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ENVIRONMENTAL PERMITS, REGULATORY BURDEN, AND FIRM OUTCOMES

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Abstract. Effective regulatory design requires an understanding of how regulatory burden affects regulated entities. Using novel data on all applications for environmental permits in five Indian states and a natural experiment, we estimate how regulatory burden of environmental permitting affects firms. Difference-in-difference estimates show that deregulation induces smaller firms to enter and increases entry. Standard data sources would miss these substantial effects, underscoring the importance of collecting data across the firm size distribution. We also use full texts of permit certificates to create novel measures of regulatory burden. Firms in industries with reduced regulations face fewer, less stringent, permit conditions.

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1. Introduction

Effective regulatory design requires an understanding of how regulatory burden affects regulated entities such as firms. These impacts can be substantial – worldwide, senior managers spend 8.2% of their time dealing with regulation, and in South Asia, the focus of this study, the number is higher, about 12.6% (World Bank, 2021). Furthermore, while regulatory burden depends on firm size (Trebbi and Zhang, 2022), influential evidence on the impacts of regulation in developing countries comes disproportionately from studies of larger firms, such as those covered by India's Annual Survey of Industries (Aghion et al., 2008; Besley and Burgess, 2004; Martin, Nataraj and Harrison, 2017), the Prowess database (Bau and Matray, 2023; De Loecker et al., 2016), or the Annual Survey of Industrial Firms (ASIF) in China (He, Wang and Zhang, 2020).[1] This focus on larger firms in contexts where most firms are small and informal (Hsieh and Klenow, 2014; Ulyssea, 2020) neglects potentially large impacts of regulation on smaller firms.

We estimate how environmental regulatory burden affects firms in India, focusing on one important regulation: entry permits. Permitting is a pervasive form of regulatory burden, and several cross-country studies show that entry regulations affect firm entry (Djankov, 2009; Klapper, Laeven and Rajan, 2006). Firms in most industries in India are required to acquire entry permits from the environmental regulator, and so this burden potentially affects a large proportion of economic activity.

To understand the full impact of permit regulations, we must measure regulatory burden for both small and large firms, as well as isolate their causal effects. First, we collect novel data on the universe of applications made by firms seeking an environmental permit in five Indian states. These states cover over a quarter of value added by industry in India (Reserve Bank of India, 2024). Our sample includes all firms that attempt to enter the market and those that actually enter. The applications themselves allow us to measure specific aspects of the regulatory process that affect firms. We also use the permit certificates issued to successful applicants, which list the conditions that each firm must satisfy. We use this text to construct novel firm-level measures of regulatory burden by counting and classifying the conditions attached to each certificate. Second, we combine this novel data with a natural experiment – a policy change that reduced the environmental regulatory burden in some industries but not in others. A significant aspect of this policy is that, prior to this change, industries with similar pollution potential faced different regulatory burdens. These burdens were *harmonized* by the policy, making it particularly suited to a difference-in-difference

[1] For instance, the ASIF data include private industrial enterprises with annual sales exceeding 5 million RMB and all the state-owned industrial enterprises (SOEs) (He, Wang and Zhang, 2020), while the ASI covers registered firms with at least 10 workers for firms with power and 20 for firms without power.

analysis, and allowing us to estimate the causal impact of regulatory burden on similarly polluting industries.

Under the re-categorization policy introduced in 2016, all firms in an industry received a pollution score between 0 and 100, which determined whether they were classified as Green (a score between 21 and 40), Orange (a score of 41-59), or Red (score of 60 and above) (CPCB, 2016). These scores apply to all firms in an industry. Green industries have the lowest regulatory burden, Orange industries have an intermediate regulatory burden, and Red industries have the greatest regulatory burden. While these color categories existed prior the policy, the pollution scores did not, and so many industries saw their color categories change with the introduction of pollution scores. We take downward re-categorisation as our principal measure of exposure to treatment and estimate the impact on changes from Red to Orange, i.e. from high to medium regulatory burden.[2] We focus on re-categorisation from Red to Orange, because it enables us to base identification on comparisons of industries with the same pollution score – i.e. the same pollution potential – some of which were newly subject to less regulation, and others that were not. Several industries that were categorized as Orange both before and after the re-categorisation policy were assigned the same pollution scores as firms that were initially categorized as Red and re-categorized as Orange. This set of Orange-to-Orange industries is our primary control group.

Using difference-in-difference and event study approaches, we show that moving industries from high to medium regulatory burden increased entry and changed the characteristics of new entrants. Industries in which regulatory restrictions were loosened saw an increase in new applications, particularly from smaller firms with fewer workers. These effects are sizeable. The marginal entrant was 28.5% smaller, with 5.7 fewer workers. Applications increased by 30% in re-categorized industries. We show that using a standard data source that focuses on large firms, the Annual Survey of Industries (ASI), would lead us to miss these substantial effects and incorrectly assume that the policy had no effect.

Furthermore, we use the texts of permit certificates to measure regulatory burden. Firms that move into lower-burden categories receive fewer conditions in their permits, including fewer siting requirements and pollution limit provisions. These changes capture a meaningful reduction in the requirements that permitting officers impose during the permitting process. In contrast, other measures of regulatory burden such as time to decision are unchanged, while fee reductions are economically negligible. Our results are not likely to be driven by formalization of existing firms for two reasons. First, firm registration dates are rarely prior to the date of the application. Second, we conducted a follow-up survey of a subset of firms, and find that most firms begin activity no earlier than the year of their permit application.

[2]While a small number of industries were classified upwards, most industries that changed color categories were re-categorized downward.

Our results are not driven by any one industry, are not driven by functional form assumptions or outliers, and are robust to several alternative specifications.

Our study relates to three main literatures. First, we contribute to the literature on the impact of environmental regulation on firms (Berman and Bui, 2001; Chen et al., 2025; De Simone, Naaraayanan and Sachdeva, 2024; Duflo et al., 2013; Fan et al., 2019; Gechter and Kala, 2025; Greenstone, List and Syverson, 2012; He, Wang and Zhang, 2020; Tanaka, Teshima and Verhoogen, 2022). We study a ubiquitous but under-studied form of environmental regulation – permitting – and how it acts as an entry barrier for firms. We show that using standard sources, which over-sample large firms, would lead us to miss the large effects of a change in environmental permitting.

Second, prior work has identified several regulatory barriers to firm size, especially in developing countries (Aghion et al., 2008; Amirapu and Gechter, 2020; Besley and Burgess, 2004). These studies have focused on industrial policy restrictions on firms such as industrial licensing (Chari, 2011) and labor market regulation (Besley and Burgess, 2004; Garicano, Lelarge and Van Reenen, 2016), and find such regulation keeps firms smaller than what they would be otherwise. Studies using reforms to business registration rules find similar effects (Bruhn, 2011). We, by contrast, find that the burden of entry permits can keep firms larger than they would be otherwise.

Third, the paper contributes to the recent and growing literature on measuring regulatory burden. Existing work uses occupational task data to measure compliance costs (Trebbi and Zhang, 2022), corporate disclosures to capture perceived burden (Calomiris, Mamaysky and Yang, 2020; Davis, 2017), or regulatory-text measures (McLaughlin and Sherouse, 2019), we show that environmental permits contain granular information about the regulatory burden, which also varies significantly within industries. Furthermore, while most firm-level textual measures rely on disclosures by large, public firms (Calomiris, Mamaysky and Yang, 2020; Kalmenovitz, Lowry and Volkova, 2025), and Trebbi and Zhang (2022) provides recent evidence for smaller firms using task and payroll data, we extend measurement to small firms by constructing firm-level regulatory burden measures that also characterize the types of requirements.

2. Context

2.1. **Environmental Permit Regulation in India.** Environmental regulation in India is governed by the Water (Prevention and Control of Pollution) Act of 1974 and the Air (Prevention and Control of Pollution) Act of 1981 (Ghosh, 2019). These acts helped establish the Central Pollution Control Board and the State Pollution Control Boards. The Central Pollution Control Board coordinates with and provides assistance to the State Pollution Control Boards, which undertake a wide set of functions such as setting standards, investigation and research, and organizing training programmes. The State Pollution Control Boards have a number of powers, including inspection, information gathering, and refusing or withdrawing "consent" for the establishment of any firm (Bhat, 2010; Paranjape, 2013). "Consent" is the term used for an environmental permit, and is the focus of our study.

Polluting firms must obtain approval from the State Pollution Control Board both before establishment and before beginning operations. They must renew these approvals periodically (Ghosh, 2019). In our data, we observe this process as two types of application: Consent To Establish (CTE) and Consent to Operate (CTO).[3] CTE applications are requests to establish new polluting activities or to expand existing activities. Once the new unit has been established or expansion has taken place, a firm must apply for CTO before commencing operation. A CTO has a limited validity period that depends on the pollution category of an industry (Red, Orange, or Green). After applying, firms are likely to be inspected on the status of their pollution control measures and whether these are consistent with the measures they have reported (HSPCB, 2017). When a firm seeks to renew its permission to operate, it submits a new CTO application. Accordingly, we refer to CTEs as entry permits and CTOs as renewal permits.

