Low-carbon innovation spillover through corporate ownership network: Evidence from emission trading scheme in China

Abstract

Low-carbon innovation is increasing recognized as a significant solution to carbon neutrality. This study suggests that an emission trading scheme (ETS) provides a boost to low-carbon innovation within corporate ownership networks. Leveraging China's regional ETS pilots as a quasi-natural experiment, we identify the causal effect of low-carbon innovation spillover from ETS-regulated parent firms to their unregulated subsidiaries. Using the matched difference-in-differences identification strategy, we found that unregulated subsidiaries affiliated with regulated parent firms appear to have a better low carbon innovation performance in terms of patent counts and citations compared with those similar unregulated subsidiaries affiliated with unregulated parent firms during the pre-and-post ETS periods. Such ETS-induced innovation spillover is contingent on geographical and technological proximities between parent firms and subsidiaries, member experience in top management teams, and financial slack in parent firms. These findings survived against a rich set of robustness checks on measurement errors, confounding factors, and alternative model specifications. Our study provides insights into decarbonization strategy of promoting innovation through corporate ownership network and the factors that make such strategy more effective. We discuss the implications for knowledge transfer and sustainable operations management and provide suggestions to practitioners and policymakers.

Keywords: matched difference-in-differences estimation, innovation spillover, carbon neutrality, partner proximity, top management team, financial slack

1. Introduction

Climate change and carbon neutrality are receiving increasing attention across countries, regions, and disciplines, including the management scholarly community (Howard-Grenville et al., 2014; Wright and Nyberg, 2017). Developing technologies and innovations to reduce and offset carbon emissions has been recognized as a significant solution to carbon neutrality, especially when governments are tapping environmental regulations, such as emission trading schemes (ETS), to achieve cost-effective climate mitigation while inducing low-carbon innovation (Porter and Vanderlinde, 1995). In face of those new policy constraints posed by climate changes, firms need to rethink their strategies of innovation, technology development, and diffusion (Howard-Grenville et al., 2014).

Since the seminal work of Porter and Vanderlinde (1995), it is well documented that firms would adapt their operations to developing technological innovation in response to the environmental regulations they faced (Ambec et al., 2013; Chakraborty and Chatterjee, 2017). The recent literature has explored and provided empirical evidence that there is a direct effect of the ETS on regulated firms' low-carbon innovation in the United States (Taylor, 2012), the European Union (Calel, 2020; Calel and Dechezleprêtre, 2016), and China (Cui et al., 2018). However, regulations can vary across jurisdictions. Within a corporate ownership network, any parent firm that faces a regulation likely observes such regulation in jurisdictions where its subsidiaries do not operate. Fremeth and Shaver (2014) have already noted that choosing whether and how to respond to regulations in jurisdictions where a firm does not operate is an important strategic consideration. We address a related, yet unexplored, question: Would ETS-regulated parent firms promote low-carbon innovation in their unregulated subsidiaries? We have observed some business cases showing regulated parent firms promote low-carbon innovation to their subsidiaries. For example, in 2015, SAIC Motor in Shanghai announced that SAIC has embarked on developing technologies for greenhouse gas emission and carbon emission reduction, and also promised to prepare entire corporate enterprises for entering carbon emission trading market (SAIC-Motor, 2015). Based on a series of carbon saving technologies developed by China National Petroleum Corporation (CNPC) in Beijing, Jilin Oilfield, an unregulated subsidiary of CNPC, further develops the carbon storage technologies (CNPC, 2022). However, to what extent and how ETS-regulated parent firm lead to an increase of low-carbon innovation in its unregulated subsidiaries still need empirical evidence for causal impact.

We predict that ETS-regulated parent firms will promote low-carbon innovation in their unregulated subsidiaries, i.e., the enforcement of ETS in a parent firm will lead to an increase of low-carbon innovation in its unregulated subsidiaries. The underlying theoretical mechanisms that drive our prediction of such regulation-induced low-carbon innovation spillover are from two sides. On the one side, regulated parent firms would have willingness to promote low-carbon innovation in non-regulated subsidiaries. Considering the deterrence effect of ETS (Zhu et al., 2019), regulated parent firm is more likely to be forward-looking, that is, regulated parent firms anticipate unregulated subsidiaries' operations may be constrained for decarbonization in the future, thus regulated parent firms are motivated to promote low-carbon innovation to equip unregulated subsidiaries for future regulatory change. Literature has suggested that regulated parent firms would transfer environmental liabilities to subsidiaries as a strategic response to shift pressure (Akey and Appel, 2020; Bartram et al., 2022), which could potentially influence subsidiaries' environmental performance and innovation development as well. On the other side, regulated parent firms have the knowledge base to achieve successful knowledge transfer to promote low-carbon innovation in unregulated subsidiaries. The recent empirical literature has documented the induced-innovation effect of the ETS on regulated firms' low-carbon innovation (e.g., Cui et al., 2018; Zhu et al., 2019), thus, with accumulated low-carbon innovation, regulated firms have knowledge stock and capability to enable such innovation spillover. Meanwhile, ownership networks provide parent firms with the flexibility to realize intra-organizational low-carbon innovation spillover. In sum, our logic is drawn on the arguments in the intra-organizational knowledge transfer and innovation spillover literature that successful knowledge transfer and innovation spillover would be increasingly likely to occur because the transferors (parent firms) are capable and willing to transfer knowledge and spillover innovation (Argote et al., 2022; Argote et al., 2003; Gupta and Govindarajan, 2000; Michailova and Mustaffa, 2012; Van Wijk et al., 2008; Wang et al., 2004). We contribute to this research stream by empirically exploring the ETS-induced low-carbon innovation spillover effects through corporate ownership networks.

Moreover, literature has also suggested that innovation spillover does not appear easily even between organizational units affiliated with the same corporate (Argote et al., 2022; Feinberg and Gupta, 2004; Gupta and Govindarajan, 2000). We further enhance our examination of such ETS-induced low-carbon innovation spillover by focusing on three dimensions of organizational factors that are important determinants of innovation spillover within organizations. The first dimension is the attribution proximity between the parent firm and its subsidiaries. Knowledge transfer and innovation spillover literature have suggested that in addition to transfers' motivation and ability, recipients' absorptive capacity matters as well (Argote et al., 2022; Feinberg and Gupta, 2004; Wang et al., 2004). Specifically, the attribution proximity of partners, such as geographical and technological proximity, is associated with the knowledge transmission channel and absorptive capacity of the target unit (Gupta and Govindarajan, 2000), thus it might influence the effectiveness of innovation spillover. The second dimension is the related working experience of members of the top management team (TMT) of parent firms. Following Fremeth and Shaver (2014), we argue that regulated parent firms choosing whether and how to promote low-carbon innovation in unregulated subsidiaries is an important strategic consideration. Studies based on the strategic choice (Child, 1972) and upper echelons (Hambrick and Mason, 1984) perspectives have documented that top executives significantly affect organizational outcomes, including the decision in environmental management (Kumar and Paraskevas, 2018; Pagell and Wu, 2009) and knowledge transfer (Liu et al., 2022). Previous studies have explored the impact of executives' personality characteristics on learning and knowledge-transferring (Gupta and Misangyi, 2018; Liu et al., 2022), yet little is known about how the functional backgrounds of TMT members affect intra-organizational knowledge spillover for innovation. The innovation outcome brings a sharp focus on the importance of experiences like research and development (R&D) and production in the TMT (Heyden et al., 2017). Thus, we further explore whether executives with R&D and production experience within TMTs enable such innovation spillover. The third dimension is the parent firm's financial resource position. Knowledge transfer and innovation spillover is a resource-intensive process and its cost can hardly be considered trivial (Teece, 1977). In this vein, a critical factor for accomplishing knowledge spillover concerns the abundance as well as the motivational devotion of necessary resources (Szulanski, 1996). Considering the importance of financial resources on innovation development, we argue that a parent firm's financial resource position serves as an important contingency that governs the extent of the innovation spillover effect. In doing so, we conceptualize and test a model that answers these research questions: 1) to what extent do ETS-regulated parent firms influence their unregulated subsidiaries' low-carbon innovation? and 2) what is the role of attribution proximity of partners (i.e., geographical and technological proximity between parent and subsidiaries), R&D and production experience in TMTs, and financial slack in the relationship of such ETS-induced innovation spillover?

Our empirical research questions face pressing identification challenges. First, one prerequisite for the plausible ETS-induced innovation spillover is the variation of ETS across regions. Such regional variations provide a parent firm opportunity to make a strategic choice. Second, whether regulated firms that have developed low-carbon innovation in the absence of the ETS pressure be substantially different from unregulated firms poses another daunting threat to the identification strategy. We overcome these challenges by taking advantage of China's regional ETS pilots as a quasi-natural experiment. The ETS pilots cover firms in the manufacturing and utility sectors, providing us with a measure for firm-level exposure to ETS. One could identify a list of treated firms as those participating in the carbon trading program. One could also construct a comparison group by searching those similar firms in the same sector but located in non-ETS regions. We further leverage a unique dataset linking corporate ownership networks with patenting activities in low-carbon technologies. This novel dataset allows us to pin down treated and control firms within the same corporate. We then adopt a matched difference-in-differences (DID) approach to identify the causal effects of ETS-regulated parent firms on the low-carbon innovation of unregulated subsidiaries (i.e., ETS-induced low-carbon innovation spillover).

Specifically, we assemble a unique Chinese patent dataset representing the economic and innovation activities of all Chinese listed firms and their subsidiaries between 2003 and 2016. The data pertain to the publicly listed firms in the manufacturing and utility sectors, integrating detailed firm-level information about granted patent applications in all technological fields, R&D expenditure, and economic fundamentals. Moreover, for each listed firm, we retrieve its corporate tree including a list of subsidiary firms, shareholdings, sector information, geographic location, and patent applications. Lastly, we retrieve the working experiences of TMT members associated with listed firms during the study period. Our matched-DID findings suggest unambiguous evidence for the existence of the significant positive impact of ETS-regulated parent firms on the low-carbon innovation of their unregulated subsidiaries. This finding is robust against a rich set of alternative checks on measurement errors, confounding factors, and other matching algorithms. Our results further empirically demonstrate the different moderating roles of geographical and technological proximities, production and R&D experience of TMTs, and financial slack in such ETS-induced low carbon innovation spillover.

Our study represents an important contribution to carbon neutrality research in operations management due to the significant role of low-carbon innovation spillover in achieving the carbon neutrality target. It is necessary to understand how firms take strategic consideration to adapt their operations and reallocate their resources including knowledge in response to climate change pressures. The emerging literature has mainly concentrated on the direct relationship between environmental regulations and regulated firm innovation (Calel, 2020; Calel and Dechezleprêtre, 2016; Cui et al., 2018; Porter and Vanderlinde, 1995; Zhu et al., 2019). We extend this stream by recognizing the regulations' jurisdictions' variation and exploring to what extent regulated parent firms would increase low-carbon innovation of unregulated subsidiaries through corporate ownership networks. Leveraging the unique quasi-experiment design of China's regional ETS pilots, we comprehensively document the causal evidence of regulated parent firms promotes low-carbon innovation in unregulated subsidiaries. Our findings may inspire the OM research to further explore the role of corporate ownership networks in addition to the well-known supply chain networks (Chakraborty and Chatterjee, 2017), for decarbonization innovation. Furthermore, we contribute to knowledge transfer and innovation spillover literature by examining the role of three dimensions of important organizational factors. Firstly, extant research has not reached a consensus on how the attribution proximity of partners in the network influences the innovation spillover (Guan and Yan, 2016; Liang and Liu, 2018). We add to this literature by providing empirical evidence that it is technological proximity rather than geographical proximity enables such ETS-induced low-carbon innovation spillover. Secondly, while the existing literature recognizes the influence of member experience in TMTs in influencing a focal firm's environmental management, our knowledge about whether and how parent firms' TMTs could exert influence on network partners' environmental practices like low-carbon innovation is limited. In our study, we identify two important working experiences that can influence this relationship, including R&D and production experience, which present conflicting roles in inducing low-carbon innovation spillover through corporate ownership networks. Lastly, our research also contributes to the environmental innovation literature by revealing an alternative, i.e., depending on the internal knowledge network, to resolve the dilemma of environmental innovation pressure from the regulation and constrained financial resources (Calel, 2020; Milliman and Prince, 1989).

The rest of this study is organized as follows. The next section presents our conceptual development and formal hypotheses (Section 2). In Section 3, the methodology is described. This is followed by a presentation of our empirical results (Section 4). We discuss the managerial and theoretical implications of the findings of our study and conclude the paper in Section 5.

2. Background and Hypotheses Development

2.1 Institutional background of China ETS

China has gradually participated in global climate mitigation. In the 2009 Copenhagen Accord, China first-time pledged to reduce its carbon intensity (carbon emissions per unit of GDP) by 40 to 45 percent from 2005 levels by 2020. To curb the ever-increasing carbon emissions cost-effectively, on October 29th of 2011, National Development Reform Committee (NDRC) formally announced to launch of seven regional carbon market pilots, including *Beijing, Shanghai, Chongqing, Tianjin, Shenzhen, Hubei, and Guangdong*[1]. Following the general guideline from NDRC, these regional pilots were granted flexibility in designing carbon market rules, including covered sectors, allowance allocation schemes, monitoring, reporting, and verification (MRV), as well as compliances. Since June 2013, seven pilot markets started operating carbon trading programs. Regulated firms then started trading allowances within each jurisdiction but not across pilots. With a total of 1.2 billion tons of carbon emissions allowances from all seven pilots combined in the early trading phase, China's regional ETS pilots then became the world's second-largest carbon market and embarked on its first milestone toward climate change (Zhang et al., 2014; Zhang et al., 2017). Given such importance of China's regional ETS, exploring how regulated parent firms influence unregulated subsidiaries' low-carbon innovation could provide significant managerial implications in implementing proper strategies and operations practices in response to the rising carbon pricing pressures.

[1] For a detailed introduction to China's regional ETS pilots, one could refer to Zhang et al. (2017), which provides an overview of the performance of seven ETS pilots.

The regional ETS pilots exhibit wide heterogeneity across regions and years, providing a quasi-experimental setting for teasing out the causal relationship. As mentioned above, regional pilots experience two phases: announcement and trading phases. The NDRC announced seven regional pilots in late 2011 and then launched carbon trading in some pilots in 2013 and others in 2014. However, firms in pilot regions did not know whether they are mandatorily selected to participate in carbon trading until the trading phase begins. Thus, the variation across years offers us an opportunity to compare the innovation outcome of interests between covered firms and similar control firms during the pre-and post-ETS trading periods.

ETS pilots present another distinct feature of the variation in the ETS stringency across regions and years. The unique design of ETS pilots gives rise to two additional variations in carbon market performance: allowance trading turnover rates and carbon prices. All covered firms could only trade carbon allowances within the pilot but not across pilots. Hence, they are subject to the carbon pricing stringency within the jurisdiction. The average national carbon price started with an initial price of 65 RMB per ton in late 2013 and then was declining and ended at 20 RMB per ton at the end of 2016. Despite this downward trend for the national average carbon price, carbon prices exhibited a substantial variation across pilots. Beijing and Shenzhen are two active markets during the trading phase with carbon prices fluctuating around 50 RMB per ton. Other pilots have carbon prices varying around 20 RMB per ton.

