Improving Quality through Regulation or Reputation

Theory and Evidence from the Environmental Impact Assessment Industry

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Abstract

Ensuring reliable provision of high-quality goods and services remains a central challenge in many markets. This paper studies how reputation interacts with entry regulation and shapes optimal regulatory policies using empirical, theoretical, and quantitative approaches. Empirically, I show that an entry deregulation reform in the Environmental Impact Assessment (EIA) industry leads to a persistent decline in service quality. I also document that negative reputation shocks sharply reduce firms' market share by half, indicating that both regulation and reputation are powerful devices. Theoretically, I develop a firm entry game in which reputation partially substitutes for regulatory screening, weakening the quality-improving effect of entry barriers. Structurally, I estimate a dynamic oligopoly model within a Moment-based Markov Equilibrium framework that incorporates endogenous reputation formation. Counterfactual simulations reveal that accounting for reputation substantially alters the optimal stringency and timing of entry regulations. These results underscore that effective regulation in emerging markets must be designed jointly with the market's reputation forces.

Keywords: Service Quality, Information Asymmetry, Entry Regulation, Entry Barriers, Reputation

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1 Introduction

The lack of reliable, high-quality goods and services is a pervasive issue across many industries. A central driver of this problem is information asymmetry: consumers are often unaware of true product quality and unable to differentiate producers. As a result, firms face weak incentives to supply high-quality variants. To address this market failure, governments worldwide often implement administrative entry barriers, such as licensing systems and minimum upfront investments, that restrict market access. This practice is supported by conventional economic theory, specifically the "public interest" view (Pigou, 1938; Shapiro, 1983), which posits that the welfare gains from quality improvements under entry regulation are substantial. According to this view, even if entry regulation induces market power and deadweight loss, the net outcome in a regulated market can still yield higher welfare.

However, this conventional framework rests on a strong assumption that consumers cannot dynamically update their beliefs about quality. In reality, reputation mechanisms serve as a powerful market-based institution that mitigates information asymmetries: clients revise their perception of quality over time, often moving from highly inaccurate to considerably more accurate assessments, by observing firms' track records, including historical lawsuits, penalties, and scandals. Despite the widespread coexistence of entry regulation and reputation mechanisms across industries, key questions remain underexplored: To what extent do reputation and regulation interact? And how does the presence of reputational learning alter the optimal stringency and timing of entry regulatory policies?

In this study, I empirically, theoretically, and quantitatively investigate how reputation mechanisms shape the optimal design of entry regulation. First, I document causal evidence on the effects of separate shocks of reputation and entry regulation on market outcomes. Motivated by these reduced-form findings, I develop an illustrative model embedding reputation and market power in a three-period setting. This model characterizes 1) the effect of entry regulation on quality provision and 2) how this effect is moderated by reputation. Building on the theoretical insights, I estimate a rich empirical model to incorporate information asymmetry and reputation in the dynamic oligopoly framework. Finally, I use counterfactual simulations to analyze the welfare implications of adjusting both the level and timing of regulatory intervention.

My study is grounded in the context of China's environmental impact assessment (EIA) industry, which provides the assessment of the environmental consequences of proposed construction projects. The EIA procedure has long been regarded as a milestone of modern environmental governance. It was first launched under the U.S. National Environmental Policy Act (NEPA) (1969) and has since then adopted by over 180 of the 193 member states of the

United Nations as of 2011 (Morgan, 2012). In particular, firms seeking to launch new projects are required by regulation to commission EIA reports from third-party agencies (EIA agencies, hereafter); these reports provide critical information regarding environmental impacts, serving an essential public interest function. However, the EIA quality is almost unverifiable to clients before the project is fully constructed. According to the data used in this study, approximately one in every hundred EIA reports in China is found to have significant quality issues. To curb the information asymmetry problem, both the entry regulation and reputation mechanisms are under play: Chinese government implemented strict entry regulatory policies on the EIA industry in history; customers also pay attention to the historical performance of EIA agencies before deciding their service providers.

