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Publication date:
2023

Document Version
Other version

Link to publication in Discovery Research Portal

Citation for published version (APA):
Sun, P., Zhu, T., & Loeschel, A. (2023). *Regulation through revelation: The effect of pollution monitoring on labour demand*. (pp. 1-33).

Regulation through revelation: The effect of pollution monitoring on labour demand

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Regulation through revelation: The effect of pollution monitoring on labour demand

Abstract

For any environmental regulation to be effective it requires adequate monitoring and enforcement. This paper aims at studying the causal effects of a real-time pollution monitoring programme on the level of firms' employment. Employing entropy balancing on a unique firm-level dataset, we find that the enhanced regulatory monitoring has a significant and robust positive impact on the employment of monitored firms. Further investigations suggest that positive employment effects are primarily driven by changes in capital investment and subsequent output increase. Our results are independent from ownership and other energy policies during the same period. The study sheds new light into the benefits of regulatory monitoring and enforcement activities.

JEL codes Q52; Q58; D22
Keywords: Environmental enforcement; firm behaviour; employment

1 Introduction

Enforcement of environmental regulation relies on accurate information of pollutant release and compliance behaviour. Although environmental goals can be ambitious and comprehensive at an aggregate level, weak enforcement and insufficient monitoring can impede the effectiveness of environmental regulations. A recent survey conducted by the UN Environment Programme in 176 countries highlights that weak enforcement of environmental regulation is a global trend exacerbating environmental threats (UNEP, 2019). In developed counties such as the U.S., regulators have increasingly emphasized non-traditional enforcement strategies, including the use of remote sensing technologies and high-frequency tracking systems targeted at extreme violators. Novel enforcement tools help allocate limited enforcement resources more effectively. Furthermore, the accountability of local regulators is strengthened in the context of environmental federalism.

The present study investigates the impact of a real-time pollution monitoring scheme on the economic performance and labour demand of manufacturing firms. Specifically, we make use of the National Specially Monitored (NSM) Firms programme launched by the central government of China in 2007 as a quasi-experiment. Key measures of the programme include that emitters above a certain threshold are required to install automatic monitoring systems and submit real-time pollutant release data to the national monitoring network operated by the State Environmental Protection Administration (SEPA). Compared to conventional self-reporting and intermittent auditing, the closer scrutiny of polluting behaviour eliminates potential information asymmetry between emitters and regulators. Therefore, the programme exerts influence on regulated firms' perceptions of the effectiveness of environmental regulations (Earnhart and Friesen, 2017). From the perspective of environmental federalism, the programme lowers the possibility of collusions between emitters and local regulators, as the monitoring network is run by the national agency SEPA. Potential pitfalls associated with discretionary enforcement of environmental regulations are likely to be reduced at the local level (Zhang et al., 2018; Duflo et al., 2018; Yu and Zhang, 2020).

The present study aims to deepen the understanding of strategic responses by firms facing enhanced environmental monitoring and enforcement. The contribution of the study is three-fold. First, this study contributes to the growing literature on the economics of environmental monitoring and enforcement, particularly from the perspective of developing countries. Currently most of existing studies focus on developed countries, especially the U.S. (e.g. Evans, 2016; Earnhart and Friesen, 2017). A pervasive pollution monitoring system is perhaps particularly important to developing countries such as China and India, as it promotes data accuracy and accountability that are often questioned in developing countries. We study the impact of a nationwide pollution monitoring network in China. As one of the largest greenhouse gases emitters globally, effective implementation and enforcement of environmental regulations is crucial to achieve China's pledge to become carbon neutral by 2060. This implies that our study is particularly relevant to current academic and policy discussions.

Second, the present study is to be one of the first to examine the labour and economic responses of firms facing enhanced environmental enforcement. Recent evidence suggests that enforcement tools have played a significant role in reducing emissions and curbing noncompliance behaviour (e.g. Evans, 2016; Zhang et al., 2018). However, a still unsolved question is concerning the medium- and long-term substitution of economic activities of firms under enhanced pollution monitoring. The current study contributes to narrowing this gap. The NSM programme sets no specific requirements on emissions reduction and technology adoption, increasing firms' flexibility to search for the optimal means to improve environmental records. Moreover, as the NSM programme includes firms according to their relative ranking positions in emissions, our study is also related to the growing literature on the relative performance mechanism in the environmental context (e.g. MacKenzie et al., 2008, 2009; Kuosmanen and Johnson, 2020).

The third contribution of the study is that we disentangle different channels through which enhanced pollution monitoring impacts labour demand. Past studies have suggested mixed responses of firms facing environmental regulations (e.g. Berman and Bui, 2001; Morgenstern et al., 2002; Cole and Elliott, 2007; Walker, 2011). Various intermediate effects associated with stringent environmental regulations may contradict each other, eventually leading to ambiguous conclusions. In the present study we set up a causal mediation framework using the entropy re-weighted sample, and estimate the direct and indirect effects of pollution monitoring on firm employment. Four factors that are likely to contribute to the employment effect are identified, namely output, capital investment, management costs and innovation.

Our methodological approach is to combine the entropy balancing approach with a difference-in-differences (DID) estimator to identify the causal relationship between the NSM programme and the subsequent effect on the economic performance of polluting firms. The raw sample is re-weighted using the technique of entropy balancing so that the control firms (firms that have never been included in the NSM programme) are virtually identical to the treated firms (firms that are subject to the NSM programme) in terms of key firms characteristics (Hainmueller, 2012; Hainmueller and Xu, 2013). To briefly preview the results, we find that the NSM programme had a statistically significant and robust positive impact on the level of employment of monitored firms. After the NSM programme is in place, the total number of employees of NSM firms increases by approximately 11.4% compared to non-NSM firms everything else bing equal. This effect is significant and consistent across specifications with different fixed effects being considered. The increase in skilled labour tends to be larger than the increase in unskilled labour. The positive job effect is found to be particularly prominent after two years of being monitored and to NSM firms that join the programme within the first two years of its initiation. We did not find evidence showing that state-owned firms are affected differently than non-state-owned firms by the NSM programme. Results from the mediation analysis suggest that the increase in labour demand was partially driven by the increase in capital input and subsequent production expansion. Our results hold up to a variety of robustness checks, e.g. testing the validity of the assumptions to causal mediation analysis.

The economic theory on environmental monitoring and enforcement stems from the public enforcement of law literature, and often involves the development of game-theoretic models on the strategic interaction between regulators and firms (Gray and Shimshack, 2011; Shimshack, 2014). Under this framework, a polluting firm gains economic benefits from low level of abatement activities. Firm weights the economic benefits of inadequate abatement efforts and the penalties of being caught in noncompliance. Firm's decision on abatement efforts is a function of several factors such as the perceived probability of being detected if noncompliance, the possibility of collusion with regulators, and the magnitude of penalties if it is levied. As Gray and Shimshack (2011) suggest, effective monitoring is assumed to raise the probability of an inspection, the probably of a sanction, and/or sanction severity. The compliance actions are hypothesized to increase, and pollution actions decreased due to the enhanced regulatory threat.

Recent empirical work on environmental monitoring and enforcement include Evans (2016); Zhang et al. (2018); Duflo et al. (2018); Raff and Earnhart (2019); Blundell (2020); Blundell et al. (2020). Zhang et al. (2018) investigates the impact of the NSM programme on firm wastewater discharge and finds that the central supervision on local enforcement reduces local waste water discharge significantly. Blundell (2020) and Blundell et al. (2020) study the impact of dynamic enforcement, where penalties are set based on firms' past compliance history. Substantial improvement in abatement efforts are found among firms with the highest expected costs of compliance. Evans (2016) studies the impact of a watch list designed by U.S. Environmental Protection Agency and subsequently released publicly. The average violation probability fell between 10-15% as a result of the creation of the watch list, and fell between 15-23% as a result of the public release of the watch list. Duflo et al. (2018) consider a dynamic model of pollution regulation in India and find that discretionary inspection of regulators improved abatement significantly. A closely related study to the present one is Raff and Earnhart (2019). The difference between the current study and Raff and Earnhart (2019) is that we look at the changes in different types of labours, input adjustment and economic performance for industrial firms over the recent decade, while Raff and Earnhart (2019) only focuses on environmental labour in chemical manufacturers between 1999 and 2001. Our study highlights the dynamics of the effectiveness of the monitoring programme.