In this study, we further leverage the spatial variation in corporate ownership networks, in particular subsidiaries and parent firms with and without ETS-regulated. These variations could make the casual inference on the potential ETS-induced innovation spillovers through the corporate ownership network.

2.2 Hypothesis development

2.2.1 The impact of regulated parent firms on the low-carbon innovation of unregulated subsidiaries

Literature has suggested that changes in the regional environment could lead to responsibility distribution and resource reallocation across corporate ownership networks. For example, in response to positive changes, such as new airline routes between headquarters and affiliated plants, Giroud and Mueller (2015) find out capital flows and investment reallocations across plants within the same corporate network. Meanwhile, ownership networks also provide business units with the flexibility to transfer production or investment from affected units to unaffected units within a corporation to mitigate local negative changes (Giroud and Mueller, 2019), and environmental pressures (Bartram et al., 2022; Cui and Moschini, 2020).

Along this line, we argue that changes in the regional environment -- the enforcement of regional ETS in China -- could lead to low-carbon innovation spillover through corporate ownership networks. Literature suggests that the ability and motivation of transferors are significant factors to realize successful knowledge transfer and innovation spillover (Argote et al., 2022; Argote et al., 2003; Gupta and Govindarajan, 2000; Michailova and Mustaffa, 2012; Van Wijk et al., 2008; Wang et al., 2004). ETS could increase the regulated firms' knowledge base and willingness to transfer low-carbon innovation through corporate ownership networks. First, abundant evidence has suggested that ETS can stimulate low-carbon innovation of regulated firms (Calel and Dechezleprêtre, 2016; Cui et al., 2018; Taylor, 2012). And the newly developed innovation of a regulated parent firm represents non-duplicative knowledge that also has significant relevance to the subsidiaries given that low carbon and carbon neutrality are receiving global attention. Collectively, from the perspective of knowledge transfer, the knowledge stock of the parent firm (i.e., the transferors) is of greater value to other units (i.e., the recipients) within the ownership network (Gupta and Govindarajan, 2000), which could lead to higher knowledge spillover. Second, regulated firms are more likely aware of the decarbonization pressure as a commonly held challenge for future development, thus they would have a stronger motivation of promoting low-carbon innovation in unregulated subsidiaries to help subsidiaries prepare for environmental pressure in advance (Argote et al., 2022). Since intraorganizational transferring knowledge is generally easier than knowledge transfer across independent organizations (Argote et al., 2003; Darr et al., 1995), the regulated parent firm could leverage their valuable knowledge to help subsidiaries understand and better prepare for the changing environment (Argote et al., 2022). Thirdly, the literature also suggests that knowledge spillover from parent firms to subsidiaries could enable knowledge recombination that offers an opportunity for developing novel knowledge and innovation, which represents a positive motivation for parent firms to realize the returns of investment in their R&D efforts and help maintain the competitiveness of the entire corporate network under stringent environmental regulation (Argote et al., 2022; Feinberg and Gupta, 2004). Collectively, considering regional ETS as a local shock, we expect its impact to be propagated by a regulated parent firm to its unregulated subsidiaries in the way of motivational transfer of relevant valuable knowledge, leading to the observation of low-carbon innovation development in unregulated subsidiaries. Thus, we propose:

H1. A regulated parent firm has a positive impact on the low-carbon innovation of its unregulated subsidiaries.

2.2.2 The moderating effects of geographical and technological proximity between parent firm and subsidiaries

Geographical proximity is denoted as the spatial distance between partners (Knoben and Oerlemans, 2006). Extant literature consistently reveals that innovation spillover tends to be localized (e.g., Audretsch and Feldman, 1996; Chu et al., 2019; Jaffe et al., 1993). The underlying logic is that shorter physical distance encourages frequent interactions between the partners, facilitating exchanges of tacit information and knowledge that are essential to the innovation spillover (Capaldo and Petruzzelli, 2014; Knoben and Oerlemans, 2006). In this regard, geographically proximate parent firms and subsidiaries are more likely to develop knowledge-incentive routines that increase the chance of innovation spillover (Argote et al., 2022), which implies rich transmission channels of knowledge. Moreover, low-carbon innovations are expected to have an agglomeration effect (Chu et al., 2019). That is, when parent firms and subsidiaries locate closely, they may share common environmental characteristics like natural resources and topographical features. In this connection, the parent firm and its subsidiaries tend to develop low-carbon knowledge along similar technological trajectories, which the subsidiaries can easily absorb for improving innovation (Orlando, 2004). In sum, subsidiaries tend to have the higher absorptive capability of low-carbon knowledge from a geographically proximate parent firm. Therefore, we propose:

H2a. The impact of a regulated parent firm on the low-carbon innovation of its unregulated subsidiaries is positively moderated by the geographical proximity between the regulated parent firm and its unregulated subsidiaries.

Technological proximity refers to the similarity of technological knowledge pools between the partners, which associates with two determinants of knowledge spillovers, namely value recognition of the source's knowledge stock and the absorptive capability of the recipient (Cohen and Levinthal, 1990; Gupta and Govindarajan, 2000; Liang and Liu, 2018). First, proximate technological backgrounds indicate that the innovation activities between the parent firm and the subsidiaries are more relevant (Isaksson et al., 2016). In this vein, a higher proportion of the parent firm's knowledge pool can be potentially identified as valuable by the subsidiaries for subsequent absorption (Gupta and Govindarajan, 2000; Jaffe, 1986). Second, successful knowledge spillover also depends on the organization's capability of assimilating and elaborating the knowledge that is recognized as a valuable asset (Guan and Yan, 2016). In this regard, a greater overlap between the knowledge bases of the parent firm and its subsidiaries can save effort for the subsidiaries to absorb knowledge outcomes from the parent firm and integrate them into their innovations more easily. Collectively, there is more valuable knowledge that can be recognized and absorbed more easily by the subsidiaries when they have higher technological proximity to the parent firm, which implies a stronger spillover effect. Therefore, we propose:

H2b. The impact of a regulated parent firm on the low-carbon innovation of its unregulated subsidiaries is positively moderated by the technological proximity between the regulated parent firm and its unregulated subsidiaries.

2.2.3 The moderating effects of R&D and production experience of members in TMTs of parent firms

Upper echelons theory (UET) proposes that the experiences, values, and personalities of managers shape their idiosyncratic interpretation of the strategic situation confronting and affecting their subsequent decisions and behaviors (Hambrick, 2007). Previous research has studied TMT composition in dimensions like gender and nationality (e.g., Dezső et al., 2016; Nielsen and Nielsen, 2013), yet the dimension of functional backgrounds of TMT members is relatively overlooked. Simultaneously, while the majority of TMT research focuses on organizational outcomes like firm performance (Dezsö and Ross, 2012; Menz, 2011), scholars have recently begun to study the relevance of top executives in the intraorganizational knowledge flow (Argote et al., 2022). For instance, Gupta and Misangyi (2018) and Liu et al. (2022) documented the impact of executives' personality characteristics like narcissism on organizational learning and knowledge transferring. However, little is known about how the previous experience of members in TMT affects intra-organizational innovation spillover. This represents a crucial omission given that TMT members can be functionally biased in decision situations given their career experience and expertise (Carpenter et al., 2004; Dearborn and Simon, 1958), and the depth and breadth of TMT director's experience-based expertise can affect knowledge transfer and subsequent organizational outcomes like innovation (Lungeanu and Zajac, 2019). Accordingly, it is necessary to consider the influences of top executives when exploring the organizational outcomes in face of environmental regulation pressure. The range of activities included in technology and innovation development and spillover brings a sharp focus on the importance of production and R&D experiences in the TMT (Heyden et al., 2017).

Literature has suggested that top executives having experience in throughput functions such as production would prioritize the efficiency of transforming inputs into outputs. Therefore, when the parent firms are regulated, their TMTs with more production-backgrounded members are more attentive to optimizing the efficiency of operating practices and procedures, which could lead to low-carbon improvements in dimensions like energy conservation and waste management (Garza-Reyes, 2015). Simultaneously, relevant literature also posits that adopting consistent rather than separate green practices and procedures across jurisdictions is a more efficient approach for multi-unit corporates to manage green operations (Fremeth and Shaver, 2014; King and Shaver, 2001). Collectively, we expect that the TMT of the regulated parent firm with more production experience would have a stronger motivation of transferring low-carbon knowledge to its extra-jurisdictional subsidiaries, consequently provoking a stronger innovation spillover effect. Therefore, we hypothesize:

H3a. The impact of the regulated parent firm on the low-carbon innovation of its unregulated subsidiaries is positively moderated by the production experience of the members in the TMT of the regulated parent firm.

Executives with output function experience (e.g., R&D and marketing) favor innovation strategies (Barker and Mueller, 2002). As aforementioned, regulated parent firms may leverage their internal knowledge network for low-carbon innovation, which involves allocating and leveraging corporate knowledge networks and R&D resources (Dellestrand and Kappen, 2011). In this connection, top managers with R&D experience in parent firms are more inclined to develop a mental model regarding environmental innovation under stringent environmental regulation and possibly transfer it to the subsidiary level via mandates for possible knowledge recombination (Konara et al., 2021; Phene and Almeida, 2008). In other words, more R&D experience in the TMT leads to higher motivation of transferring knowledge at the transferor end. Moreover, when more TMT members have an R&D background, the parent firms are also more likely to establish knowledge exchange routines with their subsidiaries (Achcaoucaou et al., 2014; Barker and Mueller, 2002), which implies richer channels of knowledge transfer. Besides, top managers with R&D experience in parent firms may also guide inter-unit knowledge exchange and help the subsidiaries absorb and assimilate knowledge into innovation output. Collectively, we propose that:

H3b. The impact of a regulated parent firm on the low-carbon innovation of its unregulated subsidiaries is positively moderated by the R&D experience of the members in the TMT of the regulated parent firm.

2.2.4 Competing views of the moderating effect of financial slack in parent firms

There are some reasons to believe that financial slack enhances a firm's effort to promote low-carbon innovation spillover. On the one side, the literature suggests that a firm uses slack resources to improve its environmental performance because financial slack provides a firm with the flexibility it needs to invest in environmental strategies (Greve, 2003). That is, a parent firm may use its financial slack resources to develop low-carbon innovation, which could enable the parent firm to develop a high level of capability (e.g., knowledge base) for achieving successful low-carbon innovation spillover. On the other side, because they are neither charged with emission cost nor receive additional benefits (Calel and Dechezleprêtre, 2016; Milliman and Prince, 1989), unregulated firms lack economic incentives to invest in environmental innovation that is usually costly and with uncertain financial returns (Berrone et al., 2013). However, when the parent firm has a high financial slack, it has both the incentive and capability to equip unregulated subsidiaries with innovation resources for future regulatory change, hence its unregulated subsidiaries are more likely to receive financial support from the parent firm and are more motivated to receive low-carbon innovation and reinvent on it. Collectively, we propose:

H4a. The impact of a regulated parent firm on the low-carbon innovation of its unregulated subsidiaries is positively moderated by the financial slack of the parent firm.

While we contend that financial slack could positively moderate the influence of regulated parent firms on the low-carbon innovation of their unregulated subsidiaries, resource dependency theory also proposes that firms with constrained resources will seek to obtain the needed resources from external parties for desired organizational outcomes (Pfeffer and Salancik., 1978, p.2). In response to the ETS, parent firms with limited financial resources (i.e., low financial slack) tend to be inherently biased toward optimizing the positive returns of investment in their R&D efforts by leveraging corporate ownership network as an opportunity to reinvent existing knowledge through knowledge transfer (Argote et al., 2022; Yang and Steensma, 2014). In other words, parent firms with low financial slacks may depend on resources in their ownership networks to cope with the innovation pressure of ETS regulation, which results in a stronger motivation of transferring knowledge and consequently a stronger spillover effect. Even though the subsidiaries may be less devoted to accomplishing knowledge transfer, the parent firm can still intervene by providing strategic direction to the subsidiaries or even exerting the control power to force innovation transfer to take place (Dellestrand and Kappen, 2011; Foss and Pedersen, 2002). Moreover, the literature suggests that financial slack has the potential to insulate a firm from the external environment and creates structural inertia, which might dull the parent firm's strategic response to the deterrence effect of ETS (Cheng and Kesner, 1997; Kraatz and Zajac, 2001; Modi and Cantor, 2021). That is, parent firms with higher financial slack are less motivated to seek uncertain benefits from innovation spillover through corporate ownership networks, which reduces the effect of ETS-induced innovation spillover. Hence, a competing view is proposed:

H4b. The impact of a regulated parent firm on the low-carbon innovation of its unregulated subsidiaries is negatively moderated by the financial slack of the parent firm.

3. Methodology

3.1 Data sources

Our dataset pertains to the publicly listed firms in the Chinese stock markets of Shanghai and Shenzhen. It covers public utility and manufacturing sectors from 2010 to 2016.[2] We assemble this

[2] By 2016, there are around 2,600 publicly listed firms, ranging from manufacturing to public utility sectors, in the stock markets of Shanghai and Shenzhen. These two sectors include further 33 subsectors. The total market value of these publicly listed firms was 1,200 billion RMB, accounting for 1/5 of China's GDP in 2014. The publicly-listed firm data have been widely used in the existing OM literature (Li et al., 2022; Shen et al., 2022). We study the sample period of 2010-2016 due to the availability of patent data. A comprehensive coverage of citation data associated with

data from three main sources. The NDRC reports regulated firms under the seven ETS pilot regions. China Stock Market and Accounting Research Solution (CSMAR) provides corporate ownership networks, economic fundamentals for parent firms, and TMTs information for parent firms. China National Intellectual Patent Administration (CNIPA) and Google Patent provide patent applications and citations, respectively. The CSMAR provides ownership linkage between parent firms and subsidiaries in publicly listed corporates in Chinese stock markets, including firm names and shareholding ratios of the ownership.[3] We also collect fundamental and financial information about the corporate and parent firms from the CSMAR. However, the CSMAR fails to report subsidiaries' fundamental information, which is needed to capture subsidiaries' geographical and sectoral variation and measure geographic distances to parents. Since most subsidiaries are based in China, we complement their city location and sectoral information from the National Enterprise Credit Information Publicity System of China.[4] We use patent applications and grant data from the CNIPA to measure firms' low-carbon innovation quantity. The CNIPA supplies detailed patent information in China, including application numbers, application data, and International Patent Classification (IPC) code. Moreover, we collect citation information associated with patents filed by our sample firms from the Google Patent to measure innovation quality.[5] We merge parent firms and subsidiaries in Chinese publicly listed corporates with their

Chinese patents in the Google Patent starts from 2010, which is set as the starting point of our sample period. Considering the average time from a patent application to a grant decision is around 18 months in China (Dang and Motohashi, 2015), our sample focuses on the period before 2017 to avoid the truncation bias (patent applications in recent years are still under examination and not published yet) as our patent data was collected in 2019. This sample period covers both the pre-and post-ETS periods, allowing us to observe variations in innovation outcomes and the corporate's exposure to carbon prices across the year.

[3] In our sample, around 95% of subsidiary firms are dominantly owned by their parent firms (with shareholding ratios larger than 50%). Around 70% of subsidiary firms are fully owned by their parent firms (shareholding ratios are 100%).

