# Financing Climate Change Mitigation Projects: Cost and Environmental Performance of Government Green Bonds*

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**Abstract:**

Many nations use government bonds to finance climate change mitigation projects. Since 2018, Chinese local governments have identified 'local green projects' and raised funds using local bonds. We find that primary dealers win with different rates for six green bond types compared to regular bonds. As the Central Government backs these bonds, revenue rankings could be interpreted as a direct indicator of willingness to pay for green goods. This research also suggests that dealers may be motivated to acquire green bonds as it positively influences their Environmental, Social, and Governance (ESG) scores, contributing to their long-term viability. While the counterfactually calculated cost of green bonds to the government is minimal, the study finds a correlation between the revenues from green bonds and improvements in local environmental outcomes, indicating a positive impact on both the market and environmental sustainability.

**JEL Classification:** G14, G18, Q52, Q54

**Keywords:** Climate Change; Green Bonds; Sustainable Finance; Willingness to Pay.

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## 1. Introduction

Climate change and environmental degradation have been high on the public and political agenda in recent years, given the damage that they cause to society.[1] Governments, businesses, and civil society members are engaged in climate change mitigation initiatives to reduce greenhouse gas emissions and remove them from the atmosphere. As a result, nations have signed several international treaties to coordinate their actions to prevent emissions linked to human activities, such as the Kyoto Protocol, United Nations Framework Convention on Climate Change, International Carbon Action Partnership, and others. However, compliance with emission-reduction targets has been mixed, with several countries undershooting their targets (see de Silva and Tenreyro, 2021.)

In 2015, 196 nations negotiated and adopted the *Paris Agreement* at the United Nations Climate Change Conference, the most recent agreement to fight climate change.[2] The agreement aims to help countries adapt climate change efforts and mobilize enough finance. Under the agreement, no uniform global mechanism forces a country to set specific emissions targets or suggests how to finance them. Adopting the agreement is costly and one estimate suggests that keeping the world below the 2-degree Celsius scenario will require $12 trillion over the next 25 years (Bloomberg New Energy Finance, 2015).

[1] Climate change and environmental degradation deteriorate human health (Deschênes et al., 2009; Currie and Neidell, 2005; Chen et al., 2013; Landrigan et al., 2018), reduce economic growth (Nordhaus, 2006; Dell et al., 2012; Carleton and Hsiang, 2016), and increase social instability (Burke et al., 2010; Hsiang et al., 2013), among other effects.

[2] As of November 2021, 193 members of the United Nations Framework Convention on Climate Change (UNFCCC) have committed to the agreement. Out of the four UNFCCC members that have not ratified the agreement, the only major emitter is Iran. Also, note that the United States withdrew from the Agreement in 2020 but rejoined in 2021.

Bond markets have been central to financing these government interventions for many nations. For example, China, one of the largest emitters of greenhouse gases (GHG), signed on to the Paris Agreement on April 22 2016. During the signing ceremony, they emphasized three targets.[3] First, China would join the Paris Agreement and would complete the legal proceedings before September 2016. Second, China promised to achieve the Carbon Peak in 2030. Based on the 13th Five-Year Plan, carbon emissions would decrease by 18% over the next five years. Finally, China would attend the post-Paris Agreement negotiations.

To achieve these goals and improve overall environmental quality, starting in 2018, the Central Government allowed local (provincial) governments to identify 'local green projects' and raise funds using local government green bonds backed by the Central Government. These local government green bonds cover six primary categories: 1) energy conservation, 2) pollution prevention and control, 3) resource conservation and recycling, 4) green transportation, 5) green energy, and 6) ecological protection and adaptation to climate change. The natural questions are as follows: 1) Is the green bond market competitive? 2) Why do bidders buy green bonds, and what is their '*willingness to pay*' for green financing compared to regular bonds? 3) What is the cost to the government? and 4) Is the policy effective in reducing GHG?

Hence, in this paper, using transaction-level data from 2,762 auctions from the newly created provincial (local) government bond market, we first examine whether there are any

[3] Minister of Foreign Affairs of the People's Republic of China.
https://www.mfa.gov.cn/web/ziliao_674904/zyjh_674906/201604/t20160423_9869836.shtml

differences in competition (the number of submitted bids in an auction) between green and non-green bond auctions. Next, we compare the revenue ranking between green and non-green bonds issued by the 31 Chinese local governments. Further, our data allow us to identify the green bond categories defined above, including unclassified 'regular bonds.' We can also identify transportation bonds classified as regular transportation (non-green). We have a unique opportunity to directly compare green and non-green transportation bond revenues. Note that all bonds are auctioned off using the uniform auction format. Note that all the local bonds in China are backed by the Central Government. Therefore, they are identical in terms of the default risk involved. Consequently, these revenue rankings can be interpreted as a direct indicator of willingness to pay (WTP) for green goods. Next, we provide possible reasons why primary dealers purchase green bonds. We also examine the cost for the government to raise funds using green bonds compared to using regular bonds to raise similar funds. Finally, we analyze the efficacy of green bonds on local pollution outcomes.

Note that our data trace back to the inception of this market, including the pilot program conducted in 2011 by four provinces (Shanghai, Zhejiang, Guangdong, and Shenzhen) on the administrative feasibility of selling provincial bonds.[4] All local governments were allowed to issue bonds independently in 2015 to fund their local projects (Li and Qian, 2017; Shen and Cao, 2010). In a nutshell, our analysis is based on about 562 billion renminbi (¥) (approximately $83.4 billion) worth of green bonds and more than ¥9.89

[4] In 2013-2014, Jiangsu, Shandong, Beijing, Jiangxi, and Ningxia were added to the list of pilot provinces.

trillion (approximately $1.46 trillion) worth of regular bonds. This setup provides an opportunity to observe primary dealers entering a provincial market and compare their bidding behaviors to incumbents. Further, as we observe this market from its origins, we construct a proxy for bidder experience using a primary dealer's past number of wins. The results indicate that experienced bidders bid more aggressively (by about six basis points.)

Our results indicate that, on average, green bond rates are about a basis point higher than non-green bonds. Note that, as in Hortaçsu et al. (2018), we normalized the auction yield rate constructed as the auction winning rate minus the prior day's corresponding market yield of Chinese treasury bonds based on maturity. However, a deeper examination into revenues by green bond types reveals that primary dealers win with low rates for green transportation (about ten basis points) and green energy (about six basis points) bonds, yielding higher revenues for local authorities, while winning with high rates for energy conservation (about seven basis points), ecological protection bonds (about three and a half basis points), and pollution prevention (about four and a half basis points) yielding lower revenues for local authorities. Further, when comparing green and non-green transportation bonds, we observe that bidders bid more aggressively on green transportation bonds with rates about ten basis points lower than regular transportation bonds. We do not observe any statistical difference between the winning rates of bonds used for green recycling projects and non-green projects. As the Central Government backs all local bonds in China, we interpret these revenue rankings as a direct indicator of willingness to pay (WTP) for green goods. We also show evidence that dealers may be willing to purchase these green bonds as they help them survive and qualify to continue in the market in addition to policy dividends.

While the cost for the government is about one percent of all bonds, summary results show that by 2020, compared to 2005 to 2015 averages, China has been able to reduce provincial averages of nitrogen oxides ($NO_X$) and sulfur dioxide ($SO_2$) by 40 and 75 percent, respectively, while improving forests and water resources by 10 and 37 percent, respectively (see Figures 1 and 2). Additionally, we empirically analyze how local-level environmental outcomes evolve after the issuance of green bonds. Using yearly provincial-level data on carbon dioxide (CO2), SO2, $NO_X$, water resources, and forest areas gathered from the National Bureau of Statistics of China, we estimate the relationship between these local environmental outcomes and their share of green bonds issued. We find that the issuance of energy conservation bonds has reduced per capita $CO_2$ emissions. Further, the issuance of green transportation and green energy bonds has helped reduce per capita $SO_2$ and $NO_X$ emissions. This is somewhat expected as $CO_2$, $SO_2$, and $NO_X$ emissions are highly correlated with transportation and energy production using fossil fuels. Forest resources have improved with investment in pollution prevention and recycling projects. These findings are consistent with the idea that the issuance of green bonds is a successful policy to achieve environmental goals. These findings are important for policymakers implementing and financing climate mitigation measures.

We also contribute to the growing literature on green bonds. Several studies have addressed the effects of non-pecuniary incentives on bond yield differentials. Green bonds, whose funds are used to improve the environment, are considered a good indicator for examining investors' behaviors in green bond markets. However, the conclusions on the yield difference between green and ordinary bonds are ambiguous. Using US municipal securities data, Larcker and Watts (2020) examined investors' preferences for green bonds and showed a minimal price differential between green and regular bonds. Likewise, Flammer (2021) compared corporate green and non-green bonds and found no difference. Zerbib (2019) found a two-basis point difference between green bonds and corresponding conventional bonds but argues that this difference is too small to indicate investors' preference for green bonds. In addition, Menz (2010) investigated the relationship between corporate social responsibility (CSR) and bond issuance rates and demonstrated that CSR has no effect on the cost of debt for companies.[5]

On the other hand, Baker et al. (2018) studied bonds whose proceeds were used to support US municipal environmental projects. They found that green bond yields were lower than ordinary bond yields (also see Karpf and Mandel, 2017). Conversely, Diaz and Escribano (2021) observed that green bond issuers obtained lower debt costs than non-green issuers. Their results are consistent with Oikonomou et al. (2014), who established the link between the bonds' risk and their corporate social performance (CSP) and found that companies with high CSP ranking can lower their debt cost.

[5] However, they indicated that this may be due to the fact that the proxy they used to measure the CSR is not ideal.

Our paper also contributes to the literature on the WTP for environmental initiatives. Considering WTP literature in the green bond market, Lau et al. (2022) developed a theoretical framework to examine the greenium in the bond market. They found that investors are unwilling to pay for green bonds. They show that the premium of a green bond essentially represents a combination of the non-pecuniary environmental benefit of the bond, as perceived by the investor, and the effective cost of issuing it, as measured by the additional issuing costs of the bond netted off a range of monetary and non-monetary benefits associated with the issuance. Using a survey, Zenno and Aruga (2022) introduced a contingent valuation method and found that institutional investors' WTP for green bonds is about 0.47 percent lower (yield) than conventional bonds. Similarly, using a survey, Aruga (2022) investigated the retail investors' WTP for green bonds in Japan and found that investors' expectation of an annual return on green bonds is about 1.1 percent—lower than for ordinary assets.

Further, a few studies have investigated the effect of bond issuers' institutional types and third-party certification on investors' WTP for green bonds. For example, Fatica et al. (2021) found that investors are willing to pay a premium on green bonds if the issuers are supranational institutions and corporations. Further, green bonds with third-party certification yielded more for issuers than self-labeled green bonds. Wang et al. (2019) studied the factors that affect the green bonds' risk premium by using Chinese green corporate bonds and found that third-party certification on green bonds can reduce the risk premium.

In the next section, we provide the institutional background of the Chinese local bond market. Section 3 describes the data and estimates auction outcomes in Section 4. We analyze primary dealers' secondary-market returns and provide possible reasons to purchase green bonds in Section 5. We assess the revenue difference in Section 6 and examine provincial-level pollution outcomes in Section 7. We conclude the paper in Section 8.

## 2. Chinese local government bonds

### 2.1. The development of local government bonds

In China, before 2009, local governments were prohibited from issuing bonds unless authorized by law or the State Council (The Budget Law of the People's Republic of China, 1994).[6] Expansionary fiscal policies were introduced by the Central Government in 2008, but local governments found it difficult to implement these policies due to lack of funds. As a result, the Central Government decided to allow local governments to issue their own bonds in 2009 (Jin et al., 2009.)

These bonds were backed by the Chinese Ministry of Finance (MOF) and have the same credit ratings as government securities issued by the MOF as a benchmark reference.[7] In 2011, the State Council approved four provinces—Shanghai, Zhejiang, Guangdong, and Shenzhen—as pilot provinces to issue bonds independently. In 2013 and 2014, Jiangsu,

[6] The 28th rule in *The Budget Law of the People's Republic of China*

[7] In February 2009, the Chinese MOF noted, in their official document, *The Budget Management of Local Government Bonds in 2009*, that all local government bonds and their issuing fees are issued and paid by the Chinese MOF on behalf of local governments.

Shandong, Beijing, Jiangxi, and Ningxia were added to the list of pilot provinces. The Central Government allowed all local governments to issue bonds independently in 2015 (Li and Qian, 2017; Shen and Cao, 2010).

### 2.2. The development of green bonds in China

Over the past 30 years, the Chinese economy has been growing rapidly, but it has also been restricted by and criticized for the lack of attention to pollution. For many nations, financing projects related to pollution prevention and ecological protection has been difficult compared to other investment opportunities. However, in his report to Congress (2012), the former President of China, Jintao Hu promoted economic growth with overall societal balance and harmony, including ecological awareness.[8]

With this as a reference point, in 2014, the International Finance Corporation issued the first green bond in ¥ currency. Next, CGN Wind Energy Limited issued "carbon bonds" in the domestic bond market on May 08 in the same year. Both are predecessors of current Chinese green bonds. By the end of 2015, the Chinese government promulgated the process of issuing green bonds and stipulated the contents of projects to be supported by these green bonds. As defined in the introduction, green bonds are pricing securities issued by financial organizations to raise funds to support green projects. In 2016, the Chinese green bond market increased sharply, and China became the largest green bond-issuing market in the world (Yu & Li, 2017).

