Environmental Regulation and Firm Innovation: Evidence from China

Ruotao Tang*

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Abstract

This paper studies the impact of a unique environmental regulatory policy called mandatory participation in Cleaner Production Audit (CPA) programs on innovation of Chinese listed companies during the 2001–2010 period. Using firm-level patent and CPA program enrollment data, I employ a difference-in-differences approach to examine the effect of mandatory CPA participation. The analysis confirms that CPA participation enhanced firm innovation proxied by patent applications, since the program's implementation in 2005. I also find that this positive impact is stronger after substantial improvements had been made to the evaluation framework of CPA programs in 2009, in economically more developed regions where stringent policy implementation was combined with financial incentives, and for larger companies with the resources needed to adapt to regulatory pressure. Hence, this paper provides empirical support for the Porter Hypothesis, which suggests a stimulative impact of environmental regulation on firm innovation, in the context of a developing economy.

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*Department of Economics, University of Alberta, ruotao@ualberta.ca

1 Introduction

In recent decades, developing economies, including China, have been tightening environmental regulations to address growing concerns over environmental deterioration. Regulatory efforts, such as the adoption of developed-country standards and the elimination of government subsidies for pollution-intensive industries, have led to substantial improvements in environmental performance (Dasgupta et al., 2002). In addition, these policies have also been said to boost innovation and competitiveness of the regulated industries. For example, an official document from the Chinese central government states that addressing environmental issues through regulation can facilitate technological improvements and promote innovation (see National People's Congress, 2010). While previous studies have examined the impact of environmental policy on technological change in developed countries, research that examines this relationship in the context of developing economies is scarce.[1] This paper provides evidence for a positive effect of environmental regulation on innovation by Chinese firms.

Traditionally, environmental regulation has been viewed as a burden on business activities, and as detrimental to firm performance as measured by research and development (R&D) expenditures, sales, and profits (Iraldo et al., 2011).[2] However, the Porter Hypothesis, formulated by Porter (1991) and Porter and van der Linde (1995), argues that strict environmental regulation can foster innovation and, in addition, lead to improvements in commercial competitiveness. Jaffe and Palmer (1997) refine the hypothesis, by stating three different versions of it. First, the "weak" version posits that environmental regulation places additional constraints on firms' profit-maximizing decisions and encourages them to innovate as a response, although the resulting innovation may not necessarily be socially beneficial. Second, the "narrow" version suggests that only well-designed and well-enforced policies are likely to achieve this effect. Finally, the "strong" version states that innovation motivated by environmental regulation can not only facilitate environmental improvements but also increase firm competitiveness, measured by productivity or profitability. The vast majority of previous empirical studies cover the "weak" and the "strong" versions of the Porter Hypothesis (see Ambec et al., 2013). The findings in this paper support the "weak" and the "narrow" versions.

The paper focuses on a unique environmental policy tool: mandatory participation in Cleaner Production Audit (CPA) programs in China. Launched nationwide in 2005, the aim of CPA programs is to address environmental problems that accompany rapid industrial growth, through regulating pollution-intensive firms in various sectors. Each Chinese provincial-level government announces a list of companies within its jurisdiction as candidates for mandatory CPA participation every year.[3] The selection of candidates is based on either their past environmental performance or the inputs used in their production processes. Every company on the list is obligated to disclose its pollutant emissions,[4] conduct firm-wide CPA projects, and pass an assessment and an acceptance inspection conducted by local environmental agencies. Thus, firms

[1] I will discuss the literature on environmental regulation and innovation in Section 2 below.

[2] This view is sometimes called the "Structure–Conduct–Performance" paradigm.

[3] China also encourages companies to voluntarily participate in CPA programs. However, in regions where cleaner production was well enforced, the voluntary participation rates for firms with annual sales of more than RMB5,000,000 were all less than one-ninth of the mandatory participation rates in 2012 (Song et al., 2012). Thus, the present paper focuses on mandatory CPA participation.

[4] These disclosures are through local media and not collected by environmental agencies. Therefore, a database containing firm-level information on both CPA participation and environmental performance is lacking.

participating in CPA programs face public supervision and regulatory pressure simultaneously.

I examine the impact of mandatory CPA participation on firm innovation from 2001 to 2010. To do so, I construct a new dataset containing information on patenting activity, CPA participation, and key financial indicators for 733 Chinese companies listed in Shanghai and Shenzhen stock exchanges. The dataset is constructed by using name-matching algorithms to combine information obtained from the Chinese Patent database, the Osiris database, and a series of lists of companies that passed CPA assessments and acceptance inspections, which was released by the Ministry of Environmental Protection of China. The Chinese Patent database covers more than 190,000 published patent applications by Chinese listed companies between 1990 and 2010. The Osiris database contains up to 20 years of financial statistics on listed and major unlisted or delisted companies in more than 190 countries, including China. The MEP lists record the start and the end years of CPA programs participated in by 17,862 firms in 31 provincial-level regions between 2005 and 2012.[5]

I use a firm's number of patent applications as a measure of its innovative activities. Other firm-specific variables that potentially affect innovation are firm size, cash flow, capital intensity, and prior innovation. I then use a difference-in-differences (DID) approach to identify the average effect of mandatory CPA participation on firm innovation. My results indicate that companies innovate more when they are placed under stringent environmental regulation through CPA enrollment. The confirmed positive effect of mandatory CPA participation is on overall innovation, instead of environmental innovation in other plant- or firm-level studies on the "weak" version of the Porter Hypothesis. Theoretical literature on the "weak" version of the hypothesis indicates that innovation triggered by regulation can be either environmentally friendly, or efficiency-enhancing, or both (see Brännlund and Lundgren, 2009; Ambec et al., 2013). Hence, this paper provides more general evidence for the "weak" version, through confirming the positive link between environmental regulation and firms' overall innovation performance.

Substantial changes were made to the CPA regulatory framework in 2009, when the audit was coupled with financial incentives to improve environmental performance in 11 eastern Chinese provincial-level regions. To capture the effect of these regulatory changes, I also divide CPA participation into two periods, 2005–2008 and 2009–2010. I find that the positive effect of CPA participation on firm innovation is more pronounced in 2009 and 2010, and mainly driven by firms in eastern China. Furthermore, the stimulative effect of CPA participation on innovation is stronger for larger companies with the resources needed to adapt to regulation. These findings lend support to the "narrow" version of the Porter Hypothesis, which emphasizes the importance of enforcement and flexibility for the effectiveness of environmental regulation. It argues that performance- or market-based instruments, such as tradable permits and pollution charges, are more likely to motivate innovation than command and control measures, such as emission standards and equipment specifications. In eastern China after 2008, the diversified financial incentives provided to CPA participants and strong performers make the regulatory scheme fall more toward the performance-based side. These government-funded subsidies and rewards allow firms to take a more flexible approach to meet the evaluation standards for CPA programs. In addition, higher environmental awareness has also driven local

[5] These provincial-level regions, formally provincial-level administrative divisions, include: 22 provinces, such as Liaoning and Zhejiang; 5 autonomous regions, such as Guangxi and Xinjiang; and 4 municipalities, such as Beijing and Shanghai.

governments in eastern China to enforce CPA-related regulatory policies more stringently. Given these facts, I view CPA programs implemented in eastern China after 2008 as closer to a "strict but flexible" regulatory scheme as described in Porter and van der Linde (1995).

My empirical methodology has a number of advantages over previous estimates of the effect of environmental policy on innovation. First, measures of environmental regulation discussed in earlier studies include pollution abatement costs and perceived environmental stringency obtained from survey data.[6] Because these variables are self-reported, systematic measurement errors as well as potential endogeneity can bias the estimations. The measure for environmental regulation employed here—mandatory participation in CPA programs—is publicly available for verification and unlikely to be affected by individual firms. In this aspect, it is similar to measures of government monitoring activity (e.g., the number of government on-site inspections) to capture the strength of regulation (see Berrone et al., 2013). However, government monitoring activities are performed only to ensure policy compliance, and thus fall into the category of command and control approaches. Mandatory CPA participation, as previously described, tends to be more performance-based, especially in eastern China after 2008.

A second potential endogeneity issue can arise if a firm's CPA enrollment status and innovation are both correlated with its environmental performance, which is not observed in my dataset. However, analyzing firm-level data throughout the period of 2001 to 2009, I find no systematic differences between the pre-regulation innovation patterns of listed companies that were later enrolled in CPA programs (CPA participants) and those that were not. I also perform a falsification test to show that innovation patterns of CPA participants did not differ from non-participants, even when the participants were soon to be enrolled in the programs. Finally, to eliminate the possibility that the selection of CPA participants is based on firm characteristics other than environmental performance, I use a propensity score matching approach to construct a sub-dataset, in which each CPA participant is matched with a financially similar firm that had never participated in any CPA program. Estimation results based on the sub-dataset confirm the main findings in this paper.

Findings from this study have policy implications worth considering, as China has been making remarkable efforts in recent years to reduce pollution, while striving to maintain economic growth driven by energy- and pollution-intensive industries. As a unique policy tool, mandatory participation in CPA programs has shown the determination of the Chinese central government to address this issue, since similar programs in other countries operate on a voluntary basis. This policy has shown its potential to improve environmental performance and stimulate firm innovation simultaneously, especially when combined with financial incentives to encourage compliance and enhance performance. As a policy currently in force, it may deserve stronger supportive measures, such as financial support from the central government instead of only being funded provincial and municipal governments, to extend its scope and strengthen its effectiveness.

The rest of the paper proceeds as follows. Section 2 reviews previous research on environmental regulation and innovation and locates this paper in the existing literature. Section 3 reviews the development of environmental regulation, and in particular the CPA programs, in China. Section 4 describes the empirical methodology employed in the analysis, including model specifications and identification strategy. Section 5

[6] Jaffe and Palmer (1997), Brunnermeier and Cohen (2003), Yang et al. (2012), and Rubashkina et al. (2015) employ pollution abatement costs to measure environmental regulation. Arimura et al. (2007) and Lanoie et al. (2011) use perceived environmental stringency as an alternative measure. I will discuss these studies in Section 2 below.

describes how the data were collected and consolidated, and the procedures taken to construct the key variables used in the estimation. Section 6 contains the main results and shows that effects of mandatory CPA participation are heterogeneous across regions and firms of different sizes. In Section 7, I conduct several robustness checks and show that the main results are not sensitive to a number of alternative model specifications. Section 8 concludes with a discussion on future work.

2 Related Literature on Environmental Regulation and Innovation

Since its formulation in the 1990s, the Porter Hypothesis has received plenty of criticisms for its contradiction with the assumption of profit-maximizing firms (see Palmer et al., 1995). To provide a theoretical foundation for the hypothesis, over the last twenty years researchers have investigated possible reasons for firms under-investing in innovation and not maximizing profits, and how environmental policies may contribute to the correction of these deficiencies. One consensus among these studies is that a scenario consistent with Porter's predictions usually involves an additional market failure besides negative environmental externalities (see Mohr and Saha, 2008).

