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Blockchain for Environmental Monitoring: Theory and Empirical Evidence from China

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Abstract

We present the first piece of empirical evidence on blockchain adoption for environmental monitoring. Using a staggered difference-in-difference (DID) framework, we find that the concentrations of SO2, NO2, CO in blockchain adopting cities in China are on average lower by 17%, 8% and 4% compared to other cities. However, the blockchain monitoring system is also coming with a decrease in economic activities. The quarterly GDP growth is reduced by 1.6%-2.6% in blockchain adopting cities, which is mostly driven by the reduction in the industrial sector. Further evidence shows that firms in adopting cities open more plants in other cities to avoid regulation. We then build a theory of endogenous pollution behaviors, environmental monitoring, and blockchain adoption to elucidate how blockchains without crypto affect environmental monitoring efficiency and pollution levels. The model implies that adopting blockchains reduces the pollution level in a city, however, it also decreases its production and market share of firms as firms relocate to other cities. The city that cares more about the environment quality is more likely to adopt the blockchain. Lastly, high adoption costs and pollution benefits may cause inefficient under-adoption, and a wealth transfer is necessary to coordinate full adoption and thus achieve the social optimum.

JEL Classification: D50, G30, G38, Q52, Q55, Q56
Keywords: Blockchain, Environmental Monitoring, Pollution, Secure MPC, Sustainability

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1. Introduction

Environmental monitoring is crucial for sustainability because it supplies the foundational data necessary for environmental protection. Accurate monitoring data is indispensable for ensuring effective ecological management. However, data quality remains a significant concern in practice. Issues such as reporting manipulation are prevalent. In addition, because environmental monitoring facilities and reporting entities are independently managed, valuable data is siloed and not cross-validated, failing to realize its value in aggregate. Similar data quality issues also plague ESG disclosures and ratings, which often lack accountability and proper audits, creating greenwashing (Marquis et al., 2016; Christensen et al., 2021; Raghunandan and Rajgopal, 2022) and inaccurate rating.[1] Companies themselves are unclear about how to effectively implement ESG practices and fall behind on their green commitments (Aldy et al., 2023), not to mention institutional investors' withdrawal from ESG funds due to the unreliability of standardized scores.[2]

It has taken accounting literature nearly four decades to thoroughly understand and regulate financial disclosure. However, emergent distributed ledger technologies such as blockchains, as an innovative solution for establishing algorithmic trust at low costs without conventional trusts, offers an arguably quicker path (e.g., Abadi and Brunnermeier, 2020; Cong and He, 2019). Blockchain's inherent features, such as tamper-resistance and traceability, ensure data integrity, while its consensus mechanisms ensure data reliability (e.g., Chiu and Koeppl, 2019). Moreover, the decentralized nature of blockchains enables privacy-preserving/secure multiparty computation (secure-MPC) which features multiple applications in financial and corporate reporting settings (see Chen, Cong, and Xiao, 2021, Hastings, Falk, and Tsoukalas, 2023, Cao, Cong, and Yang, 2024, and Chinco, 2024).[3]

Recently, blockchain has been adopted by some governments to enhance environmental sustainability (Glavanits, 2020; Erwin and Yang, 2023), because blockchain facilitates the adoption of new green production techniques and enhances the monitoring, storage, and analysis of data concerning pollution and environmental degradation. Equipped with blockchain, the regulator can subsequently monitor and detect pollution violations through comprehensive data analysis. For instance, by comparing the power usage of pollutant treatment equipment with that of the production lines in a factory, the regulator can infer whether the treatment equipment is operating normally, thereby detecting pollution violations. Thanks to encryption techniques such as secure MPC in the blockchain system, violations are

[1] Many greenwashing scandals have been reported in news. One such example is the German asset manager DWS, who needs to pay $19mn to the US securities regulator in a greenwashing probe after being accused of making "materially misleading statements". Source: https://www.ft.com/content/cf9001ab-e326-4264-af5e-12b3fbb0ee7b

[2] Clients have withdrawn a net $40 billion from ESG funds this year according to the website: https://www.ft.com/content/cf9001ab-e326-4264-af5e-12b3fbb0ee7b

[3] This is typically aided by encryption technologies such as Zero-Proof Knowledge and other commitment schemes, through which one can cross-validate information and analyze data in aggregate without seeing the details of the raw data. See Cao et al. (2020) and Cao, Cong, and Yang (2024) for technical details.

validated without revealing proprietary information[4]. It also enables the real-time collection and analysis of green or low-carbon data, which is crucial for timely decision-making (Bai and Sarkis, 2019; Mora et al., 2021; Saberi et al., 2019). Furthermore, the immutability feature of blockchain prevent the recorded data from being revised.

Studies on blockchains often entail the discussion of their cryptocurrencies. CZ from Binance even famously claimed in 2022 that "You can't have blockchain without crypto." We make a key contribution by analyzing the economic impact of blockchains without crypto. To that end, although some articles have suggested that blockchain technology can enhance economic and environmental sustainability (Pazaitis et al., 2017; Varsei et al., 2014), none establishes a theoretical foundation for the economic design and socioeconomic implications of blockchain-based environmental monitoring systems. Empirical data on blockchain applications in environmental monitoring or from a setting of blockchain without crypto are extremely hard to obtain. Our paper takes an initial step to bridge these gaps.

We start with documenting stylized empirical facts regarding the impact of blockchain adoption on pollution emission and real economy. As cryptocurrencies and tokens are banned in China, the Chinese context offers a unique opportunity to isolate the effect of implementing blockchains as databases from complications brought by token incentives and price volatility. We explore six cities that applied the blockchain technology in environmental monitoring in China. Using a multivariate logit regression setting, we document that local pollution level, fiscal income and environmental attention are the main drivers of local governments' adoption decisions.

We then investigate the impact of blockchain adoption on pollution mitigation. Using the cohort matching difference in difference method, we find that on average, the SO2, NO2 and CO concentration decreased by 17%, 8% and 4% respectively in one-year after the blockchain adoption for treated cities, compared to control groups. The results are robust to an entropy balanced sample constructed using blockchain adoption determinants as covariates. The strict monitoring imposed by blockchain also have side effect on economic activity. We present supporting evidence that after the adoption of blockchain system, the quarterly GDP growth of treated cities is reduced by 1.6%-2.6%, which implies a hidden costs of 1.7-2.7 billion RMB per year. We show further evidence that almost all the reduction of economic activities come from the secondary industry.

Given the real impact of blockchain environmental monitoring on economics, firms may have the incentive to delocalize their activities and shift the emission to other areas. We find that firms headquartered in blockchain adopting cities do open more factories in other cities in the post-adoption period. The evidence supports the argument that non-universal climate policy may lead to the regulatory arbitrage activities of firms (Bartram, Hou and Kim, 2022). Nevertheless, the separate dynamics of treatment and control groups indicate that the blockchain adoption effects on pollution emission are mostly come from the reduction in adopting cities and not the opposite.

Furthermore, we develop a theoretical model to demonstrate how blockchains and the

[4] Appendix 1 provides more details about the secure multi-party computation.

secure-MPC they enable can enhance the efficiency of environmental monitoring and mitigate pollution. We derive conditions under which equilibria with full adoption, partial adoption, or no adoption of blockchain can be achieved, and analyze their corresponding social welfare. We demonstrate that adopting blockchain helps reducing a city's pollution levels, but it also has a reduction effect on its economic output (production) and the number of firms. We also highlight that high blockchain adoption costs or high economic benefits from pollutions may prevent economy from reaching socially optimal equilibria with full adoption. In these scenarios, a social planer plays a pivotal role in providing subsidies to the regulator or the firms for achieving full adoption and thus increasing the social welfare.

Specifically, the economy consists of two regulators in two cities, who only differ in their preference for environment quality, and multiple firms, who differ only in their location preference for cities. Firms' productions emit harmful pollutants, and the regulator monitors the firms' pollution levels and imposes penalties if they are found to violate pollution standards. However, due to high monitoring costs, the regulator can only verify the pollution for a small fraction of the firms. As firms can generate additional revenues from pollution violations, they are incentivized to violate and to manipulate the pollutant discharge data to avoid the violation penalty. In this model, the regulator's objective is to maximize the economic benefit from production, which is increasing in pollution, while taking into account the social costs of pollution violations (both detected and undetected violations) and the verification costs, by selecting the optimal verification intensity. Conversely, each firm chooses the city in which it operates and the violation probability to maximizes its utility from uncaught violations while taking into account the potential loss from violations being caught and its location preference for two cities.

Within this framework, a unique equilibrium exists. A firm's optimal violation probability, increases with the regulator's verification cost and the firm's economic benefits from pollution violations. Conversely, the violation probability decreases with the social loss the regulator faces for failing to catch violations and the penalties the firm faces if violations are detected. From the regulator's perspective, the optimal verification intensity decreases with its verification cost, the firm's violation penalty, but increases with the regulator's social loss and the firm's economic benefits from uncaught violations. The regulator who faces higher social loss from undetected violations, or cares more about environment quality, get a lower market share of firms in the equilibrium.

We subsequently integrate blockchain technology into this monitoring framework. By establishing a federated blockchain, one that allow a permissioned set of firms to be nodes in the network, the regulator can collect and analyze pollution-related data with greater accuracy, enabling cost-free verification of pollution levels for firms on the blockchain. As a result, the firm's optimal strategy is not to violate at all. We model the interactions between the regulator and firms as a two-stage game: in the first stage, the regulator decides whether to adopt the blockchain; in the second-stage, firms and regulators play the previous game.

We first show that adopting blockchain not only reduces pollution levels, but also decreases the market share as well as the and total production of the city. Then we derive the conditions under which no adoption, partial adoption, or full adoption exists. We show that no adoption and full adoption can coexist under certain conditions, however, both of them cannot coexist with partial adoption. In a partial adoption, the regulator who faces higher social loss from uncaught violations is more likely to adopt the blockchain. However, high blockchain adoption cost or high economic benefits from pollutions for regulators can impede the adoption of blockchain and leads to inefficient social outcome. In particular, when regulators gain high economic benefits from pollutions, there exist cases where full adoption is social optimal but not an equilibrium. In this case, a central or higher-level government plays an important role by providing a wealth transfer to coordinate the full adoption and thus achieve the social optimum.

Our study contributes to a nascent literature on the real effects of blockchains, especially without introducing any native cryptocurrencies. Early studies have theoretically examined issues related to consensus algorithms (Biais et al., 2019; Saleh, 2021), cryptocurrency mining (e.g., Cong et al., 2021a; Lehar and Parlour, 2020; Prat and Walter, 2021), scalability (e.g., Abadi and Brunnermeier, 2020; John et al., 2020), fee designs (Easley et al., 2019; Basu et al., 2019; Huberman et al., 2021), tokenomics (e.g., Cong et al., 2021b; Cong et al., 2022ab; Malinova and Park, 2023), DeFi (e.g., Harvey et al., 2021; Capponi and Jia, 2021), and so on. Recently, researchers pay increasing attention to the fundamental value-creation of blockchain systems, including the role on business collaboration (Narang et al., 2019), firm operations (Chod et al., 2020), counterfeiting combat (Pun et al. 2021), supply chains (Iyengar et al., 2022; Ma et al., 2022; Chen et al., 2023), auditing (Cao et al., 2020; Cao, Cong, and Yang, 2024). While blockchain technologies such as immutability and smart contracts are expected to significantly facilitate the implementation of environmental regulations (Li, Lim, and Wang, 2022), empirical studies are limited.[5] Our research is among the earliest empirical investigation of the economic impact of blockchains without crypto, and is the first on blockchain adoption in environmental monitoring.