[4] Only a handful of subsidiaries are located outside of mainland China, hence are excluded from our sample study. Thus, we rule out the possibility of carbon pricing pressures from other jurisdictions/countries.

[5] Unlike other patent offices, such as European Patent Office (EPO), patent examiners in China are not subject to mandatory requirements for adding citations when filing patent applications. Hence, there is little citation information

patent information.

3.2 Variable construction

We present definition of key variables in the Table A1 in Online Appendix. Specifically, the dependent variable is the low-carbon innovation of unregulated subsidiaries measured by firms' low-carbon patents. To define low-carbon patents, we resort to the IPC Green Inventory codebook developed by the World Intellectual Property Organization (WIPO)'s IPC Committee of Experts. The IPC Green Inventory defines environmentally friendly technologies based on the list by the United Nations Framework Convention on Climate Change (UNFCCC). Low-carbon patents in our analysis are then defined as the technologies' IPC codes involved in alternative energy production, energy conservation, and waste management.[6]

China's patent system differentiates patents into three categories based on their inventiveness and functionality: invention, utility model, and design patents (Wei et al., 2017).[7] Our analysis includes only invention and utility model patents as they are most relevant to low-carbon innovation and their IPC codes are in line with the WIPO.[8] We distinguish the quantity and quality of low-carbon innovation. Specifically, we count the number of low-carbon patents that are successfully granted to indicate the quantity of firms' innovation.[9] In addition to the quantity

is documented in CNIPA and we need to supplement patent citation from another data source, e.g., Google Patent.

[6] The EPO has developed a category of CPC codes, labeled the Y02 class, about technologies for climate mitigation or adaptation. Although CNIPA does not adopt the Y02 class yet, we have cross-checked the CPC Y02 class and IPC Green Inventory and found these two classes are similar in the scope of low-carbon technologies. In addition, most of the transportation technologies in China are related to the development of highspeed railways rather than mitigation related to the transportation sector. Hence, this category of transportation is removed from our sample.

[7] The official definition of the invention, utility model, and design patent is available in Article 2, Patent Law of the People's Republic of China (2021). The following link also provides a summary of the difference between the three types of patents in China:https://english.cnipa.gov.cn/col/col2995. In general, invention patents are related to practical, inventive, and new technical innovations, while utility model patents represent technical solutions to the shape or structure of an object.

[8] Design patents are only targeted to the external appearance of products and are not related to climate mitigation or adaptation functionality. Hence, our analysis excludes design patents.

[9] The time dimension of each granted patent in our analysis is the year when its patent application is filed because that is the period when the involved new technology is used in firms' production and operation.

measurement, we capture the quality of innovation by using low-carbon patent counts weighted by the number of forward citations received in the subsequent five years (Hall et al., 2005; Harhoff et al., 1999; Trajtenberg, 1990). That is, we calculate the logarithm one plus the number of citations to measure the patent quality.

We further illustrate variable construction for key moderators. First, geographical proximity between parent firms and their subsidiaries, captured by GeogDist, is the time-invariant geographical distance computed by the longitude and latitude of the locations where firms lie in. We then follow the approach proposed by Jaffe (1986) and construct a time-invariant index measuring technology proximity between subsidiaries firm *i* and its parent firm *m*:

$$TechProx_{im} = \frac{F_i F_m'}{\sqrt{(F_i F_i')(F_m F_m')}},$$

where $F_i = (F_i^1, F_i^2, \ldots, F_i^{\mathrm{n}}, \ldots, F_i^N)$ is a multidimensional vector and each element F_i^{n} indicates the ratio of patents in the technological field *n* to all patents that are owned by subsidiary firm *i*. Similarly, F_m captures parent firm *m*'s technology spectrum. This approach is also adopted by recent operations management literature like Chu et al. (2019). This time-invariant index pools the patent data during the entire sample period, enabling us to pin down firms' positions in the technological space more accurately. On the other hand, this time-invariant index makes us less worried about the possible endogeneity of technology proximity. Put differently, technology similarity could vary across years due to the ETS pressure. As an alternative check, we also experiment with the patent subsample of the pre-ETS period. The classification of technological fields relies on the IPC class (3-digit code) and there are 123 fields in our samples (i.e., *N*=123).[10]

[10] A more disaggregated technological class under IPC, while deemed more precisely to capture the difference of knowledge enclosed in a pair of technological fields, would also downplay the technology relation and potential technology spillover between them. Detailed information on the IPC system is available at: https://www.wipo.int/classifications/ipc/en/.

The proximity measure varies between 0 and 1, and higher values stand for a more similar distribution of technological fields between subsidiaries and parent firms. There is no consensus on which level of IPC is the best for calculating technology proximity. In our main results, we use the IPC class (3-digit) to classify technological fields (Balsmeier et al., 2014; Belderbos et al., 2014; Chu et al., 2019). As a robustness check, we also adopt the IPC subclass (4-digit), another commonly used classification (Dibiaggio et al., 2014; Diemer and Regan, 2022; Guan and Liu, 2016).

Next, we dive into the TMT professional background. TMT reported in the CSMAR includes the board director, CEO, and chief manager for each publicly listed firm. Besides, it reports the TMT's historical professional working experiences in production, R&D, human resources, marketing, accounting, and litigation. We retrieve production and R&D to measure production and R&D experience respectively. Specifically, following the relevant OM literature (Kumar and Paraskevas, 2018), we let Ratio_Pro and Ratio_R&D denote the percentage of TMT members who have work experience in production and R&D, respectively. As an alternative, we also account for the number of TMT members who have production or R&D experience.

Following the OM literature (Klöckner et al., 2022; Wiengarten et al., 2017), we measure financial slack by the quick ratio and financial leverage. The former is calculated as current assets minus inventories scaled by current liabilities, while the latter is the ratio of debt to equity following the existing literature. These two proxies run in the opposite direction by their definitions. A higher level of financial leverage means a firm has less financial slack, while a higher quick ratio indicates the opposite (Palmer and Wiseman, 1999). We put the quick ratio in the main moderating effect and account for the financial leverage as the robustness checks.

Finally, we combine the data from multiple sources and clean the data in the following steps. In Online Appendix, Figure A1 illustrates the major steps. (1) We remove around 20% of subsidiaries due to the lack of industry and region information. (2) Around 10% of subsidiaries dropped due to no observations between 2010 and 2016. (3) We further remove subsidiaries that are only observed either in the pre-ETS (before 2013) or post-ETS period (after 2013), that is, 35% of firms in our original sample. (4) Subsidiaries exiting the markets during 2010-2016, nearly 5%, are excluded from our sample. (5) Since our identification strategy focuses on unregulated subsidiaries as described in the following section, we remove all subsidiaries directly regulated by the ETS pilots, which are accountable for around 3% of subsidiaries. In the end, we obtain 18,202 subsidiaries over the 2010-2016 period for the empirical analysis.

3.3 Identification strategy

To estimate the ETS-induced low carbon innovation spillover effect, we leverage the variations of ETS and corporate ownership networks across regions and years. Our empirical exercise is carried out at the subsidiary level while controlling for both subsidiaries' and parent firms' innovation and economic fundamentals.[11] We carefully set the treatment and control groups at the subsidiary level. In Online Appendix, Figure A2 illustrates the empirical setting under corporate ownership networks. The treated groups defined in our analysis are unregulated subsidiaries (marked in shaded blue), whose parent firms are regulated by the ETS (in black). The control groups are then unregulated subsidiaries, whose parent firms are free from any ETS pressures (in grey).[12] A

[11] Due to the availability of corporate information, the data retrieved from CSMAR does not have a full record of sub-subsidiary firms or ones with further layers of ownership relationship, which only consist of around 10% of observations in the raw data. Although it would be interesting to explore how the spillover effect varies with different layers of ownership structure, our dataset is not perfectly suitable for this further discussion. Considering the possible unobservable influence brought by the layers of ownership structure, our analysis is carried out at the level of subsidiary firms, i.e., the business entities directly owned by parent firms.

[12] Since we aim to explore the spillover effect via corporate ownership networks rather than the direct effect of China's ETS, the focus of this paper is on unregulated subsidiary firms in both the treatment and control groups while

comparison in innovation outcomes between unregulated subsidiaries with and without regulated parent firms before and after the ETS may suggest the ETS-induced innovation spillover effect.

This DID approach is subject to a pressing concern regarding the development of a reasonable counterfactual for the treatment group.[13] If the treated and control subsidiaries differ substantially in the pre-treatment characteristics that affect the selection of the ETS treatment and innovation outcomes, the DID estimate is unlikely to yield an unbiased estimate (Dehejia and Wahba, 2002). This concern further arises when comparing the mean values of some key variables between the treatment and control group during the pre-ETS periods, as shown in Columns (1) to (3) in Table 1. Among 1,022 treated subsidiaries and 17,180 control subsidiaries, one could note that treated groups outperform control groups along the dimension of almost all innovation and economic variables before the ETS.

To construct the tenable and transparent estimate of counterfactual outcomes, our regression analysis adopts a one-to-one propensity score matching (PSM) approach. Each treated firm is paired with a control one that is operating within the same sector and has the closest propensity score. Using a logistic model, the propensity score is then estimated based on pre-treatment innovation and other predictors of innovation and treatment assignment.[14] Specifically, the pre-

excluding all subsidiary firms that are directly regulated by the ETS pilots. To further avoid the possible carbon pressure from affiliated regulated sister subsidiaries, we restrict a control unit to an unregulated subsidiary that does not have any regulated firms within its ownership networks (including its parent and other sister subsidiary firms). We do not observe the cross-holding of any subsidiary firms in our final dataset.

[13] One may also worry about the stable unit treatment value assumption (SUTVA) required by the DID approach. The SUTVA states that the outcome of a unit depends solely on its treatment assignment rather than the treatment of another unit. It seems that our identification may violate this assumption. However, the unit of interest is set on all unregulated subsidiaries, while the treatment assignment is whether this subsidiary is owned by a regulated parent firm. The innovation outcome of a treated subsidiary is less likely affected by other treated subsidiaries if they are not cross-holding by the same parent firm. Such cross-holdings are not observed in our sample. Moreover, our research setting is akin to the one adopted by Bartram et al. (2022), which examines the emission leakage within corporate ownership network by comparing changes in emissions between unregulated plants with and without regulated parent firms.

[14] There is a lack of consensus on which covariates should be included for estimating propensity scores. Several covariates and restrictions added in the matching procedure, while deemed stringent and safe, tend to result in fewer matched pairs. As suggested by Austin et al. (2007), we choose the covariates that might strongly affect both the

treatment attributes include three-year averages of registered capital, total patent, and low-carbon patent at both the subsidiary and parent firm levels before the ETS. It also includes the accumulative levels of the total and low-carbon patents at the subsidiaries and parent firms during one year before the ETS. The selection of innovation covariates into the matching process is to ensure the similarity in the innovation outcome before the ETS, while the selection of registered capital is for capturing the similar size between the matched control and treated group before the ETS. All covariates used in the matching are log-transformed to better fit the distribution assumption for the logistic model. Considering the matching quality, we set a caliper of 0.2 of the standard deviation of the propensity score to remove matched pairs with a larger distance of propensity scores.[15] Replacement is allowed in the matching procedure to ensure that each treated unit matches the closest control unit and avoid extra bias in selecting control units (Austin et al., 2007).

outcomes and the treatment assignment.

[15] There is no gold standard for the maximal acceptable caliper of propensity scores. Following the method proposed by Austin (2011), a caliper width equal to 0.2 of the standard deviation of propensity scores could minimize the mean squared error of the estimated treatment effect, hence eliminating much of the bias in the estimators.

Table 1: Mean Statistics for Matched and Unmatched Sample

Variables	Unmatched Sample 1,022 treated vs 17,180 control subsidiaries			Matched Sample 636 treated vs 636 control subsidiaries		
	Treated	Control	P-value	Treated	Control	P-value
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: 3 periods before ETS						
Total patent (subsidiaries)	0.231	0.181	0.046	0.217	0.298	0.122
Low carbon patent (subsidiaries)	0.015	0.021	0.334	0.014	0.028	0.242
Total patent stock (subsidiaries)	0.357	0.264	0.004	0.321	0.415	0.149
Low carbon patent stock(subsidiaries)	0.038	0.034	0.686	0.034	0.043	0.589
Registered Capital (subsidiaries)	7.531	7.405	0.125	7.359	7.259	0.507
Total patent (Parent)	1.449	0.929	0.000	1.371	1.478	0.418
Low carbon patent (Parent)	0.291	0.161	0.000	0.300	0.242	0.298
Total patent stock (Parent)	1.963	1.228	0.000	1.844	1.850	0.970
Low carbon patent stock (Parent)	0.453	0.236	0.000	0.421	0.313	0.115
Panel B: 2 periods before ETS						
Total patent (subsidiaries)	0.285	0.208	0.001	0.249	0.294	0.312
Low carbon patent (subsidiaries)	0.028	0.026	0.846	0.024	0.017	0.490
Total patent stock (subsidiaries)	0.412	0.303	0.000	0.361	0.429	0.227
Low carbon patent stock(subsidiaries)	0.047	0.042	0.635	0.040	0.039	0.962
Registered Capital (subsidiaries)	7.539	7.385	0.026	7.358	7.264	0.449
Total patent (Parent)	1.841	1.056	0.000	1.805	1.932	0.283
Low carbon patent (Parent)	0.466	0.201	0.000	0.433	0.442	0.879
Total patent stock (Parent)	2.381	1.377	0.000	2.289	2.361	0.583
Low carbon patent stock (Parent)	0.660	0.293	0.000	0.635	0.569	0.345
Panel C: 1 period before ETS						
Total patent (subsidiaries)	0.297	0.232	0.005	0.289	0.270	0.649
Low carbon patent (subsidiaries)	0.036	0.031	0.481	0.030	0.021	0.378
Total patent stock (subsidiaries)	0.478	0.356	0.000	0.440	0.449	0.878
Low carbon patent stock(subsidiaries)	0.062	0.054	0.433	0.052	0.042	0.491
Registered Capital (subsidiaries)	7.481	7.392	0.151	7.317	7.125	0.078
Total patent (Parent)	1.819	1.167	0.000	1.666	1.931	0.017
Low carbon patent (Parent)	0.484	0.221	0.000	0.449	0.413	0.494
Total patent stock (Parent)	2.496	1.557	0.000	2.368	2.491	0.323
Low carbon patent stock (Parent)	0.696	0.343	0.000	0.673	0.618	0.406

Note: All variables are defined in a log fashion. Columns (1) – (3) report the mean statistics for the treated and control subsidiaries for the unmatched sample, while the remaining columns report that for the matched sample.

To examine the matching quality, we perform a balancing test by comparing the sample means of covariates between the treatment and matched control groups. In Table 1, Columns (4) – (6) report the results. Among 1,022 treated subsidiaries, 636 are successfully matched with 636 control subsidiaries. For all historical innovation activities, there exist no statistically significant differences for the matched sample. These results suggest that the matching procedure performs well in selecting control subsidiaries to mimic historical innovation patterns and economic characteristics of treated subsidiaries before the ETS. Based on the matched sample, Table 2 provides descriptive statistics for variables of interest.