The main additional market failures under discussion, as summarized in Brännlund and Lundgren (2009) and Ambec et al. (2013), include information asymmetries, imperfect competition, and R&D spillovers. Information asymmetry may prevent firms from investing in innovation and maximizing profits, since managers and other employees do not share the same objective functions with firm owners (Aghion et al., 1997; Gabel and Sinclair-Desgagné, 1998), or because consumers cannot easily distinguish "green" products from less environmentally friendly goods (Rege, 2000; Constantatos and Herrmann, 2011). In an oligopolistic market, environmental stringency can enhance the development of less-pollutive but cost-inefficient technology, when firms are able to reduce output and raise prices as a response to an increase in regulatory compliance costs (André et al., 2009; Lambertini and Tampieri, 2012). Models with economies of scale in environmental innovation, or inter-firm diffusion of technology developments can also generate results consistent with the "weak" version of the Porter Hypothesis (Simpson and Bradford, 1996; Mohr, 2002; Greaker, 2003). Innovation discussed in these studies may refer to environmental innovation, or overall innovative activities that may not have direct impacts on the environment.

Many researchers have also examined the Porter Hypothesis empirically. Studies testing the "weak" version generally fall into two categories: those exploring the impact of regulation on environmental innovation, and those investigating policies' effect on overall innovation. Most studies testing the "strong" version assess the changes in firm productivity under regulation, while a few researchers study the link between environmental stringency and firm profitability.[7] Research that tests the "narrow" version of the hypothesis is scarce.

Examining only environmentally related innovative activities, Popp (2003), Arimura et al. (2007), Lanoie et al. (2011), and Berrone et al. (2013) find a positive correlation with environmental policies by using plant- or firm-level data in the U.S. and other members of the Organisation for Economic Co-operation and

[7] Rassier and Earnhart (2010), Lanoie et al. (2011), and Rexhäeuser and Rammer (2014) find that environmental regulation impairs firm profitability, although regulation-driven innovation can improve resource efficiency and offset part of the compliance costs.

Development (OECD); Brunnermeier and Cohen (2003) and Kneller and Manderson (2012) also show the positive relationship by using industry-level data in the U.S. and the United Kingdom (UK); Popp (2006) and Johnstone et al. (2010) provide country-level evidence for the positive link through analyzing data for OECD members. Findings from these studies confirm the effectiveness of environmental policies in promoting environmentally friendly new technologies.

Studies investigating the link between environmental regulation and overall innovation show mixed results. Using industry-level data for the U.S. manufacturing sector, Jaffe and Palmer (1997) find a positive relationship between pollution abatement costs and total R&D expenses. On the other hand, successful patent applications did not increase with environmental compliance expenditures. Subsequent studies, all using industry-level data for manufacturing industries in developed economies, continue to employ pollution control expenditures to measure environmental stringency. In a study covering both environmental and total R&D investments, Kneller and Manderson (2012) show that regulation-led environmental R&D investments crowded out investments for other types of innovation in the UK. Nevertheless, findings from other studies are in favor of the "weak" version of the Porter Hypothesis. Hamamoto (2006) and Yang et al. (2012) find environmental regulation to be positively correlated with R&D expenditures in Japan and Taiwan; Rubashkina et al. (2015) show the positive link between regulation and patent applications in 17 European countries, but find no evidence for a similar relationship with R&D expenditures.

Among the literature discussing the "weak" version of the Porter Hypothesis, Hamamoto (2006), Yang et al. (2012), and Rubashkina et al. (2015) also extend their analyses to explore the impact of environmental regulation on industry productivity. They all find that productivity rises with environmental stringency, which is in line with the "strong" version of the hypothesis. This finding is supported by Berman and Bui (2001) using plant-level data for the oil refinery industry in the U.S., and by Lanoie et al. (2011) using survey-based plant-level data for the manufacturing sector in seven OECD countries. However, some other studies find evidence against the "strong" version. Jaffe et al. (1995) review several earlier studies and conclude that they all support a negative link between environmental regulation and productivity, despite the strength of the link varying. Gray and Shadbegian (2003) echo this argument by showing that productivity for pulp and paper mills in the U.S. are negatively correlated with pollution abatement costs. Focusing on air quality regulations in the U.S., Greenstone et al. (2012) also suggest that these policies led to a 2.6% decline in total factor productivity (TFP) of manufacturing plants. One possible reason for these studies finding an adverse effect of regulation, as suggested by Jaffe et al. (1995) and Telle and Larsson (2007), is that the commonly used methods to compute productivity measures do not include emissions as inputs.

This paper adds to the literature in the following ways. First, this study provides evidence for the positive link between environmental policy and overall innovation at the firm level in a developing country. As reviewed above, all previous literature discussing the "weak" version of the Porter Hypothesis uses data for manufacturing industries in developed economies; moreover, all of the studies on regulation and overall innovation use industry-level data. Through adopting two firm-specific indicators—annual patent applications and CPA enrollment status—to measure innovation and environmental regulation in China, this paper examines the effect of environmental policy at a more micro level. It provides evidence against the argument that regulation-driven environmental investments crowd out investments for other types of innovation. The results support the effectiveness of environmental stringency in enhancing overall firm innovation in developing countries.

This paper is also one of the few to investigate the "narrow" version of the Porter Hypothesis. Only a few earlier studies, including Popp (2003) and Lanoie et al. (2011), have discussed this version and provided circumstantial evidence. My results show that the positive effect of CPA participation on innovation is strongest in eastern China after 2008. This fact highlights the importance of stringent policy enforcement supported with diversified financial incentives. Hence, this paper provides more direct evidence for the "narrow" version of the hypothesis, by showing that well-enforced and more performance-based regulatory regimes are more effective in terms of bolstering innovation.

3 Cleaner Production Policy in China (1993–2010)

Accompanied with rapid industrial growth and urban developments, environmental degradation in China became evident in late 20th century and early 21st century. Besides serious social issues, environmental problems had also induced substantial economic costs for the fast-growing economy. An official report of the Chinese central government estimates that the annual cost of pollution averaged about seven percent of the nation's annual Gross National Product (GNP) between 1981 and 1985 (National Environmental Protection Agency, 1990). Studies in subsequent years suggest that the economic burden of environmental degradation in China was between six and eight percent of the nation's Gross Domestic Product (GDP) in the early 1990s, and this ratio stayed above three percent in 2004 (Smil, 1997; Wang and Yu, 2006). To address the environmental issues, China started to put the cleaner production concept into practice in the 1990s. The success of pilot projects eventually led to nationwide implementation of CPA programs in 2005.

The development of cleaner production practices and CPA-related policies in China before 2010 can be divided into three main phases. The first phase (1993–2004) involved the Chinese central government identifying CPA as the main policy tool to implement cleaner production, and disaggregating pilot projects launched and supported by provincial-level governments. In the next phase (2005–2008), the central government clarified the implementation procedures and criteria that need to be met to pass the assessments and acceptance inspections (hereinafter, the "passing criteria") for CPA programs. However, provincial-level governments had not fully incorporated these guidelines and standards into their diversified local practices until the end of this phase. The last stage (2009–2010) involved provincial and municipal governments localizing the interpretation and execution of the improved regulatory framework.

With support from the World Bank and the United Nations Environmental Programme (UNEP), the first cleaner production project, "Cleaner Production Promotion in China," was carried out on 27 companies during the 1993–1996 period. Despite the success of this project and several other provincial-level pilot programs, the scope and impact of cleaner production in China was limited in the 1990s through the early 2000s, partly due to its incompatibility with the then-existing environmental practices that favor end-of-pipe treatments (Shi, 2003). One significant characteristic of the enforcement and promotion of cleaner production in China at this early stage is that both were carried out "almost entirely on a provincial or local level" (Hicks and Dietmar, 2007, p. 4).

The announcement of the "Cleaner Production Promotion Law" (CPPL) in June 2002 was the first substantial move by the Chinese central government to consolidate and normalize local policies. As the first law of its kind in the world, CPPL clearly defines cleaner production and its scope, and introduces CPA as the main instrument for its implementation. Although the word "mandatory" is not employed in the CPPL text, the law implies that implementing CPA programs is not merely optional for firms that exceed pollutant discharge quotas or do not meet pollution discharge standards ("Category 1 firms"). For firms using or discharging toxic or hazardous materials ("Category 2 firms"), CPA participation is not only required, but is required on a "periodical" basis.

After CPPL came into force in January 2003, more than 20 provincial-level regions (hereinafter, "regions") launched pilot projects. Hundreds of firms participated in demonstrative CPA programs as part of these pilot projects in 2003 and 2004. However, implementation procedures for CPA programs were not clearly specified until the central government released the "Interim Measures on Cleaner Production Audit" in August 2004. In December 2005, the central government released a similar but more detailed document, "Provisions on Procedures of Cleaner Production Audit of Key Enterprises" (the Procedures document). According to that document, every year each county- or district-level environment agency is responsible for reporting to its superior authority a list of companies that are candidates for mandatory CPA participation. The selection of candidates should be based only on environmental monitoring reports for Category 1 firms, and receipts or analytical reports of toxic or hazardous materials for Category 2 firms. After collecting reports from its subordinates, a provincial-level environmental agency is in charge of determining a final list of companies for mandatory CPA participation within its jurisdiction.

Within one month of being identified by any provincial-level list, a company is obligated to make its own pollutant emission information known to the public. The information to be disclosed includes but is not limited to pollutant names and intensities, emission types and destinations, overall amount of emissions, emission quotas assigned, and pollution charges paid to environmental agencies. Under public supervision, firms can choose between participating in CPA programs by themselves or cooperating with qualified external consulting agencies. Either way, they have to launch CPA projects within two months of the list release date, complete these projects within another 10 months and submit summary reports to local authorities.[8]

The Procedures document assigns provincial-level environmental agencies to assess effects of companies' CPA projects and conduct acceptance inspections upon receipt of summary reports. However, the document provides little information on passing criteria and implementation procedures for the two major steps. Hence, there were again inconsistencies and deficiencies in CPA practices at provincial level, which called for further clarification and consolidation efforts from the central government.

Between 2006 and 2008 the Chinese central government announced cleaner production standards for 41 industries. These standards dealt with the issue of unclear criteria. The release of the "Implementation Guide on Assessment and Acceptance Inspection of Cleaner Production Audit of Key Enterprises" in July 2008 (the Guide document) greatly alleviated the issue of inconsistent evaluation procedures across regions. The Guide document clearly indicates that within one month of submitting CPA summary reports, to qualify

[8] This rule was not strictly applied in practice at least before 2012. Thus, there could be a lag as long as two years between the announcement date of a provincial list and the date when a company on the list actually launched its CPA projects.

for government financial support firms need to pass assessments organized by local environment agencies. These assessments focus primarily on evaluating the performance of non- and low-cost cleaner production options that have been carried out, and the plausibility of medium- and high-cost options planned for future implementation. Within two years of completing CPA programs, firms are again obligated to apply for and pass final acceptance inspections. Different from assessments conducted with advices from environmental and industrial experts, acceptance inspections are performed solely by local environmental agencies and put more emphasis on verifying whether firms have implemented the medium- and high-cost options.

