Going green when you are pinned: Do climate action plans work? Evidence from Chinese firms

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Abstract

We use China's new climate action plan submitted to the United Nations Framework Convention on Climate Change (UNFCCC) on 30 June 2015 as a quasi-natural experiment to examine the causal relationship between carbon risk and how Chinese corporations make diversification decisions. This action plan demonstrates the determination of China, the largest manufacturing country in the world for decades, in combating climate change and reducing industrial waste emitting from business operations. By employing alternative measures of carbon risk, our difference-in-differences analysis shows that heavy emitters (firms with more carbon risk) tend to diversify their revenues more after the new climate action plan is submitted to UNFCCC, while it is not the case for light emitters. The empirical result is robust to alternative model specifications, variable measurements, controls of firm-level characteristics, macroeconomic factors including the effective period of the Kyoto Protocol (2008-2012), and a matched sample.

The findings imply that when the government signals a new action plan on climate change, heavy emitters turn to diversification strategies to redirect their resources away from carbon-intensive operations. We suggest that heavy emitters use diversification strategies to hedge the carbon risk associated with their business operations and the government's climate policy. Further analyses indicate three channels through which the event influences corporate diversification decision-making: state ownership, corporate innovation, and asset liquidation values. Ultimately, our study puts forward several implications for policymaking and corporate investment.

JEL Classification Codes: G30, G31, Q51, Q58

Keywords: asset liquidation value; carbon risk; China; corporate diversification; corporate innovation; state ownership

"Smog is affecting larger parts of China, and environmental pollution has become a major problem, which is nature's red-light warning against the model of inefficient and blind development."

Chinese Premier Li Kegiang (2014)[2]

"We called for strong ambition, for remarkable partnerships, for mobilization of finance, and for implementation of national climate plans. Paris delivered. Now the job becomes our shared responsibility."

World Bank Group President Jim Yong Kim (2015)[3]

1. Introduction

The effects of climate change on firms have been drawing scholars' attention over the last decades. The study of Addoum *et al*. (2020) reported non-result between extreme temperature exposures and firm sales with a large population. There is a noticeable marginal effect that is statistically significant on average firms under low temperatures with a higher likelihood of energy sectors. Previous studies do not only emphasize the environmental changes but also link to climate changes such as water consumption, biodiversity, greenhouse gas emission, and so forth, to corporate activities that have contributed to the current literature (Gallego-Álvarez *et al*., 2015; Boiral *et al*., 2012; Pulver, 2007). However, it is worth mentioning that carbon emission is the key element to capture how green economies have been performing since the carbon-related and climate change issues become a part of public and academic interest (Li *et al*., 2020; Ihan *et al*., 2021; Balachandran and Nguyen, 2018; Oestreich and Tsiakas, 2015; Ramiah *et al*., 2013). Concomitantly, the understanding of '*carbon risk*', which is defined as a firm's financial vulnerability to the transition away from fossil fuel-based to a lower-carbon economy (Nguyen and Phan, 2020), remains inconclusive since there are many approaches designed to measure this type of risk. For example, the '*carbon beta*' stemming from the '*Brown-Minus-Green*' portfolio (Görgen *et al*., 2020) and '*carbon premium*' for bond and equity based on the assumption of homogeneous effects due to financial integration around the globe (Bolton *et al*., 2020; Ravina, 2022) are typical measurements in the strand of literature. Accordingly, firms facing a high level of carbon risk have their own business nature, which is

[2] China declares war on pollution: https://www.ft.com/content/5c9b4d18-a437-11e3-b915-00144feab7de

[3] Statement by World Bank Group President Jim Yong Kim on Global Climate Change Agreement at COP21 in Paris: https://www.worldbank.org/en/news/press-release/2015/12/12/statement-by-world-bank-group-president-jim-yong-kim-on-global-climate-change-agreement-at-cop21-in-paris

associated with a huge amount of carbon emission or the industries' characteristics (for example, car production). It can also be the stringent regulations from governments to require firms in adopting carbon reduction practice (Balachandran and Nguyen, 2018; Nguyen and Phan, 2020; Nguyen, 2018; Dobler *et al*., 2014). Although there exists ongoing literature to explore the linkage between firm natures and carbon risk, the effects of regulation changes on firms' perspectives are still promising. Therefore, this paper seals the gap by looking at two sources of 'carbon risk' in China: firms' nature and stringent regulation in China.

China, the largest manufacturing country and the largest emitter in the world has committed to fight climate change by showing its ambitious goal of being carbon-neutral in 2060[4]. In December 2020, President Xi Jinping repeated the commitment at the Climate Ambition Summit and emphasized that China's carbon footprint shrinks to over 65% of 2005 level by 2030[5]. China agrees to cut CO2 emissions by around 25% of its current level, which is approximately 13.92 million metric tons of CO2 in 2019[6]. Being the largest coal consumer and emitter of carbon dioxide gas worldwide[7], such statements of the Chinese government raise both the international community's hope and questions on how the nation can reach its goal. The commitment of China in reducing greenhouse gas (GHG) emissions has a crucial meaning to international efforts against climate change, especially since the second-largest GHG emitter, the United States, exited the Kyoto Protocol in 2001 and the Paris Agreement in 2016. The approval of the Paris Agreement by China in 2015[8] is an important milestone in the country's sustainable development. Not only creating a positive outlook to global warming, but the event may also exert a significant economic impact on the decision-making of Chinese corporations. "*How do Chinese firms react to China's national climate action plan, given that the CO2 emissions cut might hurt their business operations?*" This paper makes numerous efforts in searching for an answer to the aforementioned question, implying possible channels between a '*firm nature*' as well as a '*stringent regulation*' and institution at the corporate level.

[Please insert Figure 1 here]

[4] China vows carbon neutrality by 2060 in major climate pledge: https://www.bloomberg.com/news/articles/2020-09-22/china-pledges-carbon-neutrality-by-2060-and-tighter-climate-goal

[5] China nudges up its commitment to reduce carbon dioxide emissions: https://www.scmp.com/business/article/3113737/china-pledges-cut-carbon-footprint-65-cent-2030

[6] Preliminary China emissions estimates for 2019: https://rhg.com/research/preliminary-china-emissions-2019/#:~:text=Based%20on%20preliminary%20economic%20and,in%202019%20(Figure%201)

[7] China's coal consumption on the rise: https://chinadialogue.net/en/business/11107-china-s-coal-consumption-on-the-rise/

[8] China submits its climate action plan ahead of 2015 Paris Agreement: https://unfccc.int/news/china-submits-its-climate-action-plan-ahead-of-2015-paris-agreement

Our motivation is supported using Figure 1 which exhibits the amount of carbon emission from the five largest emitters over the period from 1992 to 2014. China has supplanted the US as the largest carbon emitter and energy (BP, 2015). The country overtook the leading role in emitting the amount of carbon dioxide during this period with a slight reduction after 2010. The proportion of raw coal is more pronounced to carbon emission in five provinces, namely Henan, Shandong, Jiangsu, Inner Mongolia, and Hebei (see Figure 2). It is obvious that the carbon emission intensity results from raw materials such as raw coal or coke. However, the recent study provides empirical evidence of linkage between the uncertainties and firm carbon emission, measured by the actual consumption of various energies (Yu *et al*., 2021). Accordingly, Chinese firms are likely to respond to the economic policy uncertainties by using cheap and dirty fossil fuels.

[Please insert Figure 2 here]

In the same vein, there is a considerable distinction between eastern coastal and western inland areas in China. While Andersson *et al*. (2018) recorded a relatively larger proportion of private sectors along the east coast and a lower amount of carbon dioxide in 2010, Yu *et al*. (2021) provide contradictory evidence that eastern coastal areas represent a higher likelihood of uncertainties, associated with an increase in firms' carbon emission from 2008 to 2011. Figure 3 indicates a higher amount of green gashouse emission in the eastern and northern coast in 2015, which is attributable to China's carbon transfer regional path for building infrastructure (Zhou *et al*., 2018). Moreover, the current literature confirms that the pilot carbon emissions trading scheme (ETS) significantly decreases carbon dioxide emission and intensity (Zhang, Zhang, and Yu, 2019). Moreover, there might be a variant for firms that locate in the pilot market areas in terms of their responses to the environmental changes. As a part of the ETS, China implemented seven pilot carbon markets in seven provinces from 2013 to 2014. These seven zones thrive on industrial and energy production, those are the most polluting sources of pollution. Intuitively, firms in pilot carbon market zones in China can trade their carbon emission permits for finance and thus have more financing options to go green. Consequently, there are two samples that need examination: (i) firms from the pilot carbon market (Beijing, Chongqing, Guangdong, Hubei, Shanghai, Shenzhen, and Tianjin) and (ii) firms from the remaining areas. To sum up, there could be two following research questions: "*How do Chinese firms, having different access to carbon finance, react to China's national climate action plan, given that the CO2 emissions cut might hurt their business operations?*."

[Please insert Figure 3 here]

Coming up with the existing literature about the heterogeneity in the economy and institutional quality across provinces in China (Kusnadi *et al*., 2015), this study offers further analyses on how the '*state ownership*' trait could respond to the Paris Agreement and China's national climate action plan from 2015 onward, which could be the potential channel of firms' responses. Looking deeper into the literature of how firms react to uncertainty, we identify two other potential channels of effect through which the Paris Agreement might affect corporate diversification decision-making of Chinese firms: corporate innovation and asset liquidation value. The investigation into those mechanisms is important as it helps to enhance understanding of how Chinese firms, especially heavy-emitter firms react to climate policy uncertainty.

To sum up, the case of China should be considered as a unique setting to measure the impacts of carbon risk and firm responses due to three main reasons. First, China is the most dominating country in carbon-emitting; therefore, the stringent regulations might force firms to strictly comply. Despite the literature evidence in supporting the relationship between carbon risk and firm responses, there is limited knowledge regarding how the largest emitter and consumer reacts to the carbon risk at the firm level. This shortage of evidence would lead to severe consequences. For instance, China is the country that asserts voluminous efforts to comply with the international agreement to curb environmental pollution (Sam and Zhang, 2020). Contradictorily with the United States which decides to withdraw from the majority of climate change agreements due to the losses to its economy, China is persistent to raise the highest awareness of financial market participants in terms of environmental responsibilities. Therefore, our results are not limited to academic evidence but also as forthcoming lessons for the followers who would be an uptake of reducing the Green Gashouse emission. Second, the economy of China, especially financial markets, has unique characteristics regarding ownership structure (stated-owned or private, political connection) (Liu *et al*., 2021), the government intervention to corporate innovation (Li *et al*., 2020). Third, apart from the heaviest emitter, China is actively engaging in sustainable and green financial studies over the last decade (Zhang, Zhang, and Managi, 2019). This country has been considered as the key player of green finance; therefore, the actions from this country could act as a model for not only emerging but also advanced economies. Hence, these aforementioned reasons motivate us to carry out this research.

Our study uses the submission of the national climate action plan of China to the United Nations Framework Convention on Climate Change (UNFCCC) in 2015 during the negotiation of the Paris Agreement as a quasi-natural experiment to investigate how corporate diversification strategy, especially in heavy emitters, react to a higher degree of carbon risk. Using the difference-in-difference analysis, this study finds that firms known as heavy emitters are likely to find alternative sources for their revenue diversification to respond to climate change's required actions submitted to UNFCCC considered as carbon risk. Nevertheless, the results are not pronounced to light emitters. Specifically, our study employs two proxies to measure corporate diversification such as the Entropy index (Denis *et al*., 1997; Gu *et al*., 2018; Hoang *et al*., 2021) and the number of segments in the firm revenues. Our battery of robustness checks confirms the validity of the first and central results. Interestingly, our findings are consistent with different measurements for firms' effects in diversifying their revenue in comparison with the baseline models. Moreover, our findings still hold when using the matching sample with similar firm characteristics such as firm size, capital structure, firm profitability, revenue growth, and Tobin's Q. Furthermore, our results support the hypothesis that Chinese firms in pilot carbon market should pursue higher revenue diversification than firms in the remaining zones. Concomitantly, we find that equity firms with high carbon emission are more motivated to diversify their revenue than financial leveraged firms, suggesting the corporate's nature as the firms' behaviors. Eventually, our study explores three potential mechanisms, including state intervention via state ownership, corporate innovation, and asset liquidation value.

There are several contributions that this paper can add to the existing literature as well as business practices. First, our study contributes to the embryonic literature on firms' behaviors in the context of environmental degradation. Differing from the current evidence from the advanced economies, this manuscript focuses on China, the largest GHG emitter and the central manufacturer in the Asia-Pacific region. Concomitantly, this country asserts to follow the international convention to introduce more stringent regulations to encourage a reduction in carbon emission. Therefore, China is an excellent case for the investigation of how heavy-emitter firms react to increasing carbon risk. Second, while the other studies provide a broad view of firms' financial status such as a relocation (Martin *et al*., 2014), financial leverage and its cost (Nguyen and Phan, 2020; Jung *et al*., 2018), firm performance (Nguyen, 2018), dividend policies (Balachandran and Nguyen, 2018), and so forth, to the best of our knowledge, this is the first study which sheds new light on corporate diversification when facing the higher level of carbon risk. Third, using the Paris Agreement where China submitted its new climate action plan to UNFCCC on 30 June 2015 as a quasi-natural experiment, this study expands the methodology contribution regarding the alleviation of endogeneity concern in firms. Accordingly, the current literature employs the Kyoto Protocol ratification as the exogenous shocks on firms whereas our study directs to another event that is another indication for carbon risk about climate policy change. Fourth, this paper explores three potential channels driving the diversification strategy of Chinese firms to adapt to the stringent carbon policies by the government. For exploration strategy, we find that the firm ownership, firm innovation, and asset liquidity matter to the transition process from brown to green business fields. Therefore, these mechanisms offer insights for not only academic but also practical parties to foster the firm adaptation of government policy. Finally, policy implications are of utmost importance to policymakers and market participants, including investors and corporate managers of firms that have high exposures to carbon risk stemming from the new carbon regulations.