Table 2: Summary Statistics

Variable	N	Mean	S.D.	Min.	Max.
Panel A. Patent Information					
Low-carbon patents	7531	0.100	0.870	0	26
Low-carbon patent citations	7515	0.240	2.990	0	173
Panel B. Policy Indicators					
ETSParent	7531	0.500	0.500	0	1
Post	7515	0.590	0.490	0	1
CarbonPriceParent (yuan)	7531	11.44	19.89	0	64.83
TurnoverRateParent	7531	0.010	0.020	0	0.140
Panel B. Moderation Factors					
Geographical distance	7521	579.4	686.2	0	3387
Technological proximity	7531	0.150	0.300	0	1
No. of production TMT members	7531	1.390	2.010	0	20
Ratio of production TMT members	7531	0.060	0.090	0	0.590
No. of R&D TMT members	7531	2.750	2.790	0	30
Ratio of R&D TMT members	7531	0.130	0.130	0	0.750
Quick Ratio	7440	1.580	2.480	0.070	37.20
Financial Leverage	7434	1.210	1.430	0.020	44.54
Panel C. Other Firm Attributes					
Registered Capital (subsidiary)	7525	274.3	3459	0.01	100000
Asset (parent) (million yuan)	7524	19697	33360	45.87	271267
Capital (parent) (million yuan)	7524	9092	14704	7.70	131421
Sale (parent) (million yuan)	7525	13033	23302	36.26	222505

Note: Summary statistics for the matched sample. All variables are displayed in raw form in this table.

With the matched sample, our analysis further leverages the DID approach to compare the innovation outcomes between treated subsidiaries with similar control ones during the pre- and post-ETS periods. For an unregulated subsidiary *i* in sector *j* from region *r*, with a parent firm *m* in sector *s* from region *n*, and at year *t*, the baseline DID model is specified as:

$$Y_{ijt} = \beta_0 + \beta_1 ETSParent_i \times Post_t + X_{imt} + \gamma_i + \delta_{jt} + \eta_{rt} + \lambda_{st} + \mu_{nt} + \varepsilon_{ijt}, \quad (1)$$

In this specification, the outcome variable Y_{ijt} refers to unregulated subsidiaries' low-carbon innovation (patent counts and citations). The dummy $ETSParent_i$ is an indicator for the treatment assignment, equaling one if an unregulated subsidiary is affiliated with a parent firm regulated by the ETS, and zero otherwise. The dummy $Post_t$ equals one if the period is after the launch of the ETS (2013 and afterward), and zero otherwise. X_{imt} is a vector of control variables at both subsidiary and parent firm levels, such as subsidiaries' registered capital, and parent firms' assets, capital, and sale.

To control for unobservable confounding factors, we add a series of fixed effects at different levels. Subsidiary-level fixed effects, denoted by γ_i, absorb any time-invariant subsidiary-specific characteristics. One may worry about co-existing regional or industrial policies that affect subsidiaries' innovation direction. We include the subsidiaries' sector-year and province-year fixed effects, represented by δ_{jt} and η_{rt}, respectively. These fixed effects could absorb the time-variant sectoral and regional shocks that affect subsidiaries. Similarly, we add the parent sector-year fixed effects λ_{st} and province-year fixed effects μ_{nt} to capture sectoral and regional time-varying unobservable factors. Lastly, ε_{ijt} is an idiosyncratic error term.

Of our central interest is the coefficient of the interaction terms between ETSParent and Post dummies. The estimate, denoted by β_1, captures the ETS-induced low carbon innovation spillover effect via ownership networks. It compares the innovation outcomes between similar unregulated subsidiaries affiliated with and without a regulated parent firm during the pre-and post-EST launching periods while controlling for a rich set of fixed effects.

We further consider potential mechanisms that moderate such ETS-induced low carbon innovation spillover effect. Based upon the matched DID model equation (1), we interact with moderating factors using the following model specification:

$$Y_{ijt} = \beta_0 + \beta_1 ETSParent_i \times Post_t + \beta_2 ETSParent_i \times Post_t \times Mechanism_{imt} +$$
$$\beta_3 Mechanism_{imt} + \beta_4 ETSParent_i \times Mechanism_{imt} + \beta_5 Post_t \times Mechanism_{imt} +$$
$$X_{imt} + \gamma_i + \delta_{jt} + \eta_{rt} + \lambda_{st} + \mu_{nt} + \varepsilon_{ijt}, \quad (2)$$

Besides similar variables defined in the above equation (1), $Mechanism_{imt}$ in the equation (2) captures the three types of moderating factors, including geographical distance, technology proximity, TMT professional backgrounds, and financial slackness. The parameter of interest is the estimate of the triple interaction term, captured by β_2. This estimate indicates the moderating effect.

4. Results

4.1 Baseline result

Using the matched-DID model, we first investigate whether ETS-regulated parent firm would increase the low-carbon innovation of their unregulated subsidiaries.[16] Table 3 shows the results.[17] In all columns, we include the subsidiary fixed effect to absorb subsidiary-specific unobservable that may affect the innovation activities. Besides, we add subsidiary province-year and sector-year fixed effects to control for provincial and sectoral time-variant confounding factors that boost subsidiaries' innovation toward low-carbon technologies, such as provincial coexisting

[16] In Online Appendix, we also present the direct effect of ETS on low-carbon innovation of parent firms. Table A2 reports the results. We document the significant positive impact of ETS on regulated parent firms.
[17] In Online Appendix, we also present the estimated coefficients for covariates for subsidiaries and parent firms.

environmental policy or industry policy for the relevant low-carbon innovation. Standard errors clustered at the industry level allow for serial correlation for error terms across industries.

In Table 3, columns (1) and (2) report the results on low carbon innovation quantity. The estimated coefficient for the interaction term between ETSParent and Post in column (1) is positive and statistically significant at the 1% level. One may worry about confounding factors in the parent firm's region and industry may coexist with parent firms' ETS carbon pressures. To further address this concern, we add a set of province-year and sector-year fixed effects at the parent firm level in Column (2). The estimated coefficient for the interaction term remains positive and statistically significant at the 1% level. That is, as suggested in Column (2), the estimate of 0.040 indicates an unregulated subsidiary affiliated with a regulated parent firm would have 4.08% more low-carbon patents than an unregulated subsidiary affiliated with an unregulated parent firm after the ETS period (2013 onward).[18] Columns (3) and (4) show the results for low-carbon innovation quality, which is proxied by citations received in the subsequent five years. Both columns document positive and statistically significant coefficients for the interaction terms at the 1% level. In our preferred model in Column (4), the estimate of 0.043 indicates that an unregulated subsidiary affiliated with a regulated parent firm would have 4.39% more low-carbon patent citations than an unregulated subsidiary affiliated with an unregulated parent firm after the ETS period (2013 onward). Overall, we document robust and consistent evidence supporting that ETS-regulated parent firms lead to the increase low carbon innovation outcome (both the quantity and quality) in their unregulated subsidiaries. Thus, H1 is supported. Moreover, we also examine how the heterogeneity of carbon market performance across ETS pilots affects such ETS-induced low

[18] For the log-transformed variable, one should reinterpret the estimate as exp(β)-1 as the percent change rather than simply reading β itself. Thus, the coefficient 0.040 indicates a 4.08% increase in low-carbon patents.

carbon innovation spillover effects. Since it's not our main focus of this study, we present the model extension in Section A.1 and estimated results in Table A4 in Online Appendix for interest.

Table 3: ETS-induced Low-carbon Innovation Spillover Effects

VARIABLES	Low Carbon Patent Count		Low Carbon Patent Citation	
	(1)	(2)	(3)	(4)
ETSParent×Post	0.026***	0.040***	0.033***	0.043***
	(0.006)	(0.007)	(0.007)	(0.007)
Observations	7,505	7,489	7,505	7,489
R-squared	0.562	0.578	0.569	0.588
Firm Attributes	Y	Y	Y	Y
Subsidiary FE	Y	Y	Y	Y
Subsidiary Province-Year FE	Y	Y	Y	Y
Subsidiary Sector-Year FE	Y	Y	Y	Y
Parent Province-Year FE		Y		Y
Parent Sector-Year FE		Y		Y

Note: Dependent variables are logarithm one plus the number of low-carbon patent counts, and the logarithm one plus the number of low-carbon patent count weighted by citations received in the subsequent five years in unregulated subsidiary. ETSParent is a binary indicator, equaling one if an unregulated subsidiary is affiliated with a regulated parent firm, and zero otherwise. Post is a year dummy, equaling one if 2013 and afterward, and zero otherwise. All columns include the firm-level attributes including subsidiaries' registered capital, and parent firms' assets, capital, and sale, as well as a rich set of fixed effects at the subsidiary, subsidiary province-year, subsidiary sector-year, parent province-year, and parent sector-year levels. For the sake of brevity, we only report the estimated coefficients for the interaction terms. Table A3.1 reports the estimated coefficients for control variables. Standard errors in the parenthesis are clustered at the industry level. ***, **, *, indicate the significance at the 1% level, 5% level, and 10% level, respectively.

4.2 Moderating Effects

We further explore the roles of five moderators in the above innovation spillover effect. Our regressions adopt the model specification with a flexible form of fixed effects controlling for unobservable confounding factors as shown in Column (2) of the baseline Table 3. Table 4 shows the results of the moderating effects on the quantity and quality of low-carbon innovation.

First, we examine the roles of geographic and technology proximity between parent firms and subsidiaries. Columns (1) and (2) of Table 4 report the results on the patent count. The estimate for the triple interaction term for GeogDist is positive but not statistically significant at any convention level. Thus, H2a is not supported. That is, it indicates a non-significant impact of the geographical distance on the ETS-induced innovation spillovers through corporate ownership networks. Standing in sharp contrast, in Column (2), the estimated coefficient for the interaction term of TechProx is positive and statistically significant at the 1% level, indicating the positive moderating role of technology proximity between parent firms and subsidiaries. Thus, H2b is supported. When it comes to innovation quality, Columns (6) and (7) report the corresponding results. The estimated coefficient for GeogDist is statistically insignificant, while the coefficient for TechProx is significant at the 1% level.[19] These findings further suggest that H2a is not supported but H2b is supported.

Next, we look at whether specific experience in TMT of parent firms would facilitate the ETS-induced innovation spillover from parent firms to subsidiaries. Columns (3) and (8) in Table 4 show the results of production experiences in TMT. We document consistently negative estimates for the triple interaction terms with Ratio_Pro. The estimates are statistically significant for the patent count and patent quality, indicating the negative moderating roles of production experience in TMT in the ETS-induced innovation spillovers effect. Thus, H3a is not supported. On the contrary, as shown in columns (4) and (9), the estimated coefficients for the triple interaction term of Ratio_R&D are consistently positive and significant. These findings indicate that R&D experiences in TMT contribute to such low-carbon innovation spillover to unregulated subsidiaries.[20] Thus, H3b is supported.

---

[19] In Online Appendix, we provide the robustness check on different measures of technology proximity based on 3-digit or 4-digit IPC during the pre-ETS periods. Table A5 shows the relevant results. All estimates are positive and statistically significant, indicating the positive role of technology proximity.

[20] We also account for additional TMT measures as control variables, including average tenure period, TMT size, and the female ratio in the TMT. In Online Appendix, Table A6 shows the corresponding results. Our findings on the TMT moderating effect do not alter.

Lastly, we investigate how parent firms' financial slack affects the innovation spillover effects. Parent firms' financial slack is proxied by the quick ratio. The large the quick ratio, the more financial slack the parent firm faces with. Column (5) reports the results on the low-carbon patent count, while column (10) shows the results on the quality. In both columns, the estimates for the triple interaction term are consistently negative and statistically significant. These estimates suggest the negative moderating role of the financial slack. Thus, between competing hypotheses of H4a and H4b, H4b is supported.

Table 4: The Moderating Effects on ETS-induced Low-carbon Innovation Spillover

VARIABLES	Low Carbon Patent Count					Low Carbon Patent Citation				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ETSParent×Post	0.034***	0.012	0.065***	0.003	0.056***	0.045**	0.009	0.081***	-0.005	0.054***
	(0.012)	(0.008)	(0.010)	(0.015)	(0.013)	(0.021)	(0.007)	(0.013)	(0.018)	(0.018)
ETSParent×Post×GeogDist	0.002					-0.000				
	(0.003)					(0.006)				
ETSParent×Post×TechProx		0.140***					0.178***			
		(0.028)					(0.031)			
ETSParent×Post×Ratio_Pro			-0.426***					-0.644***		
			(0.121)					(0.163)		
ETSParent×Post×Ratio_R&D				0.251**					0.333***	
				(0.089)					(0.104)	
ETSParent×Post×QuickRatio					-0.026**					-0.026*
					(0.010)					(0.015)
Observations	7,480	7,489	7,489	7,489	7,402	7,480	7,489	7,489	7,489	7,402
R-squared	0.578	0.584	0.579	0.579	0.579	0.588	0.591	0.589	0.589	0.589
Firm Attributes	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Subsidiary FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Subsidiary Province-Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Subsidiary Sector-Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Parent Province-Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Parent Sector-Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: Dependent variables are logarithm one plus the number of low-carbon patent counts, and the logarithm one plus the number of low-carbon patent count weighted by citations received in the subsequent five years. ETSParent is a binary indicator, equaling one if an unregulated subsidiary is affiliated with a regulated parent firm, and zero otherwise. Post is a year dummy, equaling one if 2013 and afterward, and zero otherwise. All columns include the firm-level attributes including subsidiaries' registered capital, and parent firms' assets, capital, and sale, as well as a rich set of fixed effects at the subsidiary, subsidiary province-year, subsidiary sector-year, parent province-year, and parent sector-year levels. For the sake of brevity, we only report the estimated coefficients for the interaction terms. Table A3.2 reports the estimated coefficients for control variables. Standard errors in the parenthesis are clustered at the industry level. ***, **, *, indicate the significance at the 1% level, 5% level, and 10% level, respectively.

4.3 Robustness Checks

4.3.1 Robustness on the baseline model

To test the validity assumption on the pre-trend, we adopt the event-study model by recalling the period into years before and after the ETS launching phase based upon the baseline-matched DID model. A variant of the baseline model specification is proposed as follows,

$$Y_{ijt} = \beta_0 + \sum_{m=1}^{3} \beta_{1m} ETSParent_i \times Post_{t-m} + \sum_{n=0}^{3} \beta_{2n} ETSParent_i \times Post_{t+n}$$

$$+X_{imt} + \gamma_i + \delta_{jt} + \eta_{rt} + \lambda_{st} + \mu_{nt} + \varepsilon_{ijt}, \quad (4)$$

In the form, the variable $Post_{t-m}$ is a pre-ETS policy dummy indicating the mth lag of launching ETS pilots in 2013, while the $Post_{t+n}$ denotes a post-ETS dummy for the nth lead, where $m \in [1,3]$ and $n \in [0,3]$. We set one year before ETS as the benchmark in the event-study model.