The remainder of the paper is organized as follows. Section 2 introduces the NSM programme and describes the data. Section 3 presents the empirical approach and Section 4 presents the results. In Section 5 we investigate the impact mechanism. The final section concludes.

2 Background and data

2.1 The National Specially Monitored firms programme

The NSM programme was launched in 2007 by the SEPA as part of the nation's commitment towards effective pollution control during the Eleventh Five-Year Plan period (2006-2010). To facilitate the progress, the SEPA initiated the nationwide pollutant release monitoring programme, which requires firms that discharge certain types of pollutants above the threshold to submit real-time pollutant release data to the monitoring network run by the SEPA. The participant list was posted on the SEPA website for the first time on 30th March 2007, and subsequently reported by the press and online media.[1] The purpose of the programme is to not only collect accurate information on pollutant release, but also draw firms' attention to the pressing environmental issue, empower the regulator to fight pollution with increased knowledge and transparency.

Taking the 2007 list as an example, the screening process consists of three steps: first, industrial firms that emit (or discharge) one of the certain substances are ranked in a descending order according to the emissions information in 2005. The substances include industrial sulphur dioxide, soot, industrial dust for air emissions, and chemical

[1] The 2007 list is posted on the central government website with the descriptions of the screening criteria (in Chinese) http://www.gov.cn/govweb/zfjg/content_566589.htm. Major online media, e.g. Sina (http://news.sina.com.cn/c/2007-03-30/150112655629.shtml) and Sohu (https://business.sohu.com/20070330/n249091896.shtml) reported the NSM programme subsequently.

oxygen demand (COD) and ammonia nitrogen ($NH_3 - N$) for wastewater discharge. The firm-level emissions and discharge information is collected from the administrative dataset of Chinese Environmental Statistics 2005. Second, top emitters that contribute to 65% of the total national emissions are assigned to be NSM firms. Third, all urban waster water treatment plants are included in the monitoring programme. The list of participants is updated annually based on pollution data from two years ago. For example, the 2009 list was issued on 23th March 2009, based on the pollution data of 2007.[2] After the initial ranking, the preliminary list is sent to local environmental protection bureaus for confirmation. Firms that cease operations or close permanently will be removed from the list. Modifications to screening criteria have been made continuously in the following years. For example, additional types of substances are added to the screening criteria in 2011.[3] Livestock farms above certain scales and firms that produce hazardous waste above thresholds are included in the programme in 2013 and 2015 respectively.

Presumably the NSM programme influences firm behaviour due to at least four reasons. First, the implementation of environmental standards is enhanced. NSM firms are required to install real-time monitoring equipments, and are subject to instantaneous regulatory oversight on polluting and compliance behaviour. Particularly, they are the focus of the issuance of the Pollutant Discharge Permit, and the collection of the Pollution Discharge levy. The Pollutant Discharge Permit system was introduced in the early 1990s, and every polluter is required to register with local environmental protection bureaus and apply for permits which limit both the quantities and concentrations of pollutants. The system is considered to be fragmented at the initial stage and not coherently applied across the country due to insufficient resources and lack of consistent binding provisions (Michalak and Mazur, 2006; Liu et al., 2019). The pollution levy provides economic incentives for emissions reduction with sanctions in case of non-compliance. While in practice, the charges are usually negotiated between local regulators and polluters rather than calculated using formulas detailed in the regulation (Wang et al., 2003; Michalak and Mazur, 2006). The NSM programme provides fundamental support to the application of the permit system and the collection of pollution levy. Meanwhile, it implies that NSM firms may face higher payments of pollution levies and may therefore response to rising costs of pollution.

Furthermore, the NSM programme is likely to incur additional management costs,

[2]The 2009 list can be found in the following website http://govinfo.nlc.cn/hbsfz/xxgk/hbsdsj/201111/t20111121_1104386.html. To our best knowledge, no name list was issued for 2008.

[3]The 2011 list with the description of screening criteria (in Chinese) can be found in the following website http://guoqing.china.com.cn/zwxx/2011-10/23/content_23703043.htm. For wastewater discharging, five types of heavy metal are taken into consideration apart from COD and NH3-N, including Arsenic (As), lead (Pb), mercury (Hg), cadmium (Cd), hexavalent chromium (Cr(VI)).

as NSM firms are the focus of on-site examination, off-site reviews and forward-looking supervision. Local environmental agents conduct on-site pollution audits at least once per month to NSM firms. Frequent and complicated reporting process may imply increased administrative burdens and additional paper work to NSM firms. Third, the possibilities of data manipulation and collusions between polluters and local regulators are ruled out. Duflo et al. (2018) and Zhang et al. (2018) argue that under the principal-agent model with asymmetric information, the decentralized system of environmental governance empowers local authorities considerable regulatory discretion towards the implementation of environmental regulations at the local level. With the NSM programme, pollutant release is monitored in near-real time and overseen by the national regulator SEPA. The discretionary power of local regulators in law enforcement is significantly reduced, as well as the likelihood of collusion. Fourth, the NSM programme prioritizes monitored polluters in terms of technical assistance, financial support, education and trainings, technology transfer, and demonstration projects. NSM firms benefit from these supports and are incentivised to identify strategies and options for emissions reduction. Consequently, NSM firms are more likely to identify cost-effective practices to reduce their impact on the environment while staying competitive and profitable.

2.2 Data

Our data are derived from the combination of two unique datasets. The first is the list of NSM firms collected from the SEPA website. The list data contain information on the name, address of the NSM firms, and if it is under air pollution monitoring or water pollution monitoring, or both. The second is a dataset containing information of all mainland-based listed enterprises in China, collected from the WIND database. The following steps outline the cleaning and merging process. We use A-shares manufacturing firms listed in the Shanghai Stock Exchange (SHSE) and Shenzhen Stock Exchange (SZSE). We drop firms that are under "Special Treatment" as they are likely to be delisted.[4] We drop firms where the listing year is earlier than the establishment year. Firms are also dropped if the values of key covariates are missing for the years before the NSM programme. We winsorize the top 1% and the bottom 1% of the dataset to eliminate influences of outliers. As the monitoring programme is implemented at plant level, we aggregate the NSM list data up to the firm level. A firm is defined as a NSM firm if any subordinate plant is subject to the NSM programme. Similarly, a

[4] In both stock exchanges, stocks in danger of being delisted (e.g. losing in two successive fiscal years) are labelled as "special treatment" stocks and are subject to an administrative review by the Chinese Securities Regulation Commission. Please refer to Li et al. (2014) and Geng et al. (2015) for more information on the "special treatment" status of listed firms.

multi-plant firm may have more than one subordinate plant that are subject to the monitoring programme. Our final sample is a balanced panel consisting of 450 firms (4950 firm-year observations). The use of a balanced panel dataset enables us to trace the history of firm performance before the monitoring programme, and excludes the impact of market entry and exit on our analysis.

The list of NSM firms is usually released in the fist quarter of the year. A total of 136 firms, approximately 30% of our final sample, showed up on the NSM list at least once between 2007 and 2016. The average number of years that a NSM firm is monitored is 6.6 years, while the median is 7 years. Approximately 47% of the NSM firms join the programme in 2007, the starting year of the programme; approximately 60% of the NSM firms stay in the programme and never exist. Figure 1 depicts the dynamics of NSM firms over the period of 2006 to 2016. The red line and the green line describe the numbers of firms joining and dropping out of the programme in a given year; the blue line represents the total number of NSM firms in a year. Figure 1 shows that the number of NSM firms has been growing over time and remains relatively steady since 2012.