I begin by presenting reduced-form empirical evidence on the separate roles of entry regulation and reputation within the EIA market. 1) I examine the 2019 entry deregulation reform in China's EIA industry to identify the causal effect of new entry on service quality. To address endogeneity concerns—such as concurrent shifts in local environmental enforcement or demand conditions—I employ an instrumental variable strategy based on net import dependence to isolate exogenous variation in the number of post-reform entrants. Service quality is proxied using the number of administrative penalties and corresponding fines imposed on low-quality EIA projects. The baseline results indicate that the sharp entry deregulation reform reduced average service quality by approximately 43% in a typical market. 2) I evaluate the role of reputation by analyzing how clients respond to new information about service quality. Particularly, using publicly disclosed penalty records as negative reputation shocks, I apply a staggered Difference-in-Differences (DiD) design to estimate the elasticity of market share with respect to these shocks. The results show that firms experiencing a penalty saw their market share decline by nearly half, underscoring both the severity of information asymmetry and the sensitivity of firms' reputation to credible quality signals.

Secondly, motivated by these empirical findings, I develop a theoretical model of entry and quality choice that explicitly incorporates reputation formation. The model extends a classical entry game by incorporating consumer updating of beliefs about quality. Initially, firms with heterogeneous productivity choose whether to enter and subsequently engage in a two-period Bertrand competition subgame. In the first period, firms choose quality levels, accounting for how this choice will affect second-period reputation and two-period overall profits. Demand depends on each firm's own and rivals' prices and reputations. The model yields two important insights: (1) under information asymmetry, entry regulation improves average industry quality; yet (2) when reputation concerns are incorporated, the marginal benefit of entry regulation diminishes. These results highlight the nuanced role of reputation in moderating regulatory efficacy, though welfare implications remain a subject for further

inquiry.

Thirdly, building upon the theoretical framework, I estimate a rich dynamic oligopoly model to evaluate the welfare implications of entry regulation when reputation dynamics are present. I adopt the dynamic oligopoly framework (Ericson & Pakes, 1995; Pakes & McGuire, 1994) and employ the concept of moment-based Markov equilibrium (MME) (Ifrach & Weintraub, 2017). This approach is computationally tractable even under extremely lax regulatory environments with hundreds of firms in one market, allowing for a realistic simulation of industry evolution. I calibrate and estimate model parameters using a two-step procedure adapted from Bajari et al. (2007). In the first step, I estimate static parameters, transition parameters, and policy functions. In the second step, I estimate dynamic parameters using a minimum distance estimator with forward simulation. To track reputation transitions that are unobservable to researchers, I recover expected quality as residuals from demand estimation based on the discrete choice structure, then estimate the reputation evolution process from these residuals. The results reveal that consumers are highly sensitive to reputation and that reputation evolves rapidly, implying that firms in oligopolistic markets have strong incentives to invest in reputation through high-quality provision.

While the penalty-based measure of service quality used in the reduced-form analysis is robust, it is not well-suited for the quantitative model since most agencies receive no penalties within the sample period. To obtain a continuous measure of EIA quality for the full agency sample, I employ natural language processing techniques applied to the complete text of EIA reports, which are the final products of the EIA service. This approach is motivated by regulatory findings that plagiarism constitutes a major quality issue in EIA reporting. Specifically, I develop a plagiarism detection system to compare each report against all existing reports in the market using the Word2Vec model and cosine similarity. This text-based quality measure passes several robustness checks, reveals the negative impact of entry deregulation reform, and aligns closely with the penalty-based measure.