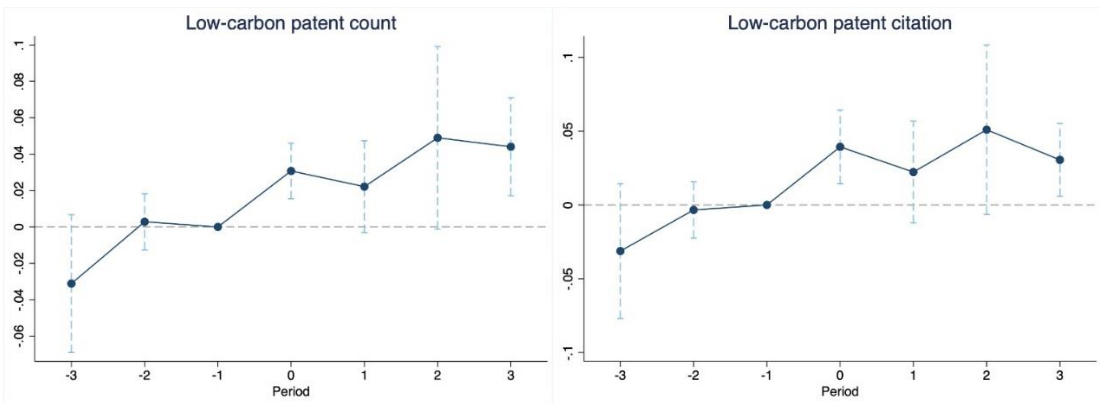

Figure 1: Dynamic Effects on Low-carbon Innovation

Notes: the left and right panels report the dynamic effect results on unregulated subsidiaries' innovation quantity and quality, respectively. The dot indicates the point estimates for periods before and after the ETS launching year. The intercept indicates the 95% confidence interval. The benchmark is set one year before the launching year.

Figure 1 plots the estimated coefficients for the year-specific pre- and post-ETS effects and the 95% confidence intervals. The left panel shows the dynamic effects for the patent count, while the right panel displays the results for the patent quality. In both plots, the estimated coefficients for the pre-ETS periods are statistically insignificant, lending strong support to the pre-trend assumption, in which no statistically significant differences in both low-carbon innovation quantity and quality are found between treated and matched control groups. Moreover, the point estimates for the post-ETS dummies are trending up and started to display some significant levels three years after the carbon trading. These findings further suggest the contemporaneously positive ETS-induced low carbon innovation spillover effect.

To further test the stability of our baseline conclusions, we account for additional confounding factors and adopt two alternative matching methods. Table 5 reports the results of robustness checks, which suggest H1 is supported consistently.

Table 5: Robustness Checks on the Baseline Model

VARIABLES	Number of Regulated Sister Subsidiaries as Control	Patent Growth Rate as Control	Mahalanobis Distance Matching	Inverse Probability Treatment Weighting	One-year Lag	Poisson Pseudo Maximum Likelihood
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Dependent Variable: Low Carbon Patent Count						
ETSParent×Post	0.037***	0.037***	0.016***	0.015***	0.031***	0.838***
	(0.012)	(0.007)	(0.005)	(0.004)	(0.011)	(0.143)
Observations	7,489	6,723	7,370	103,523	7,494	7,505
R-squared	0.578	0.608	0.553	0.540	0.577	0.700
Panel B: Dependent Variable: Low Carbon Patent Citation						
ETSParent×Post	0.041***	0.035***	0.022***	0.026***	0.027**	0.596***
	(0.010)	(0.008)	(0.008)	(0.005)	(0.010)	(0.110)
Observations	7,489	6,723	7,370	103,523	7,489	7,505
R-squared	0.588	0.611	0.547	0.543	0.588	0.726
Firm Attributes	Y	Y	Y	Y	Y	Y
Subsidiary FE	Y	Y	Y	Y	Y	Y
Subsidiary Province-Year FE	Y	Y	Y	Y	Y	Y
Subsidiary Sector-Year FE	Y	Y	Y	Y	Y	Y
Parent Province-Year FE	Y	Y	Y	Y	Y	N

Parent Sector-Year FE	Y	Y	Y	Y	Y	N

Note: Dependent variables are logarithm one plus the number of low-carbon patent counts, and the logarithm one plus the number of low-carbon patent count weighted by citations received in the subsequent five years. ETSParent is a binary indicator, equaling one if an unregulated subsidiary is affiliated with a regulated parent firm, and zero otherwise. Post is a year dummy, equaling one if 2013 and afterward, and zero otherwise. All columns include the firm-level attributes including subsidiaries' registered capital, and parent firms' assets, capital, and sale, as well as a rich set of fixed effects at the subsidiary, subsidiary province-year, subsidiary sector-year, parent province-year, and parent sector-year levels. Standard errors in the parenthesis are clustered at the industry level. ***, **, *, indicate the significance at the 1% level, 5% level, and 10% level, respectively.

Firstly, within corporate ownership network, an unregulated subsidiary may have affiliated sister subsidiaries that are regulated under the ETS program, giving rise to another potential channel for intraorganizational knowledge transfer. To cope with this concern, we account for the number of regulated sister subsidiaries as a control variable in the DID regression. Column (1) reports the corresponding results. In both panels, the estimates are positive and statistically significant at the 1% level. The magnitude of these estimates is slightly smaller than those in the baseline columns (2) and (4) of Table 3. The effect is attenuating due to some explanatory power absorbed by the innovation spillover arising from the regulated sister subsidiaries. Overall, we still document the positive and significant ETS-induced low-carbon innovation from parent regulated firms to unregulated subsidiaries.

Secondly, the baseline matching process selects the low-carbon patent stock and total patent stock as two key variables to ensure the similarity in innovation capability between treated subsidiaries and control ones during the pre-ETS period. One may conjecture that treated subsidiaries may follow a different innovation growth path than control ones. To further address this concern, we add the patent growth rate as a control variable to the

DID regression.[21] Column (2) reports the DID results. Our estimates for the interaction terms remain positive and statistically significant at the 1% level, reassuring the baseline conclusions.

Thirdly, the baseline matched DID model adopts the PSM approach. PSM is a widely used matching approach, which projects all covariates onto one scalar (i.e., propensity score). PSM can achieve a similar distribution of covariates between treated and control units while containing a higher dimension of information (Austin, 2011). But it also potentially increases model dependence and imbalance on matching variables (King and Nielsen, 2019). Alternatively, one could also use other two popular matching tools: Mahalanobis distance matching and inverse probability treatment weighting (IPTW) methods. Instead of projecting all covariates down to one single index of the propensity score, the Mahalanobis method matches the closest control firms with the treated firms by the shortest Mahalanobis distance. We calculate this distance based on the same key covariates used in the PSM approach. In addition, we allow matching within the sector to control for sector-specific unobservable affecting both treatment and control groups. Column (3) presents the corresponding results on the patent count and quality of low-carbon innovation. Our baseline findings are robust against this alternative method.

Fourth, another potential concern in our baseline is the loss of observations during the matching procedure. To address this, we use the IPTW method to transform the estimated propensity scores to weight firms (Hirano and Imbens, 2001), though this may

[21] The historical low-carbon patent stock and patent stock used in the matching process could be a proxy for the innovation trajectory. Thus, we only add patent growth rates as control variables in the matched-DID regression not in the matching part.

cause a large variance if the weights are extreme (Stuart, 2010). More specifically, each treated firm is weighted by $1/\hat{p}$ and each control firm is weighted by $1/(1-\hat{p})$, where $\hat{p}$ is the propensity score estimated from the matching procedure (Guadalupe et al., 2012). Column (4) shows the results for the IPTW method. In these columns, we still document positive and statistically significant estimates for the DID interaction terms, providing corroborating evidence supporting the baseline conclusion.

Fifthly, to tackle any potential time-lag issue, we add a one-year time lag in our robustness checks, respectively. Column (5) shows the corresponding results. When taking the possible time lag into account, the baseline findings do not alter.

Lastly, we estimate our baseline model by Poisson pseudo maximum likelihood as it may fit our count outcomes well. The corresponding results are shown in Column (6). The estimation method change doesn't alter our baseline conclusion.[22]

4.3.2 Robustness on Moderating Effects

We further test the stability of our moderating effects against alternative measures on technological proximity, professional experience in TMT, and financial slack. Table 6 reports the results of these robustness checks.

The baseline adopts the IPC class (3 digits) to compute the technological proximity between each subsidiary firm and its parent firm. As a robustness check, we consider the

[22] Although there is a concern that a simple Poisson estimator may not perform well for over-dispersed count data, a Poisson model estimated by pseudo maximum likelihood can solve this issue (Silva and Tenreyro, 2006; Silva and Tenreyro, 2011). The conditional negative binomial model, as another commonly used method, does not truly condition out the fixed effects (Allison and Waterman, 2002; Guimaraes, 2008). However, a very higher number of fixed effects causes serious numerical instability to the Poisson pseudo maximum likelihood estimator and usually fails to reach convergence (Bratti et al., 2014; Henn and McDonald, 2014). Hence, we are only able to estimate the baseline model with subsidiary-level fixed effects by the Poisson model. Since our interest is to estimate the spillover effects by controlling both subsidiary and parent firm-level unobservable factors, we mainly use the ordinary least squares estimator in our analyses.

IPC subclass (4 digits). Columns (1) and (5) report the corresponding results. Technological proximity still plays a positive and significant moderating role in the ETS-induced innovation spillover. Thus, H2b is supported consistently.

We use the number of managers with production experience and the number of managers with R&D experience. Columns (2) and (6) show the results of the moderating effect of production experience in TMT. We still find statistically significant but negative estimates for the triple interaction terms. Thus, H3a is still not supported. Columns (3) and (7) show the results of the moderating effect of R&D experience in TMT. The estimates remain positive and statistically significant. Thus, H3b is supported consistently.

We test the alterative financial slack by adopting the financial leverage, another popular indicator in the OM literature (Klöckner et al., 2022; Wiengarten et al., 2017). In contrast to the quick ratio, the larger the financial leverage, the more serious the financial constraint the parent firm confronts. Columns (4) and (8) report the patent count and quality results. We document the consistently positive estimates for the triple interaction terms in both columns. Thus, H4b is supported consistently.

Table 6: Robustness Checks on the Moderating Effects

	Low Carbon Patent Count				Low Carbon Patent Citation			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ETSParent×Post	0.018**	0.059***	-0.006	0.002	0.016*	0.075***	-0.022	-0.015
	(0.008)	(0.010)	(0.016)	(0.010)	(0.008)	(0.013)	(0.020)	(0.018)
ETSParent×Post×TechProx(4-digit)	0.142***				0.176***			
	(0.022)				(0.027)			
ETSParent×Post×Num_Pro		-0.015**				-0.025***		
		(0.006)				(0.008)		
ETSParent×Post×Num_R&D			0.015***				0.022***	

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			(0.005)				(0.006)	
ETSParent×Post×FinLeverage				0.056**				0.082**
				(0.021)				(0.031)
Observations	7,489	7,489	7,489	7,414	7,489	7,489	7,489	7,414
R-squared	0.582	0.579	0.580	0.579	0.590	0.589	0.589	0.590
Firm Attributes	Y	Y	Y	Y	Y	Y	Y	Y
Subsidiary FE	Y	Y	Y	Y	Y	Y	Y	Y
Subsidiary Province-Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Subsidiary Sector-Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Parent Province-Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Parent Sector-Year FE	Y	Y	Y	Y	Y	Y	Y	Y

Note: Dependent variables are logarithm one plus the number of low-carbon patent counts, and the logarithm one plus the number of low-carbon patent count weighted by citations received in the subsequent five years. ETSParent is a binary indicator, equaling one if an unregulated subsidiary is affiliated with a regulated parent firm, and zero otherwise. Post is a year dummy, equaling one if 2013 and afterward, and zero otherwise. All columns include the firm-level attributes including subsidiaries' registered capital, and parent firms' assets, capital, and sale, as well as a rich set of fixed effects at the subsidiary, subsidiary province-year, subsidiary sector-year, parent province-year, and parent sector-year levels. Standard errors in the parenthesis are clustered at the industry level. ***, **, *, indicate the significance at the 1% level, 5% level, and 10% level, respectively.

5. Discussion and Conclusions

5.1 Discussion of findings

This paper seeks to explore whether the ETS-regulated parent firms has positive impact on low carbon innovation of their unregulated subsidiaries, and the role of geographical and technological proximity between parent and subsidiaries, a parent firm's TMTs experience and financial slack in such ETS-induced low carbon innovation spillover through corporate ownership network.

Our findings demonstrate that ETS-regulated parent firms increase the low-carbon innovation outputs of their unregulated subsidiaries. That is, ETS-induced low carbon innovation spillover through corporate ownership network exists. Moreover, we identify several organizational enablers and inhibitors. Specifically, we find out that technological proximity between subsidiaries and parent firms acts as an important enabler for promoting such ETS-induced innovation spillover effect, but geographical proximity has no significant effect. Between the competing views of the role of financial slack in parent firms, our finding suggests it is an inhibitor rather than enabler. As of the experience of TMTs, R&D experience enables the low-carbon innovation spillover from regulated parent firms to their unregulated subsidiaries; production experience puts as a barrier to such an innovation spillover effect, which is opposite to our hypothesis. The potential explanation for such an opposite finding is as below. Some scholars consider that commensuration environmental policies, like ETS, which link environment and economic activities can hardly trigger grand changes in corporate environmental practices because market discourses are an enduring feature of the business (Wright and Nyberg, 2017). Considering that cost, productivity and efficiency are key indicators for production and operations performance, within regulated parent firms, their TMTs with higher production experience might incline to more secure options like energy conservation and emission reduction in response to political discourses while simultaneously reallocating emissions to subsidiaries with lower regulatory costs (Akey and Appel, 2020; Bartram et al., 2022), so that the overall operation performance in is not threatened. In other words, it may be production emission transfer rather than innovation spillover to their unregulated subsidiaries. In this connection, the unregulated subsidiaries serve as an extra production base instead of a knowledge contributor. Thus, a significant negative moderating effect is founded on the production experience of members in TMT on low-carbon innovation spillover to subsidiaries.

5.2. Implications for research

This paper makes several theoretical contributions. First, we enrich sustainable operations management research by exploring a firm's strategic consideration of whether and how to respond to environmental regulations in jurisdictions where a firm does not operate. We provided empirical evidence that ETS-regulated parent firms can choose to promote low-carbon innovation in their unregulated subsidiaries as an alternative to environmental liability shift that has been widely documented (Akey and Appel, 2020; Bartram et al., 2022). Thus, ETS-induced low-carbon innovation spillover effect within corporate ownership networks is revealed. While the low-carbon economy has gained incremental attention in OM research (Atasu et al., 2020), empirical evidence regarding the firm's operational choices like green innovation under environmental regulations is still rare. Leveraging the unique quasi-experiment design of China's regional ETS pilots and comprehensive corporate ownership, we document the causal evidence of the influence of regulated parent firms on the low-carbon innovation outcomes of their unregulated subsidiaries. This finding enlightens us that transferring low-carbon knowledge instead of carbon emission may be a novel operational strategy in responding to climate change pressures (Drake, 2018), which inspires the OM research to further explore the role of corporate ownership networks in the transition to a low-carbon operation.