With China joining the Paris Agreement, the provinces focused on a targeted

[8] Jingtao Hu's report at 18th Party Congress, 2012.11.08.

approach to reducing pollution, increasing access to clean water, recycling facilities, and ecological awareness. Hence, in 2018, local governments first issued local green bonds. From 2018 to 2021, local government green bonds increased by 74 percent. Local government green bonds cover all six primary categories mentioned before. For example, Shandong province issued a green bond in 2019 under the energy conservation category (bond id: 1905086.IB) to update the heating system in Qingdao city. Shenzhen city issued a green bond (bond id: 1805299.IB) to deal with water pollution in 2018. In the same year, Guangdong province issued a green bond to allocate water resources in the Pearl River Delta (bond id: 1805197.IB.) Based on the official documents, this bond falls within resource recycling. Hubei province issued a green bond (bond id: 1805231.IB) to raise funds to construct the urban rail transit system in its capital city, Wuhan. In the fifth category, Shanxi province issued bonds to support infrastructure construction of clean energies (bond id: 1905193.IB). In the last category, local governments issued green bonds to protect natural ecological resources, like bonds for the ecological construction of the Guangdong-Hong Kong-Macao Greater Bay Area issued by Guangdong Province (bond id: 104620.IB; 1905218.IB and 1905219.IB and 1905220.IB.)

### 2.3. Auction rules

Provinces are required to follow strict security issuance guidelines set by the People's Bank of China. Local Governments must release bond information such as maturity, volume, credit rating, and bond type (green or regular) five days before the bond issuance.[9] Note that all bonds are sold using uniform auction format. This public information is posted on Chinabond.com and the government website. Further, the local government has to display the current local economy and debt volumes on its public website. Local MOFs published the auction results on their websites when the auctions were completed. Primary dealers needed to settle within three business days after the auction and the local government needed to pay the issuance fee to dealers within five business days after the settlement.

For example, consider two auctions. Once the first auction's transactions are settled and the outcome is made public, the institutions only announce the specific details of the second auction. Hence, two auctions in the same local government never overlap. On average, the time gap between two auctions in the same local government is 40 days. However, the time gap between different provincial governments is about two days, and about 95 percent of auctions fall within five days. Researchers use the bid-to-cover ratio as a measure of auction competitiveness (for example, see Gordy, 1999; Goldreich, 2007; Barbosa et al, 2022). In our study, the bid-to-cover ratio is about 13.5, indicating that the auctions are very competitive. Importantly, the primary market rules set by the Central Government prohibit issuers from subscribing or subscribing in disguised financial bonds issued by themselves. Further, all potential bidders are required to submit both rate and quantity when submitting bids, and all tenders are treated as competitive bids.

[9] Note that all local government bonds have homogeneous credit ratings within each year as all government securities are backed by the MOF categorized equivalently. The credit ratings are awarded by three foreign agencies: Moody's, Standard & Poor's, and Fitch.

All primary dealers must be prequalified and registered with each local government to bid in these auctions. The prequalification process is similar in all provinces and is similar to the rigorous prequalification requirements one must satisfy to bid in MOF auctions. Moreover, past performance influences continuation as a primary dealer. For example, in 2015, Guangdong's local government standards (Standards of Auctions and Payment of Guangdong General Bonds, 2015) were comparable to Central Government policies. In their specification, Guangdong's local government built a qualified primary dealers' group for 2015-2017 based on dealers' capital storage, solvency, and net capital. Further, the MOF required Guangdong's local government to set the number of qualified primary dealers as more than 15. Participating in these auctions is strictly voluntary. However, in these local bond auctions, primary dealers are required to be active bidders and win a substantial amount of local bond auctions to retain their primary dealership status in the future.

## 3. Data

### 3.1. Provincial auction market data

We obtain data on the provincial Chinese bond market from two data sources—the Wind Database and China Central Depository & Clearing Co., Ltd. (CCDC). The Wind Information Co. Ltd., an entity that provides financial data and information, maintains the Wind Database. CCDC is a State Council-authorized agency (also approved by the China Banking Regulatory Commission) that records all government bond-related transactions, including provincial trades. Also, CCDC is the only government bond depository authorized by the MOF and is responsible for establishing and operating the government bond depository system.

The Wind Database provides access to details of the provincial bond auctions. Our data contain bond specific information such as bond ID, maturity, auction method, size of the auction, tender subjects (e.g., price or yield), the auction outcomes of winning yield rate (or price), allotment per auction, number of bidders, number of bids, number of winning bids, number of winners, final coupon rate for each auction, and the highest and lowest losing and winning rates. We also know the unique bidder ID, their corresponding submitted bid quantities for securities, and their winning or losing status. Being able to identify potential primary bidders is important as it allows us to identify the differences in winning rates when they bid in green and regular bonds. Further, it allows us to identify this market's entrants and incumbents by province. Following De Silva et al. (2003, 2009), we define any bidder who has bid in an auction in a given province before August 2018 as an incumbent. Any potential dealer observed for the first time in a province since August 01, 2018, as an entrant and their subsequent participation in that province are treated as activities by incumbents. Further, we collect supplementary information from Chinabond.com. These data provide auction-level information such as bond types, subsidies, coupon payments, and the date of each bond issued by the province. The definitions of the variables used in this paper are in Table A.1. in the Appendix.

### 3.2. Data summary

In the analysis, we use data from August 2018 to September 2020. The start time of August 2018 represents the first instance we observe green bonds in the market. Table 1 reports the summary statistics for regular and green bonds issued by Chinese local governments. We observe 2,440 regular bonds and 322 green bonds in our sample.[10] When considering the six categories of green bonds, we observe 11 energy conservation bonds, 81 pollution prevention bonds, six recycling bonds, 55 green transportation bonds, nine green energy bonds, and 160 ecological protection bonds. We also observe that primary dealers submitted 26,919 bids for regular bonds and 3,445 bids for green bonds. In green bonds, ecological protection attracted 1,704 bids, while pollution prevention and green transportation attracted 925 and 576 bids, respectively. In our sample, the total value of regular bonds is about ¥9.89 trillion, while the total value of green bonds is about ¥562 billion. When considering different types of green bonds, ecological protection (¥309 billion) and green transportation (¥161 billion) bonds have the largest values. The green energy bonds have the smallest value—about ¥5.064 billion.

Finally, we also report the winning rates for bond types—our main outcome variable. The average winning bid rate is 3.211 for regular bonds and 3.206 for green bonds. We also depict distributions of winning rates by bond type in Figure 3. The probability density functions cross in multiple auctions, which makes it obvious that there is no clear stochastic dominance relation between regular or green bonds. However, we need to be cautious in

[10] We also observe 123 partial green bonds which we will not use in our analysis. However, we used these 123 auctions to construct bidder-specific experience measures and province-level value of maturing bonds.

interpreting them as they are not controlled for any auction and market characteristics. In Table 1 Column 5, we report the average market yield of the Central Government bonds a day before the auction date. According to Section II of the province standards of local government bond issuance documents, provincial governments use the Central Government's day before the auction date's treasury bond average rate (by maturity) as the benchmark. This market yield rate is the one we take to normalize bids. Similarly, we report the average winning bid rate and market yield for different green bonds.

Table 2 reports summary statistics for auction characteristics, market controls, and dealer specific characteristics. For all auctions, there are, on average, 22.484 bidders and 23.32 potential bidders. We observe a similar number of bidders for regular bond auctions (22.342) and green bond auctions (23.562.) Out of all auctions, 11.7 percent of bonds are green bonds. Out of the six categories, 5.8 percent belong to ecological protection bonds. As noted in Column 3, almost half of the green bonds are ecological protection bonds (49.7 percent). The mean of the market yield of local government bonds one day before the auction day for all auctions is 3.189. The average market yields for regular and green bonds are 3.188 and 3.193, respectively. The durations for all, regular, and green bond auctions are 6.262, 6.111, and 7.412, respectively.[11] Also, we calculate the time lags between auctions for the same provinces. The average time lag for all auctions for the same province is 40.778 days. The time lag for regular bonds is 40.616 days, and it is 42.003 days for green bonds. In

[11] The duration refers to the Macaulay duration which is the weighted average term to maturity of the cash flows from a bond. A similar duration variable is used by Simon (1994).

addition, we report the average time lags for local government bond auctions, ignoring provinces. This time gap is 2.161 days for all auctions, 2.148 days for regular bonds, and 2.270 days for green bonds. The mean of the five-day volatility is 0.015 for all auctions, 0.015 for regular bonds, and 0.013 for green bonds.

Since bond reserves affect dealers' participation, we construct the value of the maturing bonds by the local government for each month for all, regular, and green bonds, respectively. On average, ¥48.956 million bonds mature in a given month by province. We also separately report these values for regular bonds (¥50.127 million) and green bonds (¥40.084 million). When considering the bid-to-cover ratio as a measure of competition, means are similar in all, regular, and green bond auctions—13.629, 13.489, and 14.691, respectively (for example, see Gordy, 1999 and Goldreich, 2007).

When considering bidder characteristics, we first identify entrant and incumbent dealers. De Silva et al. (2003, 2009) noted that entrants have less experience and less knowledge about the local market. Hence, we hope to control for asymmetries arising from these dealer groups by identifying these types of potential bidders. In our sample, we observe 6.7 percent potential entrants for all auctions. Further, we identify incumbent bidders who face these entrants in auctions as potential bidders. These incumbents also face asymmetries as they face new bidders they know little about. In our sample, we observe that about 31.4 percent of potential bidders face entrants. Our summary statistics show that entrants and incumbents facing entrants bid less aggressively compared to incumbents who do not face entrants. We show these unconditional bidding patterns in Figure 4. Next, we control for experience by counting the number of winning bids a dealer has submitted in the past. As bidders gain market experience, they tend to bid more aggressively (De Silva et al., 2003; De Silva, 2005.) These kinds of asymmetries have not been addressed in the bond market literature.

Table 3 reports the auctions and primary dealers' bidding patterns by province. In the first two columns, we list the number of all bond auctions and the number of green bond auctions for 31 provinces in China. Guangdong's provincial government conducted the most auctions during our analysis period (274); 72 out of 274 were green bond auctions. The Anhui, Beijing, Chongqing, and Jiangsu provincial governments did not auction green bonds during the sample period.

In the third column, we provide the number of dealers located in the same province as the government bond issuers (local dealers). Guangdong province and Sichuan province have the most home members in their dealer groups, while Shanghai and Beijing have only one home member in their dealer groups. In the fourth column, we report the number of unique registered dealers. Yunnan province has the largest group of primary dealers, while Beijing has the smallest. On average, there are about 8.5 local dealers. In all, there are 261 unique dealers. Out of these 261 primary dealers, 159 are commercial banks, 85 are security companies, 15 are credit cooperatives, and two are financial companies. A breakdown of bond values by dealer types is presented in Table A.2. The unique number of registered dealers by province is given in Column 4. On average, there are about 60 registered dealers in each province. While Yunnan province has the highest number of registered dealers – 83, Beijing has the smallest number – 12.

In Table 3 Column 5, we report the potential dealers. The last two columns present the total number of submitted and winning bids for auctions. The most bids submitted (2,936) and the winning bids (1,584) are observed at the Guangdong local government bond auctions. Notably, the number of submitted bids is the same as the number of winning bids in Beijing (560 in total.) Interestingly, 96.4 percent (62,102/64,411) of potential bidders submit bids, while only about 49 percent submit winning bids (30,364/62,102.) Hence, we see that these auctions are highly competitive, and almost all potential bidders participate in all auctions. Further, note that the bid-to-cover ratio is equal to one or more for all types of auctions. Barbosa et al. (2022) reported a similar competition pattern in their study of Chinese treasury bond markets.

De Silva (2005), De Silva et al. (2005), and Gentry et al. (2022) noted that bidders could extract synergies when bidding in their local province. In our study, we also observe bidders bidding in their home province. In Table 4, we summarize the bidding pattern of primary dealers by province type—'local' and 'foreign.'[12] We observe that Anhui, Liaoning, Sichuan, Xinjiang, and Yunnan provinces' dealer groups have more local than foreign dealers. On the other hand, Gansu, Heilongjiang, Hunan, Jiangxi, and Sanxi provinces recruit more potential dealers from other provinces. However, the number of local winners in these

[12] Local dealers are those whose home province is the same as the bidding province, while 'foreign' dealers are those bidding in a province other than their home province.

provinces is higher than winners based in other provinces, indicating that local bidders may have synergies. The remaining provinces attract more foreign dealers than local dealers, bidders, and winners. Hence, our regressions include an indicator variable to identify when a dealer bids in its home province. The percentage of bidding in the same province for all, regular and green bonds are 12.7, 12.2, and 16.1 percent, respectively. On average, dealers bid in about seven different provinces, including their own.

Additionally, we include an indicator variable that captures whether an auction takes place at the beginning (first seven days) or the end (last seven days) of the month. This variable captures large financial transactions concentrated at the end of the month as financial institutions prefer to keep relatively large liquidities at that time. Further, we include a market drift term in addition to year, month, and province fixed effects (Park and Reinganum, 1986; Ogden, 1987; Barbosa et al., 2022.) The market drift variable is constructed by counting the number of weeks since the start of the analysis by dividing each week by the total number of weeks of the study. Simon (1994) notes that a market-drift variable controls for gradual unobservable changes that bidders face during the period. Although a model of long-term relationships with dynamic trade-offs is beyond the scope of this study, Skrzypacz and Hopenhayn (2004) point out that a repeated auction environment can sustain a variety of strategies in equilibria and this time-shifting variable parsimoniously controls for potential gradual changes in long-term interactions among bidders regardless of auction type.