From late 2008 to early 2009, provincial-level governments released detailed local implementation rules for the Guide document. These rules established a multi-level regulatory system for CPA programs. Although they generally follow the structure of the Guide document, there is a disparity in interpretation and enforcement across regions; because the eastern regions are economically more developed, they have more detailed passing criteria, standardized implementation procedures, and diversified financial support for assessments and acceptance inspections.

One leading example of stringent policy enforcement is the local CPA regulatory policy introduced in Shanghai on January 1, 2009. In its official technical guide for CPA implementation, the Shanghai government adds an additional "pre-assessment" stage. This stage includes site investigations and expert discussions. For each stage of the CPA evaluation process, to ensure consistency, the Shanghai government document includes a standardized evaluation sheet with detailed subcategories. In addition to subsidies funded through pollution charges, the Shanghai government also arranges special subsidies for CPA-related expenses, half of which would be available at the launch of firms' CPA programs and half of which could be claimed upon passing assessments.

Liaoning is another province with a relatively comprehensive regulatory system. The Liaoning government assigns the Liaoning Centre for Cleaner Production (LCCP), which was co-founded with the European Union (EU) in 1997, to take charge of CPA assessments. This differs from many other provincial authorities, which assign that responsibility to provincial environmental protection bureaus. Liaoning offers a unique type of financial support—subsidized loans from the €10 million Liaoning Cleaner Production Revolving Fund, co-funded by the EU—to firms implementing medium- and high-cost options in CPA programs.

Although a local regulatory and promotional framework for CPA programs had been in place in each region since 2009, efforts devoted to enforcing these policies differ greatly across regions. There is a great deal of variation in the amount of CPA assessment and acceptance inspection expenses covered by funding from the finance department in each region every year. The latest statistics released by the central government show that among the 10 regions reporting these expenses in 2010, three eastern provinces—Zhejiang, Jiangsu and Shandong—were ranked as the top three and accounted for nearly 70% of the total amount spent.[9] Regional characteristics are also reflected in various supportive policies. For example, to ensure that policies are effectively carried out, the vice governor of Liaoning in charge of economic development personally signs yearly agreements with all the regional mayors to set up targets for the number of companies that should be participating in CPA programs within each city (see Geng et al., 2010). The Guangdong government

[9] Due to lack of data for other regions and the pre-2007 period, this indicator cannot be used in the empirical analysis to reflect the disparity in policy enforcement across regions.

provides incentives as part of an approach to stimulate performance in CPA programs; it gives a RMB50,000 bonus to each firm that performs well in CPA programs, while one of its subordinate—the Dongguan government—gives an additional RMB300,000 to each qualified firm within its jurisdiction.

4 Empirical Methodology

The empirical models in this paper investigate the impact of mandatory CPA participation on innovation performance of Chinese listed companies. Since the status of CPA participation varies across individual firms and over time, I employ an individual fixed effects log-linear model and the difference-in-differences (DID) approach to identify the *treatment* effect of CPA enrollment on firms' patent applications. This section introduces the models and discusses the identification strategy.

4.1 Econometric Models

I first consider a *uniform impact* model, in which the level of innovative activities *innov* for a Chinese listed company i in industry s and region r at year t is given by

$$innov_{i,s,r,t} = \alpha_i + \beta_{s,t} + \gamma_{r,t} + \theta\, CPA_{i,s,r,t} + \rho\, X_{i,s,r,t} + \varepsilon_{i,s,r,t}. \tag{1}$$

In the baseline regressions I employ the natural logarithm of the aggregate number of invention, utility model and design patent applications as the main indicator for innovation.[10] Since invention and utility model patents are usually considered as more valuable and innovative, I also include the logarithm of the aggregate number of these two types of patent applications as an alternative indicator to represent the level of firms' core innovative activities.[11]

The right-hand side of the model contains the firm fixed effects α_i to capture the potential impact from time-invariant and firm-specific factors. Note that firm fixed effects subsume industry and region fixed effects, which are correlated with firm characteristics such as core industry and headquarter location.[12] Since the patterns of innovation can differ significantly by industry and over time, the model contains industry-year fixed effects $\beta_{s,t}$ to control for such differences. Similarly, the trend of innovation can differ across regions because of China's considerable regional differences in economic development and innovation-related policies. The region-year fixed effects $\gamma_{r,t}$ control for the regional differences in development of innovation over time.

The key variable, $CPA_{i,s,r,t}$, measures whether firm i in industry s and region r was enrolled in a CPA program and thus facing stringent environmental regulation at year t. This binary variable takes the value 1 if the company was participating in a CPA program at year t, and 0 otherwise. $X_{i,s,r,t}$ represents a series of variables controlling for characteristics of firm i in industry s and region r at year t, including *size*, *cash*

[10] The definitions of the three types of patents are discussed in Section 5.1.

[11] I add one to each of the two patent variables when taking logarithms, since the number of patent applications can be zero for a listed company in a particular year. This method is arbitrary but in line with many previous studies including Bloom et al. (2012).

[12] As will be noted later, switching core industry or changing headquarter location usually signals reorganization or a take-over. These changes can alter the unobserved heterogeneity of a listed company. Thus, the main dataset employed in the subsequent analysis does not include any firm changing its core industry or the location of its headquarters (at the provincial level) during the sample period.

flow, *capital intensity* and *prior innovation*. The coefficient of interest is θ. It measures the impact of environmental regulation on firm innovation, by capturing the difference in the change of patent applications for firms participating in CPA programs and the change for those not regulated under the scheme.

Because the sample period is 2001 to 2010 and CPA programs were not implemented until 2005, I use contemporaneous independent variables in the model to utilize as many observations as possible. Nevertheless, to examine whether the main results still hold if environmental regulation and other firm characteristics are assumed to have a delayed impact on innovation, I also perform a sensitivity test in which the independent variables are lagged by one year. The corresponding estimation results presented in Section 7.1 are consistent with the main results.

The effect of mandatory CPA participation is assumed to be constant over the 2005–2010 period in the uniform impact model. However, the implementation and enforcement of CPA-related policies did vary over time. As outlined in Section 3, CPA programs started to be widely implemented in 2005; however, a comprehensive regulatory framework was not in place until 2009. Between 2006 and 2008, the Chinese central government published cleaner production standards for 41 industries. These standards were part of a regulatory framework that the government was establishing. The framework was solidified when provincial-level governments released local implementation rules for the Guide document in late 2008 and early 2009. The less ambiguous standards and evaluation procedures detailed in these documents greatly reduced inconsistencies in the assessments and acceptance inspections of CPA projects, and thus improved the efficiency and effectiveness of CPA programs (Bai et al., 2012). In addition, financial incentives provided based on policies specified in these documents made mandatory CPA participation fall more toward a performance-based policy.

In recognition of the possible differences in environmental stringency and enforcement measures for companies participating in CPA programs at different stages of policy development, I also estimate a *differential impact* model as follows:

$$innov_{i,s,r,t} = \alpha_i + \beta_{s,t} + \gamma_{r,t} + \theta_1\, CPA\ 2005\text{–}2008_{i,s,r,t} + \theta_2\, CPA\ 2009\text{–}2010_{i,s,r,t} + \rho\, X_{i,s,r,t} + \varepsilon_{i,s,r,t}. \quad (2)$$

In the above equation, CPA enrollment status is reflected in two separate binary variables, *CPA 2005–2008* and *CPA 2009–2010*. The value of *CPA 2005–2008* is equal to 1 only if a listed company was participating in a CPA program at year t between 2005 and 2008. Similarly, the value of *CPA 2009–2010* is equal to 1 only if a company was regulated through mandatory CPA participation at year t in either 2009 or 2010. This model is also estimated using log-liner specifications, in which the coefficients θ_1 and θ_2 respectively capture the impact of CPA participation on innovation in the two periods.[13]

4.2 Identification

The coefficient of interest θ (and θ_1, θ_2) can be identified through the DID method under the assumption that after controlling for observed and unobserved heterogeneity, the patterns of innovative activities over time are

[13] Since the numbers of patent applications are non-negative integers, an alternative approach is to estimate both the uniform impact and the differential impact model using negative binomial specifications. The corresponding regression results are qualitatively consistent with the main results shown in Section 6.3 and are available upon request.

similar among firms. In Equation (1) and Equation (2), the observed firm-level heterogeneity is controlled by variables in $X_{i,s,r,t}$. The firm fixed effects α_i capture systematic unobserved heterogeneity that is firm-specific and time-invariant. The industry-year fixed effects $\beta_{s,t}$ and region-year fixed effects $\gamma_{r,t}$ capture systematic unobserved fluctuations in innovation over time, assuming the impacts of these fluctuations are constant across firms in a given industry and a certain region respectively.

Once a listed company i in industry s and region r is required to participate in a CPA program at year t, the change in innovation between year t and year $t-1$ resulted form the status of being regulated and other regulation-independent factors can be expressed as

$$innov\,(CPA_{i,s,r,t} = 1) - innov\,(CPA_{i,s,r,t-1} = 0).$$

The counterfactual benchmark is

$$innov\,(CPA_{i,s,r,t} = 0) - innov\,(CPA_{i,s,r,t-1} = 0),$$

which is the difference in innovation between the two years if firm i had not participated in the CPA program. This benchmark is unobservable, but it can be approximated by a variation in the innovation of another listed company, j, which did not participate in any CPA program at either year t or year $t-1$. The observed difference between innovation of firm j in industry s and region r at year t and year $t-1$ captures only the change led by regulation-independent factors, and can be written as

$$innov\,(CPA_{j,s,r,t} = 0) - innov\,(CPA_{j,s,r,t-1} = 0).$$

Therefore, the coefficient, θ, can be identified by the following difference in differences:

$$[innov\,(CPA_{i,s,r,t} = 1) - innov\,(CPA_{i,s,r,t-1} = 0)] - [innov\,(CPA_{j,s,r,t} = 0) - innov\,(CPA_{j,s,r,t-1} = 0)],$$

which reflects the change in innovation between year t and year $t-1$ induced by CPA participation.

A potential endogeneity problem arises if mandatory CPA participation, as an environmental policy implemented by local governments, is linked to companies' innovation performance. CPA enrollment is mainly determined by prior environmental performance, which was disclosed at the time of program enrollment but not collected to be associated with each participant. Whether innovation is an advantage or a disadvantage for heavy polluters depends on the interaction between abatement costs, environmental innovation, and investments for other types of innovation in a particular industry. Further, the trend of environmental performance might be substantially different for pollution-intensive firms and other companies, as the top polluters within a region might choose to lower emissions to avoid CPA enrollment. Thus, not only the level but also the trend of innovation can differ systematically between pollution-intensive firms and others.