The rest of the paper proceeds as follows. Section 2 provides the related review and hypotheses development. We summarize the data, variables and empirical models are in Section 3. Section 4 presents the regression results of the baseline model, additional tests, and sensitivity tests. Section 5, 6, and 7 present how state ownership, corporate innovation, and asset liquidation value influence the relationship, respectively. Section 8 concludes our study.

2. Related studies and hypothesis development

This paper aims to explore the firms' responses, particularly in corporate diversification decision-making, to the carbon risk exposure, captured by the stringent regulations by the Chinese government. The question of how carbon risk impacts firm diversification remains unsolved. One plausible explanation can be that firms are encouraged to voluntarily switch from the 'brown' business model to a 'greener' one by less using carbon-intensive technologies or upgrading the environmentally-friendly materials. However, not all firms act the same. Firms having carbon intensity might struggle to find the solutions because of the negative association between carbon risk and firm performance (Nguyen, 2018). However, firms doing business in heavy-emission industries are likely to decrease the level of financial leverage due to financial distress. Interestingly, the empirical evidence shows that firms do not change their investment behaviors when facing carbon risk (Nguyen and Phan, 2020). Hence, firms might have another strategy to direct their business models towards greener platforms. In this section, we first justify the choice of the Paris Agreement as well as carbon risk measurement (in subsection 2.1) and then develop the relevant hypothesis regarding the firms' strategy, particularly revenue diversification, of heavily-emitted firms and lightly-emitted ones.

2.1. Climate actions in the Paris Agreement

It is noteworthy that Krüger (2015) shows that markets significantly react to sustainable news regarding legal and economic information content. Therefore, the event of China submitting its climate action plan to the United Nations Framework Convention on Climate Change (UNFCCC) on 30th June 2015 does not only exhibit the source of carbon risk[9] but also has an association with the market expectations. This viewpoint has been supported by the study of Monasterolo and De Angelis (2020) that investors start keeping their eyes on low-carbon assets with the climate announcement in the Paris Agreement. Indeed, this action remarks the leading position of the largest manufacturing center while the United States decided to exit the 2015 Paris Agreement. Thus, the current literature has complimented this Asian country as an alliance with European economies to tackle climate change[10]. Furthermore, China has pioneered to introduce a national emissions-trading system (ETS), which has a mixture of agreement and disagreement to incentivize behavior changes (Gallagher *et al*., 2019). Even though this nation's process of achieving its goal is doubtful, the submission plan can be considered as an exogenous shock to firms in carbon-intensive industries. Moreover, there was a remarkable point in 2015 that allows us to capture the difference in firms' behaviors before and after the policy change.

Was the Kyoto protocol effective? The answer may be 'yes' (Maamoun, 2019). While the current literature intensively focuses on the ratification of the Kyoto Protocol for a single country, for example, Australia (Nguyen, 2018; Balachandran and Nguyen, 2018; Nguyen and Phan, 2020) or cross-country comparison, for example, firms in Fortune 500 (Freedman and Jaggi, 2005; Ott *et al*., 2017), the study about effects of Paris Agreement on firms is still promising (Monasterolo and De Angelis, 2020). It is also worth mentioning that the Paris Agreement, known as the replacement of the Kyoto Protocol, offers clear and detailed plans to decarbonize the 'brown' economy and motivates firms to switch to more sustainable business models (He *et al*., 2021). Therefore, there is space for this study to fill the gap with the new data from China and provides empirical evidence of the Paris Agreement.

[9] Carbon risk can be also considered as the replacement or change in environmental policies (Aldy & Gianfrate, 2019).

[10] As the U.S. leaves Paris climate accord, some see shifts in global leadership: https://www.washingtonpost.com/world/national-security/as-the-us-leaves-paris-climate-accord-some-see-shifts-in-global-leadership/2017/06/01/4c916554-4634-11e7-a196-a1bb629f64cb_story.html

2.2. Carbon risk and corporate diversification

Carbon risk, a terminology to measure the uncertainties of climate change, might be raised from two sources: (1) the nature of industries (heavily-emitted or lightly-emitted business field) and (2) the promulgation of stringent carbon regulations. When firms experience carbon risk exposure, they could behave the trade-off decisions between spending costs for compliance and ignorance for risk. While the empirical evidence suggested that firms neglecting to take proper actions might potentially have financial losses due to customers' boycott or penalties (Karpoff *et al*., 2005; Liu, 2018; Jung *et al*., 2018), the debate whether the adoption of business performance could support firm's value or not has persisted over last decades (Endrikat *et al*., 2014; Gonenc and Scholtens, 2017). Görgen *et al*. (2020) propose a novel methodology to measure 'carbon risk', explicitly related to firms' sensitivities in the changing process to a green economy and left a space for future research on the linkage between carbon risk and firm investment, firm performance. It is still unanswered yet.

Although the strand of literature in finance has discussed the effects of changes in environmental policies on the Australian firms' behaviors in their performance (Nguyen, 2018), capital structure (Nguyen and Phan, 2020), and the dividend payout policy (Balachandran and Nguyen, 2018), empirical evidence on whether firms can differently react to the environmental news from different markets; to be more precise, China, from various perspectives, including revenue diversification and other underlying economic mechanisms, is still lacking. Why is the firm's revenue diversification strategy? Intuitively, the highly committed policies of China to cut down the carbon emission would challenge Chinese firms in their operation due to shocks to firm management. Firms might have two options in adopting this concern. One is to diversify their portfolio to less carbon-intensive operations to maintain their operating revenue. Another solution is to invest in 'greener' technologies. However, the literature indicates that the environmental policy change has insignificant relation with corporate investment in the Australian sample (Nguyen and Phan, 2020). Thus, Chinese heavy emitter firms are likely to choose the second measure, implying the diversification strategy as a response to heightened carbon risk. To sum up, when the government decided to introduce the new and stringent policies regarding carbon reduction on the economy, firms have no other choices rather than overlooking this information. Thus, under this external pressure, Chinese heavy emitter firms are more likely to diversify their revenue around and after the Paris Agreement announcement in 2015. Following this conjecture, we predict:

Hypothesis 1: *Ceteris paribus, firms with higher carbon risk tend to pursue diversification strategies during the Paris Agreement.*

Recent studies have established a preliminary understanding of the pilot carbon markets in seven zones. Newell *et al*. (2013) confirm the beneficial role of a carbon trading scheme to reduce the amount of carbon dioxide. In the same vein, other studies also discuss similar findings in the role of mitigating emission (Gao *et al*., 2020; Chen *et al*., 2021). China has been implementing a national carbon trading scheme and seven pilot carbon markets in seven zones: Beijing, Chongqing, Guangdong, Hubei, Shanghai, Shenzhen, and Tianjin[11]. These seven zones thrive on industrial and energy production, including cement, electricity, and petroleum extraction, which are considered the most polluting sources of GHG emissions. The Progress of China's Carbon Market Report 2017 indicates that the total carbon dioxide emissions covered by the pilot carbon markets is approximately 1,280 million tons of CO2 equivalents and accounts for about 50 percent of China's total carbon emissions (Environmental Defense Fund, 2017). By implementing pilot carbon markets, carbon emission permits can be traded between pollution discharge units within these zones. As such, diversification might help firms to have access to carbon finance by selling their redundant emission permits to firms in need. Given this special feature in these areas, there might be differences in how heavy emitters react to the Paris Agreement across pilot zones and other zones. Thus, we construct the hypothesis that:

Hypothesis 2: *Heavy emitter firms located in the pilot carbon markets experience stronger revenue diversification after the Paris Agreement, relative to those who are in other areas.*

There are three possible mechanisms of the carbon-risk effects on firms' diversification, namely state intervention via state ownership, corporate innovation, and asset liquidity. Accordingly, the strand of literature highlights that firm decision-making can be driven by corporate ownership (Tan, 2001; Delios and Wu, 2005; Zhu and Yang, 2016). There are inconclusive findings of the relationship between ownership and firms' behaviors. While Kusnadi*et al*. (2015) and Yan *et al*. (2020) advocate that non-state-owned firms are likely to adapt with the corporate carbon reduction engagement, the following studies offer an opposite view that state ownership could be a key driver of greener behavior (Cazla *et al*., 2016; Ji,

[11] Shenzhen market is the first pilot carbon market of China, which is launched in June 2013, followed by Shanghai, Beijing, Guangdong, and Tianjin pilots at the end of 2013. In 2014, Hubei and Chongqing pilots joins the carbon markets.

2020) due to the market distortion as well as the simulation packages for environmental followers.

The dominance of the public sector is a prominent feature of China's economy. State ownership has a strong impact on corporate investment and decision-making in China (Tan, 2001; Delios and Wu, 2005; Zhu and Yang, 2016). Therefore, state ownership might play an important role as a channel of transmission of environmental policy to the economy for public goods. From this perspective, China's new climate action plan might be better transmitted to firms with state ownership compared to their counterparts. This conjecture is in line with the findings that state ownership acts as a stimulating driver for firms' proactive environmental strategies (Cazla *et al*., 2016) and reduces industrial pollution intensity due to factor market distortion (Ji, 2020). If this is the case, we should expect the impact of climate policies, such as the Paris Agreement, on corporate environmental performance to be more pronounced in firms with state ownership (FSO). Following this argument, if Chinese firms pursue diversification strategies to decarbonize under the Paris Agreement, we might observe more diversification intensity in FSO than in other firms. This understanding forms our third research hypothesis as follows:

Hypothesis 3: *Ceteris paribus, corporate diversification subjective to the Paris Agreement is more pronounced for the state-owned firms than other firms.*

There is a strand of literature about the relationship between environmental protection and innovation (Huang and Yang, 2021; Calel and Dechezleprêtre, 2016; Böhringer *et al*., 2009). These studies emphasize the direct relationship between environment and firm innovation without taking into account any specific events or financial perspectives. Because green technologies are the essence of decarbonization and carbon productivity (Åhman *et al*., 2017; Du and Li, 2019), corporate innovation is crucial for heavy emitters to reduce carbon intensity as required by the authorities. Intuitively, heavy emitters can always choose between moving their business toward less carbon-intensive segments and reinvesting into more environment-friendly technologies. Assuming that the choice of heavy emitters being diversified or innovative is a function of innovation, the outcome may vary significantly among heavy emitters depending on their technology innovation. On the one hand, heavy emitters with more carbon-productive technologies may be less affected by the climate policy risk than heavy emitters with more carbon-intensive technology bases. Therefore, the carbon-productive heavy emitters have less incentive to transform their business model to deal with carbon risk given the risk of diluting their incomes as well as losses. On the other hand, carbon-intensive heavy emitters may find it too costly to reinvest and replace their technologies and thus being hit hard by climate policy uncertainty. Purchasing carbon permits might be a countermeasure for the policy problem, however, it also adds to the cost of goods sold and is not likely an optimal solution in the long term. The other option left is diversification. Based on this discussion, corporate innovation can be a channel to explain how the Paris Agreement influences the diversification decision-making of Chinese heavy emitters. More specifically, we expect firms with higher degrees of innovation are less likely to have an incentive to diversify their revenue. In other words, a higher degree of corporate innovation may loosen the impact of increased carbon risk on corporate diversification decision-making and vice versa. Thus, we predict:

Hypothesis 4: *Ceteris paribus, the impact of carbon risk on corporate diversification is weaker for firms with higher degrees of innovation.*

If a heavy emitter decides not to expand its core business and diversifies its operations, the firm might need to redirect its resources to new investment projects. Generally, a firm tends to retrench or even reverse its core investments under uncertainty (Gulen and Ion, 2016; Kim and Kung, 2017) with a certain cost of asset liquidation. Heavy emitters are likely heavy industrial and energy-related businesses whose core investments are likely less reversible in comparison to their counterparts. Also, firms operating in highly cyclical industries that are sensitive to negative demand shocks likely experience lower asset liquidation value if they liquidate their assets under uncertainty (Gulen and Ion, 2016). The intuition is that their potential buyers (firms within the same sector or industry) tend to face the same situation due to the same external shock (Shleifer and Vishny, 1992). Finlay *et al*. (2018) support this conjecture by adding empirical evidence that during periods of industry-wide distress, buyers of the disinvest assets are also facing liquidity constraints, thus leading to lower liquidation value. This is likely the typical case of Chinese heavy emitters under the impact of the Paris Agreement. When they decide to pursue diversification to hedge the carbon risk, it is a must that they divert resources from carbon-intensive operations to decarbonize. To do that, they must liquidate the assets from these operations. However, their potential buyers (other heavy emitters in the same industry) are also likely to disinvest themselves, resulting in lower liquidation value for heavy emitters. This leads to more frictions in asset liquidation and higher investment irreversibility for those firms. Therefore, it becomes costlier for heavy emitters to disinvest and adopt new technologies for their core operations. In this regard, heavy-emitting firms might be more inclined to diversify their corporate portfolios in response to the Paris

Agreement, rather than invest in the same operations with new technologies due to the increased cost of asset liquidation. They may have other ways to liquidate the asset, for example, exporting their technologies and fixed assets outbound to less developing countries, but the process is not likely to be completed in the short term. Either way, lower asset liquidation value implies higher cost sunkness (Gulen and Ion, 2016) that associates with corporate diversification strategy (O'Brien and Folta, 2009).