The Central Pollution Control Board assigns a color code to each industry depending on its pollution potential. These codes apply to all firms in an industry, and so do not differ across firms within an industry. Highly polluting industries are classified as Red and face the highest regulatory burden, followed by Orange and Green. Table A.1 summarizes the differences in regulatory burden across categories. Firms in the Red category pay higher fees. They are inspected more frequently (every 2 years) as compared to firms in the Orange and Green categories (10-14 years). Red firms must renew their permit more often (every 5 years). Red and Orange firms tend to include more supporting documents with their applications. We use survey data to show, in Figure A.1, that firms notice these differences. Red firms report higher perceived compliance burden than Orange and Green firms (Panel A). They also report higher total costs and training costs associated with compliance (Panels B and C), and are more likely to adopt environmental management measures.

Once the application is approved, firms receive a permit certificate. This certificate outlines the firm's activities and lists all conditions they must meet to comply with pollution control board regulations. Conditions can be general requirements or specific. A non-compliant firm may struggle to renew its permit or may be forced to shut down temporarily.

2.2. **India's Re-Categorization Policy.** In 2015, the government of India declared a plan to re-categorize industries by color, based on their pollution potential (CPCB, 2016). Directions to all State Pollution Control Boards were sent in March 2016. However, states only

[3]These applications could be for a permit to pollute air or water, or for hazardous waste management.

adopted the new categorization by the end of 2016.[4] We refer the time period between March-December 2016 as the "Announced" phase and post-2016 as the "Implemented" phase.

The primary aim of the policy was to harmonize how industries were classified throughout India, since prior classification had largely been based on industry size and resource use, rather than on pollution and likely health impacts (CPCB, 2016). A pollution scoring system was introduced to overcome the perceived "random basis" of classification (CPCB, 2016). Under the new policy, industries received a pollution score between 0 and 100, which determined whether they were classified as Green (21-40), Orange (41-59), or Red (60 and above) (CPCB, 2016). Pollution scores allow us to focus on the industries that were regulated differently before the policy change but treated the same afterwards. For example, before the re-categorization, "manufacturing of glass" was considered Red, but it received a pollution score of 50 under the new methodology, and thus was classified as Orange. On the other hand, "reprocessing of waste plastic including pvc" also received pollution score of 50, but it was classified as Orange both before and after the policy change.

The pollution score is based on three sub-indices – water, air, and hazardous waste (CPCB, 2016) – each further divided into rule-based components. For example, part of the water index assigns 25 points for high-strength but non-toxic wastewater with biological oxygen demand of 1000-5000 milligrams per litre, provided pollutants are biodegradable.[5] Most industries that changed color categories were re-categorized downward. 26 of 85 initially Red industries became Orange, and 3 became Green (CPCB, 2016). 19 of 73 initially Orange industries became Green (CPCB, 2016).

3. Data

Our main data source is the universe of environmental permit applications from five Indian states between 2015 and 2018: Haryana, Kerala, Odisha, Punjab, and Tamil Nadu. We use these states because we have data for at least four quarters before the re-categorization policy came into effect, enabling us to test for parallel pre-trends. These five states account for over a quarter of value added by industry in India (Reserve Bank of India, 2024). They are geographically dispersed across the country.

3.1. Environmental Permit Applications .

All firms likely to discharge sewage, trade effluent, or air pollution must obtain CTE from their state's Pollution Control Board before establishing or expanding (Ghosh, Lele and Heble, 2018). We obtain data on applications from each state's Consent Management & Monitoring System, which firms use to submit entry and renewal permit applications (MoEFCC, 2019). In an application form, several details and documents are mandatory, including the industry type, which the State Pollution

[4]The delay was mostly caused by a) categorization of industries that were missing in the Central Pollution Control Board's notification and b) approval process of State Pollution Control Boards.

[5]Details on the scoring methodology can be found in CPCB (2016).

Control Board uses to assign the color code. Required documents usually verify information in the form, such as the proposed location of the firm (HSPCB, 2017). After submission, the authorities may inspect the unit and then approve or reject the application based on the inspection report.

3.1.1. *Main Outcomes.* From these applications, we extract several variables. We use the number of workers as our principal outcome variable for firm size. Because of extreme values, we winsorize this variable at the 1st and 99th percentiles of the distribution and take the inverse hyperbolic sine.[6] The number of workers is consistently reported across states and has few missing values.[7] It is not used in determining the level of scrutiny or fees, and so is unlikely to be manipulated by applicants. As an alternative size measure, we use total capital investment (in 00,000 Indian rupees). We again winsorize at the 1st and 99th percentiles of the distribution and take the inverse hyperbolic sine. Total capital investment affects application fees, and so firms might misreport it. Therefore, our primary measure of firm size is the number of workers.

To capture entry, we construct a panel of firm $\times$ month observations that follows each potential entrant over time. Our principal outcome variable is an indicator equal to one in the month in which a firm first submits a CTE application and zero in all earlier months. Firms exit the panel after this entry month.

To avoid possible strategic reporting by firms, we exclude from our baseline sample any industries for which classification as "Red" or "Orange" depends on any measure of size, such as "Rice Mills with less than 10 tons per day capacity." Such applications are 17% of the sample. Applications in our data report the industry classifications that the Pollution Control Boards use to assign pollution scores. We obtain pollution scores and color classifications for each industry before and after the reforms from Central Pollution Control Board policy documents (CPCB, 2016).[8]

3.2. **Regulatory Cost Measures.** We use the applications to compute several measures of regulatory burden. These include time to decision (in days), total fee (in rupees), and a dummy for whether the application was accepted.[9] For time to decision and total fee, we winsorize at the 99th percentile and take the inverse hyperbolic sine. We focus on these measures because they are available for all states in our data.

[6] 1.2% of firms report zero workers. In the Appendix we show that using the number of workers in levels rather than in inverse hyperbolic sine form yields comparable treatment effect estimates.

[7] 9.5% of applications do not report the number of workers. In Appendix Table A.2, we show that reporting pattern is not affected by treatment status.

[8] Some applications report incomplete or vague industry information; we drop these from our main analysis. For robustness, we use a fuzzy string matching algorithm (Jaro-Winkler distance) to assign industries and re-estimate our specifications including these applications (Table A.3).

[9] We drop applications where information is either missing or ambiguous. In Appendix A.3, we summarize the steps taken to obtain the sample used in the analysis.

We also measure regulatory burden using the conditions that State Pollution Control Boards attach to permits. Firms receive a certificate outlining the conditions they must comply with. We count the total number of conditions. In addition, we decompose the total number of conditions into "Generic conditions," which are typically listed under the "General Conditions" section of the permit, and (b) "Specific Conditions," which appear under "Specific," "Additional," or "Special" sections. General conditions include requirements such as "The unit shall raise the stack height of the DG set/boiler in accordance with the Boards norms." Specific conditions include requirements such as "The unit shall provide a septic tank followed by a soak pit for sewage treatment and disposal." Specific conditions are precisely the types of provision over which officers have discretion.[10]

We also analyze the text to detect two specific types of condition. First, using keyword searches, we identify whether the certificate includes any siting-related conditions, such as references to "siting," "set back," or "location." Second, we evaluate whether the certificate includes conditions specifying pollution limits, using as phrases like "parameters within limit" or "quantity of effluent."

Together, our certificate-based measures capture both the overall regulatory burden imposed on the firm and specific restrictive requirements that increase the compliance burden it faces.

3.3. **Other Potential Data Sources .** Several data sources in India contain information on firms. Four standard sources of data on firms in India are the Economic Census, the ASI, the National Sample Survey (NSS), and the Center for Monitoring the Indian Economy's Prowess dataset. The last available waves of the Economic Census and NSS predate the re-categorization reform, which took place in 2016, and so cannot be used to evaluate it. There are two main differences between our data and the ASI. First, the permits data cover all firms applying for a permit, regardless of size, and so are much more representative of the relevant firm population (as we detail below, the data we collect has over three times the number of firms as in the ASI in relevant sectors). Second, standard sources do not contain information on the regulatory process, which allow us to create novel measures of regulatory burden.

We use 7 rounds (2010-2017) of the ASI, and compare the results we find to those from the ASI. This data is conducted by the National Sample Survey Office annually. The ASI oversamples larger firms. The sampling frame covers all registered manufacturing firms with more than 100 workers, and a random sample of registered firms with more than ten workers (20 if without power).

[10]In our survey sample around 76.38% of the firms report that they are aware of the conditions attached to the consent certificate.

To define the pollution categories, we match industrial classifications used by the Central Pollution Control Board with the National Industrial Classification (NIC) system reported in the ASI. We do this match by hand, dropping 5-digit NIC codes where the treatment status was ambiguous. We approximate firms seeking entry permits using new entrants in the ASI in a given year. Similarly, we use the total number of workers as the main measure of firm size, and capital stock as the supplemental measure of firm size. The ASI is annual, and so gives a coarse measure of timing.

There are many more firms in our data than in the ASI, and they are smaller. We record 4,463 new permit applications in 2015, before the policy reform, in the five states for which we have data. In the ASI, there are only 1,020 new firms in these states in 2015.[11] Table A.4 compares our baseline sample to the one we construct using the ASI. On average, ASI firms employ nearly four times as many workers as firms in the main application sample, with even larger differences at the upper end of the size distribution. Firms in the 75th percentile of the ASI sample have about 90 workers, while those at the 75th percentile of our main sample have about 15 workers. Discrepancies in the size of capital stock between our sample and the ASI are similar. Smaller firms that may have entered because of the re-categorization policy are thus likely to be under-sampled by the ASI.