Finally, I conduct two sets of counterfactual analyses to assess policy efficacy. First, I quantify how information asymmetry and reputation affect the optimal stringency of entry regulation by simulating three scenarios: full information, asymmetric information, and asymmetric information with reputation. Under full information, entry regulation reduces both service quality and social welfare—consistent with the classic prediction by Spence (1975) that price competition and quality competition are substitutable. The welfare difference between optimal and least optimal entry regulation levels is 10.32 billion CNY (1.45 billion USD),[1] demonstrating the critical importance of properly calibrated regulation. Under asymmetric information, however, tighter entry regulation improves product quality and

[1]Conversion based on the 2025 average exchange rate of 0.14 USD per CNY.

can enhance welfare, aligning with Pigou (1938). The optimal policy increases the entry cost by 2.10 million CNY (0.29 million USD). When reputation mechanisms are introduced, the marginal benefit of regulation diminishes substantially, corroborating my theoretical predictions. Neglecting the reputation channel results in 54% excessive entry regulation and a net welfare loss of 2.85 billion CNY (0.40 billion USD).

Second, I evaluate the importance of regulatory timing through two complementary exercises. When comparing delayed loosening, where administrative entry barriers are unexpectedly removed ten years into the market's operation, against a consistently laissez-faire market, I find that delayed liberalization achieves a welfare gain of 2.26 billion CNY (0.32 billion USD). During the initial regulated period, consumers lose 0.23 billion CNY due to market power, while firms gain 0.50. After liberalization, the reputation gains outweigh the market power losses, resulting in a net welfare gain relative to an unregulated market. Conversely, when comparing delayed tightening, where entry requirements increase unexpectedly ten years after market launch, against consistent regulation from market inception, I find that early and sustained regulation more effectively curbs market power and mitigates information asymmetry, generating a net welfare gain of 3.54 billion CNY (0.50 billion USD). By varying the speed of reputation formation, I find that the welfare advantage of delaying regulation depends on the relative magnitudes of reputation updating benefits and market power costs. When reputation updating generates larger welfare gains than the costs imposed by market power during the early regulated period, delaying regulation is preferable. These results suggest an optimal dynamic regulatory strategy: impose relatively stringent entry barriers during the market's formative stage, then gradually and unexpectedly reduce these barriers over time as reputation mechanisms mature, allowing market-based disciplinary forces to increasingly govern quality provision.

This paper contributes to four strands of literature. First, this paper echos the long-standing debate over entry regulation. One prevalent view advocates for the removal of such regulation, arguing that it enhances market power among incumbents and results in deadweight loss (Djankov et al., 2002). An alternative perspective—often termed the "public interest" rationale—supports entry regulation in markets where product quality is unobservable to buyers (Pigou, 1938; Shapiro, 1983). However, a limiting assumption in this latter strand of literature is that information asymmetry remains constant over time. In this study, I relax this assumption by introducing dynamic reputation formation: consumers update their beliefs about quality based on observed firm performance, and firms invest in reputation over time. I also speaks to the more recent entry literature endogenizing the quality choices upon entry (Jia, 2008; Mazzeo, 2002) and contribute by incorporating the information asymmetry and reputation in this context.

Methodologically, this research extends the empirical dynamic oligopoly framework pioneered by Ericson and Pakes (1995), which has been widely used to model firms' dynamic decisions such as entry/exit, physical capital investment, capacity expansion, R&D, and learning-by-doing. This paper is the first to incorporate endogenous reputation dynamics into this class of models, examining its implications for service quality, environmental externalities, and the efficacy of entry regulation. To achieve this, I extend the estimation procedure developed by Bajari et al. (2007) in two key ways: 1) by recovering firm reputation within demand estimation, and 2) by distinguishing between fringe and dominant firms using the MME framework (Ifrach & Weintraub, 2017).

Furthermore, this study connects to the theoretical and empirical literature on consumer learning and reputation. While prior theoretical work has explored reputation dynamics of quality (Atkeson et al., 2015; Board & Meyer-ter-Vehn, 2013, 2022; Liu, 2011), empirical studies have largely treated quality as exogenous, incorporating consumer learning primarily within demand systems (Hui et al., 2016; Newberry & Zhou, 2019; Saeedi, 2019; Zhao et al., 2013). This paper extends this literature by analyzing reputation in a richer strategic and dynamic setting, where firms "invest" in reputation through flexible quality choices and respond strategically to competitors' reputations. In doing so, I provide an empirical answer to how reputation dynamics affect market quality, social welfare, and optimal regulation.