### 3.3. Auction types and number of bidders

A major concern is the equality of the number of bidders in these auctions. Recall that, to bid in this market, dealers need to be prequalified to participate. In our sample, each province has about 60 unique prequalified dealers, and we observe that more than 98 percent of dealers continued from year to year during the period of analysis. However, the local governments do not require mandatory participation in green and non-green auctions or minimum purchasing volumes for these dealers. Hence, we first examine bidders' participation behavior. In this case, we estimate the following auction-level empirical model:

$$n_{apt} = \gamma G_{apt} + A'_{apt}\varphi + M'_{pt}\omega + \rho_p + \tau_t + \mu_{apt},$$

where our dependent variable is the number of bidders in an auction *a* held by a province *p* at a given time *t* . The indicator variable, *G*, controls for the auction type (*G* = 1 for green bond auctions). Other observable auction-level characteristics such as the number of potential bidders, time gap between auctions, bid-to-cover ratio of bonds, duration of the bond sold, market conditions such as volatility, the value of maturing bonds by the local government, first and last week of the month, and market drift are represented by vectors *A* and *M*, respectively. Local governmental effects and time effects are denoted by $\rho$ and $\tau$, respectively, and $\mu$ is the error term.

Given that the number of bidders is a count, we estimate equation (1) using the Poisson Pseudo Maximum Likelihood (PPML) method.[13] Table 5 reports these results, and our primary interest is in the coefficient of the *Green bond* indicator. Our results in Column

[13] The PPML adjust for over- and under-dispersion and the only condition required for consistency is the correct specification of the conditional mean of the independent variable (Santos Silva and Tenreyro 2006, 2010 and Wooldridge 1999).

1 show that there is no statistical difference in the number of bidders for green and regular bonds. An in-depth analysis of green bond types also reveals that there are no strong statistical differences in the number of bidders in these green and regular bonds (Column 3.) The coefficient of the potential bidders indicates an almost perfect predictability of the number of bidders based on potential bidders. This is because 96.4 percent of potential bidders participate in auctions.

Further, we estimate a sample that takes advantage of within-day variation to control for unobserved auction heterogeneity. This empirical strategy could identify dependencies in demand for treasury bills of different maturities on the same day (Allen et al., 2020). Primary dealers could strategically exploit these differences and participate accordingly. In this same-day sample, we observe 1,237 auctions. As before, we observe no statistical differences in the number of bidders in these green (and green bond types) and regular bonds.

In 26 provinces, all potential bidders participated in all auctions they intended to bid in. Only in Anhui, Guangxi, Hubei, Jiangsu, and Shanxi provinces did primary dealers not participate in all auctions. Given this, we estimate our models for auctions where the number of bidders equals potential bidders. In this exercise, we loose 369 total auctions and 97 same-day auctions where the number of bidders differed from the potential bidders. We present the results from this alternate sample in Table 6. The results are qualitatively similar to the ones we observe in Table 5.

In the above empirical models, we have used the time lags between auctions in the same province. As a robustness check, we estimate the models using time lags between auctions, ignoring provinces. These results are presented in Table A.3, and they are similar to what we observe in Table 5. Additionally, we estimate these models with the alternate sample where the number of bidders equals potential bidders and observe similar results to those presented in Table 6. We do not present these results, but they are available upon request.

### 3.4. Probability of selecting a green bond

However, the above exercises do not address the possible selection issue of green versus non-green bonds by primary dealers. The traditional method to deal with selection is to use a Heckman type selection model. However, note that 96.4 percent of potential bidders bid in these auctions, and we do not observe the bids above the market clearing rate (losing bids.) Further, in 26 provinces, the number of actual bidders was equal to the number of potential bidders. Hence, we take the following two approaches. We construct a sample of potential bidders for a given local government on a given day based on all primary dealers present on that auction day. This construction expands the data from 64,411 to 72,725 observations. The assumption is that all active bidders in a given province on a given day had the potential to participate in either green or non-green auctions but decided to participate selectively. Then, we see if there is a difference in this participation, using a simple probit model, where the dependent variable is submitting a bid (= 1) or not (= 0), and the independent variables are auction and dealer characteristics. The dealer characteristics include entrant or incumbent status, experience, and the distance to the local government location from the dealer's location.

Table 7 reports results for the full sample with expanded data. Column 1 indicates no statistical difference in primary dealers choosing to submit bids for green or non-green bonds. However, in this model, we do not control for any dealer heterogeneities. In Column 2, we reestimate this probit model with dealer-specific random effects, while in Column 3, we include dealer effects using dealer-specific indicator variables. All results indicate that bidders are indifferent in bidding for green or non-green bonds. In Columns 4-6, we reestimate these models with indicators for green bond types. The results indicate that dealers have a slightly higher probability of submitting bids in pollution prevention and green energy bond auctions while less likely to bid on green transportation auctions. But these probabilities are extremely small.

We also estimate these models with the alternative day gap measure and excluding provinces that did not sell green bonds. Further, there are five provinces where the number of potential bidders was not equal to the actual bidders. As a robustness check, we use these samples and estimate the probability of bidding conditional upon being a potential bidder and see if there is a selection of green or non-green bonds. These results indicate no specific selection bias relating to green and non-green auctions, even when considering different types of green auctions with non-green auctions. We also estimate these models using a linear probability model, including dealer fixed effects. The qualitative interpretation of these results is similar to what we observe in our main probit estimates presented in Table 7. We do not report these results but can provide them upon request. With these findings, we are cautiously confident that bidders are indifferent about entering green or non-green auctions. Hence, selection bias is not a major issue in our analysis.

## 4. Estimating auction outcomes

With the above results in mind, we now focus on bidding outcomes. We consider the following empirical model:

$$y_{iapt} = \delta G_{apt} + X'_{it}\beta + A'_{apt}\vartheta + M'_{pt}\theta + \alpha_i + \rho_p + \tau_t + \epsilon_{iapt},$$

where $y_{iapt}$ is the normalized winning bid for dealer $i$ in auction $a$ in province $p$ at time $t$. $G_{apt}$ is the green bond dummy as before. $X$ controls for dealer-specific characteristics that include experience, entrant or incumbent status, and bidding in the home (same) province. $A$ and $M$ are controls for auction and market characteristics as before. $\alpha$, $\rho$, and $\tau$ are dealer, province, and time-fixed effects.

### 4.1. Green versus non-green bonds

First, we consider the difference in winning bid rates between green and non-green bonds for all provinces and present our results in Table 8. In the first three columns, we report our results for all auctions. In Column 3, we include the entrant status and the number of bidders in the auction. Our primary variable of interest—the 'Green Bond' dummy—indicates that, for green bonds, the winning bid rates are about 1.2 basis points higher than non-green bonds. Interestingly, entrants bid less aggressively, and their winning rates are about 12 basis points higher than incumbents'. Additionally, our results indicate that when incumbents face entrants, they bid less aggressively (by about two basis points). As dealers gain experience, our results suggest that they bid aggressively. For example, at the mean value of experience, the marginal effect of experience is about 37 basis points, based on Column 2 results.

Next, we take advantage of within-day variation to control for dependencies in demand for treasury bills of different maturities on the same day, as in Allen et al., 2020. We estimate the model presented in Column 2 with the same day sample and report in Columns 3 and 4. Our results indicate that green bond winning rates are about 2.8-3.1 basis points higher than non-green bonds. Alternatively, we estimate the empirical model with dealer-specific random effects and report in Column 4. These results are consistent with results reported in Columns 1 through 3. As the magnitudes of coefficients are similar in Columns 3 and 4, we can infer that our empirical specifications control most of the observable and unobservable heterogeneities.

Next, in Table 9, we present results for the alternate sample, where the number of bidders was equal to the potential number of bidders in auctions. Our results indicate that green bonds are about 1.5 basis points higher than non-green bonds for all auction days and about three basis points higher when controlling for the same-day demand variation. Our other main results on entrants, incumbents, and experience are consistent with what we reported in Table 8.

### 4.2. Green bond types versus non-green bonds

Now, we use our details of the data and reestimate these models, expanding the green bond indicator by green categories. Our results in Table 10 indicate that dealers have different valuations for different types of green bonds. For energy conservation bonds, dealers' winning rates are about six to seven basis points higher than non-green bonds, indicating that dealers are less willing to pay a higher price for these bonds. This means the government revenues generated by these energy conservation bonds will be lower than non-green bonds. Similarly, winning rates are higher (lower price) for pollution prevention (4.5 to 6.7 basis points) and ecological protection (3.5 to 5.0 basis points) bonds. On the other hand, winning rates are lower for green transportation (-6.9 to -10.3 basis points) and green energy (-3.3 to -6.1 basis points) bonds, indicating that dealers are willing to pay a higher price for these bonds. In this case, the government generates more revenues from these types of green bonds than from non-green bonds. Based on these findings, at the mean, we could rank the revenues generated from green and non-green bonds as: Green transportation ≥ Green energy ≥ Recycling ≥ Non-green ≥ Ecological protection ≥ Pollution prevention ≥ Energy conservation. These revenue rankings can also be interpreted as willingness to pay for green goods. We also reestimate these empirical models with our alternate sample and present these results in Table 11. The results are qualitatively consistent with what we reported in Table 10 using the full sample.

As mentioned, our data allows us to identify green and non-green transportation bonds. Next, we use this sample to examine the revenue rankings of green and non-green transportation bonds. The winning rates for green transportation bonds are about 11 to 12 basis points lower than non-green transportation bonds, indicating higher revenues for local governments from green transportation bonds compared to non-green transportation bonds. Further, this transportation bonds exercise is a clear like-to-like comparison of green and non-green bonds and indicates that dealers are willing to pay a higher price for green transportation bonds. These results are presented in Table 12.

As a robustness check, we estimate the models using time lags between auctions, ignoring provinces. These results are presented in Table A.4 and are qualitatively similar to what we have observed in Tables 8 and 10. Additionally, we estimate these models with the alternate sample where the number of bidders equals potential bidders and observe similar results to what we presented in Tables 9 and 11. We do not present these results, but they are available upon request.

## 5. Why buy green bonds?

So far, we have shown that dealers' WTP for green bonds seems to be based on types. Given that the central government backs these bonds and no additional 'risk' is involved in these green bonds compared to non-green bonds, we interpret these results as a clear indication of WTP for green goods. In this case, the natural question is what motivates primary dealers to purchase these green bonds?

According to Jie Chen, the head of debt Capital Markets at JP Morgan China, Chinese governments promulgate policies to support the development of green bonds and improve the market. Further, green bonds have 'good liquidity' in the secondary market, and green bonds' performance is relatively stable. "Therefore, investors' willingness to invest is stronger in green bonds."[14]

[14] See “Commercial banks adopt multiple strategies to support green and low-carbon development.”

Additionally, our examination of official documents issued by the China Securities Regulatory Commission indicates that the primary dealers' performance on green bonds underwriting will be crucial to ESG ranking for security companies.[15] Hence, evidence suggests that primary dealers adopt multiple strategies to support green, low-carbon development in China and improve their ESG standings. Further, industry insiders generally believe that green bonds are a blue ocean market, not only because of the "policy dividends" they enjoy and the "special attention" from regulatory authorities but also due to their broad prospects in the green finance market. Ming Wu, who is the head of Haitong Securities' Division of Bond Finance, said that Haitong Securities, one of the earliest underwriters of green bonds in China, has 'policy dividends' and favorable market reaction than other dealers.[16]

If the above said, at least partially, drives the green bond market in China, then one should see primary dealers gaining from short-term returns and a positive correlation between ESG values and green bond activities. Hence, in the following two subsections, we investigate primary dealers' secondary-market returns and the impact of green bonds on ESG scores and market survival.

### 5.1. Primary dealers' secondary-market return

If green bonds are highly liquid, it is possible that primary dealers could gain from short-term returns in the secondary market. These gains could be unequal based on green bond

https://www.chinabond.com.cn/cb/cn/xwgg/zsxw/hgjj/20221102/161415638.shtml

[15] See https://www.ndrc.gov.cn/xwdt/ztzl/gbmjcbzc/zjh/201807/t20180704_1209239.html

[16] See http://finance.takungpao.com/gscy/q/2017/0824/3486449.html

types, which may be why primary dealers' winning rates are different by green bond types. To examine primary dealers' short-term gains, we look at the secondary market sales of these bonds.

We define short-term return for a dealer as the difference between the yield of a bond acquired in a primary market auction minus the yield of the same bond sold in a secondary market transaction on the debut day. The debut day is the initial secondary market trading day in which a given security is allowed to be resold. That corresponds to the primary dealers' actual debut-day return in the secondary market, as it is based on primary-to-secondary transaction data. In our sample, we observed that 1,355 auctions (out of 2,762) were sold in the secondary market. Our results in Table 13 indicate no statistical difference in the secondary-market debut-day return for primary dealers by bond type.[17] This result suggests that, at least partially, green bonds are as liquid as non-green bonds.

### 5.2. Impact of green bonds on ESG scores

The China Securities Regulatory Commission has indicated that the primary dealers' performance on green bonds underwriting will be crucial to ESG ranking for security companies. If the above is true, at least partially, it drives the green bond market in China, and then one should see a positive correlation between ESG values and green bond activities. Hence, we consider the correlation between the ESG (environmental) rankings provided by

[17] We do not observe any recycling bonds being auctioned off in the secondary market. There may be over-the-counter transactions that we do not observe.

popular Syn Tao Green Finance Company Ltd. (STGF) and the total and relative value of green bonds per dealer by year. The total value of green bonds (or segmented by green bond type) held by each dealer at a specific moment is calculated by considering the sum of green bonds (or by green bond type) they have previously acquired. The relative values of all green bonds and by green bond types are calculated by dividing total green bond values by the total value of all bonds they have procured. These total and relative values are updated each period. When calculating Pearson correlation coefficients, we make use of the year-end relative values and the annual ESG score. It's crucial to emphasize that the ESG score is an annual metric.

In 2015, STGF introduced its in-house ESG rating system and pioneered the creation of the inaugural ESG database for publicly traded firms in China. These ESG assessments encompass all Mainland Chinese listed corporations, Hong Kong-listed entities participating in the Shanghai-Hong Kong Stock Connect and Shenzhen-Hong Kong Stock Connect programs, as well as prominent bond issuers. STGF is a well-recognized independent consultancy in China specializing in CSR consulting, sustainability, and ESG.[18] STGF's rating objective is to establish a scientifically grounded, impartial, transparent, and comprehensive evaluation of a company's sustainability value. This assessment takes into account both internal and external ESG factors. The primary purpose of their ESG ratings is to provide a dependable foundation for investors, regulators, and other stakeholders to make informed judgments about a company's overall performance.