3.4. **Summary statistics.** A.5 reports summary statistics for the pre-announcement sample relevant to our main analysis. An average firm in our sample has 18 workers, though the median, at 8, is smaller. Capital investment averages ₹542,107,000, though this measure is also right-skewed. 76.5% of applications are accepted. The mean application is decided in 137 days, and firms pay around ₹18,911 in application fees. Permit certificates specify an average of 27.45 conditions, with 71% including at least one reference to siting criteria or pollution limits.

4. Empirical Strategy

4.1. **Application Characteristics.** To estimate how the reduction in regulatory burden affected firms, we use both difference-in-difference and event study approaches. Our main specification is the following for the difference-in-difference:

$$\begin{aligned} y_{aidq} = &\beta_1 \text{Red to Orange}_i \times \text{Announced}_q + \beta_2 \text{Red to Orange}_i \times \text{Implemented}_q \\ &+ \delta_i + \eta_q + \theta_{dy} + \lambda_{py} + \epsilon_{aidq} \end{aligned} \tag{1}$$

Here, y_{aidq} is an outcome for application a in industry i in district d in quarter q. Red to Orange$_i$ is the indicator for exposure to the policy change, which is 1 if the industry i was re-categorized downward in regulatory burden from Red to Orange, and zero

[11]Out of the 4,463 applications, 3,683 were approved and the remainder either pending or rejected.

if the industry was Orange both before and after the reform. Other industries are excluded from the baseline sample. Announced_q is a dummy variable that takes the value one for the last three quarters of 2016 (and zero otherwise). Implemented_q is a dummy variable that takes the value one for 2017 and later, and is zero otherwise. Thus, β_1 identifies the treatment effect for 2016, when the central government directed state governments to set up implementation protocols, and β_2 identifies treatments effects for the period after states declared implementation had begun by circulating a formal statement on their websites. This "Implemented" phase began in the first quarter of 2017.

We control for several fixed effects. δ_i is an industry fixed effect, which controls for time-invariant characteristics of industries. These industries define the treatment group into which an application falls. η_q is a quarter fixed effect that accounts for time-varying unobservable variables that affect all applications in a given quarter in the same way. δ_{qy} is a district $\times$ year fixed effect. Districts define the local offices of the Pollution Control Board over time, and will control for any time-varying local idiosyncrasies in how applications are treated, as well as any other regulatory changes in the district. λ_{py} is a pollution score $\times$ year fixed effect that focuses identification on applications having the same pollution potential that were regulated differently before the re-categorization policy and regulated similarly afterwards. ϵ_{aidq} is the error term. We cluster standard errors by industry, the level at which treatment varies. Our data are not a panel of applications, as we see each application only once.

We estimate an analogous specification for the event study:

$$y_{aidq} = \sum \beta_q \text{Red to Orange}_i + \delta_i + \eta_q + \theta_{dy} + \lambda_{py} + \epsilon_{aidq} \tag{2}$$

β_q is a different coefficient for every quarter q. β_q is normalized to 0 in Q1 of 2016, the final quarter before the policy announcement. The other variables are the same as for equation (1), and standard errors are again clustered at the industry level.

4.2. **Firm Entry.** To estimate the impact of the re-categorization policy on firm entry, we construct a panel of firm $\times$ month observations and define an indicator for entry, Enter_{at}, which equals one in the month t in which firm a first submits the first CTE application and zero in all earlier month. Firms exit the set after this entry month. We estimate this hazard model using the same specifications as in equation (1) and (2).

5. Results

5.1. **First Stage: Classification.** We show, first, that the re-categorization policy did affect the color assigned to applications. Figure 1a shows event study estimates of Equation (2), while Table 1, Column 1, reports the analogous difference-in-difference estimates of equation (1). In both, the dependent variable is whether the color listed on an application is Orange.[12] Applications in industries that were Red before the policy change but Orange after the change indeed became more likely to be classified as Orange. But this change was gradual. Treated firms are 30 percentage points more likely to be classified as Orange in the "Announced" phase and 62.8 p.p. more likely to be classified as Orange in the "Implemented" phase. This gradual execution helps account for results we show below on firm size, as many of these are not apparent until the "Implemented" phase begins.

5.2. **Main Results.**

5.2.1. *Size.* Next, we test whether the marginal applicant had fewer workers after the policy. In Figure 1b, we present event study estimates of Equation (2) using the inverse hyperbolic sine of the number of workers as an outcome. In Table 1, Column 2, we report the corresponding difference-in-difference estimates of equation (1). New entrants in affected industries were smaller after the policy. In particular, they had fewer workers during the "Implemented" phase. The magnitude of this reduction is equivalent to 28.5%.[13] In Figure A.2, we report the corresponding event study estimates using the number of workers in levels rather than the inverse hyperbolic sine and find a similar pattern. In Appendix (Figure A.3), we show similar effects on capital investment, which we use as a different measure of firm size. Thus, regulatory burden related to environmental permitting regulation has a large impact on the size of the marginal firm that enters the economy.

5.2.2. *Entry.* Turning to entry, we report event study results in Figure 1c and difference-in-difference results in Table 1, Column 3. We estimate a hazard model and so the unit of observation becomes a firm-month cell, with a firm exiting the panel after the month in which it enters. The outcome is a dummy equal to one in the month when the firm submits a new Consent to Establish (CTE) application. During both the "Announced" and "Implemented" phases, the number of new applications in affected industries rises by roughly 30% relative to the control mean, and a similar pattern appears in the event study.

5.3. **Mechanisms: Regulatory Burden.** Several models could link reduced environmental regulation to the entry of smaller firms. A long tradition of models (e.g. Lucas (1978); Ulyssea (2018)) allows more productive firms to operate at a greater scale, while firms below a productivity cutoff do not enter the market. Our results are consistent with a model of this type – presented in Appendix A.4 – in which firms pay fixed entry costs. Re-categorization lowers these costs, inducing greater entry and reducing the size of the new entrants. In this section, we show evidence of lower entry costs.

[12] In some states, applicants choose an activity from a portal drop-down and the system auto-assigns the colour category. Where no drop-down exists, applicants self-classify using State Pollution Control Board lists, and the Board reviews and corrects.

[13] We follow Bellemare and Wichman (2020, p. 53) and compute the elasticity as $e^{\beta} - 1$, where $e^{-0.336} - 1 \approx -0.285$.

5.3.1. *Monetary Costs, Processing Time, and Acceptance.* For fees, processing time, and acceptance, we show event studies in Figure A.4, and report difference-in-difference results in Panel A of Table 2. Firms that were re-categorized downwards paid lower fees, with reductions of 79% during the "Announced" phase and 66% during the "Implemented" phase. This implies an average saving of approximately ₹10,350. While the reduction in fees is large in percentage terms, the monetary saving is economically negligible: it represents less than 3% of the total capital investment of firms at the 5th percentile of the control group in the pre-treatment period. We find no evidence that such applications were decided on more quickly nor were they more likely to be accepted.

5.3.2. *Permit Conditions.* Table 2 (Panel B) and Figure A.5 present results from our data on permit conditions. Firms that were re-categorized downward see a significant reduction in the total number of conditions included in their permit certificates (Column (1)). The coefficient is 8% of the control mean. It is larger and statistically significant only in the "Implemented" phase. In Columns (2) and (3), treated firms become less likely to face conditions related to siting or pollution limits. These effects are also on statistically significant only in the "Implemented" phase. Siting conditions are informative; all industries in our sample face some siting requirements (for instance, minimum distances from schools), and higher-pollution categories face stricter siting restrictions. Treated firms are 7.2 p.p. less likely to have any siting requirement explicitly written into their permit.[14]

Changes in the total number of conditions in Table 2 would be mechanical if states follow preset templates for each colour category. This is unlikely. First, even within states there is substantial variation in the number of conditions across firms in the same colour category. In the final pre-treatment year (2015), the average interquartile range in the number of conditions within a state-category cell is 8.6. Even within the same state and industry, the average interquartile range is 5. A substantial share of the variation in conditions, then, reflects firm-specific requirements rather than category or industry templates.

Second, Table A.6 shows that the decline in the total number of conditions is driven by a reduction in specific conditions – the conditions over which officers have more discretion, and that vary most across firms within an industry. The coefficient for specific conditions is 20% of the control mean and is significant only during the "Implemented" phase.

Overall, these patterns suggest that the effective burden on firms depends on the scope of specific mandates – which are typically unobserved in standard data – rather than procedural frictions. Consequently, studies relying primarily on administrative indicators to measure

[14]We also examine a smaller group of industries that were re-categorized from Orange to Green (19 of 73 Orange industries), using always-Green industries as the control group. We find no effect of Orange-to-Green change re-categorization on the number or size of new CTE applications (Table A.7, Panel A). Consistent with a regulatory-burden mechanism, we do not see meaningful changes in consent conditions in Table A.7, Panel C.

regulatory burden may fail to capture a significant component of the costs associated with compliance.

5.4. **Comparison with Standard Data Sources.** What are the advantages of our novel applications data? Consider the results that we would have obtained using the Annual Survey of Industries (ASI). The ASI does not include district identifiers, and so our specification includes only state $\times$ year, pollution score $\times$ year, and 5-digit NIC fixed effects, rather than the more demanding and precisely defined fixed effects in equation (2).

We show event study results in Figure A.6a and Table 3, using the inverse hyperbolic sine of the firm's labor as the outcome. The results in the "Implemented" phase are insignificant at conventional levels. That is, the reductions in firm size that we observe in Figure 1b would not have been apparent had we used the ASI data. In Column 2 (and Figure A.6b), we reach the same conclusion using capital as an outcome.