Our paper therefore contributes to the growing literature on environmental regulation and sustainability. Prior research highlights the indispensable role of government enforcement (Heyes and Rickman, 1999; Grainger and Schreiber, 2019; Zou, 2021), corporate behavior (Bolton et al., 2022; Friesen, 2003; Shimshack and Ward, 2008; Duflo et al., 2013; Evans, 2018), and public awareness (Berg et al., 2024; Barwick et al., 2024), on environmental regulations and sustainability. Environmental monitoring remains a challenge despite various technological breakthroughs (e.g., Yang, et al., 2024). In this context, blockchain enables multi-party computation and supervision, effectively enhancing data integrity (Abadi and Brunnermeier, 2020; Cong and He, 2019; Hu et al., 2022). Our theory provides an initial framework to analyze environmental monitoring with endogenous pollution and monitoring technology adoption. It further illustrates that the adoption of blockchain technology, coupled with government subsidies, can significantly reduce the violation probabilities.

Finally, our study is broadly related to the evaluation of new technology on social welfare. Previous literature suggests that technological innovation can drive social welfare through economic growth (Jones and Williams, 1998). In particular, Iyengar et al., (2023) found that blockchain can reduce information asymmetry, benefiting consumer welfare. However,

[5] See "White Paper on Blockchain Applications for Environmental Regulation" published by Ministry of Industry and Information Technology in 2021.

technology hardly solves the principal-agent problem in environmental monitoring (Greenstone, et al., 2022; Yang, et al., 2024). We contribute by describing how in theory and in practice blockchains helps environmental monitoring. We also investigate how adoption cost and economic incentives may hinder adoption---a social suboptimum mitigated by government subsidies, which relates to recent studies showing how a planner facilitates the reduction of environmental externalities (e.g., Inderst and Opp, 2024).

The remainder of the paper is structured as follows: Section 2 provides the institutional background; Section 3 presents empirical evidence of the environmental benefits of blockchain adoption on environment monitoring in China. Section 4 models the regulator's monitoring of firm pollution without blockchains and derives the equilibrium strategies for the regulator and firms. Section 5 characterizes the equilibrium with endogenous blockchain adoption. Section 6 explores policy implications before Section 7 concludes.

2. Institutional Background

The integrity and accuracy of environmental data are of paramount importance for competent ecological governance. To mitigate the severe air and water pollution accompanied with the rapid economic growth over the past two decades, the Chinese central government has launched a series of environmental regulation policies since the early 2000s to incentivize local governments to tackle and reduce pollution, including evaluating environmental performance for local officials (He et., 2020), taxing large polluters (Gowrisankaran et al., 2020), deploying automatic pollution monitoring stations (Greenstone et al., 2022), setting up various environmental appeals centers to encourage public participation (Buntaine et al., 2024).

In 2004, to improve the quality of environmental monitoring, the Ministry of Environmental Protection (MEP) launched the Continuous Emissions Monitoring System (CEMS) to automatically monitor the key polluting firms nationwide. The system monitors the emission concentrations of both water pollutants (COD and NH3-N) and air pollutants (SO2, PM, NOX) for all the key polluters in an hourly frequency through the installed monitoring equipment at the pollution sites and a centralized data processing center. A firm's inclusion into the system depends on its emissions in the previous two years, and the MEP has relaxed the inclusion criteria and expanded the CEMS coverage over time. As of early 2020, CEMS monitored almost 25,000 firms, representing more than 75% of China's industrial emissions of air and water pollutants (Buntaine et al., 2024). Since 2013, the Chinese government mandated that environmental protection authorities publicly disseminate real-time hourly emissions data via the CEMS website, promoting public engagement in emissions compliance monitoring.

Despite the government's enormous effort, challenges such as data distortion and manipulation remain prevalent. For instance, in 2021 alone, China prosecuted 270 cases involving the falsification of monitoring data from critical pollutant discharging entities.[6] To address these challenges, some cities have begun to incorporate blockchain technology into their environmental monitoring frameworks because blockchain's attributes—decentralization, immutability, and traceability—make it an ideal solution to enhance data credibility and

[6] Data source: "Blockchain White Paper" published by the China Academy of Information and Communications Technology in 2021.

traceability in environmental monitoring. It also ensures the accuracy and reliability of evidence used in legal proceedings and therefore provides a solid legal foundation for law enforcement (Zhong et al., 2022; Jin and Chang, 2023).

For instance, Zouping, a city in Shandong Province, has pioneered the development and implementation of a blockchain-based ecological environment supervision platform in December 2020, marking the first of its kind in China. The platform integrates the automatic pollution monitoring data with power usage data of the pollutant treatment facilities into a federated blockchain. By analyzing the correlation between electricity consumption and the operation of pollutant treatment equipment, the platform can accurately identify and record tamper-proof violations in real-time, effectively enhancing the timeliness and accuracy of environmental supervision. For example, if a firm consumes a significantly higher electricity than what its reported pollution level would imply, and heightened SO2 level in the region is detected, the firm can be red-flagged for further investigation. If any data require privacy protection, they can be encrypted using Zero-Knowledge-Proof or other commitment schemes from computer science that would mask sensitive information while still allowing the needed cross verifications.

Furthermore, these data are also shared with the local environmental protection department, big data center, police office, and judiciary department in the blockchain, thereby providing robust technical and legal support for legal enforcement actions. The platform encompasses over 1,000 enterprises, mandating participation for most polluting companies. It operates with more than 6,000 trusted terminal devices and manages over 600 million pieces of data with significant legal and enforcement implications. The introduction of blockchain has markedly improved real-time supervision efficiency to over 90%, while the rate of false alarms has decreased from 10% to 1% in less than a year.[7]

The main features of the blockchain based environmental monitoring platform in Zouping are summarized as follows:

(1) Enhanced accuracy of monitoring and improved off-site regulation efficiency. Real-time production and pollution data such as power consumption, temperature, switch timing, and switching status will be uploaded to the blockchain. The encryption method such as secure MPC in blockchain guarantees the all-weather monitoring without revealing proprietary information and facilities the accurate implementation of production suspension decisions.[8]

(2) Improved credibility of data and improved law enforcement efficiency. The immutable nature of blockchain prevent anyone from tempering with the uploaded environmental data. Also, blockchain nodes enables the preservation and verification of environmental regulatory evidence, facilitates information sharing across different departments, and provides support for law enforcements.

Given the significant improvement in environmental monitoring quality brought by the blockchain technology, Hengshui, a city in Hebei province, built a similar but much bigger system in November 2022 that has over 4,000 enterprises as permissioned nodes on-chain,

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[7] Data source: https://caifuhao.eastmoney.com/news/20231224120150112105750

[8] Appendix 1 provides more details about the secure multi-party computation.

linking approximately 20,000 devices to the blockchain network.[9] The blockchain based monitoring system not only ensures rigorous environmental compliance but also addresses challenges in environmental data forensics, the complexity of electronic evidence evaluation in legal contexts, and enhances judicial linkage and data sharing.

Other than Zouping and Hengshui, many other cities also applied the blockchain technology in environment monitoring. Beijing's Big Data Sharing and Integration System for the Ecological Environment leverages a "Catalog Blockchain" to provide a robust data support for ecological environment governance through data sharing among different government departments. Hebi in Henan Province, relying on the municipal government cloud platform, constructed a unified portal known as "Smart Atmosphere." By integrating industrial internet identifier resolution and blockchain technology, it has enhanced the real-time performance and accuracy of air quality monitoring and online monitoring of pollution sources, offering novel technological means for environmental supervision. Zhejiang Province has also achieved remarkable results in applying blockchain technology to environment supervision. City Ningbo innovatively introduced the concept of health codes and launched the "Blockchain + Environmental Protection Code" model, achieving digital transformation of core environmental management services. City Jiaxing, on the other hand, established a pioneering "Coal Sample Chain Management" digital platform to incorporate power generation enterprises' carbon emission data into blockchain management, and thereby realize transparent and traceable monitoring of carbon emissions.

3. Empirical Patterns and Initial Investigation

3.1 Data Description

We refer two sources to identify cities that adopt blockchain technologies in environmental monitoring. The first source is the list of blockchain applications cases disclosed by the Ministry of Industry and Information Technology (hereinafter referred to as MIIT) every year.[10] These cases present different practices on blockchain from different cities (districts). The second source is the list of environmental monitoring innovation cases disclosed by China National Environmental Monitoring Centre (CNEMC), affiliated to the Ministry of Ecology and Environment.[11] Similarly, these cases present different practice on environmental monitoring innovation from different cities (districts). For both data sources, we select cases (cities) explicitly indicating their usage of blockchain technology on environmental monitoring.[12] Finally, we identify 6 cases with the adoption of blockchain technologies on environmental

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9 Data source: https://hbepb.hebei.gov.cn/hbhjt/xwzx/jicengfengcai/101699834137936.html.

10 Here is an example for 2023:https://www.cac.gov.cn/2024-01/18/c_1707243870538299.htm

11 See the website:
https://mp.weixin.qq.com/s?__biz=MzI0MDYzMzIxNA==&mid=2247564745&idx=1&sn=3947420c953fb9d0817bdeea8b45085a&chksm=e91469d8de63e0ce38a3477ff0415400ed9898baacc0f59c8740cc0ddc1c2876704aa51f6122&scene=27

12 To further check the completeness and reliability of the data, we search the official website of Bureau of Ecology and Environment for each city with the keyword "blockchain". The outcomes are consistent with what we collect from the above two sources. (For example, we search "blockchain" at the website for Bureau of Ecology and Environment, Hengshui city (http://sthjj.hengshui.gov.cn/).

monitoring and summarize them in Table A1. The related cities are Zouping, Ningbo, Beijing, Jiaxing, Hengshui, Hebi and the adoption time ranges from Dec., 2020 to Dec., 2023.

Insert Table A1 about here.

We obtain the pollutant concentration data from the *China National Environmental Monitoring Center*' platform. The platform releases hourly pollutant concentrations at all monitoring stations for each city. We average these data at the city-month level. For cities with missing pollutant concentration data, we supplement the data obtained from the monthly urban air quality status reports disclosed by official websites of local governments. In the end, our database includes pollution concentration data for 333 prefecture-level cities and 37 county-level cities in China from January 2018 to August 2024.

The regional economic information data comes from several sources. *Firm registration database*. This database is released by SAIC and covers the universe of all registered firms in China, which is over 300 million during our sample period. The firm registration data contains information on the 4-digit industry classification code, registration date, registration location, branches and history of changes (if any). We aggregate these data to the city-level. The data for regional GDP and fiscal income is obtained from *CEIC database.* The data reginal balance of loans from financial institutions is hand collected from *the China City Statistical Yearbook* and *the China District and County Statistical Yearbook*. The definitions of variable used in the paper are provided in the Table A2.