[18] See https://en.syntaogf.com/pages/about01

The ESG Rating System employed by STGF assesses a company's ESG performance by quantifying its level of ESG management and exposure to associated risks. According to STGF, their ESG scores, especially the E-scores, are contingent on a company's commitment to various aspects of environmental responsibility. These aspects include environmental policies (such as environmental management systems, objectives, energy and water conservation policies, green procurement policies, etc.), energy and resource consumption (covering metrics like energy consumption, energy conservation efforts, water conservation, and energy usage monitoring), climate action (assessing greenhouse gas emissions, carbon intensity, and climate change management systems), as well as biodiversity (evaluating biodiversity conservation goals and measures). These criteria are thoughtfully aligned with the six distinct categories of green bonds we discussed.[19]

The SynTao database categorizes dealers into ten levels: A+ (the highest), A, -A, B+, B, -B, C+, C, C-, and D (the lowest). To facilitate computation, we transform these rankings into scores ranging from 1 to 10, with 10 indicating the best performance (see Table A. 5). Additionally, we provide information on the number of dealers falling into each category. While ESG rankings are getting popular in China, it is still somewhat new, and we have ESG ranking for 62 out of 261 unique dealers. In 2018, 47 firms sought ESG ratings; in 2019 and 2020, 58 firms sought ESG ratings.

In Column 1 of Table 14, we report the Pearson correlation coefficients for the relationship between ESG and total green bond values. Our results indicate that the Pearson

[19] See https://en.syntaogf.com/pages/esg01

correlation coefficient is 0.2706 (with a significance of 0.0005) for the relationship between ESG and total green bond value. Results also suggest that the value of green bonds by type correlates positively and significantly with the ESG score. To provide some additional evidence of this pattern, since 2018, Haitong Securities's green bond share has been about ten percent relative to the total bonds purchased, and their ESG score improved from a 'B' in 2017 to a 'B+' in 2018.

Table 14, Column 2, shows the Pearson correlation coefficient of 0.1779 (with a significance of 0.0289) for the relationship between ESG and relative green bond value. However, when examining the correlation coefficient based on relative green bond values categorized by type, it becomes evident that only energy conservation, recycling, green energy, and ecological protection bonds exhibit statistical significance. Notably, all types of green bonds demonstrate a positive correlation with ESG rankings.

### 5.3. Impact of green bonds on market survival

Next, if primary dealers receive 'special attention' from regulators as they buy green bonds, then their continuation in this market should be improved. Hence, we provide a simple analysis of market exit. In this exercise, we consider all dealers who have entered provincial bond markets since August 2018 and track their monthly market activities in each province. If a dealer has no activity for nine months, we consider that the dealer has exited the given provincial market in the last month we observed. During our exit analysis, we observed 821 unique registered entrants (dealers participating in a specific province for the first time). We find 329 exit events out of these entrants—a dealer exiting a particular provincial bond market. We do not consider any firms that entered a province after January 2020. Since the last period in our sample is September 2020, we consider a dealer who did not exit the market before January 2020 to be still active.

We estimate a simple probit model with the dependent variable *exit* being equal to one if a firm exited from a specific provincial market in a given month and zero otherwise (continuing in the market.) Our main interest is understanding the impact of green bond purchases on dealer survival in the market. Hence, we include the proportion of the total value of green bonds a dealer has purchased in the past as a control variable. This proportion is updated every month. We also include the number of rivals in a province, dealer experience, the value of maturing bonds by the Local Government for a given month, and the planned value of issuing bonds by the Local Government for a given month in our base specification.

We also include a proxy for expected profits for these dealers if they sell all bonds in the secondary market on the debut day. We calculate these pseudo-expected profits using the empirical model reported in Table 13, Column 2. We interpolate the expected secondary market rates for a given bond using point estimates from this initial regression. Next, we calculate the predicted market gap and total profits or losses for each bond if it was sold on the secondary market debut day. We calculate the cumulative pseudo-expected profits for dealers from each provincial market at a given month using these bond-level pseudo-expected profits. We use these total pseudo-expected profits to control for dealer heterogeneities in addition to experience.

These results are presented in Table 15. In the first three columns, we report results using relative green bonds. In Columns 4-6, we consider a specification using the log difference in green bonds and all bonds. Columns 1, 2, 4, and 5 include dealer-specific random effects to control for unobservable dealer heterogeneities. In Columns 3 and 6, we have included a set of dummies to control individual dealer effects. Overall, we find that purchasing green bonds helps continue in the market. Considering other variables, dealer experience and located in the same province help continue in the market. Note that the profits could be negative; hence, we take the absolute value when taking logs of total pseudo-expected profits. However, we include an indicator variable to identify negative total pseudo-expected profits observations. Our results indicate that when expected profits are high, firms survive longer. This simple exercise supports the claims by practitioners that purchasing green bonds helps them enjoy "special attention" from regulatory authorities in continuing in the market in addition to "policy dividends."

## 6. Assessing revenue difference

Our next inquiry is what is the cost for the government. In Section 4, we analyzed the normalized yield rates between green and non-green bonds. Our results indicated that the point estimates are not equal to zero, and signs and magnitudes of coefficients also differ based on the type of green bonds. Given the large sums of money involved in Treasury auctions, it raises questions about the cost of green bonds for local governments. Therefore, we investigate the cost of green bonds by type compared to non-green bonds. Using point estimates from Column 2 in Table 10, we counterfactually calculate the costs for green bond types and report them in Table 16.

Our results indicate that the average net costs are about ¥5.1 billion (about 0.9 percent of total green bonds). A deeper look into costs and savings by green bond types indicates that the largest savings (¥5.5 billion) come from green transportation bonds. Green transportation bonds account for 28.7 percent of all green bonds. Our findings also show that energy conservation bonds are relatively expensive for local governments compared to non-green bonds. However, these direct savings (and costs) do not tell the total impact on society and the environmental benefits of green projects undertaken by selling green bonds. Examining the total effect is beyond the objectives of this paper. However, one of the objectives of the local bond market was to provide autonomy to local governments to identify provincial projects that help reduce toxic emissions and improve access to clean water and ecological resources. Hence, we provide a province-level pollution outcome analysis in the next section.

## 7. Pollution outcomes

This section examines the correlation between yearly per capita pollution outcomes and the share of green bonds. We estimate a simple regression model where the dependent variable is the pollution outcome. As a proxy for pollution outcomes, we consider $CO_2$, $SO_2$, and $NO_X$ emissions levels, clean water resources, and forest areas available for public use. We gather provincial-level $SO_2$ emissions, $NO_X$ emissions, water resources, and forest areas from the National Bureau of Statistics of China. The $CO_2$ emission data are collected from Carbon Emission Accounts and Datasets (CEADs), an academic organization providing accurate carbon emission data that is funded and monitored by the National Natural Science Foundation of China, the Ministry of Science and Technology of China, Natural Environment Research Council (U. K.), University of Cambridge, University College London, and University of Groningen. To be specific, our dependent variable is either log per capita $CO_2$, $SO_2$, $NO_X$ emissions levels (in tons per person) or log per capita clean water resources (in cubic meters) and useable forest areas (hectares per person.) While $SO_2$, water, and forest data are available from 2005 to 2020, $CO_2$ and $NO_X$ data are available only for the years between 2005 and 2019 and 2011 and 2020, respectively.

Reducing carbon emissions could be achieved in many ways, including regulation, improving infrastructure, or a combination of these. For example, regulation could set standards to be achieved by a specific year—as in the Paris Agreement. To achieve these standards, the nations could concentrate on energy conservation. Energy conservation could lessen the energy demand, reduce energy production using oil and gas, and reduce carbon emissions. Carbon emissions (as well as $SO_2$ and $NO_X$ emissions) could also be reduced by moving to green transportation methods. However, most green transportation relies on electricity, and unless that electricity is generated from 'clean energy,' the overall environmental benefits of green transportation may not be obvious (see Holland et al, 2016.) Hence, we use the ratio of green bond types used by each province to examine the impact of expenditures on green projects undertaken by provinces on pollution outcomes.

Additionally, we collect provincial-level population and gross domestic product. We also include indicator variables to capture the effects of former President Jingtao Hu's report to the18$^{th}$ Party Congress before the Paris Agreement (2013-2015), the period after joining the Paris Agreement and the COVID-19 period. We also include provincial-level fixed effects. We present these results in Table 17.

Our results indicate that projects related to energy conservation have reduced per capita $CO_2$ emissions, and investing in green transportation and green energy projects has helped reduce per capita $SO_2$ and $NO_X$ emissions. This is somewhat expected as $CO_2$, $SO_2$, and $NO_X$ emissions are highly correlated with fossil fuel-based transportation and energy production. Forest resources have improved with investment in pollution prevention and recycling projects. All types of per capita emissions have been significantly reduced since former President Jingtao Hu's report (2013-2015) and after the Paris Agreement. The COVID-19 pandemic has also reduced $SO_2$ and $NO_X$ emissions.

A concern may be that the emissions, water, and forest resources are serially correlated. If that is the case, our results could be biased, and hence, we used the Baltagi and Wu (1999) technique to overcome this possible issue. We present these results in Table A.6, which are qualitatively similar to what we observe in Table 17.

## 9. Conclusion

We analyze a local government bond market in China from its inception. The market had evolved to include green bonds in order to tackle local pollution and climate change objectives as a part of the Paris Agreement. We use 2,762 auctions worth more than ¥10.45 trillion (approximately $1.55 trillion) to analyze the dealers' bidding pattern, selection, and winning bid outcomes in green and non-green auctions.

First, we document that there is no difference in the number of bidders in green and non-green auctions. Second, we show that dealers are indifferent in selecting green or non-green auctions. Given that there are no differences in the number of bidders and major selection issues, using more than 30,000 winning bids, we find that, in general, the pricing differential between green and regular bonds is very small—about one to two basis points. However, a detailed analysis of green bonds by types indicate that dealers have different WTP and at the mean, we could rank the revenues generated from green and non-green bonds as: Green transportation ≥ Green energy ≥ Recycling ≥ Non-green ≥ Ecological protection ≥ Pollution prevention ≥ Energy conservation. Additionally, we demonstrate that engagement in purchasing green bonds further substantiates the claims by practitioners, asserting that investing in green bonds enables them to obtain higher ESG scores and "special attention" from regulatory entities, supporting their continued engagement in the market.

Additionally, our results indicate that entrants and dealers facing entrants bid less aggressively. As dealers gain experience, they bid more aggressively. These types of asymmetries have not been addressed in the bond market literature before.

Further, our simple counterfactual analysis shows that all green bonds cost local governments about ¥5.1 billion, while green transportation bonds save local governments about ¥5.5 billion. However, these direct costs and savings do not account for the total impact on society and the environmental benefits of green projects undertaken by local governments. Our analysis of local pollution outcomes reveals that green investments in energy conservation have reduced per capita $CO_2$ emissions. Further, investments in green transportation and green energy projects have helped reduce per capita $SO_2$ and $NO_X$ emissions. Forest resources have also improved with investment in pollution prevention and recycling projects. Finally, all types of per capita emissions have been significantly reduced since 2013 and after the Paris Agreement. The COVID-19 pandemic has also reduced $SO_2$ and $NO_X$ emissions.

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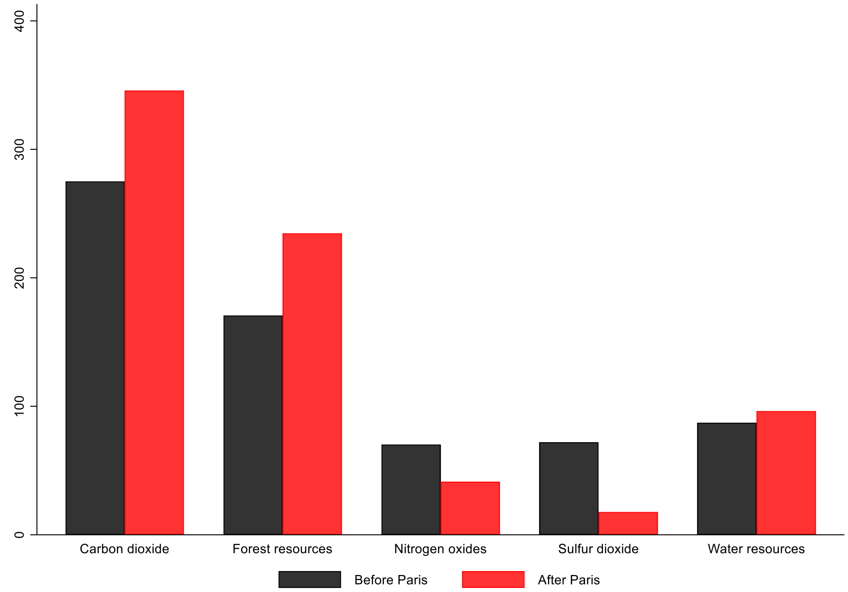
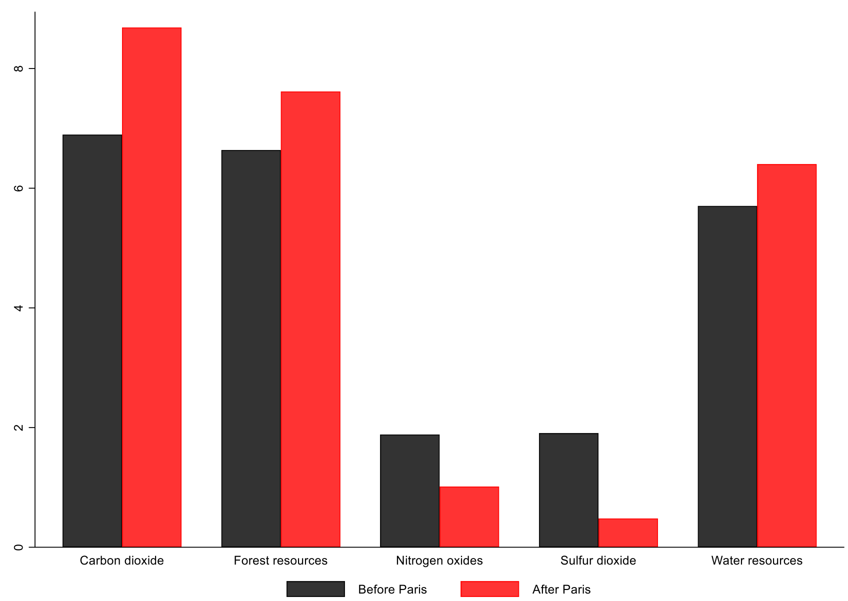
**Figure 1: Average total releases by provinces before and after the Paris Agreement**