5.5. **Robustness.** One possible threat to identification would be if our results were to capture formalization rather than entry. We find little evidence of this. First, Pollution Control Boards verify the "date of commissioning" – when commercial production begins – as part of the review process. In the subset of applications for which this date is available, 84% report a commissioning date subsequent to the application submission date. Second, very few firms register with other government bodies before making an application. Registration on the same date as the CTE application or after does not rise in response to re-categorization (Figure A.7).[15] Lastly, We fielded a firm survey in 2025 and obtained activity start dates for 105 firms. For the majority of firms in our sample, activity begins either after the CTE application is submitted or within the same calendar year. On average, the difference between submission and start dates is 0.3 years, and the median applicant submits one year before starting the activity.

The impacts we find on firm size are not driven by any one industry. Dropping each industry in turn, we continue to find impacts of re-categorization that are similar in magnitude and significance to our baseline estimates (Figure A.8). Nor does the inverse hyperbolic sine transformation drive our results. Results using the levels of winsorized number of workers look similar to our baseline (Figure A.2). Winsorizing does not drive our results, which are largely unchanged if we do not winsorize or winsorize the 5% right tail of the distribution (Table A.8).

In Table A.9, Column 1, we restrict the sample to applications receiving pollution scores that exist both for industries that were initially coded as Red and were later coded as Orange, and for industries that remained Orange throughout. That is, we only include

[15]For one state (Odisha), we have the registration date of all firms. We also have the registration date for some applications in other states. For more than 98% of these observations, the registration date of the firm was not before the application date for the CTE.

pollution scores that exist in both the treatment and control groups. Column 2 further restricts the sample to industries with pollution scores of 50 – the most common pollution score for which there are both treated and control industries. We find similar results using this restricted sample.

Our choice of specification does not drive our results. We find similar results on firm size using several alternative fixed effects and trends as controls, district × quarter fixed effects, state × quarter fixed effects, and month of submission fixed effects (Table A.10). Our results retain their conventional levels of significance whether we cluster by industry, by year, or by the intersection of state and pollution score (Table A.11).

6. Conclusion

Effective policies require understanding how firms respond to regulatory burden, which in developing countries is likely to fall more heavily on smaller firms and to be applied unevenly by regulators. We show that environmental permitting regulations can change the rate and composition of entry substantially, and disproportionately affect smaller firms. Reductions in this regulatory burden do not change processing times, but cause other changes to the regulatory process, namely, application fees as well as the number of permit conditions.

Our results have several implications. First, the impacts of regulation may not be detectable without data covering the whole firm size distribution – data not available in many standard sources. Second, regulatory burden itself may not be captured completely by available metrics such as fees, processing time, and acceptance rates. Standard sources may miss other aspects, such as the firm-specific conditions applied by the regulator.

These results also raise other questions. For instance, how to optimally match regulatory burden with environmental costs remains an interesting question for future work. Second, dispersion in regulatory capacity and its implications for economic outcomes remain under-researched (Besley et al., 2022), as does implications of such regulatory burden in changing market concentration. These and related aspects of regulatory burden, remain interesting questions for future work.

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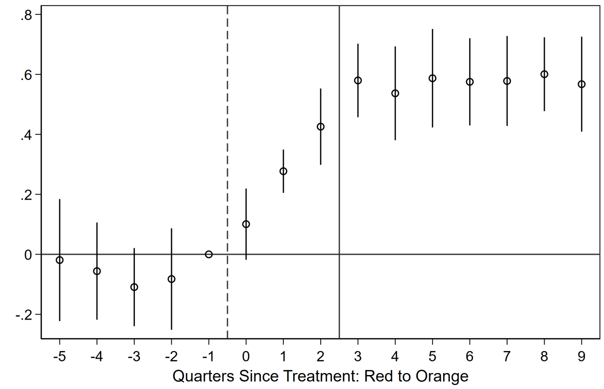
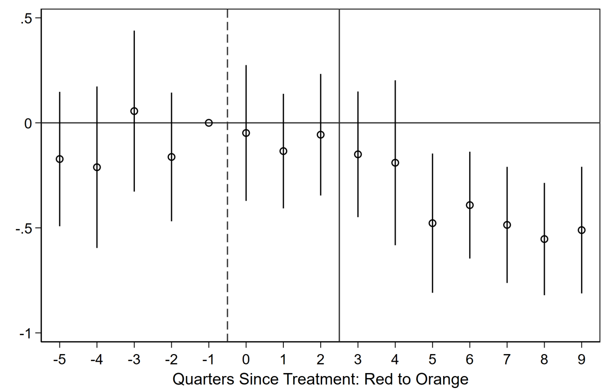
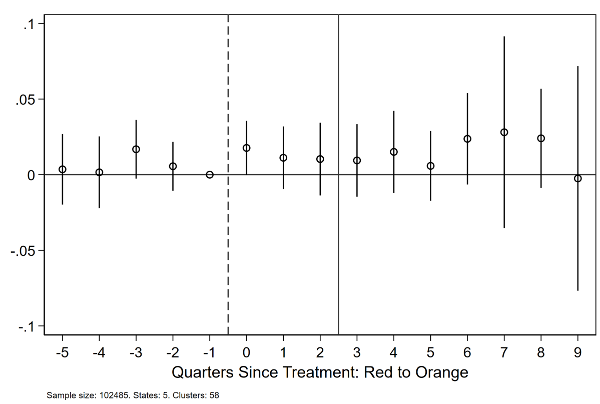
FIGURE 1. Event studies



(A) Classified as Orange



(B) Number of Workers



(C) Firm Entry

Notes: The figure plots event study coefficients β_q from the estimation of equation (2). Vertical bars represent 95 percent confidence intervals. The omitted category is the first quarter of 2016. In Panel (A), the dependent variable is an indicator equal to one if the application is classified as "Orange." In Panel (B), the dependent variable is the inverse hyperbolic sine of the number of workers (winsorized). Panel (C) reports estimates from a hazard model where the dependent variable is an indicator equal to one in the month the firm submits its first CTE application; firms exit the sample after the month of entry. All specifications include industry, quarter, district $\times$ year, and pollution score $\times$ year fixed effects. Standard errors are clustered at the industry level.

Table 1. Difference-in-Difference Results: Firm Characteristics and Entry

	Application-Level Data		Firm Entry Hazard Panel
	(1) Classified as Orange	(2) IHS Total Number of Workers	(3) Number of New CTE Applications
Red to Orange × Announced	0.300***	-0.007	0.009*
	(0.033)	(0.106)	(0.005)
Red to Orange × Implemented	0.628***	-0.336***	0.010
	(0.050)	(0.077)	(0.006)
Observations	4224	4224	102485
Control Mean	0.894	2.939	0.033

Notes: The table reports difference-in-differences estimates of equation (1). The dependent variable in Column (1) is an indicator equal to one if the application is classified as "Orange." The dependent variable in Column (2) is the inverse hyperbolic sine of the number of workers (winsorized). Column (3) estimates a hazard model where the dependent variable is an indicator equal to one in the month the firm submits its first application; firms exit the sample after the month of entry. All specifications include industry, quarter, district × year, and pollution score × year fixed effects. Standard errors are clustered at the industry level and reported in parentheses. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 2. Difference-in-Difference Results: Regulatory Burden

	(1) Total Fee Applied	(2) Time to Decision	(3) Accepted
Panel A: Conventional Measures			
Red to Orange × Announced	-1.582***	-0.026	-0.051
	(0.545)	(0.197)	(0.043)
Red to Orange × Implemented	-1.089***	0.046	0.018
	(0.235)	(0.145)	(0.037)
N	3359	4024	4003
Control Mean	7.326	4.751	0.809
	(1) Total Conditions	(2) Any Siting Condition	(3) Any Pollution Limit Conditions
Panel B: Permit Conditions			
Red to Orange × Announced	-1.126*	-0.011	-0.050*
	(0.563)	(0.037)	(0.026)
Red to Orange × Implemented	-2.134***	-0.072***	-0.115***
	(0.566)	(0.023)	(0.026)
N	3230	3230	3230
Control Mean	26.364	0.743	0.618

Notes: The table reports difference-in-differences estimates of equation (1). In Panel A, the dependent variables are the inverse hyperbolic sine of the winsorized total application fee (Column 1), the inverse hyperbolic sine of the winsorized time to decision in days (Column 2), and an indicator equal to one if the application was accepted (Column 3). In Panel B, the dependent variables are the total number of conditions listed in the permit certificate (Column 1), an indicator equal to one if the permit includes any siting conditions (Column 2), and an indicator equal to one if it includes any pollution limit conditions (Column 3). All specifications include industry, quarter, district × year, and pollution score × year fixed effects. Standard errors are clustered at the industry level and reported in parentheses. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

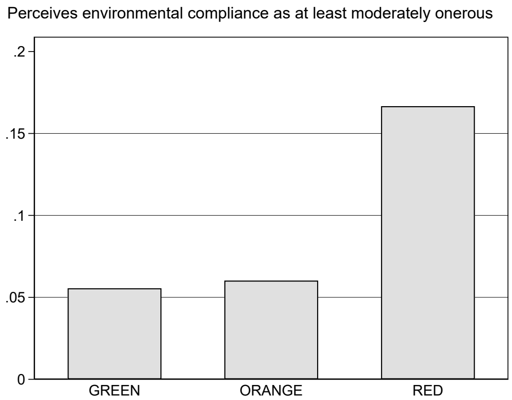
Table 3. Difference-in-Difference Results: ASI Data