Secondly, our study further contributes to knowledge transfer and innovation spillover literature, particularly the network-based innovation literature, by revealing the contingency effects of geographical and technological proximity along with corporate ownership networks. Our results suggest that innovation spillover in ownership networks is not significantly affected by geographical proximity, which challenges the conventional view that geographical distance negatively influences network-based innovation (e.g., Chu et al., 2019; Sharma et al., 2019). Extant literature proposes that spatial complexity presents significant challenges, for instance, coordination difficulties and different management styles or organizational cultures, in supply network or alliance innovation activities (Capaldo and Petruzzelli, 2014; Dong et al., 2020). Consistent with previous intraorganizational knowledge transfer literature (Argote et al., 2022; Argote et al., 2003), our research implies that innovation spillover within the ownership network is also free from the above challenges, which enlightens an alternative channel of leveraging external knowledge and deepens our understanding of the circumstances under which network base innovation activities can be more effective (e.g., promote integration). Moreover, this study also extends the ongoing debate on the contradictory effects of technology proximity between a focal actor and its partners in innovation (Gao et al., 2015; Liang and Liu, 2018). There is literature arguing that dissimilar and heterogeneous basis of knowledge may stimulate collaborative innovation (Gao et al., 2015; Rosenkopf and Almeida, 2003), yet we emphasize that the larger knowledge pool and enhanced absorptive capacity induced by knowledge homogeneity outperform the possible benefits of knowledge heterogeneity when considering knowledge spillover. In this way, we assert that technological proximity is a positive contingent factor for promoting knowledge spillover in ownership networks, thereby contributing to the extant literature (Faems et al., 2020; Guan and Yan, 2016).

Thirdly, this study also contributes to knowledge transfer literature by examining the moderating effects of the production and R&D experience of members in the TMT on innovation spillover through the corporate ownership network. Recent studies reveal the relationship between the individual characteristics of top managers and knowledge transfer (Liu et al., 2022), yet our understanding is still limited on how top teams, which may have greater influences on organizational outcomes (Kumar and Paraskevas, 2018; Menz, 2011), can affect knowledge transfer. Our results suggest that the production and R&D experience of members in the TMT can exert conflicting influences, either as a barrier or enabler, on the low-carbon innovation spillover within corporate ownership network. With higher R&D experience in the parent firm's TMT, a firm is more likely to recognize the opportunities and take strategic initiatives in support of an active innovation spillover to its subsidiaries. However, with higher production experience presence in the parent firm's TMT, a firm might feel more rational to diffuse a bunch of production plan to the subsidiaries to mitigate the operation pressure caused by the environmental regulation on the parent firm (Bartram et al., 2022; Fremeth and Shaver, 2014), rather than in support of subsidiaries' technological innovation. This also echoes conclusions from previous literature that executives with output career experience (e.g., R&D) favor innovation strategies whereas executives with throughput career experience (e.g., production) are more likely to perceive R&D as a discretionary expense subject to efficiency concerns (Barker and Mueller, 2002; Heyden et al., 2017). Our findings also extent the upper-echelon theory in the environmental management (Kumar and Paraskevas, 2018) and echo the perspective that the experiences managers shape their idiosyncratic interpretation of the strategic situation confronting and affecting their subsequent decisions and behaviors (Hambrick, 2007).

Fourth, we extend the theoretical and empirical debate of how firms would respond to environmental regulation pressure from the resource dependency view. When the regulated parent firm lacks financial resources, i.e., in the presence of low quick ratio or high financial leverage, it may respond to the carbon pressure by transferring knowledge to unregulated subsidiaries and leveraging them as innovation resources to achieve desired decarbonization. Indeed, slack resources can be viewed as organizational buffers that allow firms to be more passive to external pressures (Kraatz and Zajac, 2001). Finance-rich firms are more likely to be satisfied with the status quo and less sensitive to increasing environmental misfit and urgency of adaption, whereas firms with lower financial slack are more motivated to take actions in response to external threats or pressures (Kraatz and Zajac, 2001). In this connection, when confronting the pressure of ETS, proactively leveraging resources within their corporate ownership networks for low-carbon innovation becomes a reasonable and necessary strategy for parent firms to sustain not only themselves but also their subsidiaries. This finding oechoes and extends recent OM literature that argues low financial slack promotes firms to improve environmental performance by leverage their rivals' knowledge base (Modi and Cantor, 2021). Our finding also challenges the traditional economic perspective that predicts extra-jurisdictional firms were less incentive to invest in environmental innovation if few financial incentives are provided (Calel and Dechezleprêtre, 2016). We provide an alternative, i.e., depending on ownership network resources, to resolve the dilemma of environmental innovation pressure from the regulation and constrained financial resources (Calel, 2020; Milliman and Prince, 1989), which represents a novel angle of applying resource dependency theory in environmental management literature.

Lastly, we also shed light on the knowledge transfer and innovation spillover literature by identifying changes in the regional environment -- the enforcement of regional ETS in China -- as an enabler of the intraorganizational knowledge transfer (Argote et al., 2003). ETS potentially increases the knowledge base and willingness of regulated firms to transfer low-carbon innovation knowledge. While conventional literature mainly concentrates on three categories (i.e., knowledge, organizational, and relational) of characteristics that may affect knowledge transfer (Liu et al., 2022; Van Wijk et al., 2008), recent literature starts to emphasize the characteristics of the context where knowledge transfer takes place (Argote et al., 2022). Still, scant attention has been paid to the dynamics of knowledge transfer when confronting environmental changes. Our work indicates that local shocks such as the launch of new regional regulations can be an overlooked motivational mechanism of knowledge transfer in the extant literature.

5.3. Implications for practices

This study sheds light on several important managerial implications. First, the potential innovation spillover effect could extend the understanding of how firms may exert their flexibility within the ownership network in response to strict local climate policy by minimizing their abatement costs and optimizing returns of their low-carbon innovation. For example, we found that innovation spillover through corporate ownership networks might be more effective than through external networks (Argote et al., 2022; Calel and Dechezleprêtre, 2016), as the former is exempted from spatial difficulties that trouble supply base innovation (Sharma et al., 2019) and could benefit from technological proximity which the latter cannot (Isaksson et al., 2016). Therefore, firms confronting regional environmental policy pressure should not neglect the potential of their internal knowledge network.

Second, our findings suggest that corporates should consider the composition of TMTs in parent firms. Recent years, we observe that growing public announcements on corporate decision toward carbon neutrality target. However, different composition of TMTs in parent firm may present conflicting roles in increasing low carbon innovation outcomes within entire corporate. For example, the presence of TMT members who have R&D experience contributes to the low carbon innovation spillover process, whereas executives with production backgrounds may impede it. Thus, we suggest that the composition of TMTs could be aligned with corporate strategy toward carbon neutrality.

Thirdly, we also provide insights for firms with different financial resource levels to strategically reallocate resources in response to environmental regulation. Firms with low financial slack could consider leveraging resources in the ownership network for knowledge spillover.

Lastly, our paper also provides implications for policymakers. Firstly, for the nationwide China ETS with the power sector included in the current stage. Although regional climate policies are criticized for potential emission leakage, they may also create knowledge spillovers to other unregulated regions linked through firm internal ownership networks. Increasing awareness of this fact offers a more eclectic perspective on regional carbon regulations for policymakers. Secondly, the policymakers may worry about the economic downside of ambitious national ETS rolling over to the carbon-intensive manufacturing sectors expected in the next stage. Our findings provide another overlooked, yet critical benefit of carbon ETS that the ETS pressure would stimulate the potential knowledge transfer, that is, parent firms utilize the internal R&D resources and induce low-carbon innovation spillover through a corporate ownership network. Without accounting for the firm's internal network, the conventional estimation of the ETS-induced innovation effect would be underestimated.

5.4. Limitations and future research

This paper has several limitations, leaving some interesting research venues worthy of further investigation. First, our analysis focus on identifying the causal impacts of the ETS-regulated parent firms on the low-carbon innovation of unregulated subsidiaries. An interesting research venue is to further explore and verify the underlying mechanisms of intraorganizational innovation spillover between parent firms and subsidiaries. To answer this, one would expect to collect detailed intraorganizational information such as citations flows, innovation collaboration, shared R&D resources, mobility of talents between parent and subsidiaries, network position of subsidiaries etc.. Second our study provides the implications of the low-carbon innovation spillover effect along with the corporate ownership network, which supports the understanding of how to reduce Scope 1 and 2 carbon emissions. It would be also interesting to examine such innovation spillover effects along with the supply chain network since it would be valuable to reduce Scope 3 carbon emissions. Another data limitation is a lack of subsidiaries overseas, leading to a failure to account for the potential spillovers across borders. Future research should consider exploring low-carbon innovation spillover in other institutional contexts such as multinational companies. Besides, our study mostly concentrates on the moderating effects of parent firm's (i.e., the knowledge transferor's) features on low-carbon innovation spillover, future research could explore the impacts of subsidiaries' (i.e., the knowledge recipients) characteristics on such spillover. Simultaneously, since our results regarding geographical proximity deviate from extant literature, future research may also consider using alternative measures like travel time to explore possible explanations.

6. Reference

Achcaoucaou, F., Miravitlles, P., and León-Darder, F. (2014). Knowledge sharing and subsidiary R&D mandate development: A matter of dual embeddedness. *International business review,* 23(1), 76-90.

Akey, P. A. T. and Appel, I. A. N. (2020). The Limits of Limited Liability: Evidence from Industrial Pollution. *The Journal of Finance,* 76(1), 5-55.

Allison, P. D. and Waterman, R. P. (2002). Fixed-Effects Negative Binomial Regression Models. *Sociological methodology,* 32(1), 247-265.

Ambec, S., Cohen, M. A., Elgie, S., and Lanoie, P. (2013). The Porter Hypothesis at 20: Can Environmental Regulation Enhance Innovation and Competitiveness? *Review of environmental economics and policy,* 7(1), 2-22.

Argote, L., Guo, J., Park, S.-S., and Hahl, O. (2022). The Mechanisms and Components of Knowledge Transfer: The Virtual Special Issue on Knowledge Transfer Within Organizations. *Organization Science,* 33(3), 1232-1249.

Argote, L., McEvily, B., and Reagans, R. (2003). Managing Knowledge in Organizations: An Integrative Framework and Review of Emerging Themes. *Management Science,* 49(4), 571-582.

Atasu, A., Corbett, C. J., Huang, X., and Toktay, L. B. (2020). Sustainable Operations Management Through the Perspective of Manufacturing & Service Operations Management. *Manufacturing & Service Operations Management,* 22(1), 146-157.

Audretsch, D. B. and Feldman, M. P. (1996). R&D Spillovers and the Geography of Innovation and Production. *The American economic review,* 86(3), 630-640.

Austin, P. C. (2011). Optimal caliper widths for propensity-score matching when estimating differences in means and differences in proportions in observational studies. *Pharmaceutical statistics: the journal of the pharmaceutical industry,* 10(2), 150-161.

Austin, P. C., Grootendorst, P., and Anderson, G. M. (2007). A comparison of the ability of different propensity score models to balance measured variables between treated and untreated subjects: a Monte Carlo study. *Statistics in medicine,* 26(4), 734-753.

Balsmeier, B., Buchwald, A., and Stiebale, J. (2014). Outside directors on the board and innovative firm performance. *Research Policy,* 43(10), 1800-1815.

Barker, V. L. and Mueller, G. C. (2002). CEO Characteristics and Firm R&D Spending. *Management Science,* 48(6), 782-801.

Bartram, S. M., Hou, K., and Kim, S. (2022). Real effects of climate policy: Financial constraints and spillovers. *Journal of Financial Economics,* 143(2), 668-696.

Belderbos, R., Cassiman, B., Faems, D., Leten, B., and Van Looy, B. (2014). Co-ownership of intellectual property: Exploring the value-appropriation and value-creation implications of co-patenting with different partners. *Research Policy,* 43(5), 841-852.

Berrone, P., Fosfuri, A., Gelabert, L., and Gomez-Mejia, L. R. (2013). Necessity as the mother of 'green' inventions: Institutional pressures and environmental innovations. *Strategic Management Journal,* 34(8), 891-909.

Bratti, M., De Benedictis, L., and Santoni, G. (2014). On the pro-trade effects of immigrants. *Review of world economics,* 150(3), 557-594.

Calel, R. (2020). Understanding Technological Responses to Cap-and-Trade. *American Economic Journal: Economic Policy,* 12(3), 170-201.

Calel, R. and Dechezleprêtre, A. (2016). Environmental Policy and Directed Technological Change: Evidence from the European Carbon Market. *Review of Economics and Statistics,* 98(1), 173-191.

Capaldo, A. and Petruzzelli, A. M. (2014). Partner Geographic and Organizational Proximity and the Innovative Performance of Knowledge-Creating Alliances. *European management review,* 11(1), 63-84.

Carpenter, M. A., Geletkanycz, M. A., and Sanders, W. G. (2004). Upper Echelons Research Revisited: Antecedents, Elements, and Consequences of Top Management Team Composition. *Journal of management,* 30(6), 749-778.

Chakraborty, P. and Chatterjee, C. (2017). Does environmental regulation indirectly induce upstream innovation? New evidence from India. *Research Policy,* 46(5), 939-955.

Cheng, J. L. C. and Kesner, I. F. (1997). Organizational Slack and Response to Environmental Shifts: The Impact of Resource Allocation Patterns. *Journal of management,* 23(1), 1-18.

Child, J. (1972). Organizational structure, environment and performance: The role of strategic choice. *Sociology,* 6, 1-22.

Chu, Y., Tian, X., and Wang, W. (2019). Corporate Innovation Along the Supply Chain. *Management Science,* 65(6), 2445-2466.

CNPC. 2022. *Jilin Oilfield develops upadted version of CCUS anti-corrosion technology with high standards* [Online]. Available: http://csr.cnpc.com.cn/cnpccsr/carbontec/202203/fd6f468f69fd4adaafb8ac0da0cfb77c.shtml [Accessed 2 December 2022].

Cohen, W. M. and Levinthal, D. A. (1990). Absorptive Capacity: A New Perspective on Learning and Innovation. *Administrative science quarterly,* 35(1), 128-152.

Cui, J. and Moschini, G. (2020). Firm internal network, environmental regulation, and plant death. *Journal of Environmental Economics and Management,* 101.

Cui, J., Zhang, J., and Zheng, Y. (2018). Carbon Pricing Induces Innovation: Evidence from China's Regional Carbon Market Pilots. *AEA papers and proceedings,* 108, 453-457.

Dang, J. and Motohashi, K. (2015). Patent statistics: A good indicator for innovation in China? Patent subsidy program impacts on patent quality. *China Economic Review,* 35, 137-155.

Darr, E. D., Argote, L., and Epple, D. (1995). The Acquisition, Transfer, and Depreciation of Knowledge in Service Organizations: Productivity in Franchises. *Management Science,* 41(11), 1750-1762.

Dearborn, D. C. and Simon, H. A. (1958). Selective Perception: A Note on the Departmental Identifications of Executives. *Sociometry,* 21(2), 140-144.

Dehejia, R. H. and Wahba, S. (2002). Propensity Score-Matching Methods for Nonexperimental Causal Studies. *The review of economics and statistics,* 84(1), 151-161.

Dellestrand, H. and Kappen, P. (2011). Headquarters Allocation of Resources to Innovation Transfer Projects within the Multinational Enterprise. *Journal of international management,* 17(4), 263-277.

Dezsö, C. L. and Ross, D. G. (2012). Does female representation in top management improve firm performance? A panel data investigation. *Strategic Management Journal,* 33(9), 1072-1089.

Dezső, C. L., Ross, D. G., and Uribe, J. (2016). Is there an implicit quota on women in top management? A large-sample statistical analysis. *Strategic Management Journal,* 37(1), 98-115.

Dibiaggio, L., Nasiriyar, M., and Nesta, L. (2014). Substitutability and complementarity of technological knowledge and the inventive performance of semiconductor companies. *Research Policy,* 43(9), 1582-1593.