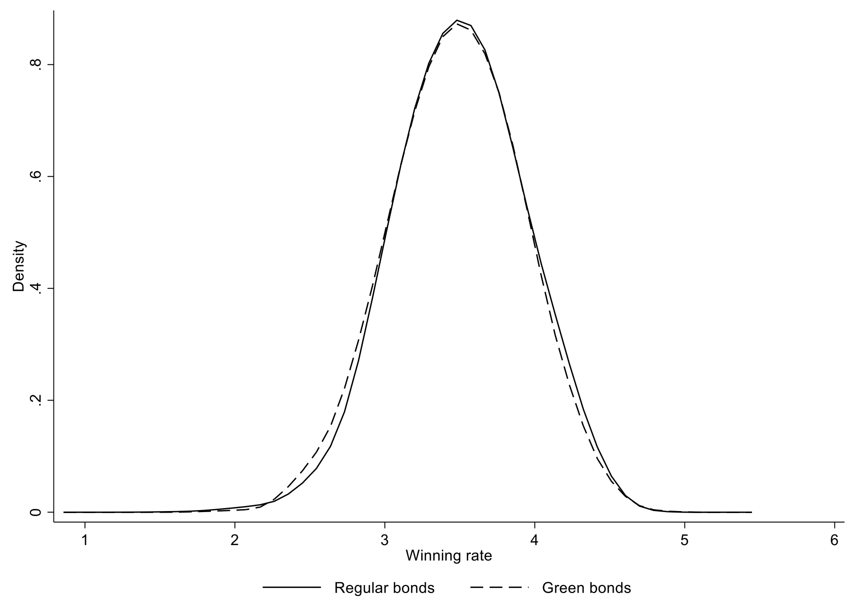

$CO_2$, $SO_2$, and $NO_X$ are measured in millions of tons. Water resources are measured in tens of millions of cubic meters. Forest resources are measured in millions of hectares.

**Figure 2: Average per capita releases by provinces before and after the Paris Agreement**



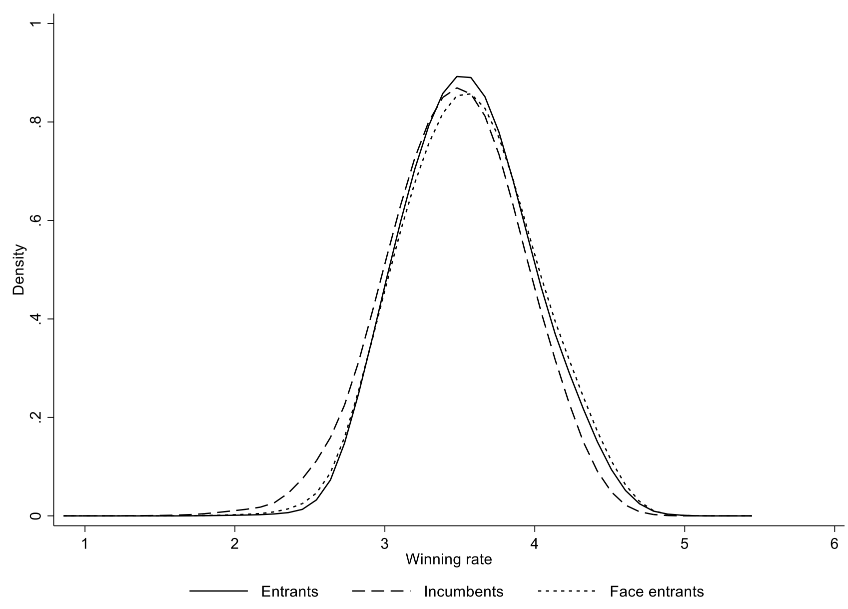

$CO_2$, $SO_2$, and $NO_X$ are measured in tons per person. Water resources are measured in tens of cubic meters per person. Forest resources are measured in hectares per person.

**Figure 3: Regular and green bonds' winning rates**




These are the winning bid rate distributions for green and non-green bonds.

**Figure 4: Entrant and incumbents' bidding patterns**




We define any bidder who has bid in an auction on a given province before August 2018 as an incumbent. Any dealer submitting a bid for the first time in a local authority since August 01, 2018, as an entrant and their subsequent participation in that province is treated as activity by incumbents.

**Table 1: Summary statistics by bond types**

| Bond type | Number auctions | Number of winning bids | Value in ¥[a] | Winning rate | Market yield[b] |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Regular bonds | 2,440 | 26,919 | 9,892,586 | 3.502 | 3.211 |
| Green bonds | 322 | 3,445 | 562,079 | 3.478 | 3.206 |
| Energy conservation | 11 | 91 | 8,228 | 3.539 | 3.242 |
| Pollution prevention | 81 | 925 | 69,565 | 3.421 | 3.140 |
| Recycling | 6 | 52 | 7,708 | 3.321 | 3.051 |
| Green transportation | 55 | 576 | 161,672 | 3.631 | 3.359 |
| Green energy | 9 | 97 | 5,064 | 3.453 | 3.212 |
| Ecological protection | 160 | 1,704 | 309,842 | 3.469 | 3.200 |

a: Value in millions of ¥.

b: Average market yield of Central Government bonds one day before the auction date.

**Table 2: Summary statistics**

| Variable | Mean/count | | |
|---|---|---|---|
| | All auctions | Regular auctions | Green auctions |
| | (1) | (2) | (3) |
| Number of auctions | 2,762 | 2,440 | 322 |
| Number of potential bidders | 23.320 | 23.211 | 24.152 |
| | (17.761) | (17.777) | (17.650) |
| Number of bidders | 22.484 | 22.342 | 23.562 |
| | (17.930) | (17.917) | (18.022) |
| Green bond | 0.117 | | 1.000 |
| | (0.321) | | |
| Energy conservation | 0.004 | | 0.034 |
| | (0.063) | | (0.182) |
| Pollution prevention | 0.029 | | 0.252 |
| | (0.169) | | (0.435) |
| Recycling | 0.002 | | 0.019 |
| | (0.047) | | (0.135) |
| Green transportation | 0.020 | | 0.171 |
| | (0.140) | | (0.377) |
| Green energy | 0.003 | | 0.028 |
| | (0.057) | | (0.165) |
| Ecological protection | 0.058 | | 0.497 |
| | (0.234) | | (0.501) |
| Market yield of the Central Government bonds one day before the auction date | 3.189 | 3.188 | 3.193 |
| | (0.333) | (0.336) | (0.311) |
| Market yield of the Local Government bonds one day before the auction date | 3.527 | 3.528 | 3.524 |
| | (0.356) | (0.361) | (0.316) |
| Duration | 6.262 | 6.111 | 7.412 |
| | (3.699) | (3.692) | (3.557) |
| Time lag between Local Government auctions | 40.778 | 40.616 | 42.003 |
| | (36.182) | (36.107) | (36.784) |
| Time lag between any Local Government auction | 2.161 | 2.148 | 2.270 |
| | (2.630) | (2.639) | (2.562) |
| Volatility | 0.022 | 0.022 | 0.021 |
| | (0.014) | (0.014) | (0.012) |
| Value of maturing bonds by the Local Government for a given month | 48.956 | 50.127 | 40.084 |
| | (74.245) | (76.278) | (66.335) |
| Bid-to-cover ratio | 13.629 | 13.489 | 14.691 |
| | (9.051) | (9.225) | (7.531) |
| Entrant | 0.067 | 0.070 | 0.042 |
| | (0.250) | (0.255) | (0.200) |
| Face an entrant | 0.314 | 0.316 | 0.295 |
| | (0.464) | (0.465) | (0.456) |
| Experience (past win counts) | 1,033.101 | 1,027.925 | 1,070.790 |
| | (1,561.967) | (1,554.857) | (1,612.400) |
| Bidding in the same province | 0.127 | 0.122 | 0.161 |
| | (0.333) | (0.328) | (0.368) |

Standard deviations are in parentheses.

**Table 3: Auctions and primary dealer bidding patterns by province**

| Province | Auction type | | Dealers' home province | Registered dealers | Potential bidders | Bids submitted | Winning bids |
|---|---|---|---|---|---|---|---|
| | All | Green | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Anhui | 35 | | 6 | 43 | 867 | 727 | 480 |
| Beijing | 56 | | 1 | 12 | 560 | 560 | 560 |
| Chongqing | 36 | | 5 | 57 | 1,045 | 1,045 | 581 |
| Fujian | 88 | 11 | 5 | 61 | 1,370 | 1,370 | 947 |
| Gansu | 39 | 4 | 9 | 75 | 1,196 | 1,196 | 390 |
| Guangdong | 274 | 72 | 30 | 75 | 9,518 | 9,518 | 3,983 |
| Guangxi | 69 | 3 | 9 | 65 | 1,660 | 1,249 | 464 |
| Guizhou | 87 | 12 | 7 | 79 | 2,541 | 2,541 | 1,790 |
| Hainan | 48 | 1 | 4 | 77 | 677 | 677 | 402 |
| Hebei | 96 | 3 | 12 | 60 | 2,262 | 2,262 | 1,247 |
| Heilongjiang | 68 | 1 | 3 | 46 | 1,532 | 1,532 | 707 |
| Henan | 82 | 15 | 9 | 61 | 1,321 | 1,321 | 704 |
| Hubei | 141 | 3 | 9 | 56 | 2,925 | 2,220 | 1,210 |
| Hunan | 108 | 18 | 9 | 69 | 3,176 | 3,176 | 1,231 |
| Jiangsu | 41 | | 6 | 72 | 1,064 | 924 | 654 |
| Jiangxi | 63 | 4 | 8 | 81 | 2,026 | 2,026 | 847 |
| Jilin | 71 | 6 | 5 | 36 | 1,274 | 1,274 | 855 |
| Liaoning | 80 | 2 | 6 | 76 | 1,801 | 1,801 | 723 |
| Neimenggu | 73 | 4 | 5 | 55 | 1,198 | 1,198 | 499 |
| Ningxia | 51 | 2 | 4 | 36 | 926 | 926 | 406 |
| Qinghai | 50 | 6 | 2 | 70 | 1,179 | 1,179 | 513 |
| Sanxi | 91 | 2 | 7 | 51 | 2,021 | 2,021 | 837 |
| Shandong | 186 | 30 | 15 | 80 | 4,120 | 4,120 | 2,177 |
| Shanghai | 31 | 3 | 1 | 23 | 378 | 378 | 363 |
| Shanxi | 83 | 14 | 9 | 75 | 1,937 | 1,024 | 572 |
| Sichuan | 271 | 35 | 30 | 78 | 6,582 | 6,582 | 2,399 |
| Tianjin | 147 | 49 | 5 | 59 | 3,435 | 3,435 | 1,707 |
| Tibert | 34 | 1 | 2 | 24 | 322 | 322 | 135 |
| Xinjiang | 76 | 4 | 4 | 44 | 922 | 922 | 756 |
| Yunnan | 74 | 9 | 17 | 83 | 2,888 | 2,888 | 991 |
| Zhejiang | 113 | 8 | 17 | 70 | 1,688 | 1,688 | 1,234 |
| Total | 2,762 | 322 | 261 | 1,849 | 64,411 | 62,102 | 30,364 |
| Average | 89.097 | 11.926 | 8.419 | 59.645 | 2,077.774 | 2,003.290 | 979.484 |