Figure 1: Dynamics of the NSM programme (2006-2016)

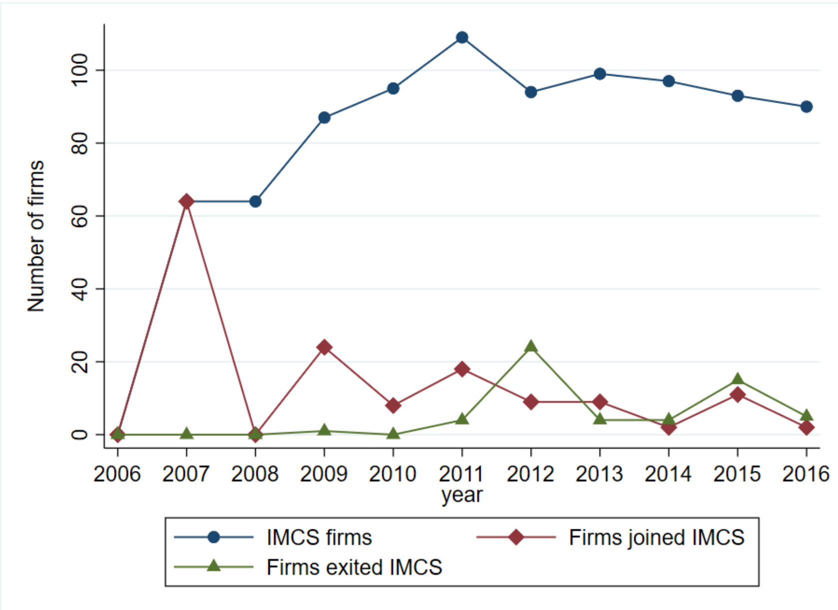


Table 1 presents the proportion of NSM and non-NSM firms in our sample. Among the 450 firms, there are 136 firms that have been included in the monitoring programme for at least one year during the period of 2006 to 2016 (NSM firms); among the 136 NSM firms, there are 54 NSM firms exit the monitoring programme at some point of the sample period. The number of firm-year observations in each category is eleven times the number of firms. Table 2 reports summary statistics for NSM firms and non-

Table 1: Types of firms (2006-2016)

Types		Firm no.	Firm no.(%)	Firm-year obs.
NSM firms	Incumbent	82	18.22	902
	Exiters	54	12.00	594
Non-NSM firms		314	69.78	3,454
Total		450	100	4,950

Note: A NSM firm is a firm that has been subject to the NSM programme for at least one year during the sample period. An incumbent is a NSM firm that joins the programme and never exits during the sample period. A exiter is a NSM firm that joins and exits the programme during the sample period. A non-NSM firm is a firm that has never been subject to the programme during the sample period.

NSM firms respectively. NSM firms are substantially different from non-NSM firms. Difference of means tests indicate significant differences between NSM and non-NSM firms for most of our variables reported in the table. On average, NSM firms are larger than non-NSM firms in terms of employment, total asset, output, cost and capital, and more likely to be state-owned with government officials in corporate boards. Table 2 hints at the challenges of estimating the impact of pollution monitoring by merely comparing the performances of NSM and non-NSM firms.

Table 2: Summary statistics for NSM firms and non-NSM firms (2006-2016)

	NSM firms		Non-NSM firms	
Variable	Mean	Std.Dev.	Mean	Std.Dev.
Employment	8.375*	1.011	7.913	1.147
Total asset	22.303*	1.223	21.894	1.200
Output	21.910*	1.474	21.472	1.334
Cost	21.622*	1.553	21.181	1.380
Capital	21.140*	1.424	20.305	1.313
Profitability	0.537	0.604	0.510	0.554
Management cost	0.072*	0.050	0.089	0.054
Non-operating income	0.014*	0.027	0.017	0.029
Non-operating cost	0.004	0.007	0.004	0.008
SOE dummy	0.684*	0.465	0.557	0.497
Concurrent dummy	0.137	0.344	0.144	0.351
Gov. relation dummy	0.511*	0.500	0.453	0.498

Note: Definitions of variables are presented in Table A1 in the appendix. * indicates differences are significant at the 5% level.

Table 3 presents the industrial distribution of NSM firms according to the Sectoral Classification System GB/T4754-2011. A number of sectors stands out with relatively high numbers (percentages) of NSM firms. Manufacture of paper and paper products (22), Smelting and processing of ferrous metals (31), and Manufacture of foods (14) are the top three sectors with the highest percentages of NSM firm-year observations. Table 3 indicates that systematic differences exist across sectors in terms of the likelihood of being monitored, with certain sectors hosting a large proportion of NSM firms for a long period. Another observation is that not only firms in traditionally capital-intensive sectors, but also firms in labour-intensive sectors are likely to be included in the NSM programme. This highlights the intrinsic difference between the pollution monitoring programme and interventions that typically target capital-intensive firms (Berman and Bui, 2001; Cole and Elliott, 2003).

Table 3: Sector distribution of firm-year observations (2006-2016)

Code	Manufacturing sector	Total firm-year obs.	NSM firm-year obs.	Ratio (%)
13	Processing of food from agric. products	99	18	18
14	Manufacture of foods	110	53	48
15	Manufacture of alcohol, beverages, and refined tea	253	89	35
17	Manufacture of textiles	165	48	29
18	Manufacture of textile, clothing; apparel industry	55	4	7
19	Manufacture of leather, fur, feather and related products; footwear industry	22	1	5
22	Manufacture of paper and paper products	132	79	60
25	Processing of petroleum, coking, processing of nuclear fuel	66	27	41
26	Manufacture of chemical raw materials and chemical products	495	180	36
27	Manufacture of medicines	726	90	12
28	Manufacture of chemical fibers	66	31	47
29	Manufacture of rubber and plastics	110	14	13
30	Manufacture of non-metallic mineral products	154	39	25
31	Smelting and processing of ferrous metals	132	67	51
32	Smelting and processing of non-ferrous metals	231	86	37
33	Manufacture of metal products	99	12	12
34	Manufacture of general purpose machinery	231	8	3
35	Manufacture of special purpose machinery	341	6	2
36	Manufacture of automobiles	308	14	5
38	Manufacture of electrical machinery and equipment	462	4	1
39	Manufacture of computers, communication and other equipment	374	22	6
	Total	4,950	Median	18

Note: We employ Sectoral Classification System GB/T4754-2011 in the present study.

3 Empirical strategy

Because of the substantial differences between NSM firms and non-NSM firms, we cannot straightforwardly compare NSM and non-NSM firms in terms of their labour demand to gauge the impact of pollution monitoring. We address this by using entropy balancing, a generalized weighting procedure to align the treatment and the control group. Specifically, entropy balancing enables us to retrieve the average difference between NSM and non-NSM firms in terms of the treatment status after conditioning on a set of observables. Similar to traditional matching approaches, entropy balancing involves a selection into the treatment group on observed covariates that jointly determine the status of treatment and the outcome variables (Hainmueller, 2012; Hainmueller and Xu, 2013). However, traditional matching approaches match treated and controls unconditional on the distributions of covariates between the treated and the control group. Differences in the distributions of the treated and the control may confound any identification of the parametric or non-parametric relationship between the treatment and the outcome. Entropy balancing avoids this issue by identifying weights that ensure covariates balancing at high moments (e.g., means, variances, and skewness). Entropy balancing performs particularly well compared to traditional matching approaches when non-linear relations exist between treatment status and pre-determined covariates (McMullin and Schonberger, 2020).

We focus on the average treatment effect on the treated (ATT), i.e. the employment changes as a result of the NSM programme experienced by firms that are actually included in the monitoring programme. Formally, it is defined as follows:

$$ATT = E[Y|T=1] - \int E[Y|T=1, X=x] f_{X|T=1}(x)\,dx \tag{1}$$

where $Y(.)$ is the outcome variable, namely firm employment in our study; T is a dummy variable indicating if a firm falls into the treatment group ($T = 1$). Vector X includes a set of observed covariates that determine the treatment status and outcome variables, and $f_{X|T=1}$ denotes the density of the covariates in the treatment group. ATT is identified such that after controlling for these covariates, potential outcomes are independent of the treatment status. This holds as long as there are treated and untreated units at all values of X (i.e. overlap) in the support of $f_{X|T=1}$. To obtain the last term in Equation 1, entropy balancing reweights the dataset to match the covariates distribution of the control group to the covariates distribution of the treated. In other words, this enforce the orthogonality of the treatment indicator T and the observed covariates, which is required for a causal inference of the treatment effect. The estimated effect of the NSM programme on the outcome variable is the same under entropy balancing when drawing a random unit from the treated and the control group. The gap between ATT and average treatment effect (ATE) is automatically closed, which is not the case if distribution balance is not ensured (Hainmueller and Xu, 2013; Egger et al., 2020).

