CAN ENVIRONMENTAL REGULATIONS STIMULATE THE INDUSTRIAL-LEVEL PORTER EFFECT? EVIDENCE FROM THE KCAPC POLICY IN CHINA.

A Thesis

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ABSTRACT

According to the Porter Hypothesis, well-designed environmental regulations may lead, counter to established wisdom, to increased innovation and productivity as firms reduce pollution and make optimal production decision changes. Finding the causal relationships between environmental regulation, firms' innovation, and competitiveness is challenging. As a result, researchers continue to find inconsistent evidence concerning the Porter Hypothesis. In this thesis, we examine the influence of a national air pollution control policy on innovation and labor productivity at the industry-city level in China using a firm-level panel dataset from 1999 to 2009. We analyze this policy as a quasi-natural experiment using propensity score matching and difference-in-difference analysis. We find that environmental regulations stimulated industrial innovation in China, supporting the weak Porter Hypothesis. Regarding the validity of the strong Porter Hypothesis in this case, the translation of these new innovative practices into labor productivity increases hinges upon firm and industry characteristics. Both patent applications and labor productivity significantly increased in industries where more firms were entering. In industries where entry and exit were minimal, the increase in innovation was concentrated among private firms with small positive profits, and the rise in labor productivity was concentrated among private firms with low pollution levels.

BIOGRAPHICAL SKETCH

Xiaorui Wang is a second-year M.S. student in Applied Economics and Management at Cornell University's Charles H. Dyson School. Before she came to Cornell, she obtained her B.S. in Economics and Statistics with the highest distinction from the University of Illinois Urbana-Champaign. Her current research interest is examining economic decision-making in business and the role of markets in allocating real and financial resources. After graduating from the M.S. program, Xiaorui will continue her Ph.D. study in Applied Economics and Management at Cornell University's Charles H. Dyson School.

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Introduction

Environmental protections have been traditionally seen as a burdensome cost to businesses that negatively affect their competitiveness (McGuire, 1982). It is often argued that environmental regulations to reduce pollution force firms to divert precious resources away from more productive investments. While environmental measures may offer environmental or health benefits to society, they are seen as unproductive from a business standpoint (Ambec et al., 2013).

In the early 1990s, some economists challenged this traditional paradigm, most notably Michael Porter (Porter 1991) and Claas van der Linde (Porter and van der Linde 1995a). They used case studies to argue that if environmental regulations are appropriately designed, they can result in "innovation offsets," which not only enhance environmental performance but may also partially or wholly offset the additional costs associated with abatement (*the Porter Hypothesis*). Since its introduction, the Porter Hypothesis has inspired 30 years of research into the relationship between environmental regulation and technological innovation.

In contrast to the traditional view that firms are profit-maximizing, the Porter Hypothesis is based on a different assumption. According to the hypothesis, strict but flexible environmental regulations can motivate firms' innovation (*the Weak Porter Hypothesis*) and may increase firms' productivity and competitiveness (*the strong Porter Hypothesis*). Having established that environmental regulations could enhance corporations' innovation or overall competitiveness, why do firms only make these economically beneficial improvements under government pressure? Brannlund and Lundgren (2009) and Ambec et al. (2013) note that, in addition to the environmental problem, the Porter Hypothesis requires another market failure that can be alleviated or neutralized by environmental regulation.

Several types of market failures can trigger the innovation effect of environmental policy intervention. One of them is the asymmetric information problem resulting from environmental degradation. Without policy intervention, firms have no incentive to reduce emissions in production because pollution is not priced. Ambec and Barla (2007) point out that asymmetric information about environmental quality results in a "market for lemons," in which only dirty products are produced under fierce competition between firms. With appropriate environmental policy interventions, companies are encouraged to invest in emission-reducing and production-efficiency-improving technologies (Popp, 2019). In addition, environmental regulations like green labels reveal valuable information for firms that supply environmentally friendly products (Ambec et al., 2013). Companies specializing in “dirty” products may be able to differentiate their products vertically, thereby reducing competition among them (Ambec et al., 2013).

Another market failure supporting Porter’s theory is the public good nature of knowledge (Geroski, 1995, Ambec et al., 2013). It is usually necessary for the inventor to make new technologies available to the public before the inventor can reap the benefits of innovation (Popp, 2019). Upon making these new inventions public, some (if not all) of the knowledge that the invention embodies becomes public knowledge. As a result of this public knowledge, additional innovations may be developed, or existing innovations may be copied. The initial innovator, however, does not benefit from knowledge spillovers (Popp, 2019). According to Mohr (2002), firms underinvest in cleaner and more productive technologies when their competitors partially capture the returns on their research and development (R&D) investments. Therefore, environmental regulations that force adoption may shift the industry from an equilibrium with low R&D investments to a Pareto-improving equilibrium with higher R&D investments (Mohr, 2002).

Multi-level interactions and dynamic responses from firms and the broader environment result from environmental policies' innovation effects. According to Dechezlepretre and Sato (2017), policies affecting the environment invoke changes to relative production costs (*the first-order effect*) and prompt companies to respond differently. As a result, firms may change their price, output, or investment decisions (*second-order effects*). In turn, these responses influence outcomes at various economic, technological, international, and environmental levels (*third-order effects*).

Empirical studies testing the weak Porter Hypothesis have reached a relatively consistent conclusion, namely that they confirm it, but the same cannot be said of the strong Porter Hypothesis. Evidence from the European manufacturing sectors supports the weak Porter Hypothesis but not the strong one, i.e., environmental regulations encourage innovation but do not improve productivity (Rubashkina et al., 2015). However, Albrizio et al. (2017) find temporary productivity boosts associated with environmental policy in most technologically advanced OECD countries, but only for pre-policy productive firms. In Quebec, Lanoie et al. (2008) confirm the strong Porter Hypothesis in sectors more exposed to competition and those in less polluting industries. In general, there is a positive association between environmental regulation and technological innovation, although the strong Porter Hypothesis remains controversial.

It takes time for innovation to occur from a dynamic perspective. Based on their study of 17 Quebec manufacturing sectors, Lanoie et al. (2008) find that stricter regulations modestly improved productivity over time. By using the difference-in-differences approach, Shen et al. (2021) found that changes in firms' total factor productivity (TFP) were insignificant when regulated under China's low-carbon city pilot policy. As R&D's innovation effect gradually appeared, the policy positively impacted total factor productivity but only partially counterbalanced the compliance cost (Shen et al., 2021).

Considering the Chinese case, the literature has inconsistent conclusions on the Porter Hypothesis. By studying the low-carbon city pilot policy, Shen et al. (2021) confirm the weak Porter Hypothesis in China. However, implementing the low-carbon city pilot policy negatively affected firm total factor productivity, especially for larger firms and those located in the eastern region. In contrast, Nie et al. (2021) claim that no regional Porter effect exists in China, as represented by the carbon emissions trading pilot policy.