Selection of CPA participants based on the prior level of innovation does not lead to bias in the estimations, since firm fixed effects are included to eliminate the potential impact of this heterogeneity. On the other hand, selection based on differences in the trend of innovation would lead to bias in the estimated parameter θ, because firm fixed effects do not vary over time to reflect the trend heterogeneity. Although industry-year and region-year fixed effects are included in the models, they may not fully capture the differences in innovation patterns between CPA participants and other firms. In addition, endogeneity may also arise from reversed causality, as holding environmentally friendly patents may improve the environmental performance of a firm. Benefiting from the improvements in environmental performance, a firm may pass the acceptance inspection for a CPA program earlier than without innovation.

Generally, environmental innovation accounts for only a small fraction of granted patents. For example, of more than four million U.S. patents examined by Nameroff et al. (2004), only 3,235 were "green chemistry" patents. It is likely that the fraction of environmental innovation is even smaller for Chinese firms, as environmental concerns were not emphasized in Chinese industrial policy until very recently. This suggests that the link between innovation and environmental performance itself is likely very weak in the main dataset. However, I do not observe whether any given patent is a "green patent" or not. I employ a pre-treatment model to test for systematic differences in innovative activities across firms that participated in at least one CPA program from 2005 to 2010 (*CPA participants*) and those had not participated in any CPA program during the same period (*CPA non-participants*). For each year t_1 since 2005, I compare the patterns of innovation from 2001 to year $t_1 - 1$ between a group of firms that participated in at least one CPA program after t_1 ($Regulated_{i,s,r,t_1} = 1$, the *treatment* group at year t_1) and the group of CPA non-participants ($Regulated_{i,s,r,t_1} = 0$, the *control* group at year t_1). The following model reveals whether there were systematic differences in both the level and the trend of innovation between the two groups of firms from 2001 to year $t_1 - 1$:

$$innov_{i,s,r,t} = \delta_{s,r,t} + \lambda\, Regulated_{i,s,r,t_1} + \phi\,(t \cdot Regulated_{i,s,r,t_1}) + \rho\, X_{i,s,r,t} + \varepsilon_{i,s,r,t}. \tag{3}$$

The binary variable $Regulated_{i,s,r,t_1}$ is firm-specific and time-invariant between 2001 and year $t_1 - 1$. In the above equation, to avoid perfect collinearity, I replace firm fixed effects α_i, industry-year fixed effects $\beta_{s,t}$, and region-year fixed effects $\gamma_{r,t}$ with industry-region-year fixed effects $\delta_{s,r,t}$. Significant estimates of λ and ϕ would indicate that the level and the trend of innovative activities differed systematically between the two groups of firms. Although the difference in level can be accounted for by the inclusion of firm fixed effects in the models, the difference in trend signalled by a significant ϕ could impair the validity of the DID approach employed in the analysis.[14]

I also perform a falsification test to examine if innovation patterns of CPA participants and non-participants started to differ only a few years before CPA program enrollment. For each firm participated in its first CPA program at year t_2, I assume it had been in the program since year $t_2 - k$, where k is a positive integer. I only include observations from 2001 to year $t_2 - 1$ for each CPA participant in this falsification exercise. On the other hand, I include observations from 2001 to 2009 for each CPA non-participant. The

[14] One may argue that environmental performance may be correlated with observable firm characteristics other than innovative activities, or the selection of mandatory CPA participation is based on firm characteristics other than environmental performance. As a result, the two groups of firms may systematically differ in other aspects. In Section 7.3, I employ a propensity score matching method to construct a sub-dataset, where observable characteristics of firms in the treatment group and the control group do not differ systematically. Estimation results for the universal impact and the differential impact models are similar to the main results presented in Section 6.3.

following model indicates whether there were systematic differences in the trend of innovation between the two groups of firms from year $t_2 - k$ to year $t_2 - 1$:

$$innov_{i,s,r,t} = \alpha_i + \beta_{s,t} + \gamma_{r,t} + \kappa\, Pseudo\text{-}CPA_{i,s,r,t} + \rho\, X_{i,s,r,t} + \varepsilon_{i,s,r,t}. \tag{4}$$

The binary variable $Pseudo\text{-}CPA_{i,s,r,t}$ takes the value 1 if firm i in industry s and region r participated in its first CPA program at year t_2, and the year t is between year $t_2 - k$ and year $t_2 - 1$. Significant estimates of κ would suggest a systematic deviation in innovation patterns appeared k years before companies participated in CPA programs. This pre-treatment deviation could also impair the validity of the DID approach.

5 Data and Descriptive Statistics

I combine several publicly available datasets to construct key variables measuring firm innovation, environmental regulation and other characteristics. The main data sources include the Chinese Patent database, which is constructed through the Chinese Patent Data Project (CPDP); a series of lists of companies that passed CPA assessments and acceptance inspections, which was released by the Ministry of Environmental Protection of China (the MEP lists); and the Osiris database, which is managed by the information provider Bureau van Dijk (BvD).

The Chinese Patent database covers more than 190,000 published patent applications by Chinese listed companies between 1990 and 2010. The MEP lists record the start and the end years of CPA programs participated by 17,862 firms in 31 regions between 2005 and 2012. The Osiris database contains up to 20 years of financial statistics on listed and major unlisted or delisted companies in more than 190 countries, including China. This section briefly introduces the three source databases, details the process to construct the indicators and the main dataset used in subsequent analyses, and provides summary statistics for the key variables.

5.1 Innovation

I use the annual number of patent applications extracted from the Chinese Patent database, which became publicly available in 2013, to measure a listed company's innovative activities. The database includes more than 190,000 published patent applications that companies listed in Shanghai and Shenzhen stock exchanges filed with the State Intellectual Property Office (SIPO) of China between 1990 and 2010. For each firm year, the database lists the respective numbers of applications filed for invention patents, utility model patents, and design patents (hereinafter, "invention, utility model, and design patents"). Among the three types of patents, invention patents are granted for "technical innovations that are practical, inventive and new;" utility model patents are granted for "technical solutions related to the shape or structure of an object;" design patents are granted to "protect the shape, colour, or combination of both of an object" (Canadian Trade Commissioner Service, 2015, p. 1). The Chinese patent database also distinguishes between patent applications filed by a listed company's head office and those filed by its majority- and minority-owned subsidiaries.[15]

I use the aggregate number of applications for invention, utility model and design patents by the headquarter and the majority-owned subsidiaries of a listed company as the main indicator of its innovation. This indicator exclude patent applications by a company's minority-owned subsidiaries to better capture the overall innovation output that is closely linked with its own R&D input. Since design patents are often viewed as less valuable and less strategic than the other two types, I include the aggregate number of applications for invention and utility model patents as an alternative indicator. Because China's patent law was substantially revised in 2000 and the number of listed companies covered by the Chinese Patent database also increases substantially after 2000, I choose 2001 as the start year of the sample period and compute these two indicators for each year from 2001 through 2010.[16]

One limitation of the Chinese Patent database is that it does not provide commonly-used indicators, such as citations that a patent received or a patent's family size (the number of countries in which this patent is protected), to reflect the heterogeneity in patent value. As SIPO required invention patent applicants to include citation information in their applications only between 1997 and 2003 and after 2007, it is impossible to create a consistent measure for tracking the citations that each patent received. The user documentation of the CPDP also confirms that very few Chinese listed companies filed applications with foreign offices during the sample period (He et al., 2013). Thus family size cannot be employed as an indicator of patent value.

The Chinese Patent database offers several indirect measures as potential candidates for indicating patent value. The database records how many of each company's invention patent applications had been granted by January 2012. The database also records the number of unique International Patent Classification classes assigned to the invention and the utility model patents. For each of the three types of patents, the database records the number of granted patents that had expired by January 2012. However, when it comes to usefulness as a satisfactory indicator, none is as good as citations received. Therefore, I do not incorporate these statistics into the indicator of innovation. Instead, I only use simple patent counts as the dependant variable to produce the results shown in Section 6.

5.2 Environmental Regulation

I use a binary variable *CPA* to indicate whether a listed company is under more stringent environmental regulation. The value of *CPA* is equal to 1 when a company was participating in a CPA program, and equal to 0 otherwise.

I rely on the MEP lists to determine the length of the period during which a specific firm was participating in CPA programs (the "enrolled period"). The MEP lists contain four variables regarding the timing of CPA programs: the "announcement year" (the year in which a company was identified by a provincial-level list for mandatory CPA participation), the "report year" (when summary reports of CPA projects were

[15] Majority-owned subsidiaries are referred to as "subsidiary companies" and "sub-subsidiary companies" in annual reports of listed companies and the user documentation of the Chinese patent database. Minority-owned subsidiaries are referred to as "joint ventures" and "associated enterprises."

[16] China's patent law was first released in 1984 and revised in 1992, 2000 and 2008. The second revision, in 2000, confirmed for the first time the effectiveness of contracts between R&D staff and their employers on the attribution of patents. This reform greatly boosted patents applications in the subsequent years.

submitted), the "assessment year" (when the company passed the assessment organized by local authorities), and the "acceptance inspection year" (when the company passed the acceptance inspection conducted by local authorities).

As reviewed in Section 3, firms are obligated to disclose pollution information to the public within one month after being identified by any provincial-level list. Also, until they pass acceptance inspections, these firms are required to continuously devote efforts to the medium- and high-cost options to which they committed in their CPA summary reports. Thus I view firms as under regulation and public supervision from the "announcement year" until the "acceptance inspection year," and consider these two variables as the start and the end years of the enrolled period respectively. In any case where the value of the "announcement year" is missing, I use, as the start year, the value of "report year." Similarly, I use the value of the "assessment year" as a substitute for the value of "acceptance inspection year" when the latter is not available.

5.3 Firm-specific Control Variables

I use financial statistics of Chinese listed companies extracted from the Osiris database to measure firm-specific characteristics that may affect their innovative activities. The Osiris industrial company dataset contains general information such as names, major stock changes and industries, and financial indicators such as assets, liabilities and net profits of more than 80,000 listed and delisted companies around the world. To keep the sample consistent with the Chinese Patent database, in the analysis I include any company for which the major stock exchange is either the Shanghai or Shenzhen exchange, or is listed in one of the exchanges as well as in the Hong Kong Stock Exchange between 2001 and 2010.

Due to the inconsistent disclosure requirements from Chinese authorities, R&D expenditure—the most accurate measure of innovation input and thus highly correlated with its output—is not reported by most of listed companies in the sample.[17] Hence, I construct four other control variables—*size*, *cash flow*, *capital intensity* and *prior innovation*—to measure innovation-related firm characteristics. First, to represent a company's *size*, I use the natural logarithm of the number of employees. Second, to indicate a company's *cash flow*, I use the natural logarithm of the cash flow-to-revenue ratio, which is defined as the ratio of total cash flow to operating revenue. *Size* and *cash flow* are the two most thoroughly examined firm-level determinants of innovation in past decades. Economies of scale and scope may result in the former having a positive impact on innovation. The imperfection of capital markets and the uncertain nature of returns to R&D investment can jointly contribute to the importance of the latter (see Cohen, 2010).