Finally, this study also contributes to the growing economics literature that employs text-based algorithms to construct quantitative measures. A well-established strand of research uses cosine similarity, often combined with TF-IDF or word-embedding models, to analyze textual objects such as patents, products, and news reports. These applications have successfully measured technological evolution, product differentiation, and media originality (Bertrand et al., 2021; Cagé et al., 2020; Hoberg & Phillips, 2016; Kelly et al., 2021). My research advances this methodology in two key ways. First, I mitigate a critical concern noted by Cagé et al. (2020) and others: standard plagiarism detection can underestimate similarity by capturing only exact verbatim matches while missing paraphrased or conceptually similar content. To overcome this, I develop and fine-tune a Word2Vec model on a domain-specific corpus, enabling a "fuzzy matching" capability that identifies semantic similarity beyond mere word overlap. Second, I extend the application of these tools to a new and policy-relevant context: measuring the service quality of information intermediaries. By applying this refined algorithm to the textual content of EIA reports, I construct a continuous, scalable quality metric for a regulatory industry whose final product is text. This approach provides a framework for assessing the performance of a wide range of information intermediaries—from credit rating agencies to auditing firms—that produce text-based reports as their terminal output.

The remainder of this paper is organized as follows: Section 2 introduces the EIA industry, the information asymmetry problem, the entry deregulation reform, and anecdotes of reputation formation. Section 3 describes the data, including quality measures, used in the analysis. Section 4 presents reduced-form evidence on the impacts of entry regulation and reputation in the EIA market. Section 5 develops an illustrative model predicting the effects of entry regulation and the role of reputation. Section 6 presents the empirical model, and Section 7 discusses model estimation and results. Section 8 presents counterfactual analyses, and Section 9 concludes.

2 Context

2.1 Environmental Impact Assessment and Quality Unobservability

EIA is a procedure used to evaluate the potential environmental consequences of proposed projects, such as industrial facilities, manufacturing plants, and large-scale buildings, before they are constructed.[2] EIA was first formally mandated under the U.S. NEPA of 1969. Since then, it has been widely adopted worldwide.

China introduced EIA procedures in 1979 and began establishing specialized consulting institutes to conduct these assessments. The country's formal *EIA Law* was enacted in 2002, marking the start of a comprehensive regulatory framework for environmental reviews (FAO, 2003; World Bank, 2006). Under this law, firms operating in pollutive industries are required to commission EIA reports from independent third-party agencies before beginning construction. A standard EIA report includes environmentally relevant information mandated by local regulators, such as production processes, pollution control measures, and anticipated impacts—both on public health and local ecosystems—throughout the construction and operational phases.

The formal EIA process in China, as stipulated by the *EIA Law*, is illustrated in Figure 1 and unfolds as follows: 1) A customer hires a certified EIA agency to prepare an assessment report, which is then submitted to the national environmental authority, the State Environmental Protection Administration (SEPA) [3], or its successors. 2) The report is disclosed to the public for review. Due to challenges in motivating public participation[4], SEPA also

[2]While EIA broadly encompasses the assessment of policies and urban planning strategies, this study focuses exclusively on project-level assessments. Since the 1990s, policy-oriented evaluations have largely been incorporated under Strategic Environmental Assessment.

[3]SEPA, analogous to the U.S. Environmental Protection Agency, was responsible for national environmental policy and supervision. It was restructured into the Ministry of Ecology and Environment (MEE) in 2018. Its functions are carried out through affiliated agencies at the provincial, municipal, and county levels.

[4]Over 95% EIA reports do not obtain any feedback at all based on my interviews.

employs third-party experts to review submissions. 3) If no objections are raised within a statutory review period (typically two months), the project is approved. Otherwise, the firm must revise the report and repeat the process until it gains approval.