Apart from environmental innovations that sometimes focus on end-pipe pollution abatement, firms can compensate for compliance costs by improving efficiency and productivity through general innovation (e.g., process innovation and input-saving technologies). For China's Key Cities for Air Pollution Control (KCAPC) policy that this paper investigates, the majority of research focuses on pollution reduction, labor demand, economic growth, and green technology, among others (Liu et al.,2021; Jiang et al., 2021)., but few studies investigate general innovations of polluted firms and their labor productivity.

This paper investigates whether China's Key Cities for Air Pollution Control (KCAPC) policy affects innovation and labor productivity at the industrial city level, testing the Porter Hypothesis. Using KCAPC policy as a quasi-natural experiment, we first use propensity score matching (PSM) to form control cities and then conduct difference-in-differences (DID) analysis to test the Porter Hypothesis. In addition, we consider the spillover effects of policy on reallocating firms by disaggregating industry types. This study is consistent with the weak Porter Hypothesis. The strong Porter Hypothesis is validated in certain industries and firm types. Our results provide new insights into the Porter Hypothesis in China by delivering nuance into industries and firm types.

Policy Regime: China’s Key Cities for Air Pollution Control (KCAPC) Policy

The concept of China's Key Cities for Air Pollution Control (KCAPC) was initially proposed in 1998 by the Ministry of Ecology and Environment (MEE) to address air quality issues in specific cities (Liu et al.,2021). The central government designated 47 prefecture-level cities, including municipalities like Beijing, Shanghai, Chongqing, and Tianjin, provincial capitals, cities in special economic zones, coastal regions, and tourist destinations, as the first batch of KCAPC cities. In December 2001, an additional 66 cities were selected based on a comprehensive economic analysis and assessment of air pollution levels at the time, with the goal of further improving air quality and enhancing public health (Ministry of Ecology and Environment of the People’s Republic of China, 2001).

KCAPC was enforced using a top-down performance-based appraisal system. In accordance with the policy, the prefecture-level cities listed in the KCAPC must comply with the National Ambient Air Quality Standards. Their obligations include improving law enforcement, establishing an environmental monitoring network, and being assessed by the MEE (Liu et al.,2021).

KCAPC has received significant attention from both the country’s upper and local government levels (Liu et al., 2021). In China’s annual environmental status report, a section summarizing the implementation of KCAPC pollution control in selected cities is included every year. This indicates continuous attention from the central government to KCAPC and, in turn, continues to pressure regulated cities. MEP will display non-conforming cities, which could affect the evaluation process for cities and administration promotion.

Local governments or KCAPC cities may impose their own performance-based regulations and establish monitoring sites to promote cleaner production of firms at their discretion. Under this emission reduction pressure, firms in KCAPC cities may be encouraged to conduct technological innovation, including but not limited to green technology innovation, and increase productivity to improve overall competitiveness and efficiency.

Due to the lack of data before 1998 and the unique economic and political characteristics of the first batch of KCAPC cities, we focus on the newly designated KCAPC cities of December 2001 in this paper.

Conceptual Framework

Assume the average production function of an industry is approximately $Y = AK^{\alpha}L^{1-\alpha}$, then $\frac{Y}{L} = A(\frac{K}{L})^{\alpha}$.

If the values and ratio of inputs prices (e.g., wages and rents) are close across cities[1], then, under the assumption that firms optimize their profits, the capital per labor $\frac{K}{L} = \frac{w}{r}\frac{\alpha}{1-\alpha}$ will also be close across cities. Therefore, labor productivity $\frac{Y}{L}$ will be proportional to A. Assume an implicit positive relationship between A and the number of patent applications; then labor productivity and the number of patent applications can both partly measure the total factor productivity from the aspect of technological innovation.

[1] Liu et al. (2021) show that, under the affection of KCAPC, the wage is an insignificant factor for labor demand, and the wage's effect on labor demand is almost zero. So, the difference in labor productivity is unlikely caused by different rations between wages and other input prices across cities.

Empirical Framework

PSM-DID Strategy

DID method is most appropriate when the treatment is randomly assigned. The requirement of random experiments, however, is rarely met by real-world policies. In this case, it is possible to use PSM first to solve endogenous problems caused by deviations in sample selection (Dehejia and Wahba, 2002).

Using the DID strategy, our empirical analysis aims to estimate the causal effect of the KCAPC policy on firms' innovation and labor productivity. The DID methods capture pre-existing differences between firms in treatment cities and firms in non-treatment cities, eliminating selection bias, assuming the differences can be captured through observable characteristics that you use in matching. In addition, the method controls for possible confounding variables that may have changed in the 11 years from 1999 to 2009, which may have affected both groups of firms simultaneously.

As in our case, the assignment of regulated cities is not random but rather based on the economic conditions and previous pollution levels of cities. For this reason, we construct a comparative control group using a PSM approach. To assess cities' comprehensive economic situation, we include the log of average wages from 1999 to 2001, the average proportion of secondary and tertiary industries from 1999 to 2001, and the number of patent applications from 1999 to 2001. We use SO_2 total emission in 2001 as an indicator of environmental performance.

Based on logistic regression, PSM uses a dependent variable equal to 1 for KCAPC cities and 0 otherwise, and independent variables that describe pretreatment factors that influence "propensity" to be included in KCAPC. Cities are matched with their nearest neighbor based on their propensity scores. We exclude provincial cities from potential control city groups because of their unique economic and political characteristics.

After matching treated and control cities based on pretreatment characteristics, 53 out of 66 cities have matched control group cities. Fig. 1 shows the distribution of treatment and matched control cities. We examine the covariate balance in the matched sample in Table 1. The treatment and control groups have nearly identical means in the covariates indicating the economic situation of cities. The t-tests also show that the differences in means are not statistically significant.

