# Mandatory Environmental Information Disclosure and Directed Technological Change: Evidence from the Large Chinese Firms

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January, 2025

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**Abstract**

While empiric demonstrates that mandatory environmental information disclosure can deter pollution, it remains unclear whether it can redirect technological changes away from dirty innovation toward clean innovation. This study uses a difference-in-differences approach to evaluate the effects of China's 2014 environmental monitoring reform, which required large, heavy polluters to disclose their emissions publicly. Our findings reveal only a short-lived increase in clean innovation among regulated firms, suggesting that the reform did not induce sustainably directed technological change toward clean innovation. The firms' profitability declined accordingly, showing that the reform brought economic costs and implicating it may not be optimal.

**JEL Codes:** D22, O31, O44, P28, Q55, Q58

# 1 Introduction

In recent decades, economists have shown that mandatory environmental information disclosure can effectively deter pollution. A prominent example is the Toxics Release Inventory (TRI) program in the United States, which obliges facilities to report their annual emissions of hazardous substances. By making these data publicly accessible, the program empowers citizens, NGOs, and local governments to hold polluters accountable and reduce their pollution (Konar and Cohen, 1997; Khanna et al., 1998)[1]. Building on this line of work, Yang et al. (2021) investigated a mandatory disclosure program on power plants and found that disclosure reduces their emissions. Beyond the United States, evidence from other contexts, such as China, suggests that mandatory environmental information disclosure also mitigates pollution in economies governed by different political regimes[2]. For instance, recent studies reveal that publicly available pollution data enable public and private appeals, significantly encouraged local governments to strengthen enforcement. As a result, targeted firms reduce violations of pollution standards (Buntaine et al., 2024).

Although mandatory environmental information disclosure has been shown to curb pollution, limited evidence exists on whether it fosters economic incentives for endogenous technological change toward cleaner production[3]. Empirically Addressing

[1]The effectiveness of such programs often hinges on additional environmental inspections or public engagement. While some studies document a correlation between disclosure and heightened regulatory oversight(Oberholzer-Gee and Mitsunari, 2006), others find that this is not always the case (Bui and Mayer, 2003; Maniloff and Kaffine, 2021).

[2]Similar effects of environmental disclosure have been observed in India. See Powers et al. (2011)

[3]The economic incentives applied in this paper are defined as the ongoing incentives for firms to adopt or invent new and better technologies and processes to reduce pollution, thereby promoting endogenous technological change (Nordhaus, 1994; Jaffe et al., 1995). Command-and-control regulatory instruments, such as emission standards, are are generally viewed as offering minimal

this gap is important for at least two reasons. First, clarifying whether mandatory environmental information disclosure contributes to endogenous technological change can expand the set of policy tools available for promoting cleaner production (Jaffe et al., 1995; Newell et al., 1999; Jaffe et al., 2002; Brunnermeier and Cohen, 2003; Fischer et al., 2003; Aghion et al., 2016; Calel and Dechezleprêtre, 2016; Bloom et al., 2019; Calel, 2020). Although mandatory disclosure is generally not expected to generate enduring incentives for pollution reduction (Konar and Cohen, 1997; Sterner and Coria, 2013) or to enhance the market's information environment (Weksler and Zik, 2023), it might still induce one-off clean innovation[4]. Second, disclosure policies typically enjoy broad support from the public, which values the right to know about nearby polluters (Buntaine et al., 2024). This can lower political obstacles to policy implementation and may be particularly relevant for low- and middle-income countries, which often hesitate to adopt stringent environmental regulations due to concerns about potential economic drawbacks (Greenstone and Jack, 2015). In these contexts, mandatory disclosure policies can serve as a strategic interim step toward the cooperative global equilibrium described by Acemoglu et al. (2014), in which both the Global North and South coordinate their pollution abatement efforts and

incentives for innovation (Perman, 2003; Aghion et al., 2019), earning them the label "non-market-based" regulation. By contrast, carbon taxes or tradable pollution permits are considered "market-based" regulations because they provide continuous motivation for firms to invest in pollution-reducing technologies (Aghion et al., 2016), (Calel and Dechezleprêtre, 2016). Hence, much of the existing literature on endogenous technological change focuses on these market-based policies.

[4]Unlike market-based regulatory instruments (e.g., carbon taxes or marketable emission permits), which impose ongoing economic costs on firms and thus maintain lasting profitability for cleaner technologies (Acemoglu et al., 2012; Dechezleprêtre and Sato, 2017), non-market-based regulations (e.g., mandatory disclosure policies) could spur short-term investments in clean technologies. For recent empirical evidence, see Chen et al. (2023).

foster globally directed technological change[5].

To guide our empirical analysis, outline a simple conceptual framework linking mandatory environmental information disclosure to endogenous clean innovation. In our framework, regulators face budget constraints in enforcing pollution penalties (Helland, 1998; Polinsky and Shavell, 2000; Telle, 2013). Making pollution data publicly available complements these limited budgets by enabling citizen engagement, as residents can file reports, complaints, or appeals regarding pollution violations once they have access to the information[6]. Regulatory agencies, in turn, respond to heightened public pressure by stepping up enforcement efforts[7]. Our framework assumes that clean technologies can fully replace more polluting alternatives, so that higher regulatory costs for polluting processes raise the relative profitability of innovations in cleaner alternatives[8]. Due to increased regulatory enforcement on pollution violation, the profitability of developing clean technologies rises for firms firms required to disclose their emissions data compared to those that do not face such requirements[9]. Nevertheless, once firms have developed cleaner technologies

[5]In their paper, politics in the South are not considered, raising questions about the feasibility of "optimal" global coordination, such as a global carbon market coupled with substantial grants for developing clean technologies.

[6]While we lack direct evidence on how the public leverages such data, Barwick et al. (2024) find that disclosure policies do prompt tangible reactions from Chinese citizens, suggesting similar effects may be at work here.

[7]In our data, this is evident as the 2014 reform led to an increase in environmental penalties for National Key Monitoring Firms (NKMFs) compared to their counterparts. Detailed text in the data reveals that most penalties were related to violations of emission standards.

[8]This is a common assumption in empirical studies on environmentally directed technological change (Aghion et al., 2016; Calel and Dechezleprêtre, 2016; Calel, 2020).