Table 4: Primary dealer bidding patterns by province

| Province | Potential bidders | | Bidders | | Winners | |
|---|---|---|---|---|---|---|
| | Different province | Same province | Different province | Same province | Different province | Same province |
| Anhui | 57 | 66 | 57 | 66 | 12 | 48 |
| Beijing | 21,832 | 388 | 20,938 | 388 | 14,464 | 388 |
| Chongqing | 348 | 0 | 348 | 0 | 74 | 0 |
| Fujian | 3,147 | 174 | 2,913 | 174 | 1,499 | 133 |
| Gansu | 147 | 71 | 147 | 71 | 6 | 41 |
| Guangdong | 8,237 | 3,399 | 7,871 | 3,399 | 2,600 | 1,144 |
| Guangxi | 354 | 182 | 354 | 68 | 83 | 2 |
| Guizhou | 530 | 268 | 530 | 268 | 90 | 237 |
| Hainan | 95 | 0 | 95 | 0 | 52 | 0 |
| Hebei | 622 | 190 | 622 | 190 | 147 | 126 |
| Heilongjiang | 187 | 180 | 187 | 180 | 23 | 104 |
| Henan | 157 | 47 | 157 | 47 | 23 | 22 |
| Hubei | 928 | 557 | 928 | 223 | 169 | 117 |
| Hunan | 157 | 116 | 157 | 116 | 29 | 69 |
| Jiangsu | 1,927 | 160 | 1,927 | 160 | 568 | 132 |
| Jiangxi | 169 | 87 | 169 | 87 | 47 | 72 |
| Jilin | 306 | 145 | 306 | 145 | 56 | 108 |
| Liaoning | 96 | 110 | 96 | 110 | 75 | 81 |
| Neimenggu | 157 | 18 | 157 | 18 | 72 | 1 |
| Ningxia | 62 | 27 | 62 | 27 | 55 | 13 |
| Qinghai | 721 | 20 | 721 | 20 | 134 | 0 |
| Sanxi | 1,661 | 538 | 1,661 | 538 | 209 | 330 |
| Shandong | 11,782 | 143 | 11,664 | 143 | 5,559 | 137 |
| Shanghai | 478 | 0 | 229 | 0 | 22 | 0 |
| Shanxi | 174 | 0 | 174 | 0 | 29 | 0 |
| Sichuan | 626 | 875 | 626 | 875 | 165 | 174 |
| Tianjin | 364 | 53 | 364 | 53 | 90 | 20 |
| Tibert | 299 | 0 | 299 | 0 | 84 | 0 |
| Xinjiang | 11 | 44 | 11 | 44 | 1 | 18 |
| Yunnan | 4 | 92 | 4 | 92 | 0 | 79 |
| Zhejiang | 586 | 240 | 586 | 240 | 165 | 166 |
| Total | 56,221 | 8,190 | 54,360 | 7,742 | 26,602 | 3,762 |

**Table 5: Regression results for the number of bidders**

| Variable | All days | | Same day | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Green bond | -0.0004 | | 0.0006 | |
| | (0.0029) | | (0.0023) | |
| Energy conservation | | -0.0045 | | 0.0027 |
| | | (0.0124) | | (0.0045) |
| Pollution prevention | | 0.0075* | | 0.0046** |
| | | (0.0039) | | (0.0022) |
| Recycling | | -0.0009 | | 0.0004 |
| | | (0.0057) | | (0.0038) |
| Green transportation | | -0.0152* | | -0.0056 |
| | | (0.0086) | | (0.0048) |
| Green energy | | -0.0076 | | -0.0043 |
| | | (0.0121) | | (0.0072) |
| Ecological protection | | 0.0007 | | 0.0004 |
| | | (0.0039) | | (0.0038) |
| Log Number of potential bidders | 1.0352*** | 1.0352*** | 1.0086*** | 1.0086*** |
| | (0.0027) | (0.0027) | (0.0027) | (0.0027) |
| Market yield | 0.0252*** | 0.0252*** | 0.0203** | 0.0206** |
| | (0.0083) | (0.0083) | (0.0099) | (0.0101) |
| Log of duration | -0.0159*** | -0.0154*** | -0.0132** | -0.0127* |
| | (0.0053) | (0.0053) | (0.0066) | (0.0066) |
| Log of the time lag between Local | -0.0026*** | -0.0026*** | -0.0011 | -0.0012 |
| Government auctions | (0.0008) | (0.0008) | (0.0008) | (0.0008) |
| Volatility | -0.1527 | -0.1614 | -0.3144* | -0.3164* |
| | (0.1284) | (0.1287) | (0.1858) | (0.1865) |
| Log value of maturing bonds by | 0.0002 | 0.0002 | 0.0000 | 0.0001 |
| the Local Government | (0.0009) | (0.0009) | (0.0007) | (0.0007) |
| The planned value of issuing | -0.0017 | -0.0016 | 0.0015 | 0.0016 |
| bonds | (0.0012) | (0.0012) | (0.0011) | (0.0011) |
| Bid-to-cover ratio | 0.0001 | 0.0002 | 0.0003** | 0.0003** |
| | (0.0002) | (0.0002) | (0.0001) | (0.0001) |
| Other controls | Yes | Yes | Yes | Yes |
| Market drift | Yes | Yes | Yes | Yes |
| Year effects | Yes | Yes | Yes | Yes |
| Month effects | Yes | Yes | Yes | Yes |
| Provincial effects | Yes | Yes | Yes | Yes |
| Observations | 2,762 | 2,762 | 1,237 | 1,237 |
| R-squared | 0.727 | 0.727 | 0.731 | 0.731 |

All regressions include the market yield of Central Government bonds one day before the auction date, log of duration, log of the time lag between local government auctions, volatility, log value of maturing bonds by the local government for a given month, the planned value of issuing bonds, bid-to-cover ratio, first and last week of the month, and market drift. The variable duration refers to the Macaulay duration, which is the weighted average term to maturity of the cash flows from a bond. We estimate these models using the Poisson Pseudo Maximum Likelihood (PPML) method. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

**Table 6: Regression results for the number of bidders: alternate sample**

| **Variable** | **All days** | | **Same day** | |
|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** |
| Green bond | -0.0109 | | 0.0264 | |
| | (0.0402) | | (0.0372) | |
| Energy conservation | | 0.0394 | | 0.0493 |
| | | (0.1594) | | (0.1471) |
| Pollution prevention | | 0.0119 | | 0.0275 |
| | | (0.0695) | | (0.0591) |
| Recycling | | 0.2320 | | 0.1126 |
| | | (0.1947) | | (0.1525) |
| Green transportation | | -0.1115 | | -0.1034 |
| | | (0.0801) | | (0.0874) |
| Green energy | | 0.0905 | | 0.1552 |
| | | (0.1870) | | (0.1491) |
| Ecological protection | | -0.0169 | | 0.0454 |
| | | (0.0567) | | (0.0517) |
| Other controls | Yes | Yes | Yes | Yes |
| Market drift | Yes | Yes | Yes | Yes |
| Year effects | Yes | Yes | Yes | Yes |
| Month effects | Yes | Yes | Yes | Yes |
| Provincial effects | Yes | Yes | Yes | Yes |
| Observations | 2,393 | 2,393 | 1,140 | 1,140 |
| R-squared | 0.219 | 0.212 | 0.343 | 0.344 |

All regressions include the market yield of Central Government bonds one day before the auction date, log of duration, log of the time lag between local government auctions, volatility, log value of maturing bonds by the local government for a given month, the planned value of issuing bonds, bid-to-cover ratio, first and last week of the month, and market drift. The variable duration refers to the Macaulay duration, which is the weighted average term to maturity of the cash flows from a bond. We estimate these models using the Poisson Pseudo Maximum Likelihood (PPML) method. Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

**Table 7: Probit results for auction entry**

| **Variable** | **Probability of bidding** | | | | | |
|---|---|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
| Green bond | 0.0026 | 0.0019 | 0.0004 | | | |
| | (0.0022) | (0.0023) | (0.0004) | | | |
| Energy conservation | | | | | | |
| Pollution prevention | | | | 0.0092*** | 0.0165*** | 0.0028*** |
| | | | | (0.0033) | (0.0044) | (0.0005) |
| Recycling | | | | | | |
| Green transportation | | | | -0.0053 | -0.0105* | -0.0028* |
| | | | | (0.0062) | (0.0056) | (0.0017) |
| Green energy | | | | 0.0169** | 0.0194 | 0.0032** |
| | | | | (0.0078) | (0.0148) | (0.0013) |
| Ecological protection | | | | 0.0028 | 0.0000 | -0.0000 |
| | | | | (0.0028) | (0.0030) | (0.0006) |
| Log number of potential bidders | Yes | Yes | Yes | Yes | Yes | Yes |
| Other controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Market drift | Yes | Yes | Yes | Yes | Yes | Yes |
| Year effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Month effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Provincial effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Dealer effects (RE) | | Yes | | | Yes | |
| Dealer effects | | | Yes | | | Yes |
| Observations | 72,725 | 72,725 | 72,725 | 72,725 | 72,725 | 72,725 |
| Wald $\chi^2$ | 13819 | 10213 | 13118 | 13820 | 10208 | 13089 |

All regressions include the face entrant dummy, experience (log of past win counts), the market yield of the Central Government bonds one day before the auction date, log of duration, log of the time lag between local government auctions, volatility, log value of maturing bonds by the local government for a given month, the planned value of issuing bonds, bid-to-cover ratio, bidding in the same province, distance to auction province, first and last week of the month, and market drift. The variable duration refers to the Macaulay duration, which is the weighted average term to maturity of the cash flows from a bond. Marginal effects are reported. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

**Table 8: Regression results for normalized winning bids**

| **Variables** | **All days** | | **Same day** | |
|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** |
| Green bond | 0.0012* | 0.0012* | 0.0031*** | 0.0028*** |
| | (0.0006) | (0.0006) | (0.0006) | (0.0006) |
| Entrant | | 0.0126*** | 0.0214*** | 0.0209*** |
| | | (0.0028) | (0.0037) | (0.0031) |
| Face an entrant | | 0.0019** | 0.0104*** | 0.0101*** |
| | | (0.0008) | (0.0013) | (0.0013) |
| Experience | -0.0073*** | -0.0056*** | -0.0039* | -0.0008** |
| | (0.0011) | (0.0012) | (0.0020) | (0.0003) |
| Log of duration | -0.0056*** | -0.0054*** | -0.0045*** | -0.0042*** |
| | (0.0005) | (0.0005) | (0.0007) | (0.0006) |
| Log of the time lag between Local | 0.0030*** | 0.0030*** | 0.0012** | 0.0014** |
| Government auctions | (0.0004) | (0.0004) | (0.0006) | (0.0006) |
| Volatility | -0.6092*** | -0.6318*** | -0.1401*** | -0.1313*** |
| | (0.0208) | (0.0201) | (0.0490) | (0.0480) |
| Log value of maturing bonds by the Local | 0.0035*** | 0.0035*** | 0.0065*** | 0.0066*** |
| Government | (0.0002) | (0.0002) | (0.0005) | (0.0004) |
| The planned value of issuing bonds | -0.0012*** | -0.0009*** | 0.0005** | 0.0004 |
| | (0.0002) | (0.0002) | (0.0002) | (0.0003) |
| Bid-to-cover ratio | 0.0004*** | 0.0004*** | -0.0001 | -0.0001 |
| | (0.0000) | (0.0000) | (0.0001) | (0.0001) |
| Bidding in the same province | -0.0014 | -0.0012 | -0.0016 | -0.0039*** |
| | (0.0014) | (0.0014) | (0.0018) | (0.0014) |
| Log number of bidders | | -0.0045*** | -0.0091*** | -0.0094*** |
| | | (0.0006) | (0.0015) | (0.0014) |
| Year effects | Yes | Yes | Yes | Yes |
| Month effects | Yes | Yes | Yes | Yes |
| Provincial effects | Yes | Yes | Yes | Yes |
| Dealer effects (FE) | Yes | Yes | Yes | |
| Dealer effects (RE) | | | | Yes |
| Observations | 30,364 | 30,364 | 13,120 | 13,120 |
| R-squared | 0.6834 | 0.6846 | 0.6706 | 0.6658 |

All regressions include entrant and face entrant dummies, experience (log of past win counts), the market yield of Central Government bonds one day before the auction date, log of duration, log of the time lag between local government auctions, volatility, log value of maturing bonds by the local government for a given month, the planned value of issuing bonds, bid-to-cover ratio, bidding in the same province, first and last week of the month, and market drift. The variable duration refers to the Macaulay duration, which is the weighted average term to maturity of the cash flows from a bond. We estimate these models using OLS. In Columns 1-5, we include dealer fixed effects while, in Column 6, we include random effects. Robust standard errors clustered by primary dealers are in parentheses. *** p<0.01, ** p<0.05, * p<0.

**Table 9: Regression results for normalized winning bids: alternate sample**

| **Variables** | **All days** | | **Same day** | |
|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** |
| Green bond | 0.0015** | 0.0015** | 0.0035*** | 0.0032*** |
| | (0.0006) | (0.0006) | (0.0007) | (0.0007) |
| Entrant | | 0.0115*** | 0.0222*** | 0.0219*** |
| | | (0.0030) | (0.0037) | (0.0032) |
| Face an entrant | | 0.0009 | 0.0122*** | 0.0119*** |
| | | (0.0008) | (0.0016) | (0.0016) |
| Experience | -0.0061*** | -0.0042*** | -0.0042** | -0.0008*** |
| | (0.0012) | (0.0013) | (0.0020) | (0.0003) |
| Log number of bidders | | -0.0056*** | -0.0103*** | -0.0105*** |
| | | (0.0007) | (0.0016) | (0.0015) |
| Year effects | Yes | Yes | Yes | Yes |
| Month effects | Yes | Yes | Yes | Yes |
| Provincial effects | Yes | Yes | Yes | Yes |
| Dealer effects (FE) | Yes | Yes | Yes | |
| Dealer effects (RE) | | | | Yes |
| Observations | 26,984 | 26,984 | 12,530 | 12,530 |
| R-squared | 0.6780 | 0.6797 | 0.6758 | 0.6711 |

All regressions include entrant and face entrant dummies, experience (log of past win counts), the market yield of Central Government bonds one day before the auction date, log of duration, log of the time lag between local government auctions, volatility, log value of maturing bonds by the local government for a given month, the planned value of issuing bonds, bid-to-cover ratio, bidding in the same province, first and last week of the month, and market drift. The variable duration refers to the Macaulay duration, which is the weighted average term to maturity of the cash flows from a bond. We estimate these models using OLS. Robust standard errors clustered by primary dealers are in parentheses. *** p<0.01, ** p<0.05, * p<0.