We employ firm characteristics data from 2005 to conduct the balancing because the majority of the treated firms join the monitoring programme in 2007, and the 2007 list is designed based on emissions data from 2005. We consider that firms are unlikely to be able to modify the records two years before the programme launch to avoid being monitored. Our choice of the baseline year is in line with the literature (Zhang et al., 2018). Table 4 presents covariates and moments that we target in entropy balancing. Balancing is achieved for representative variables in several dimensions, including scale (employment, total asset, output, cost, profitability), structure ($\frac{\text{capital}}{\text{output}}$, $\frac{\text{management cost}}{\text{output}}$, $\frac{\text{non-operating income}}{\text{output}}$, $\frac{\text{non-operating cost}}{\text{output}}$), and bargaining power (SOE dummy, sector dummy, concurrent dummy, government relation dummy). These attributes are suggested to be closely related the level of pollution of a firm (Jiang et al., 2014; Zhang et al., 2016; Chen et al., 2018). Table 5 presents the balancing results in three horizontal blocks: the moments of covariates for the treated group (columns (1)-(3)), the moments of covariates for the control group before balancing (columns (4)-(6)), and the moments of covariates for the control group after balancing (columns (7)-(9)). A comparison of the first and the second block suggests that NSM firms tend to be larger in terms of almost all relevant characteristics, which is in line with Table 2. The third block of Table 5 presents covariates statistics of the control group after balancing, and the aforementioned difference is minimized after reweighting. Particularly, entropy balancing improved the compatibility of covariates between the treated and the control group at high moments. All covariates of interests are virtually balanced at each moment with the tolerance level 0.015. We are confident that the control group in the subsequent empirical analysis is comprised of credible counterfactuals for the sample of NSM firms.

Table 4: Targeted moments of observable variables in the entropy balancing

Pretreatment covariates	Targeted moments		
	Mean	Variance	Skewness
Employment	Yes	Yes	Yes
Total asset	Yes	Yes	Yes
Output	Yes	Yes	No
Cost	Yes	Yes	No
Profitability	Yes	Yes	No
$\frac{\text{Capital}}{\text{Output}}$	Yes	Yes	No
$\frac{\text{Management cost}}{\text{Output}}$	Yes	Yes	No
$\frac{\text{Non-operating income}}{\text{Output}}$	Yes	Yes	No
$\frac{\text{Non-operating cost}}{\text{Output}}$	Yes	Yes	No
SOE dummy	Yes	No	No
Sector dummy	Yes	No	No
Concurrent dummy	Yes	No	No
Gov. relation dummy	Yes	No	No

Note: Gov. relation dummy if corporate executives are government officials obtained from Zhang et al. (2016). Concurrent dummy if CEO also serves as chairman of the board.

With the aid of entropy balancing weights we seek to estimate the causal effect of the NSM programme on employment . We consider the following empirical model:

$$Emp_{it} = \beta_0 + \beta_1 T_i + \beta_2 NSM_{it} + \boldsymbol{Z_{it}}\Gamma + \tau_t + \mu_{it} \tag{2}$$

where i indexes firms and t indexes year. The dependent variable is the log of one of our employment measures. Dummy variable T_i denotes treatment assignment, and dummy variable NSM_{it} indicates when a NSM firm is under monitoring. Thus NSM_{it} captures the changes in employment of NSM firms, relative to non-NSM firms, associated with the treatment. The remaining variates include year-specific shocks τ_t and $\boldsymbol{Z_{it}}$ which is a set of firm and regional characteristics, including total asset, sector dummies capturing persistent sectoral differences, and province dummies controlling for the conditions

Table 5: Covariates balancing results

VARIABLE	(1) Treated Mean	(2) Treated Variance	(3) Treated Skewness	(4) Control Mean	(5) Control Variance	(6) Control Skewness	(7) Control balanced Mean	(8) Control balanced Variance	(9) Control balanced Skewness
Employment	8.168	0.797	0.556	7.599	1.074	-0.204	8.167	0.799	0.548
Total asset	21.580	0.918	0.977	21.114	0.850	0.159	21.580	0.918	0.977
Output	21.201	1.441		20.633	1.247		21.200	1.442	
Cost	20.911	1.647		20.359	1.381		20.910	1.648	
Profitability	0.425	0.199		0.309	0.143		0.425	0.224	
$\frac{\text{Capital}}{\text{Output}}$	0.617	0.097		0.506	0.085		0.617	0.093	
$\frac{\text{Management cost}}{\text{Output}}$	0.077	0.004		0.097	0.005		0.077	0.003	
$\frac{\text{Non-operating income}}{\text{Output}}$	0.005	0.000		0.007	0.000		0.005	0.000	
$\frac{\text{Non-operating cost}}{\text{Output}}$	0.004	0.000		0.005	0.000		0.004	0.000	
SOE dummy	0.684	0.218		0.557	0.248		0.684	0.217	
Concurrent dummy	0.132	0.116		0.120	0.106		0.133	0.115	
Gov. relation dummy	0.419	0.245		0.430	0.246		0.419	0.244	

Note: Statistics of entropy balancing with tolerance level 0.015. Balancing results of sector dummies are suppressed in the table.

of local labour markets. In alternative specifications we include time-variant sector and province dummies, and firm fixed-effect dummies. We relax the assumption of independence of the errors and allow for correlations in errors across years for the same firm by using standard errors that are robust to within-firm correlation over time.

We employ several measures of employment in our study, including the total employment, the numbers of skilled workers and unskilled workers, and the ratio of skilled workers over unskilled workers. Total employment is the most commonly used indicator among researchers and policy-makers, while we may expect to observe different impacts of pollution monitoring on skilled and unskilled labour. To comply with abatement requirements, specialists may be needed to deal with administrative procedures, and to operate monitoring and abatement equipments. Furthermore, rising production costs may lead to heterogeneous impacts on the demand for skilled and unskilled labour. Employing alternative measures of labour allows for a better understanding of firm responses to enhanced pollution monitoring.

4 Results

Table 6 presents the estimates of the impact of the NSM programme on a firm's employment corresponding to Equation 2. The difference between the specifications in column (1) and in column (2) is that the results in column (2) are obtained conditional on the balancing of pre-treatment covariates, as are the results in column (3) and (4). The difference between columns (2) (3) and (4) is the inclusion of alternative sets of fixed-effect dummy variables. Overall, the estimates of our main variable of interest, NSM, are statistically significant at the 1% or 5% level across all specifications conditional on the balancing of pre-treatment covariates. This implies that, after the policy change, firms under stringent pollution monitoring employed significantly more workers than firms that are not monitored. Particularly, the specification in column (4) controls for unobserved firm heterogeneity and is our preferred specification. The results in column (4) suggest that the employment of NSM firms rises by approximately 11.4% relative to non-NSM firms as a result of the enhanced pollution monitoring. Given the average number of employees in our sample as of 3141, our estimates indicate that a random assignment of the NSM status leads to an increase of firm employment by approximately 11.4% or 358 employees on average. Estimates in columns (2) (3) and (4) are similar in terms of size and significant level, while the unconditional estimate in column (1) is small and statistically nonsignificant. A plausible explanation could be the pre-treatment difference in trends of employment. As non-NSM firms are on average smaller than NSM firms, the growth rate of non-NSM firms are likely to be larger than NSM firms. The unconditional results in column (1) may thus be underestimated due to the lower growth rate of NSM firms.

Table 6: The effect of NSM on firm employment – baseline (2006-2016)

VARIABLE	(1) Employment (uncon.)	(2) Employment	(3) Employment	(4) Employment
NSM	0.065	0.154***	0.133**	0.114***
	(0.048)	(0.051)	(0.058)	(0.042)
T	0.098	-0.045	-0.037	
	(0.063)	(0.066)	(0.070)	
Fixed effects	Sector, province, year	Sector, province, year	Sector-year, province-year	Firm, year
Observations	4950	4950	4950	4950
Adj. R2	0.670	0.779	0.792	0.878

Note: The table presents the effect of the NSM programme on total employment of a firm. NSM is a dummy denoting if a firm is subject to the NSM programme in a given year. T is a dummy denoting if a firm has ever been included in the NSM programme. Firm total asset is included in all specifications. Standard errors in parentheses are clustered at the firm level. *** and ** indicate levels of statistical significance at 1 and 5 percent, respectively.