[9]An alternative perspective is that public disclosure reduces regulatory uncertainty, incentivizing firms to invest in abatement technologies in anticipation of more lenient treatment by regulators (Greenstone et al., 2006). However, in our context, regulators already had access to emissions information prior to the policy, so public disclosure did not significantly alter regulatory uncertainty (see Institutional Background).

and complied with regulations, the impetus from public complaints diminishes, as noncompliance becomes less common. This mechanism implies that incentives for ongoing clean innovation may wane over time. We thus hypothesize that mandatory disclosure will generate a transitory—rather than permanent—increase in clean innovation by treated firms relative to untreated ones.

We examine the causal impact of mandatory environmental information disclosure on clean innovation by exploiting a 2014 monitoring reform in China that required certain major polluters to publicly disclose their emissions data. Specifically, the government established online platforms disclosing the pollution levels of these firms, designated as "National Key Monitoring Firms" (NKMFs)[10]. The disclosure policy introduced public participation in the environmental monitoring of the targeted firms (NKMFs). The public gained the ability to track violations of pollution standards on these websites and report infractions to local authorities, effectively broadening the scope of environmental oversight. Since not all listed firms fell under the NKMF category, we implement a quasi-experimental design to identify the policy's impact on firms' innovation activities.

We construct panel data on 271 Chinese A-share–listed firms subject to the mandatory disclosure reform (NKMFs) and 1,373 non-monitored firms (non-NKMFs) spanning 2010–2023. As assignment to the NKMF list was not random, we use a

[10]China began introducing continuous emissions monitoring systems (CEMS) for industrial firms in 2003. To encourage public participation in environmental regulation, the government launched the National Key Monitoring Firms Automatic Monitoring Information Disclosure Program in 2014, compelling NKMFs to publicize their pollution data via official websites. NKMFs are defined as those entities collectively responsible for approximately 65 percent of local emissions (air pollution, water pollution, heavy metals, and waste). This study focuses on the policy's effect on these designated firms.

propensity-score–matching (PSM) strategy based on pre-policy covariates to address selection biases. Our matched sample consists of 188 NKMFs and 188 non-NKMFs. We then employ a differences-in-differences (DiD) approach to estimate the policy's effect on firms' clean innovation, measured by their green patenting activity[11]. We control for firm fixed effects, along with industry, year, and provincial fixed effects, and also include firm size, age, prior patent stock, and financial constraints as additional regressors. To investigate whether the policy's effect on clean innovation is short-lived, we adopt two complementary strategies. First, we split the sample into two periods—a shorter window (2010–2016) and the full window (2010–2023)—and compare the policy impact across these intervals. Second, we implement an event study to analyze the time dynamics of the policy's effect.

Our main finding is that mandatory environmental information disclosure leads to a short-term increase in firms' clean innovation.The DiD estimates for 2010–2016 show that treated firms experience an approximately 7.32% increase in clean patenting relative to non-treated firms. However, this effect dissipates over the longer horizon (through 2023), indicating that the policy mainly induces temporary innovation gains. The event-study results further confirm that the policy's effect peaks around 2016, with no persistent impact thereafter.

We also examine the potential economic costs of the policy by evaluating whether it undermines firm profitability. The DiD estimates reveal a significant decrease in profitability (measured by Tobin's Q) among NKMFs compared to non-NKMFs,

[11]Following the IPC Green Inventory by WIPO, we classify a patent as clean if it belongs to specified green technology categories. We add one to each firm's annual patent count and take the natural logarithm.

amounting to roughly 9% through 2016. These findings suggest that while mandatory disclosure spurs clean innovation, it imposes tangible economic burdens on regulated firms. Notably, however, the rise in clean innovation does not appear to crowd out "dirty" innovation during the same period, implying that firms are not merely reallocating effort away from conventional technology paths. In line with the innovation outcomes, the downturn in profitability also vanishes by the longer horizon (2023). We conduct multiple robustness checks to substantiate our main results. These include a placebo test, different standard-error specifications (firm-level clustering and bootstrap), and estimating a Poisson model on the raw patent count. We also analyze the share of clean patents as an alternative metric. Across all these checks, our core findings remain consistent.

This study makes several contributions to the literature. First, we provide the first causal evidence on how mandatory environmental information disclosure—a non-market-based regulatory tool—shapes firms' incentives for clean innovation. Consistent with the notion that such disclosure does not sustain ongoing pollution abatement incentives(Konar and Cohen, 1997), our results show a short-term surge in green patenting, followed by a reversion to incumbents' baseline innovation trajectories once public pressure wanes. This corroborates theories positing that only market-based regulations exert enduring effects on both pollution reduction and environment-oriented economic growth (Acemoglu et al., 2012; Aghion et al., 2019; Hémous and Olsen, 2021). Second, even a transient boost in clean innovation can generate notable economic impact on regulated firms. In line with the broader understanding that regulations can carry significant costs (He et al., 2020), we show that mandatory

disclosure exerts downward pressure on firm profitability. Finally, our findings shed light on the political economy of globally coordinated environmental policies (Acemoglu et al., 2014; Greenstone and Jack, 2015). In settings where comprehensive market-based instruments face strong political barriers, mandating firms to disclose their emissions may represent a less contentious option. Although its effect on clean innovation may be only short-lived, mandatory disclosure can still yield improvements in environmental performance and may contribute incrementally to global clean technology capital stocks—particularly if knowledge spillovers extend from the Global South to the Global North[12].

# 2 Related Literature

This paper aligns with the large body of literature regarding regulation-induced innovation (Nordhaus, 1994; Jaffe et al., 1995; Porter and Linde, 1995; Jaffe and Palmer, 1997; Newell et al., 1999; Popp, 2002; Brunnermeier and Cohen, 2003; Popp, 2004; Acemoglu et al., 2012; Aghion et al., 2016; Calel, 2020). The literature strand pronounces that (environmental) regulatory policies impose costs with a firm's dirty input and induce it to invest in the (substituted) clean input to offset the cost. Modern theory with this respect further suggests that optimal environmental regulatory policies must encourage economic incentives that stimulate firms to lastingly change their incumbent dirty innovation path to a cleaner one at the same time (Popp, 2004; Gans, 2012; Acemoglu et al., 2012; Aghion et al., 2019; Hémous and

[12]See Witajewski-Baltvilks and Fischer (2023) for recent evidence on cross-border technology spillovers.