Insert Table A2 about here.

3.2 Determinants of Blockchain Adoption

The decision of building blockchain system to monitor the pollution emission is made by the local government, and clearly this choice is not randomly assigned. In this section, we explore the determinants of blockchain adoption decision. We estimate a logit model where the dependent variable equals 1 if city adopt the blockchain for environmental monitoring and 0 otherwise. The independent variables are constructed using information from the most recent fiscal year ended before the adoption date. We hypothesize the adoption decision is related to three factors: pollution level, local fiscal condition and environmental attention. The main variables we used in the model are as follows:

Pollution level. Cities with sever pollutions suffer more from environmental problems, and the local governments are more willing to adopt the new technology for environmental monitoring. Thus, we expect that the past pollution level is positively related to the blockchain adoption decision.

Fiscal revenue. It is costly to build up the blockchain monitoring platform in addition to the existing CNEMC system, so local governments with better fiscal condition are more likely to pay for the equipment. Thus, local fiscal revenue should increase the probability of blockchain adoption.

Environmental attention. Pollutions not only impose environmental costs but also social costs. For areas where people care more about environment than economics, one unit emission of pollution lead to higher social cost. We use the local Baidu search index on "wumai" (haze) to measure the local environmental attention. We expect it is positively associated with the blockchain adoption decision.

Insert Table 1 about here.

Table 1 presents the results from a pooled regression. Column 3 reports the estimation from the benchmark model and shows that all the coefficients are significant with the expected sign. Column 4 and 5 further include other predictors such as industrial firm numbers (*InduFirm_num*) and loan balance of banks (*loan*) in the area. We find that these two variables are highly correlated with factors in the benchmark model (Column 3) and are not significant in a horserace regression.

As in any experiment we worry about endogenous selection to treatment, the analysis of treatment selection here facilitates us to construct a more comparable sample to estimate the real impact of blockchain adoption. Specifically, we employ the Entropy Balancing method (Hainmueller, 2012) to generate a control group that is balanced on observable characteristics (i.e. variables in Column 3 of Table 1). This method allows us to directly establish covariate balance within the weighting function (Hainmueller and Xu, 2013) without losing any sample. Following prior literature (Karplus and Wu, 2023), we balance on the first-order covariates and our results are also robust to higher-order moments of the covariate distributions.

Insert Table 2 about here.

We compare the covariates in treatment and control group in Table 2. We can see that the values of covariates are closer between treat and control cities after entropy balancing. For example, in the cohort of Zouping, the average fiscal revenue of control group is 9.9 μg/m³ before balancing and it drops to 7.6 μg/m³ after balancing, which is more closed to that of Zouping (6.9 μg/m³). The similar is true for other covariates and cohorts.

3.3 Impact of Blockchain Monitoring on Pollution Concentrations

We adopt the cohort-matching approach suggested by Gormley and Matsa (2011) to estimate a difference-in-differences model that accounts for multiple events. Specifically, we compare the changes in pollutant concentrations between cities that have implemented blockchain technology for environmental supervision (treatment group) and those that have not (control group), around the time of blockchain technology implementation. For each new implementation of blockchain technology, we construct a cohort of the treatment and control cities using city-level monthly observations for 12 months before and after the implementation. Specifically, we estimate the following model:

$$Pollutions_{i,c,t} = \beta_0 + \beta_1 Treat_{i,c} \times Post_{c,t} + \gamma_{i,c} + \lambda_{c,t} + \epsilon_{i,c,t}\ , \qquad (3.1)$$

where i denotes the city, c denotes the cohort, and t denotes the month. The dependent variable is the logarithm of SO2, NO2, O3 or CO. *Treat* is equal to 1 if city *i* in cohort *c* applied blockchain technology in ecological environment supervision and 0 otherwise. *Post* is equal to 1 if blockchain is implemented in ecological environment supervision in year-month *t* in cohort *c* and 0 otherwise. We include city-cohort fixed effects, $\gamma_{i,c}$, to control for any fixed differences between cities, and year-month-cohort fixed effects, $\lambda_{c,t}$ to control for any time trends. We allow the city and time-fixed effects to vary by cohort. If the application of blockchain technology in environmental supervision improves air quality and reduces pollution, we expect $\beta 1$, which captures the average treatment effect across multiple events, to be negative and statistically significant. Our treatment group consists of cities that have implemented blockchain technology for environmental supervision (as listed in our Table A1). As for the control group, it includes other prefecture-level cities that have refrained from adopting blockchain technology for environmental oversight during the corresponding period. Notably, since Zouping is a county-level city, we deliberately selected other county-level cities to constitute our control group.

Insert Table 3 about here.

Table 3 presents the average treatment effects under the Difference-in-Differences (DiD). Column 1-4 reports the estimates using unbalanced sample and shows a significant decrease of 16.6%, 7.6% and 4.4% respectively for concentrations of SO2, NO2 and CO after the implementation of blockchains for environmental supervision. According to the statistics of key emission sources report in China, 75% SO2 and 37% NOX are emitted by industrial firms. Thus, the estimates from DID model indicate that the decrease of pollution after the blockchain adoption are likely driven by the reduction of pollutants emitted from industrial sector. The results using covariate entropy balancing sample (Column 5-8) yield consistent conclusions.

Insert Figure 1 about here.

Figures 1 shows the dynamic effects of blockchain adoption on pollution reduction estimated from unbalanced Difference-in-Difference regressions. Prior to the integration of blockchain technology in environment supervision, the coefficient for concentrations were generally insignificant, indicating the parallel trend between treat and control group. After the blockchain adoption, the concentrations of SO2, NO2 and CO show a clear downtrend pattern and revert a bit afterwards. For example, the concentrations of SO2 drop about 40% after 7 month of adoption and revert to 20% reduction after one year. In an untabulated table, we show that in a longer window (post 2-year), the decrease of SO2 is stable at around 20%, but the concentrations of NO2 and CO revert to the level before treatment. It is due to the fact that SO2 is a better indicator to capture the pollutions from stationary industrial sources (Karplus and Wu, 2023).

3.4 Impact of Blockchain Monitoring on Economic Activities

As the adoption of blockchain for environmental monitoring significantly reduce the pollutants emissions, it possibly also impacts on the economic activities. We employ the similar DID framework in eq (1) to investigate how the blockchain adoption influence the real economy:

$$GDP\ growth_{i,c,t} = \beta_0 + \beta_1 Treat_{i,c} \times Post_{c,t} + \gamma_{i,c} + \lambda_{c,t} + \epsilon_{i,c,t}\ , \qquad (3.2)$$

where i denotes the city, c denotes the cohort, and t denotes the quarter. The dependent variable is the year-on-year growth rate of GDP in sum, GDP from primary industry, secondary industry or tertiary industry. The independent variables are similarly defined with Equation (3.1). Our treatment group consist of Ningbo, Jiaxing, Beijing and Hengshui. We drop Zouping and Hebi because there are many missing or negative GDP value in these two cities and we also drop other cities in the control group with similar data problem.

Insert Table 4 about here.

Table 4 shows the estimations from a set of regression in Equation (3.2). Column 1-4 reports the estimates using unbalanced sample and Column 5-8 reports the estimates using entropy-balanced sample. The quarterly growth rate of GDP drops 1.6% to 2.6% after the blockchain adoption. Given that the average annual GDP of treat group is 556.4 billion RMB with an average 4.7% growth rate before treatments, the indirect economic costs of blockchain adoption for environmental monitoring yields about 1.7 billion RMB (556.4×4.7%×1.6%×4) to 2.7 billion RMB per year. While blockchain adoption imposed little impact on the primary industry and tertiary industry, it largely reduced the economic activities in secondary industry which is mainly consist of industrial firms. On average, secondary industry accounts for 38% of total GDP and its growth rate decreased by 7.4% after blockchain adoption, which implies a 2.8% decrease of total GDP growth. In other words, the reduction of economic activities induced by blockchain monitoring is mainly driven by the secondary industry. This evidence is consistent with the estimates of distribution across different pollutants in Table 3.

Even though the adoption decision is made by the local government, the firms have the option to delocalize their activities in other cities without blockchain. In other words, a non-universal blockchain platform opens the door for firms to shift polluting operations to other places. We test the hypothesis using the following DID model:

$$Relocate_{i,c,t} = \beta_0 + \beta_1 Treat_{i,c} \times Post_{c,t} + \gamma_{i,c} + \lambda_{c,t} + \epsilon_{i,c,t}\ , \tag{3.3}$$

where i denotes the city, c denotes the cohort, and t denotes the quarter. The dependent variable is the number of relocations for firm in city i, which is proxied by *branch_num* and *locatechg_num. branch_num* is calculated as the total number of non-local branches newly opened by firms in city i each quarter. *locatechg_num* is calculated as total number of firms in city i that changed their headquarters to other cities each quarter. As blockchain adoption mainly affects the secondary industry, we only account for industrial firms when calculating these two proxies. The independent variables are similarly defined as in Equation (3.1).

Insert Table 5 about here.

Table 5 presents the results of regressions from Equation (3.3). Column 1 and 3 reports the estimates for *branch_num* using unbalanced sample and entropy-balanced sample respectively and both of the coefficients are significantly positive. It implies that after the adoption of blockchain monitoring, industrial firms open more plants in non-local cities to shift emissions. Column 2 and 4 reports the estimates for *locatechg_num* and the coefficients are not significant. It indicates that firms do not change their headquarters or registrations to avoid the regulation, which may incur higher costs and more likely to be hurdled by local governments.

Insert Figure 2 about here.

Given the facts that firms may open more plants in non-local cities to shift emissions, a worry is that the treatment effect of blockchain adoption maybe driven by the increase of pollution in control group cities. To rule out this possibility, we depict the dynamics of SO2 and NO2 concentrations in 48-month window separately for treatment and control groups in Figure 2. We find that the pollutions in the control group do not increase after the treatment, while the pollutions in the treat group show a significant downward trend. The potential reason why emission shifts do not result in higher level pollution out of adoption city is that, the destinations of new plants are evenly distributed across the cities. The diversification of emissions should absorb the hurts of pollutants to the air quality.

4. A Model of Environmental Monitoring

We introduce an economic framework featuring multiple firms and two regulatory authorities in two cities a traditional setting without blockchains. Each firm endogenously chooses one of the two cities to operate, and engages in a production process that result in environmental pollution, e.g., a chemical plant emits exhaust gases with high concentrations of SO2. To mitigate environmental harm, the regulator in each city sets up a continuous monitoring system to oversee firms' pollutant emission levels, and imposes penalties for non-compliance when their emission levels surpass the maximum allowed levels, which are set by national environmental laws. Despite of these measures, there are instances when the monitoring system fails to accurately detect pollution violations. For example, firms may physically obstruct monitoring sensors or directly manipulate the emission data. These actions undermine the efficacy of the environmental regulatory framework, presenting challenges in maintaining environmental compliance.