Base on this understanding, asset liquidity might be another channel through which carbon risk influence corporate diversification. Firms choosing to not diversify their revenue subject to the carbon risk might increase the level of alternative investment, which is associated with the cost of asset liquidation (Gulen and Ion, 2016; Kim and Kung, 2017). As such, firms are less able to liquidate their assets at their desired prices when facing uncertainties with negative effects on disinvested assets' values (Finlay *et al*., 2009; Gulen and Ion, 2016). This intuition motivates that Chinese firms experiencing more asset liquidity tend to choose revenue diversification subsequent to the submission of China's climate action plan to UNFCCC in 2015. This argument leads to our fifth hypothesis:

Hypothesis 5: *Ceteris paribus, the impact of carbon risk on corporate diversification of heavy polluters is stronger for firms with higher degrees of asset liquidity value*.

To sum up, we propose five hypotheses in this subsection to explore the relationship between carbon risk and firms' responses. In which, the first and the second hypotheses aim to revisit the long-standing debatable issue about what it takes to decarbonize from the corporate diversification perspective. The remaining hypotheses would like to offer insights into the potential mechanisms which drive firms' diversification between heavy-emitters and light-emitters when facing the carbon risk. The following section acknowledges our data selection and processing before discussing the main findings and results.

3. Data, variables, and empirical model

3.1. Carbon risk measurement

We follow the previous studies in the literature (Nguyen, 2018; Nguyen and Phan, 2020; Ilhan *et al.*, 2021) to measure carbon risk by defining heavy and light emitters. Heavy emitters are more prone to changes in carbon policy and have more inherent risks associated with carbon emission constraints. Specifically, heavy emitters are firms in carbon-intensive industries, including the largest energy consumers and the greenhouse gas emitters defined by the

Greenhouse Gas Protocol (GHG Protocol). Based on the classification of the Carbon Disclosure Project (CDP, 2012) and the Global Industry Classification Standard (GICS), Nguyen (2018) and Nguyen and Phan (2020) define heavy emitters as firms belonging to the following nine GICS industries: Chemicals; Construction Materials; Electric utilities; Gas utilities; Independent power producers and energy traders; Metals and mining; Multi-utilities; Oil, gas, and consumable fuels; and Paper and forest products. Ilhan *et al*. (2021) classify carbon intensity by sector using the ratio of total Scope 1 carbon emissions of a firm during a fiscal year scaled by the firm's equity market value. Ilhan *et al*. (2021) identify five S&P 500 sectors, namely Utilities, Energy, Materials, Industrials, and Consumer staples as the most carbon-intensive sectors[12]. Using an indirect approach to carbon risk measurement, Nguyen and Phan (2020) proxy carbon risk by stock market reaction to climate policy change in Australia. The authors calculate the cumulative abnormal returns (CAR) of stocks surrounding Australia's ratification of the Kyoto Protocol and define that firms with negative CAR during that time are firms most affected by the Kyoto Protocol, or in other words, heavy emitters.

We adopt all three abovementioned approaches to proxy corporate carbon risk in the literature. We generate a dummy variable (*EMITTER*) that equals one for firms in the carbon-intensive industries based on the definition of GHG Protocol and zero otherwise. We classify firms that are not carbon-intensive as light emitters (*EMITTER* = 0). Firms in carbon-intensive industries are likely to face more carbon risk associated with changes in carbon emission policy and market penalties. We also follow Ilhan *et al*. (2021) to construct an alternative industry-level measure of carbon risk using their top five carbon-intensive S&P 500 sectors. The dummy variable *TOP5EMITTER* equals one if the firms belong to one of the five sectors: Utilities, Energy, Materials, Industrials, and Consumer Staples, zero otherwise.

From the market approach, we calculate CAR of Chinese stocks in 3-day and 5-day windows surrounding 30th June 2015, the date that China submitted its national climate action plan to the United Nation Framework Convention on Climate Change (UNFCCC). The CAR windows include (t-1; t+1) and (t-3, t+1) in which the t is the date of China submitting its national climate action plan (the event date). To calculate CAR, we subtract average daily market returns from the daily stock return of each stock, then take the total of CAR during the designated windows. Following Nguyen and Phan (2020), we expect heavy emitters' CAR to be negative as a result of market reaction to carbon risk surrounding the event date. Therefore,

[12] The detailed GICS industry and sector codes for carbon-intensive industries (Nguyen and Phan, 2020) and S&P 500 sectors (Ilhan et al., forthcoming) are presented in Appendix A1.

we code stocks with negative CAR surrounding the event date as heavy emitters using dummy variables that equal one if the stock's CAR is negative and zero otherwise. Using both dividend-reinvested and non-dividend-reinvested stock prices, we end up with four different firm-level proxies of carbon risk. The proxies include dividend-reinvested and dividend-non-reinvested CAR using the 3-day and 5-day windows, namely *CAR3D_DR*, *CAR3D_NDR*, *CAR5D_DR*, and *CAR5D_NDR*, respectively.

Following Nguyen (2018) and Nguyen and Phan (2020), we use *EMITTER* as the main proxy for carbon risk in the baseline analysis, while the other five carbon risk measures (*TOP5EMITTER*, *CAR3D_DR*, *CAR3D_NDR*, *CAR5D_DR*, and *CAR5D_NDR*) are used in the sensitivity tests to confirm the results. Firms with higher carbon risk (EMITTER = 1) are defined as the treated group, while their counterparts (*EMITTER* = 0) are the control group that is less likely affected by the carbon risk induced by climate policies.

3.2. Corporate diversification

Following previous studies in the corporate diversification literature (Denis *et al*., 1997; Gu *et al*., 2018; Hoang *et al*., 2021), we use two proxies of corporate diversification, including the number of segments in a firm's revenues and the Entropy Index. The Entropy Index is calculated as follows:

$$ENTROPY = \sum_{i=0}^{NSEGMENTS} w_i \times \ln\left(\frac{1}{w_i}\right) \tag{1}$$

where: *ENTROPY* is the Entropy Index, *NSEGMENTS* is the number of segments in the revenues of a firm, and w_i is the weight of revenues from the segment *i* in the total revenues of the firm. The higher the Entropy Index, the more diversified the firm is. Similarly, the more segments (the higher *NSEGMENTS*) the firm has, the more revenue streams the firm has. We use *ENTROPY* as the dependent variable in our research model, while *NSEGMENTS* is used for the sensitivity test.

3.3. Baseline models

We use the following baseline empirical model to investigate the impact of carbon risk on corporate diversification:

$$\begin{aligned} ENTROPY_{i,t} = \ & \alpha + \beta EVENT_t \times EMITTER_i + \gamma EVENT_t + \delta EMITTER_i \\ & + CONTROL + \varepsilon_i \end{aligned} \tag{2}$$

where $ENTROPY_{i,t}$ is the Entropy Index of firm *i* in year *t*; $EVENT_t$ is the dummy variable indicating whether the year t is from 2015 forward or not; $EMITTER_i$ is the dummy variable that equals one if the firm is a heavy emitter or not; is a vector of firm-level and macro-level control variables, including firm size (*SIZE*), financial leverage (*LEVERAGE*), profitability (*ROA*), revenues growth rate (*GROWTH*), Tobin's Q (*TOBINSQ*), China's total carbon dioxide emissions during the year (*CO2EMISSION*), China's economic policy uncertainty index from Baker *et al*. (2016) (*EPU*), annual GDP growth rate (*GDP*), annual Consumer Price Index (*CPI*), and unemployment rate (*UNEMPLOYMENT*). The uses of the control variable follow the previous studies in the literature on corporate diversification (Gu *et al*., 2018; Hoang *et al*., 2021).

We use four alternative difference-in-differences (DID) regression specifications of the baseline model with and without the fixed effects and time dummies to ensure that the regression results are consistent and reliable. The time dummies include three dummies representing years before and during the commitment period of the Kyoto Protocol (2008-2012), and the Global Financial Crisis period (2007-2009). This is to control for the potential time-variant impact of the Kyoto Protocol on corporate diversification in China because China was a member of the Kyoto Protocol. Firstly, we use a simple regression model of *ENTROPY* on the interaction term *EVENT×EMITTER* and its components, *EVENT* and *EMITTER* variables, and the time dummies but not the fixed effect. Secondly, we add all the control variables listed above to the regression to have better control for potential confounding factors that may affect our analysis. Thirdly, we employ a reduced-form (bivariate) regression specification[13] of *ENTROPY* on the interaction term *EVENT×EMITTER* using the firm-fixed effect to control for firm-level heterogeneity. Ultimately, the final model specification include is the third one with the inclusion of all control variables and time dummies. We expect the results from these regression specifications to be consistent.

3.4. Data and sample

The data used in this current study are from various sources: (i) GICS industry classification of Chinese firms is collected from Bloomberg database; (ii) corporate financial data and environmental data are from Bloomberg, CSMAR, and WIND databases; (iii) China's carbon

[13] Because EMITTER and firm-fixed effect are strongly collinear, the interaction term's components (EVENT and EMITTER) are excluded from the third model specification.

emission data is from Our World In Data and China Emission Accounts and Datasets (CEADs); (iv) China's macroeconomic data are from World Bank database; and (v) economic policy uncertainty index is from Baker *et al*. (2016). The data covers Chinese firms listed on Shenzhen and Shanghai Stock Exchanges during the period from 2001 to 2017. In this study, we do not cover the 2018-2020 period to exclude the complicated impacts of the trade war between the United States and China (from 2018 to present) and the unprecedented COVID-19 pandemic (from 2020 to present) on corporate decision-making and carbon dioxide emissions in China.

Using the industry classification of heavy emitters from the GHG Protocol helps to maximize the sample size of our study, which would be very limited if we use a direct measure of carbon risk at the firm-level. We also exclude all financial firms because of the clear differences in the nature of business and carbon-intensity between them and other firms. The end sample consists of 19,832 firm-year observations from 2,249 unique Chinese listed firms for the 2001-2017 period. All the variables are winsorized at the 1^{st} and the 99^{th} percentile to alleviate the impact of outliers on our analysis.

4. Empirical results

4.1. Descriptive statistics

Table 1 reports the descriptive statistics and pairwise correlation matrix of variables used in this study.

[Please insert Table 1 about here]

The descriptive statistics in Panel A, Table 1, show that *ENTROPY* has a mean of 0.395 and ranges from 0 to 1.431, while *NSEGMENTS* has a mean of 2.154 and ranges from 0 to 5. This indicates that on average, Chinese listed firms have around two segments. Figure 4 highlights an increase in both the Entropy index and the average of firms' segments after the event China submitting its climate action plan to UNFCCC in 2015. The sharp increases in *ENTROPY* and *NSEGMENTS* from 2015 onward relative to the previous periods support our conjecture on the impact of the event on corporate diversification decision-making.

[Please insert Figure 4 about here]

EMITTER has a mean of 0.187, meaning that 18.7% of firm-year observations in our sample belong to the heavy emitting firm group based on the classification of the GHG

Protocol. *TOP5EMITTER* has a mean of 0.276, meaning that 27.6% of observations in our sample belong to the top five most carbon-intensive sectors following Ilhan *et al*. (2021). Furthermore, using the definition of carbon risk based on market reaction to climate policy news (Nguyen and Phan, 2020), the means of CAR proxies range from 0.642 to 0.648, suggesting that around 64% of observations in our sample subject to higher carbon risk than the others. This market approach to measure carbon risk results in a remarkably larger heavy emitter group compared to those of the industry-level approaches. Given that this is an indirect method of measuring carbon risk, it might result in certain measurement errors in unknown directions. That is the reason why we only use the CAR proxies as carbon risk measures for robustness tests.

Panel B, Table 1, shows the pairwise correlation matrix of variables used in the baseline regressions. We see that *ENTROPY* and *NSEGMENTS* have a correlation coefficient of 0.81 (p-value < 0.01), which is reasonable as they are proxies of corporate diversification. Other pairs of variables' correlation coefficients are generally smaller than 0.7 and significant. Therefore, there is no potential correlation issue among our variables that can affect our analysis.

4.2. Univariate analysis

Table 2 reports the results of the univariate analysis of firm-level characteristics. We perform t-tests of mean-differences of firm-characteristics between two emitter groups, and between two periods surrounding the Paris Agreement in 2015.