Olsen, 2021). This results in the focus of the following empirical studies on market-based regulatory instruments because only market-based regulations could encourage economic incentives[13]. However, few comprehensive empirical studies have been conducted to assess the effect of non-market-based regulations, such as mandatory disclosure policy, on directing firms to develop clean technologies.

The key driver for environmental regulation-induced clean innovation is the incentive at which regulated firms develop new technologies for pollution abatement (Nordhaus, 1994; Acemoglu et al., 2012). It is important to distinguish economic and non-economic incentives provided by environmental regulations, as the former would induce firms' profit-seeking (the so-called market-based) responses and the latter would not. To our best knowledge, there are no rigorous empirical papers regarding mandatory information disclosure regulations that clearly formulate hypotheses with this perspective[14]. This article, therefore, fills the gap by empirically indicating that mandatory information disclosure is indeed a non-market-based regulation(Konar and Cohen, 1997; Weksler and Zik, 2023).

# 3 Institutional Background

China operates the world's largest Continuous Emissions Monitoring System (CEMS) introduced by the Ministry of Environment and Ecology (MEE) in 2004[15]. The

[13]For example, Aghion et al. (2016); Calel and Dechezleprêtre (2016); Calel (2020).

[14]There is a literature stream discussing the incentive induced by mandatory disclosure (Greenstone et al., 2006; Doshi et al., 2013; Ernstberger et al., 2017; Grewal et al., 2019; Johnson, 2020; Chen et al., 2023). Unfortunately, these studies did not articulate whether the induced incentive in their cases is market-based or non-market-based.

[15]Other countries use similar systems for various regulatory purposes. For example, the United States EPA and many state governments require firms to install CEMS equipment to demonstrate

system requires installing automatic monitoring devices at discharge points—such as flow meters and CCTV cameras—to capture real-time data on key pollutants. Local Environmental Protection Agencies (EPAs) operate monitoring centers that automatically gather real-time data on key pollutants from each installed meters. The CEMS tracks both water pollutants (e.g., Chemical Oxygen Demand [COD] and ammonia nitrogen [NH3-N]) and air pollutants (e.g., sulfur dioxide [SO2], particulate matter [PM], and nitrogen oxides [NOX]). By January 2020, this CEMS infrastructure had been installed in more than 24,620 plants, collectively responsible for over 75 percent of China's industrial air and water pollution.

In 2014, China launched a nationwide environmental monitoring reform targeting large polluters, formally designated as National Key Monitoring Firms (NKMFs)[16]. Firms that exceeded a certain emissions threshold for any pollutant in the preceding two years were deemed NKMFs, following a selection process that involved both local and central government assessments[17]. Under the reform, NKMFs were mandated

compliance with permitted emission levels (United States EPA 2021). In India, specific provinces have started to require firms to install continuous monitoring equipment to support emissions trading (Greenstone et al. 2020). Likewise, the European Union has made continuous emissions monitoring support operation of its Emissions Trading Scheme (EU 2021). Yet none of these schemes have approached the scale of the CEMS in China, where it is used as a systematic regulatory tool for all key industrial polluters.

[16]The reform was launched by the MEE in a set of guidelines—"Regulations for Corporate Self-Monitoring and Information Disclosure of NKMF"—available on the central government website, see`http://www.gov.cn/gongbao/content/2013/content_2496407.htm`

[17]Although the Chinese central government did not set uniform national criteria for designating NKMFs, local governments typically submitted lists of major emitters that accounted for a large share of local pollution, and the central government aggregated these lists to form a nationwide roster. The final list of NKMFs is published on the MEE website `https://www.mee.gov.cn/gkml/hbb/bgt/201312/t20131231_265877.htm`. Since we do not have access to historical firm-level emissions data, we cannot independently verify that local governments relied solely on emissions levels. To mitigate potential selection bias, we use a matching approach on observable covariates, which we detail later in the paper.

to disclose their hourly emissions via online platforms operated by provincial EPAs. Firms had to maintain this information for at least one year, including not only real-time emissions data but also basic corporate information, monitoring plans, and annual reports[18]. The standards for different emission concentrations are also available, allowing the public to check whether each plant violates the standards hour by hour. The NKMFs themselves assumed responsibility for the accuracy and reliability of the published information.

Local regulators often face incentives to avoid stringent enforcement, partly due to concerns about harming local economic growth or employment. Local EPAs have considerable discretion in determining whether and when to penalize offenders (Becker and Stigler, 1974). Indeed, Buntaine et al. (2024) find that local officials typically act on CEMS-reported violations only after receiving public complaints (in their study, these were initiated by the researchers). This finding is consistent with an interview conducted with local EPA officials in a city in Sichuan province. Upon detecting excessive emissions via the CEMS, the standard response is to contact the firm for further explanation; fines are issued only if subsequent investigations verifying the "authenticity" of the detected violation.

Requiring NKMFs to disclose real-time emissions effectively reduces the scope for regulatory forbearance, as it introduces public participation into the environmental monitoring. The central government has also encouraged citizens to engage in

[18]Some recent studies identified the monitoring reform as central policies requiring local EPA to publicize in real time the hourly emissions data of every monitored plant to the public (Buntaine et al., 2024). According to the policy document, it de facto mandated the NKMFs emission disclosure. The hourly emission data of the firms should not only be transmitted to the local EPA's monitoring centers, but also to the provincial public platforms through CEMS for disclosure.