Third, to proxy *capital intensity*, I use the natural logarithm of capital to labour ratio, which is defined as the ratio of the book value of plants and machinery to the number of employees. Capital-intensive firms may be more likely to patent "strategically" to hold up their rivals with litigations, or "defensively" to increase bargaining power and make credible counter-threats (Hall and Ziedonis, 2001; Bessen and Hunt, 2007). Fourth, to capture a company's *prior innovation* that reflects its ability to develop new patents, I use the natural logarithm of labour productivity, which is defined as the ratio of annual net sales to the number of

[17] Another source, the China Stock Market & Accounting Research Database, provides R&D investment after amortization that is recorded in a company's asset account. This indicator, which can at best serve as an approximate measure of actual R&D expenses every year, is only available for Chinese listed companies after 2007. Therefore I do not include this variable in the main dataset.

employees. The ideal indicator for a company's *prior innovation* is suggested to be its patent stock—total number of granted patents since its establishment or in recent years (Berrone et al., 2013; Yanadori and Cui, 2013). However, this approach does not apply to the analysis in this paper, as the Chinese patent database does not cover all of the patent applications by listed companies.[18] Therefore, I choose labour productivity as an alternative indicator of *prior innovation*, as productivity growth reflects efficiency improvements and is closely linked with innovation.

5.4 Construction of the Main Dataset

The main dataset used in the empirical analysis contains statistics for innovation, environmental regulation, and other characteristics of 733 Chinese listed companies between 2001 and 2010. To construct the dataset, I first merged patent data from the Chinese Patent database with financial statistics from the Osiris database, since these two datasets are linked through unique stock codes assigned to listed companies. The joint dataset was then merged with the MEP lists through name matching, because the MEP lists are in Chinese and only record basic company information such as names, addresses, and sectors.

Following the mapping strategy described in the user documentation of the CPDP, I took three major steps to match company names in Chinese. First, I obtained the so-called "stem" names of listed companies in the Chinese Patent-Osiris joint dataset and the MEP lists, by removing all special characters, punctuation marks, and various designators such as "group," "inc." and "ltd." (all in Chinese) in the original company names.

Second, I calculated the following similarity score based on the Levenshtein edit distance between each pair of the stem names in the two datasets:

$$Similarity = 1 - Levenshtein\ Distance = 1 - \frac{n}{N_l + N_m}.$$

N_l and N_m in the above equation represent the length of the stem names in the Chinese Patent-Osiris joint dataset and the MEP lists respectively, and n is the minimum number of editing operations required to transform one stem name to the other (Levenshtein, 1966; He et al., 2013). In the calculation of the Levenshtein edit distance, I allowed all three types of edit operations, including insertion, deletion, and substitution of any single character.

After the 1,842 listed companies included in the Chinese Patent-Osiris joint dataset were matched with companies in the MEP lists, I then exported the top 10 matches according to the similarity score and manually checked these 18,420 name pairs to ensure that the merged dataset only included "true matches." Since the MEP lists can record either the headquarters of a listed company or its local subsidiaries, or both, as the targets of CPA programs, I consider a company as under stringent environmental regulations as long as its headquarters or any of its subsidiaries was participating in a CPA program.

To ensure that firms in the final dataset share similar innovation patterns, I excluded companies in industries with zero CPA participant between 2005 and 2010, based on the three-digit U.S. Standard Industry

[18] The user documentation of the CPDP indicates that researchers were only able to match about 190,000 of five million patent applications with listed companies and their subsidiaries. Since many annual reports published before 1999 were missing, the coverage in early years is particularly limited.

Classification (SIC) code assigned to each listed company in the Osiris database. In the same vein, I excluded companies in Hainan and Tibet—the two regions with zero CPA participant between 2005 and 2010. I kept only firms operating in the three key sectors with detailed cleaner production standards: the mining sector (SIC 101–149), the manufacturing sector (SIC 201–399), and the public utilities sector (SIC 481–497). I also excluded companies that exited the stock market during the sample period, as their choices might be affected by innovation performance or environmental regulation, and this correlation could lead to potential endogeneity issues. Finally, I excluded any firm changing its core industry or the location of its headquarter (at the provincial level), as these changes are usually linked with substantial reorganization or takeovers, which may enhance or weaken unobserved firm-specific factors related to innovation.

5.5 Descriptive Statistics

Among the 733 companies included in the main dataset, 617 filed at least one patent application between 2001 and 2010. As shown in Figure 1, the number of firms filing patent applications continuously increased from 44 (out of 122) in 2001 to 466 (out of 667) in 2010. Meanwhile, the average number of patent applications filed by these listed companies also rose dramatically from about 8 in 2001 to more than 42 in 2010, indicating the growing trend of attaching more importance to innovation and standardizing protection for innovation. Between 2005 and 2010, 217 listed companies in the main dataset had participated in at least one CPA program. The number of firms under regulation each year climbed from 30 (out of 576) in 2005 to 111 (out of 667) in 2010. On average, CPA participants applied for more patents than non-participants. Since the number of observations for CPA participants is limited in 2001 and 2002, the significant gap between the average numbers of patent applications by CPA participants and non-participants in these two years was driven largely by outliers. The gap remained relatively stable between 2003 and 2006, substantially narrowed in 2007 and 2008, then enlarged to about 17 in 2010. This fact suggests that there exists a stronger positive correlation between mandatory CPA participation and firm innovation after 2008.

Figure 2 reveals the distribution of CPA participants and non-participants by two-digit SIC industry in the main dataset. 646 companies in the main dataset operate in the manufacturing sector, 50 in the public utilities sector, and 37 in the mining sector. Over 29% of manufacturing companies had participated in at least one CPA program. The corresponding rate is 20% for companies in the public utilities sector, and 49% for those in the mining sector. The two-digit SIC industries containing over 100 listed companies are the chemicals and allied products industry (SIC 28), and the electronic and other electrical equipment and components except computer equipment industry (SIC 36). Other industries with at least 50 companies in the main dataset are the food and kindred products industry (SIC 20), the primary metal industries (SIC 33), the industrial and commercial machinery and computer equipment industry (SIC 35), the transportation equipment industry (SIC 37), and the electric, gas and sanitary services industry (SIC 49).

Table 1 presents the descriptive statistics, including the means, standard deviations, minimums, and maximums of the aforementioned variables across all 29 regions, 67 three-digit SIC industries for 10 years. In addition to the two innovation indicators listed in the table, it is worth mentioning that the mean of invention patent applications in the sample is 10.95. In other words, an average Chinese listed company in the main dataset applied for roughly 11 invention patents, 9 utility model patents and 4 design patents each year between 2001 and 2010. The value for *size* before log transformation averages 5,988 employees, reflecting that the main dataset is composed of large firms which could potentially yield a significant overall environmental impact.

6 Empirical Results

In this section I present the estimation results for the pre-treatment model, the falsification test, the uniform impact and the differential impact models. I start with comparing the general pre-treatment innovation patterns between CPA participants and non-participants. Then I perform the falsification test to examine whether the innovation patterns of CPA participants systematically deviate from others only when they were soon to be regulated. After showing that innovation patterns of CPA participants did not differ from non-participants before participating in CPA programs, I present the main results showing that mandatory CPA participation increased firms' patent applications. I find that the effect is stronger after improvements in the regulatory system had been made. Sub-sample estimation results show that the positive effect is more significant in eastern China than in other regions. Estimations with the policy indicators interacted with firm size show that larger companies innovate more than smaller ones when facing environmental regulation.

6.1 Pre-treatment Innovation Patterns

Before the Chinese central government released the "Interim Measures on Cleaner Production Audit" in August 2004, the efforts devoted by local governments to promote cleaner production were largely lacking. An official report from the central government appraised the work of five provincial-level governments, and criticized others for not launching demonstrative CPA programs and sticking with policies favoring end-of-pipe treatment (Sate Environmental Protection Administration, 2004). Thus, before 2005, environmental pressure was not sufficiently strong to induce Chinese listed companies to alter their environmental performance, let alone innovative activities. However, since the nationwide implementation of CPA programs in 2005, companies that had yet participated in CPA programs might adjust its innovation strategy to avoid being selected, or prepare for upcoming mandatory enrollment.

To examine whether the level and the trend of patent applications differed systematically between CPA participants and non-participants before mandatory CPA participation, I perform a pre-treatment analysis as specified in Equation (3). For each year t_1 between 2005 and 2009, a listed company in the main dataset must belong to one of the three following groups: firms that had participated in CPA programs before year t_1, firms that participated in CPA programs for the first time at or after year t_1 (the treatment group at year t_1), or firms that had not participated between 2001 and 2010 (the control group at year t_1).[19] If the pre-treatment trend of innovation did not differ significantly between firms in the treatment and the control groups at each year between 2005 and 2009, the DID approach detailed in Section 4 should identify the effect of mandatory CPA participation on firm innovation.

[19] There are only 35 firms in the treatment group in 2010. I do not perform the pre-treatment analysis for these firms and those in the control group in 2010, since the results could be driven by outliers and cluster-robust standard errors could not be computed.

The results of the pre-treatment analysis are reported in Table 2, in which columns (1) through (5) show the regression results using the number of all patent applications as the measure of innovation, while columns (6) through (10) contain the results for invention and utility model patents. Columns (1) and (6) present the results for firms in the treatment and the control groups in 2005, using observations from 2001 to 2004. Similarly, columns (2) and (7), (3) and (8), (4) and (9), (5) and (10) report the results, respectively, for firms in the treatment and the control groups in 2006, 2007, 2008, and 2009. Results in all columns are produced by models with firm characteristics including *size*, *cash flow*, *capital intensity* and *prior innovation* to control for observable factors that may affect firm innovation. The models also include industry-region-year fixed effects to control for unobservable factors that differ across industries and regions, and over time. Standard errors are reported in parentheses and are two-way clustered by three-digit SIC industry and year. This approach corrects for industry-wide and year-specific technology and policy shocks uncorrelated with the independent variables, which allows variations in innovative activities of firms to be correlated both within industry and in the same year.[20]

Coefficient estimates for *Regulated* and *Trend* $\times$ *Regulated* are not statistically significant at the 10% level in any year. These results indicate that, after controlling for industry-region-year fixed effects and firm characteristics, Chinese listed companies later enrolled in CPA programs did not systematically innovate more (or less), or experience higher (or lower) variations in innovation than those did not participate. Since the selection of CPA participants is based on firms' prior environmental performance, it is likely for firms in the treatment and the control groups differ substantially in this aspect. However, the results of the pre-treatment analysis confirm that these differences did not significantly affect either the level or the trend of firm innovation, even after the nationwide implementation of CPA programs in 2005. Hence, mandatory CPA participation can be treated as independent from firm innovation, and the DID approach should correctly identify the impact of this policy.