Fig. 1. the Distribution of Treatment and Matched Control Cities in Mainland China

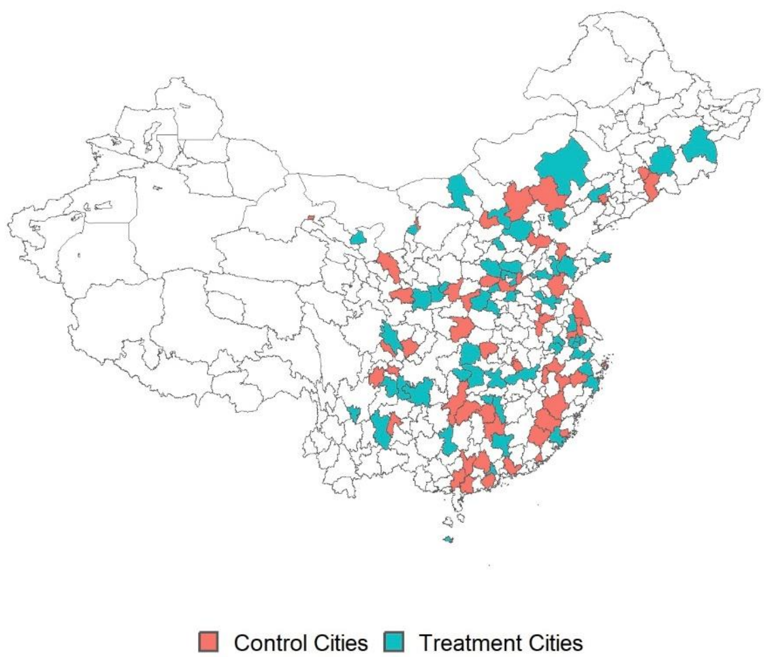


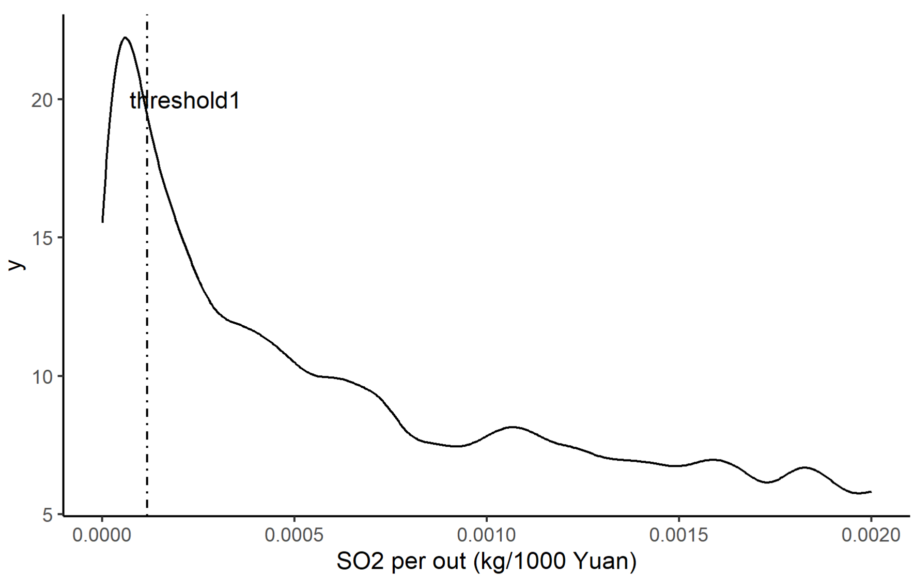
Table 1. Covariate Balance in the Matched Samples

Treatment	ln(wage)	Secondary industry %	Tertiary industry %
0	2.178	45.47	32.624
1	2.182	48.78	32.815

Determine Firms' SO_2 Pollution Thresholds

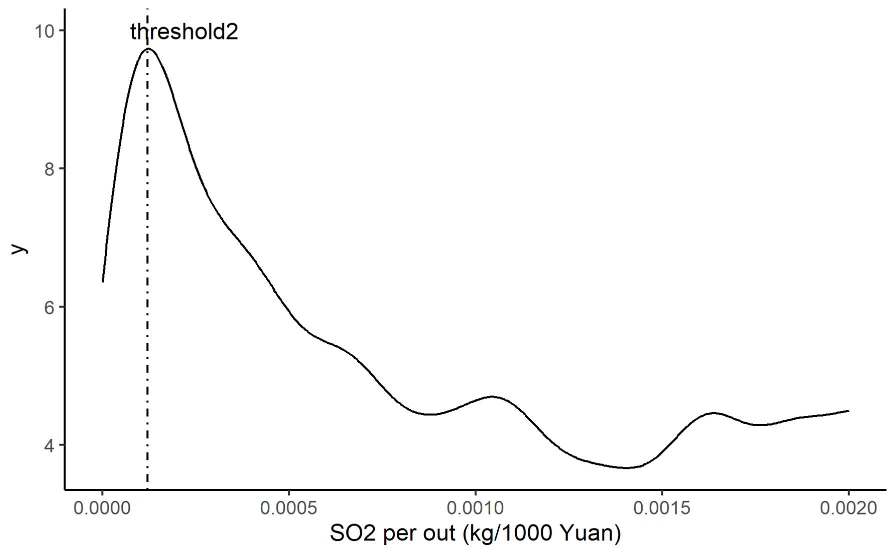
According to the KCAPC policy, local governments may impose different abatement requirements and standards on firms in particular industries or with certain pollution levels. In this case, some firms may not be affected by this policy because their pollution levels are relatively low. Thus, we use an SO_2 pollution threshold to determine which polluting firms may be affected by KCAPC policy. In the first step, we plot the density of all firms nationwide with SO_2 per output greater than zero and less than 99% quantiles from 1999 to 2009 (Fig.2). As a first SO_2 threshold, we set it to two times the mode of SO_2 per output produced, which is 0.0001174 kg/1000 Yuan. We define polluting firms as those whose SO_2 levels exceed the threshold. In this case, 15.7% of firms (including zero SO_2 emission firms) are below the threshold.

Fig. 2. the Density of Firms' SO2 per output (1999 to 2009)



Additionally, we set another SO_2 pollution threshold based on the mode of SO_2 per output between 1999 and 2001 since it is ideal if the pollution threshold remains external to KCAPC. The threshold is 0.0001213 kg/1000 Yuan (see Fig.3) and is used in the robustness check.

Fig. 3. the Density of Firms' SO2 per output (1999 to 2001)



<u>Determine Industrial Mobility</u>

Environmental regulations can lead to a sectoral reallocation of firms. Companies with high pollution levels tend to move to regions with fewer environmental regulations (Walter & Ugelow, 1979). Environmental regulations may also result in industrial firms closing or limiting entry because the cost of compliance is too high for them to make a profit (e.g., List et al. (2003)). As a result, most remaining firms could either have low pollution levels or low abatement costs. Consequently, empirical results will be undermined if the firms in the treated area cannot be compared to those in other areas.

Considering that our empirical research is conducted at the industry-city level, we separate the industries into three categories: exiting, entering, and industries with minimal entry and exit. In order to determine industrial mobility, we use the DID method to determine if the trend in gross industrial output, as a percentage of the industry at the country level, moves in the same direction in the treatment and control groups. The equation is as follows:

$$y_{ct} = \beta_0 post_t + \beta_1 KCAPC_{ic} + \beta_2 (KCAPC_{ic} \times post_t) + \epsilon_{ct}$$

The p-value threshold used to determine industries with minimal exit and entry levels is 15% at each tail (two tails). A 5% (one-tail) p-value is used to determine net entering and net exiting industries. Fig.4 explains how we determine industry categories and Table 2 shows the summary statistics for each of the three industry categories.