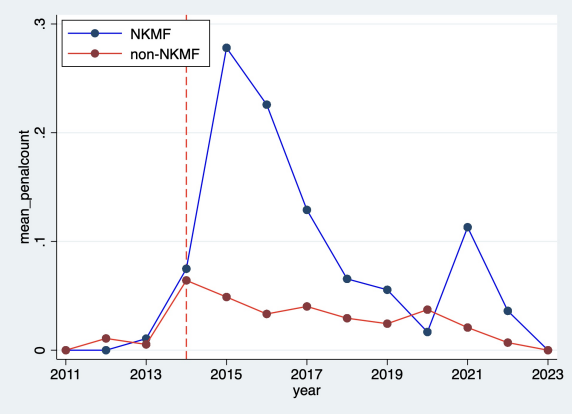



Figure 1: Count of Pollution Penalties: NKMF v.s. non-NKMF

environmental protection by mandating that local EPAs open official accounts on popular social media platforms, such as Weibo and WeChat. NGOs and individual citizens use these channels to flag apparent violations by NKMFs, generating public pressure that compels local EPAs to increase inspections and enforce penalties more rigorously. Figure 1 provides descriptive evidence of a substantial spike in pollution-related fines levied on NKMFs shortly after the policy was implemented in 2014. The increased frequency of inspections and heightened likelihood of penalties driven by emission disclosure and public participation further incentivized the monitored NKMFs to comply with emission standards and reduce pollutionBuntaine et al. (2024). To achieve these abatement goals, many firms likely invest in cleaner technologies, reflected in a surge in green patent applications. Figure 2 contrasts the trends in green patenting between NKMFs and non-NKMFs over this period, indicating a pronounced divergence that coincides with the introduction of mandatory real-time emissions disclosure.

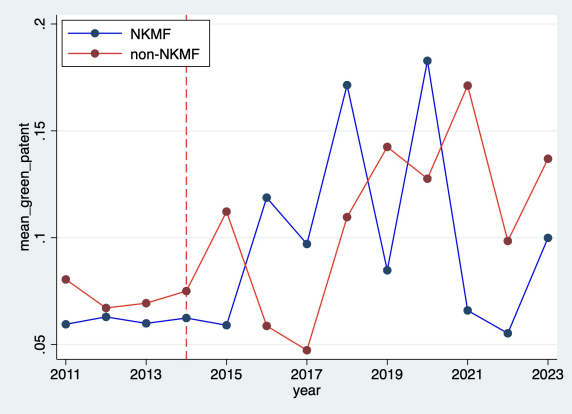



Figure 2: Green Patent (log formed): NKMF v.s. non-NKMF

# 4 Data and Empirical Strategy

## 4.1 Data and Variables

Our empirical analysis draws on data from official Chinese government websites, the China Stock Market and Accounting Research (CSMAR) database, and the China Research Data Service Platform (CNRDS). To identify the treated group, we use annual NKMF rosters published on the website of the Ministry of Ecology and Environment (MEE). A firm is classified as an NKMF if it appears on the roster for at least one pollutant category in every year from 2014 onward. Because the NKMF classification occurs at the plant level, we aggregate this information to the firm level for publicly traded entities, thus designating a listed firm as NKMF if it operates at least one monitored plant. Non-NKMF firms are those not included on any NKMF lists, excluding those in finance, agriculture, or services[19]. We combine these

[19]To ensure consistency, we further exclude firms that were not continuously designated as NKMF throughout the study period from our sample.

NKMF records with patent data from CNRDS and additional firm-level characteristics from CSMAR. Environmental penalty data come from the Institute of Public and Environmental Affairs (IPE) website [20], a non-profit organization in China that focuses on public pollution data. Merging these sources produces a panel spanning 2010–2023 for publicly listed Chinese firms. We focus on firms already listed in 2010, resulting in an unbalanced panel of 20,748 observations for 271 NKMF firms and 1,373 non-NKMF firms.

Our key dependent variable, firms' clean innovation (Log_Green Patent), is identified by the number of Chinese green patent applications of the firm in a given year according to the IPC Green Inventory directory by WIPO[21]. We transformed the patent count data into natural logarithms by applying the natural logarithm function to the original values incremented by one (i.e., $\log(x + 1)$)[22], a widely used method to address zero values and stabilize variance in count data. We incorporate a two-year lag in the patent data to account for the time between a firm's R&D efforts and patent applications (Hall et al., 1984). For the profitability of firms, we use Tobin's Q as reported by CSMAR.

In our difference-in-differences (DiD) framework, the treatment indicator ($KMF_i$) equals 1 if the firm is NKMF since 2014 and 0 otherwise. A post-policy indicator ($Post_t$) equals 1 in years following the policy and 0 in earlier years. Also, we controlled for variables potentially influencing firms' innovation incentives. First,

[20]https://wwwen.ipe.org.cn/

[21]https://www.wipo.int/classifications/ipc/green-inventory/home we identify the green patent according to the coverage of IPC Green Inventory except for Agriculture/Forestry as we focus on the manufacturing industries.

[22]We also use count data for robustness check.

following Aghion et al. (2016), we construct variables to capture the knowledge path dependence of the firm. Specifically, we create the knowledge stock relevant to clean technologies (Green_Stock) in a given year by the firm's accumulated patent application[23]. To account for firms' overall innovation capability, the total knowledge stock (All_Stock) is added as well. Massive empirical studies on firms' R&D articulated the significant role of firm size (Cohen, 2010). In this paper, we operationalize firm size with annual revenue, presented in natural logarithms (Log_Revenue). In addition, the cash flow (Cash_Flow) was used to reflect the financial constraint that may influence the R&D investment (Hall and Lerner, 2010). The age of the firms (Age) is also considered (Cohen, 2010). All the monetary variables are deflated by their appropriate deflators in each year published by the national bureau of statistics (NBS).

## 4.2 Propensity Score Matching

Because NKMF assignment is non-random, sample selection bias may arise. We therefore employ propensity score matching (PSM), following (Heckman et al., 1997). Using 2013 as the pre-policy year, we estimate a Probit model that includes firm-level covariates—namely revenue, cash flow, and patent stocks—to generate propensity scores. We then conduct non-replacement nearest-neighbor matching within industries. The matched sample comprises 376 firms (188 NKMFs and 188 non-NKMFs) spanning 27 industries. The summary statistics of the matched sample are presented in Table 1.

[23]Similar to Aghion et al. (2016), we introduce the annual depreciation of this knowledge capital to be 20 percent. The depreciation is applied in the total knowledge stock as well.