	(1) IHS(Number of Workers)	(2) IHS(Capital Stock)
Red to Orange × Announced	-0.438*	-0.671*
	(0.247)	(0.366)
Red to Orange × Implemented	0.062	-0.166
	(0.207)	(0.464)
Observations	3911	3960
R^2	0.275	0.346
Control Mean	4.429	16.505
State × Year FE	Yes	Yes
Pollution × Year FE	Yes	Yes
Industry FE	Yes	Yes

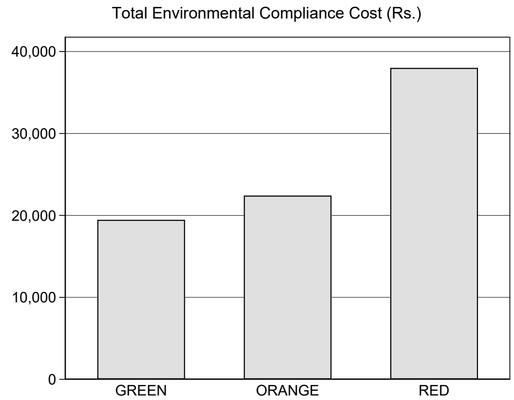
Notes: The table reports difference-in-differences estimates using data from the Annual Survey of Industries (ASI) for the years 2010–2017. The sample is restricted to new entrant firms (firms observed in their year of initial production) The dependent variable in Column (1) is the inverse hyperbolic sine of the number of workers (winsorized). The dependent variable in Column (2) is the inverse hyperbolic sine of the capital stock (winsorized). All specifications include industry, state × year, and pollution score × year fixed effects. Standard errors are clustered at the industry level and reported in parentheses. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Appendix A.1. Additional Figures

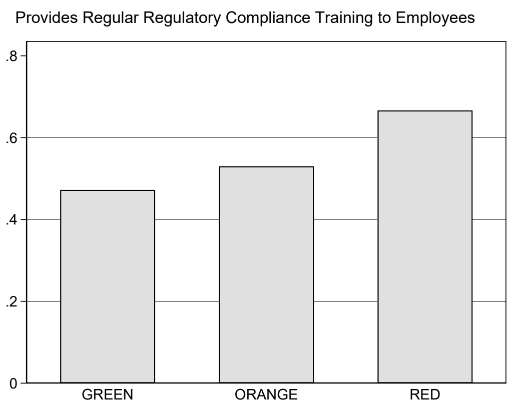
Figure A.1. Environmental Compliance by Category: Survey Data



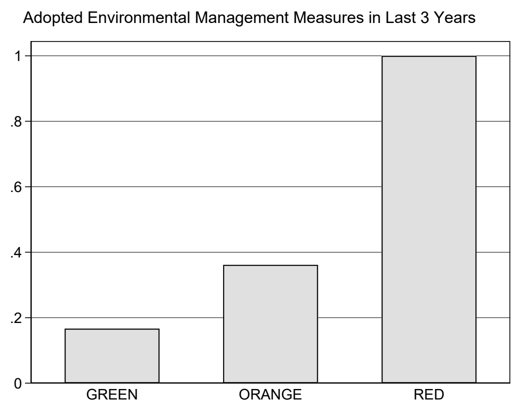
(A) Perceived Compliance Burden



(B) Compliance Cost (Rupees)



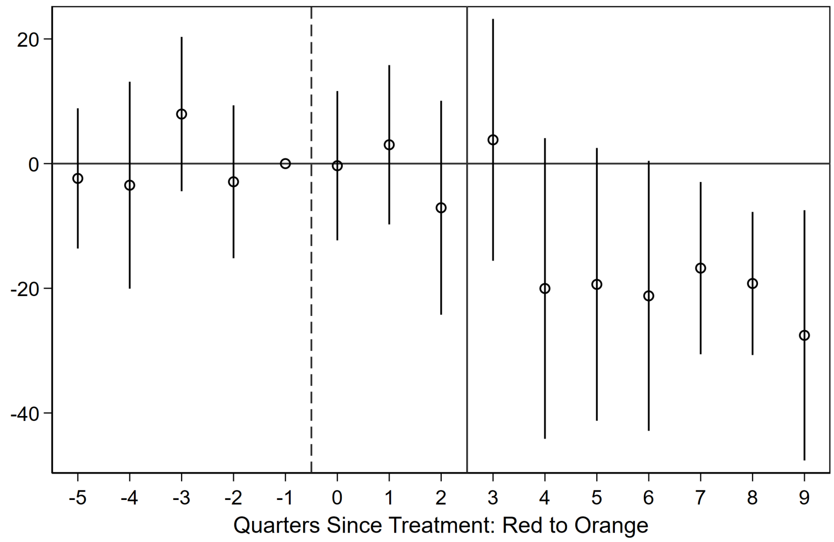
(C) Compliance Training Provided



(D) Environmental Measures Adopted

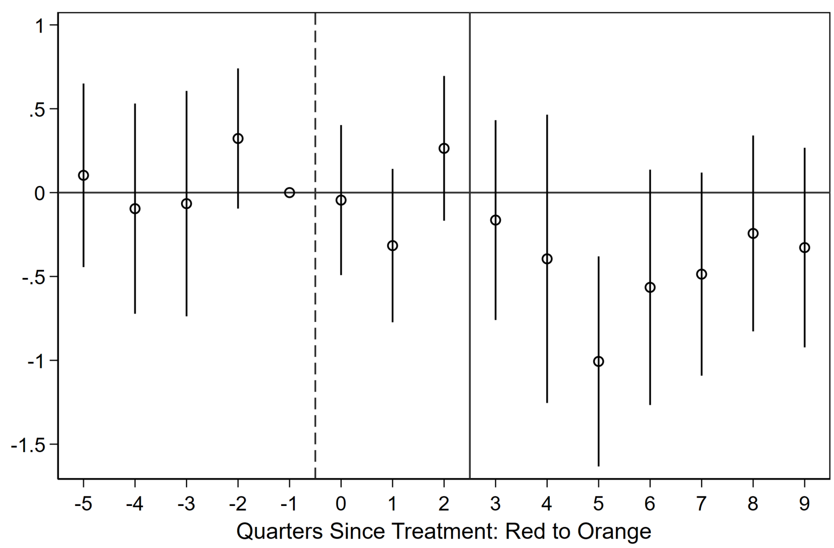
Notes: The figure reports descriptive statistics from the 2025 firm owner survey, averaged by pollution category. Panel (A) plots the share of firms that perceive environmental compliance as at least "moderately onerous". Panel (B) plots the average total environmental compliance cost in Indian Rupees. Panel (C) plots the share of firms that provide regular regulatory compliance training to employees. Panel (D) plots the share of firms that adopted specific environmental management measures in the last three years. The sample is restricted to survey respondents classified in the Green, Orange, or Red pollution categories.

FIGURE A.2. Event study: Number of Workers (Levels)



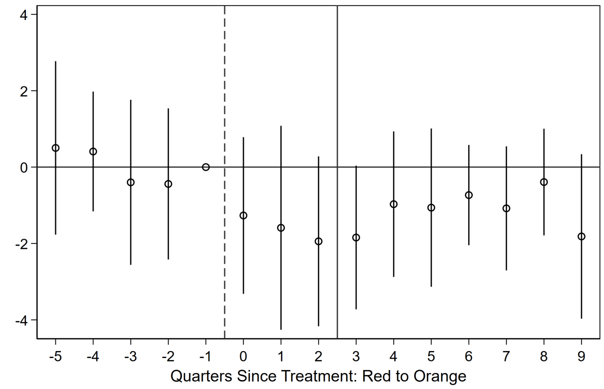
Notes: The figure plots event study coefficients β_q from the estimation of equation (2). Vertical bars represent 95 percent confidence intervals. The dependent variable is the number of workers (winsorized). The omitted category is the first quarter of 2016. All specifications include industry, quarter, district $\times$ year, and pollution score $\times$ year fixed effects. Standard errors are clustered at the industry level.

FIGURE A.3. Event study: Capital

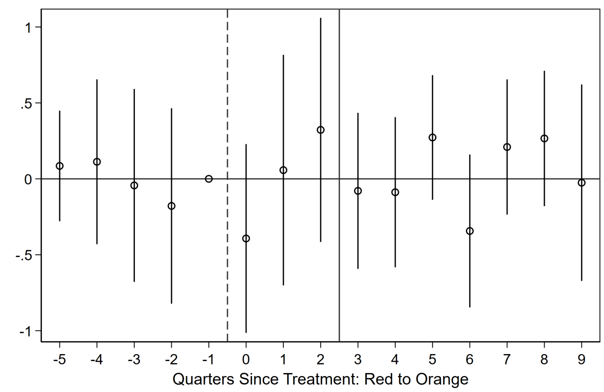


Notes: The figure plots event study coefficients β_q from the estimation of equation (2). Vertical bars represent 95 percent confidence intervals. The dependent variable is the inverse hyperbolic sine of capital investment (winsorized). The omitted category is the first quarter of 2016. All specifications include industry, quarter, district $\times$ year, and pollution score $\times$ year fixed effects. Standard errors are clustered at the industry level.