Fig. 4. Determine Exit and Entry Level for Each Industry

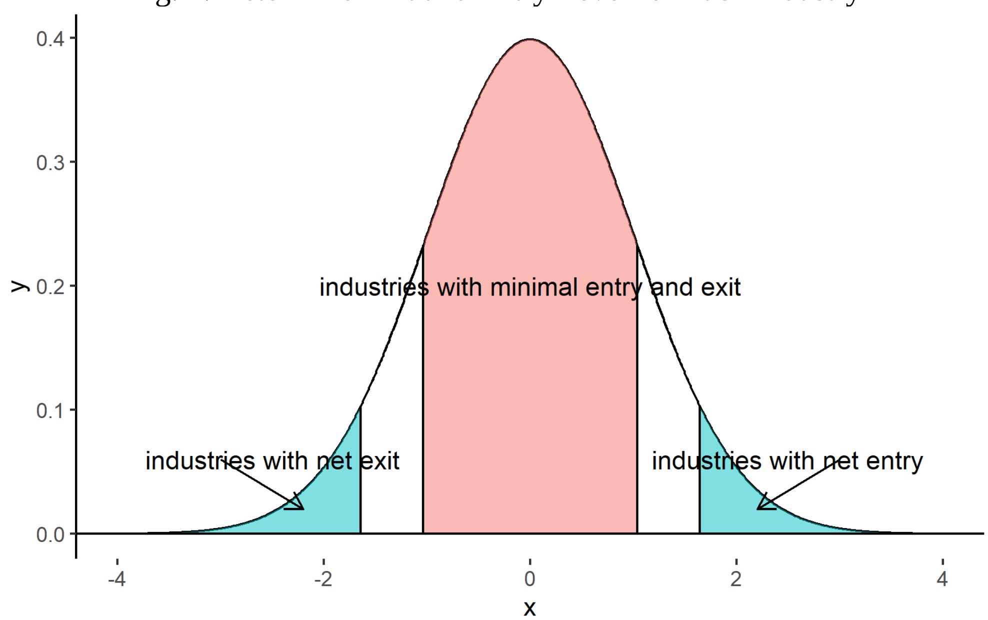


Table 2. Summary of Industry Types

Categories	Percentages[1]
Minimal entry and exit	42.449
Net entry	25.701
Net exit	3.790

[1]Note: net entry (at 5% significance level); net exit (at 5% significance level); minimal entry and exit (after excluding net entry and net exit industries at 15% significance level)

DID Estimations

Before analyzing KCAPC's effects on innovation and labor productivity, examining whether the KCAPC policy has successfully reduced pollution emissions is necessary. Following our estimation of KCAPC policy impacts on pollution reduction, we examine KCAPC policy impacts on innovation and labor productivity at the industrial city level. These variables are measured by the logarithm of the number of patent applications, the number of patent applications normalized by gross industrial output, and gross industrial output per labor.

The overall DID equation we use is:

$$\log(y_{ict}) = \beta_0 + \beta_1(KCAPC_{ic} \times post_t) + \alpha_{ct} + \gamma_{it} + \eta_{ic} + \epsilon_{ct}$$

The industry- city level data for each city are aggregated from polluting firms (those above the chosen SO_2 threshold). At the industrial level, we are interested in y_{ict} (SO_2 emissions, patent applications, labor productivity, etc.) for each city from 1999 to 2009. $KCAPC_{ic}$ equals 1 if an industrial level observation is in the KCAPC cities and otherwise equals 0. $post_t$ equals 1 for all years after 2001 (policy start year) and otherwise equals 0. $(KCAPC_{ic} \times post_t)$ is the interaction term which captures how much KCAPC cities differ on average from control cities in terms of y_{ict} at the industry-city level. $\alpha_{ct}, \gamma_{it}, \eta_{ic}$ are fixed effects variables. The standard errors are clustered at the city level.

Data Sources

In this study, we examine the effects of KCAPC policies on firms' innovation and labor productivity at the industry-city level using two firm-level panel datasets, China's Environmental Statistics Database (CESD) and China's Industrial Enterprise Database (CIED), that cover the period 1999-2009. Additionally, we use city-level data, such as the China City Statistical Yearbook (CCSY).

Firm-level Environmental Data

As China's most comprehensive micro dataset on environmental pollution, the CESD includes approximately 85% of each county's annual primary pollutant emissions (e.g., SO_2). CESD provides information on a firm's basic information (e.g., name, industry code), pollution emissions, equipment (e.g., number of waste treatment facilities), and environmental information at the firm level (e.g., abatement facility capacity and abatement cost). The CESD data we use for our empirical analysis pertains to SO_2 emissions, statistical year, ownership type, and industry code.

Firm-Level Economic and Patent Data

Another extensive database is the Chinese Industrial Enterprise Database (CIED). It contains over one hundred variables on the production and finances of state-owned and non-state-owned firms with an annual business revenue exceeding five million Chinese Yuan (CNY). China's CIED comprises more than 40 industries and more than 600 subindustries. The total output of these industries accounts for approximately 90% of all industrial output in the country. The CIED data we use for our empirical analysis include gross production output, ownership type, number of employees, and industry code.

The data from China's national intellectual property bureau contains patent applications and authorizations for industrial companies on a larger scale. Statistics include the basic information about the enterprises (e.g., name, industry code), three patent applications (invention, utility, and design patents), and three patent authorization statistics.

Other Data Sources

We also use city-level data from China City Statistical Yearbook (CCSY). CCSY is an annual city-level statistical publication produced by the National Bureau of Statistics of China. It covers the primary socioeconomic statistical data in 659 cities. Specifically, we use the information on average wages and proportions of the secondary and tertiary industries from 1999 to 2001. The city-level SO2 emissions and number of patent applications are aggregated from the firm-level CESD data.

Key Dependent Variables

The two critical dependent variables, both measured at the industry-city level, are: (1) the number of patent applications and (2) labor productivity.

The number of patents is a commonly used variable to measure innovation. However, many papers use patents per firm as indicators, disregarding the firm's scale. Considering that large firms usually have more patents than small firms, higher patent numbers may only indicate a higher proportion of large firms in cities rather than increased innovations. Moreover, we believe that the number of patent applications – as opposed to granted patents – is a more appropriate metric to evaluate firms' current innovation levels. Considering that patent applications may take a long time to process, this resulting lag time between patent application and patent approval implies the number of granted patents may not necessarily reflect the current innovation level of firms. To circumvent this, we use the number of patent applications normalized by gross production output per firm in the current year. When summing the number of patent applications each year, we only consider utility and invention patents, omitting design patents because they are less innovation driven. By imposing an innovation factor, we put more weight on invention patents than utility patents since the former usually have a higher level of innovation. The innovation factor is set to three. This is because it is the average number of years for invention patents to be granted, compared to less than a year for utility patents.