Diemer, A. and Regan, T. (2022). No inventor is an island: Social connectedness and the geography of knowledge flows in the US. *Research Policy,* 51(2), 104416.

Dong, Y., Skowronski, K., Song, S., Venkataraman, S., and Zou, F. (2020). Supply base innovation and firm financial performance. *Journal of Operations Management,* 66(7-8), 768-796.

Drake, D. F. (2018). Carbon Tariffs: Effects in Settings with Technology Choice and Foreign Production Cost Advantage. *Manufacturing & Service Operations Management,* 20(4), 667-686.

Faems, e., Bos, B., Noseleit, F., and Leten, B. (2020). Multistep Knowledge Transfer in Multinational Corporation Networks: When Do Subsidiaries Benefit From Unconnected Sister Alliances? *Journal of management,* 46(3), 414-442.

Feinberg, S. E. and Gupta, A. K. (2004). Knowledge spillovers and the assignment of R&D responsibilities to foreign subsidiaries. *Strategic Management Journal,* 25(89), 823-845.

Foss, N. J. and Pedersen, T. (2002). Transferring knowledge in MNCs: The role of sources of subsidiary knowledge and organizational context. *Journal of international management,* 8(1), 49-67.

Fremeth, A. R. and Shaver, J. M. (2014). Strategic rationale for responding to extra-jurisdictional regulation: Evidence from firm adoption of renewable power in the US. *Strategic Management Journal,* 35(5), 629-651.

Gao, G. Y., Xie, E., and Zhou, K. Z. (2015). How does technological diversity in supplier network drive buyer innovation? Relational process and contingencies. *Journal of Operations Management,* 36(1), 165-177.

Garza-Reyes, J. A. (2015). Lean and green – a systematic review of the state of the art literature. *Journal of cleaner production,* 102, 18-29.
Giroud, X. and Mueller, H. M. (2015). Capital and Labor Reallocation within Firms. *The Journal of finance (New York),* 70(4), 1767-1804.
Giroud, X. and Mueller, H. M. (2019). Firms' Internal Networks and Local Economic Shocks. *The American economic review,* 109(10), 3617-3649.
Greve, H. R. (2003). A Behavioral Theory of R&D Expenditures and Innovations: Evidence from Shipbuilding. *Academy of Management Journal,* 46(6), 685-702.
Guadalupe, M., Kuzmina, O., and Thomas, C. (2012). Innovation and Foreign Ownership. *The American economic review,* 102(7), 3594-3627.
Guan, J. and Liu, N. (2016). Exploitative and exploratory innovations in knowledge network and collaboration network: A patent analysis in the technological field of nano-energy. *Research Policy,* 45(1), 97-112.
Guan, J. C. and Yan, Y. (2016). Technological proximity and recombinative innovation in the alternative energy field. *Research Policy,* 45(7), 1460-1473.
Guimaraes, P. (2008). The fixed effects negative binomial model revisited. *Economics Letters,* 99(1), 63-66.
Gupta, A. and Misangyi, V. F. (2018). Follow the leader (or not): The influence of peer CEOs' characteristics on interorganizational imitation. *Strategic Management Journal,* 39(5), 1437-1472.
Gupta, A. K. and Govindarajan, V. (2000). Knowledge flows within multinational corporations. *Strategic Management Journal,* 21(4), 473-496.
Hall, B. H., Jaffe, A., and Trajtenberg, M. (2005). Market Value and Patent Citations. *The Rand journal of economics,* 36(1), 16-38.
Hambrick, D. C. (2007). Upper Echelons Theory: An Update. *The Academy of Management review,* 32(2), 334-343.
Hambrick, D. C. and Mason, P. A. (1984). Upper Echelons: The Organization as a Reflection of Its Top Managers. *The Academy of Management review,* 9(2), 193-206.
Harhoff, D., Narin, F., Scherer, F. M., and Vopel, K. (1999). Citation Frequency and the Value of Patented Inventions. *The review of economics and statistics,* 81(3), 511-515.
Henn, C. and McDonald, B. (2014). Crisis Protectionism: The Observed Trade Impact. *IMF economic review,* 62(1), 77-118.
Heyden, M. L. M., Reimer, M., and Van Doorn, S. (2017). Innovating Beyond the Horizon: CEO Career Horizon, Top Management Composition, and R&D Intensity. *Human Resource Management,* 56(2), 205-224.
Hirano, K. and Imbens, G. W. (2001). Estimation of causal effects using propensity score weighting: An application to data on right heart catheterization. *Health services and outcomes research methodology,* 2(3-4), 259-278.
Howard-Grenville, J., Buckle, S. J., Hoskins, B. J., and George, G. (2014). Climate change and management. *Academy of Management Journal,* 57(3), 615-623.
Isaksson, O. H. D., Simeth, M., and Seifert, R. W. (2016). Knowledge spillovers in the supply chain: Evidence from the high tech sectors. *Research Policy,* 45(3), 699-706.
Jaffe, A. B. (1986). Technological opportunity and spillovers of R&D: evidence from firms' patents, profits, and market value. *The American economic review,* 76(5), 984.

Jaffe, A. B., Trajtenberg, M., and Henderson, R. (1993). Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations. *The Quarterly journal of economics,* 108(3), 577-598.

King, A. A. and Shaver, J. M. (2001). Are aliens green? Assessing foreign establishments' environmental conduct in the United states. *Strategic Management Journal,* 22(11), 1069-1085.

King, G. and Nielsen, R. (2019). Why Propensity Scores Should Not Be Used for Matching. *Political analysis,* 27(4), 435-454.

Klöckner, M., Schmidt, C. G., and Wagner, S. M. (2022). When Blockchain Creates Shareholder Value: Empirical Evidence from International Firm Announcements. *Production and operations management,* 31(1), 46-64.

Knoben, J. and Oerlemans, L. A. G. (2006). Proximity and inter-organizational collaboration: A literature review. *International journal of management reviews,* 8(2), 71-89.

Konara, P., Lopez, C., and Shirodkar, V. (2021). Environmental innovation in foreign subsidiaries: The role of home-ecological institutions, subsidiary establishment mode and post-establishment experience. *Journal of World Business,* 56(6).

Kraatz, M. S. and Zajac, E. J. (2001). How Organizational Resources Affect Strategic Change and Performance in Turbulent Environments: Theory and Evidence. *Organization science (Providence, R.I.),* 12(5), 632-657.

Kumar, A. and Paraskevas, J. P. (2018). A Proactive Environmental Strategy: Analyzing the Effect of SCM Experience, Age, and Female Representation in TMTs. *The journal of supply chain management,* 54(4), 20-41.

Li, Y., Wang, X., Gong, T., and Wang, H. (2022). Breaking out of the pandemic: How can firms match internal competence with external resources to shape operational resilience? *Journal of Operations Management*.

Liang, X. and Liu, A. M. M. (2018). The evolution of government sponsored collaboration network and its impact on innovation: A bibliometric analysis in the Chinese solar PV sector. *Research Policy,* 47(7), 1295-1308.

Liu, X., Zhang, L., Gupta, A., Zheng, X., and Wu, C. (2022). Upper echelons and intra-organizational learning: How executive narcissism affects knowledge transfer among business units. *Strategic Management Journal*.

Lungeanu, R. and Zajac, E. J. (2019). Thinking Broad and Deep: Why Some Directors Exert an Outsized Influence on Strategic Change. *Organization Science,* 30(3), 489-508.

Menz, M. (2011). Functional Top Management Team Members: A Review, Synthesis, and Research Agenda. *Journal of management,* 38(1), 45-80.

Michailova, S. and Mustaffa, Z. (2012). Subsidiary knowledge flows in multinational corporations: Research accomplishments, gaps, and opportunities. *Journal of World Business,* 47(3), 383-396.

Milliman, S. R. and Prince, R. (1989). Firm incentives to promote technological change in pollution control. *Journal of Environmental Economics and Management,* 17(3), 247-265.

Modi, S. B. and Cantor, D. E. (2021). How Coopetition Influences Environmental Performance: Role of Financial Slack, Leverage, and Leanness. *Production and operations management,* 30(7), 2046-2068.

Nielsen, B. B. and Nielsen, S. (2013). Top management team nationality diversity and firm performance: A multilevel study. *Strategic Management Journal,* 34(3), 373-382.

Orlando, M. J. (2004). Measuring Spillovers from Industrial R&D: On the Importance of Geographic and Technological Proximity. *The Rand journal of economics,* 35(4), 777-786.

Pagell, M. and Wu, Z. (2009). Building a more complete theory of sustainable supply chain management using case studies of 10 exemplars. *The journal of supply chain management,* 45(2), 37-56.

Palmer, T. B. and Wiseman, R. M. (1999). Decoupling risk taking from income stream uncertainty: a holistic model of risk. *Strategic Management Journal,* 20(11), 1037-1062.

Pfeffer, J. and Salancik., G. R. (1978). *The External Control of Organizations: A Resource Dependence Perspective*, New York: Harper & Row.

Phene, A. and Almeida, P. (2008). Innovation in Multinational Subsidiaries: The Role of Knowledge Assimilation and Subsidiary Capabilities. *Journal of international business studies,* 39(5), 901-919.

Porter, M. E. and Vanderlinde, C. (1995). Toward a New Conception of the Environment-Competitiveness Relationship. *The Journal of economic perspectives,* 9(4), 97-118.

Rosenkopf, L. and Almeida, P. (2003). Overcoming Local Search Through Alliances and Mobility. *Management Science,* 49(6), 751-766.

SAIC-Motor (2015). *SAIC Motor Social Responsibility Report*, Shanghai: SAIC Motor Corporation.

Sharma, A., Pathak, S., Borah, S. B., and Adhikary, A. (2019). Is it too complex? The curious case of supply network complexity and focal firm innovation. *Journal of Operations Management,* 66(7-8), 839-865.

Shen, L., Zhou, K. Z., Wang, K., and Zhang, C. (2022). Do political ties facilitate operational efficiency? A contingent political embeddedness perspective. *Journal of Operations Management*.

Silva, J. M. C. S. and Tenreyro, S. (2006). The Log of Gravity. *The review of economics and statistics,* 88(4), 641-658.

Silva, J. M. C. S. and Tenreyro, S. (2011). Further simulation evidence on the performance of the Poisson pseudo-maximum likelihood estimator. *Economics Letters,* 112(2), 220-222.

Stuart, E. A. (2010). Matching Methods for Causal Inference: A Review and a Look Forward. *Statistical science,* 25(1), 1-21.

Szulanski, G. (1996). Exploring Internal Stickiness: Impediments to the Transfer of Best Practice Within the Firm. *Strategic Management Journal,* 17(S2), 27-43.

Taylor, M. R. (2012). Innovation under cap-and-trade programs. *Proceedings of the National Academy of Sciences - PNAS,* 109(13), 4804-4809.

Teece, D. J. (1977). Technology Transfer by Multinational Firms: The Resource Cost of Transferring Technological Know-How. *The Economic journal,* 87(346), 242-261.

Trajtenberg, M. (1990). A Penny for Your Quotes: Patent Citations and the Value of Innovations. *The Rand journal of economics,* 21(1), 172-187.

Van Wijk, R., Jansen, J. J. P., and Lyles, M. A. (2008). Inter- and Intra-Organizational Knowledge Transfer: A Meta-Analytic Review and Assessment of its Antecedents and Consequences. *Journal of Management Studies,* 45(4), 830-853.

Wang, P., Tong, T. W., and Koh, C. P. (2004). An integrated model of knowledge transfer from MNC parent to China subsidiary. *Journal of World Business,* 39(2), 168-182.

Wei, S.-J., Xie, Z., and Zhang, X. (2017). From "Made in China" to "Innovated in China": Necessity, Prospect, and Challenges. *The Journal of economic perspectives,* 31(1), 49-70.

Wiengarten, F., Fan, D., Lo, C. K. Y., and Pagell, M. (2017). The differing impacts of operational and financial slack on occupational safety in varying market conditions. *Journal of Operations Management,* 52(1), 30-45.

Wright, C. and Nyberg, D. (2017). An inconvenient truth: How organizations translate climate change into business as usual. *Academy of Management Journal,* 60(5), 1633-1661.

Yang, H. and Steensma, H. K. (2014). When do firms rely on their knowledge spillover recipients for guidance in exploring unfamiliar knowledge? *Research Policy,* 43(9), 1496-1507.

Zhang, D., Karplus, V. J., Cassisa, C., and Zhang, X. (2014). Emissions trading in China: Progress and prospects. *Energy policy,* 75, 9-16.

Zhang, J., Wang, Z., and Du, X. (2017). Lessons Learned from China's Regional Carbon Market Pilots. *Economics of Energy and Environmental Policy,* 6(2), 19-38.

Zhu, J., Fan, Y., Deng, X., and Xue, L. (2019). Low-carbon innovation induced by emissions trading in China. *Nature Communications,* 10(1), 1-8.

Online Appendix

A.1 Model Extension

The performance of carbon markets varies across pilots, allowing us to explore the heterogeneous spillover effects. Carbon price signals the marginal cost of emission abatement, indicating the regulatory stringency, while turnover rate captures the activeness of allowance trading in the markets. Using carbon price and turnover rate, we further examine how different carbon market performances affect the spillover effect of ETS. The model is as follows:

$$Y_{ijt} = \beta_0 + \beta_1 MarketParent_{it} \times Post_t + \beta_2 MarketParent_{it} + X_{imt}$$

$$+\gamma_i + \delta_{jt} + \eta_{rt} + \lambda_{st} + \mu_{nt} + \varepsilon_{ijt}, \quad (1)$$

In this model, $MarketParent_{it}$ stands for the two indicators of carbon market performance: the carbon price and turnover rate of the ETS pilots where unregulated subsidiary *i*'s regulated parent locates. As a variant of the dummy indicator $ETSParent_i$ in equation (1), $MarketParent_{it}$ is a continuous variable that measures the heterogeneity of carbon market performance across pilots and years. The coefficient of our interest, denoted by β_1, captures whether carbon pricing and trading activeness facilitate the spillover effect of the ETS pilots.

As we can find in the Table A4, the estimated coefficients for carbon price are positive and statistically significant at the 1% level. These findings suggest that a higher carbon price imposed on regulated parent firms facilitates the ETS-induced low carbon innovation spillover, but allowance trading turnover rate doesn't have significant impact.