We assume a continuum of firms $j \in [0,1]$ that are the same in every aspect except different location preference $d_{j,i}$ for city i. Each firm j regularly submits a continuum of pollutant emission levels, denoted by $\hat{x}_{j,k} \geq 0, k \in [0, N]$, to the regulator, where N represents the total number of submissions. The true value of firm j's emission level is $x_{j,k} \geq 0$, which is assumed to be a linearly increasing function of its output for simplicity. Due to potential manipulations, the reported emission level $\hat{x}_{j,i}$ may deviate from its true value $x_{j,i}$.

The environmental law sets the maximum permissible pollution level $\bar{x}$, and the regulator punishes the firm if it pollutes more than that level. Consequently, the firm has incentives to underreport its pollution level as $x_{j,k} \leq \bar{x}$ whenever $x_{j,k} > \bar{x}$. For simplicity, given a firm j is regulated under the regulator i, we assume that each of its submissions either violates the maximumly limited pollution level by a constant amount $\mu > 0$, i.e., $x_{j,k} = \bar{x} + \mu$, with a probability $p_i \in [0,1]$, or pollutes at the maximum level $x_{j,k} = \bar{x}$ with a probability $1 - p_i$. However, the firm always reports $\hat{x}_{j,i} = \bar{x}$ to the regulator in both cases. In other words, when it violates the pollution standards, $x_{j,k} > \bar{x}$, it falsifies its pollution reports by submitting $\hat{x}_{j,i} = \bar{x}$ to comply superficially with regulations.

Therefore, for each submission, the regulator receives a pollution level reported by the firm that is always equal to $\bar{x}$, but some of them are actually false. In order to find out whether a firm violates, the regulator needs to obtain his own estimate of the true pollution level. The regulator could either accept the firm's submitted number, i.e., setting $\tilde{x}_{j,k} = \hat{x}_{j,k} = \bar{x}$, or spend effort to verify the true pollution level, i.e., setting $\tilde{x}_{j,k} = x_{j,k}$. Verification is inherently costly as it typically involves on-site inspections. We assume that each regulator i randomly picks $s_i \in [0,1]$ fraction of the firms and verifies all submissions of each firm. In other words, a firm has a probability of s_i to be verified by the regulator i.

We define the regulator's cost of verification on a single firm as $c(s)$ with $c'(s) > 0$ and $c''(s) > 0$. The convexity of the function captures the growing resource demands and logistical complexities associated with higher levels of verification efforts. Specifically, we assume that the cost function is of the following quadratic form:

$$c(s, N) = as^2N^2 + b, \text{where } a, b > 0.$$

The constant term b represents the regular monitoring cost for the regulator. Furthermore, we assume that pollution violations cause social losses that are linear in the violation amount and undetected violations cause addition losses that are convex in the violation amount. However, pollutions also bring economic benefits to the city, e.g., the economic development and tax revenues from firms' productions, and they are assumed to be linear in the violation amount. Therefore, the regulator i chooses s_i to maximum the economic benefits from pollutions while considering the social losses accompanied by pollutions and the relevant verification costs.

Since all firms' violation probabilities under the same regulator are the same, we suppress the subscription j for firms afterwards for convenience. Furthermore, we assume each regulator independently verifies each firm. That is, for each firm in its city, the regulator i maximizes the following utility function:

$$\max_{s_i\in[0,1]} L(s_i) = \theta E\left[\int_0^N x_k d_k\right] - \pi E\left[\int_0^N (x_k - \bar{x}) d_k\right] - \beta_i E\left[\int_0^N (\tilde{x}_k - x_k)^2 d_k\right] - a s_i^2 (N)^2 - b,$$

where $\theta > 0$ and $\pi > 0$ are scaling parameters reflecting the economic benefit and social losses from pollution violations, respectively, and we assume $\theta > \pi$ to make it non-trivial. $\beta_i > 0$ is a scaling parameter reflecting the additional social loss for undetected pollution violations. Note that β_i is the only difference between two regulators, representing their different preferences on environment quality. Since $(1 - s)p_i$ is the probability that a firm violates and not being detected by the regulator i and sp_i is the probability that the violation is caught, the regulator's optimization problem therefore reduces to:

$$\max_{s_i\in[0,1]} L_i(s_i) = \theta N\bar{x} + (\theta - \pi) p_i N\mu - \beta_i (1 - s_i) p_i N\mu^2 - a s_i^2 N^2 - b,$$

The first order condition implies that the optimal verification size is equal to:

$$s^* = min\left(\frac{\beta_i p_i \mu^2}{2aN}, 1\right) \tag{4.1}$$

On the firm side, conditional on being verified by the regulator i, each firm determines the probability p_i of pollution violation by trading off the economic benefits from violations and the penalties from violations if caught by the regulator. Specifically, the firm's economic benefit from pollutions is assumed to be proportional to the pollution level with a parameter γ, which measures the production efficiency or the economic incentive of firm's pollutions. However, if pollution violations are detected, the firm needs to pay a penalty that is convex in the violation amount μ and the violation frequency with a punishment intensity parameter δ, i.e., increasing incremental punishment for severe violations or highly frequent violations. Furthermore, firms' location preference d_i for regulator i are assumed to be uniformed distributed in [0,1], and for each firm, $d_i + d_{-i} = 1$, where $-i$ represents the other regulator. In sum, the firm maximizes the following utility function:

$$\underset{p_i\in[0,1]}{Max} F_i(p_i) = \gamma N\bar{x} + p_i \gamma N\mu - \delta_i (s_i p_i N\mu)^2 - e d_i, \;\; \delta > 0$$

The firm's production output is proportional to $N\bar{x} + p_i N\mu$. Solving the first order condition yields the optimal violation probability:

$$p_i^* = \min\left(\frac{\gamma}{2\delta_i N\mu s_i^2}, 1\right) \tag{4.2}$$

Combing Equation (4.1) and (4.2) yields the following optimal strategies (s_i^*, p_i^*) for the regulator and firms.

$$\mathrm{s_i^*} = \min\left(\left[\frac{\beta_i\gamma\mu}{4\mathrm{aN^2\delta_i}}\right]^{\frac{1}{3}}, 1\right) \tag{4.3}$$

$$\mathrm{p_i^*} = \min\left(\left[\frac{2a^2N\gamma}{\mathrm{\beta_i^2}\mu^5\mathrm{\delta_i}}\right]^{\frac{1}{3}}, 1\right) \tag{4.4}$$

Each firm then chooses which city to operate by comparing its maximized utilities under two regulators. Note that a firm's optimized utility under regulator i can be written as

$$F_i^* = p_i^*\gamma N\mu - \delta_i(s_i^* p_i^* N\mu)^2 + \gamma N\bar{x} - ed_i$$

Assuming interior solution, dividing both sides of equation (4.2) by $p_i^{*2}$and then plugging it in to the above equation yields:

$$F_i^* = W_i + \gamma N\bar{x} + ed_i,$$

where $W_i = \frac{p_i^*\gamma N\mu}{2} = \frac{2aN^2\gamma s_i^*}{\beta\mu}$. Therefore, a firm chooses to operate in city i if

$$W_i + \gamma N\bar{x} - ed_i > W_{-i} + \gamma N\bar{x} - e(1 - d_i),$$

and the market share d_i^* of the regulator i is given by the marginal firm who is indifferent between two regulators:

$$W_i + \gamma N\bar{x} - ed_i^* = W_{-i} + \gamma N\bar{x} - e(1 - d_i^*)$$

Solving the equation gives us:

$$d_i^* = \frac{1}{2} + \frac{W_i - W_{-i}}{2e}$$

Definition 1. *An equilibrium of the model without blockchain is defined as an assignment of firms to regulators and given a match between a firm and a regulator, the firm choose the optimal violation probability and the regulator selects the best verification intensity to maximize their utilities.*

Proposition 1. There exists a unique equilibrium in the economy that is characterized as follows: Given a firm regulated by the regulator i in city i,

1. the regulator and the firm's optimal strategies $(\mathrm{s_i^*}, \mathrm{p_i^*})$ are determined by equations (4.3) and (4.4).

2. The regulator's optimal verification intensity $\mathrm{s_i^*}$ is increasing in β_i, μ, γ, and decreasing in a, N, δ. A firm's optimal violation probability $\mathrm{p_i^*}$ is increasing in a, N, γ, and decreasing in β_i, μ, δ.

3. The regulator's maximized utility from each firm it regulates and each firm's maximized utility are:

$$\mathrm{L}_{\mathrm{i}}^{*} = \theta N\bar{x} + V_i, \tag{4.5}$$

$$F_i^{*} = W_i + \gamma N\bar{x} - ed_i \tag{4.6}$$

where $W_i = \frac{\gamma N\mu p_i^*}{2} = \frac{2aN^2\gamma s_i^*}{\beta_i\mu}$, and $V_i = \frac{\theta-\pi}{\gamma}W_i + aN^2 s_i^*(s_i^* - 2) - b$. Furthermore, W_i, V_i, $\mathrm{L}_{\mathrm{i}}^{*}$, and F_i^* are decreasing in the regulator's awareness of environment quality parameter β_i.

4. The market share of regulator i is given by:

$$d_i^* = \frac{1}{2} + \frac{W_i - W_{-i}}{2e},$$

where $W_i = \frac{\gamma N\mu p_i^*}{2} = \frac{2aN^2\gamma s_i^*}{\beta_i\mu}$ is decreasing in the regulator's social loss on undetected violation β_i. Therefore, the regulator who cares less about undetected violations, or care less about environment quality, attracts more firms.

5. The regulator i's maximized utility from all firms operate in its city is given by:

$$\mathrm{TL}_{\mathrm{i}}^{*} = d_i^*(\theta N\bar{x} + V_i), \tag{4.7}$$

and the total production P_i^* in each city is proportional to $d_i^*(N\bar{x} + p_i^*\mu)$

In this economy, the relationship between the firm's violation probability p_i^* and the regulator's verification intensity s_i^* is conceptually inverse. Specifically, an increase in the firm's frequency of pollution violation corresponds to a decrease in the regulator's verification efforts, and vice versa. The equilibrium behaviors of both parties are thus generally opposed concerning various parameters. For instance, if the unit cost of verification a, the submission volume *N*, a firm tends to violate more frequently (increasing p_i^*), while the regulator opts to verify a smaller proportion of the firm's submissions (decreasing s^*). Conversely, higher social losses for undetected violations (increasing β_i) or pollutions (increasing μ) leads the firm to reduce its pollution violation frequency (decreasing p_i^*), prompting the regulator to intensify verification efforts (increasing s^*).

Interestingly, certain parameters affect the firm's and the regulator's equilibrium decisions in the same direction. An increase in the penalty for pollution violation δ results in both parties lowering their respective decision variables (p_i^* and s_i^*decrease). However, if the unit extra benefit from pollution violation γ rises, the firm is more likely to violate (increasing p_i^*) and the regulator responds by increasing the verification frequency (increasing s_i^*). Lastly, A single firm's pollution size p_i^*N and the auditor's verification size s^*N are increasing in the number of emission submissions N.

The fourth result of Proposition 1 implies that the regulator who cares less about the undetected violations, or more broadly speaking, cares less about environment quality, receives a higher market share. This is because the regulator sets a lower verification intensity, and as a result, firms violate more frequently and get higher utilities. Therefore, more firms choose this regulator. In other words, firms prefer the city with looser regulation on pollutions. However, not all firms choose the city with lower regulation intensity thanks to their location preference.