The main advantage of patent statistics over other R&D indicators is that they provide a measure of successful research results. In addition, they can be analyzed objectively since accounting practices are not taken into account. However, patents have several limitations in their capacity to quantify innovation effectively. According to Cohen et al. (2000), many firms prefer to keep their innovations confidential instead of disclosing them. Due to occurrences of concealment of innovations, patents can only measure a fraction of innovation that enhances productivity. Patents also cannot account for the efficiency gains resulting from implementing the most efficient technologies and effective managerial practices (Correa & Ornaghi, 2014).

We also use labor productivity as an alternative measure of technological and innovative progress. Labor productivity is measured as the industrial gross output per labor. Technology advances through process innovation can be captured in productivity indices such as labor productivity. Despite some firms' upgrading their production procedures with new technology, the market is still close to perfect competition, assuming highly similar final products. For future research, it would also be interesting to measure product innovation through relevant price indices considering quality improvements in new goods.

Descriptive Statistics

We obtained 7180 industry-city-year observations for the primary analysis (approximately 59% from KCAPC cities and 41% from non-KCAPC cities). Industry data are gathered from firms within industries that have consistently existed from 1999 to 2009. During the 11 years, 34 unique industries (e.g., metal product industry, textile industry, petroleum processing industry) remained in existence.

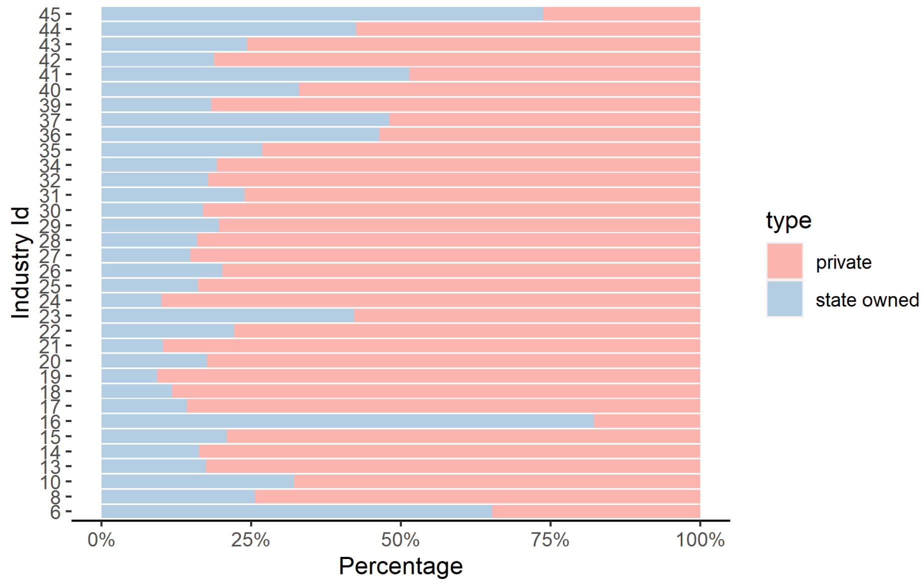
Table 3 shows the summary statistics (mean value, median value, standard deviation, and the number of observations) of the major variables that we used. Table 3 demonstrates that the observations in our sample exhibit great variation regarding nearly every variable.

Table 3. Summary Statistics at Industry-City Level (1999 - 2009)

Variable	N	Mean	Median	Std.Dev.	Range
SO2 emissions (kg)	7180	18658	3747	60395	1-2217616
Numbers of employees (persons)	7180	2255	702	6399	0-194410
Total industrial output value (one thousand Yuan)	7180	1142454	225612	4055011	686-128398005
Patent applications (unit)	7180	3.2	0	24.9	0.0-1158.0

Fig. 5 shows the proportion of state-owned versus non-state-owned firms in 34 industries. On average, 27.8% of firms in an industry are state-owned. A higher than 50% share of state-owned firms is found in five industries.

Fig. 5. The Percentage of Private vs State-Owned firms in Each Industry



Identification Assumption Checking

We first check on the identification assumption to ensure that the treatment group would have tracked the same trend as the control group in SO_2 emissions without the KCAPC policy. Figs. 6-7 provide coefficients and 95% confidence intervals for KCAPC-year interactions from 1999 to 2009 based on DID regressions for ln(SO2) and ln(SO2 per output). Before the policy was implemented, KCAPC-year interactions did not significantly differ from zero, indicating that pollution emission trends are similar for KCAPC and non-KCAPC firms. After the policy, SO2 emissions decreased significantly.