6.2 Falsification Test

Analyses in Section 6.1 assume that innovation patterns of CPA participants and non-participants were stable during the pre-treatment period. However, a company might only adjust its environmental performance and innovative activities when management believed that mandatory CPA participation would be likely in the foreseeable future. It is also possible that when selecting candidates for mandatory CPA participation, environmental agencies put more emphasis on recent environmental performance and chose heavy polluters in the past few years. In these cases, the validity of the DID approach depends on whether innovation patterns differ systematically between CPA participants and non-participants in a several-year period before mandatory CPA enrollment.

I perform a falsification test as specified in Equation (4) to examine if the trend of innovation for CPA participants differed from non-participants between year $t_2 - k$ and year $t_2 - 1$, where t_2 is the year in which participants were enrolled in CPA programs for the first time. In this analysis I only include observations from 2001 to year $t_2 - 1$ for each CPA participant, and observations from 2001 to 2009 for each non-participant.

[20] I have also experimented with other two-way clustering strategies, including by region and year, and by industry and region. The patterns of coefficient significance remain consistent in the pre-treatment estimation results and results presented in other sections.

Since the average length of CPA programs in the main dataset is about 2.4 years, I set the value of k to be 2 and 3 and perform two sets of falsification exercises.

Table 3 reports estimates of the coefficients in Equation (4). Columns (1) and (3) show results of the model assuming CPA participation to be two years earlier than the actual enrollment year, while columns (2) and (4) contain the results of the model assuming CPA participation to be three years earlier. All coefficients for the imaginary CPA participation indicator, *Pseudo-CPA*, are statistically insignificant at the 10% level. This fact indicates that innovation patterns of CPA participants and non-participants did not differ significantly from each other, even when CPA participants would be facing environmental regulation within two to three years. Thus, the results of the falsification test provide further support to the argument that the selection of CPA participants is independent from firm innovation, and the DID approach would identify the effect of mandatory CPA participation.

6.3 Main Results

Given the results of the pre-treatment analysis and the falsification test, I now employ the DID approach to investigate the impact of mandatory CPA participation on firm innovation. Table 4 presents log-linear fixed effects estimates of the coefficients in Equation (1) and Equation (2). Note that columns (1) and (3) show the regression results for the uniform impact model, while the results for the differential impact model are presented in columns (2) and (4). The coefficients for three of the four control variables fit predictions from previous literature: larger firms, firms with more fixed assets, and more productive firms perform better in innovation. The coefficient estimate for the indicator of cash flow is insignificant, suggesting that innovative activities of Chinese listed companies may not be substantially liquidity constrained.

In columns (1) and (3), the coefficients for *CPA* are both positive and significant at the 10% level or above, indicating that on average, mandatory CPA participation stimulates innovation. More specifically, these coefficients suggest that CPA participation can raise all patent applications of a Chinese listed company by 11.6%, and this effect increases slightly to 14.2% for invention and utility patent applications. Using the means of these two innovation indicators for listed companies in the main dataset, I can infer that on average, CPA enrollment could lead to approximately 3 more invention and utility model patent applicaitons by a firm each year.

The results in columns (2) and (4) show that coefficient estimates for *CPA 2005–2008* are insignificant while those for *CPA 2009–2010* are significant at the 5% level or above. This discrepancy suggests that, in their early stages, CPA programs did not have a stimulative effect on firm innovation. However, a positive link between environmental regulation and innovation appeared after substantial improvements were made to the evaluation standards and procedures for CPA projects in 2009. The coefficients for *CPA 2009–2010* are more significant, and larger, than those for *CPA*. They indicate that CPA participation in 2009 and 2010 raised all patent applications and invention and utility patent applications of a listed company by 24.4% and 25.6% respectively. The average positive impact of mandatory CPA participation on firms' patent applications is largely driven by the positive interaction between environmental regulation and innovation since 2009.

6.4 Heterogeneous Effects of CPA across Regions

As discussed in Section 3, the Chinese central government delegates to each provincial-level government the enforcement and promotion of cleaner production within its own jurisdiction. When it comes to implementation of CPA programs, local governments are not only responsible for identifying the key sectors and announcing the lists of firms required to participate in each year, but also for specifying detailed implementation procedures and supportive policies, and for organizing assessments and conducting acceptance inspections for completed projects. Due to China's significant regional differences in both economic development and environmental awareness, it is not uncommon for regulations, incentives, and enforcement strategies to differ substantially from region to region.

In general, the economically more developed eastern regions are in the lead to have tighter environmental standards. For example, Shanghai's CPA evaluation process incudes an additional "pre-assessment" stage, during which site investigations are conducted and expert discussions are held.[21] Shanghai is also one of the leading regions to use online monitoring devices, in combination with periodic inspections conducted by technicians, to monitor effluent and exhaust gas from heavy polluters. The automated monitoring systems have enhanced the accuracy of pollution statistics, and thus facilitated the enforcement of CPA evaluation process. Finally, the Shanghai government provides special subsidies for CPA expenses to firms, of which half are available at the launch of CPA programs. The other half can be claimed after assessments are passed. Similar financial incentives are also provided by the Guangdong government in the form of a RMB50,000 bonus to firms that performed well in assessments, while one of its subordinates—the Dongguan government—pays an additional RMB300,000 to qualified firms within its jurisdiction. The argument that environmental regulation is better enforced in eastern regions is also supported by case studies of the Liaoning and Zhejiang provinces (Hicks and Dietmar, 2007; Geng et al., 2010), and the fact that three eastern provinces—Zhejiang, Jiangsu and Shandong—accounted for nearly 70% of CPA assessment and acceptance inspection expenses covered by government funding in 2010.[22]

To examine if stricter regulations, stronger incentives, and better enforcement in eastern regions stimulate more innovation, I classify the 31 Chinese provincial-level regions into two groups: Eastern China and Other Regions. To do so, I follow the approach proposed in the seventh five-year plan of China (1986–1990) and also adopted in the tenth five-year plan (2001–2005). The following 11 regions comprise a group that called Eastern China: Beijing, Tianjin, Shanghai, Liaoning, Hebei, Shandong, Jiangsu, Zhejiang, Fujian, Guangdong, and Hainan. The remaining 20 regions belong to the group of Other Regions. I then divide the data into two sub-samples—one containing companies in Eastern China, and the other containing companies in Other Regions. I estimate the uniform impact and the differential impact models using separate observations from each of the sub-samples.[23]

Estimation results for both models on the two sub-samples are presented in Table 5. Again, results for the

[21] See "Provisions on Procedures of Cleaner Production Audit of Key Enterprises in Shanghai," which was released by the Shanghai Environmental Protection Bureau in 2008, for details on the CPA evaluation process.

[22] See Section 3 for a more detailed discussion.

[23] An alternative approach is to restrict the link between other variables and innovation to be the same across the two groups of regions, and estimate models with a dummy for Eastern China interacted with the policy indicators. Since the economic structure and innovation policies implemented differ greatly between Easter China and Other Regions, I split the sample to allow for differences in links between firm characteristics and innovation across regions.

uniform impact model are shown in columns (1) and (3), while the results for the differential impact model are in columns (2) and (4). There are substantial differences in coefficient estimates across the two sub-samples, suggesting that the environmental policy was not equally effective in all regions. The results in columns (1) and (3) indicate that if mandatory CPA participation is viewed as homogeneous across the 2005–2010 period, the effect of this policy is insignificant in either Eastern China or Other Regions. However, the estimates for *CPA 2005–2008* and *CPA 2009–2010* in columns (2) and (4) reveal that only firms participating in CPA programs in eastern regions after 2008 innovated significantly more. These results suggest that the details of the design and enforcement of environmental policies play an important role in encouraging firm innovation.

6.5 Heterogeneous Effects of CPA across Firms of Different Sizes

The effectiveness of mandatory CPA participation may depend not only on the details of the regulatory framework, but also on the characteristics of the regulated firms. One potentially important such characteristic is firm size. Due to scale effects, larger companies may have lower compliance costs per unit of output. These companies may also be better able to allocate resources to innovative activities, including environmental R&D investments (Bartel and Thomas, 1987; Thomas, 1990; Sanchez, 1997). Thus, it is possible that small and large firms differ in their responses to environmental regulations.

To explore whether mandatory CPA participation provides stronger innovation incentives for larger companies, I add an interaction variable, *Size* × *CPA*, to the right-hand side of the uniform impact model. This variable is equal to *CPA* times the natural logarithm of the number of employees in a company. Similar interaction terms (*Size* × *CPA 2005–2008* and *Size* × *CPA 2009–2010*) appear on the right-hand side of the differential impact model.

Table 6 contains estimation results for the above specifications. Results for the uniform impact model with the interaction variable *Size* × *CPA* are reported in columns (1) and (3), while the results for the differential impact model with the interaction variables *CPA 2005–2008* and *CPA 2009–2010* are in columns (2) and (4). Compared with the main results of Section 6.3, a notable difference is that all estimates for the policy indicators are now statistically significant at the 5% level or above, although significance is still weaker for *CPA 2005–2008* than for *CPA 2009–2010*. The positive coefficients for all three interaction terms suggest that larger companies innovate more as a result of CPA participation than smaller companies. Based on an average firm size of 7.76 (measured in log employees) in my sample, the results in Table 6 imply that mandatory CPA participation stimulates annual patent applications by 6.0%. The effect becomes significant and more pronounced after 2008, when its magnitude increases to 16.1% for all patent applications and 15.3% for invention and utility model patent applications.

7 Sensitivity Tests and Robustness Results

This paper has shown so far that mandatory CPA participation enhanced the innovation performance of Chinese listed companies, and that the effectiveness of this policy varied over time, across regions, and across firms of different sizes. In this section, I perform sensitivity tests to demonstrate that these findings are robust against changes in model specifications.

7.1 Delayed Impact of Environmental Regulation

Given the complex and uncertain nature of innovation, it is reasonable to presume that environmental pressure, financial performance, and other firm characteristics may have a delayed instead of immediate impact on patent applications. Nevertheless, I use contemporaneous independent variables to produce the main results in Section 6.3, since the sample period 2001 to 2010 for the main dataset is relatively short, and the regulatory framework for CPA programs improved substantially after 2008. Lagging the independent variables for one year would not only cut down the number of observations but also make it difficult to analyze the heterogeneity in policy effectiveness over time, as the observations for *CPA 2009–2010* would be cut down by more than half.

In this subsection I lag all the independent variables for one year and re-estimate the uniform impact and the differential impact models to check the robustness of the main results. Table 7 presents the estimation results for the uniform impact model in columns (1) and (3), and the results for the differential impact model in columns (2) and (4). Compared with the main results reported in Table 4, the number of firms included in the analysis decreases only slightly, from 733 to 723. However, the number of observations drops over-proportionally, by about 14%, as the annual number of observations in the main dataset increases over time. The coefficient estimates for *CPA* are positive and significant at the 5% level. The coefficients for *CPA 2005–2008* are insignificant, while those for *CPA 2009–2010* are positive and significant at the 1% level. These patterns are in line with findings in Section 6.3, except that mandatory CPA participation is suggested to have a delayed, more significant average impact on firm innovation under this specification.