Figure A1: Data Cleaning Process

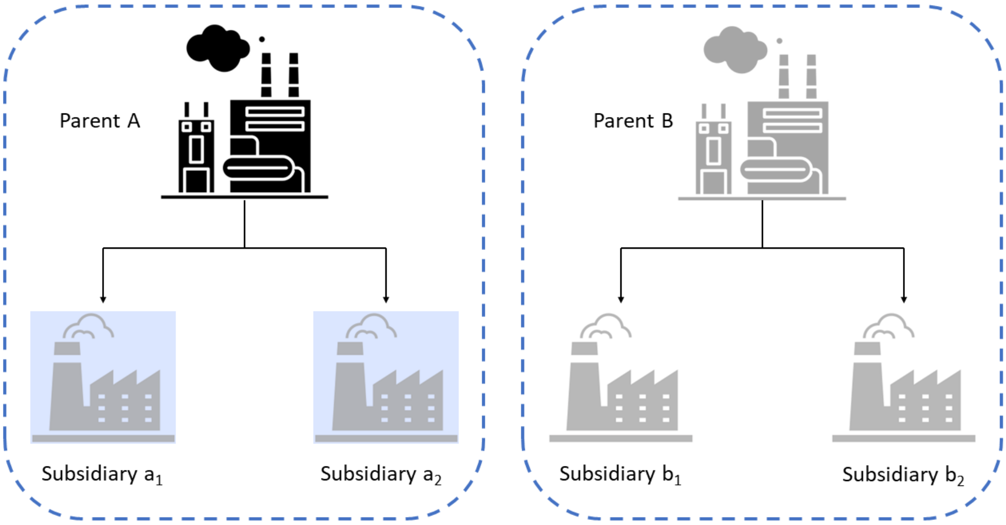

Figure A2: Illustration of the Treatment and Control Group Setting

Note: Dash outline marks corporate ownership networks. ETS-regulated firms are in black, while non-ETS-regulated firms are in grey. The treated units in blue shade are defined as unregulated subsidiary firms owned by a regulated parent firm (i.e., Subsidiary a1 and a2. Control units in grey are defined as unregulated subsidiary firms owned by an unregulated parent firm (i.e., Subsidiary b1 and b2).

Table A1: Definition of Key Variables

Panel A: Dependent variables	
Low-carbon patent count	Logarithm of number of low-carbon patent applications that are successfully granted (patents are counted according to the date of application)
Low-carbon patent citation	Logarithm of number of forward citations that low-carbon patents receive in the subsequent five years.
Panel B: Independent variables	
ETSParent	Dummy variable for whether an unregulated subsidiary firm has a parent firm regulated by China's ETS pilots
Post	Dummy variable for whether the period is after the launch of China's ETS pilots
CarbonPriceParent	Logarithm of carbon prices of the ETS pilot where a regulated parent firm locates each year
TurnoverRateParent	Turnover rate (exchanged allowance/total allowance) of the ETS pilot where a regulated parent firm locates each year
Panel C: Moderation variables	
Geographical distance	Logarithm of the Euclidian distance between a subsidiary firm and its parent firm
Technology proximity	Normalized inner product of a subsidiary and its parent firm's patent portfolio vector (firm's patent distribution across IPC technology classes)-See text for specific formula
Number of production TMT members	Number of top management team members who have work experience in production prior to the year of observations
Number of R&D TMT members	Number of top management team members who have work experience in R&D prior to the year of observations
Ratio of production TMT members	Ratio of top management team members who have work experience in production prior to the year of observations
Ratio of R&D TMT members	Ratio of top management team members who have work experience in R&D prior to the year of observations
Quick ratio	(Current assets - Inventories) / Current liabilities
Financial leverage	Debt / Equity
Panel D: Other control variables	
Subsidiary registered capital	Logarithm of subsidiary firm's registered capital in the fiscal year
Parent asset	Logarithm of parent firm's total assets in the fiscal year
Parent capital	Logarithm of parent firm's capital (total assets - total liabilities) in the fiscal year
Parent sale	Logarithm of parent firm's sales revenue in the fiscal year

Table A2: Direct Effect of ETS on Low Carbon Innovation of Regulated Parent Firms

VARIABLES	Low Carbon Patent Count	Low Carbon Patent Citation
	(1)	(2)
ETS×Post	0.102***	0.223***
	(0.023)	(0.037)
Observations	1,082	1,082
R-squared	0.752	0.731
Firm Attributes	Y	Y
Parent Firm FE	Y	Y
Parent Province-Year FE	Y	Y
Parent Sector-Year FE	Y	Y

Note: Dependent variables are logarithm one plus the number of low-carbon patent counts, and the logarithm one plus the number of low-carbon patent count weighted by citations received in the subsequent five years. ETSParent is a binary indicator, equaling one if an unregulated subsidiary is affiliated with a regulated parent firm, and zero otherwise. Post is a year dummy, equaling one if 2013 and afterward, and zero otherwise. All columns include the firm-level attributes including subsidiaries' registered capital, and parent firms' assets, capital, and sale, as well as a rich set of fixed effects at the parent firm, parent province-year, and parent sector-year levels. Standard errors in the parenthesis are clustered at the industry level. ***, **, *, indicate the significance at the 1% level, 5% level, and 10% level, respectively.

Table A3.1: ETS-induced Low-carbon Innovation Spillover Effects

VARIABLES	Low Carbon Patent Count		Low Carbon Patent Citation	
	(1)	(2)	(3)	(4)
ETSParent×Post	0.026***	0.040***	0.033***	0.043***
	(0.006)	(0.007)	(0.007)	(0.007)
Subsidiary Registered Capital	0.001	-0.001	-0.000	-0.002
	(0.007)	(0.007)	(0.007)	(0.008)
Parent Asset	0.009	0.005	0.002	0.000
	(0.021)	(0.019)	(0.030)	(0.027)
Parent Capital	0.000	0.011	0.005	0.017
	(0.011)	(0.012)	(0.013)	(0.014)
Parent Sale	0.020	0.016	0.024	0.018
	(0.013)	(0.013)	(0.017)	(0.016)
Observations	7,505	7,489	7,505	7,489
R-squared	0.562	0.578	0.569	0.588
Firm Attributes	Y	Y	Y	Y
Subsidiary FE	Y	Y	Y	Y
Subsidiary Province-Year FE	Y	Y	Y	Y
Subsidiary Sector-Year FE	Y	Y	Y	Y
Parent Province-Year FE		Y		Y
Parent Sector-Year FE		Y		Y

Note: Dependent variables are logarithm one plus the number of low-carbon patent counts, and the logarithm one plus the number of low-carbon patent count weighted by citations received in the subsequent five years. ETSParent is a binary indicator, equaling one if an unregulated subsidiary is affiliated with a regulated parent firm, and zero otherwise. Post is a year dummy, equaling one if 2013 and afterward, and zero otherwise. All columns include the firm-level attributes including subsidiaries' registered capital, and parent firms' assets, capital, and sale, as well as a rich set of fixed effects at the subsidiary, subsidiary province-year, subsidiary sector-year, parent province-year, and parent sector-year levels. Standard errors in the parenthesis are clustered at the industry level. ***, **, *, indicate the significance at the 1% level, 5% level, and 10% level, respectively.

Table A3.2: The Moderating Effects on ETS-induced Low-carbon Innovation Spillover

VARIABLES			**Low Carbon Patent Count**					**Low Carbon Patent Citation**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ETSParent×Post	0.034***	0.012	0.065***	0.003	0.056***	0.045**	0.009	0.081***	-0.005	0.054***
	(0.012)	(0.008)	(0.010)	(0.015)	(0.013)	(0.021)	(0.007)	(0.013)	(0.018)	(0.018)
ETSParent×Post×GeogDist	0.002					-0.000				
	(0.003)					(0.006)				
ETSParent×Post×TechProx		0.140***					0.178***			
		(0.028)					(0.031)			
ETSParent×Post×Ratio_Pro			-0.426***					-0.644***		
			(0.121)					(0.163)		
ETSParent×Post×Ratio_R&D				0.251**					0.333***	
				(0.089)					(0.104)	
ETSParent×Post×QuickRatio					-0.026**					-0.026*
					(0.010)					(0.015)
Subsidiary Registered Capital	-0.001	-0.002	-0.001	-0.001	-0.001	-0.002	-0.004	-0.003	-0.003	-0.003
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)
Parent Asset	0.004	0.002	0.008	0.002	0.006	-0.000	-0.002	0.005	-0.003	-0.001
	(0.020)	(0.017)	(0.018)	(0.020)	(0.012)	(0.028)	(0.024)	(0.025)	(0.028)	(0.017)
Parent Capital	0.009	0.009	0.007	0.010	0.005	0.014	0.014	0.011	0.016	0.012
	(0.013)	(0.010)	(0.011)	(0.011)	(0.011)	(0.015)	(0.012)	(0.013)	(0.014)	(0.015)
Parent Sale	0.017	0.011	0.012	0.017	0.025*	0.019	0.013	0.012	0.019	0.030*
	(0.013)	(0.011)	(0.013)	(0.013)	(0.013)	(0.017)	(0.014)	(0.016)	(0.015)	(0.017)
Observations	7,480	7,489	7,489	7,489	7,402	7,480	7,489	7,489	7,489	7,402
R-squared	0.578	0.584	0.579	0.579	0.579	0.588	0.591	0.589	0.589	0.589
Firm Attributes	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Subsidiary FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Subsidiary Province-Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Subsidiary Sector-Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Parent Province-Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Parent Sector-Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: Dependent variables are logarithm one plus the number of low-carbon patent counts, and the logarithm one plus the number of low-carbon patent count weighted by citations received in the subsequent five years. ETSParent is a binary indicator, equaling one if an unregulated subsidiary is affiliated with a regulated parent firm, and zero otherwise. Post is a year dummy, equaling one if 2013 and afterward, and zero otherwise. All columns include the firm-level attributes including subsidiaries' registered capital, and parent firms' assets, capital, and sale, as well as a rich set of fixed effects at the subsidiary, subsidiary province-year, subsidiary sector-year, parent province-year, and parent sector-year levels. For the sake of brevity, we only report the estimated coefficients for the interaction terms. Table A3.2 reports the estimated coefficients for control variables. Standard errors in the parenthesis are clustered at the industry level. ***, **, *, indicate the significance at the 1% level, 5% level, and 10% level, respectively.

Table A4: The Heterogeneous Spillover Effects

VARIABLES	Low Carbon Patent Count		Low Carbon Patent Citation	
	(1)	(2)	(3)	(4)
CarbonPriceParent×Post	0.011***		0.012***	
	(0.002)		(0.002)	
TurnoverRateParent×Post		0.516		0.343
		(0.395)		(0.438)
Observations	7,489	7,489	7,489	7,489
R-squared	0.578	0.577	0.588	0.577
Firm Attributes	Y	Y	Y	Y
Subsidiary FE	Y	Y	Y	Y
Subsidiary Province-Year FE	Y	Y	Y	Y
Subsidiary Sector-Year FE	Y	Y	Y	Y
Parent Province-Year FE	Y	Y	Y	Y
Parent Sector-Year FE	Y	Y	Y	Y

Note: Dependent variables are logarithm one plus the number of low-carbon patent counts, and the logarithm one plus the number of low-carbon patent count weighted by citations received in the subsequent five years. CarbonPriceParent is logarithm one plus carbon price of the ETS pilots where regulated parent firms locate. TurnoverRateParent is a ratio of exchanged allowance to total allowance of the ETS pilots where regulated parent firms locate. Post is a year dummy, equaling one if 2013 and afterwards, and zero otherwise. All columns include the firm-level attributes including subsidiaries' registered capital, and parent firms' assets, capital, and sale, as well as a rich set of fixed effects at the subsidiary, subsidiary province-year, subsidiary sector-year, parent province-year, and parent sector-year levels. Standard errors in the parenthesis are clustered at the industry level. ***, **, *, indicate the significance at the 1% level, 5% level, and 10% level, respectively.

Table A5. Robustness Checks on Alternative Measures for Technology Proximity

VARIABLES	Low Carbon Patent Count		Low Carbon Patent Citation	
	(1)	(2)	(3)	(4)
ETSParent×Post	0.024*	0.023**	0.021	0.020*
	(0.013)	(0.010)	(0.014)	(0.011)
ETSParent×Post×TechProx(3-digit,PreETS)	0.119**		0.165***	
	(0.043)		(0.045)	
ETSParent×Post×TechProx(4-digit,PreETS)		0.170***		0.212***
		(0.030)		(0.030)
Observations	7,489	7,489	7,489	7,489
R-squared	0.580	0.581	0.589	0.589
Firm Attributes	Y	Y	Y	Y
Subsidiary FE	Y	Y	Y	Y
Subsidiary Province-Year FE	Y	Y	Y	Y
Subsidiary Sector-Year FE	Y	Y	Y	Y
Parent Province-Year FE	Y	Y	Y	Y
Parent Sector-Year FE	Y	Y	Y	Y

Note: Dependent variables are logarithm one plus the number of low-carbon patent counts, and the logarithm one plus the number of low-carbon patent count weighted by citations received in the subsequent five years. ETSParent is a binary indicator, equaling one if an unregulated subsidiary is affiliated with a regulated parent firm, and zero otherwise. Post is a year dummy, equaling one if 2013 and afterward, and zero otherwise. All columns include the firm-level attributes including subsidiaries' registered capital, and parent firms' assets, capital, and sale, as well as a rich set of fixed effects at the subsidiary, subsidiary province-year, subsidiary sector-year, parent province-year, and parent sector-year levels. Standard errors in the parenthesis are clustered at the industry level. ***, **, *, indicate the significance at the 1% level, 5% level, and 10% level, respectively.

Table A6. Robustness Check with Alternative TMT Measures as Control Variables

VARIABLES	Low Carbon Patent Count				Low Carbon Patent Citation			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ETSParent×Post	0.058***	-0.005	0.064***	0.004	0.074***	-0.020	0.079***	-0.004
	(0.010)	(0.015)	(0.010)	(0.014)	(0.014)	(0.018)	(0.013)	(0.016)
ETSParent×Post×Num_Pro	-0.015**				-0.024***			
	(0.006)				(0.008)			
ETSParent×Post×Num_R&D		0.015***				0.022***		
		(0.005)				(0.006)		
ETSParent×Post×Ratio_Pro			-0.420***				-0.628***	
			(0.121)				(0.156)	
ETSParent×Post×Ratio_R&D				0.243**				0.323***
				(0.086)				(0.103)
TMT Average Tenure	-0.001	-0.000	-0.001	-0.000	0.002	0.003	0.002	0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.002)	(0.003)
TMT Size	0.002	0.002	0.002	0.002	0.003	0.003	0.003	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)
TMT Female Ratio	-0.033	-0.030	-0.020	-0.022	-0.055	-0.060	-0.041	-0.050
	(0.050)	(0.052)	(0.054)	(0.054)	(0.083)	(0.089)	(0.090)	(0.092)
Observations	7,489	7,489	7,489	7,489	7,489	7,489	7,489	7,489
R-squared	0.579	0.580	0.580	0.579	0.589	0.590	0.590	0.589
Firm Attributes	Y	Y	Y	Y	Y	Y	Y	Y
Subsidiary FE	Y	Y	Y	Y	Y	Y	Y	Y
Subsidiary Province-Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Subsidiary Sector-Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Parent Province-Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Parent Sector-Year FE	Y	Y	Y	Y	Y	Y	Y	Y

Note: Dependent variables are logarithm one plus the number of low-carbon patent counts, and the logarithm one plus the number of low-carbon patent count weighted by citations received in the subsequent five years. ETSParent is a binary indicator, equaling one if an unregulated subsidiary is affiliated with a regulated parent firm, and zero otherwise. Post is a year dummy, equaling one if 2013 and afterward, and zero otherwise. All columns include the firm-level attributes including subsidiaries' registered capital, and parent firms' assets, capital, and sale, as well as a rich set of fixed effects at the subsidiary, subsidiary province-year, subsidiary sector-year, parent province-year, and parent sector-year levels. Standard errors in the parenthesis are clustered at the industry level. ***, **, *, indicate the significance at the 1% level, 5% level, and 10% level, respectively.