[Please insert Table 2 about here]

Panel A, Table 2, presents the mean difference test results of firm characteristics between heavy and light emitters. The results show that on average, heavy emitters are less diversified than light emitters, evident by the significant differences in means of *ENTROPY* and *NSEGMENTS* among two firm groups. Specifically, the means of *ENTROPY* are 0.379 and 0.401 for heavy and light emitters, respectively; the difference is -0.022 which is significant at 1% level. *NSEGMENTS*'s means for heavy and light emitter groups are 2.076 and 2.183, respectively, while their difference is -0.107, significant at 1% level.

The univariate analysis results regarding other firm-level are also worth mentioning. The differences in firm size (*SIZE*), financial leverage (*LEVERAGE*), profitability (*ROA*), revenues growth, and Tobin's Q (*TOBINSQ*) between heavy and light emitters are 0.366, 0.066,

-0.003. 0.622, and -0.437, respectively, and all are significant at 1% level. On the one hand, the *t*-test results indicate that heavy emitters in China are generally larger in total assets, use more debt financing, and have a higher revenue growth compared to their counterparts. On the other hand, it seems that heavy emitters tend to have lower profitability and smaller Tobin's Q in comparison to light emitters. This is consistent with capital market penalizes heavy polluters by lowering their market value (Konar and Cohen, 2001).

Panel B, Table 2, shows the differences in *ENTROPY* of heavy emitters and light emitters between the pre and during Paris Agreement periods. In general, the results indicate that *ENTROPY* of both firm groups in the Paris Agreement period (2015-2017) is higher than that of the pre-agreement period. However, the change is more prominent in heavy emitters relative to light emitters (0.044 compared to 0.012, respectively). We find similar findings when comparing *NSEGMENTS* of the two firm groups between the period before and during the Paris Agreement (Panel C, Table 2).

Generally, the univariate analysis results indicate that there are statistically significant differences between corporate diversification measures of heavy emitters and light emitters, and between the pre and during Paris Agreement periods. These findings are important and support our use of difference-in-differences analysis to explore the relationship between carbon risk and corporate diversification surrounding the Paris Agreement.

4.3. Multivariate analysis

In this section, we estimate the baseline model and its specifications to investigate the impact of carbon risk on corporate diversification using the event of China joining the Paris Agreement as a quasi-natural experiment. Table 3 reports the DID regression results.

[Please insert Table 3 about here]

Column 1, Table 3, presents the reduced-form DID regression with time dummies. In Column 1, the coefficient of the interaction term *EVENT×EMITTER* is positive and significant at 5% level; EVENT's coefficient is positive and significant at 1% level; however, EMITTER's coefficient is negative and significant at 1% level. We document similar results in Column 2 when we include control variables at the firm- and macro-level to the regression. The results indicate that the stand-alone effect of the Paris Agreement is positive, meaning corporate diversification increases after 2015. There is also an evident association between carbon risk and corporate diversification, which is consistent with the results of the univariate analysis in

Section 4.2. More importantly, the positive coefficient of *EVENT×EMITTER* suggests that after the event, heavy emitters are more likely to pursue corporate diversification strategies than light emitters. This finding is evidence of heavy emitters use diversification strategies to hedge their increased carbon risk induced by the Paris Agreement. The impact of the Paris Agreement is economically meaningful to the relationship between carbon risk and corporate diversification. Columns 3 and 4 present the results of the DID regression with the inclusion of firm fixed effect to control for unobservable firm-level heterogeneity. The coefficient of *EVENT×EMITTER* remains positive and significant, indicating that the main finding is qualitatively unchanged to alternative model specifications.

One may argue that heavy emitters may diversify their investment portfolios to other or even more carbon-intensive operations, therefore, do not change their exposure to carbon risk. We exclude this possibility because China commits to cut its carbon dioxide intensity by 60-65% [14]by 2030 compared to the 2005 level; new heavy-emitting industrial projects are put under tight supervision and limited by the Chinese government via the Emission Permit System (EPS). China has undergone a large-scale reform to promote ecological progress and passed the Environmental Protection Law in 2014 that requires all pollution emitters must hold an emission permit to discharge pollutants starting from January 2015. As such, heavy emitters are not likely and not able to diversify to similar or more carbon-intensive operations after the event. Based on this institutional setting of China, we suggest that heavy emitters turn to diversification strategies to redirect their resources from carbon-intensive operations to more environment-friendly business models in response to the government's new climate policy.

To summarize, the outcomes of our analysis support Hypothesis 1 that firms with higher carbon risk are more likely to pursue diversification strategies following the official event of China joining the Paris Agreement relative to their counterparts. The findings are highly consistent across the univariate and multivariate analyses.

4.4. Regression using a matched sample

The Paris Agreement is an exogenous shock to heavy emitters in China. This event might cause variations in unobserved factors that affect decision-making in Chinese corporations via various known and unknown mechanisms. As a result, there is a potential functional form misspecification (FFM) problem in our DID analysis. To mitigate this inherent risk, we use the

[14] Based on the statement of the office of Chinese Premier Li Keqiang on 30 June 2015. See https://www.bbc.com/news/science-environment-33317451 (Last access on 6 March 2021).

propensity score matching (PSM) procedure to isolate the impact of different firm-level factors and claim the validity of our findings.

The PSM procedure consists of two steps: the matching step and the matching diagnostics. First, we match each observation from the treated group (heavy emitters) with an observation from the control group (light emitters) based on their similar firm characteristics: firm size (*SIZE*), financial leverage (*LEVERAGE*), profitability (*ROA*), revenues growth (*GROWTH*), and Tobin's Q (*TOBINSQ*). This procedure should generate a subsample of our full sample that represents firms that are uniformly influenced by the climate action plan China submitted to the UNFCCC as a part of the Paris Agreement. Second, we conduct a probit regression of *EMITTER* on the firm characteristic variables to test whether firms in the treated and control groups share identical characteristics before and after the matching. If the post-match test results are satisfactory, it is ready for the DID analysis. The regression results of the diagnostic tests and the DID analysis are reported in Panels A and B of Table 4.

[Please insert Table 4 about here]

From Column 1 of Panel A, Table 4, we find that the pre-match coefficients of *SIZE, LEVERAGE,* and *GROWTH* are significant at 1% level, while the pre-match coefficient of ROA and *TOBINSQ* are statistically insignificant. The post-match probit regression results in Column 2, Panel A, show that all the coefficients are statistically insignificant, meaning that there is no clear difference in firm characteristics between firms from the treated and control groups. Moreover, the pseudo R-squared decreases noticeably from 0.048 (pre-match) to 0.001 (post-match), suggesting that the PSM procedure is successful.

In Panel B, Table 4, we use both a reduced-form and the full baseline model with firm-fixed effect to re-perform the DID regression using the matched sample (PSM-DID). As we expected, the PSM-DID regression results of all regression specifications in Table 4 are consistent with those reported in Table 3, thus confirming the validity of our findings.

4.5. Sensitivity tests

To obtain the validity of our findings, we test the sensitivity by employing several measurements of firms' diversification as well as our selection of heavy emitters. This approach could be our robustness to assure two main indicators (carbon risk – not only choosing the heavy-emitter in specific industries but also selecting the return reactions to environmental news). We adopt alternative measures of carbon risk including Ilhan *et al.*

(2021)'s measure (*TOP5EMITTER*) and Nguyen and Phan (2020)'s indirect measures of carbon risk based on market responses to the climate policy change to see whether our findings are sensitive to different carbon risk measurements. We also use the number of revenue segments (*NSEGMENTS*) instead of *ENTROPY* as the dependent variable to control for the potential measurement error issue following Gu *et al*. (2018) and Hoang *et al*. (2021). Table 5 reports the regression results of the baseline model using *NSEGMENTS* and *TOP5EMITTER* separately as the dependent variable and the measure of carbon risk.

[Please insert Table 5 about here]

In general, the results of the DID regression results in Table 5 are similar to those reported in the baseline model in Table 3. Specifically, the coefficients of the interaction terms *EVENT×EMITTER* and EVENT × *TOP5EMITTER*S are positive and statistically significant, indicating that our primary finding still holds to different measures of corporate diversification and industry-level definition of carbon risk. To elaborate the findings with carbon risk measures at the firm-level, we use the market reaction variables (*CAR3D_DR*, *CAR3D_NDR*, *CAR5D_DR*, and *CAR5D_NDR*) as alternative measures of carbon risk in substitute them for EMITTER in the baseline model. By using these firm-level carbon risk measures, we report the real responses of the market returns to the event of China joining the Paris Agreement as penalties for heavy emitters. We expect the regression outputs to be similar to those reported in Tables 3, 4, and 5.

[Please insert Table 6 about here]

Table 6 presents the DID regression results. In line with our expectation, the results show similar positive coefficients of the interaction terms between *EVENT* and CAR variables, indicating that our findings are robust to the market-based approach to measure carbon risk associated with the Paris Agreement.

Diversification discount is an essential factor to consider when a firm makes decisions on corporate diversification. If the diversification discount is too high, it will add to the cost of diversification and drive firms from making such decisions. Mansi and Reeb (2002) indicate that there is no evidence of diversification discount in equity firms and show that diversification discount is a function of financial leverage. From this perspective, one may argue that the impact of the Paris Agreement on corporate diversification of heavy emitters varies across different levels of financial leverage. Specifically, equity heavy emitters should have a lower cost of diversification and therefore they have fewer incentives to retrench diversification compared to their counterparts. We follow this argument and test the impact of the Paris Agreement on corporate diversification of Chinese firms using subsamples of equity firms and financial leveraged firms separately. The regression results are presented in Table 7. We find the coefficient of the interaction term *EVENT×EMITTER* is higher for equity firms (0.050) in comparison to that of leveraged firms (0.032); both are statistically significant. These empirical results suggest that there are cross-sectional variations in the effect of the Paris Agreement on corporate diversification of heavy emitters in China regarding the capital structure of firms.

[Please insert Table 7 about here]

To summarize, after using the rigorous control variables and sensitivity tests, our findings still persist, which allows us to come to conclude that firms with higher carbon risk are likely to diversify their revenue under the new stringent regulations. The sensitivity tests confirm the positive impact of the Paris Agreement on corporate diversification of heavy emitters in China, however, such an impact varies across different degrees of diversification discount.

4.6. Pilot carbon market zones and corporate diversification

To demonstrate the difference between corporate diversification strategy between firms in pilot carbon markets and firms in other areas, we re-perform the DID regression using the subsample of firms from the abovementioned seven pilot carbon market zones and firms from other provinces. The difference in the coefficient of the interaction term *EVENT×EMITTER* will determine whether or not the reactions of heavy emitters to the Paris Agreement vary geographically.

[Please insert Table 8 about here]

Columns 1 and 2, Table 8, report the regression results. We notice that the coefficient of the interaction term *EVENT×EMITTER* in Column 1 (firms from pilot zones) is noticeably higher than that in Column 2 (firms from other zones) (0.060 and 0.021, respectively); both are statistically significant. These results indicate that the incentives for firms in carbon pilot markets to pursue diversification strategies during the Paris Agreement are stronger for firms in the seven pilot zones. Following our discussion in the development of Hypothesis 2, we attribute this finding to the benefit of accessing carbon finance on top of the incentive to hedge carbon risk associated with the climate action plan of China. The implementation of pilot carbon markets in China allows Chinese firms to trade carbon emission permits and have access to carbon finance. This is a good drive for heavy emitter firms to diversify their investment given there are more financing options available for their investments. The empirical evidence support our Hypothesis 2.

The empirical evidence from the baseline model regression, sensitivity tests, and pilot carbon market test suggest that on average, heavy emitters in China use diversification strategies to hedge the carbon risk associated with the changes in the government's climate action plan. However, such a finding is placed under the *Ceteris Paribus* (all else equal) assumption that is not likely to meet in practice. There might always be some heterogeneous factors that determine the impact of the Paris Agreement on the diversification decision-making of heavy emitters. To provide a better understanding of the impact of the Paris Agreement on the relationship between carbon risk and corporate diversification, we identify three channels of effect through which carbon risk stimulates corporate diversification of Chinese firms, namely: state intervention via state ownership, corporate innovation, and asset liquidation value.

5. State intervention via state ownership in Chinese firms

To investigate the role of state ownership in the newfound relationship between carbon risk and corporate diversification, we use a difference-in-difference-in-differences (DDD) analysis to examine whether heavy emitters among FSO diversify more than other firms under the impact of the Paris Agreement. We construct a dummy variable (*STATE_OWNERSHIP*) that equals one if the firm is an FSO and zero otherwise. The model for investigating diversification intensity of FSO heavy emitters under the impact of the Paris Agreement is as follows:

$$\begin{aligned} ENTROPY_{i,t} = {} & \alpha + \beta EVENT_t \times EMITTER_i \times STATE\_OWNERSHIP_{i,t} \\ & + \gamma EVENT_t \times EMITTER_i + \gamma EVENT_t \times STATE\_OWNERSHIP_{i,t} \\ & + \eta EMITTER_i \times STATE\_OWNERSHIP_{i,t} + CONTROL + \varepsilon_i \end{aligned} \tag{3}$$

In Model 3, we use the same control settings as in the baseline model to control for firm-level observed and unobserved factors, macroeconomic factors, and time-variant factors.