As interior solutions are more interesting, we focus on the interior solutions of the equilibrium.

5. **Environmental Monitoring with Blockchains and Secure Multi-Party Computation**

In the conventional approach, regulatory agencies are often constrained in budget and technological infrastructure, necessitating random sampling for compliance verification. However, the advent of blockchain technology offers a transformative shift in monitoring and verifying industrial pollution for regulators. A practical implementation involves the establishment of a federated blockchain where various stakeholders can contribute relevant data to monitor pollution levels. Participants might include not only the firms themselves but also utilities managing power, water, and gas, as well as meteorological departments. This collaborative data repository is encrypted to maintain privacy and ensure the security of the information, which is crucial considering its sensitive nature and the potential for misuse. Encryption algorithm such as the secure MPC can be implemented to ensure the automatic verification while protecting the proprietary information of data contributors. Within this federated blockchain, data integrity is preserved, and entries are tamper-proof and fully traceable.

For example, the power utility department could install additional meters to measure power consumption of pollutant treatment facilities within a chemical plant. These data, representing the electricity usages for the normal production and pollutant treatment, can be automatically uploaded to the blockchain. In scenarios where a firm might bypass treatment processes—discharging untreated wastewater directly into water bodies—and manipulate data to mislead the regulator, the blockchain provides a reliable countermeasure. If the recorded power usage for pollutant treatment is anomalously low compared to overall production usage, it signals potential misconduct even if the firm's monitored pollution levels do not exceed the regulatory allowed level. Furthermore, the benefit of the blockchain increases with the volume of pertinent data uploaded, allowing for more precise assessments of environmental compliance. For example, the participation of multiple firms from the same industry in the blockchain allows for cross-sectional analyses. Such analyses can identify outliers whose emission levels significantly deviate from industry norms, and help the regulator pinpoint and verify instances of pollution violations more efficiently.

Thus, blockchain technology allows the regulator to verify the on-chain firms' pollution at almost zero cost and focus on monitoring those off-chain firms. Furthermore, if the smart contracts are also designed in the system, the punishment on firm's violations can also be automatically collected. This not only enhances the capacity for monitoring but also significantly elevates the efficiency and accuracy of environmental regulation compared to traditional systems. However, the installation and operation cost of a blockchain system can also be excessive. So, the regulator is not necessarily better off with the blockchain technology, and it needs to compare its utility with and without blockchain before it determines to set up the federated blockchain system. On the firm side, it is mandatory required to join the blockchain if its regulator adopts the blockchain, however it can relocate to a city without blockchain adopted if that makes it better off. Therefore, regulators' blockchain adoption decision may lead to a change in the market share of each regulator or city.

To elucidate this concept, we model the economy with blockchain as a two-stage game. In the first-stage, the regulators decide whether or not to adopt the blockchain. In the second-stage, the firms endogenously choose which city to operate, and regulators and firms play the game as described in the previous section. The equilibrium behaviors of the regulator and the firms as well as their optimized objective functions in the second-stage have been described in the previous section, and the equilibrium in the first-stage is defined as follows.

Definition 1. *A first-stage equilibrium of the model is defined as an assignment of firms to regulators and blockchain adoption decisions by two regulators that satisfy the following conditions:*

(i) Given the blockchain adoption decisions of the regulators, each firm chooses the regulator that maximizes its utility.

(ii) Anticipating the other regulator's blockchain adoption decision, a regulator's blockchain adoption decision maximizes its utility.

We solve this two-stage game backward, and assume that the regulators and firms play the equilibrium strategies determined by Propositions 1 in the second-stage. In the first-stage, we assume that the regulator subsumes the blockchain adoption costs which consists of a fixed set up cost $c_f > 0$ and a variable operational cost $c_v > 0$ for each firm on the chain. When a firm joins the blockchain, its pollution violations will be automatically verified, i.e., $\mathrm{s_i} = 1$, and the regulator no longer needs to spend efforts to verify on-chain firms, in other words, the regulator now can automatically verify all pollutions at zero cost. In response to the blockchain adoption, firms choose to not violate at all[13].

Assuming the regulator i adopts the blockchain, then optimized utility becomes of the firms in its city becomes: $F_i^b = \gamma N\bar{x} - ed_i$, and the firm's production is proportional to $N\bar{x}$, lower than that in the previous model without blockchain. The regulator i's utility from each firm is: $L_i^b = \theta N\bar{x} - c_v - c_f$, and the market share of the regulator i given two regulators' different choices of blockchain adoption decision are as follows:

Scenario 1: If both regulators adopt the blockchain, then the regulator i's market share $d_i^{*b}(A,2)$ is determined by the following equation:

$$F_i^b = \gamma N\bar{x} - ed_i^{*b}(A,2) = F_{-i}^b = \gamma N\bar{x} - e\left(1 - d_i^{*b}(A,2)\right),$$

where the first argument of $d_i^{*b}(.,.)$ represents the blockchain adoption decision of the regulator i and takes values of A for adopt or N for NOT adopt blockchain, and the second argument indicates the number of regulators that adopt the blockchain. Solving the equation gives us:

$$d_i^{*b}(A,2) = \frac{1}{2}$$

So, if both regulators adopt the blockchain, they equally share the market as firms choose

[13] Interior solutions imply $p_i^*\gamma N\mu - \delta_i(p_i^* N\mu)^2 < 0$ if $p_i^* > 0$. So, firms no longer violate.

the city according to their location preference.

Scenario 2: If the regulator i adopts and $-i$ does not adopt the blockchain, then regulator i's market share $d_i^{*b}(A, 1)$ is determined by the following equation:

$$F_i^b = \gamma N\bar{x} - e\, d_i^{*b}(A, 1) = F_{-i}^* = W_{-i} + \gamma N\bar{x} - s_{-i}^* k\gamma - e\left(1 - d_i^{*b}(A, 1)\right)$$

Solving the equation yields:

$$d_i^{*b}(A, 1) = \frac{1}{2} - \frac{W_{-i}}{2e} < \frac{1}{2}$$

Scenario 3: If regulator i does not adopt while $-i$ adopts, then by symmetry, the regulator i's market share is:

$$d_i^{*b}(N, 1) = \frac{1}{2} + \frac{W_i}{2e} > \frac{1}{2}$$

Scenario 4: If neither adopts the blockchain, then then the regulator i's market share is the same as that in Proposition 1:

$$d_i^{*b}(N, 0) = d_i^* = \frac{1}{2} + \frac{W_i - W_{-i}}{2e}$$

It is clear from the discussions above that adopting blockchain leads to a reduction in a regulator's market share as some firms choose to relocate to the other city to maximize utilities. For example, for a regulator that is less concerned about undetected violations, its market share is greater than 1/2 if neither regulator adopts the blockchain, however, its market share drops below 1/2 if it first adopts the blockchain and drops to 1/2 if both adopt the blockchain. The main reason is that its comparative advantage of lower verification intensity no longer exists after the blockchain adoption, and causes the relocation of some firms to the other city. Furthermore, the adoption of blockchain also leads to a decrease in the total production of the city as both the market share and production of a single firm decrease.

We summarize the above results in the following proposition.

Proposition 2: (Effects of Blockchain Adoption)

(1) Adopting blockchain reduces firms' violation probability to zero, and consequently decreases the firms' pollution levels and production levels.

(2) Adopting blockchain leads to reductions on both the market share, pollution level, and total production of the city.

Knowing the market share, two regulators' total utilities in the equilibrium given two regulators' blockchain adoption can be summarized in Table 6. A no-deviation analysis for two regulators implies the following equilibrium conditions.

Proposition 3: (First-stage Equilibria)

(1) The conditions for the existence of a **full adoption** equilibrium are the following inequality holds for $i = 1,2$:

$$\frac{1}{2}\theta N\bar{x}-\frac{1}{2}c_v-c_f>\left(\frac{1}{2}+\frac{W_i}{2e}\right)(\theta N\bar{x}+V_i) \quad (5.1)$$

(2) The conditions for the existence of a **no adoption** equilibrium are the following inequality holds for $i=1,2$:

$$(\frac{1}{2}+\frac{W_i-W_{-i}}{2e})(\theta N\bar{x}+V_i)>\left(\frac{1}{2}-\frac{W_{-i}}{2e}\right)(\theta N\bar{x}-c_v)-c_f \quad (5.2)$$

So, for sufficient large c_f, no adoption is an equilibrium

(3) The conditions for the existence of a **partial adoption** equilibrium, where only the regulator $i=1, or\ 2$ adopts blockchain, are the following two inequalities hold:

$$\left(\frac{1}{2}-\frac{W_{-i}}{2e}\right)(\theta N\bar{x}-c_v)-c_f>(\frac{1}{2}+\frac{W_i-W_{-i}}{2e})(\theta N\bar{x}+V_i) \quad (5.3)$$

$$\left(\frac{1}{2}+\frac{W_{-i}}{2e}\right)(\theta N\bar{x}+V_{-i})>\frac{1}{2}\theta N\bar{x}-\frac{1}{2}c_v-c_f \quad (5.4)$$

(4) No adoption and full adoption can coexist if and only if $c_v+V_i<0$ for i=1,2.

(5) Both no adoption and full adoption equilibrium cannot coexist with Partial Adoption equilibrium.

(6) If there only exists one partial equilibrium, then it must be the one where only regulator with higher β_i adopts the blockchain. Moreover, if two regulators have similar preference β_i for undetected violations and $c_v<V_i$ for $i=1,2$,, then both partial equilibria can coexist.

The first part of the proposition defines an upper bound of the blockchain adoption cost for the existence of the full adoption equilibrium, and it requires $V_i<0$. So, if the regulators have low economic benefits from pollutions (low θ) or cares a lot about the environment quality (high β), then the upper bound is high and therefore a full adoption is more likely to achieved. Oppositely, the second part of the proposition defines a lower bound of the blockchain adoption cost for the existence of the no adoption equilibrium. If the regulators have high economic benefits from pollutions (high θ) or cares a little about the environment quality (low β), then the lower bound is low and therefore a no adoption equilibrium is more likely to achieved.

6. Social Welfare and Policy Implications

Although blockchain adoption in environmental monitoring significantly reduces the pollution level, it also reduces the firm productions in the economy. Furthermore, high adoption cost or regulators' competition for firms impede the adoption of blockchain that may cause a sub-optimal solution. Therefore, it is important to analyze the effect of blockchain adoption from the viewpoint of the social welfare, which is defined as the sum of utilizes of all firms and the two regulators. Since both the no adoption equilibrium and the full adoption equilibrium cannot coexist with the partial equilibrium, we focus on the social welfare analysis of the no adoption and full adoption equilibria.

Using the results in Proposition 1 and Table 6, the social welfare in the no adoption equilibrium is:

$$S_0 = \theta N\bar{x} + d_1^* V_1 + d_2^* V_2 + d_1^* W_1 + d_2^* W_2 + \gamma N\bar{x} - \frac{1}{2}e,$$

and the social welfare in the full adoption equilibrium is:

$$S_b = \theta N\bar{x} - c_v - 2c_f + \gamma N\bar{x} - \frac{1}{2}e$$

The following proposition lays out the conditions for the social optimality of a full adoption equilibrium, and discuss the role of central government's subsidy in helping the society reaching the full adoption when it is social optimal but not an equilibrium.