In practice, however, the implementation of EIA often deviates significantly from this ideal. A major issue is the prevalence of low-quality EIA reports that, even when approved, misreport or conceal environmental risks and endanger public health and ecological safety. According to the data used in this study, approximately one in every hundred EIA reports is found to have significant quality issues. A tragic example is the chemical plant explosion in May 2019 that resulted in approximately 700 casualties, severely polluted nearby rivers, and led to the permanent shutdown of an entire industrial park (Ramzy & Hernández, 2019; Wikipedia, 2023). The official investigation revealed that the EIA agency had misrepresented the manufacturing process and underreported risks, leading to inadequate safety measures (Accident Investigation Team, 2019).

While outright fraud represents the most egregious violation, plagiarism constitutes a more pervasive problem in the industry. Engineers routinely produce low-quality reports by copying content from existing assessments rather than conducting proper site-specific analyses (MEE, 2019). Two recent cases illustrate the severity of this practice. First, an EIA report for the Shenzhen Bay Waterway Dredging Project referenced "Zhanjiang"—a city located over 500 kilometers away—35 times throughout the document. One example stated: "Shenzhen Bay Waterway Dredging Project is an implementation of Zhanjiang City's 13th Five-Year Plan for National Economic and Social Development." The report had been copied wholesale from a Zhanjiang project assessment, with the authors failing to update even basic geographic references. After this case gained widespread attention on social media, the responsible agency was permanently banned from providing EIA services (Yang, 2025). Second, in another plagiarism case, fraudsters admitted to completing entire EIA reports within 30 minutes by copying analyses from existing documents and superficially adjusting parameters to create an appearance of authenticity (GreenNet, 2021).

These quality failures persist because of the fundamental quality unobservability problem. Firms cannot distinguish between rigorous, model-based assessments and hastily plagiarized reports, as both appear technically sophisticated on paper. Regulatory oversight suffers from similar limitations. During an interview I conducted with a provincial environmental authority official, I learned that only one EIA report had been rejected during the previous six months of review. Most deficiencies surface only during post-construction inspections—long after environmental damage may have occurred. This pattern reveals a systemic challenge in *ex ante* review processes, where the very mechanisms designed to prevent environmental harm consistently fail to identify substandard assessments until projects are already operational.

2.2 Entry Deregulation Reform in EIA Industry

China's EIA industry has long been subject to stringent administrative entry barriers, most notably a licensing system instituted in 1999. Under this system, firms were required to obtain approval from the SEPA before conducting EIAs—a process contingent upon meeting rigorous criteria.[5] Key requirements included employing at least ten full-time EIA engineers—each of whom must hold a bachelor's degree in environmental science, possess a minimum of five years of relevant experience, and pass a rigorous professional examination with a pass rate of only 5–10%.[6] Given the scarcity of qualified graduates, the difficulty of the exam, and the attractive outside options available to potential engineers, it was exceedingly difficult for new entrants to recruit a sufficient number of certified EIA engineers. Even after meeting these requirements, firms typically faced an additional one-year waiting period for SEPA approval, further elevating the cost of entry.

These stringent regulations significantly curtailed entry into the EIA market. Prior to 2019, the monthly entry rate averaged just 1.95 new firms—implying that fewer than 5% of agencies operating in any two-year period were new entrants. This figure is only half the global average entry rate of 13.35% across all industries (Klapper et al., 2006). Meanwhile, the monthly exit rate stood at 6.55 agencies, more than triple the entry rate. The combination of low entry and high exit led to a steady decline in the number of EIA agencies over time. As shown in Figure 2, the number of agencies decreased consistently between 2006 and 2019. By early 2019, only around one thousand agencies remained nationwide—averaging thirty per province—to serve thousands of firms requiring EIA services.