Table 7 presents the results using alternative measures of employment for our baseline model. All specifications are conditional on the balancing of pre-treatment firm fundamentals. As the data for alternative measures of employment are only available from 2011 to 2016, we cannot apply firm fixed effects as a large share of the NSM firms joined the NSM programme before 2011. Instead, we employ the estimates of firm fixed effect obtained from the specification in column (4) of Table 6 to proxy the size premium of a firm associated with unobserved heterogeneity.[5] The results in 7 suggest that NSM firms employ more skilled and unskilled workers relative to non-NSM firms after being monitored, but the demand for skilled workers is higher.

[5]This is called sorting in the literature. For example, Roca and Puga (2017) investigate the wage premium of working in big cities. Individual fixed effects is argued to capture the initial unobserved ability of workers. Spatial sorting implies that workers who are inherently more productive are more likely to choose to locate in bigger cities and have higher earnings.

This is confirmed by using the number of skilled workers and the skilled-unskilled worker ratio as the dependent variable. The results highlight the prospect of additional technology adoption by NSM firms compared to non-NSM firms due to the enhanced pollution monitoring. Despite with a short panel, Table 7 serves as a good supplement and robustness check to the results presented in Table 6.

Table 7: The effect of NSM on firm employment – skilled and unskilled workers (2011-2016)

VARIABLE	(1) Unskilled workers	(2)	(3) Skilled workers	(4)	(5) Skilled/unskilled ratio	(6)
NSM	0.139**	0.147**	0.211***	0.235***	0.020**	0.024**
	(0.059)	(0.068)	(0.077)	(0.087)	(0.009)	(0.010)
T	-0.058	-0.065	-0.044	-0.066	-0.009	-0.012
	(0.070)	(0.078)	(0.097)	(0.101)	(0.011)	(0.012)
Fixed effects	Sector, province, year	Sector-year, province-year	Sector, province, year	Sector-year, province-year	Sector, province, year	Sector-year, province-year
Observations	2371	2361	2397	2390	2397	2390
Adj. R2	0.904	0.906	0.806	0.811	0.308	0.325

Note: The table presents the effect of the NSM programme on the employment of skilled and unskilled workers. NSM is a dummy denoting if a firm is subject to the NSM programme in a given year. T is a dummy denoting if a firm has ever been included in the NSM programme. Firm total asset and size premium are included in all specifications. Standard errors in parentheses are clustered at the firm level. *** and ** indicate levels of statistical significance at 1 and 5 percent, respectively.

Duration of the impact

The NSM programme was launched in 2007 and is updated annually. To better understand firms' dynamic response to enhanced pollution monitoring, we investigate the effect of the NSM programme years after the policy treatment is delivered. Column (1) of Table 8 presents the estimates of the effect on firm employment one to ten years after a firm joins the NSM programme ($age = 1...10$). The results show that the enhanced pollution monitoring has a statistically significant effect on firm employment up to five years of monitoring. The overall trend in the estimated coefficients is positive and increasing over time from year one to year five, before tailing off in year six onwards. There is a contemporaneous effect of the policy intervention ($age = 1$), but there seems to be a stronger, delayed positive impact on firm employment three to six years after the policy intervention, likely through the investment response.

Furthermore, column (2) of Table 8 considers the effect of enhanced pollution monitoring by distinguishing the joining years of NSM firms ($joining\ \ year = 2007...2015$). The results show that the impact of the NSM programme on firm employment is statistically significant only for firms that joined the programme in 2007 and 2009. In other words, we observe no significant impact of enhanced pollution monitoring on firm employment for firms that join the programme two years after its announcement. A plausible explanation could be, as hypothesized by Zou (2021), polluting firms anticipate the possibility of being monitored after the announcement of the NSM programme, and adjust its polluting activities in advance. We therefore cannot observe the changes of employment in firms joined the programme at a later stage, as the changes may occur before the policy treatment. Another possible reason could be the fact that roughly 65% of the NSM firms in our sample joined the NSM programme between 2007 to 2009. There is less variation in the treatment indicator for the period after 2010.

Table 8: The effect of NSM on firm employment – dynamic effects (2006-2016)

VARIABLE	(1) Employment	VARIABLE	(2) Employment
NSM age = 1	0.078**	NSM joining year = 2007	0.166**
	(0.032)		(0.066)
NSM age = 2	0.066	NSM joining year = 2009	0.136**
	(0.040)		(0.062)
NSM age = 3	0.139***	NSM joining year = 2010	0.103
	(0.047)		(0.144)
NSM age = 4	0.155***	NSM joining year = 2011	0.058
	(0.053)		(0.088)
NSM age = 5	0.184***	NSM joining year = 2012	-0.055
	(0.061)		(0.079)
NSM age = 6	0.165**	NSM joining year = 2013	0.116
	(0.080)		(0.128)
NSM age = 7	0.113	NSM joining year = 2014	-0.085
	(0.094)		(0.134)
NSM age = 8	0.150	NSM joining year = 2015	0.167
	(0.103)		(0.176)
NSM age = 9	0.173		
	(0.104)		
NSM age = 10	0.233		
	(0.119)		
Fixed effects	Firm, year		Firm, year
Observations	4950		4950
Adj. R2	0.878		0.878

Note: The table presents the effect of the NSM programme on the total employment of a firm. NSM is a dummy denoting if a firm is subject to the NSM programme in a given year. Firm total asset is included in all specifications. Standard errors in parentheses are clustered at the firm level. *** and ** indicate levels of statistical significance at 1 and 5 percent, respectively.

Ownership

The NSM programme covers top polluters that account for 65% of national waste water discharge and air emissions. Many of these top polluters are state-owned enterprises (SOEs) that play a substantial role in natural resource sectors. By generating significant revenue, SOEs may have bargaining power with local authorities and are able to influence the implementation of environmental standards and pollution levies (Wang et al., 2003; Zhang et al., 2018). If this is the case, we would expect to observe a stronger impact of the NSM programme on SOEs relative to non-SOEs. We examine this hypothesis and test if the effect of enhanced pollution monitoring on firm employment differs across firm ownerships. Table 9 documents the ownership structure of the sample and the proportion of NSM firms under each category. There are three types of ownerships, namely central SOEs, local SOEs, and non-SOEs. Central SOEs are ultimately operated by the central government and affiliated to the State-owned Assets Supervision and Administration Commission of the State Council; local SOEs are controlled and affiliated to local governments at the provincial, municipal, and county level (Chen et al., 2011, 2020). Non-SOEs consist of privately owned enterprises, foreign-owned enterprises, collectively enterprises, public-owned enterprises, and other enterprises. Table 9 shows that the numbers of SOEs and non-SOEs are similar, but there are slightly more local SOEs than central SOEs.

Table 10 presents the results of a modified specification by adding interaction terms between the policy intervention NSM and $SOEs$ dummies. In the first three columns we compare SOEs to non-SOEs; in the remaining three columns we distinguish central SOEs, local SOEs from non-SOEs. An immediate observation is that the estimates of NSM are positive and statistically significant across all specifications, confirming again the robustness of our previous findings. Meanwhile, the coefficients on the interaction terms are all statistically nonsignificant. This implies that non-SOEs are affected by the monitoring programme similar to that of central and local SOEs in terms of employment. A plausible interpretation could be that all the NSM firms are large in terms of revenue and tax contribution, and they have similar levels of bargaining power. Therefore we did not observe significant differences between the impacts of pollution monitoring on SOEs and non-SOEs. The negative sign of the interaction terms gives a hint on the possibility that SOEs are less sensitive to enhanced pollution monitoring in terms of labour demand. This may be because SOEs are less flexible regarding recruitment and retention of employees as compared to non-SOE. If SOEs outsource abatement activities to contractors, we are unable to capture its employment changes led by the NSM programme.

Table 9: Ownership

NSM	non-SOEs	SOEs		Total
		Central SOEs	Local SOEs	
0	163	75	76	314
1	57	19	60	136
Total	220	94	136	450

Note: The table presents ownership distribution of NSM and non-NSM firms.