Proposition 4 (Social Optimum).

(1) Full adoption is social optimal, i.e., $S_b > S_0$, if and only if $c_v + 2c_f < C_0$, where C_0 is a positive constant.

(2) When regulators' economic benefits from pollutions θ is higher than a threshold $\theta_0 > 0$, there exists a constant $0 < C_1 < C_0$ such that full adoption is social optimal but not the equilibrium when $C_1 < c_v + 2c_f < C_0$. In this case, a central government or social planner can provide subsidies or wealth transfer to local regulator and coordinate the full adoption equilibrium to achieve the social optimum.

7. Conclusion

We study the endogenous adoption of blockchain technology for mitigating industrial pollution. We present the first piece of evidence using data from China on how blockchains as an infrastructure for secure multi-party computation impact on industrial pollution levels and economic activities. The concentration of SO2, NO2 and CO decreased by 17%, 8% and 4% respectively in one-year after the blockchain adoption. Then, we document the evidence that blockchain adoption also has a side effect on economic activities. The quarterly GDP growth in adopting cities is reduced by 1.6-2.6%, giving a hidden cost of 1.7-2.7 billion RMB. Further evidence shows that the non-universal blockchain monitoring results in the delocalized activities of firms.

We then construct a theoretical framework to rationalize the observations and further elucidate the relationship among endogenous firm production and pollution, environmental monitoring, and blockchain adoption. Our model consists of two regulators in two cities and multiple firms. In a unique equilibrium of environmental monitoring and reporting without blockchains, a firm's probability of violating pollution standards increases with the regulator's verification cost and its economic benefits from violations, and decreases with the social loss from undetected violations and penalties for detected violations. The regulator's optimal verification intensity decreases with verification costs, but increases with social losses caused by pollutions and firms' additional benefits from violations.

Introducing blockchain technology allows the regulator to collect and analyze pollution data more accurately and verifying on-chain firms at zero cost. We derive the conditions under which no adoption, partial adoption, or full adoption equilibrium can be achieved and show that the firms' violation probabilities and the total pollution amounts are reduced in the equilibria with blockchain adoption. However, blockchain adoption also reduces the correspond city's production and market share. Lastly, high adoption cost or high economic benefits from pollutions may cause under-adoption in the equilibrium that is socially inefficient. In these cases, a wealth transfer provided by a central government is necessary to promote full adoption and therefore to increase the social welfare.

Our theoretical findings not only explain the empirical patterns we document but also offer pragmatic implications into the economic tradeoffs arisen in blockchain adoption. This study provides an initial guidance for policymakers and industry leaders who are exploring blockchains to enhance regulatory effectiveness and achieve sustainable environmental outcomes.

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Table AI: Variable definition

The sample period of pollutants is from January 2018 to August 2024. The pollutant concentration data is from the China National Environmental Monitoring Center data platform, supplemented by data hand-collected from the monthly urban air quality status reports disclosed by local governments. The regional economic data is from CEIC database and the China City (District and County) Statistical Yearbook. The industrial firm information is obtained from firm registration database released by SAIC. All of the variables are constructed at the city level.

Variable	Definition
Pollutants	
SO2	The logarithm of monthly average SO2 concentration (μg/m³).
NO2	The logarithm of monthly average NO2 concentration (μg/m³).
O3	The logarithm of monthly average O3 concentration (μg/m³).
CO	The logarithm of monthly average CO concentration (μg/m³).
Pollution level	Average concentration of SO2 and NO2 over past 6 months.
Regional economy	
Fiscal revenue	General public budget fiscal revenue (billion RMB).
Environmental attention	Baidu search index for the key word "wumai" (haze) scaled by GDP.
InduFirm num	The logarithm of the number of operating industrial enterprises in city *i*.
Loans	The logarithm of the balance of loans from financial institutions at the end of the year scaled by GDP.
GDP growth	Year-over-Year growth rate of quarterly GDP.
GDP1 growth	Year-over-Year growth rate of quarterly GDP in Primary Industry.
GDP2 growth	Year-over-Year growth rate of quarterly GDP in Secondary Industry.
GDP3 growth	Year-over-Year growth rate of quarterly GDP in Tertiary Industry.
branch num	Total number of non-local branches newly opened by firms in city *i* each quarter.
locatechg num	Total number of firms in city *i* that changed their headquarters to other cities each quarter.

Table A2: Cities Adopting Blockchain for Environmental Monitoring

This table shows the cities adopting blockchain technology for environment monitoring, along with the timing of the implementation and specific case or project names.

City	Date	Case or Platform Name
Zouping	Dec-2020	Blockchain Ecological Environment Supervision Platform
Ningbo	Nov-2021	Ecological Environment 'Smart Management and Service' System
Beijing	Apr-2022	Research and Demonstration Application of New Ecological Environment Governance System Project
Jiaxing	Jun-2022	"Coal Sample Chain Management" Platform for Emission
Hengshui	Nov-2022	Ecological Environment Data Notarization Platform
Hebi	Dec-2023	Air Quality Monitoring and Supervision Integrated Platform

Figure 1: Dynamic effect of blockchain adoption on pollutants

This figure shows the coefficient dynamics concerning the effect of blockchain adoption on pollutants using unbalanced DiD e
of blockchain as the base. The x-axis represents months before and after the event and y-axis shows the magnitude of polluta

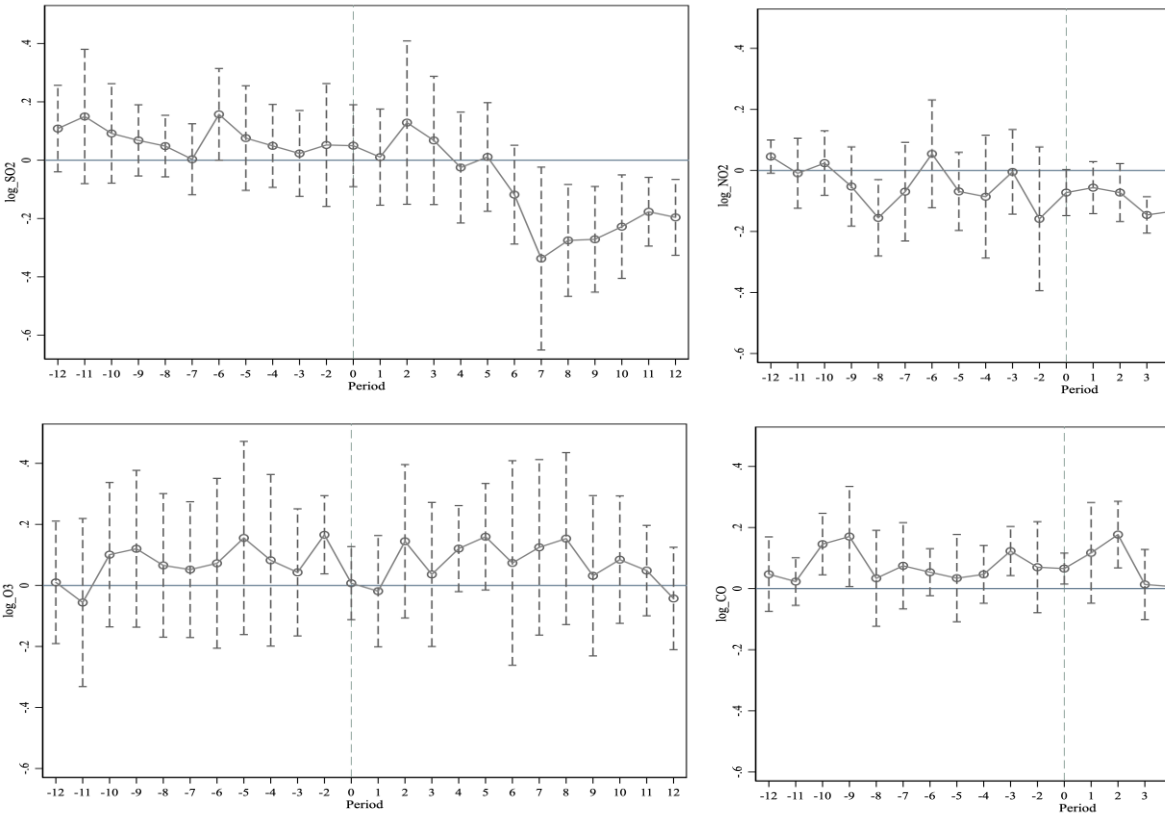
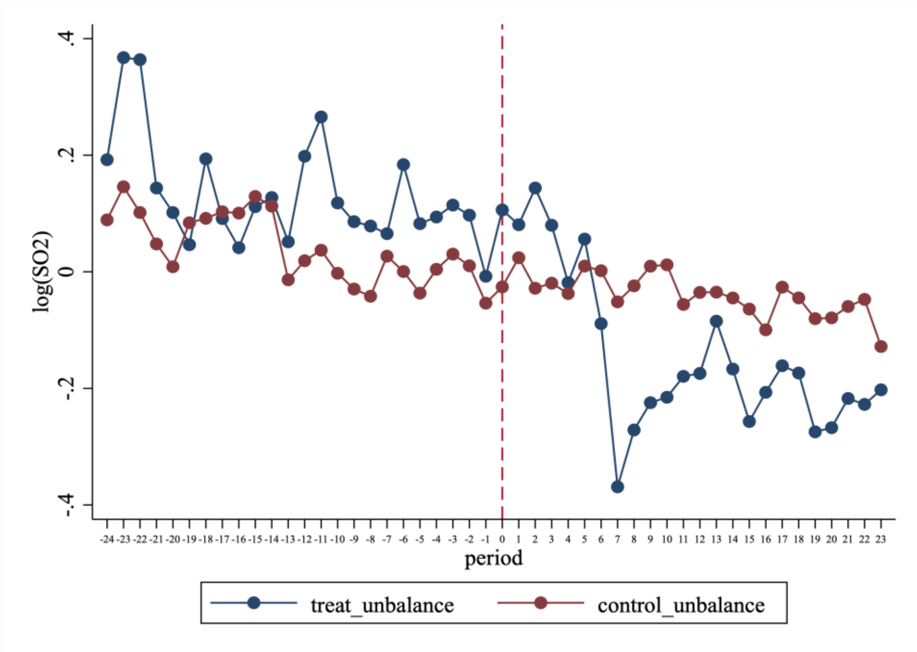


Figure 2: Dynamics of SO2 and NO2 concentrations for treats and controls

This figure shows the dynamics of SO2 and NO2 concentrations in 24-month before and after the adoption separately for treat (blue line) and control groups (red line). The x-axis represents months before and after the event and y-axis shows the magnitude of pollutants.