Standard errors are double-clustered by both firm and year. We use both the full sample and the matched sample to perform the regressions of Model 3 to alleviate any potential misspecification in the functional form of the model. Based on the above proposition, we expect a positive coefficient of the three-way interaction term *EVENT×EMITTER×STATE_OWNERSHIP*. Table 9 reports the estimation results.

[Please insert Table 9 about here]

Table 9 shows the DDD regression results using three regression specifications: a reduced-form regression that includes only the interaction terms (Column 1), a regression with the inclusion of the control variables (Column 2), and a matched sample regression (column 3). Consistent with our expectation, the coefficient of the three-way interaction *EVENT×EMITTER×STATE_OWNERSHIP* is positive and significant across three columns, indicating a positive impact of that state ownership of heavy emitters on corporate diversification under the Paris Agreement. This suggests the role of state ownership as a transmission channel of the government's environmental policy to reduce carbon intensity. Moreover, the coefficient of the interaction term *EVENT×EMITTER* remains positive and significant in all columns and is consistent with those reported in the baseline regression. Therefore, our empirical results in this section are not likely driven by potential collinearities between variables.

In summary, we find that state ownership plays an important role in implementing the government's climate action plan. The evidence suggests that state ownership stimulates heavy emitters to pursue diversification strategies as a method to reduce the policy risk of carbon-intensive operations, thus supporting our Hypothesis 3.

6. Corporate innovation as a channel of effect

To test Hypothesis 4, we classify firms by their R&D expenditure and construct a three-way interaction term between R&D intensity, heavy emitters (*EMITTER*), and the exogenous shock (*EVENT*) to investigate where corporate innovation matters to the impact of the Paris Agreement on the relationship between diversification strategy of heavy emitters. To measure corporate innovation, we calculate the R&D expenditure on sales ratio of Chinese firms and define a dummy variable (R&D) that equals one if the ratio of the firm is higher than its median and zero otherwise. The following DDD model is employed for the data analysis.

$$ENTROPY_{i,t} = \alpha + \beta EVENT_t \times EMITTER_i \times R\&D_{i,t} + \gamma EVENT_t \times EMITTER_i + \gamma EVENT_t \times R\&D_{i,t} + \eta EMITTER_i \times R\&D_{i,t} + CONTROL + \varepsilon_i \quad (4)$$

We use the same control settings as in the baseline model to control for firm-level observed and unobserved factors, macroeconomic factors, and time-variant factors. We perform the regression of Model 4 using the full sample and the matched sample. Based on the above proposition, we expect a negative coefficient of the three-way interaction term *EVENT×EMITTER×R&D*. The intuition is that heavy emitters with more corporate innovation are less likely to pursue diversification strategy as a response to the Paris Agreement, and vice versa. The estimation results are reported in Table 10.

[Please insert Table 10 about here]

Column 1, Table 10, reports the DDD regression results without the control variables. Columns 2 and 3 present the regression results of the full model with control variables using the full sample and the matched sample, respectively. The coefficient of the three-way interaction term *EVENT×EMITTER×R&D* is consistently negative and significant at 1% in all regression specifications, thus supporting the proposition that the impact of the Paris Agreement on corporate diversification of heavy emitters in China to be weaker in firms with higher degrees of innovation. In other words, heavy emitters might be more proactive in response to the Paris Agreement by spending more on research and development activities and adopting more environmental-friendly technologies.

In summary, we find that corporate innovation plays a moderating role in the impact of the Paris Agreement on the relationship between carbon risk and corporate diversification. The empirical evidence support our Hypothesis 4.

7. Asset liquidation value under increasing carbon risk

To test Hypothesis 5, we follow Sharpe (1994), Almeida and Campello (2007), and Gulen and Ion (2016) to construct a measure of asset liquidation values based on revenue cyclicality at both the firm- and industry-level via three steps. First, we calculate the correlation between each firm's operating revenues and China's Gross National Product (GNP) during the sample period. Second, we use a dummy variable that equals one if the firm's correlation with GNP higher than the sample median and zero otherwise. By doing this, we obtain the firm-level proxy of asset liquidation values (*ALV_FIRM*). Third, we aggregate the firm-level correlations at the GICS industry level to create an industry-level correlation measure. Similar to the construction of *ALV_FIRM*, we generate another dummy variable that equals one if the industry-level correlation is above its sample median and zero otherwise (*ALV_IND*). If a firm (industry)'s *ALV_FIRM* (*ALV_IND*) equals one, they are defined as cyclical firms and their investments are likely less reversible under uncertainty. The model to investigate asset liquidation values as a channel of the impact of the Paris Agreement on heavy emitters' diversification strategies is presented as follows:

$$ENTROPY_{i,t} = \alpha + \beta EVENT_t \times EMITTER_i \times ALV_{i,t} + CONTROL + \varepsilon_i \tag{5}$$

where *ALV* is the proxy of asset liquidation values at firm-level (*ALV_FIRM*) or industry-level (*ALV_IND*); CONTROL is the vector of firm-level and macroeconomic variables as included in the baseline regression. Firm-fixed effect and time dummies are included to control for firm-level and time-varying heterogeneity. We do not include the stand-alone variables and two-way interaction terms because the firm-fixed effect is strongly correlated to *ALV_IND* and *ALV_FIRM* because *ALV_IND* and *ALV_FIRM* are time-invariant. Standard errors are clustered by firm and year. Because we hypothesize that asset liquidation value is a channel that stimulates the impact of the Paris Agreement on heavy emitters' diversification strategies, the coefficient of the three-way interaction terms *EVENT×EMITTER×ALV_FIRM* and *EVENT×EMITTER×ALV_IND* are expected to positive and significant. The regression results are reported in Table 11.

[Please insert Table 11 about here]

We present the firm-level estimation results in Columns 1-3, Table 11 using three regression specifications: a reduced-form model of ENTROPY on the three-way interaction term, firm-fixed effect, and time dummies only (Column 1); the full sample regression with the inclusion of all control variables, fixed effect and time dummies (Column 2); and a PSM-matched sample regression with full control (Column 3). A similar estimation setting is employed for the industry-level regressions in Columns 4-6, Table 11. Consistent with our prediction, the coefficients of *EVENT×EMITTER×ALV_FIRM* and *EVENT×EMITTER×ALV_IND* are positive and significant at 1% level. The empirical evidence suggests the incremental effect of asset liquidation values on how the Paris Agreement affects corporate diversification decision-making in China. Specifically, Chinese heavy emitters tend to diversify more in response to the Paris Agreement if there are more frictions in asset liquidation. Our findings indicate the importance of the business strategy of heavy emitters that determine their available options for responding to climate policy uncertainty. Specifically, non-cyclical heavy emitters face fewer frictions to liquidate their fixed assets and adopt new green technologies for their core businesses, relative to cyclical heavy emitters.

In summary, we unveil the asset liquidation values channel through which the Paris Agreement affects Chinese heavy emitters' diversification strategies. On average, cyclical heavy emitters likely have more investment irreversibility under climate policy uncertainty such as the Paris Agreement, and therefore resort more to diversification strategies to reduce carbon risk associated with their core businesses. On the other hand, all else equal, non-cyclical heavy emitters encounter less market friction in liquidating their investment assets and thus have less incentive to pursue diversification. The empirical findings well support our Hypothesis 5.

8. Conclusion

The recent decades witness various actions from the international community to cope with climate changes, specifically through the most-mentioned action plans of the Kyoto Protocol and the Paris Agreement. Individual countries also carry out their own action plans to meet the agreement requirements, which might exert substantial influence on firm behaviour. Literature shows a few studies on the influence, however to date, our knowledge of the impact on firms' business diversification has remained meagre, especially in countries with heavy emission such as China. This paper uses the Paris Agreement where China submitted its new climate action plan to the United Nations Framework Convention on Climate Change (UNFCCC) on 30 June 2015 as a quasi-natural experiment to examine the causal relationship between carbon risk and corporations' diversification decisions in China during 2001-2017. Employing different measures of carbon risk, the results show that heavy emitters (firms with more carbon risk) tend to diversify their revenues more after the new climate action plan is submitted to UNFCCC, while it is not the case for light emitters. In other words, heavy emitters turn to diversification strategies to redirect their resources from carbon-intensive operations to more environment-friendly business models in response to the government's new climate policy. The results are valid through different robustness and sensitivity tests.

Furthermore, our study shows that state ownership in Chinese firms stimulates heavy emitters to pursue diversification strategies as a hedge to the policy risk of carbon-intensive operations. We also find a weak impact of the Paris Agreement on corporate diversification of heavy emitters with higher degrees of innovation, implying that heavy emitters might be more proactive in response to the Paris Agreement by spending more on R&D activities and adopting more environmental-friendly technologies. Additionally, our study reveals that cyclical heavy emitters likely resort more to diversification strategies to reduce carbon risk associated with their core businesses while non-cyclical heavy emitters have less incentive to pursue diversification.

Our study has offered relevant implications for investors, firms, and policy makers. The findings provide an insight into the corporates' use of business diversification to tackle the carbon risk. Therefore, investors should adjust their valuation model taking diversification behaviors into account as the risk factors. Accordingly, to earn equity premia for investments, investors should expand their portfolios to the green investment fields, since corporates will likely diversify their businesses to the fields when confronting carbon policy risk. However, attention should be paid to other corporates' strategies as well, since changes in environmental policies might lead to different responses. Corporates also can tap into our results by focusing on R&D in green technologies and diversifying to greener businesses, since these are channels to hedge the climate policy risk. To cope with environmental changes, it is vital to enhance business strategy to search for newly available investment options in the future rather than green businesses. To policymakers, the results show that strong carbon policy enforcement and the government's commitment to combating climate change could encourage firms to decarbonize. Therefore, policies related to establishing carbon markets, carbon trading permits, and state intervention via state ownership might promote carbon policy implementation at the firm-level. Additionally, increasing support to corporate R&D, investment asset liquidation, and more carbon-effective technologies are incentives to firms' decarbonization when firms are encountering climate-change policy risk.

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Table 1. Summary statistics and correlation matrix.

Panel A. Summary statistics

Variable	Obs	Mean	Std.Dev.	Min	Max
ENTROPY	19,832	0.395	0.414	0	1.431
NSEGMENTS	19,832	2.154	1.560	0	5
EVENT	19,832	0.187	0.390	0	1
EMITTER	19,832	0.276	0.447	0	1
TOP5EMITTER	19,832	0.506	0.500	0	1
CAR3D_DR	19,832	0.643	0.479	0	1
CAR3D_NDR	19,832	0.643	0.479	0	1
CAR5D_DR	19,832	0.648	0.478	0	1
CAR5D_NDR	19,832	0.648	0.478	0	1
SIZE	19,832	21.657	1.192	18.992	25.358
LEVERAGE	19,832	0.173	0.150	0	0.612
ROA	19,832	0.037	0.071	-0.225	0.316
GROWTH	19,832	0.058	2.614	-15.161	14.323
TOBINSQ	19,832	1.997	1.833	0.214	11.489
CO2EMISSION	19,832	8.035	2.108	3.430	9.840
EPU	19,832	155.938	79.440	64.962	364.833
GDP	19,832	0.088	0.020	0.067	0.142
CPI	19,832	0.024	0.018	-0.007	0.059
UNEMPLOYMENT	19,832	0.045	0.002	0.038	0.047
ENVI_DISCLOSURE	4,966	10.237	6.109	0.775	55.208
EMISSION_REDUCTION	6,247	0.681	0.466	0	1
STATE	19,832	0.070	0.254	0	1
ALV_FIRM	19,832	0.508	0.500	0	1
ALV_IND	19,832	0.491	0.500	0	1
R&D	19,832	0.298	0.458	0	1

Panel B. Pairwise correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) ENTROPY	1.00													
(2) NSEGMENTS	0.81***	1.00												
(3) EVENT	-0.02***	0.06***	1.00											
(4) EMITTERS	-0.01	-0.02***	-0.02***	1.00										
(5) SIZE	0.10***	0.20***	0.16***	0.12***	1.00									
(6) LEVERAGE	0.13***	0.08***	-0.12***	0.20***	0.10***	1.00								
(7) ROA	-0.04***	0.02***	0.10***	-0.02***	0.28***	-0.29***	1.00							
(8) GROWTH	0.00	0.03***	0.00	0.10***	0.44***	0.04***	0.30***	1.00						
(9) TOBINSQ	-0.13***	-0.15***	0.22***	-0.10***	-0.44***	-0.31***	0.07***	-0.25***	1.00					
(10) CO2EMISSION	-0.09***	0.12***	0.47***	-0.02***	0.24***	-0.28***	0.14***	0.00	0.13***	1.00				
(11) EPU	-0.03***	0.054***	0.65***	-0.02***	0.16***	-0.12***	0.13***	0.00	0.11***	0.54***	1.00			
(12) GDP	0.05***	-0.04***	-0.61***	0.02***	-0.15***	0.23***	-0.12***	-0.00	-0.11***	-0.59***	-0.67***	1.00		
(13) CPI	-0.01*	0.05***	-0.25***	0.01	0.03***	-0.00	-0.01**	0.00	-0.10***	0.18***	-0.09***	0.33***	1.00	
(14) UNEMPLOYMENT	-0.06***	0.11***	0.00	-0.00	0.11***	-0.15***	0.03***	0.00	-0.04***	0.54***	-0.00	-0.20***	0.12***	1.00

This table reports the summary statistics and pairwise correlation matrix of variables used in this study. ***, **, and * denote statistical significance at 1%, 5%, and 10%, respectively.