**Table 10: Regression results for normalized winning bids by bond types**

| **Variables** | **All days** | | **Same day** | |
|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** |
| Energy conservation | 0.0071*** | 0.0067*** | 0.0073*** | 0.0085*** |
| | (0.0025) | (0.0023) | (0.0025) | (0.0025) |
| Pollution prevention | 0.0045*** | 0.0048*** | 0.0067*** | 0.0066*** |
| | (0.0007) | (0.0007) | (0.0009) | (0.0009) |
| Recycling | -0.0019 | -0.0017 | -0.0108*** | -0.0110*** |
| | (0.0038) | (0.0039) | (0.0028) | (0.0028) |
| Green transportation | -0.0102*** | -0.0103*** | -0.0069*** | -0.0073*** |
| | (0.0018) | (0.0017) | (0.0013) | (0.0014) |
| Green energy | -0.0061*** | -0.0059*** | -0.0033*** | -0.0036*** |
| | (0.0010) | (0.0010) | (0.0011) | (0.0011) |
| Ecological protection | 0.0035*** | 0.0033*** | 0.0050*** | 0.0046*** |
| | (0.0009) | (0.0009) | (0.0010) | (0.0009) |
| Entrant | | 0.0123*** | 0.0206*** | 0.0203*** |
| | | (0.0028) | (0.0037) | (0.0031) |
| Face an entrant | | 0.0018** | 0.0102*** | 0.0100*** |
| | | (0.0008) | (0.0014) | (0.0014) |
| Experience | -0.0073*** | -0.0057*** | -0.0042** | -0.0007** |
| | (0.0011) | (0.0012) | (0.0020) | (0.0003) |
| Bidding in the same province | -0.0014 | -0.0012 | -0.0016 | -0.0038*** |
| | (0.0014) | (0.0014) | (0.0018) | (0.0013) |
| Log number of bidders | | -0.0045*** | -0.0093*** | -0.0096*** |
| | | (0.0006) | (0.0014) | (0.0014) |
| Year effects | Yes | Yes | Yes | Yes |
| Month effects | Yes | Yes | Yes | Yes |
| Provincial effects | Yes | Yes | Yes | Yes |
| Dealer effects (FE) | Yes | Yes | Yes | |
| Dealer effects (RE) | | | | Yes |
| Observations | 30,364 | 30,364 | 13,120 | 13,120 |
| R-squared | 0.6839 | 0.6851 | 0.6721 | 0.6673 |

All regressions include entrant and face entrant dummies, experience (log of past win counts), the market yield of Central Government bonds one day before the auction date, log of duration, log of the time lag between local government auctions, volatility, log value of maturing bonds by the local government for a given month, the planned value of issuing bonds, bid-to-cover ratio, bidding in the same province, first and last week of the month, and market drift. The variable duration refers to the Macaulay duration, which is the weighted average term to maturity of the cash flows from a bond. We estimate these models using OLS. Robust standard errors clustered by primary dealers are in parentheses. *** p<0.01, ** p<0.05, * p<0.

**Table 11: Regression results for normalized winning bids by bond types: alternate sample**

| **Variables** | **All days** | | **Same day** | |
|---|---|---|---|---|
| | **(1)** | **(3)** | **(4)** | **(5)** |
| Energy conservation | 0.0063** | 0.0061** | 0.0078*** | 0.0092*** |
| | (0.0026) | (0.0024) | (0.0027) | (0.0027) |
| Pollution prevention | 0.0047*** | 0.0050*** | 0.0074*** | 0.0074*** |
| | (0.0007) | (0.0007) | (0.0009) | (0.0009) |
| Recycling | -0.0029 | -0.0025 | -0.0100*** | -0.0101*** |
| | (0.0038) | (0.0038) | (0.0027) | (0.0027) |
| Green transportation | -0.0104*** | -0.0105*** | -0.0070*** | -0.0073*** |
| | (0.0020) | (0.0019) | (0.0015) | (0.0016) |
| Green energy | -0.0057*** | -0.0051*** | -0.0031** | -0.0034*** |
| | (0.0010) | (0.0010) | (0.0012) | (0.0012) |
| Ecological protection | 0.0039*** | 0.0037*** | 0.0050*** | 0.0046*** |
| | (0.0009) | (0.0009) | (0.0010) | (0.0010) |
| Entrant | | 0.0110*** | 0.0215*** | 0.0214*** |
| | | (0.0030) | (0.0037) | (0.0032) |
| Face an entrant | | 0.0008 | 0.0120*** | 0.0118*** |
| | | (0.0008) | (0.0016) | (0.0017) |
| Experience | -0.0061*** | -0.0043*** | -0.0045** | -0.0008*** |
| | (0.0012) | (0.0013) | (0.0020) | (0.0003) |
| Bidding in the same province | -0.0012 | -0.0015 | -0.0017 | -0.0039*** |
| | (0.0016) | (0.0015) | (0.0017) | (0.0013) |
| Log number of bidders | | -0.0057*** | -0.0105*** | -0.0107*** |
| | | (0.0007) | (0.0015) | (0.0015) |
| Year effects | Yes | Yes | Yes | Yes |
| Month effects | Yes | Yes | Yes | Yes |
| Provincial effects | Yes | Yes | Yes | Yes |
| Dealer effects (FE) | Yes | Yes | Yes | |
| Dealer effects (RE) | | | | Yes |
| Observations | 26,984 | 26,984 | 12,530 | 12,530 |
| R-squared | 0.6786 | 0.6802 | 0.6773 | 0.6726 |

All regressions include entrant and face entrant dummies, experience (log of past win counts), the market yield of Central Government bonds one day before the auction date, log of duration, log of the time lag between local government auctions, volatility, log value of maturing bonds by the local government for a given month, the planned value of issuing bonds, bid-to-cover ratio, bidding in the same province, first and last week of the month, and market drift. The variable duration refers to the Macaulay duration, which is the weighted average term to maturity of the cash flows from a bond. We estimate these models using OLS. Robust standard errors clustered by primary dealers are in parentheses. *** p<0.01, ** p<0.05, * p<0.

**Table 12: Regression results for normalized winning bids in transportation auctions**

| **Variables** | **Full sample** | | **Alternate sample** | |
|---|---|---|---|---|
| | **All days** | **Same day** | **All days** | **Same day** |
| | **(1)** | **(2)** | **(3)** | **(4)** |
| Green transportation | -0.0119*** | -0.0097*** | -0.0126*** | -0.0090*** |
| | (0.0026) | (0.0032) | (0.0027) | (0.0034) |
| Other controls | Yes | Yes | Yes | Yes |
| Year effects | Yes | Yes | Yes | Yes |
| Month effects | Yes | Yes | Yes | Yes |
| Provincial effects | Yes | Yes | Yes | Yes |
| Dealer effects (FE) | Yes | Yes | Yes | Yes |
| Observations | 1,707 | 1,471 | 1,589 | 1,381 |
| R-squared | 0.7095 | 0.7097 | 0.6826 | 0.6846 |

All regressions include entry status indicator, facing an entrant indicator, experience (log of past win counts), the market yield of Central Government bonds one day before the auction date, log of duration, log of the time lag between local government auctions, volatility, log value of maturing bonds by the local government for a given month, the planned value of issuing bonds, bid-to-cover ratio, bidding in the same province, first and last week of the month, and market drift. The variable duration refers to the Macaulay duration, which is the weighted average term to maturity of the cash flows from a bond. We estimate these models using OLS. Robust standard errors clustered by primary dealers are in parentheses. *** p<0.01, ** p<0.05, * p<0.

**Table 13: Regression results for the market gap**

| **Variable** | **Primary rate - secondary rate** | |
|---|---|---|
| | **(1)** | **(2)** |
| Green bond | -0.0028 | |
| | (0.0027) | |
| Energy conservation | | 0.0163 |
| | | (0.0108) |
| Pollution prevention | | -0.0035 |
| | | (0.0050) |
| Recycling | | |
| Green transportation | | -0.0024 |
| | | (0.0026) |
| Green energy | | 0.0025 |
| | | (0.0058) |
| Ecological protection | | -0.0034 |
| | | (0.0035) |
| Note | 0.0084*** | 0.0084*** |
| | (0.0015) | (0.0015) |
| Log of lag of days between primary market and the secondary market | -0.0010<br>(0.0026) | -0.0009<br>(0.0026) |
| Volatility | 0.0553 | 0.0550 |
| | (0.0757) | (0.0758) |
| Government yield gap between primary auction date and the day before the secondary market | 0.0483***<br>(0.0147) | 0.0487***<br>(0.0148) |
| Log value of maturing bonds by the Local Government | -0.00003<br>(0.0005) | -0.00004<br>(0.0005) |
| First and last week of the month | Yes | Yes |
| Market drift | Yes | Yes |
| Year effects | Yes | Yes |
| Month effects | Yes | Yes |
| Provincial effects | Yes | Yes |
| Observations | 1,355 | 1,355 |
| R-squared | 0.1482 | 0.1489 |

All regressions include the Government yield gap between the primary auction and the day before the secondary market, an indicator for bonds, volatility of the secondary market, log of lag of days between the primary market and secondary market, log value of maturing bonds by the local government for a given month, first and last week of the month, and market drift. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

**Table 14: Pearson correlation among Syn Tao ESG scores and green bond values**

| Variable | Syn Tao ESG score | |
|---|---|---|
| | Total value | Relative value |
| | (1) | (2) |
| All green bonds | 0.2706 | 0.1779 |
| | [0.0005] | [0.0289] |
| Energy conservation bonds | 0.2241 | 0.1461 |
| | [0.0040] | [0.0735] |
| Pollution prevention bonds | 0.3078 | 0.1062 |
| | [0.0001] | [0.1943] |
| Recycling bonds | 0.2823 | 0.1395 |
| | [0.0003] | [0.0876] |
| Green transportation bonds | 0.2551 | 0.0368 |
| | [0.0010] | [0.6541] |
| Green energy bonds | 0.3093 | 0.1549 |
| | [0.0001] | [0.0576] |
| Ecological protection bonds | 0.2603 | 0.2210 |
| | [0.0008] | [0.0064] |

The relative value of total green bonds (or categorized by green bond type) for each bidder at a specific point in time is determined as the total value of green bonds (or by green bond type) they have acquired in the past, divided by the total value of all bonds they have purchased. These total and relative values are updated each period. When computing Pearson correlation coefficients, we utilize the year-end relative values and the annual ESG score. It's important to emphasize that the ESG score is an annual measure. Significances are reported in brackets.

**Table 15: Probability of exiting a provincial bond market**

| Variable | Probability of exit | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Relative total green bonds | -0.1238* | -0.1157* | -0.0480* | | | |
| | (0.0711) | (0.0682) | (0.0256) | | | |
| Log of relative total green bonds | | | | -0.0008* | -0.0035*** | -0.0010*** |
| | | | | (0.0004) | (0.0006) | (0.0002) |
| Experience | -0.0239*** | -0.0092*** | -0.0062*** | -0.0262*** | -0.0072** | -0.0047*** |
| | (0.0027) | (0.0031) | (0.0014) | (0.0031) | (0.0029) | (0.0011) |
| Same province | -0.0415*** | -0.0038 | -0.0064* | -0.0476*** | -0.0001 | -0.0052* |
| | (0.0136) | (0.0133) | (0.0035) | (0.0142) | (0.0125) | (0.0029) |
| Log number of rivals | -0.0216** | -0.0214** | -0.0045 | -0.0212** | -0.0160* | -0.0023 |
| | (0.0101) | (0.0095) | (0.0036) | (0.0101) | (0.0091) | (0.0031) |
| Log of absolute value total | | -0.0049*** | -0.0013*** | | -0.0091*** | -0.0024*** |
| pseudo-expected profits | | (0.0009) | (0.0004) | | (0.0012) | (0.0004) |
| Negative total pseudo-expected | | 0.0021 | -0.0001 | | 0.0042 | 0.0008 |
| profits | | (0.0077) | (0.0027) | | (0.0074) | (0.0023) |
| Other controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Dealer effects (RE) | Yes | Yes | | Yes | Yes | |
| Dealer effects | | | Yes | | | Yes |
| Observations | 7,378 | 7,378 | 7,378 | 7,378 | 7,378 | 7,378 |
| Wald $\chi^2$ | 258.06 | 287.14 | 764.65 | 256.00 | 294.37 | 756.66 |

We consider all dealers who have entered provincial bond markets since August 2018 and track their monthly market activities in each province. If a dealer has no activity for nine months, we consider that the dealer has exited the given provincial market in the last month we observed. We do not consider any firms that entered a province after January 2020. Since the last period in our sample is September 2020, we consider a dealer who did not exit the market before January 2020 as still active. In all regressions, experience is the log of past win counts. Other controls include the log value of maturing bonds and the local government's planned value of issuing bonds for a given month. We estimate these models using Probit technique. Robust standard errors clustered are in parentheses. *** p<0.01, ** p<0.05, * p<0.

**Table 16: Cost of green bonds**

| Bond type | Value in ¥[a] | Estimates | Cost for the government | | |
|---|---|---|---|---|---|
| | | | Lower | Mean | Upper |
| Energy conservation | 8,228 | 0.0067 | 193 | 196 | 199 |
| | | (0.0023) | | | |
| Pollution prevention | 69,565 | 0.0048 | 1,897 | 1,906 | 1,916 |
| | | (0.0007) | | | |
| Recycling | 7,708 | -0.0017 | -208 | -203 | 197 |
| | | (0.0039) | | | |
| Green transportation | 161,672 | -0.0103 | -5,531 | -5,463 | -5,395 |
| | | (0.0017) | | | |
| Green energy | 5,064 | -0.0059 | -164 | -163 | -161 |
| | | (0.0010) | | | |
| Ecological protection | 309,842 | 0.0033 | 8,914 | 8,974 | 9,035 |
| | | (0.0009) | | | |
| Total | 562,079 | | 5,101 | 5,247 | 5,791 |

a: Value in millions of ¥.