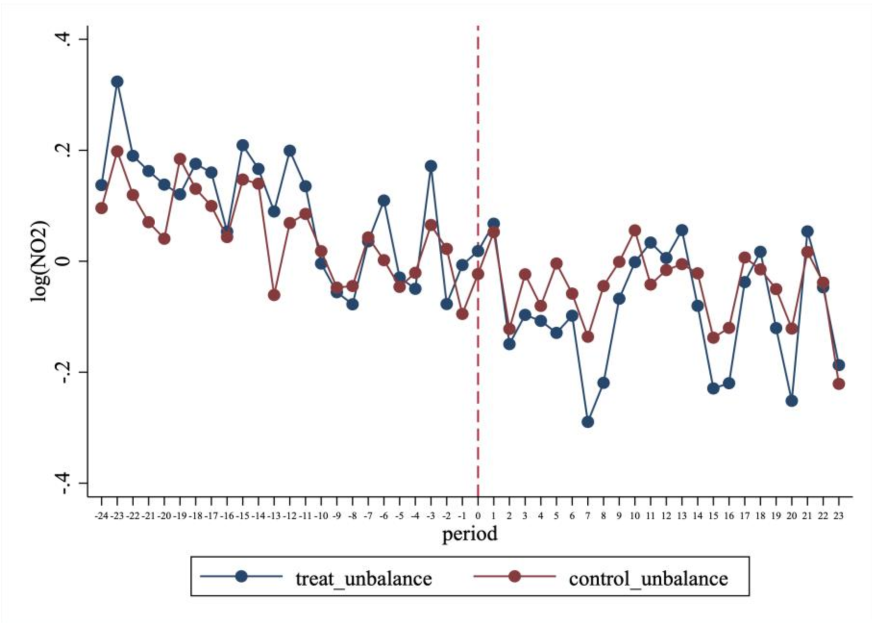


Table 1: Determinants of blockchain adoptions

This table reports the results from a set of logit regressions. The dependent variable is a dummy that equals 1 if a city implements blockchain-based environmental monitoring and 0 itherwise. The independent variables a series of regional economic variables by the end of most recent fiscal year before the adoption date. *Pollution level* is the average pollutants concentrations over the past six months. *Fiscal revenue* is the general public budget revenue. *Environmental attention* is Baidu Search Index of haze scaled by GDP. *InduFirm num* is the number of operating industrial enterprises. *Loans* is balance of loans from financial institutions. Variables are defined in Table AI. All variables, except for dummy variables, are winsorized at the 1% level for each cohort group. Standard errors are clustered at the city-cohort level. *** and ** denote statistical significance at the 1% and 5% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Pollution level	2.6180***	2.5416**	2.5882**	2.5707**	2.4824*
	(2.61)	(2.28)	(2.17)	(2.00)	(1.92)
Fiscal revenue		0.0503***	0.0528***	0.0414*	0.0399*
		(3.05)	(3.27)	(1.68)	(1.65)
Environmental attention			0.0132**	0.0166***	0.0165***
			(2.19)	(2.65)	(2.65)
InduFirm num				0.5217	0.4863
				(0.79)	(0.76)
Loans					0.2807
					(0.45)
Observations	1445	1445	1445	1445	1445
R^2	0.043	0.102	0.117	0.130	0.131

Table 2: Summary Statistics for Entropy-Balanced Variables

This table shows the mean values of the covariates before and after entropy balancing. *Pollution level* is the average pollutants concentrations (μg/m³) over the past six months. *Fiscal revenue* is the general public budget revenue (billion RMB). *Environmental attention* is Baidu Search Index of haze scaled by GDP.

		Before		After	
Treat-group	**Covariate variable**	**Control**	**Treat**	**Control**	**Treat**
Zouping	*Pollution level*	3.539	3.830	3.758	3.830
	Fiscal revenue	9.909	6.948	7.637	6.948
	Environmental attention	108.524	86.187	98.102	86.187
Ningbo	*Pollution level*	3.575	3.872	3.872	3.872
	Fiscal revenue	29.239	172.314	172.215	172.314
	Environmental attention	10.221	6.022	6.023	6.022
Beijing	*Pollution level*	3.605	3.498	3.472	3.498
	Fiscal revenue	29.239	593.231	520.749	593.231
	Environmental attention	10.223	5.230	5.652	5.230
Jiaxing	*Pollution level*	3.522	3.800	3.800	3.800
	Fiscal revenue	29.239	67.480	67.479	67.480
	Environmental attention	10.221	7.750	7.750	7.750
Hengshui	*Pollution level*	3.221	3.423	3.423	3.423
	Fiscal revenue	29.239	13.664	13.693	13.664
	Environmental attention	10.221	15.934	15.932	15.934
Hebi	*Pollution level*	3.288	3.637	3.637	3.637
	Fiscal revenue	28.741	7.731	7.731	7.731
	Environmental attention	10.785	9.803	9.803	9.803

Table 3: Average Treatment Effects of Blockchain Adoption on Air Pollution Concentration

$$Pollutions_{i,c,t} = \beta_0 + \beta_1 Treat_{i,c} \times Post_{c,t} + \gamma_{i,c} + \lambda_{c,t} + \epsilon_{i,c,t}$$

This table presents the results of the regression equation mentioned above. The dependent variable is the logarithm of the cor each new adoption of blockchain technology, we construct a cohort consisting of treated and control cities. Treat is equal to technology in ecological environment supervision and 0 otherwise. Post is equal to 1 if blockchain is implemented in environn c and 0 otherwise. In Columns (1)-(4), we display unbalanced Difference-in-Differences (DiD) estimates. In Columns (5)-(8) past pollutant concentrations, general public budget revenue, environmental attention as covariates. We include City×cohort a analysis. All variables, except for dummy variables, are winsorized at the 1% level for each time-cohort group. Standard er *** and ** denote statistical significance at the 1% and 5% levels, respectively.

	Unbalanced DiD					
	(1)	(2)	(3)	(4)	(5)	(
Variable	SO2	NO2	O3	CO	SO2	N
Post x Treat	-0.1655***	-0.0757**	0.0042	-0.0438**	-0.1633***	-0.0
	(-3.71)	(-2.32)	(0.33)	(-2.17)	(-7.01)	(-1
Observations	39,248	39,248	38,369	38,369	33,832	33
R^2	0.709	0.865	0.675	0.729	0.910	0.
City x Cohort FE	Yes	Yes	Yes	Yes	Yes	Y
YearMonth x Cohort FE	Yes	Yes	Yes	Yes	Yes	Y

Table 4: Impact of Blockchain Adoption on Economic Activities

$$GDP\ growth_{i,c,t} = \beta_0 + \beta_1 Treat_{i,c} \times Post_{c,t} + \gamma_{i,c} + \lambda_{c,t} + \epsilon_{i,c,t}$$

This table presents the results of the regression above. The dependent variables are the year-on-year growth rates of total industry GDP, and tertiary industry GDP. For each new adoption of blockchain technology, we construct a cohort consisting to 1 if city i in cohort c applied blockchain technology in ecological environment supervision and 0 otherwise. Post is eq environment supervision in year-month t in cohort c and 0 otherwise. In Columns (1)-(4), we display unbalanced Difference-in (5)-(8), we present Entropy-DiD estimates using past pollutant concentrations, general public budget revenue, environme City×cohort and YearQuater×cohort fixed effects in our analysis. All variables, except for dummy variables, are winsorized at at the city-cohort level. *** and ** denote statistical significance at the 1% and 5% levels, respectively.

	Unbalanced DiD					
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	GDP growth	GDP1 growth	GDP2 growth	GDP3 growth	GDP growth	GDP1 grov
Post x Treat	-0.0262**	0.0016	-0.0744*	-0.0055	-0.0162**	-0.0152
	(-2.51)	(0.18)	(-1.74)	(-1.34)	(-2.24)	(-1.30)
Observations	4119	4087	4086	4096	4086	4086
R^2	0.740	0.416	0.665	0.736	0.887	0.540
City x Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
YearQuarter x Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 5: Relocation between Treat and control cities

$$Relocate_{i,c,t} = \beta_0 + \beta_1 Treat_{i,c} \times Post_{c,t} + \gamma_{i,c} + \lambda_{c,t} + \epsilon_{i,c,t}$$

This table presents the results of the regression above. The dependent variables are *branch_num* and *locatechg_num*. *branch_num* is calculated as the total number of non-local branches newly opened by firms in city i each quarter. *locatechg_num* is calculated as total number of firms in city i that changed their headquarters to other cities each quarter. For each new adoption of blockchain technology, we construct a cohort consisting of treated and control cities. Treat is equal to 1 if city i in cohort c applied blockchain technology in ecological environment supervision and 0 otherwise. Post is equal to 1 if blockchain is implemented in environment supervision in year-month t in cohort c and 0 otherwise. In Columns (1)-(2), we display unbalanced Difference-in-Differences (DiD) estimates. In Columns (3)-(4), we present Entropy-DiD estimates using past pollutant concentrations, general public budget revenue, environmental attention as covariates. We include City×cohort and YearQuater×cohort fixed effects in our analysis. All variables, except for dummy variables, are winsorized at the 1% level. Standard errors are clustered at the city-cohort level. *** and ** denote statistical significance at the 1% and 5% levels, respectively.

	Unbalanced DiD		ebDiD	
	(1)	(2)	(3)	(4)
Variable	branch num	locatechg num	branch num	locatechg num
Post x Treat	5.3068***	0.1227	3.5471***	0.3360
	(2.63)	(0.24)	(4.31)	(0.99)
Observations	13,366	11,520	11,603	10,188
R^2	0.853	0.620	0.967	0.636
City x Cohort FE	Yes	Yes	Yes	Yes
YearQuarter x Cohort FE	Yes	Yes	Yes	Yes

Table 6: Regulators' Utilities

This table presents the total utilities of two regulators in the first-stage under different scenarios of their blockchain adoption decisions. c_f if the fixed cost of blockchain adoption, and c_v is the variable operational cost for each firm on the blockchain. $W_i = \frac{\gamma N \mu p_i^*}{2}$, $V_i = \frac{\theta - \pi_i}{\gamma} W_i + aN^2 s_i^*(s_i^* - 2) - b$, p_i^* is the firm's optimal pollution violation probability if regulated by regulator i in the second stage, and s_i^* is regulator i's optimal verification intensity in the second stage. The notation $-i$ denotes the regulator other than i in the economy.

Regulators' blockchain adoption decisions		Total utility	
		Regulator i	Regulator $-i$
Scenario 1:	Both adopt	$\frac{1}{2}\theta N\bar{x} - \frac{1}{2}c_v - c_f$	$\frac{1}{2}\theta N\bar{x} - \frac{1}{2}c_v - c_f$
Scenario 2:	i adopts, - i not	$\left(\frac{1}{2} - \frac{W_{-i}}{2e}\right)(\theta N\bar{x} - c_v) - c_f$	$\left(\frac{1}{2} + \frac{W_{-i}}{2e}\right)(\theta N\bar{x} + V_{-i})$
Scenario 3:	i not, - i adopts	$\left(\frac{1}{2} + \frac{W_i}{2e}\right)(\theta N\bar{x} + V_i)$	$\left(\frac{1}{2} - \frac{W_i}{2e}\right)(\theta N\bar{x} - c_v) - c_f$
Scenario 4:	Neither adopts	$(\frac{1}{2} + \frac{W_i - W_{-i}}{2e})(\theta N\bar{x} + V_i)$	$(\frac{1}{2} - \frac{W_i - W_{-i}}{2e})(\theta N\bar{x} + V_{-i})$

Appendix 1: Secure Multi-Parity Computation

Secure multi-party computation (MPC) is a subfield of cryptography that enables multiple parties to collaboratively compute a function over their inputs while keeping those inputs private. This technology addresses concerns on data breaches and information misuse arising from traditional methods which require a third party to perform computations on behalf of the involved parties. MPC provides a robust framework for secure and privacy-preserving computation that are important in many scenarios such as decentralized systems. The concept of MPC was first introduced by Yao (1986) through the formulation of the two-party Millionaires' Problem. Goldreich, Micali, and Wigderson (1987) extend it to the multi-party case. Wang, Ranellucci, and Katz (2017a, b) provide efficient algorithms for two-party and multi-party secure computations.

