−1.26)			(−0.92)		
Ln (1+GPI (invention))		0.494			0.596	
		(2.24)			(1.56)	
Treat × Ln (1+GPI (invention))		−0.425			−0.400	
		(−1.33)			(−1.10)	
Ln (1+GPI (utility model))			0.732*			0.773
			(4.07)			(2.09)
Treat × Ln (1+GPI (utility model))			−0.064			0.000
			(−0.79)			(0.00)
Treat	−0.156	−0.151	−0.270	−0.167	−0.147	−0.259
	(−2.54)	(−2.82)	(−2.05)	(−2.91)	(−2.21)	(−2.26)
Firm-level controls and constant	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	122	122	122	152	152	152
Adjusted R^2	0.472	0.440	0.600	0.385	0.354	0.519

Panel D3: Number of discounted green patents

Variables	(1) CO_2 (0, 1)	(2) CO_2 (0, 1)	(3) CO_2 (0, 1)	(4) CO_2 (0, 5)	(5) CO_2 (0, 5)	(6) CO_2 (0, 5)
Ln (1+Dis. GP (sum))	0.517			0.605		
	(2.52)			(1.69)		
Treat × Ln (1+Dis. GP (sum))	−0.266			−0.263		
	(−1.21)			(−1.00)		
Ln (1+Dis. GP (invention))		0.511			0.640	
		(2.28)			(1.57)	
Treat × Ln (1+Dis. GP (invention))		−0.492			−0.508	
		(−1.42)			(−1.16)	
Ln (1+Dis. GP (utility model))			0.775*			0.854
			(3.89)			(2.18)
Treat × Ln (1+Dis. GP (utility model))			−0.133			−0.107
			(−1.29)			(−1.10)
Treat	−0.180*	−0.157*	−0.283	−0.164*	−0.138	−0.258
	(−3.84)	(−3.57)	(−2.32)	(−3.66)	(−2.72)	(−2.41)
Firm-level controls and constant	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	122	122	122	152	152	152
Adjusted R^2	0.476	0.443	0.586	0.402	0.356	0.514

Table 9

Post-merger environmental performance

This table reports the ordinary least squares (OLS) regression results of post-merger environmental performance. Panel A reports the OLS regression results based on the *Industry-, Year-, and Size-Matched* sample. Panel B reports the OLS regression results based on the *Industry-, Year-, Size-, B/M ratio-, and Leverage-Matched* sample. The dependent variables are *Environment (0, 1)* and *Environment (0, 5)*, respectively. The key independent variable is green innovation, measured by three groups of green patents (GPs) variables, i.e., number of green patents (Panel A1 and B1), green patent index (GPI) (Panel A2 and B2), and number of discounted green patents (Panel A3 and B3). Each group of green patent variables include three variables, one for overall green patents (columns (1) and (4)), the other two for subcategories of overall green patents, i.e., green invention patents (columns (2) and (5)) and green utility model patents (columns (3) and (6)). The interaction term is between green innovation and *Treat* dummy that equals one if a firm completed a CBMA deal, and zero otherwise. *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. 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%. The coefficients on the constant and controls are suppressed for brevity and available upon request.

Panel A: Industry-, Year-, and Size-Matched sample

Panel A1: Number of green patents

Variables	(1) Environment (0, 1)	(2) Environment (0, 1)	(3) Environment (0, 1)	(4) Environment (0, 5)	(5) Environment (0, 5)	(6) Environment (0, 5)
Ln (1+GP (sum))	0.024			0.017		
	(1.39)			(1.39)		
Treat × Ln (1+GP (sum))	0.001			0.002		
	(0.21)			(0.36)		
Ln (1+GP (invention))		0.012			0.007	
		(0.59)			(0.73)	
Treat × Ln (1+GP (invention))		0.007			0.015*	
		(0.85)			(1.89)	
Ln (1+GP (utility model))			0.020			0.010
			(1.00)			(0.60)
Treat × Ln (1+GP (utility model))			−0.007			−0.004
			(−1.46)			(−0.56)
Treat	0.075***	0.072***	0.088***	0.026	0.018	0.032
	(3.73)	(4.00)	(4.65)	(1.21)	(0.84)	(1.53)
Firm-level controls and constant	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	98	98	98	181	181	181
Adjusted R^2	0.436	0.431	0.432	0.311	0.310	0.307