**Table 17: Per capita pollution outcomes for provinces**

| Variable | Log ($CO_2$) 2005-2019 | Log ($SO_2$) 2005-2020 | Log ($NO_X$) 2011-2020 | Log (water) 2005-2020 | Log (forest) 2005-2020 |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Energy conservation bond share | -20.381** | -4.626 | 10.934 | -1.726 | -23.656 |
| | (8.647) | (18.473) | (8.311) | (16.949) | (23.197) |
| Pollution prevention bond share | -3.038 | -6.484* | -0.168 | -5.588 | 9.985** |
| | (3.350) | (3.774) | (1.604) | (4.012) | (4.343) |
| Recycling bond share | 5.892 | -1.846 | -1.435 | 29.356 | 55.898* |
| | (7.236) | (20.162) | (4.352) | (19.634) | (28.992) |
| Green transportation bond share | 0.331 | -5.572*** | -0.265 | 0.302 | 1.504 |
| | (3.217) | (1.460) | (0.440) | (0.630) | (1.040) |
| Green energy bond share | 6.954*** | -11.998 | -9.334* | -14.381* | 11.088 |
| | (2.189) | (17.214) | (4.978) | (8.420) | (18.044) |
| Ecological protection bond share | -0.414 | -2.072 | -0.662** | -0.778 | -3.757*** |
| | (1.902) | (1.228) | (0.303) | (0.486) | (1.264) |
| 2013-2015 | -0.079*** | -0.107** | -0.078*** | -0.046 | -0.051 |
| | (0.024) | (0.046) | (0.027) | (0.049) | (0.093) |
| After Paris Agreement | -0.182*** | -1.365*** | -0.464*** | 0.003 | -0.102 |
| | (0.036) | (0.135) | (0.072) | (0.047) | (0.120) |
| COVID-19 | | -0.327*** | -0.137*** | 0.163** | -0.109* |
| | | (0.110) | (0.045) | (0.067) | (0.056) |
| Log of provincial per capita GDP | 0.505*** | -0.119 | -0.320** | 0.012 | 0.667*** |
| | (0.031) | (0.074) | (0.149) | (0.036) | (0.121) |
| Provincial effects | Yes | Yes | Yes | Yes | Yes |
| Observations | 450 | 496 | 310 | 496 | 496 |
| R-squared | 0.946 | 0.890 | 0.938 | 0.976 | 0.870 |

Standard errors clustered by province are in parentheses. *** p<0.01, ** p<0.05, * p<0.1 $CO_2$, $SO_2$, and $NO_X$ are measured in tons per person. Water resources are measured in tens of cubic meters per person. Forest resources are measured in hectares per person.

## Appendix A

**Table A.1: Description of the variables**

| Variable | Description |
|---|---|
| Market yield of Chinese bonds one day before the auction date | This variable is the publicly announced yield curve rates by the CCDC one day before the auction date. Each business day, the CCDC publicly announces the yield curves for bonds issued by the Chinese Central Bank by maturity, which are based on the previous resale market transactions. These yield curves provide official benchmarks to general investors. The CCDC constructs the official yield curve mainly using settlement prices of government bonds in the inter-bank market. When they are unavailable, the CCDC uses bilateral quotes in the inter-bank market, bilateral quotes in the OTC market, transaction prices in the exchange market, quotes and final prices in fixed income platform of the exchange market, quotes of money broking corporations, and the estimated value of yield rate from market members. |
| Volatility | We use the variance of the yield curve from five business days before the auction date to control for volatility in the Chinese bond market. |
| Duration | The duration variable refers to Macaulay duration, which is the weighted average term to maturity of the cash flows from a bond. A similar duration variable is used by Simon (1994). |
| Bid-to-cover ratio | This variable is the ratio of the total amount of submitted bid quantities for securities divided by supply (allotment) volume. This variable controls the strength of demand and the degree of competition in an auction. A similar measure is used by Cordy (1999) and Goldreich (2007). In our sample, the total submitted bid quantities were at least equal to the allotment. |
| Lag time between auctions | This variable measures the business days since the last auction held by a province. Alternatively, we calculate the business days since any province held the previous auction. |
| Value of maturing bonds by a province for a given month | This variable controls the possibility that provinces may recycle their liquidity obtained through matured securities to bid for new issuance. |
| Number of potential bidders | This is the number of potential bidders in an auction. |
| Number of bidders | This is the number of bidders in an auction. |
| First and last week of the month | This indicator variable is equal to one if the auction date takes place seven days before or seven days after the end of the month, and equal to zero otherwise. |

**Table A.1: Description of the variables (continued)**

| Variable | Description |
|---|---|
| The total value of green bonds (and the total value of green bonds by type) | The total value of green bonds (or segmented by green bond type) held by each dealer at a specific moment is calculated by considering the sum of green bonds (or by green bond type) they have previously acquired in all provincial markets. These values are updated each period. |
| The relative value of green bonds (and the relative value of green bonds by type) | These variables are calculated by dividing the total value of green bonds (and the total value of green bonds by type) by the total value of all bonds each bidder has procured at a given period. |
| Market drift | This variable is constructed by counting the number of weeks since the start of January 2018 by dividing each week by the number of total weeks in which provinces sold bonds. Simon (1994) notes that a market-drift variable controls for gradual unobservable changes that bidders face during the period of analysis. Although a model of long-term relationships with dynamic trade-offs is beyond the scope of this study, other studies point out that a repeated auction environment can sustain a variety of strategies in equilibria (see e.g., Skrzypacz and Hopenhayn, 2004 and Barbosa et al., 2022), and this time-shifting variable parsimoniously controls for potential gradual changes in long-term interactions among bidders, regardless of the auction formats. |
| Entrant in a provincial market | The entrant indicator takes the value of one for any potential dealer observed for the first time in a province since August 01, 2018, as an entrant, and else zero. Their subsequent participation in that province is treated as activities by incumbents. We define any bidder who has bid in an auction in a given province before August 2018 as an incumbent. |
| Face an entrant | This indicator variable takes the value of one when an incumbent bidder faces an entrant in an auction as a potential bidder and zero otherwise. |
| Exit from a provincial market | If a dealer has no activity for 12 months, we consider that the dealer has exited the given provincial market. |

**Table A.2: Bond values by dealer types**

| Dealer type | Number | Value (in millions of ¥) | |
|---|---|---|---|
| | | Regular bonds | Green bonds |
| Commercial banks | 159 | 8,300,346 | 475,679 |
| Credit cooperative | 15 | 122,468 | 14,442 |
| Financial companies | 2 | 34,786 | 641 |
| Security companies | 85 | 1,434,986 | 71,317 |

**Table A.3: Regression results for the number of bidders with the alternate time gap**

| Variable | All auctions | | Same days auctions | |
|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** |
| Green bond | -0.0005 | | 0.0006 | |
| | (0.0029) | | (0.0023) | |
| Energy conservation | | -0.0033 | | 0.0034 |
| | | (0.0125) | | (0.0046) |
| Pollution prevention | | 0.0066* | | 0.0045** |
| | | (0.0038) | | (0.0022) |
| Recycling | | -0.0000 | | 0.0011 |
| | | (0.0047) | | (0.0035) |
| Green transportation | | -0.0159* | | -0.0058 |
| | | (0.0086) | | (0.0048) |
| Green energy | | -0.0072 | | -0.0042 |
| | | (0.0120) | | (0.0071) |
| Ecological protection | | 0.0010 | | 0.0004 |
| | | (0.0039) | | (0.0039) |
| Log number of potential bidders | 1.0354*** | 1.0353*** | 1.0090*** | 1.0090*** |
| | (0.0027) | (0.0027) | (0.0028) | (0.0028) |
| Other controls | Yes | Yes | Yes | Yes |
| Market drift | Yes | Yes | Yes | Yes |
| Year effects | Yes | Yes | Yes | Yes |
| Month effects | Yes | Yes | Yes | Yes |
| Provincial effects | Yes | Yes | Yes | Yes |
| Observations | 2,762 | 2,762 | 1,237 | 1,237 |
| R-squared | 0.727 | 0.727 | 0.731 | 0.731 |

All regressions include the market yield of Central Government bonds one day before the auction date, log of duration, log of the time lag between local government auctions (alternate definition), volatility, log value of maturing bonds by the local government for a given month, the planned value of issuing bonds, bid-to-cover ratio, first and last week of the month, and market drift. The variable duration refers to the Macaulay duration, which is the weighted average term to maturity of the cash flows from a bond. We estimate these models using the Poisson Pseudo Maximum Likelihood (PPML) method. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

**Table A.4: Regression results for normalized winning bids with the alternate time gap**

| Variable | All days | | Same day | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Green bond | 0.0012* | | 0.0033*** | |
| | (0.0007) | | (0.0007) | |
| Energy conservation | | | | |
| Pollution prevention | | 0.0049** | | 0.0067*** |
| | | (0.0021) | | (0.0023) |
| Recycling | | 0.0064*** | | 0.0076*** |
| | | (0.0008) | | (0.0008) |
| Green transportation | | -0.0032 | | -0.0117*** |
| | | (0.0042) | | (0.0028) |
| Green energy | | -0.0097*** | | -0.0062*** |
| | | (0.0018) | | (0.0014) |
| Ecological protection | | -0.0060*** | | -0.0034*** |
| | | (0.0010) | | (0.0011) |
| Log number of potential bidders | Yes | Yes | Yes | Yes |
| Other controls | Yes | Yes | Yes | Yes |
| Market drift | Yes | Yes | Yes | Yes |
| Year effects | Yes | Yes | Yes | Yes |
| Month effects | Yes | Yes | Yes | Yes |
| Provincial effects | Yes | Yes | Yes | Yes |
| Dealer effects | Yes | Yes | Yes | Yes |
| Observations | 30,364 | 30,364 | 13,120 | 13,120 |
| R-squared | 0.6837 | 0.6842 | 0.6708 | 0.6722 |

All regressions include the entrant dummy, face entrant dummy, experience (log of past win counts), the market yield of Central Government bonds one day before the auction date, log of duration, log of the time lag between local government auctions, volatility, log value of maturing bonds by the local government for a given month, the planned value of issuing bonds, bid-to-cover ratio, bidding in the same province, distance to auction province, first and last week of the month, and market drift. The variable duration refers to the Macaulay duration, which is the weighted average term to maturity of the cash flows from a bond. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

**Table A.5: Syn Tao Green Finance ESG rankings and number of dealers**

| ESG rank | Converted score | Number of dealers | | |
|---|---|---|---|---|
| | | 2018 | 2019 | 2020 |
| A+ | 10 | | | |
| A | 9 | | | |
| A- | 8 | | | |
| B+ | 7 | 9 | 17 | 24 |
| B | 6 | 21 | 16 | 16 |
| B- | 5 | 11 | 22 | 14 |
| C+ | 4 | 6 | 3 | 4 |
| C | 3 | | | |
| C- | 2 | | | |
| D | 1 | | | |

The Syn Tao Green Finance database categorizes dealers into ten levels: A+ (the highest), A, -A, B+, B, -B, C+, C, C-, and D (the lowest). To facilitate computation, we transform Syn Tao rankings into scores ranging from 1 to 10, with 10 indicating the best performance. Additionally, we provide information on the number of dealers in each category.

**Table A.6: Pollution outcomes for provinces with AR(1) errors**

| **Variable** | **Log ($CO_2$) 2005-2019** | **Log ($SO_2$) 2005-2020** | **Log ($NO_X$) 2011-2020** | **Log (water) 2005-2020** | **Log (forest) 2005-2020** |
|---|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** |
| Energy conservation bond share | -8.623** | -7.767 | 5.981 | -5.669 | -10.373 |
| | (3.515) | (10.226) | (6.291) | (16.502) | (25.771) |
| Pollution prevention bond share | -0.089 | -4.488* | -0.480 | -5.766* | 2.237 |
| | (1.508) | (2.337) | (1.366) | (2.973) | (5.164) |
| Recycling bond share | 2.041 | -19.886* | 0.648 | 26.668* | 11.109 |
| | (3.851) | (10.694) | (6.529) | (15.521) | (26.093) |
| Green transportation bond share | 0.547 | -0.064 | 0.183 | 0.147 | 0.782 |
| | (0.826) | (0.634) | (0.370) | (0.829) | (1.406) |
| Green energy bond share | 1.462 | -1.541 | -5.743 | -16.406 | 17.593 |
| | (4.126) | (9.413) | (5.705) | (15.599) | (23.442) |
| Ecological protection bond share | -0.334 | -0.723 | 0.013 | -0.413 | -3.318*** |
| | (0.700) | (0.586) | (0.337) | (0.692) | (1.245) |
| 2013-2015 | -0.041*** | -0.008 | 0.025 | -0.082* | 0.007 |
| | (0.010) | (0.037) | (0.026) | (0.046) | (0.089) |
| After Paris Agreement | -0.078*** | -0.867*** | -0.196*** | -0.040 | -0.155 |
| | (0.015) | (0.052) | (0.037) | (0.057) | (0.123) |
| COVID-19 | | -0.302*** | -0.117*** | 0.154*** | -0.053 |
| | | (0.042) | (0.025) | (0.058) | (0.097) |
| Log of provincial per capita GDP | 0.320*** | -0.885*** | -0.698*** | 0.085 | 0.872*** |
| | (0.065) | (0.227) | (0.148) | (0.059) | (0.170) |
| Provincial effects | Yes | Yes | Yes | Yes | Yes |
| Observations | 420 | 465 | 279 | 465 | 465 |
| $\rho$(AR) | 0.897 | 0.896 | 0.741 | 0.134 | 0.570 |
| $\rho(\sigma^2)$ | 0.987 | 0.942 | 0.949 | 0.974 | 0.928 |
| Modified Bhargava D-W | 0.259 | 0.397 | 0.750 | 1.749 | 0.912 |
| Baltagi–Wu LBI | 0.530 | 0.612 | 1.084 | 1.873 | 1.025 |

$CO_2$, $SO_2$, and $NO_X$ are measured in tons per person. Water resources are measured in tens of cubic meters per person. Forest resources are measured in hectares per person. Standard errors clustered by province are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.