MPC protocols are designed to withstand various threat models, such as semi-honest and malicious adversaries. In a semi-honest model, participants follow the protocol correctly but may attempt to extract additional information from the data they receive. In contrast, malicious adversaries may intentionally deviate from the protocol to disrupt the computation or gain unauthorized access to sensitive data. MPC protocols employ techniques such as homomorphic encryption, secret sharing, and oblivious transfer to ensure the security of data.

In recent years, the growing demand for data privacy has led to the applications of MPC in many other fields, such as privacy-preserving auctions (e.g., 2008 Danish sugar beet auction, Bogetoft et al., 2015) and auditing (Bogdanov et al., 2015).

Appendix 2: Proof of Proposition 1

The proof of (1), (2), (4) are straightforward.

Proof for (3):

The regulator i's maximized utility on each firm in the equilibrium is:

$$L(s_i) = \theta N\bar{x} + \left[(\theta - \pi_i)p_i^* N\mu - \beta_i(1 - s_i^*)p_i^* N\mu^2 - a s_i^{*2} N^2 - b\right]$$

Rewrite equation (1) as $p_i^* = \frac{2aNs_i^*}{\beta\mu^2}$ and plugging into L gives us:

$$\begin{aligned} L(s_i) &= \theta N\bar{x} + \left[(\theta - \pi_i)\frac{2aNs_i^*}{\beta_i\mu^2}N\mu - \beta_i(1 - s_i^*)\frac{2aNs_i^*}{\beta_i\mu^2}N\mu^2 - a s_i^{*2} N^2 - b\right] \\ &= \theta N\bar{x} + \left[aN^2 s_i^*\left(\frac{2(\theta - \pi_i)}{\beta_i\mu} - 2(1 - s_i^*) - s_i^*\right) - b\right] \\ &= \theta N\bar{x} + \left[aN^2 s_i^*\left(s_i^* + \frac{2(\theta - \pi_i)}{\beta_i\mu} - 2\right) - b\right] \\ &= \theta N\bar{x} + \left[\frac{\theta - \pi_i}{\gamma}W_i + aN^2 s_i^*(s_i^* - 2) - b\right] \end{aligned}$$

Define $V_i = \frac{\theta - \pi_i}{\gamma}W_i + aN^2 s_i^*(s_i^* - 2) - b$, then we have:

$$L(s_i) = \theta N\bar{x} + V_i$$

Since p_i^* is decreasing in β_i, $W_i = \frac{p_i^*\gamma N\mu}{2}$ is also decreasing in β_i. Taking derivative with respect to β_i for V_i implies:

$$\frac{\partial V_i}{\partial \beta_i} = \frac{\theta - \pi_i}{\gamma}\frac{\partial W_i}{\partial \beta_i} + aN^2(2s_i^* - 2)\frac{\partial s_i^*}{\partial \beta_i} < 0,$$

where the last inequality uses the fact that s_i^* is increasing in β_i. Therefore, L_i^*, and F_i^* are also decreasing in β_i.

Proof for (5):

The regulator's total utility from all firms operate in its city thus becomes:

$$TL(s_i) = d_i^* T(\theta N\bar{x} + d_i^* V_i)$$

The total production P_i^* in each city is proportional to $d_i^*(N\bar{x} + p_i^*\mu)$ by definition.

Q.E.D.

Appendix 3: Proof of Proposition 3

The (1)-(3) of the proposition can be easily derived using non-deviation conditions for regulators.

Proof of (4):

The full adoption equilibrium condition (5.1) implies

$$c_f < \frac{1}{2}\theta\bar{x} - \frac{1}{2}c_v - \left(\frac{1}{2} + \frac{W_i}{2e}\right)\theta\bar{x} - \left(\frac{1}{2} + \frac{W_i}{2e}\right)V_i$$
$$= -\frac{W_i}{2e}\theta\bar{x} - \frac{1}{2}c_v - \left(\frac{1}{2} + \frac{W_i}{2e}\right)V_i = C_1$$

The no adoption equilibrium condition (5.2) implies

$$c_f >= \left(\frac{1}{2} - \frac{W_{-i}}{2e}\right)\theta\bar{x} - \left(\frac{1}{2} - \frac{W_{-i}}{2e}\right)c_v - \left(\frac{1}{2} + \frac{W_i - W_{-i}}{2e}\right)\theta\bar{x} - \left(\frac{1}{2} + \frac{W_i - W_{-i}}{2e}\right)V_i$$
$$= -\frac{W_i}{2e}\theta\bar{x} - \left(\frac{1}{2} - \frac{W_{-i}}{2e}\right)c_v - \left(\frac{1}{2} + \frac{W_i - W_{-i}}{2e}\right)V_i$$
$$= C_2 = C_1 + \frac{W_i}{2e}(C_v + V_i)$$

Therefore, no adoption and full adoption coexist if and only if $C_2 < C_1$, or equivalently, $C_v + V_i < 0 \; for \; i = 1,2$.

Proof of (5):

Since inequality (5.1) and (5.4) cannot hold at the same time, full adoption and partial adoption cannot co-exist. Similarly, since inequality (5.2) and (5.3) cannot hold at the same time, no adoption and partial adoption cannot coexist.

Proof of (6):

From (3) of the proposition, inequalities (5.3) and (5.4) are the conditions for the existence of a partial adoption equilibrium where only the regulator i adopts blockchain. Inequality (5.3) implies

$$c_f < \left(\frac{1}{2} - \frac{W_{-i}}{2e}\right)\theta\bar{x} - \left(\frac{1}{2} - \frac{W_{-i}}{2e}\right)c_v - \left(\frac{1}{2} + \frac{W_i - W_{-i}}{2e}\right)\theta\bar{x} - \left(\frac{1}{2} + \frac{W_i - W_{-i}}{2e}\right)V_i$$
$$= -\frac{W_i}{2e}\theta\bar{x} - \left(\frac{1}{2} - \frac{W_{-i}}{2e}\right)c_v - \left(\frac{1}{2} + \frac{W_i - W_{-i}}{2e}\right)V_i = C_3$$

And inequality (5.4) implies:

$$c_f > \frac{1}{2}\theta\bar{x} - \frac{1}{2}c_v - \left(\frac{1}{2} + \frac{W_{-i}}{2e}\right)\theta\bar{x} - \left(\frac{1}{2} + \frac{W_{-i}}{2e}\right)V_{-i}$$
$$= -\frac{W_{-i}}{2e}\theta\bar{x} - \frac{1}{2}c_v - \left(\frac{1}{2} + \frac{W_{-i}}{2e}\right)V_{-i} = C_4$$

The partial equilibrium where only the regulator i adopts blockchain exists if and only if $C_4 < C_3$. That is:

$$\left(\frac{W_i}{2e} - \frac{W_{-i}}{2e}\right)\theta\bar{x} - \frac{W_{-i}}{2e}c_v - \left(\frac{1}{2} + \frac{W_{-i}}{2e}\right)V_{-i} + \left(\frac{1}{2} + \frac{W_i - W_{-i}}{2e}\right)V_i < 0$$

Denote the left-hand side of the inequality as C_5^i. Similarly, partial equilibrium where only the regulator $-i$ adopts blockchain exists if and only if $C_5^{-i} < 0$. If $\beta_i < \beta_{-i}$, then we must have $C_5^i < C_5^{-i}$ since both W_i and V_i are decreasing in β_i. Therefore, if there is only one partial equilibrium, then it must be the one where only the regulator i adopts the blockchain.

If two regulators have similar β_i, then W_i and W_{-i}, V_i and V_{-i} are very close and the inequality above can be approximated by:

$$\frac{W_i}{2e}(c_v - V_i) < 0 \text{ or } c_v < V_i$$

Therefore, if two regulators have similar β_i and $c_v < V_i$, both partial equilibria can exist.

Q.E.D.

Appendix 4: Proof of Proposition 4

(1) Full adoption is social optimal if and only if $S_b > S_0$, or equivalently,

$$\theta N\bar{x} - c_v - 2c_f + \gamma N\bar{x} - \frac{1}{2}e > \theta N\bar{x} + d_1^* V_1 + d_2^* V_2 + d_1^* W_1 + d_2^* W_2 + \gamma N\bar{x} - \frac{1}{2}e$$

$$2c_f + c_v < -d_1^* V_1 - d_2^* V_2 - d_1^* W_1 - d_2^* W_2$$

$$2c_f + c_v < -\frac{W_1 - W_2}{2e}V_1 - \frac{W_2 - W_1}{2e}V_2 - \frac{1}{2}(W_1 + W_2 + V_1 + V_2) - \frac{(W_1 - W_2)^2}{2e}$$

Denote the right-hand-side of the inequality as C_0.

(2) If full adoption is the equilibrium, then (5.1) holds for all i=1,2. Summing equation (5.1) over i yields:

$$\theta N\bar{x} - c_v - 2c_f > \theta N\bar{x} + \frac{W_1}{2e}\theta N\bar{x} + \frac{W_2}{2e}\theta N\bar{x} + \left(\frac{1}{2} + \frac{W_1}{2e}\right)V_1 + \left(\frac{1}{2} + \frac{W_2}{2e}\right)V_2,$$

$$2c_f + c_v < -\frac{W_1 + W_2}{2e}\theta N\bar{x} - \frac{W_1}{2e}V_1 - \frac{W_2}{2e}V_2 - \frac{1}{2}(V_1 + V_2)$$

Denote the right-hand-side of the inequality as C_0, and rewrite it as follows:

$$C_1 = C_0 - \frac{W_1 + W_2}{2e}\theta N\bar{x} - \frac{W_2}{2e}V_1 - \frac{W_1}{2e}V_2 - \frac{1}{2}(W_1 + W_2) - \frac{(W_1 - W_2)^2}{2e}$$

$$= C_0 - \frac{W_1}{2e}(\theta N\bar{x} + V_2) - \frac{W_2}{2e}(\theta N\bar{x} + V_1) - \frac{1}{2}(W_1 + W_2) - \frac{(W_1 - W_2)^2}{2e}$$

Since $V_i = \frac{\theta - \pi}{\gamma}W_i + aN^2 s_i^*(s_i^* - 2) - b$ is increasing in θ, there exists a threshold θ_0 such that $C_1 < C_0$ when $\theta > \theta_0$. Therefore, if $C_1 < 2c_f + c_v < C_0$, then full adoption is social optimal but not an equilibrium. In this case, a subsidy from the central government or social planner is needed to achieve the full equilibrium such that the social welfare is optimized.

Q.E.D.