## 4.3 Difference-in-difference Model

To estimate causal effects, we apply a difference-in-differences (DID) regression to evaluate the effect of the monitoring reform related to NKMF on firms' clean innovation performance. As a popular method to assess economic behaviors, the DID approach allows the identification of exogenous effects and alleviates endogeneity problems (Heckman et al., 1997; Angrist and Pischke, 2009). Our DID specification implemented as a fixed effects panel regression is:

$$\Upsilon_{it+2} = \alpha_1 KMF_i \times Post_t + \alpha_2 KMF_i + \alpha_3 Post_t + \beta X_{it} + \theta_i + \zeta_t + \eta_j + \delta_k + \epsilon_{it} \quad (1)$$

Where $\Upsilon_{it+2}$ is the log-transformed green patent count for firm i in year t+2, $\alpha_1$ is the DID estimate of the effect of the disclosure policy on NKMF, $KMF_i$ is a dummy variable distinguishing the NKMF ($KMF_i = 1$) from the non-NKMF ($KMF_i = 0$), $Post_i$ is a dummy variable indicating the period after ($Post_t = 1$) and before the disclosure ($Post_i = 0$). Finally, we set $X_{it}$ as the matrix of all control variables in the firm $i$ and year $t$, $\theta_i$ as the firm fixed effect, $\zeta_t$ as the year fixed effect, $\eta_j$ as the industry fixed effect, $\delta_k$ as the province fixed effect, and $\epsilon_{it}$ as the error item within the regression. We also apply the DID model to estimate the policy effect on the firms profitability (log-transformed Tobin's Q).

## 4.4 Event Study Model

To examine the dynamic effects of the disclosure policy, we estimate the following event study model:

$$\Upsilon_{it+2} = \sum_{k=-\tau}^{\tau} \gamma_k \, \text{Post}_{t+k} \cdot KMF_i + \alpha X_{it} + \theta_i + \zeta_t + \eta_j + \delta_k + \varepsilon_{it} \tag{2}$$

where: $\Upsilon_{it+2}$ represents the log-transformed green patent count for firm $i$ at time $t+2$. $\text{Post}_{t+k}$ is a series of event-time dummies, where $k = 0$ indicates the period of the event (the disclosure policy), $k < 0$ captures pre-event periods, and $k > 0$ captures post-event periods. $KMF_i$ is a dummy variable distinguishing monitored NKMFs ($KMF_i = 1$) from non-NKMFs ($KMF_i = 0$). $\gamma_k$ are the coefficients of interest, measuring how the treatment effect evolves over time. In addition to offering insights into the persistence of policy impacts, this model enables us to test for pre-existing trends, thereby reinforcing the validity of the parallel trends assumption. $X_{it}$ is the matrix of control variables for firm $i$ at time $t$. $\theta_i$ represents firm fixed effects to control for unobservable time-invariant characteristics at the firm level. $\zeta_t$ denotes year fixed effects to account for time-specific shocks affecting all firms. $\eta_j$ represents industry fixed effects, and $\delta_k$ captures province fixed effects. $\varepsilon_{it}$ is the error term.

## 4.5 Empirical Strategy

Our empirical strategy evaluates whether the mandatory disclosure policy continues to influence clean innovation and profitability beyond the short term. We first estimate Equation (\ref{eq1}) over two distinct windows—2010–2016 (short term) and 2010–2021 (long term). Next, we employ the event study to visualize the effect's trajectory, identifying whether it diminishes, stabilizes, or escalates after the policy takes effect. This two-pronged approach, combining DiD and an event study, provides

a comprehensive view of the policy's temporal dynamics and its implications for firms' technological choices and economic performance.

# 5 Results and Implications

## 5.1 Impact of Mandatory Environmental Information Disclosure

First, we check whether our DiD estimator satisfies the parallel trend assumption using the matched sample. Figure 3 shows that the difference of the green patents between NKMFs and non-NKMFs is near zero in pre-event trends, which validates our estimations for the impact of the policy.

The results presented in Table 3 demonstrate the impact of mandatory environmental information disclosure on firms' clean innovation in both the short-term and longer-term periods. The difference-in-differences (DiD) coefficient is positive and statistically significant in the short term (Column 1), indicating that the policy led to a 7.32% increase in clean innovation shortly after its implementation. In contrast, the coefficient in the longer-run specification (Column 2) remains positive yet fails to achieve statistical significance, suggesting that the initial boost to clean innovation does not persist. Additionally, the control variables reveal interesting dynamics: Green_Stock and All_Stock have statistically significant negative coefficients, implying that firms with greater existing patent stocks—either in green technologies or overall—may be less responsive to the disclosure policy. One possible explanation is that firms already holding substantial patent portfolios face diminishing marginal returns

to additional innovation, reducing their incentive to pursue new clean technologies.

Table 4 corroborates these insights through an event study specification (Column 1). The coefficients on `lag0`, `lag1`, and `lag2` are positive and significant, reinforcing the observation that mandatory disclosure drives an immediate and sizable increase in green patenting. By contrast, coefficients from `lag5` onward fail to exhibit statistical significance, indicating that the policy's effect tapers off over time, aligning with the notion that sustained clean innovation may require additional economic or market-based incentives.

## 5.2 Economic Costs to the Regulated Firms

In this section, we explore whether mandatory disclosure imposes economic costs on regulated firms. We use the changes in Tobin's Q and "dirty innovation," defined as non-green patent applications, to measure the economic cost. We run the DiD model to test the impact (See Table 5). The DiD coefficient on dirty patents is positive but statistically insignificant, suggesting that firms' investments in conventional technologies remain largely unaffected by the policy. In contrast, Tobin's Q declines significantly for treated firms in the short term. This negative coefficient implies that the policy's impetus for clean innovation may come at the expense of short-term profitability. In the long term, there is no significant difference in dirty innovation or Tobin's Q between the regulated firms and their counterparts. The event study on Tobin's Q in table 4 confirms the short-term economic cost caused by the disclosure policy. Taken together, these findings suggest that while mandatory environmental information disclosure fosters a temporary surge in clean innovation, it also entails

immediate economic costs for regulated firms.

## 5.3 Robustness Checks

To ensure the robustness of the DiD estimates, we first conduct a placebo test using a fake timing of the policy intervention. Specifically, we assign 2013 as an artificial policy shock year and re-estimate the DiD model. This approach is grounded in the parallel trend assumption, which implies that no significant treatment effect should be observed in a period when the policy was not actually implemented. If any significant effects were detected, it would indicate the presence of confounding factors unrelated to the policy intervention. Our results show that the DiD estimator is insignificant with the fake timing, providing evidence that the original model is robust to such concerns.