Table 2. Mean different test of firm-characteristic variables between heavy emitters and light emitters.

Panel A. Differences in firm characteristics between heavy and light emitters

Variable	Heavy emitters (*EMITER* = 1) (1)	Light emitters (*EMITTER* = 0) (2)	Difference (3) = (1) - (2)
ENTROPY	0.379	0.401	-0.022*** (-3.358)
NSEGMENTS	2.076	2.183	-0.107*** (-4.652)
SIZE	21.922	21.556	0.366*** (21.106)
LEVERAGE	0.221	0.155	0.066*** (30.704)
ROA	0.035	0.038	-0.003*** (-3.057)
GROWTH	0.511	-0.111	0.622*** (17.064)
TOBINSQ	1.680	2.117	-0.437*** (-16.301)

Panel B. Differences in *ENTROPY* of emitter groups before and after China joined Paris Agreement

Emitter group	Before 2015 (1)	2015 onward (2)	Difference (3) = (1) - (2)
Heavy emitters (*EMITTER* = 1)	0.370	0.414	0.044*** (3.273)
Light emitters (*EMITTER* = 0)	0.399	0.411	0.012* (1.411)

This table presents the univariate analysis results of firm-level characteristics between heavy emitters and light emitters during the sample period. Panel A reports the mean comparison test results of firm-level characteristics between heavy emitters and light emitters. Panel B reports the mean comparison test results of *ENTROPY* of firms between the pre-2015 and event period (2015 onwards). *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10%, respectively.

Table 3. Baseline regression results.

VARIABLES	(1) Reduced-form baseline model without fixed effect	(2) Baseline model without fixed effect	(3) Reduced-form baseline with fixed effect	(4) Baseline model with fixed effect
EVENT×EMITTER	0.033**	0.031*	0.079***	0.029***
	(2.015)	(1.905)	(9.138)	(2.969)
EVENT	0.050***	0.031**		
	(4.963)	(2.209)		
EMITTER	-0.030***	-0.060***		
	(-4.060)	(-8.103)		
SIZE		0.035***		0.035***
		(10.573)		(6.868)
LEVERAGE		0.269***		0.220***
		(12.177)		(9.893)
ROA		0.060		-0.056
		(1.324)		(-1.636)
GROWTH		-0.010***		0.002**
		(-8.296)		(2.263)
TOBINSQ		-0.013***		0.000
		(-7.134)		(0.180)
CO2EMISSION		-0.020***		0.001
		(-3.569)		(0.210)
EPU		0.000		0.000***
		(0.446)		(4.383)
GDP		-0.464		-0.237
		(-0.981)		(-0.813)
CPI		-0.022		0.107
		(-0.100)		(0.810)
UNEMPLOYMENT		-7.718***		-2.578
		(-2.759)		(-1.093)
Constant	0.361***	0.172	0.393***	-0.285*
	(55.101)	(1.145)	(222.306)	(-1.797)
Firm FE	No	No	Yes	Yes
Time dummies	Yes	Yes	No	Yes
SE clustered	firm, year	firm, year	firm, year	firm, year
Observations	19,832	19,832	19,832	19,832
Adjusted R-squared	0.008	0.041	0.657	0.666

This table reports the difference-in-differences analysis results. The treated group includes the heavy emitters as defined by Nguyen and Phan (2020). The control group consists of other firms labelled as light emitters. *EMITTER* equals one if the firm is in the treated group (heavy emitter) and zero otherwise (light emitter). The *EVENT* dummy variable equals one if the current firm-year observation is from 2015 onward (the year when China submitted its national climate action plan to the Paris Agreement) and zero otherwise. The dependent variable is ENTROPY. The control variables are *SIZE*, *LEVERAGE*, *ROA*, *GROWTH*, *TOBINSQ*, *CO2EMISSION*, *EPU*, *GDP*, *CPI*, and *UNEMPLOYMENT*. Variable descriptions are provided in Appendix A. Columns (1) and (2) present the OLS regression results with time dummies and without firm fixed effect. Columns (3) and (4) report the regression results with firm fixed effect and time dummies. Standard errors are double-clustered by firm and year. *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10%, respectively.

Table 4. Difference-in-differences analysis using a matched sample.

Panel A. Matching diagnostics

VARIABLES	(1) Pre-match	(2) Post-match
SIZE	0.105***	0.003
	(11.576)	(0.235)
LEVERAGE	1.635***	-0.114
	(25.355)	(-1.106)
ROA	-0.188	0.255
	(-1.307)	(1.131)
GROWTH	0.036***	0.003
	(9.320)	(0.528)
TOBINSQ	0.000	-0.014
	(0.076)	(-1.487)
Constant	-3.168***	-0.035
	(-15.789)	(-0.111)
Observations	19,832	10,493
Pseudo R-squared	0.048	0.001

Panel B

DID analysis with matched sample

VARIABLES	(1) *ENTROPY*	(2) *ENTROPY*
EVENT×EMITTER	0.079***	0.030**
	(8.912)	(2.448)
SIZE		0.022***
		(2.794)
LEVERAGE		0.145***
		(4.500)
ROA		-0.045
		(-0.929)
GROWTH		0.002
		(1.353)
TOBINSQ		-0.002
		(-0.580)
CO2EMISSION		0.001
		(0.146)
EPU		0.000**
		(2.271)
GDP		-0.014
		(-0.038)
CPI		0.134
		(0.665)
UNEMPLOYMENT		-5.616*
		(-1.727)
Constant	0.407***	0.145
	(154.107)	(0.620)
Firm FE	Yes	Yes
Time dummies	Yes	Yes
SE clustered	firm, year	firm, year
Observations	10,494	10,493

Adjusted R-squared	0.694	0.699

This table reports the difference-in-differences (DID) analysis results using a matched sample. The treated group includes the heavy emitters as defined by Nguyen and Phan (2020). The control group consists of other firms labelled as light emitters. *EMITTER* equals one if the firm is in the treated group (heavy emitter) and zero otherwise (light emitter). A treated firm-year observation is matched with a firm-year observation from the control group using the propensity score matching procedure. Panel A reports the probit regression of the pre-match and post-match sample as the matching diagnostic tests. Panel B shows the DID regression results using the post-match sample. Variable descriptions are provided in Appendix A. Standard errors are double-clustered by firm and year. *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10%, respectively.

Table 5. Baseline regression results using alternative variable measurements.

VARIABLES	(1) *NSEGMENTS*	(2) *ENTROPY*
EVENT×EMITTER	0.084**	
	(2.259)	
EVENT × TOP5EMITTERS		0.044***
		(5.291)
SIZE	0.202***	0.034***
	(11.765)	(6.654)
LEVERAGE	0.573***	0.219***
	(7.184)	(9.856)
ROA	-0.232*	-0.049
	(-1.769)	(-1.414)
GROWTH	0.006*	0.002**
	(1.665)	(2.275)
TOBINSQ	0.011*	-0.001
	(1.825)	(-0.352)
CO2EMISSION	0.098***	0.002
	(7.683)	(0.706)
EPU	0.001***	0.000***
	(7.220)	(2.790)
GDP	3.043***	-0.385
	(2.793)	(-1.309)
CPI	2.539***	0.139
	(4.789)	(1.055)
UNEMPLOYMENT	74.616***	-3.166
	(11.239)	(-1.339)
Constant	-6.899***	-0.235
	(-14.259)	(-1.476)
Firm FE	Yes	Yes
Time dummies	Yes	Yes
SE clustered	firm, year	firm, year
Observations	19,832	19,832
Adjusted R-squared	0.581	0.666

This table reports the difference-in-differences (DID) regression results using alternative variable measurements. Column (1) reports the DID regression results using the number of segments in the firm's revenues (*NSEGMENTS*) as the dependent variable instead of *ENTROPY*. Column (2) reports the DID regression results using an alternative proxy of heavy emitters (*TOP5EMITTER*) following Ilhan *et al*. (forthcoming). Variable descriptions are provided in Appendix A. Standard errors are double-clustered by firm and year. *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10%, respectively.

Table 6. Stock return reaction to the main event as the firm-level proxy of heavy emitters.

VARIABLES	(1) *ENTROPY*	(2) *ENTROPY*	(3) *ENTROPY*	(4) *ENTROPY*
EVENT×CAR3D_DR	0.048***			
	(3.676)			
EVENT×CAR3D_NDR		0.048***		
		(3.677)		
EVENT×CAR5D_DR			0.041***	
			(3.194)	
EVENT×CAR5D_NDR				0.041***
				(3.188)
SIZE	0.023***	0.023***	0.022***	0.022***
	(2.762)	(2.762)	(2.712)	(2.711)
LEVERAGE	0.324***	0.324***	0.325***	0.325***
	(8.860)	(8.860)	(8.918)	(8.917)
ROA	0.004	0.004	0.001	0.001
	(0.075)	(0.075)	(0.013)	(0.016)
GROWTH	0.001	0.001	0.001	0.001
	(0.777)	(0.778)	(0.809)	(0.809)
TOBINSQ	0.002	0.002	0.002	0.002
	(0.600)	(0.600)	(0.644)	(0.636)
CO2EMISSION	0.005	0.005	0.005	0.005
	(0.853)	(0.853)	(0.834)	(0.834)
EPU	0.000**	0.000**	0.000**	0.000**
	(2.292)	(2.292)	(2.474)	(2.475)
GDP	-0.460	-0.460	-0.416	-0.415
	(-0.964)	(-0.965)	(-0.874)	(-0.871)
CPI	-0.013	-0.013	-0.023	-0.023
	(-0.067)	(-0.067)	(-0.115)	(-0.117)
UNEMPLOYMENT	-6.942	-6.942	-6.988	-6.993
	(-1.610)	(-1.610)	(-1.622)	(-1.623)
Constant	0.090	0.090	0.097	0.097
	(0.315)	(0.316)	(0.339)	(0.340)
Firm FE	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes
SE clustered	firm, year	firm, year	firm, year	firm, year
Observations	19,832	19,832	19,832	19,832
Adjusted R-squared	0.669	0.669	0.669	0.669

This table reports the difference-in-differences (DID) regression results using stock price reaction to the Paris Agreement as the firm-level measurement of carbon risk. We use cumulative abnormal returns (CAR) of Chinese stocks calculated using a 3-day and a 5-day windows around the event of China submitting its national climate action plan to UNFCCC on 30th June 2015. Column (1) reports the DID regression results using the 3-day dividend-reinvested CAR as the proxy for carbon risk of Chinese firms. Column (2) reports the regression results using the 3-day CAR without reinvesting dividend. Column (3) reports the regression results using the 5-day dividend-reinvested CAR. Column (4) reports the regression results using the 5-day CAR without reinvesting dividend as the alternative of EMITTER. Variable descriptions are provided in Appendix A. Standard errors are double-clustered by firm and year. *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10%, respectively.

Table 7. Diversification discount analysis

VARIABLES	(1) Equity firms (without diversification discount)	(2) Financial leveraged firms (with diversification discount)
EVENT×EMITTER	0.050**	0.032***
	(2.216)	(3.030)
SIZE	-0.007	0.037***
	(-0.440)	(6.349)
LEVERAGE	7.300***	0.158***
	(2.982)	(6.368)
ROA	0.012	-0.054
	(0.189)	(-1.341)
GROWTH	0.002	0.002**
	(0.949)	(2.102)
TOBINSQ	0.006**	-0.004
	(2.039)	(-1.609)
CO2EMISSION	0.012	0.004
	(1.126)	(1.162)
EPU	0.000	0.000***
	(0.672)	(2.880)
GDP	0.173	-0.464
	(0.210)	(-1.465)
CPI	-0.429	0.182
	(-1.091)	(1.324)
UNEMPLOYMENT	3.894	-3.765
	(0.441)	(-1.540)
Constant	0.106	-0.265
	(0.200)	(-1.491)
Firm FE	Yes	Yes
Time dummies	Yes	Yes
SE clustered	firm, year	firm, year
Observations	3,725	15,728
Adjusted R-squared	0.745	0.676

This table reports the sensitivity test results using different subsamples of firms regarding their diversification discount. The classification of firms follow Mansi and Reeb (2002)' studies in which the authors show that equity firms do not exhibit diversification discount while leveraged firms do. Columns (1) and (2) report the DID regression results using two subsamples of equity firms (firms with less than 1% debt financing) and other firms. Variable descriptions are provided in Appendix A. Standard errors are double-clustered by firm and year. *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10%, respectively.