Panel A2: Green patent index (GPI)

Variables	(1) Environment (0, 1)	(2) Environment (0, 1)	(3) Environment (0, 1)	(4) Environment (0, 5)	(5) Environment (0, 5)	(6) Environment (0, 5)
Ln (1+GPI (sum))	0.037			0.022		
	(1.77)			(1.65)		
Treat × Ln (1+GPI (sum))	0.001			0.000		
	(0.15)			(0.01)		
Ln (1+GPI (invention))		0.015			0.009	
		(0.70)			(0.86)	
Treat × Ln (1+GPI (invention))		0.010			0.016*	
		(1.08)			(1.91)	
Ln (1+GPI (utility model))			0.021			0.013
			(0.88)			(0.74)
Treat × Ln (1+GPI (utility model))			−0.007			−0.005
			(−1.17)			(−0.74)
Treat	0.074***	0.069***	0.087***	0.028	0.018	0.033
	(3.51)	(3.81)	(4.57)	(1.40)	(0.87)	(1.63)
Firm-level controls and constant	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	98	98	98	181	181	181
Adjusted R^2	0.441	0.433	0.432	0.311	0.310	0.307

Panel A3: Number of discounted green patents

Variables	(1) Environment (0, 1)	(2) Environment (0, 1)	(3) Environment (0, 1)	(4) Environment (0, 5)	(5) Environment (0, 5)	(6) Environment (0, 5)
Ln (1+Dis. GP (sum))	0.029			0.017		
	(1.60)			(1.28)		
Treat × Ln (1+Dis. GP (sum))	0.004			0.003		
	(0.70)			(0.37)		
Ln (1+Dis. GP (invention))		0.017			0.007	
		(0.77)			(0.57)	
Treat × Ln (1+Dis. GP (invention))		0.005			0.012	
		(0.49)			(1.33)	
Ln (1+Dis. GP (utility model))			0.027			0.015
			(1.19)			(0.92)
Treat × Ln (1+Dis. GP (utility model))			−0.005			−0.002
			(−1.09)			(−0.29)
Treat	0.070***	0.075***	0.082***	0.026	0.021	0.030
	(3.78)	(4.10)	(4.55)	(1.20)	(1.02)	(1.49)
Firm-level controls and constant	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	98	98	98	181	181	181
Adjusted R^2	0.441	0.433	0.434	0.311	0.308	0.308

Panel B: Industry-, Year-, Size-, B/M ratio-, and Leverage-Matched sample

Panel B1: Number of green patents

Variables	(1) Environment (0, 1)	(2) Environment (0, 1)	(3) Environment (0, 1)	(4) Environment (0, 5)	(5) Environment (0, 5)	(6) Environment (0, 5)
Ln (1+GP (sum))	−0.025			−0.015*		
	(−1.66)			(−1.90)		
Treat × Ln (1+GP (sum))	0.042*			0.042***		
	(2.13)			(4.26)		
Ln (1+GP (invention))		−0.000			−0.005	
		(−0.03)			(−0.55)	
Treat × Ln (1+GP (invention))		0.036			0.047***	
		(1.63)			(4.36)	
Ln (1+GP (utility model))			−0.022			−0.009
			(−0.45)			(−0.32)
Treat × Ln (1+GP (utility model))			0.076***			0.061***
			(5.19)			(5.78)
Treat	−0.033	−0.011	−0.047	−0.011	−0.003	−0.015
	(−0.62)	(−0.18)	(−0.79)	(−0.49)	(−0.15)	(−0.69)
Firm-level controls and constant	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	124	124	124	211	211	211
Adjusted R^2	0.271	0.270	0.296	0.298	0.303	0.315