Table 10: The effect of NSM on firm employment – Ownership (2006-2016)

VARIABLE	(1) Employment	(2) Employment	(3) Employment	(4) Employment	(5) Employment	(6) Employment
NSM	0.199**	0.192**	0.147**	0.202**	0.196**	0.147**
	(0.078)	(0.091)	(0.062)	(0.079)	(0.092)	(0.062)
T	-0.041	-0.032		-0.041	-0.033	
	(0.065)	(0.070)		(0.065)	(0.070)	
SOEs	0.081	0.088				
	(0.074)	(0.079)				
NSM x SOEs	-0.088	-0.115	-0.060			
	(0.105)	(0.120)	(0.066)			
Central SOEs				-0.093	-0.079	
				(0.111)	(0.119)	
Local SOEs				0.135	0.139	
				(0.077)	(0.082)	
NSM x centrol SOEs				-0.037	-0.071	-0.025
				(0.142)	(0.166)	(0.087)
NSM x local SOEs				-0.088	-0.112	-0.071
				(0.113)	(0.130)	(0.069)
Fixed effects	Sector, province year	Sector-year province-year	Firm, year	Sector, province year	Sector-year, province-year	Firm, year
Observations	4950	4950	4950	4950	4950	4950
Adj. R2	0.779	0.793	0.878	0.782	0.795	0.878

Note: The table presents the effect of the NSM programme on the employment of a firm. Standard errors in parentheses are clustered at the firm level. *** and ** indicate levels of statistical significance at 1 and 5 percent, respectively.

Interaction with other policies

During the period of our investigation there are other energy and environmental regulations that focus on a similar group of firms as we investigate in the present study. The NSM programme was initiated during the 11th Five-Year Plan (FYP) period, and spans over the 12th and 13th FYP period. Emissions reduction and energy efficiency improvement are increasingly emphasized in recently released FYPs (Yuan and Zuo, 2011). This implies that there may be a difference in the level of policy stringency across multiple FYP phases, i.e. less strict in early years as compared to later years. Furthermore, the Top 1000 and 10,000 Enterprise Energy Saving Programme (in Chinese: Qianjia and Wanjia Enterprises Energy Conservation Programme, hereafter OJWJ) is a national action plan on energy efficiency launched in 2006. It targets on the top 1000 energy-intensive enterprises during phase I (2006-2010) and top 10,000 energy-intensive enterprises during phase II (2011-2015). Under the programme, firms were assigned explicit energy-saving targets to be achieved by the end of the phase, and were required to implement a series of energy efficiency measures (Lo et al., 2015; Karplus et al., 2020). As multiple energy and environmental policies take place during a similar period, it is possible that the employment changes that we observe in previous analysis may be driven by interventions other than the enhanced pollution monitoring programme.

To better understand the interaction between the NSM programme and alternative policies and their impacts on firm employment, we estimate the effect of the NSM programme on firm employment with an interaction between NSM and a set of dummies that denote different FYP phases and an interaction between NSM and a dummy indicating QJWJ treatment on a firm in a year respectively. Table 11 shows that the majority of the NSM firms are meanwhile covered under the QJWJ programme (96 out of 136), and vice versa. Table 12 presents the estimates of the interactive effects of multiple policies on firm employment. The first three columns consider different FYP phases; the remaining columns consider the QJWJ programme. Besides the time-variant dummies $QJWJ$, we also include a time-invariant dummy T_QJWJ set to unity if it is a treated firm. This dummy is dropped out in column (6) because of the inclusion of firm fixed effect.

Table 12 shows that our variable of interest NSM remains positive and statistically significant at 5 or 10% level across all specifications. In column (3) and (6) where firm fixed effects are included, the results indicate that firms experience an approximately 10-11% increase in employment after being included in the enhanced pollution monitoring programme. This finding is again highly consistent with our previous estimates in Table 6. Turning to the interaction terms, the impacts of alternative policy interventions seem to be independent from each other as suggested by the statistically nonsignificant interaction terms. Overall, Table 12 confirms the effectiveness of enhanced pollution monitoring as a stand-along intervention.

Table 11: QJWJ

NSM	QJWJ 0	QJWJ 1	Total
0	258	56	314
1	40	96	136
Total	298	152	450

The table presents the distribution of NSM and QJWJ firms.

Exiters and incumbents

We further single out groups of NSM firms that drop out from the monitoring programme at some point, namely exiters. The remain NSM firms are continuously present in the programme and are named incumbents. Table 13 presents the results. In column (1) we distinguish the treatment effect on incumbents from that on exiters; in columns (2) and (3) we leave out exiters and incumbents respectively, and run the baseline strategy using restricted samples. The impact of the monitoring programme does differ for incumbents and exiters - the NSM estimates for exiters are larger and statistically more significant than those for incumbents no matter the sample used. The results indicate that exiters tend to be more responsive to the enhanced pollution monitoring programme, and experienced a larger employment growth incentivized by

Table 12: The effect of NSM on firm employment – FYP and QJWJ (2006-2016)

VARIABLE	(1) Employment	(2) Employment	(3) Employment	(4) Employment	(5) Employment	(6) Employment
NSM	0.155**	0.154**	0.103**	0.122**	0.115	0.113**
	(0.063)	(0.071)	(0.050)	(0.057)	(0.065)	(0.046)
T	-0.045	-0.046		-0.005	0.001	
	(0.065)	(0.068)		(0.078)	(0.082)	
NSM x 12th FPY	-0.024	-0.023	0.001			
	(0.065)	(0.070)	(0.071)			
NSM x 13th FPY	0.116	0.070	0.086			
	(0.108)	(0.099)	(0.123)			
QJWJ				-0.076	-0.064	0.050
				(0.096)	(0.102)	(0.087)
T_QJWJ				-0.054	-0.074	
				(0.092)	(0.099)	
NSM x QJWJ				0.102	0.106	-0.007
				(0.101)	(0.105)	(0.076)
Fixed effects	Sector, province year	Sector-year province-year	Firm, year	Sector, province year	Sector-year, province-year	Firm, year
Observations	4950	4950	4950	4950	4950	4950
Adj. R2	0.779	0.793	0.878	0.780	0.794	0.878

Note: The table presents the effect of the NSM programme on the total employment taking alternative policies into account. NSM is a dummy denoting if a firm is subject to the NSM programme in a given year. Firm total asset is included in all specifications. Standard errors in parentheses are clustered at the firm level. *** and ** indicate levels of statistical significance at 1 and 5 percent, respectively.

the NSM programme.

Table 13: The effect of NSM on firm employment – incumbent and exiter (2006-2016)

	(1) Employment	(2) Employment Incumbents	(3) Employment Exiters
NSM (Incumbent = 1)	0.102		
	(0.061)		
NSM (Exiter = 1)	0.125**		
	(0.056)		
NSM		0.090	0.121**
		(0.072)	(0.059)
Fixed effects	Firm, year	Firm, year	Firm, year
Observations	4950	4356	4048
Adj. R2	0.878	0.882	0.848

Note: The table presents the effect of the NSM programme on the total employment considering firms' exit from the programme. NSM is a dummy denoting if a firm is subject to the NSM programme in a given year. Firm total asset is included in all specifications. Standard errors in parentheses are clustered at the firm level. *** and ** indicate levels of statistical significance at 1 and 5 percent, respectively.