Table 8. The role of pilot carbon markets

VARIABLES	(1) Firms in the pilot carbon market zones	(2) Firms outside of the pilot carbon market zones
EVENT×EMITTER	0.060***	0.021*
	(3.103)	(1.850)
SIZE	0.025***	0.040***
	(2.768)	(6.438)
LEVERAGE	0.224***	0.222***
	(5.538)	(8.303)
ROA	-0.035	-0.068*
	(-0.577)	(-1.645)
GROWTH	-0.000	0.003***
	(-0.008)	(2.767)
TOBINSQ	0.003	-0.001
	(0.894)	(-0.419)
CO2EMISSION	0.007	-0.003
	(1.182)	(-0.714)
EPU	0.000**	0.000***
	(2.482)	(3.785)
GDP	-0.248	-0.181
	(-0.483)	(-0.512)
CPI	-0.122	0.220
	(-0.522)	(1.379)
UNEMPLOYMENT	-7.905**	0.656
	(-2.025)	(0.222)
Constant	0.153	-0.534***
	(0.566)	(-2.715)
Firm FE	Yes	Yes
Time dummies	Yes	Yes
SE clustered	firm, year	firm, year
Observations	6,820	13,012
Adjusted R-squared	0.669	0.662

This table reports the results of the test of the role of pilot carbon markets in China. Columns (1) and (2) report the DID regression results using a subsample of firms in provinces having a pilot carbon market (Beijing, Chongqing, Guangdong, Hubei, Shanghai, Shenzhen, and Tianjin) versus a subsample of firms in other provinces. Variable descriptions are provided in Appendix A. Standard errors are double-clustered by firm and year. *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10%, respectively.

Table 9. **State intervention channel.**

VARIABLES	(1) Full sample	(2) Full sample	(3) Matched sample
EVENT×EMITTER×STATE_OWNERSHIP	0.161*	0.140**	0.174*
	(1.744)	(2.461)	(1.878)
EVENT×EMITTER	0.046***	0.024**	0.027**
	(4.583)	(2.386)	(2.153)
EVENT×STATE_OWNERSHIP	-0.066	-0.033	-0.073
	(-0.811)	(-0.868)	(-0.888)
EMITTER×STATE_OWNERSHIP	-0.007	-0.009	-0.006
	(-0.500)	(-0.708)	(-0.454)
SIZE		0.035***	0.022***
		(6.884)	(2.849)
LEVERAGE		0.221***	0.146***
		(9.918)	(4.506)
ROA		-0.057*	-0.046
		(-1.654)	(-0.951)
GROWTH		0.002**	0.002
		(2.296)	(1.379)
TOBINSQ		0.000	-0.002
		(0.230)	(-0.733)
CO2EMISSION		0.001	0.006
		(0.175)	(1.118)
EPU		0.000***	0.000
		(4.446)	(1.437)
GDP		-0.223	-0.518
		(-0.764)	(-1.177)
CPI		0.103	0.132
		(0.782)	(0.655)
UNEMPLOYMENT		-2.542	-7.093**
		(-1.077)	(-2.002)
Constant	0.436***	-0.289*	0.194
	(78.930)	(-1.818)	(0.805)
Firm FE	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes
SE clustered	firm, year	firm, year	firm, year
Observations	19,832	19,832	10,493
Adjusted R-squared	0.696	0.666	0.700

This table presents the difference-in-difference-in-differences (DDD) regression results of the state intervention as a policy transmission channel. Column (1) reports the reduced-form DDD regression results. Columns (2) reports the multivariate DDD regression results that include control variables. Column (3) shows the DDD regression results using the matched sample. *STATE_OWNERSHIP* is a dummy variable indicating whether there is state ownership in the firm. *t*-statistics are reported in parentheses. Variable descriptions are provided in Appendix A. Standard errors are double-clustered by firm and year. *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10%, respectively.

Table 10. Corporate innovation channel.

VARIABLES	(1) Full sample	(2) Full sample	(3) Matched sample
EVENT×EMITTER×R&D	-0.127***	-0.082***	-0.081***
	(-6.543)	(-4.027)	(-2.670)
EVENT×EMITTER	0.092***	0.053***	0.052***
	(8.386)	(4.269)	(3.320)
EVENT×R&D	0.082***	0.040***	0.049**
	(10.196)	(4.192)	(2.100)
EMITTER×R&D	0.023**	0.019*	0.011
	(2.137)	(1.687)	(0.950)
SIZE		0.032***	0.021***
		(6.186)	(2.594)
LEVERAGE		0.219***	0.147***
		(9.817)	(4.537)
ROA		-0.047	-0.035
		(-1.368)	(-0.724)
GROWTH		0.002**	0.002
		(2.325)	(1.361)
TOBINSQ		-0.001	-0.003
		(-0.755)	(-1.098)
CO2EMISSION		0.003	0.008
		(0.758)	(1.370)
EPU		0.000***	0.000
		(2.659)	(0.508)
GDP		-0.366	-0.670
		(-1.247)	(-1.488)
CPI		0.137	0.174
		(1.038)	(0.863)
UNEMPLOYMENT		-3.401	-7.665**
		(-1.429)	(-2.147)
Constant	0.386***	-0.188	0.258
	(193.758)	(-1.160)	(1.053)
Firm FE	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes
SE clustered	firm, year	firm, year	firm, year
Observations	19,832	19,832	19,832
Adjusted R-squared	0.655	0.666	0.666

This table presents the regression results of the corporate green innovation channel as the alternative to corporate diversification. Columns (1) and (2) reports the regression results. Column (3) shows the regression results using the matched sample. STATE is a dummy variable indicating whether there is state ownership in the firm. *t*-statistics are reported in parentheses. Variable descriptions are provided in Appendix A. Standard errors are double-clustered by firm and year. *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10%, respectively.

Table 11. Asset liquidation values channel.

	Industry-level investment irreversibility			Firm-level investment irreversibility		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Full sample	Full sample	Matched sample	Full sample	Full sample	Matched sample
EVENT×EMITTER×ALV_IND	0.080***	0.032***	0.034***			
	(8.673)	(3.092)	(2.674)			
EVENT×EMITTER×ALV_FIRM				0.102***	0.047***	0.048***
				(8.388)	(3.669)	(3.353)
SIZE		0.035***	0.023***		0.035***	0.022***
		(6.886)	(2.866)		(6.811)	(2.806)
LEVERAGE		0.220***	0.145***		0.220***	0.145***
		(9.890)	(4.480)		(9.890)	(4.505)
ROA		-0.059*	-0.049		-0.061*	-0.054
		(-1.715)	(-1.027)		(-1.801)	(-1.147)
GROWTH		0.002**	0.002		0.002**	0.002
		(2.276)	(1.334)		(2.240)	(1.289)
TOBINSQ		0.000	-0.003		0.001	-0.002
		(0.156)	(-0.827)		(0.331)	(-0.525)
CO2EMISSION		0.001	0.006		0.001	0.006
		(0.206)	(1.136)		(0.146)	(1.046)
EPU		0.000***	0.000		0.000***	0.000*
		(4.456)	(1.482)		(4.846)	(1.945)
GDP		-0.233	-0.522		-0.210	-0.475
		(-0.803)	(-1.195)		(-0.728)	(-1.101)
CPI		0.104	0.129		0.103	0.127
		(0.792)	(0.640)		(0.782)	(0.633)
UNEMPLOYMENT		-2.583	-7.141**		-2.461	-6.780*
		(-1.094)	(-2.016)		(-1.044)	(-1.925)
Constant	0.394***	-0.287*	0.193	0.395***	-0.286*	0.186
	(223.191)	(-1.809)	(0.803)	(226.421)	(-1.797)	(0.774)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
SE clustered	firm, year	firm, year	firm, year	firm, year	firm, year	firm, year
Observations	19,832	19,832	10,493	19,832	19,832	10,493

Adjusted R-squared	0.657	0.666	0.699	0.656	0.666	0.700

This table presents the regression results of the asset liquidation values channel. We borrow the idea from Gulen and Ion (2016) to proxy asset liquidation values using the correlation between firms' operating revenue and China's Gross National Product (GNP) at industry-level (*ALV_IND*) and firm-level (*ALV_FIRM*). *ALV_IND* is a dummy variable that equals one if the industry (firms)'s correlation with GNP is higher than its median, and zero otherwise. Columns (1) to (3) report the regression results using the *ALV_IND* as the measure of asset liquidation values. Columns (4) to (6) report the regression results using *ALV_FIRM* as the measure of liquidation values. Variable descriptions are provided in Appendix A. Standard errors are double-clustered by firm and year. *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10%, respectively.

Appendix A1. Carbon intensive industries

A. Carbon intensive industries following definition of CDP (2012) and Nguyen and Phan (2020)	
GICS Industry name	**GICS Industry code**
Chemicals	151010
Construction Materials	151020
Electric Utilities	551010
Gas Utilities	551020
Independent power producers and energy traders	55105010
Metals and mining	151040
Multi-utilities	551030
Oil, gas, and consumable fuels	101020
Paper and forest products	151050
B. Top 5 S&P 500 sectors by Scope 1 Carbon emission/MV (Ilhan *et al*., forthcoming)	
GICS Industry name	**GICS Sector code**
Utilities	55
Energy	10
Materials	15
Industrials	20
Consumer staples	30

Appendix A2. Variable description

Variable	Description	Data source
Variables used in the baseline regression and sensitivity tests		
ENTROPY	Entropy index as the proxy for corporate diversification	WIND
NSEGMENTS	Number of segments of the firm	WIND
EVENT	Dummy variable that equals one if the current firm-year observation is from 2015 onwards and zero otherwise.	
EMITTER	Dummy variable that equals one if the firm is a heavy emitter and zero otherwise. Emitter definition follows Nguyen and Phan (2020).	
TOP5EMITTER	Dummy variable that equals one if the firm is a heavy emitter and zero otherwise. Emitter definition follows Ilhan *et al*. (forthcoming).	
CAR3D_DR	Dummy variable that equals one if the cumulative abnormal return (dividend reinvested) of the firms for the 3-day window (from t-1 to t+1) around the date China submitted its climate action plan to UNFCCC on 30th June 2015 is negative, and zero otherwise.	CSMAR
CAR3D_NDR	Dummy variable that equals one if the cumulative abnormal return (without dividend reinvested) of the firms for the 3-day window (from t-1 to t+1) around the date China submitted its climate action plan to UNFCCC on 30th June 2015 is negative, and zero otherwise.	CSMAR
CAR5D_DR	Dummy variable that equals one if the cumulative abnormal return (dividend reinvested) of the firms for the 5-day window (from t-3 to t+1) around the date China submitted its climate action plan to UNFCCC on 30th June 2015 is negative, and zero otherwise.	CSMAR
CAR5D_NDR	Dummy variable that equals one if the cumulative abnormal return (without dividend reinvested) of the firms for the 5-day window (from t-3 to t+1) around the date China submitted its climate action plan to UNFCCC on 30th June 2015 is negative, and zero otherwise.	CSMAR
SIZE	Natural logarithm of book value of total assets.	CSMAR
LEVERAGE	Long-term debt scaled by total assets.	CSMAR
ROA	Net income divided by average total assets.	CSMAR
GROWTH	Total operating revenues' growth rate.	CSMAR
TOBINSQ	Tobin's Q ratio.	CSMAR
CO2EMISSION	China's total CO2 emission during the year.	Our World In Data
EPU	China's annualized Economic Policy Uncertainty Index (Baker *et al*., 2016).	Baker *et al*. (2016)

GDP	China's real GDP growth rate during the year.	World Bank
CPI	China's Consumer Price Index during the year.	World Bank
UNEMPLOYMENT	China's unemployment rate during the year.	World Bank
Variables used in additional analysis and mechanism tests		
STATE_OWNERSHIP	Dummy variable that equals one if the firms have state ownership and zero otherwise.	CSMAR
ALV_FIRM	Proxy of asset liquidation values at firm-level, calculated as the correlation between the firm's operating revenues and China's GNP.	CSMAR and Macrotrends
ALV_IND	Proxy of asset liquidation values at industry-level, calculated as the correlation between the industry's average *ALV_FIRM*, as suggested by Gulen and Ion (2016).	CSMAR and Macrotrends
R&D	Dummy variable that equals one if the firm's R&D expenditure on sales ratio is above the median and zero otherwise.	Bloomberg

Appendix A3. Testing the pre-treatment parallel trend assumption of the difference-in-differences analysis

The pre-treatment parallel assumption states that if corporate diversification of two groups are systematically different in the absence of the treatment effect (the Paris Agreement), then the findings drawn from the difference-in-differences (DID) regression results are invalid (Nguyen and Phan, 2020). Therefore, it is necessary to test the pre-treatment parallel trend assumption of our DID analysis. Using a matching procedure, for example, the propensity score matching might be a solution to mitigate the unobserved factors and mechanisms that drive the differences between the treatment group and the control group. Apart from the propensity score matching method, we construct a falsification test of pre-treatment parallel assumption as follows:

$$ENTROPY_{i,t} = \alpha + \sum_{t-4}^{t} \beta_n EVENT_n \times EMITTER_i + CONTROL + \varepsilon_i \quad \text{(A3.1)}$$