Panel B2: Green patent index (GPI)

Variables	(1) Environment (0, 1)	(2) Environment (0, 1)	(3) Environment (0, 1)	(4) Environment (0, 5)	(5) Environment (0, 5)	(6) Environment (0, 5)
Ln (1+GPI (sum))	−0.018			−0.017*		
	(−1.24)			(−1.88)		
Treat × Ln (1+GPI (sum))	0.043			0.045***		
	(1.78)			(3.97)		
Ln (1+GPI (invention))		0.009			−0.007	
		(0.70)			(−0.71)	
Treat × Ln (1+GPI (invention))		0.040			0.058***	
		(1.38)			(4.29)	
Ln (1+GPI (utility model))			−0.003			−0.000
			(−0.06)			(−0.02)
Treat × Ln (1+GPI (utility model))			0.073***			0.060***
			(4.59)			(5.67)
Treat	−0.023	−0.008	−0.036	−0.007	−0.005	−0.011
	(−0.42)	(−0.14)	(−0.57)	(−0.29)	(−0.23)	(−0.49)
Firm-level controls and constant	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	124	124	124	211	211	211
Adjusted R^2	0.268	0.273	0.296	0.294	0.304	0.315

Panel B3: Number of discounted green patents

Variables	(1) Environment (0, 1)	(2) Environment (0, 1)	(3) Environment (0, 1)	(4) Environment (0, 5)	(5) Environment (0, 5)	(6) Environment (0, 5)
Ln (1+Dis. GP (sum))	−0.036			−0.022*		
	(−1.33)			(−1.82)		
Treat × Ln (1+Dis. GP (sum))	0.049			0.049***		
	(1.59)			(3.36)		
Ln (1+Dis. GP (invention))		−0.012			−0.014	
		(−0.82)			(−1.09)	
Treat × Ln (1+Dis. GP (invention))		0.038			0.055***	
		(1.06)			(3.26)	
Ln (1+Dis. GP (utility model))			−0.027			−0.011
			(−0.47)			(−0.33)
Treat × Ln (1+Dis. GP (utility model))			0.085***			0.068***
			(3.84)			(4.77)
Treat	−0.035	−0.009	−0.046	−0.013	−0.003	−0.014
	(−0.79)	(−0.16)	(−0.85)	(−0.60)	(−0.15)	(−0.73)
Firm-level controls and constant	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	124	124	124	211	211	211
Adjusted R^2	0.273	0.265	0.299	0.299	0.300	0.319

Table 10

Post-merger government subsidies

This table reports the ordinary least squares (OLS) regression results of post-merger government subsidies. Panel A reports the OLS regression results based on the *Industry-, Year-, and Size-Matched* sample. Panel B reports the OLS regression results based on the *Industry-, Year-, Size-, B/M ratio-, and Leverage-Matched* sample. The dependent variables are *Subsidy (0, 1)* and *Subsidy (0, 5)*, respectively. The key independent variable is green innovation, measured by three groups of green patents (GPs) variables, i.e., number of green patents (Panel A1 and B1), green patent index (GPI) (Panel A2 and B2), and number of discounted green patents (Panel A3 and B3). Each group of green patent variables include three variables, one for overall green patents (columns (1) and (4)), the other two for subcategories of overall green patents, i.e., green invention patents (columns (2) and (5)) and green utility model patents (columns (3) and (6)). The interaction term is between green innovation and *Treat* dummy that equals one if a firm completed a CBMA deal, and zero otherwise. *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. 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%. The coefficients on the constant and controls are suppressed for brevity and available upon request.