5 Impact mechanism

Our analysis reveals that the NSM programme has a strong and robust positive impact on firm employment. What is missing, though, is to disentangle different channels to help clarify the relationship between enhanced pollution monitoring and employment. We employ a stylized model of environmental regulation to identify the impact channels via which the NSM programme affects firm employment. Berman and Bui (2001) propose that environmental regulation affects labour demand via two distinct channels: the output elasticity of labour demand, and the marginal rate of technical substitution between abatement activities and labour demand. Specifically, a firm produces output y under the production function:

$$y = f(x_1, x_2, ..., z_1, z_2...) \tag{3}$$

where x_i ($i \in 1, 2, ...$) denotes quantity of variable inputs; z_j ($j \in 1, 2, ...$) denotes the "quasi-fixed" abatement activity, the quantity of which is determined by exogenous constraints (e.g. environmental regulations) rather than cost minimization alone. Assume the inputs and outputs market are both perfectly competitive. The variable costs function is given by:

$$CV = H(p_1, p_2, ...z_1, z_2, ...y) \tag{4}$$

where $p_1, p_2, ...$ are the prices of variable inputs, and $z_1, z_2, ...$ are the quantities of abatement activities. Shephard's lemma states that the optimal factor demand can be obtained via the first derivatives of the cost function with respect to input prices. This implies that for an arbitrary level of output y, the optimal demand of variable inputs, i.e. labour, is a function of the output level, input prices, and the quantities of abatement activities, as described by:

$$L = \alpha + \rho y + \gamma_1 p_1 + \gamma_2 p_2 + ... + \beta_1 z_1 + \beta_2 z_2 + ... \tag{5}$$

The effect of environmental regulation on labour demand is then given by:

$$\frac{dL}{dR} = \rho \frac{dy}{dR} + \gamma_1 \frac{dp_1}{dR} + \gamma_2 \frac{dp_2}{dR} + ... + \beta_1 \frac{dz_1}{dR} + \beta_2 \frac{dz_2}{dR} + ... \tag{6}$$

As we assume the input markets are competitive and environmental regulation has no impact on input prices, the above equation can be rewritten as:

$$\frac{dL}{dR} = \rho \frac{dy}{dR} + \beta_1 \frac{dz_1}{dR} + \beta_2 \frac{dz_2}{dR} + ... \tag{7}$$

The first term indicates the changes in output from environmental regulations, and is generally believed to be negative under existing technologies.[6] The remaining terms in the equation reflect the abatement activities induced by environmental regulations, where the signs of $\beta_1, \beta_2 ...$, i.e. the marginal rates of technical substitution between abatement activities and labour, are not clear. Abatement activities can be classified

[6] As Berman and Bui (2001) noted, this term can be positive if abatement activities lead to a decrease in the marginal cost of output.

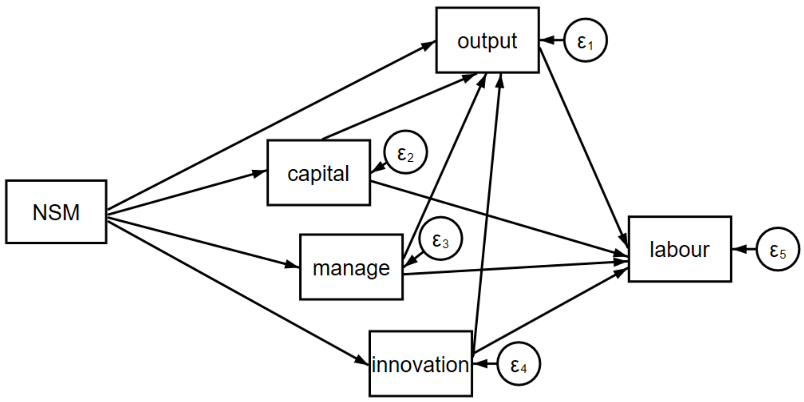
into two general groups: ”end-of-pipe” and ”changes-in-process” (Berman and Bui, 2001; He and Zhang, 2018; Sun et al., 2019) . End-of-pipe include technologies such as scrubbers and filters, which remove pollutants from existing output streams before they are released in the environment. End-of-pipe technologies are likely to be labour complement, especially production labour. Changes-in-process involves modification of polluters' production processes, such as improvement in machinery and fuel quality, and can be either labour complement or labour substitute.

We employ a mediation analysis strategy to estimate how manufacturing activity - as measured by output, capital investment, management expenditure and innovation - responds to enhanced pollution monitoring. Mediation analysis, or in general path analysis, is used to illuminate the mechanisms through which a treatment or exposure affects the outcome. The treatment effect is apportioned between the direct effect and the indirect effect through a single or multiple mediators. Such analysis becomes increasingly popular in many disciplines of social and medical sciences (Imai et al., 2011). For example, Heckman et al. (2013); Heckman and Pinto (2015); Conti et al. (2016) employ causal mediation analysis to test change pathways in evaluating behaviour impacts of public health programmes based on individual-level psychological characteristics. Corresponding to Equation 7, capital investment, management expenditure and innovation are employed to capture the changes in abatement activities. We assume environmental regulation stimulates capital investment in abatement activities.[7] Management expenditure is used to proxy inputs as staff training and paperworks associated with abatement activities and other relevant costs as part of general management expenditure. The number of patents is employed to measure firm innovation as the Porter hypothesis argues that environmental regulation may stimulate innovations, which in turn increase firm productivity.

Figure 2 depicts the path diagram that illustrates the conceptual framework of the impact channels. Equation 8-12 describe the regression strategy. A set of controls is included in each of the equations, including year fixed effects τ_t and firm characteristics $\boldsymbol{Z}_{it}$ consisting of firm fixed effect and total asset. Entropy weights are employed so that the assignment of the treatment is independent from firm characteristics listed in Table 4. Standard errors are constructed using bootstrapping, and clustered at firm level and allowed for cross-equation error correlation.

[7]Due to data limitation, we are unable to distinguish investments associated to different types of abatement activities.

Figure 2: Path diagram



$$
\begin{aligned}
Emp_{it} &= \beta_{10} + \beta_{11} NSM_{it} + \beta_{12} Output_{it} + \beta_{13} Capital \\
&\quad + \beta_{14} Manage_{it} + \beta_{15} Innovation_{it} + \boldsymbol{Z_{it}} \Gamma_1 + \tau_t + \mu_{1it} && (8) \\
Output_{it} &= \beta_{20} + \beta_{21} NSM_{it} + \beta_{22} Capital + \beta_{23} Manage_{it} \\
&\quad + \beta_{24} Innovation_{it} \boldsymbol{Z_{it}} \Gamma_2 + \tau_t + \mu_{2it} && (9) \\
Capital_{it} &= \beta_{30} + \beta_{31} NSM_{it} + \boldsymbol{Z_{it}} \Gamma_3 + \tau_t + \mu_{3it} && (10) \\
Manage_{it} &= \beta_{40} + \beta_{41} NSM_{it} + \boldsymbol{Z_{it}} \Gamma_4 + \tau_t + \mu_{4it} && (11) \\
Innovation_{it} &= \beta_{50} + \beta_{51} NSM_{it} + \boldsymbol{Z_{it}} \Gamma_5 + \tau_t + \mu_{5it} && (12)
\end{aligned}
$$

Table 14 presents the direct effect and the indirect effects of the NSM programme passed by output, capital, management costs and innovation on firm employment. The direct effect is the effect of the intervention (the NSM programme) on the outcome (firm employment) controlling for all mediating paths, corresponding to β_{11} in Equation 8. The indirect effect is the effect of the intervention on the outcome that passes through the mediators. For example, the indirect effect of the NSM programme on firm employment via capital equals $\beta_{13}\beta_{31} + \beta_{12}\beta_{22}\beta_{31}$. In the last two columns the explained effect is the sum of the direct and indirect effects that are statistically significant. The total effect is the estimated coefficients of NSM where mediators are not included, corresponding to β_2 in Equation 2. Mediation percentage (%) highlights the share of total effect explained by each significant mediators.

Panel A of Table 14 displays the unstandardized estimates, and panel B displays the standardized estimates.[8] The unstandardized estimates are useful for interpretation and the standardized estimates allow us to compare the impacts of any two independent variables. The table also details the bias-corrected bootstrapped 95% confidence intervals for each of the pathways. Among the four mediators output and capital show positive and statistically significant mediating effects. The results indicate that NSM firms have higher capital investment and output after enhanced pollution monitoring compared to non-NSM firms, and this partially explains the positive impact of the NSM programme on firm employment. Nearly fifty percent of the estimated effect of the NSM programme is mediated by output and capital investment, and the remaining half of the estimated effect is not explained by changes in output and capital investment. The results echo the findings of Morgenstern et al. (2002) that suggest the increased spending in abatement induced by stringent environmental regulations led to positive and statistically significant changes in employment in certain industries. Furthermore, the estimates of management expenditure and innovation are minimal and statistically non-significant, indicating that they may not be the pathways through which enhanced pollution monitoring impact firm employment. To sum up, the results of mediation analysis suggest that the positive impact of the NSM programme on firm employment is partially attributed to the changes in output and capital investment.