7.2 Firms in the Manufacturing Sector

The main dataset used in previous analyses covers the three key sectors with at least one firm participating in CPA programs between 2005 and 2010. Figure 2 shows that about 88% of companies in the main dataset operate in the manufacturing sector. Firms' innovation patterns may be more similar to each other within this sector, than comparing with innovative activities of firms in the mining and the public utilities sectors. Therefore, a DID analysis on companies in the manufacturing sector may better capture the effect of mandatory CPA participation on firm innovation.

In this subsection I restrict the sample to companies operating in the manufacturing sector, and present the estimation results for the models in Table 8. Columns (1) and (3) contain results for the uniform impact model, and columns (2) and (4) report the results for the differential impact model. By excluding companies in other sectors, the numbers of firms and observations included in the estimations both reduce by about 12%. The coefficient estimates for *CPA* are positive and significant at the 10% level or above. The coefficients for *CPA 2005–2008* are insignificant, while those for *CPA 2009–2010* are positive and significant at the 5% level or above. The coefficients for *CPA* and *CPA 2009–2010* are smaller than those presented in Section 6.3, indicating a slightly weaker positive effect of mandatory CPA participation in the manufacturing sector.

7.3 DID Analysis based on a Propensity Score Matching Approach

The validity of a DID analysis can greatly benefit from the similarity of patterns in the treatment and the control groups, as well as from the elimination of potential selection bias related to individual characteristics. To utilize to the greatest extent the information contained in the main dataset, in Section 6 I include in the control group 516 Chinese listed companies that had not participated in any CPA program between 2001 and 2010. I also employ a pre-treatment analysis and a falsification test to show that both the level and the trend of CPA non-participants' innovation did not differ from participants.

In this subsection, using a propensity score matching (PSM) approach, I construct a sub-dataset with 165 listed companies that later enrolled in CPA programs and 107 firms that never participated during the sample period. The PSM approach, which was developed by Heckman et al. (1997) and widely employed in DID analyses, matches the groups of firms that had similar observable characteristics in 2004, and thus shared a likelihood of being regulated in the following years. The group of non-participants selected through this approach could constitute a better control group for companies participating in CPA programs. Estimation results on this sub-dataset may better capture the effect of mandatory CPA participation, as it further alleviates the endogeneity issue arising from pre-treatment selection potentially based on firm characteristics other than prior environmental performance.

Following the implementation procedures detailed in Debaere et al. (2010) and Cozza et al. (2015), I use three steps to apply DID estimations based on a PSM approach. First, I estimate a probit model for all the listed companies in the main dataset, to predict the probability of being regulated (during the 2005–2010 period) in 2004. The firm characteristics that are assumed to be linked with the probability include *size*, *cash flow*, *capital intensity*, and *prior innovation* in 2004. The right-hand side of this model also includes industry dummies to control for industry-specific environmental performance that could lead to a higher or lower chance of being identified for CPA participation, and region dummies to take account of heterogeneity in local policies that may affect a firm's possibility of being regulated.

Second, I compute propensity scores based on the probit estimation results, and pair each later-participated firm with the most similar never-participated firm in terms of propensity score. These paired, listed companies constitute the new sub-dataset, while firms with scores higher than the maximum or lower than the minimum are dropped (see Leuven and Sianesi, 2003). I perform a balancing test to examine whether the distributions of observable characteristics are similar across the later-participated and the never-participated companies. Following Sianesi (2004), I compare the differences in means of the firm characteristics between the two groups, and the *pseudo* R^2 of the probit model, predicting the possibility of being regulated before and after matching. Results of the t-tests are presented in Table 9. They suggest that the means of all four characteristics for firms that never participated in a CPA program do not differ significantly from those did. A substantial reduction in *pseudo* R^2 reflects that the performance of the probit model improved after matching. These facts confirm that the sub-dataset can be considered well-balanced after matching.

Finally, I estimate both the uniform impact and the differential impact models on the sub-dataset, which contains observations for 272 listed companies between 2004 and 2010. The results are presented in Table 10. The coefficients for *CPA* in columns (1) and (3), and those for *CPA 2009–2010* in columns (2) and (4) are positive and significant at the 5% level or above. These facts also indicate that mandatory CPA participation fostered patent applications by Chinese listed companies, and that the impact is stronger after 2008. These results are qualitatively consistent with the main results discussed in Section 6.3. This consistency further strengthens the robustness of the main results.

8 Conclusion and Discussion

The impact of environmental regulation on firm innovation has long been under discussion, even before the Porter Hypothesis was proposed in the early 1990s. Previous studies generally confirm the promotional effect of strict environmental policies on environmental innovation, but show mixed results for overall innovative activities. This paper uses firm-level data in China to provide evidence for the positive link between environmental stringency and overall innovation, which is advocated by the "weak" version of the Porter Hypothesis. This stimulative effect is found to be stronger after a multi-level regulatory system was finally established, and in regions where regulations were better enforced and supported by plenty of financial incentives. This finding makes this paper one of the few to discuss and support the "narrow" version of the Porter Hypothesis, which emphasizes the importance of policy implementation and flexibility. This paper also adds to the literature by confirming the positive effect of environmental policies on innovation at a more micro level in a developing economy.

Despite its contributions, this paper has at least three limitations. First, the main dataset lacks some information closely related to either innovation or environmental regulation, such as R&D expenses and the environmental performance of the listed companies. Although innovation can be attributed to other firm characteristics, and the sample selection issue is addressed by the pre-treatment analysis and the propensity score matching approach, the persuasiveness of estimation results would greatly benefit from a more comprehensive dataset. Second, the measures of innovation in this paper do not distinguish environmental patents from other types of patents, and do not reflect differences in the value of patents. A comparison between environmental and non-environmental innovative activities under regulation would provide more insights into the mechanisms of environmental policy's effect. However, an analysis reflecting the heterogeneity in patent value cannot be performed as long as citation statistics are not available for Chinese patents. Third, this paper does not discuss the "strong" version of the Porter Hypothesis. Future research based on the main dataset of this paper should examine whether innovation triggered by environmental regulation enhances firm competitiveness characteristics, such as productivity and profitability.

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Appendix A

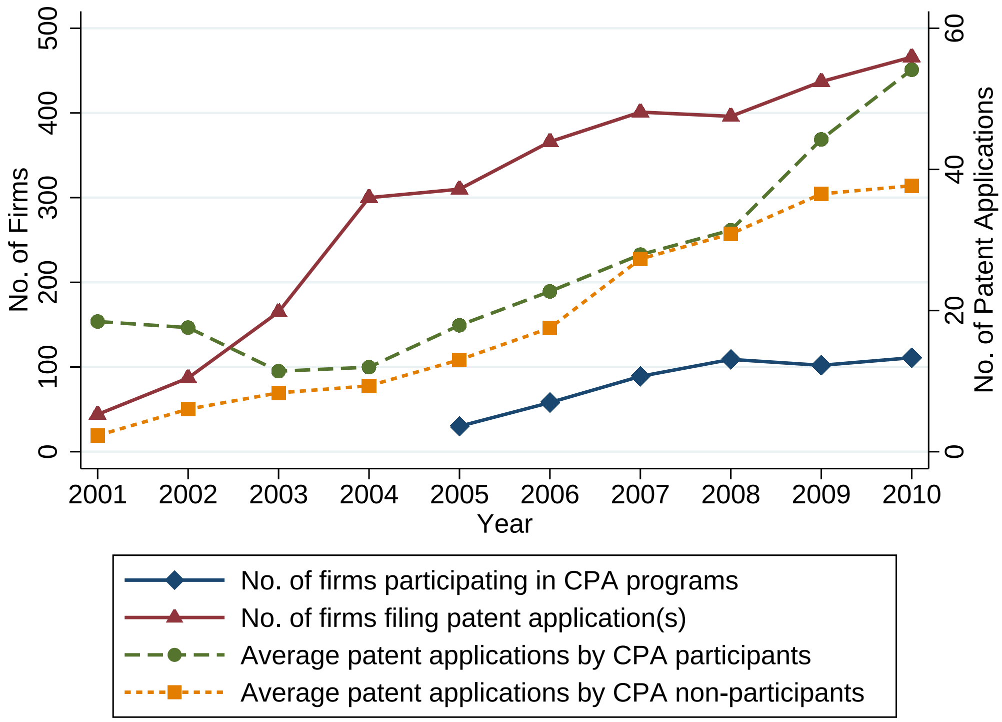

Figure 1: Mandatory CPA Participation and Patent Applications of Companies

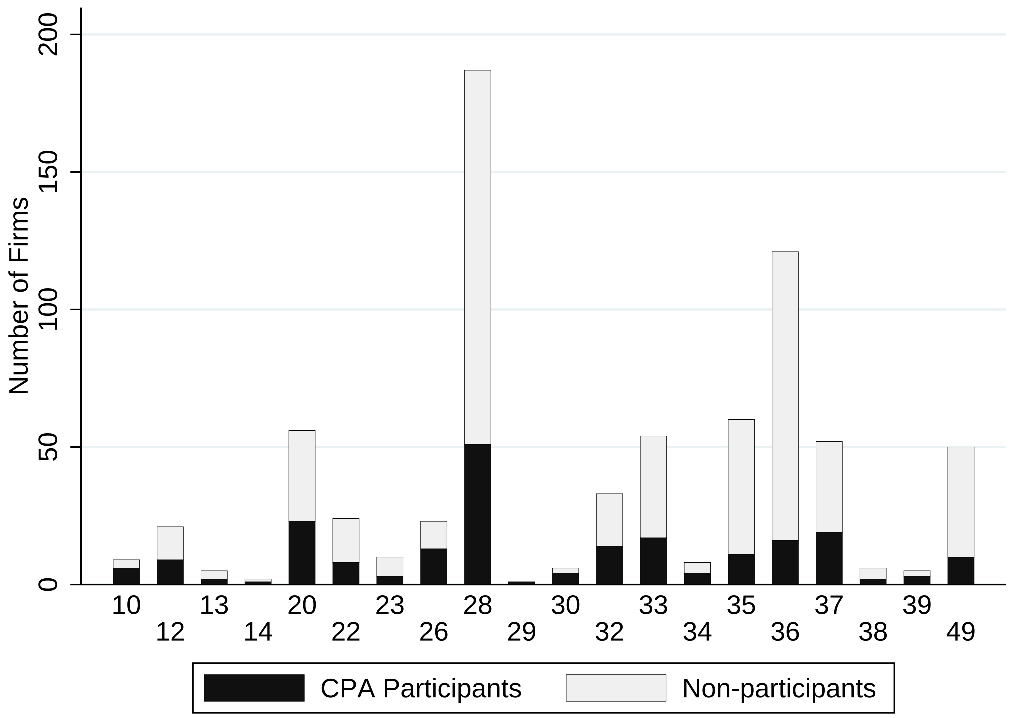

Figure 2: Number of CPA Participants and Non-participants by 2-digit SIC Industry