Panel A: Industry-, Year-, and Size-Matched sample

Panel A1: Number of green patents

Variables	(1) Subsidy (0, 1)	(2) Subsidy (0, 1)	(3) Subsidy (0, 1)	(4) Subsidy (0, 5)	(5) Subsidy (0, 5)	(6) Subsidy (0, 5)
Ln (1+GP (sum))	0.303***			0.268**		
	(3.82)			(2.69)		
Treat × Ln (1+GP (sum))	1.368***			1.072***		
	(10.50)			(5.51)		
Ln (1+GP (invention))		−0.147			−0.033	
		(−1.41)			(−0.30)	
Treat × Ln (1+GP (invention))		1.301***			0.945***	
		(7.41)			(4.25)	
Ln (1+GP (utility model))			0.176			0.134*
			(1.60)			(1.82)
Treat × Ln (1+GP (utility model))			1.667***			1.307***
			(10.59)			(6.34)
Treat	−1.266*	−0.729	−1.187*	−0.734	−0.279	−0.670
	(−2.01)	(−1.18)	(−1.89)	(−1.72)	(−0.66)	(−1.56)
Firm-level controls and constant	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	470	470	470	470	470	470
Adjusted R^2	0.148	0.116	0.146	0.143	0.118	0.140

Panel A2: Green patent index (GPI)

Variables	(1) Subsidy (0, 1)	(2) Subsidy (0, 1)	(3) Subsidy (0, 1)	(4) Subsidy (0, 5)	(5) Subsidy (0, 5)	(6) Subsidy (0, 5)
Ln (1+GPI (sum))	0.294***			0.206**		
	(3.46)			(2.27)		
Treat × Ln (1+GPI (sum))	1.472***			1.171***		
	(9.41)			(5.06)		
Ln (1+GPI (invention))		−0.181			−0.041	
		(−1.31)			(−0.37)	
Treat × Ln (1+GPI (invention))		1.452***			1.079***	
		(7.18)			(3.94)	
Ln (1+GPI (utility model))			0.175			0.110
			(1.48)			(1.65)
Treat × Ln (1+GPI (utility model))			1.719***			1.338***
			(9.79)			(5.56)
Treat	−1.198*	−0.720	−1.127*	−0.689	−0.283	−0.616
	(−1.95)	(−1.17)	(−1.86)	(−1.66)	(−0.68)	(−1.49)
Firm-level controls and constant	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	470	470	470	470	470	470
Adjusted R^2	0.142	0.116	0.141	0.137	0.119	0.136

Panel A3: Number of discounted green patents

Variables	(1) Subsidy (0, 1)	(2) Subsidy (0, 1)	(3) Subsidy (0, 1)	(4) Subsidy (0, 5)	(5) Subsidy (0, 5)	(6) Subsidy (0, 5)
Ln (1+Dis. GP (sum))	0.149			0.144		
	(1.71)			(1.41)		
Treat × Ln (1+Dis. GP (sum))	1.643***			1.341***		
	(10.48)			(5.96)		
Ln (1+Dis. GP (invention))		−0.369**			−0.215*	
		(−3.06)			(−1.88)	
Treat × Ln (1+Dis. GP (invention))		1.426***			1.101***	
		(6.88)			(4.22)	
Ln (1+Dis. GP (utility model))			0.032			0.064
			(0.22)			(0.66)
Treat × Ln (1+Dis. GP (utility model))			2.017***			1.597***
			(10.57)			(6.89)
Treat	−1.268*	−0.665	−1.197*	−0.772*	−0.255	−0.689
	(−2.07)	(−1.07)	(−1.93)	(−1.87)	(−0.60)	(−1.62)
Firm-level controls and constant	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	470	470	470	470	470	470
Adjusted R^2	0.146	0.112	0.147	0.144	0.116	0.144