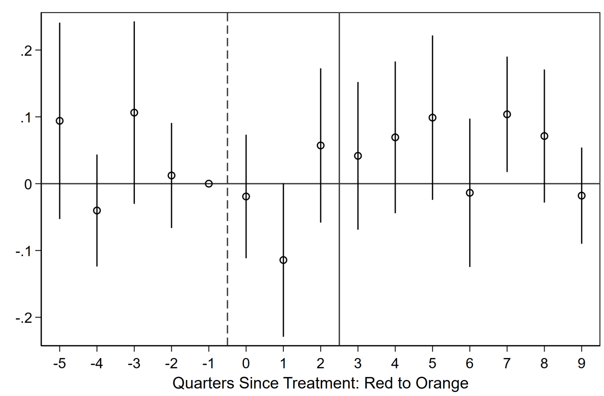
FIGURE A.4. Event studies: Fees, Time to decision, and Accepted



(A) Event study: Fees



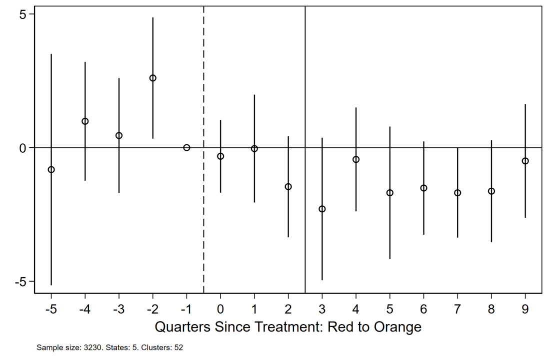
(B) Event study: Time to decision



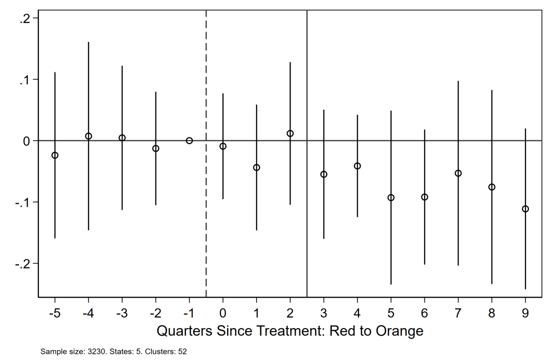
(C) Event study: Accepted

Notes: The figure plots event study coefficients β_q from the estimation of equation (2). Vertical bars represent 95 percent confidence intervals. The omitted category is the first quarter of 2016. In Panel (A), the dependent variable is the inverse hyperbolic sine of the total application fee (winsorized). In Panel (B), the dependent variable is the inverse hyperbolic sine of the time to decision in days (winsorized). In Panel (C), the dependent variable is an indicator equal to one if the application was accepted. All specifications include industry, quarter, district $\times$ year, and pollution score $\times$ year fixed effects. Standard errors are clustered at the industry level.

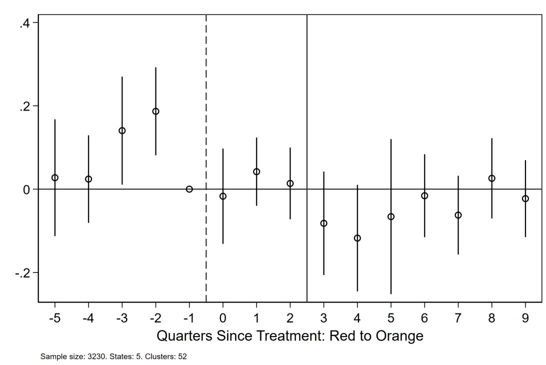
Figure A.5. Mechanism – Permit Conditions and Regulatory Burden



(A) Total Conditions



(B) Mentions Siting

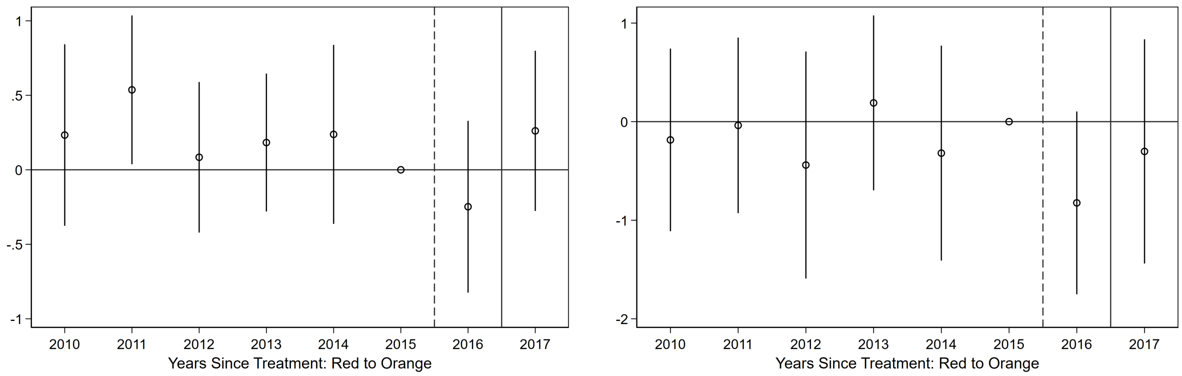


(C) Mentions Pollution Limits

Notes: The figure plots event study coefficients β_q from the estimation of equation (2). Vertical bars represent 95 percent confidence intervals. The omitted category is the first quarter of 2016. In Panel (A), the dependent variable is the total number of conditions listed in the permit certificate. In Panel (B), the dependent variable is an indicator equal to one if the permit includes any siting conditions. In Panel (C), the dependent variable is an indicator equal to one if the permit includes any pollution limit conditions. All specifications include industry, quarter, district $\times$ year, and pollution score $\times$ year fixed effects. Standard errors are clustered at the industry level.

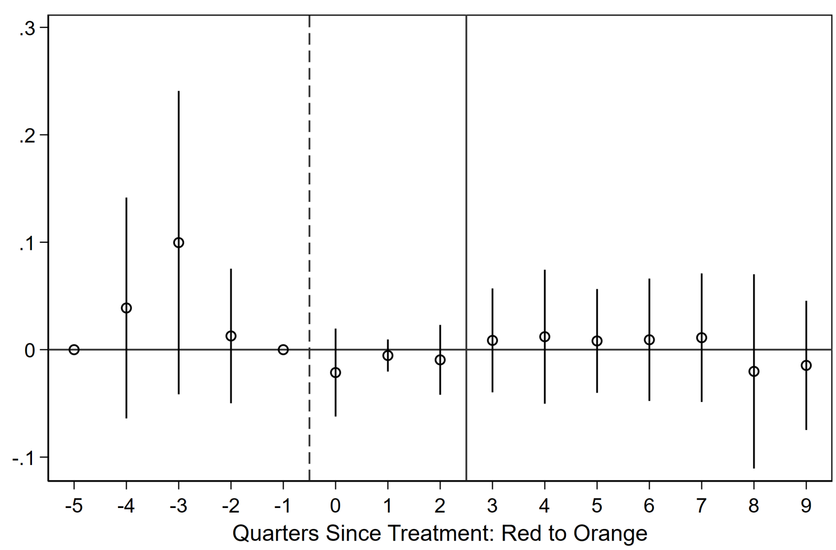
Figure A.6. Event study: Labor and capital in the ASI

(A) Labor in the ASI (B) Capital in the ASI



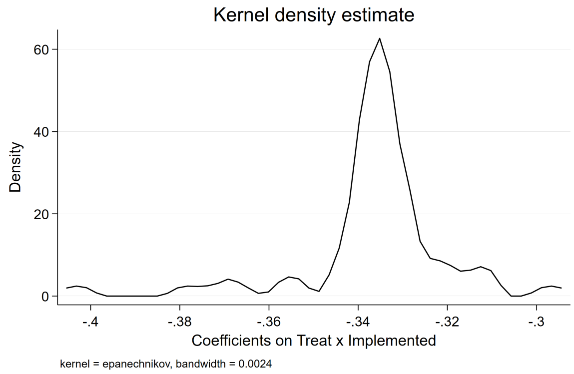
Notes: The figure plots event study coefficients from a specification analogous to equation (2), adapted for annual data from the Annual Survey of Industries (ASI). Vertical bars represent 95 percent confidence intervals. The omitted category is 2015. The sample is restricted to new entrant firms (firms observed in their year of initial production). In Panel (A), the dependent variable is the inverse hyperbolic sine of the number of workers (winsorized). In Panel (B), the dependent variable is the inverse hyperbolic sine of the capital stock (winsorized). All specifications include industry, state × year, and pollution score × year fixed effects. Standard errors are clustered at the industry level.

Figure A.7. Registered on or after application submission date

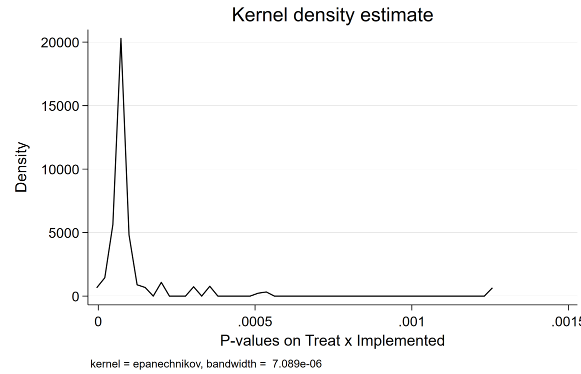


Notes: The figure plots event study coefficients β_q from the estimation of equation (2). Vertical bars represent 95 percent confidence intervals. The dependent variable is an indicator equal to one if the firm's formal registration date is on or after the date of submission of the Consent to Establish (CTE) application. The omitted category is the first quarter of 2016. The sample is restricted to applications where the registration date is observed (primarily from the state of Odisha). All specifications include industry, quarter, district × year, and pollution score × year fixed effects. Standard errors are clustered at the industry level.