Next, we assess the robustness of our findings by applying alternative standard error specifications, including firm-level clustered standard errors and the bootstrap method (Bertrand et al., 2004; Angrist and Pischke, 2009). These approaches are particularly important as they account for potential serial correlation and heteroscedasticity in the error terms, which, if unaddressed, could lead to biased standard errors and unreliable inference. Specifically, for the bootstrap, we resample the data 100 times, allowing us to empirically estimate the sampling variability and generate more reliable standard errors, especially in the presence of a relatively not very big sample, like our data. The results remain unchanged with the higher standard errors, further confirming the robustness of our findings.

Third, since many firms report zero green patent applications, we log-transform

the patent data. While this transformation helps account for the skewness in the data, it may distort the true patenting behavior of firms and potentially affect the consistency of the estimation (Hausman et al., 1984). To address this, we re-estimate the model using a Poisson regression on the raw patent count as an alternative to the log-transformed outcome. The results remain consistent when using the raw patent count, confirming that the transformation does not bias our estimation.

Finally, following the literature on directed technological change, which emphasizes that green innovation can be represented as a relative increase in clean technologies within the overall technological portfolio (Popp, 2002), we introduce an additional robustness check by replacing the absolute count of green patents with the green share. The green share is defined as the ratio of green patent applications to total patent applications in a given year. This alternative measure provides a relative perspective on green innovation. Our results show that, during the short time period (2010–2016), the mandatory disclosure policy significantly increased the green share of regulated firms relative to non-regulated firms. In contrast, during the long time period (2010-2021), the effect disappears. This finding further reinforces the robustness of our main conclusion. The detailed results of the robustness checks are presented in Appendix A.

# 6 Conclusion

Over the past several decades, economists and policymakers have grappled with the challenge of balancing environmental preservation and economic growth. Regulations

that steer technological trajectories toward cleaner production can exert far-reaching influences on sustainable development(Acemoglu et al., 2012). In this vein, mandatory pollution disclosure stands out as a non-market-based policy instrument that may yield short-term incentives for clean technological innovation—especially in settings where political or institutional constraints impede more aggressive, market-based measures.

Our paper investigates the impact of mandatory environmental disclosure on firms' directed technological change and the potential economic burden it imposes. The main finding shows a short-lived increase in clean innovation induced by the disclosure policy. It indicates that enhanced transparency and increased public oversight can encourage firms to abate pollution with clean innovation in the short run. However, these effects do not persist in the longer term, underscoring the difficulty of sustaining directed technological change through disclosure alone. Additionally, we observe an immediate decline in profitability among regulated firms, indicating that while the policy drives short-term clean innovation, it also imposes near-term economic costs.

This study has some limitations. First, we lack direct data on public participation under the disclosure regime; our inference relies on observed spikes in regulatory penalties following the 2014 policy. Second, our analysis is confined to China, a context with unique institutional, political, and regulatory frameworks. This focus may limit the external validity of our conclusions for other regions. Future research could extend this inquiry by examining multiple countries or comparative case studies, thereby offering broader insights into the role of mandatory environmental disclosure in fostering long-term clean innovation.

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# Tables

Table 1: T-test for the Difference between Groups

| "Before PSM" | | | "After PSM" | | |
|---|---|---|---|---|---|
| | Coefficient | (t-statistics) | | Coefficient | (t-statistics) |
| Green_Stock | 0.167 | (0.503) | Green_Stock | -0.175 | (0.502) |
| Total_Stock | -31.764 | (-0.68) | Total_Stock | -28.288 | (-0.994) |
| Log_Revenue | -1.24*** | (-13.745) | Log_Revenue | -0.257 | (-1.898) |
| Cash_Flow | -0.002 | (-0.056) | Cash_Flow | -0.038 | (-0.693) |
| Age | -3.609*** | (-8.825) | Age | -0.011 | (-0.018) |
| Observations | 1617 | | Observations | 376 | |

*The coefficient presents the mean difference between non-NKMF and NKMF firms. t-statistics in parentheses.*
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2: Summary Statistics of the Variables

| | (1) kmf 0 | (2) | (3) | (4) | (5) | (6) kmf 1 | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| VARIABLES | N | mean | sd | min | max | N | mean | sd | min | max |
| ln_green | 2,372 | 0.0947 | 0.433 | 0 | 4.094 | 2,505 | 0.0898 | 0.406 | 0 | 6.263 |
| ln_tobinq | 2,306 | 0.576 | 0.537 | -0.400 | 4.629 | 2,456 | 0.492 | 0.455 | -0.358 | 2.987 |
| ln_dirty | 2,372 | 1.300 | 1.459 | 0 | 6.913 | 2,505 | 1.514 | 1.565 | 0 | 9.100 |
| K_gpatent | 2,364 | 1.273 | 5.670 | 0 | 67.75 | 2,499 | 1.674 | 16.55 | 0 | 525.0 |
| K_tpatent | 2,364 | 54.16 | 193.5 | 0 | 3,357 | 2,499 | 158.5 | 1,556 | 0 | 31,582 |
| lnSale | 2,371 | 21.81 | 1.475 | 11.29 | 25.80 | 2,505 | 21.95 | 1.255 | 17.32 | 26.07 |
| cf | 2,371 | 0.210 | 0.654 | -15.31 | 5.930 | 2,505 | 0.228 | 0.358 | -2.688 | 5.696 |
| age | 2,372 | 14.12 | 7.085 | 0 | 31 | 2,505 | 14.43 | 6.625 | 0 | 31 |
| Number of id | 376 | 376 | 376 | 376 | 376 | 376 | 376 | 376 | 376 | 376 |