Panel B: Industry-, Year-, Size-, B/M ratio-, and Leverage-Matched sample

Panel B1: Number of green patents

Variables	(1) Subsidy (0, 1)	(2) Subsidy (0, 1)	(3) Subsidy (0, 1)	(4) Subsidy (0, 5)	(5) Subsidy (0, 5)	(6) Subsidy (0, 5)
Ln (1+GP (sum))	0.180			−0.212		
	(0.58)			(−0.79)		
Treat × Ln (1+GP (sum))	1.163**			1.219***		
	(2.95)			(3.54)		
Ln (1+GP (invention))		0.085			−0.443**	
		(0.30)			(−2.82)	
Treat × Ln (1+GP (invention))		0.937**			1.262***	
		(2.51)			(4.33)	
Ln (1+GP (utility model))			0.205			−0.177
			(0.57)			(−0.60)
Treat × Ln (1+GP (utility model))			1.312***			1.335***
			(2.98)			(3.38)
Treat	−0.599	−0.101	−0.475	−0.573	−0.177	−0.416
	(−1.32)	(−0.33)	(−1.22)	(−1.25)	(−0.57)	(−1.02)
Firm-level controls and constant	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	519	519	519	519	519	519
Adjusted R^2	0.066	0.044	0.064	0.066	0.053	0.064

Panel B2: Green patent index (GPI)

Variables	(1) Subsidy (0, 1)	(2) Subsidy (0, 1)	(3) Subsidy (0, 1)	(4) Subsidy (0, 5)	(5) Subsidy (0, 5)	(6) Subsidy (0, 5)
Ln (1+GPI (sum))	0.289			−0.155		
	(0.92)			(−0.65)		
Treat × Ln (1+GPI (sum))	1.250***			1.278***		
	(3.13)			(3.73)		
Ln (1+GPI (invention))		0.059			−0.458***	
		(0.22)			(−3.27)	
Treat × Ln (1+GPI (invention))		1.147***			1.473***	
		(3.24)			(4.93)	
Ln (1+GPI (utility model))			0.267			−0.219
			(0.77)			(−0.79)
Treat × Ln (1+GPI (utility model))			1.369***			1.415***
			(3.28)			(3.75)
Treat	−0.492	−0.126	−0.418	−0.445	−0.188	−0.371
	(−1.24)	(−0.45)	(−1.19)	(−1.10)	(−0.63)	(−0.99)
Firm-level controls and constant	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	519	519	519	519	519	519
Adjusted R^2	0.063	0.044	0.062	0.062	0.054	0.062

Panel B3: Number of discounted green patents

Variables	(1) Subsidy (0, 1)	(2) Subsidy (0, 1)	(3) Subsidy (0, 1)	(4) Subsidy (0, 5)	(5) Subsidy (0, 5)	(6) Subsidy (0, 5)
Ln (1+Dis. GP (sum))	0.347			−0.181		
	(1.06)			(−0.71)		
Treat × Ln (1+Dis. GP (sum))	1.114**			1.295***		
	(2.60)			(3.45)		
Ln (1+Dis. GP (invention))		0.316			−0.496**	
		(0.91)			(−2.56)	
Treat × Ln (1+Dis. GP (invention))		0.711			1.265***	
		(1.64)			(3.85)	
Ln (1+Dis. GP (utility model))			0.342			−0.185
			(0.92)			(−0.66)
Treat × Ln (1+Dis. GP (utility model))			1.328**			1.490***
			(2.85)			(3.47)
Treat	−0.450	0.054	−0.370	−0.486	−0.074	−0.370
	(−1.11)	(0.19)	(−1.08)	(−1.15)	(−0.25)	(−0.98)
Firm-level controls and constant	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	519	519	519	519	519	519
Adjusted R^2	0.065	0.040	0.065	0.065	0.049	0.065