Fig. 6. Policy Effects on Industry-City Level SO_2 Emissions

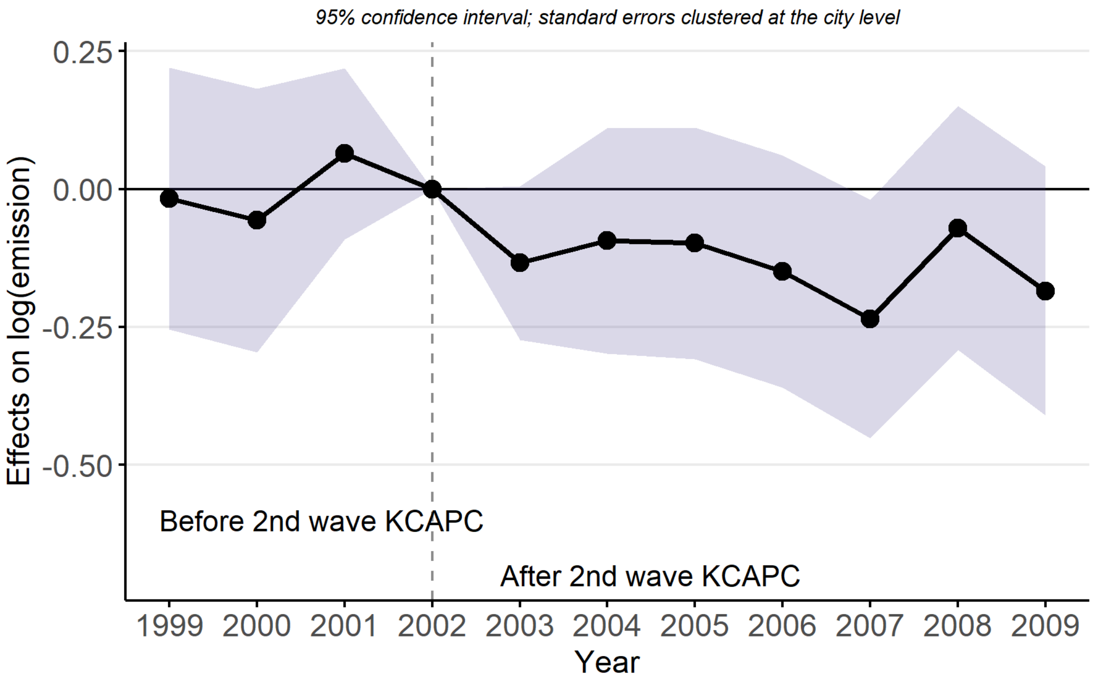
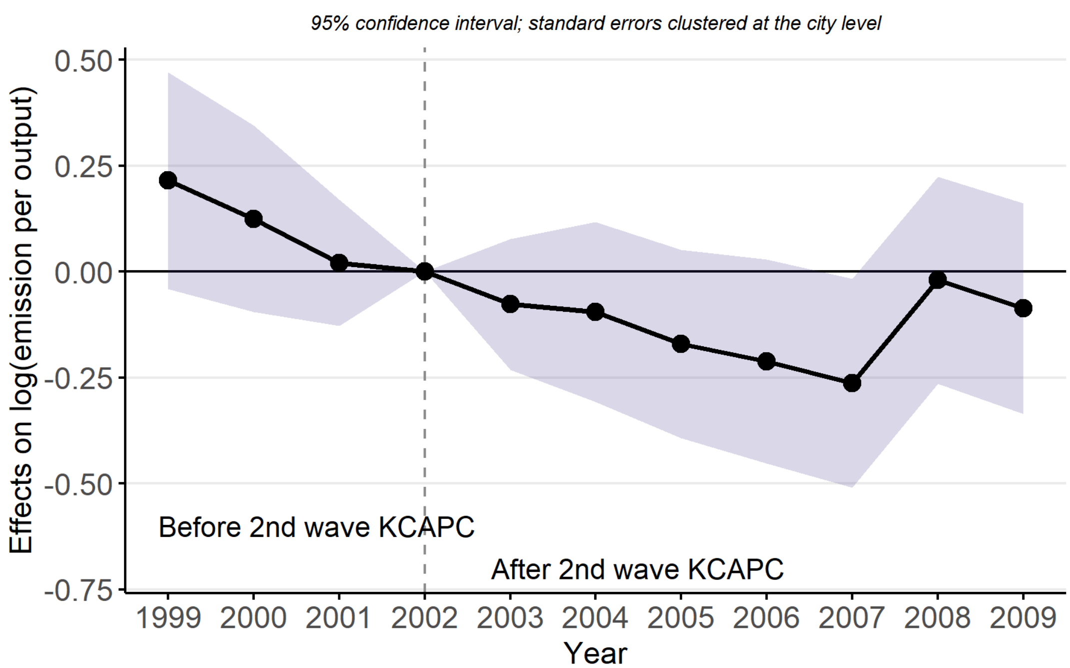


Fig. 7. Policy Effects on Industry-City Level SO_2 Emissions per Output



Results

Next, we investigate whether the KCAPC policy will boost innovation and labor productivity after demonstrating its effectiveness in reducing SO2.

Main results

This section assesses whether KCAPC systematically affects innovation measured by patent applications and labor productivity across various s. Overall, the number of patent applications increases in industries from the treatment cities – supporting the weak Porter Hypothesis – compared with that from the control counterparts.

Firms' innovation increases in treatment cities, as evidenced by the increase in innovation-driven patent applications. Estimates on KCAPC × Post, our major variable, are significantly positive when we evaluate the impact of KCAPC policy on firms' patent applications (see Table 4). Accordingly, manufacturing industries in KCPAC cities, because of stricter environmental standards after policy enaction, applied for significantly more patents than firms in the matched control group, whether they are state-owned or not. The results show that the proposed air pollution control policy has led to significant increases in innovation in treatment cities' manufacturing sector. According to the point estimate, KCAPC industries had a 7.9% higher increase in patent applications than non-KCAPC industries. Private firms have a more pronounced innovation promotion effect. In comparison to non-KCAPC industries, KCAPC industries experienced a significant increase of 10.7% in patent applications. However, there is no evidence supporting a strong Porter Hypothesis, as the impact of KCAPC policy on labor productivity improvement is not significant in general; while the effect is positive it is not statistically significant.

Table 4. Main Results at the Industry-City Level

	ln(patent applications)	ln(output per employee)	ln(patent per output)
	all firms		
KCAPC× post	0.079**	0.037	0.057
	(0.037)	(0.046)	(0.057)
	private firms only		
KCAPC× post	0.107**	0.032	0.099
	(0.045)	(0.051)	(0.066)

Standard errors clustered at the city level in parentheses.
$*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Heterogeneity

In this section, the heterogeneity of treatment effects is investigated using the same specifications as in the empirical framework. Our study analyzes KCAPC's heterogeneous effects across industry types, firm ownership types, and time horizons.

<u>Industry and Firm Ownership Heterogeneity</u>

Depending on their ownership and industry type, firms may differ in their financial status, environmental performance, technological advancement, and innovation capability. We split the sample into state-owned and non-state-owned firms while also considering industry mobility to mitigate policy spillover effects.

The innovation effect weakened or strengthened under different scenarios (see Table 5). For example, both patent applications and labor productivity significantly increased in industries and cities where more firms were entering. Labor productivity increased in entering industries are more significant when considering only private firms. The point estimate shows that private firms in KCAPC-entering industries had a 22.7% higher increase in patent applications than those in non-KCAPC industries. The innovation effect and labor productivity improvement may or may not be directly driven by the KCAPC environmental policy. It may partly be influenced by firm mobility and the broader external context, such as industry environment and firm-local government interactions.

Table 5. Heterogeneity in Industry Types

	all firms		
	ln(patent applications)	ln(output per employee)	ln(patent per output)
Entering Industries			
KCAPC× post	0.234***	0.119*	0.232**
	(0.0062)	(0.072)	(0.090)
Stable Industries			
KCAPC× post	0.043	0.022	-0.051
	(0.055)	(0.051)	(0.085)
Exiting Industries			
KCAPC× post	0.184	-0.019	0.341*
	(0.037)	(0.046)	(0.057)
	private firms only		
Entering Industries			
KCAPC× post	0.200***	0.221**	0.227**
	(0.063)	(0.084)	(0.107)
Stable Industries			
KCAPC× post	0.074	-0.09	0.084
	(0.078)	(0.061)	(0.121)
Exiting Industries			
KCAPC× post	-0.176	0.071	-0.273
	(0.257)	(0.198)	(0.468)

Standard errors clustered at the city level in parentheses.
$*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

In industries where entry and exit were minimal, the increase in innovation supporting the weak Porter Hypothesis concentrated on private firms with relatively small positive profits (See Table 6). These findings could be explained by firms with small positive profits having a larger incentive to innovate so as to increase their profitability. In these firms, labor productivity had not improved significantly since the policy was implemented. In light of these two results, it could be suggested that these firms focus primarily on improving the final product quality or reducing production costs in aspects other than labor.