FIGURE A.8. Coefficients and p-values for *Treat* × *Implemented* (IHS winsorized total workers)



(A) Coefficients on Treat × Implemented



(B) P-values on Treat × Implemented

Notes: The figure plots kernel density estimates from a "leave-one-out" robustness check. We re-estimate the baseline difference-in-differences specification (equation (1)), excluding one industry from the sample in each iteration. Panel (A) displays the distribution of the coefficient estimates for the interaction term *Red to Orange* × *Implemented* (β_2). Panel (B) displays the distribution of the corresponding p-values. The dependent variable is the inverse hyperbolic sine of the number of workers (winsorized). All specifications include industry, quarter, district × year, and pollution score × year fixed effects. Standard errors are clustered at the industry level.

Appendix A.2. Additional Tables

Table A.1. Regulatory Burden by Pollution Category

	Red	***Orange***	***Green***
Processing Time (days)	30-45	30	30
Inspection Frequency (years)	2	3-5	15
Location Restriction	Not Permitted in Ecologically Fragile / Protected Area	None	None
Permit Valid For (years)	5	10	14
Number of Documents required	13-24	12	12
Application Fees (₹)	900-2,400,000	600-1,800,000	600-1,200,000

Notes: The information on processing time, validity, and number of documents required is taken from Tamil Nadu Pollution Control Board's website. Location restrictions were mentioned in a press release listed on Press Information Bureau. The fee structure is from Punjab Pollution Control Board's website and Inspection Frequency is from Uttar Pradesh Pollution Control Board's website.

Table A.2. Missing Data for "Number of Workers"

	= 1 if Data for Number of Workers is Missing
	(1)
Red to Orange × Announced	-0.058*
	(0.030)
Red to Orange × Implemented	-0.009
	(0.019)
Observations	4683
R^2	0.419
Control Mean	0.078
District × Year FE	Yes
Pollution × Year FE	Yes
Industry FE	Yes
Quarter FE	Yes
Sample	All

Notes: The table reports difference-in-differences estimates of equation (1). The dependent variable is an indicator equal to one if the data on the number of workers is missing in the application form. All specifications include industry, quarter, district × year, and pollution score × year fixed effects. Standard errors are clustered at the industry level and reported in parentheses. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table A.3. Industry Matching

	IHS Total Number of Workers			
	(1)	(2)	(3)	(4)
Red to Orange × Announced	-0.007	-0.000	-0.001	-0.012
	(0.106)	(0.105)	(0.100)	(0.090)
Red to Orange × Implemented	-0.336***	-0.320***	-0.275***	-0.251***
	(0.077)	(0.074)	(0.077)	(0.092)
Observations	4224	4270	4395	4879
R^2	0.582	0.579	0.573	0.558
Control Mean	2.832	2.832	2.832	2.832
District × Year FE	Yes	Yes	Yes	Yes
Pollution × Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Sample	All	All	All	All
Jaro Winkler Distance	$= 1$	> 0.90	> 0.80	> 0.70

Notes: The table reports difference-in-differences estimates of equation (1). The dependent variable is the inverse hyperbolic sine of the number of workers (winsorized). The industry matching utilizes the Jaro-Winkler distance to measure the similarity between the industry description provided in the application and the industry list in the Pollution Control Board's re-categorization document. The score ranges from 0 to 1, where 1 represents an exact match. All specifications include industry, quarter, district × year, and pollution score × year fixed effects. Standard errors are clustered at the industry level and reported in parentheses. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table A.4. Comparison with the ASI

	Main Sample	ASI	ASI Sample States
Number of Employees			
25th pctile	4	12	12
50th pctile	8	31	30
75th pctile	15	93	91
Capital Stock (Million Rs.)			
25th pctile	2.00	3.95	2.47
50th pctile	5.00	21.16	12.93
75th pctile	17.04	113.30	74.45

Notes: The table compares the distribution of firm characteristics in the main analysis sample against the Annual Survey of Industries (ASI). Panel A reports the 25th, 50th, and 75th percentiles of the number of workers. Panel B reports the same statistics for capital investment (in Million Rs.). Column (1) uses the main estimation sample, restricted to new Consent to Establish (CTE) applications in Red and Orange categories (excluding industries where categorization is size-based). Columns (2) and (3) use data from the ASI, restricted to firms observed in their year of initial production. Column (2) includes all states in the ASI, while Column (3) restricts the ASI sample to the states included in the main application data analysis.

Table A.5. Pre-Announcement Summary Statistics

	Mean	SD	Min	Max	Count
Classified as Orange	0.653	0.476	0	1	1435
IHS Total Number of Workers	2.850	1.129	0	7.41	1435
IHS Capital Investment	4.568	1.833	0.77	14.0	1435
IHS Winsorized Time to Decision	4.654	1.398	0	7.57	1409
IHS Winsorized Fee Applied	7.706	4.243	0	13.9	1196
Accepted	0.765	0.424	0	1	1390
Total Conditions	27.45	10.01	0	85	1074
Mention Siting	0.710	0.454	0	1	1074
Mention Pollution Limits	0.671	0.470	0	1	1074

Notes: The table reports summary statistics for the pre-announcement sample. "Classified as Orange" is an indicator equal to one if the application is categorized as Orange. "Number of Workers", "Capital Investment", "Time to Decision", and "Total Fee Applied" are, reported as the inverse hyperbolic sine of the winsorized values. "Accepted" is an indicator equal to one if the application was approved. "Total Conditions" reports the count of conditions listed in the permit certificate. "Mentions Siting" and "Mentions Pollution Limits" are indicators equal to one if the permit certificate includes conditions related to siting criteria or pollution limits, respectively.

Table A.6. Difference-in-Difference Results: Generic vs. Additional Conditions

	(1) Total Conditions	(2) Generic Conditions	(3) Additional Conditions
Red to Orange × Announced	-1.126*	-0.054	-1.072*
	(0.563)	(0.399)	(0.568)
Red to Orange × Implemented	-2.134***	-0.497	-1.638***
	(0.566)	(0.346)	(0.464)
Observations	3230	3230	3230
Control Mean	26.364	17.492	8.872

Notes: The table reports difference-in-differences estimates of equation (1). The sample is restricted to accepted applications. The dependent variable in Column (1) is the total number of conditions listed in the permit certificate. The dependent variable in Column (2) is the count of "Generic" conditions. The dependent variable in Column (3) is the count of "Additional" conditions (specific requirements added by the pollution control officer). All specifications include industry, quarter, district × year, and pollution score × year fixed effects. Standard errors are clustered at the industry level and reported in parentheses. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table A.7. Difference-in-Difference Results: Orange to Green Sample

	(1) Classified as Green	(2) IHS Total Number of Workers	(3) Number of New CTE Applications
Panel A: Application-Level and Entry Outcomes			
Orange to Green × Announced	0.230***	-0.032	0.011
	(0.063)	(0.061)	(0.009)
Orange to Green × Implemented	0.197**	-0.006	0.006
	(0.083)	(0.097)	(0.008)
Observations	6575	6575	154582
Control Mean	0.419	1.524	0.026
	(1) Total Fee Applied	(2) Time to Decision	(3) Accepted
Panel B: Conventional Measures			
Orange to Green × Announced	-0.050	-0.070	0.020
	(0.560)	(0.190)	(0.049)
Orange to Green × Implemented	1.396***	0.066	0.002
	(0.388)	(0.147)	(0.052)
Observations	6274	6513	6494
Control Mean	6.522	4.767	0.900
	(1) Total Conditions	(2) Any Siting Condition	(3) Any Pollution Limit Conditions
Panel C: Permit Conditions			
Orange to Green × Announced	2.456***	0.125***	0.085
	(0.888)	(0.025)	(0.062)
Orange to Green × Implemented	1.468	-0.008	0.151***
	(1.066)	(0.026)	(0.047)
Observations	5880	5880	5880
Control Mean	22.561	0.920	0.557

Notes: The table reports difference-in-differences estimates of the effect of re-categorization from Orange to Green. The treatment group consists of industries re-categorized from Orange to Green, and the control group consists of industries that remained Green. In Panel A, the dependent variables are an indicator equal to one if the application is classified as "Green" (Column 1), the inverse hyperbolic sine of the number of workers (Column 2), and an indicator for firm entry estimated using a hazard model (Column 3). In Panel B, the dependent variables are the inverse hyperbolic sine of the total application fee (Column 1), the inverse hyperbolic sine of the time to decision (Column 2), and an indicator equal to one if the application was accepted (Column 3). In Panel C, the dependent variables are the total number of conditions (Column 1), an indicator for any siting conditions (Column 2), and an indicator for any pollution limit conditions (Column 3). All specifications include industry, quarter, district × year, and pollution score × year fixed effects. Standard errors are clustered at the industry level and reported in parentheses. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table A.8. Total number of workers with alternative winsorization thresholds

	IHS Total Workers	
	(1) Winsorized 5pct right tail	(2) No Winsorization
Red to Orange × Announced	-0.004	-0.008
	(0.103)	(0.106)
Red to Orange × Implemented	-0.293***	-0.339***
	(0.070)	(0.077)
Observations	4224	4224
R^2	0.596	0.581
Control Mean	2.924	2.939
District × Year FE	Yes	Yes
Pollution × Year FE	Yes	Yes
Industry FE	Yes	Yes
Quarter FE	Yes	Yes
Sample	All	All