Table 1: Descriptive Statistics

Variable	Mean	S.D.	Min	Max
Innovation				
All Patent Applications	24.55	156.23	0.00	5,284.00
Invention and Utility Model	20.17	148.2	0.00	5,035.00
Environmental Regulation				
CPA	0.10	0.30	0.00	1.00
Other Firm Characteristics				
Employment (thousand)	5.99	23.55	0.00	552.70
Cash Flow / Operating Revenue (%)	12.50	10.09	0.05	99.14
Capital Intensity (CNY million)	1.09	11.14	0.00	383.37
Labour Productivity (CNY million)	1.93	11.36	0.00	350.01

Table 2: Pre-treatment Innovation Patterns

	All Patent Applications					Invention and Utility Model				
Independent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$Regulated_{2005}$	–0.033					–0.227				
	(0.393)					(0.465)				
$Trend \times Regulated_{2005}$	0.066					0.129				
	(0.081)					(0.101)				
$Regulated_{2006}$		–0.141					–0.041			
		(0.367)					(0.489)			
$Trend \times Regulated_{2006}$		0.066					0.046			
		(0.082)					(0.109)			
$Regulated_{2007}$			–0.228					–0.078		
			(0.414)					(0.476)		
$Trend \times Regulated_{2007}$			0.068					0.029		
			(0.086)					(0.099)		
$Regulated_{2008}$				0.159					0.245	
				(0.350)					(0.513)	
$Trend \times Regulated_{2008}$				–0.025					–0.045	
				(0.071)					(0.103)	
$Regulated_{2009}$					–0.175					–0.049
					(0.222)					(0.166)
$Trend \times Regulated_{2009}$					0.017					–0.004
					(0.048)					(0.043)
No. of Firms	626	644	637	617	579	626	644	637	617	579
Observations	1,215	1,712	2,195	2,607	2,871	1,215	1,712	2,195	2,607	2,871

Notes: *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance. Industry-region-year fixed effects and firm characteristics including size, cash flow, capital intensity, and prior innovation are included to generate results but omitted from reporting. Standard errors are two-way clustered by industry and year.

Table 3: Pseudo-CPA Participation in Pre-treatment Periods

	All Patents		Invention and Utility	
Independent Variable	(1)	(2)	(3)	(4)
Pseudo-CPA	0.152	0.152	0.129	0.120
	(0.096)	(0.104)	(0.084)	(0.099)
Size	0.432***	0.432***	0.411***	0.412***
	(0.055)	(0.055)	(0.050)	(0.050)
Cash Flow	0.004	0.003	0.021	0.021
	(0.028)	(0.028)	(0.020)	(0.021)
Capital Intensity	0.121***	0.121***	0.133***	0.133***
	(0.024)	(0.024)	(0.028)	(0.028)
Prior Innovation	0.184***	0.184***	0.163***	0.163***
	(0.062)	(0.063)	(0.060)	(0.060)
No. of Firms	689	689	689	689
Observations	3,801	3,801	3,801	3,801

Notes: *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance. Firm, industry-year and region-year fixed effects are included to generate results but omitted from reporting. Standard errors are two-way clustered by industry and year.

Table 4: Main Results: Patent Applications and Mandatory CPA Participation

	All Patents		Invention and Utility	
Independent Variable	(1)	(2)	(3)	(4)
CPA	0.116*		0.142**	
	(0.068)		(0.058)	
CPA 2005–2008		0.014		0.052
		(0.052)		(0.047)
CPA 2009–2010		0.244**		0.256***
		(0.097)		(0.083)
Size	0.481***	0.478***	0.442***	0.440***
	(0.053)	(0.054)	(0.047)	(0.048)
Cash Flow	–0.004	–0.004	0.006	0.006
	(0.022)	(0.023)	(0.019)	(0.019)
Capital Intensity	0.125***	0.123***	0.128***	0.126***
	(0.030)	(0.030)	(0.030)	(0.030)
Prior Innovation	0.200***	0.199***	0.169***	0.169***
	(0.045)	(0.045)	(0.041)	(0.042)
No. of Firms	733	733	733	733
Observations	5,002	5,002	5,002	5,002

Notes: *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance. Firm, industry-year and region-year fixed effects are included to generate results but omitted from reporting. Standard errors are two-way clustered by industry and year.

Table 5: Heterogeneous Effects of CPA Participation across Regions

	All Patents		Invention and Utility	
Independent Variable	(1)	(2)	(3)	(4)
	Panel A: Firms in Eastern China			
CPA	0.087		0.131	
	(0.097)		(0.082)	
CPA 2005–2008		−0.068		−0.010
		(0.065)		(0.067)
CPA 2009–2010		0.295**		0.320***
		(0.117)		(0.093)
No. of Firms	401	401	401	401
Observations	2,770	2,770	2,770	2,770
	Panel B: Firms in Other Regions			
CPA	0.145		0.156	
	(0.128)		(0.120)	
CPA 2005–2008		0.084		0.120
		(0.121)		(0.115)
CPA 2009–2010		0.213		0.197
		(0.153)		(0.141)
No. of Firms	332	332	332	332
Observations	2,232	2,232	2,232	2,232

Notes: *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance. Firm, industry-year and region-year fixed effects, and firm characteristics including size, cash flow, capital intensity, and prior innovation are included to generate results but omitted from reporting. Standard errors are two-way clustered by industry and year.

Table 6: Heterogeneous Effects of CPA Participation across Firms of Different Sizes

	All Patents		Invention and Utility	
Independent Variable	(1)	(2)	(3)	(4)
CPA	–0.713***		–0.641**	
	(0.266)		(0.251)	
Size × *CPA*	0.100**		0.094***	
	(0.040)		(0.037)	
CPA 2005–2008		–0.443*		–0.164
		(0.249)		(0.257)
Size × *CPA 2005–2008*		0.056		0.027
		(0.037)		(0.036)
CPA 2009–2010		–0.762***		–0.941***
		(0.271)		(0.297)
Size × *CPA 2009–2010*		0.119***		0.141***
		(0.040)		(0.040)
Size	0.475***	0.472***	0.437***	0.433***
	(0.053)	(0.054)	(0.047)	(0.048)
Cash Flow	–0.004	–0.005	0.005	0.005
	(0.022)	(0.022)	(0.018)	(0.019)
Capital Intensity	0.126***	0.124***	0.128***	0.127***
	(0.030)	(0.030)	(0.029)	(0.030)
Prior Innovation	0.198***	0.197***	0.167***	0.166***
	(0.044)	(0.045)	(0.041)	(0.041)
No. of Firms	733	733	733	733
Observations	5,002	5,002	5,002	5,002

Notes: *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance. Firm, industry-year and region-year fixed effects are included to generate results but omitted from reporting. Standard errors are two-way clustered by industry and year.

Table 7: Robustness Results: Using One-year Lagged Independent Variables

	All Patents		Invention and Utility	
Independent Variable	(1)	(2)	(3)	(4)
CPA	0.152**		0.150**	
	(0.077)		(0.064)	
CPA 2005–2008		0.119		0.123
		(0.097)		(0.084)
CPA 2009–2010		0.232***		0.211***
		(0.073)		(0.067)
Size	0.445***	0.444***	0.406***	0.405***
	(0.060)	(0.060)	(0.051)	(0.051)
Cash Flow	0.023	0.023	0.026	0.026
	(0.026)	(0.026)	(0.023)	(0.023)
Capital Intensity	0.103***	0.103***	0.106***	0.106***
	(0.024)	(0.024)	(0.017)	(0.017)
Prior Innovation	0.210***	0.210***	0.195***	0.195***
	(0.062)	(0.062)	(0.058)	(0.058)
No. of Firms	723	723	723	723
Observations	4,297	4,297	4,297	4,297

Notes: *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance. Firm, industry-year and region-year fixed effects are included to generate results but omitted from reporting. Standard errors are two-way clustered by industry and year.

Table 8: Robustness Results: Restricting Sample to Firms in the Manufacturing Sector

	All Patents		Invention and Utility	
Independent Variable	(1)	(2)	(3)	(4)
CPA	0.122*		0.159***	
	(0.073)		(0.061)	
CPA 2005–2008		0.044		0.088
		(0.068)		(0.057)
CPA 2009–2010		0.221**		0.248***
		(0.100)		(0.078)
Size	0.507***	0.506***	0.466***	0.464***
	(0.054)	(0.055)	(0.046)	(0.046)
Cash Flow	0.000	0.000	0.013	0.013
	(0.023)	(0.023)	(0.019)	(0.019)
Capital Intensity	0.160***	0.159***	0.160***	0.158***
	(0.032)	(0.031)	(0.033)	(0.032)
Prior Innovation	0.188***	0.188***	0.157***	0.157***
	(0.047)	(0.047)	(0.043)	(0.044)
No. of Firms	646	646	646	646
Observations	4,409	4,409	4,409	4,409

Notes: *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance. Samples only include firms in the manufacturing sector. Firm, industry-year and region-year fixed effects are included to generate results but omitted from reporting. Standard errors are two-way clustered by industry and year.

Table 9: Balancing Test: Mean Differences before and after Matching

		Mean		t-test	
Variables	Sample	Regulated	Unregulated	t	p-value
Size	Unmatched	7.935	7.368	5.38	0.00
	Matched	7.935	7.877	0.52	0.61
Cash Flow	Unmatched	2.317	2.239	1.18	0.24
	Matched	2.317	2.369	–0.71	0.48
Capital Intensity	Unmatched	5.468	5.084	3.65	0.00
	Matched	5.468	5.342	0.99	0.32
Prior Innovation	Unmatched	6.277	6.290	–0.14	0.89
	Matched	6.277	6.222	0.53	0.60
		Pseudo R^2	LR chi^2	p-value	
	Unmatched	0.063	47.130	0.00	
	Matched	0.006	2.700	0.61	

Table 10: PSM Results: Patent Applications and Mandatory CPA Participation

	All Patents		Invention and Utility	
Independent Variable	(1)	(2)	(3)	(4)
CPA	0.159**		0.183***	
	(0.069)		(0.067)	
CPA 2005–2008		0.026		0.038
		(0.040)		(0.057)
CPA 2009–2010		0.353***		0.395***
		(0.117)		(0.072)
Size	0.607***	0.599***	0.537***	0.529***
	(0.121)	(0.123)	(0.100)	(0.103)
Cash Flow	–0.045	–0.043	–0.027	–0.025
	(0.058)	(0.056)	(0.057)	(0.055)
Capital Intensity	0.096	0.088	0.060	0.051
	(0.061)	(0.063)	(0.061)	(0.062)
Prior Innovation	0.338***	0.342***	0.301***	0.306***
	(0.091)	(0.093)	(0.079)	(0.081)
No. of Firms	272	272	272	272
Observations	2,174	2,174	2,174	2,174

Notes: *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance. Firm, industry-year and region-year fixed effects are included to generate results but omitted from reporting. Standard errors are two-way clustered by industry and year.