Table 3: Impact of Mandatory Environmental Information Disclosure on NKMFs' Clean Innovation

| VARIABLES | (1) short-term | (2) longer-term |
|---|---|---|
| DiD | 0.0732*** | 0.0350 |
| | (0.0274) | (0.0265) |
| post | -0.381*** | -0.435 |
| | (0.138) | (0.331) |
| Green_Stock | -0.0452*** | -0.00564*** |
| | (0.00453) | (0.000767) |
| All_Stock | -3.07e-05 | 9.18e-05*** |
| | (2.30e-05) | (1.22e-05) |
| Log_Revenue | 0.00626 | -0.00539 |
| | (0.0203) | (0.0144) |
| Age | 0.0733*** | 0.0430 |
| | (0.0248) | (0.0315) |
| Cash_Flow | 0.0236 | 0.00627 |
| | (0.0163) | (0.0133) |
| Constant | -0.286 | 0.136 |
| | (0.652) | (0.481) |
| Observations | 2,509 | 4,111 |
| R-squared | 0.083 | 0.036 |
| Number of id | 376 | 376 |
| Povince FE | Yes | Yes |
| Industry FE | Yes | Yes |
| Firm FE | Yes | Yes |
| Year FE | Yes | Yes |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Impact of Mandatory Environmental Information Disclosure: Event Study

| VARIABLES | (1)<br>log_Green_Patents | (2)<br>log_Tobin's Q |
|---|---|---|
| Green_Stock | -0.00568*** | -0.000813 |
| | (0.00118) | (0.000494) |
| All_Stock | 9.30e-05*** | 2.06e-05*** |
| | (1.19e-05) | (5.09e-06) |
| Log_Revenue | -0.00704 | -0.177*** |
| | (0.0113) | (0.0251) |
| Age | 0.00549 | -0.0184*** |
| | (0.00457) | (0.00354) |
| Cash_Flow | 0.00741 | 0.0492** |
| | (0.00878) | (0.0213) |
| lead4 | 0.0662 | 0.0852** |
| | (0.0499) | (0.0432) |
| lead3 | 0.0570 | 0.105*** |
| | (0.0433) | (0.0368) |
| lead2 | 0.0470 | 0.0462* |
| | (0.0484) | (0.0274) |
| lag0 | 0.119** | 0.0137 |
| | (0.0483) | (0.0265) |
| lag1 | 0.108** | -0.101** |
| | (0.0506) | (0.0436) |
| lag2 | 0.122** | 0.0648 |
| | (0.0570) | (0.0434) |
| lag3 | 0.0143 | 0.0961** |
| | (0.0510) | (0.0390) |
| lag4 | 0.122* | 0.132*** |
| | (0.0658) | (0.0380) |
| lag5 | -0.0295 | 0.128*** |
| | (0.0598) | (0.0443) |
| lag6 | 0.0528 | 0.115** |
| | (0.0489) | (0.0511) |
| lag7 | 0.0627 | 0.125** |
| | (0.0686) | (0.0537) |
| Constant | 0.364 | 5.181*** |
| | (0.317) | (0.631) |
| Observations | 4,111 | 4,732 |
| Number of id | 376 | 0.359 |
| R-squared | 0.040 | 376 |
| Povince FE | Yes | Yes |
| Industry FE | Yes | Yes |
| Firm FE | Yes | Yes |
| Year FE | Yes | Yes |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Potential Economic Cost of the Clean Innovation

| | Short Term | | Long Term | |
|---|---|---|---|---|
| VARIABLES | ln_Tobin's Q | Dirty Patent | ln_Tobin's Q | Dirty Patent |
| DiD | -0.0916*** | 0.0368 | 0.0183 | -0.0140 |
| | (0.0223) | (0.0590) | (0.0185) | (0.0524) |
| post | 0.771*** | -0.250 | 0.482* | 1.036 |
| | (0.113) | (0.298) | (0.290) | (0.655) |
| Green_Stock | -0.00753* | 0.00487 | -0.000773 | -0.000155 |
| | (0.00421) | (0.0102) | (0.000521) | (0.00151) |
| All_Stock | 1.61e-05 | 6.38e-05 | 2.14e-05** | 2.17e-05 |
| | (1.87e-05) | (4.96e-05) | (8.42e-06) | (2.40e-05) |
| Log_Revenue | -0.318*** | 0.0275 | -0.178*** | 0.0725** |
| | (0.0165) | (0.0438) | (0.00902) | (0.0284) |
| Age | -0.100*** | 0.0597 | -0.0550** | -0.0902 |
| | (0.0203) | (0.0533) | (0.0232) | (0.0622) |
| Cash_Flow | 0.0376** | -0.0348 | 0.0518*** | -0.0289 |
| | (0.0166) | (0.0350) | (0.0103) | (0.0262) |
| Constant | 9.003*** | 1.017 | 5.566*** | -0.135 |
| | (0.522) | (1.402) | (0.338) | (0.951) |
| Observations | 2,460 | 2,509 | 4,732 | 4,111 |
| R-squared | 0.441 | 0.031 | 0.350 | 0.040 |
| Number of id | 376 | 376 | 376 | 376 |
| Povince FE | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |

*** p¡0.01, ** p¡0.05, * p¡0.1

*Note:* This table examines the potential economic costs of clean innovation by focusing on the coefficients of the DiD estimator across three dependent variables: dirty patenting (Column 1), total factor productivity (TFP, Column 2), and the lead of TFP two years ahead (Column 3). Similar to green patenting, we use two-year lagged patent applications to measure the dirty innovation activities. However, considering that the change of the TFP could be quick, we use non-lagged and one-year lagged TFP.

# Figures

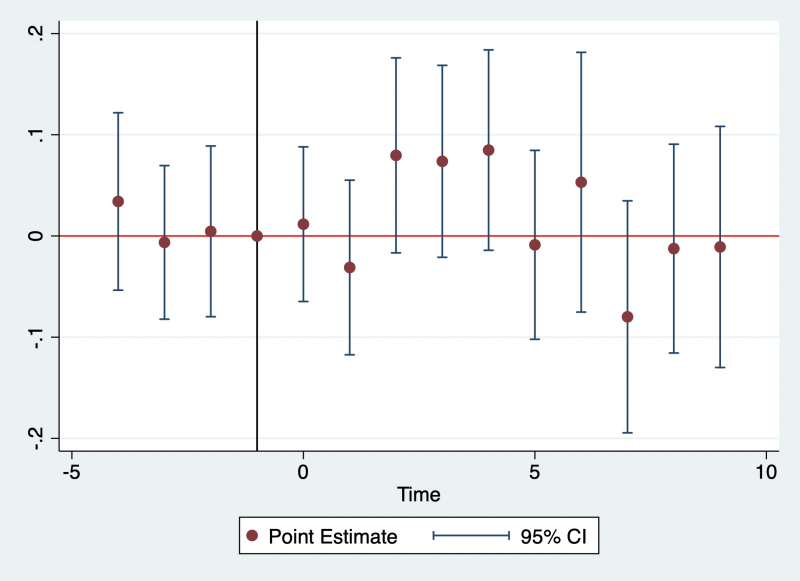



Figure 3: Difference of Green Patents between the Two groups in Trends

*Note:* This figure illustrates the difference in the number of green patents between treated and control groups over time, with time 0 representing the year of mandatory environmental information disclosure. The red dots represent point estimates, and the vertical lines indicate 95 confidence intervals. The pre-treatment periods (negative time values) show no significant differences, supporting the parallel trends assumption. Post-treatment, the estimates indicate an increase in green patents for the treated group relative to the control group, suggesting that the policy had a positive impact on clean innovation. The positive impact discontinued in the 5th year after treatment.