Table 6. Results for Low-profit Firms in Stable Industries

	ln(patent applications)	ln(output per employee)	ln(patent per output)
	all firms		
KCAPC× post	0.025	0.103	0.087
	(0.017)	(0.091)	(0.085)
	private firms only		
KCAPC× post	0.037*	-0.057	0.130*
	(0.020)	(0.117)	(0.074)

Consider firms with profits in the last 10 percentile.
Standard errors clustered at the city level in parentheses.
$*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

In industries where entry and exit were minimal, the strong Porter Hypothesis is supported by private firms in relatively low pollution quantiles, as their labor productivity increased significantly more than in the control group at a 1% level of significance (See Table 7). However, those firms with low pollutant quantiles did not experience a significant increase in patent applications following the KCAPC policy. Thus, the improvement in labor productivity may be due to overcoming organizational inertia to reduce management costs. It may also be due to the spillover of innovation from firms with more patent applications that may have higher pollution levels. In addition, those firms may find it more convenient to adjust their production and pollution abatement process without needing significant technological improvement.

Table 7. Results for Low-Pollution Firms in Stable Industries

	private firms at the lowest pollution level[1]	
	ln(patent applications)	ln(output per employee)
KCAPC× post	0.027	0.318***
	(0.064)	(0.109)

Divide all polluting firms into six pollution levels; exclude polluting firms where emission is above the top 2.5% percentile.
Standard errors clustered at the city level in parentheses.
∗p < 0.1, ∗∗p < 0.05, ∗∗∗p < 0.01.

Time Horizon Heterogeneity

We see a static average treatment effect from the baseline estimation. However, examining how KCAPC impacts firm innovation and labor productivity over the short- and medium-term horizons is needed, as it takes time for firms to respond to the policy and innovate.

There is no evidence of the innovation effect in the short run, but it is evident in the medium run. At the beginning of the policy implementation, firms in the second batch of KCAPC cities adjusted to the new regulations and engaged in more R&D activities. As a result, innovation effects were insignificant for a short initial period (until 2015) since the emerging innovation activities have yet to materialize into patent applications (see Table 8). As time progressed (until 2019), these firms' uptick in R&D activity manifested itself in patent applications, with a significant positive impact on patent applications (see Table 9).

Table 8. Main Results: Short Run (1995 to 2005)

	all firms		
	ln(patent applications)	ln(output per employee)	ln(patent per output)
KCAPC× post	0.043	0.038	0.019
	(0.027)	(0.035)	(0.053)
	private firms only		
KCAPC× post	0.039	0.03	0.018
	(0.031)	(0.042)	(0.062)

Standard errors clustered at the city level in parentheses.
$*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Table 9. Main Results: Medium Run

	all firms		
	ln(patent applications)	ln(output per employee)	ln(patent per output)
KCAPC× post	0.117**	0.038	0.095
	(0.053)	(0.065)	(0.074)
	private firms only		
KCAPC× post	0.171***	0.038	0.180**
	(0.062)	(0.066)	(0.083)

Standard errors clustered at the city level in parentheses.
$*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

. Within short periods, the innovation effect measured by patent applications increased in industries with more firms entering, and labor productivity improved for private firms in those industries (see Table 10). This finding indicates private firms' competitiveness and efficiency. Over the medium term, all firms had an overall increase in labor productivity (see Table 11). However, there is one caveat for interpreting the results of industries with a net entry. The innovation effects of these industries may be caused by the business environment or by the fact that companies are more innovative from the beginning. Thus, the innovation offsets may not directly result from environmental policies.

Table 10. Heterogeneity in Time Horizons - Short Run (1999 to 2005)

	all firms		
	ln(patent applications)	ln(output per employee)	ln(patent per output)
Entering Industries			
KCAPC× post	0.121***	0.093	0.161**
	(0.040)	(0.067)	(0.080)
Stable Industries			
KCAPC× post	0.021	0.047	-0.066
	(0.042)	(0.041)	(0.083)
	private firms only		
Entering Industries			
KCAPC× post	0.112***	0.194***	0.142
	(0.040)	(0.074)	(0.101)
Stable Industries			
KCAPC× post	0.008	-0.063	-0.03
	(0.063)	(0.059)	(0.129)

Standard errors clustered at the city level in parentheses.
$*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Table 11. Heterogeneity in Time Horizons - Medium Run

	all firms		
	ln(patent applications)	ln(output per employee)	ln(patent per output)
Entering Industries			
KCAPC× post	0.337***	0.149*	0.293**
	(0.090)	(0.085)	(0.123)
Stable Industries			
KCAPC× post	0.068	-0.001	-0.03
	(0.077)	(0.069)	(0.113)
	private firms only		
Entering Industries			
KCAPC× post	0.287***	0.243**	0.306*
	(0.105)	(0.104)	(0.156)
Stable Industries			
KCAPC× post	0.137	-0.107	0.194
	(0.100)	(0.074)	(0.133)

Standard errors clustered at the city level in parentheses.
$*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

In industries with minimal entry and exit, there is no evidence of innovation improvement or increased labor productivity in either the short- or medium-term (See Tables 10-11). This may be due to the fact that firms in stable industries are the least affected by the KCAPC policy across all three industry categories. It is possible that these industries have fewer polluting firms or that they are leading industries in KCAPC cities that are already very competitive. Furthermore, they may be able to negotiate with local governments on abatement processes and worry less about regulations. As a result, they may have less incentive to innovate and improve productivity.

It should be noted that a comparison of innovation and productivity levels between KCAPC cities and control cities may be influenced by other factors or policies in the medium-term. For instance, economic development may be better in control cities since the KCAPC cities receive more attention from the government.

Robustness Tests

<u>Changing the SO2 Pollution Threshold</u>

As part of this robustness check, we develop a new sample of polluting firms using the pollution levels prior to the policy period (as outlined in the empirical framework section). We then perform the DID on overall patent application numbers. It is almost identical to the main result in terms of coefficient magnitude and significance level (Appendix - Table 13). There is a significant increase in patent applications in industries from the treatment cities relative to the control cities at a 5% significance level.

<u>Robustness Check for Entering Industries</u>

Before 2000, there were very few patent applications in the country. Using 1999 as an example, there were 3066 patent applications at the country level (excluding design patents and weighted by the average grant year). Comparatively, 10740 patent applications were filed at the country level in 2002.