Notes: The table reports difference-in-differences estimates of equation (1) testing robustness to alternative outlier treatments. The dependent variable is the inverse hyperbolic sine of the number of workers. In Column (1), the variable is winsorized at the 95th percentile (top 5 percent). In Column (2), the variable is not winsorized. All specifications include industry, quarter, district × year, and pollution score × year fixed effects. Standard errors are clustered at the industry level and reported in parentheses. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table A.9. Difference-in-Difference Results: Overlapping Pollution Score Sample

	Orange		Total Workers		Capital Investment	
	(1)	(2)	(3)	(4)	(5)	(6)
Red to Orange × Announced	0.299***	0.292***	-0.012	-0.070	-0.086	-0.070
	(0.033)	(0.033)	(0.107)	(0.099)	(0.134)	(0.099)
Red to Orange × Implemented	0.626***	0.601***	-0.336***	-0.298***	-0.495**	-0.298***
	(0.050)	(0.049)	(0.077)	(0.086)	(0.187)	(0.086)
Observations	4191	3538	4191	3538	4191	3538
R^2	0.588	0.612	0.581	0.611	0.496	0.611
Control Mean	0.893	0.885	2.937	2.785	4.209	2.785
District × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Pollution × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Pollution Score Overlap	Same	50	Same	50	Same	50

Notes: The table reports difference-in-differences estimates of equation (1) using restricted samples. The dependent variable in Columns (1) and (2) is an indicator equal to one if the application is classified as "Orange." The dependent variable in Columns (3) and (4) is the inverse hyperbolic sine of the number of workers (winsorized). The dependent variable in Columns (5) and (6) is the inverse hyperbolic sine of capital investment (winsorized). Columns (1), (3), and (5) restrict the sample to applications with pollution scores that exist in both the treatment and control groups. Columns (2), (4), and (6) further restrict the sample to applications with a pollution score of exactly 50. All specifications include industry, quarter, district × year, and pollution score × year fixed effects. Standard errors are clustered at the industry level and reported in parentheses. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table A.10. IHS winsorized total capital investment – Alternative Specifications

	IHS Total Number of Workers					
	(1)	(2)	(3)	(4)	(5)	(6)
Red to Orange × Announced	-0.007	-0.071	-0.189	-0.143*	-0.023	-0.004
	(0.106)	(0.115)	(0.174)	(0.084)	(0.103)	(0.100)
Red to Orange × Implemented	-0.336***	-0.315***	-0.369***	-0.254***	-0.349***	-0.328***
	(0.077)	(0.086)	(0.096)	(0.073)	(0.074)	(0.079)
Observations	4224	4224	3906	4289	4224	4211
R^2	0.582	0.600	0.646	0.461	0.585	0.590
Control Mean	2.939	2.939	2.939	2.939	2.939	2.939
District × Year FE	Yes	Yes	No	No	Yes	Yes
Pollution × Year FE	Yes	Yes	Yes	Yes	Yes	No
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	No	No
District × Quarter Trend	No	Yes	No	No	No	No
District × Quarter FE	No	No	Yes	No	No	No
State × Quarter FE	No	No	No	Yes	No	No
Pollution × Quarter FE	No	No	No	No	No	Yes
Month FE	No	No	No	No	Yes	No
Sample	All	All	All	All	All	All

Notes: The table reports difference-in-differences estimates of equation (1) across alternative specifications. The dependent variable is the inverse hyperbolic sine of the number of workers (winsorized). The specific fixed effects and time trends included in each specification are indicated in the bottom rows of the table. Standard errors are clustered at the industry level and reported in parentheses. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

TABLE A.11. IHS winsorized total number of workers – Alternative Clustering

	IHS Total Number of Workers		
	(1)	(2)	(3)
Red to Orange × Announced	-0.007	-0.007	-0.007
	(0.106)	(0.121)	(0.111)
Red to Orange × Implemented	-0.336***	-0.336***	-0.336**
	(0.077)	(0.126)	(0.130)
Observations	4224	4224	4224
R^2	0.582	0.582	0.582
Control Mean	2.939	2.939	2.939
District × Year FE	Yes	Yes	Yes
Pollution × Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Sample	All	All	All
SE Clustering	Industry	District	State × PS

Notes: The table reports difference-in-differences estimates of equation (1) with alternative standard error clustering. The dependent variable is the inverse hyperbolic sine of the number of workers (winsorized). Standard errors are clustered at the industry level in Column (1), at the district level in Column (2), and at the state × pollution score level in Column (3). All specifications include industry, quarter, district × year, and pollution score × year fixed effects. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Appendix A.3. Data and Sample Construction

This section documents all the steps involved in generating the sample used in the main analysis of this paper.

(1) We have a total of 360,297 applications from five states in India – Haryana, Punjab, Kerala, Tamil Nadu, and Odisha. There are 53,468 CTE and 298,829 CTO applications
(2) We remove all the applications that were submitted before 2015 as not all states report data during this period (Remaining CTEs=51,925 and CTOs=290,678).
(3) We also remove all the applications that were submitted during or after the last quarter of 2018. During this time, additional regulations and policies were introduced that could make it difficult to evaluate the impacts of the re-categorization policy (Remaining CTEs=31,986 and CTOs=181,986).[1]
(4) There are also 3,387 applications for which information on consent type is missing, and therefore, we also remove these from our sample (Remaining CTEs=31,986 and CTOs=181,986).
(5) Information on the district is missing for 107 applications and we also drop these from our sample.
(6) We also exclude applications where industry or sector information is missing. These are the cases where applicants either did not record anything in the industry field or put down ambiguous information such as "others" (Remaining CTEs=30,427 and CTOs=172,792).
(7) In some cases, the information given in the industry field is incomplete or vague which makes it difficult to assign these applications to an industry given in the Pollution Control Board's documents. We also remove these applications from our main analysis. (Remaining CTEs=23,320 and CTOs=124,814).
(8) There are also 15,220 applications where it is not possible to assign pollution scores to corresponding industries or industry information is not sufficient to define re-categorization groups and therefore we also drop these applications from our sample (Remaining CTEs=20,671 and CTOs=112,442).[2]
(9) We are left with 20,671 CTEs. Our main analysis on the CTE applications uses only new applications that are either from Red-to-Orange or Orange-to-Orange re-categorization groups (around 7,500). In this analysis, we also remove industries where classification is based on industry size (around 17% of the sample). This

[1]The new regulations introduce an auto-renewal procedure and eliminate the requirement for a CTE for industries that need Environmental Clearance.

[2]The pollution score is provided in the document released by the PCB for the re-categorization of pollution categories, so we are unable to assign a pollution score to firms where the industry is not reported or if the reported industries are not listed in the document.

ensures that firms are unable to manipulate the treatment assignment. Lastly, to work with a consistent sample, we keep only those applications where we observe the number of workers (around 90% of the sample). The remaining 4,292 CTE applications are part of the sample used in the main CTE analysis.

Appendix A.4. Conceptual Framework

Here, we outline a simple theoretical framework that is consistent with our empirical results. The environment consists of N potential entrants, each of whom must pay a fixed cost c to obtain an environmental permit. A firm earns π if it enters. Post-entry, firms produce output Y using technology $Y = AL^{\alpha}$, where A is total factor productivity, L is labor, and $\alpha \in (0, 1)$. Output markets and labor markets are both competitive, with p denoting the output price and w denoting wages.

Firms are of two types, "good" or "bad," which they cannot change. "Bad" here can be thought of as in violation of environmental regulations, for example being located too close to a school. A regulator screens applications, accepting all good ones, and detecting a proportion θ of the bad ones, which he rejects.

In this environment, the expected return to an application by a good firm is $\pi - c$, while the return for a bad firm is $(1-\theta)\pi - c$. These payoffs generate cutoffs for each firm type: a good firm makes an application if $\pi > c$, while a bad firm applies if $\pi > \frac{c}{1-\theta}$. Gross profits, ignoring entry costs, are then given by $\pi = pAL^{\alpha} - wL$. Taking first order conditions, the optimal amount of labor for a firm already in the market, $L^{\star}$, is given by $L^{\star} = \left(\frac{\alpha pA}{w}\right)^{\frac{1}{1-\alpha}}$. $L^{\star}$ is, trivially, increasing in A; more productive firms hire more workers.

A firm will attempt to enter if optimal gross profits $\pi^{\star} = (1-\alpha)(pA)^{\frac{1}{1-\alpha}}\left(\frac{\alpha}{w}\right)^{\frac{\alpha}{1-\alpha}}$ exceed the entry cost. In particular, a good firm enters if:

$$A \geq c^{1-\alpha}\frac{1}{p}\frac{1}{(1-\alpha)^{1-\alpha}}(\frac{w}{\alpha})^{\alpha} \equiv \bar{A^{G}}.$$

A bad firm, similarly, enters if:

$$A \geq c^{1-\alpha}\frac{1}{p}\frac{1}{(1-\theta)^{1-\alpha}(1-\alpha)^{1-\alpha}}(\frac{w}{\alpha})^{\alpha} \equiv \bar{A^{B}}.$$

Cutoff productivities $\bar{A^{G}}$ and $\bar{A^{B}}$ are both increasing in entry costs c. As optimal labor $L^{\star}$ is increasing in A, it follows directly that a reduction in c will reduce $L^{\star}$ for the marginal entrant. Because a reduction in c will reduce the cutoff productivities $\bar{A^{G}}$ and $\bar{A^{B}}$, more firms will attempt to enter the market.