Table 14: Mediation analysis (2006-2016)

Panel A: Unstandardized coefficients							
	Direct effect	Indirect effect Output	Capital	Manage	Innovation	Explained effect	Total effect
NSM	0.054*** (0.026) [0.006,0.110]	0.030*** (0.011) [0.010,0.054]	0.021*** (0.008) [0.007,0.040]	-0.008 (0.007) [-0.026,0.002]	0.002 (0.003) [-0.002,0.009]	0.105*** (0.027) [0.052,0.162]	0.109*** (0.027) [0.057,0.163]
Panel B: Standardized coefficients							
	Direct effect	Indirect effect Output	Capital	Manage	Innovation	Explained effect	Total effect
NSM	0.048*** (0.023) [0.006,0.098]	0.027*** (0.010) [0.009,0.048]	0.019*** (0.008) [0.007,0.036]	-0.007 (0.006) [-0.023,0.002]	0.002 (0.003) [-0.002,0.008]	0.093*** (0.024) [0.046,0.144]	0.097*** (0.024) [0.051,0.145]
Mediation (%)	49%	28%	20%			96%	100%

Note: The table presents the decomposition of the employment effect of the NSM programme. The explained effect is the sum of the direct and indirect effects that are statistically significant at the 5% level or above. The total effect is the estimated coefficient of NSM where mediators are not included (Col. (4) Table 6). Mediation (%) marks the share of the total effect mediated via each path. Firm total asset, firm fixed effects and year fixed effects are included in all specifications. Standard errors in parentheses are clustered at the firm level and obtained using bootstrapping (1000). Confidence interval of 95% in square brackets. *** and ** indicate levels of statistical significance at 1 and 5 percent.

[8] Continuous variables are standardized in pane B of Table 14. Dummy variables including NSM, firm fixed effects, year fixed effects and entropy weights are not standardized.

6 Sensitivity

We conduct a number of sensitivity analyses to check the robustness of the findings. First, we test alternative assumptions on the independence of the standard errors. We reestimate the specifications in Table 6 and cluster the standard errors at the industry and province level respectively. Variables of interest remain positive and statistically significant at the 5% level. Second, we verify the assumption required to make a valid causal inference based on the mediation analysis, namely sequential ignorability (Imai et al., 2010; Imai and Yamamoto, 2013). Sequential ignorability implies that (a) conditional on the observable pretreatment covariates, the treatment is independent of all potential outcomes and mediators; (b) the observed mediator is independent of all potential outcomes given the observed treatment and pretreatment covariates. Regarding the first part, the treatment assignment in the present study is assumed to be independent of the outcome variable and the mediators given the entropy balancing. The second part of sequential ignorability is not directly verifiable. Following Oreopoulos et al. (2017), we employ treatment-mediator and treatment-control interactions to test if the estimates of mediating effects are the same for NSM and non-NSM firms, and if the effect of firm characteristics on firm employment do not differ by treatment status. Results in column (1) Table A2 in the appendix suggest that the estimates of mediators are not statistically different for NSM firms and non-NSM firms. Furthermore, results in column (2) Table A2 in the appendix and Table 10 show that the NSM programme affects firm employment with different characteristics (i.e. total asset and ownership) similarly. Overall, the assumptions to causal mediation analysis are likely harmless in this application.

7 Conclusions

While environmental regulations have become commonplace across the globe, insufficient implementation and enforcement may reduce their effectiveness. The present study investigates how a nationwide high-frequency pollution monitoring network - the NSM programme - affects firm-level employment and economic performance. Firms under the NSM programme are subject to real-time pollutant release monitoring, and are the focus of the national campaign on pollution control and emissions reduction.

To ensure the counterfactual analysis is appropriate, we employ entropy balancing technique to restructure the control group based on a set of covariates of interests. The results suggest that firms under enhanced pollution monitoring have experienced an approximately 11.4% increase in employment. Subsequent analysis considers different types of labour (skilled and unskilled labour), firm ownership, exiters and incumbents, as well as the interaction between the NSM programme and other policy interventions that are targeted at similar types of firms during the investigation period. We find that the impact of the NSM programme on firm employment is dynamic and sizeable between three to five years after a firm being monitored, and to firms that join the programme during the first two years of its establishment. Firms with different types of ownership are not influenced differently by the programme. A causal mediation analysis is conduced to disentangle the impact channels through which the NSM programme influences firm employment. Output and capital investment are found to be significant mediators carrying roughly half of the total effect.

A number of factors could possibly explain the positive impact of the NSM programme on firm employment. First, the NSM morning programme covers a wide range of sectors, including both capital-intensive and labour-intensive sectors. This is a distinct difference between the monitoring programme and regulations that target primarily on capital-intensive sectors. Labour input is likely to be more elastic in the present study than in studies focusing on capital-intensive sectors. Second, the NSM programme collects high-quality pollutant release data, and does not set explicit goals on emissions reduction or energy saving. It leaves great flexibility to firms to adapt their production to the changes of environmental constrains. Compared to command-and-control instruments, the monitoring programme allows firms to search for the optimal measures for abatement. Additional costs to production induced by the monitoring programme may therefore be smaller. Third, if firms adopt end-of-pipe technologies, the incentive to avoid generating pollutant during the process of production is reduced. Firms may expand production as a result of the NSM programme, leading a positive impact on firm employment.

Rigorous monitoring and enforcement are key elements for effective environmental governance. Previous studies such as Evans (2016) and Zhang et al. (2018) show that enhanced monitoring is associated with significant decreases in violation behaviour and wastewater discharge. The results from the present study show that monitored firms experience increases in capital investment, output and labour demand for a period of up to six years. This implies that it is not necessary for a firm to sacrifice competitiveness to achieve emissions reduction. The present study contributes to the debate concerning the cost of environmental regulation.

There are two potential directions for future research based on our analysis. First, the shift of employment between workers with heterogeneous skills in light of stringent environmental regulations should be explored in more detail. How do the changes in the enforcement of environmental regulations affect different types of workers? Will a certain type of workers shift from one industry (e.g. monitored polluting industries) to another (e.g. unmonitored polluting industries)? In the current study we investigated this question only briefly with a relatively short panel and by distinguishing skilled worker from unskilled worker. Longitudinal information on individual's labour market status, education and employment history, and any variation in job characteristics could be useful in exploring these heterogeneous impacts of enhanced enforcement of environmental regulations. Second, research and development activities that polluting firms conduct in response to enhanced pollution monitoring should be analysed further. In the present study we employ the number of patents to represent firms' capability of research and development due to data availability. Detailed information on research and development expenditures and the type of technologies adopted would be useful to understand further the role of innovation in helping firms to transform in an environmentally friendly way and at the same time minimising risks from losing competitiveness.

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Appendix A

Table A1: Variable definitions

Variable	Definitions
Employment	Total employment
Total asset	Total asset
Output	Sales revenue
Cost	Operating expenses
Capital	Capital stock
Return	Annual stock return
Management cost	Management cost
Non-operating income	Non-operating income
Non-operating cost	Non-operating expenses
SOE dummy	Dummy variable indicating if a firm is state-owned high probabilities to be monitored
Concurrent dummy	Dummy variable indicating if CEO also serves as chairman of the board.
Gov. relation dummy	Dummy variable indicating if corporate executives are government officials

Note: All variables (except ratios and dummies) are in natural logarithm unless specified otherwise.

Table A2: Test on the significance of the treatment-mediator and treatment-control interactions

VARIABLE	(1) Employment	(2) Employment
NSM	-0.351	-0.139
	(0.717)	(0.691)
Output	0.426***	0.427***
	(0.085)	(0.087)
Capital	0.149	0.149
	(0.085)	(0.080)
Manage	2.432***	2.434***
	(0.818)	(0.710)
Innovation	0.049***	0.044***
	(0.018)	(0.015)
NSM x output	0.024	
	(0.049)	
NSM x capital	-0.004	
	(0.049)	
NSM x manage	0.016	
	(0.708)	
NSM x innovation	-0.019	
	(0.018)	
NSM x total asset		0.009
		(0.031)
Fixed effects	Firm, year	Firm, year
Observations	4838	4838
Adj. R2	0.903	0.903

Note: NSM is a dummy denoting if a firm is subject to the NSM programme in a given year. Firm total asset is included in all specifications. Standard errors in parentheses are clustered at the firm level. *** and ** indicate levels of statistical significance at 1 and 5 percent, respectively..