Appendix

Panel A1: Variable definitions

Variables	Definition	Source
All cash deal	Dummy variable that equals one if the CBMA deal is paid in all cash, and zero otherwise.	Refinitiv Eikon (SDC)
BHAR (0, 12) *BHAR (0, 60)*	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 monthly returns during the period of 12 or 60 months after the month of cross-border deal completion (month 0), then subtracting the market returns calculated in an analogous way.	CSMAR
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*.	CSMAR
CAR (−2, 2) *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 5-day event window (−2, 2) around day 0 and use a 7-day event window (−3, 3) for robust tests.	CSMAR
CO2 (0, 1) *CO2 (0, 5)*	Carbon emissions in this paper mainly refer to the Scope 1 greenhouse gas (GHG) emissions from sources that are owned or controlled by the company (categorized by the greenhouse gas protocol). Carbon emissions data is extracted from Trucost Environmental database (Trucost) provided by S&P Capital IQ following extant studies (Azar et al., 2021; Bolton and Kacperczyk, 2021) and we scale carbon emissions by (total assets/10000). Compared with other data sources (e.g., Refinitiv Eikon (ASSET4), Bloomberg, Carbon Disclosure Project (CDP)), Trucost has a wider coverage for Chinese listed firms. *CO2 (0, 1)* is the scaled carbon emissions one year after deal completion; *CO2 (0, 5)* is the median of scaled carbon emissions five years after deal completion.	S&P Capital IQ CSMAR
Completion	Dummy variable that equals one if an announced deal is recorded as "Completed" in SDC, and zero otherwise.	Refinitiv Eikon (SDC)
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). *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. *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.	World Bank: WGI Geert Hofstede's website
Environment (0, 1) *Environment (0, 5)*	Raw environmental score scaled by 100. *Environment (0, 1)* is the scaled environmental score one year after deal completion; *Environment (0, 5)* is the median of scaled environmental scores five years after deal completion.	ASSET4
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.	Refinitiv Eikon (SDC)
Firm size	Natural logarithm of one plus the bidder's total assets in year *t–1*.	CSMAR
GDP growth	Growth rate of target economy's gross domestic product (GDP) in year *t–1*.	UNCTAD
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).	SIPO
High-tech target firm	Dummy variable that equals one if the target firm operates in high-tech industry, and zero otherwise.	Refinitiv Eikon (SDC)
Leverage	Bidder's book value of total liabilities over its book value of total assets in year *t–1*.	CSMAR
Listed overseas	Dummy variable that equals one if the bidder is cross listed overseas in year *t–1*, and zero otherwise.	CSMAR
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.	SIPO; WIPO
Ln (1+Dis. GP (invention))	Natural logarithm of one plus discounted number of green *invention* patents.	SIPO; WIPO
Ln (1+Dis. GP (utility model))	Natural logarithm of one plus discounted number of green *utility model* patents.	SIPO; WIPO

Panel A1 (*continued*)

Variables	Definition	Source
Ln (1+FCF)	Natural logarithm of one plus the bidder's free cash flow in year *t–1*.	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., 2021).	SIPO; 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.	SIPO; 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.	SIPO; 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.	SIPO; WIPO
Ln (1+GPI (invention))	Natural logarithm of one plus green *invention* patent index.	SIPO; WIPO
Ln (1+GPI (utility model))	Natural logarithm of one plus green *utility model* patent index.	SIPO; WIPO
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*.	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).	SIPO
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*.	Refinitiv Eikon (SDC) CSMAR
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).	Refinitiv Eikon (SDC)
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).	CSMAR
ROA	Return on total assets (ROA), calculated as bidder's net profit over its total assets in year *t–1*.	CSMAR
ROE (0, 1) *ROE (0, 5)*	Return on equity (ROE), calculated as bidder's net profit over its book value of equity. *ROE (0, 1)* is the firm's ROE one year after the deal completion; *ROE (0, 5)* is the median of firm's five-year ROEs after the deal completion.	CSMAR
Same industry	Dummy variable that equals one if the bidding and target firms operate in the same industry, and zero otherwise.	Refinitiv Eikon (SDC)
Subsidy (0, 1)	Natural logarithm of one plus the patent-related government subsidies received by a firm one year after deal completion.	CSMAR
Subsidy (0, 5)	Natural logarithm of one plus the median of patent-related government subsidies received by a firm five years after deal completion.	CSMAR
Tender offer	Dummy variable that equals one if the deal is a tender offer, and zero otherwise.	Refinitiv Eikon (SDC)
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.	CSMAR

Panel A2: Construction of Corporate Governance Index (CGI)

Governance mechanism	Definitions	Source
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.	CSMAR
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.	CSMAR
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.	CSMAR
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.	CSMAR
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.	CSMAR
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.	CSMAR
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.	CSMAR
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.	CSMAR
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.	CSMAR