# Appendix A

Table 6: Placebo Test for DiD Estimation

| VARIABLES | (1)<br>log_Green_Patents | (2)<br>log_Green_Patents | (3)<br>log_Green_Patents |
|---|---|---|---|
| DID_2013 | 0.0378 | 0.0213 | 0.0226 |
| | (0.0283) | (0.0290) | (0.0297) |
| Post_2013 | 0.00973 | -0.0218 | -0.356** |
| | (0.0211) | (0.0333) | (0.147) |
| Green_Stock | | -0.0447*** | -0.0456*** |
| | | (0.0111) | (0.0141) |
| All_Stock | | -2.71e-05*** | -2.82e-05*** |
| | | (7.09e-06) | (8.34e-06) |
| Log_Revenue | | 0.00295 | 0.00322 |
| | | (0.0135) | (0.0181) |
| Age | | 0.0162** | 0.0737*** |
| | | (0.00774) | (0.0275) |
| Cash_Flow | | 0.0196 | 0.0234 |
| | | (0.0136) | (0.0148) |
| Constant | 0.0671*** | -0.126 | -0.248 |
| | (0.00814) | (0.275) | (0.503) |
| Observations | 2,511 | 2,509 | 2,509 |
| R-squared | 0.003 | 0.056 | 0.080 |
| Number of id | 376 | 376 | 376 |
| Firm FE | Yes | Yes | Yes |
| Year FE | | | Yes |
| Povince FE | | | Yes |
| Industry FE | | | Yes |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

*Note:* The placebo test assigns 2013 as a fake policy year to test the parallel trend assumption. The insignificant DID_2013 coefficients confirm that no treatment effect is observed prior to the actual policy implementation, supporting the robustness of the original DiD results.

Table 7: Robustness Checks of the DID Estimation

| VARIABLES | (1)<br>Clusterd SE | (2)<br>Bootstrap | (3)<br>Poisson |
|---|---|---|---|
| DiD | 0.0732** | 0.0702** | 1.269*** |
| | (0.0307) | (0.0333) | (0.366) |
| post | -0.381** | -0.0642* | |
| | (0.149) | (0.0364) | |
| Green_Stock | -0.0452*** | -0.0418** | -0.0603** |
| | (0.0139) | (0.0197) | (0.0287) |
| All_Stock | -3.07e-05*** | -2.21e-05 | -0.00687*** |
| | (8.58e-06) | (0.000143) | (0.00229) |
| Log_Revenue | 0.00626 | 3.73e-05 | 0.0222 |
| | (0.0180) | (0.0161) | (0.329) |
| Age | 0.0733*** | 0.0222** | |
| | (0.0274) | (0.00937) | |
| Cash_Flow | 0.0236 | 0.00140 | 0.602*** |
| | (0.0152) | (0.00905) | (0.203) |
| Constant | -0.286 | -0.111 | 1.159 |
| | (0.499) | (0.324) | (7.318) |
| Observations | 2,509 | 2,173 | 622 |
| R-squared | 0.083 | 0.056 | |
| Number of id | 376 | 376 | |
| Povince FE | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes |

Robust standard errors in parentheses
*** p¡0.01, ** p¡0.05, * p¡0.1

*Note:* Column (1) uses clustered standard errors to account for intra-firm correlation. Column (2) applies the bootstrap method to ensure robustness to heteroskedasticity. Column (3) uses a Poisson model as an alternative specification to account for count data characteristics in patenting. The results consistently support the main findings, indicating that mandatory environmental information disclosure significantly increases green innovation in the short term.

Table 8: Event Study on the Share of Green Patents

| VARIABLES | (1)<br>Green_Share_lead2 |
|---|---|
| Green_Stock | -0.000403 |
| | (0.000274) |
| All_Stock | 4.23e-06 |
| | (4.35e-06) |
| Log_Revenue | -0.00601 |
| | (0.00514) |
| Age | 0.000774 |
| | (0.00153) |
| Cash_Flow | 0.00518 |
| | (0.00474) |
| lead4 | 0.0150 |
| | (0.0211) |
| lead3 | -0.00333 |
| | (0.0207) |
| lead2 | 0.00951 |
| | (0.0204) |
| lag0 | 0.0264 |
| | (0.0205) |
| lag1 | 0.0367* |
| | (0.0206) |
| lag2 | 0.0404* |
| | (0.0208) |
| lag3 | 0.0140 |
| | (0.0210) |
| lag4 | 0.0208 |
| | (0.0211) |
| lag5 | -0.00303 |
| | (0.0217) |
| lag6 | 0.00993 |
| | (0.0217) |
| lag7 | 0.0204 |
| | (0.0218) |
| Constant | 0.182 |
| | (0.152) |
| Observations | 4,111 |
| Number of id | 376 |
| R-squared | 0.023 |
| Povince FE | Yes |
| Industry FE | Yes |
| Year FE | Yes |
| Firm FE | Yes |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

*Note:* The dependent variable is the share of green patents two years ahead of the observation year (lead 2 years). This event study captures the dynamic effects of mandatory environmental information disclosure on firms' future green innovation. The significant coefficients on lagged terms (e.g., lag1 and lag2) indicate that the disclosure policy leads to an increase in the green share within one to two years after implementation, while the positive effect does not last long. Insignificant coefficients on lead terms, including lead2, suggest no anticipatory effects prior to the policy, supporting the parallel trends assumption.