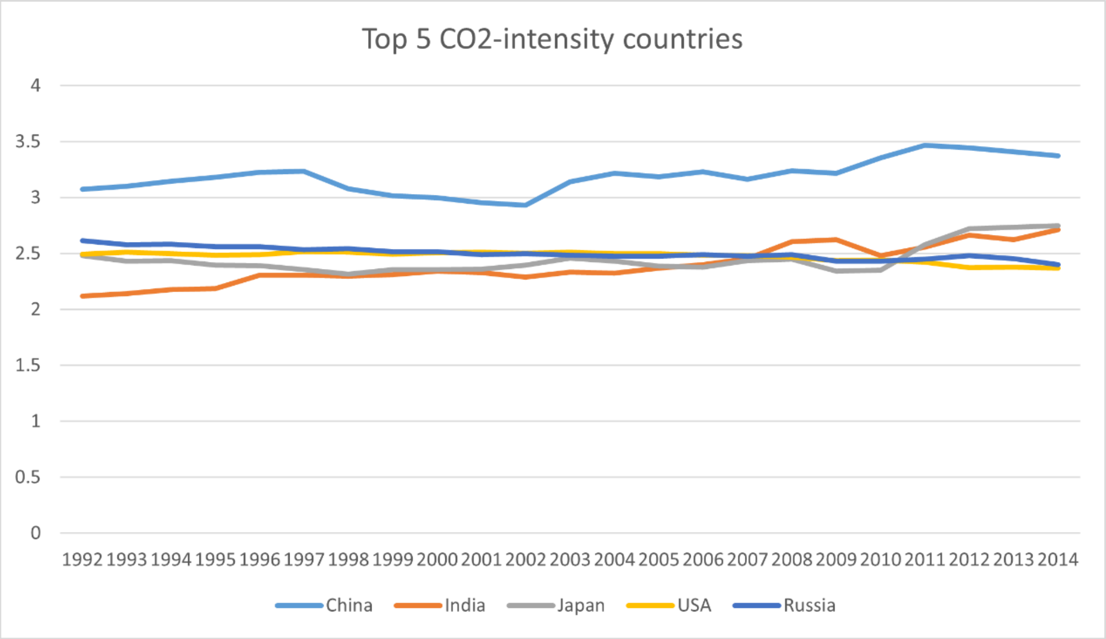
where *EMITTER* is the dummy variable that equals one if the firm is in the treated group (heavy emitter) and zero otherwise (light emitter). The *EVENT* dummy variable equals one if the current firm-year observation is from 2015 onward (the year when China submitted its national climate action plan to the Paris Agreement) and zero otherwise. The dependent variable is the Entropy Index (*ENTROPY*). The coefficients of the interaction terms $EVENT_{t-4} \times EMITTER$, $EVENT_{t-3} \times EMITTER$, $EVENT_{t-2} \times EMITTER$, and $EVENT_{t-1} \times EMITTER$ reflect the pre-treatment trend of corporate diversification between two emitter groups. If those coefficients are statistically significant, it means that there are other factors or events affecting the difference in corporate diversification between heavy and light emitters before the Paris Agreement. In that case, the pre-treated parallel trend assumption might not hold for our DID regression.

The control variables are those included in the baseline model. Variable descriptions are provided in Appendix A1. The test results are reported as follows:

VARIABLES	(1) Full sample	(2) Matched sample
$EVENT_{t-4}$×*EMITTER*	0.015	0.018
	(0.949)	(0.910)
$EVENT_{t-3}$×*EMITTER*	-0.019	-0.030
	(-1.289)	(-1.614)
$EVENT_{t-2}$×*EMITTER*	-0.005	-0.012
	(-0.399)	(-0.742)
$EVENT_{t-1}$×*EMITTER*	-0.003	-0.006
	(-0.254)	(-0.309)
$EVENT_{t}$×*EMITTER*	0.018*	0.016*
	(1.796)	(1.755)
SIZE	0.034***	0.021***
	(6.718)	(2.691)
LEVERAGE	0.222***	0.147***
	(9.954)	(4.544)
ROA	-0.041	-0.028
	(-1.193)	(-0.581)
GROWTH	0.002**	0.002
	(2.144)	(1.205)
TOBINSQ	0.000	-0.003
	(0.121)	(-1.107)
CO2EMISSION	-0.001	0.007
	(-0.192)	(0.875)
EPU	0.000***	0.000
	(4.829)	(1.642)
GDP	-0.326	-0.978*
	(-1.033)	(-1.667)
CPI	0.109	0.146
	(0.807)	(0.686)
UNEMPLOYMENT	-1.410	-5.140
	(-0.594)	(-1.406)
Constant	-0.319**	0.141
	(-2.001)	(0.582)
Firm FE	Yes	Yes
Time dummies	Yes	Yes
SE clustered	firm, year	firm, year
Observations	19,832	10,494
Adjusted R-squared	0.666	0.700

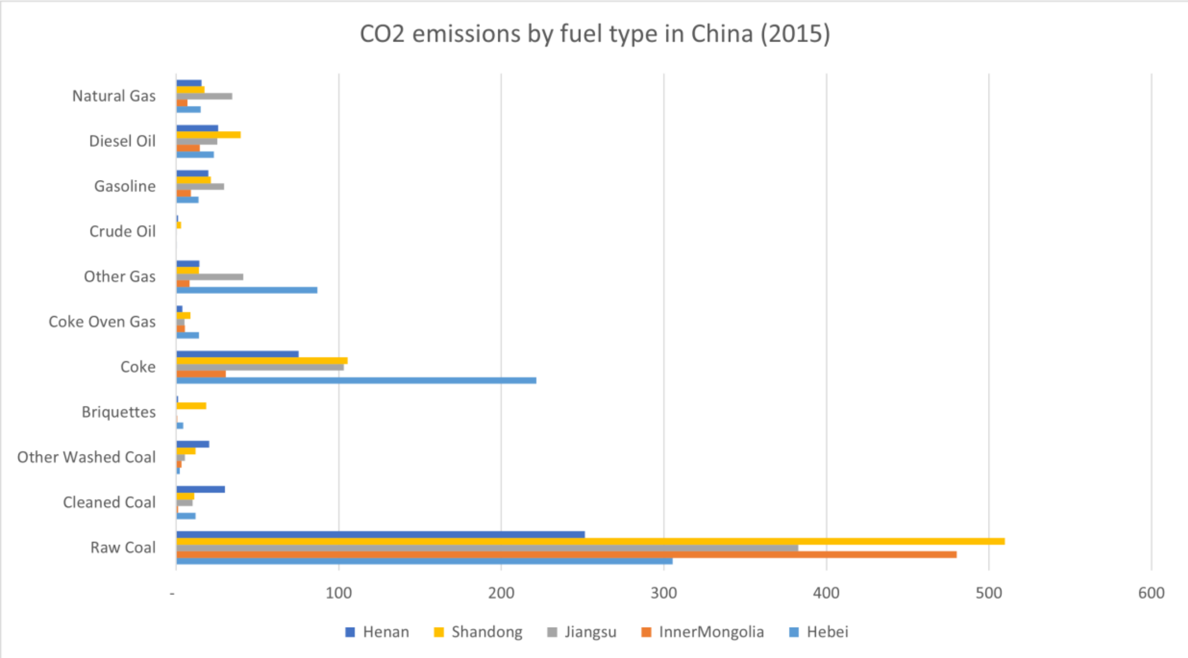
Standard errors are double-clustered by firm and year. *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10%, respectively.

Using the full sample and the matched sample generated from propensity score matching, we conduct the falsification tests. The results show that the coefficients of the interaction terms $EVENT_{t-4}$×*EMITTER*, $EVENT_{t-3}$×*EMITTER*, $EVENT_{t-2}$×*EMITTER*, and $EVENT_{t-1}$×*EMITTER* remain insignificant in both the full sample regression and the matched sample regression. This means that the pre-treatment parallel trend assumption holds and our DID regression results are valid.



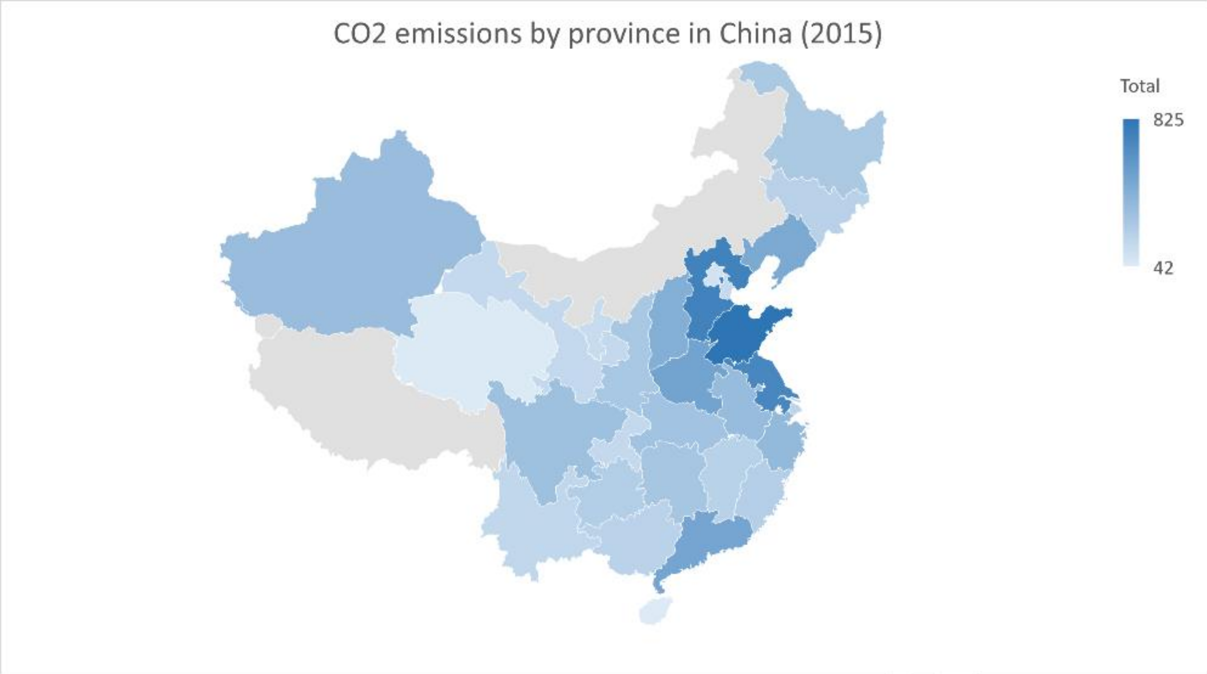
(Unit: *metric tons per GDP unit* - Source: *World Development Indicator*)

Figure 1. Top 5 of carbon-intensity countries over the 1992-2014 period.



(Unit: million tons - Source: China Emission Accounts and Datasets)

Figure 2. Carbon dioxide emission by different fuels in China (2015)



(Unit: million tons - Source: China Emission Accounts and Datasets)

Figure 3. Carbon dioxide emissions by province in China in 2015.

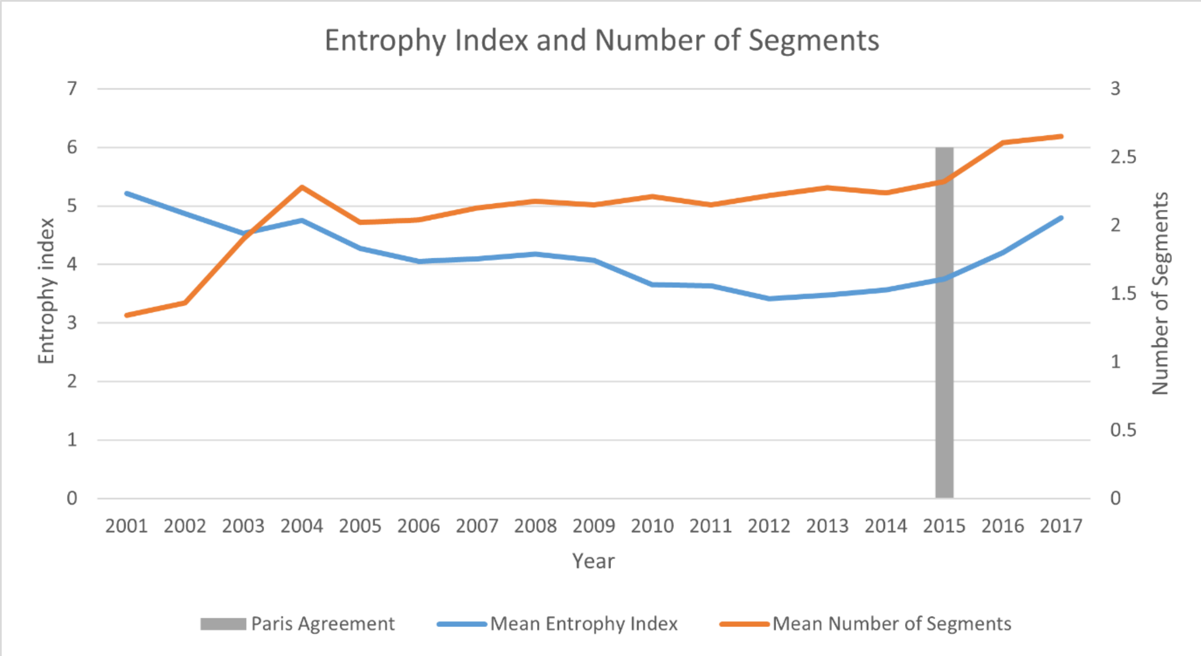


Figure 4. The average Entropy Index and the number of revenue segments of China firms during the study period.