To solve the potential concern that patent data may not be accurate before the year 2000, we conduct a different DID only after 2001. Within each industry, we split the data into two categories: firms above the emission threshold (polluting firms) and those below the emission threshold. Since the policy should only influence those polluted firms for every industry in treatment cities, the DID equation is as follows:

$$\log(y_{jct}) = \beta_0 + \beta_1(KCAPC_{jc} \times polluting_j) + \alpha_{ct} + \gamma_{jt} + \eta_{jc} + \epsilon_{ct}$$

Patent application coefficients are still statistically significant (at the 10% level this time) for industries entering treatment cities in both cases (private firms only and all firms). At a significance level of 5%, all firms in the "entering" industries experience a significant increase in labor productivity (Appendix - Table 14). Thus, the results are robust.

Permutation Test

Our test statistic for the previous main result on patent applications is recalculated using the permutation of treatment assignments in our KCAPC cities. After repeating this process 500 times, we plot an approximation to our distribution of all possible coefficients of the interaction term in DID. Observing where our initial coefficient falls within this distribution, we find that only 4% of our 500 test statistics are as extreme as our initial coefficient (Appendix - Fig 8). In this case, the result is robust.

Conclusion

This paper investigates the effect of the Key Cities for Air Pollution Control (KCAPC) policy on firms' innovation and labor productivity in China, in order to test the Porter Hypothesis. Specifically, we analyze a quasi-experiment in China in which the Beijing government imposed environmental regulations on some selected cities in 2001. We apply Propensity Score Matching to form treatment groups and conduct Difference-in-Difference analysis.

Our study has yielded three main results. First, we find that environmental regulations do stimulate industrial innovations in China in general, consistent with the weak Porter Hypothesis. Secondly, in industries with minimal entry and exit, innovation was concentrated within private firms with small positive profits, supporting the weak Porter Hypothesis. Firms with low pollution quantiles in those industries have a significant increase in labor productivity, but not in innovation, as measured by patent applications. Third, we find some evidence in favor of the strong Porter Hypothesis, particularly in industries in treatment cities where more firms were entering. In these entering industries, both patent applications and labor productivity significantly increased.

These findings are constrained by certain limitations. KCAPC numbers have increased over the years, as evidenced by more treatment cities in the second batch. Firms may therefore expect that the control group will not remain untreated for long. In this case, the results might be underestimated, especially in the long run. Further, industry characteristics, firm characteristics, or environmental factors may influence innovation. There is still a need to investigate the mechanism behind innovation and productivity improvement in "entering" industries where both weak and strong Porter Hypotheses are evident.

Our study contributes to the literature on policy implications of achieving win-win situations between better environmental quality and a high-quality economy fueled by innovation in developing countries. In light of our research, policymakers may consider developing policies in treatment cities to support low-profit private firms in industries with low entry and exit rates by increasing their innovation compensation effects resulting from environmental regulations.

APPENDIX

Table 12. Robustness Check for Main Results at the Industry-City Level

	all firms		
	ln(patent applications)	ln(output per employee)	ln(patent per output)
KCAPC× post	0.079**	0.037	0.057
	(0.037)	(0.046)	(0.057)
	private firms only		
KCAPC× post	0.107**	0.032	0.099
	(0.045)	(0.051)	(0.066)

Standard errors clustered at the city level in parentheses.
$*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

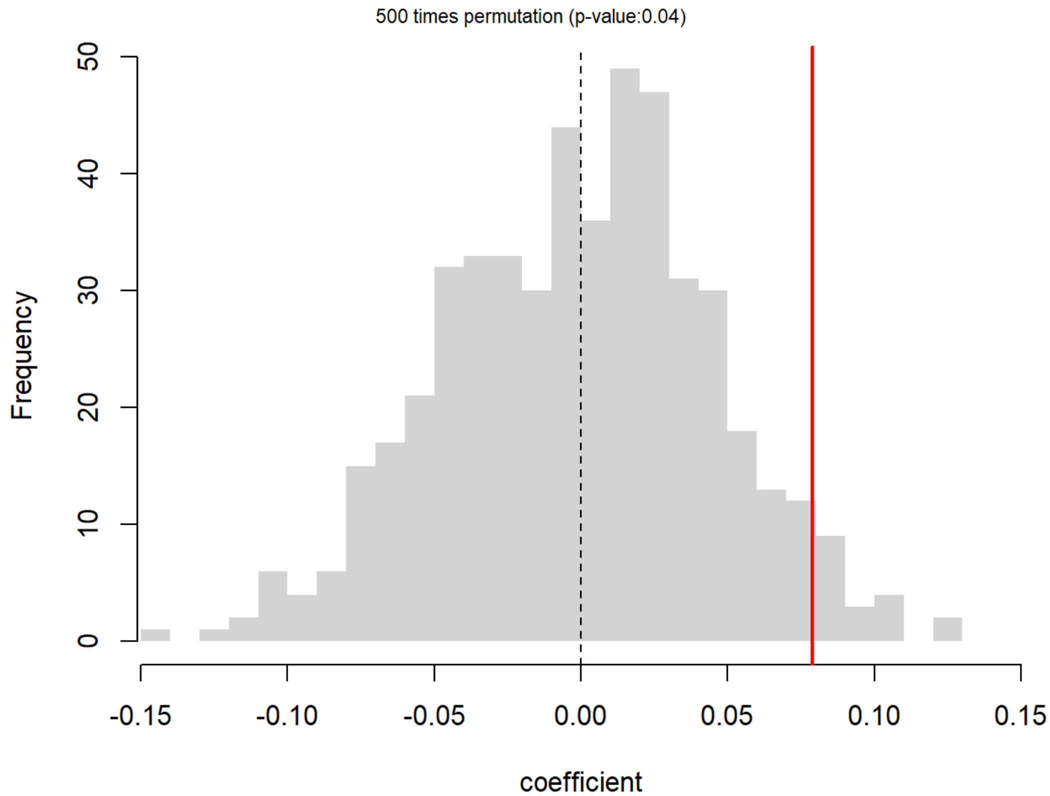
Table 13. Robustness Check for Entering Industries at the Industry-City Level

	all firms		
	ln(patent applications)	ln(output per employee)	ln(patent per output)
KCAPC× post	0.395*	0.109	0.00216
	(0.228)	(0.0874)	(0.439)
	private firms only		
KCAPC× post	0.561*	0.208**	-0.210
	(0.326)	(0.0988)	(0.779)

Standard errors clustered at the city level in parentheses.
$*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

APPENDIX

Fig. 8. The Distribution of Coefficients on the Interaction Term from the Main Regression for ln(Patent applications)



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