In contrast to the decreasing number of EIA agencies, the demand of EIA was growing in the company of the rapidly rising China's economy in this period (GDP grew by 6.9% annually, and the industry value-added 7.1%). Finally in 2019, an average agency accomplished 14.0 EIA cases per year. Considering that the median price of EIA is 289,500 CNY, the operating income of an average agency reached 49 million. If I focus on the market power of EIA agencies one month before the entry deregulation, nearly half of the market shares (47% of projects) are taken by ten largest EIA service providers in each province. The lower-than-average entry rate in comparison of high exit rate, increased business volume, and high concentration ratio all imply that EIA industry presented a low competition level at the beginning of 2019.

The entry barriers to the EIA industry was largely reduced in 2019, when the institutional

[5]SEPA initially established high entry barriers partly because all EIA agencies were state-owned, and the authority had an incentive to limit new entrants from eroding economic rents, a common reason for entry regulation found by Djankov et al. (2002). Although agencies were fully privatized by 2015, the restrictive licensing system remained in place for three more years until the deregulation reform. A timeline of regulatory milestones, including privatization, is provided in Appendix B.

[6]By comparison, the pass rate for China's Certified Public Accountant exam is nearly 20%.

driver of the oligopolized EIA industry, the licensing system was formally ended by an exogenous political reform. The premier of China at that time, Li Keqiang, announced a reform that aimed to improve the business environment in China (*Fang Guan Fu* Reform in Chinese). He urged ministries in the central government to scale back administrative power to stimulate market competition and maintain long-term economic growth (State Council, 2015). In response, the MEE announced an entry deregulation reform to abolish the licensing system in the EIA industry in October 2019. Since then, the previously one thousand licenses of EIA have become useless, and any firm, as long as it has at least one EIA engineer, can provide EIA services. The objective of the political reform was to remove the entry barrier, increase market competition, improve the quality of EIA services, and ultimately benefit the entire society (MME, (Ministry of Ecology and Environment, 2019)).

However, anecdotal evidence shows that entry deregulation in this industry, while being successful in stimulating competition, deteriorates the problems in the EIA industry, especially the quality problem. One notorious example is an EIA engineer called Jin Haiyan, who compiled over 1,600 EIA reports in four months. It is suggested that she allowed unqualified staff to conduct EIAs and sign her name (GreenNet, 2021). Finally, the regulatory authority permanently prohibited this engineer from providing EIA. Meanwhile, the increased complexity and opacity of the EIA market made it difficult for less-informed clients to find quality service providers. Motivated by the above anecdote and theoretical prediction, I empirically analyze how entry deregulation on EIA agencies affects the market structure and assessment quality.

2.3 Penalty Disclosure and Reputation

The EIA regulation can be divided into the *ex ante* review and the *ex post* scrutiny and the later part plays the major role. *Ex ante* review occurs before the project is built and given the scarcity of other materials and real projects for comparison, the reviewers can only checks the report format and the methodology. As a result, the efficacy of ex ante review is very low and leaves severe EIA quality problem. The *ex post* scrutiny happens after the project is constructed. The regulatory staffs visit the project site and compare the emission and other parameters with the estimated parameters on the EIA report. As long as they find crucial misalignment, they will punish the related parties. Over 90% of the penalties are borne by the project firm instead of the EIA agency by regulation.

The *ex post* penalty records are accessible to all of the market participants. The regulatory authority, varying from the county-level environmental inspection teams to the central-government level SEPA disclose the penalty decisions to public on their official websites and social media accounts (Panels A and B of Figure A.1). Since 2016, SEPA has published all

penalty records on a centralized online platform. [7] The website lists the name of agencies and their penalized projects, including the specific penalty reason, the date of issuance, fine amount, rationale, among other details (Panel C, Figure A.1). Based on our interviews with responsibles of firms and the managerial authority of industrial parks, customers in the EIA market view these penalty records as an important information source when selecting agencies.

3 Data

This section introduces the dataset I constructed for empirical analysis and summary statistics.

3.1 Penalty-Based Quality Measures in Reduced-Form Analysis

The primary outcome variable in the reduced-form analysis, the severity of low-quality EIA reports, is proxied using environmental penalty data from a confidential database maintained by the Ministry of Ecology and Environment (MEE). This database comprehensively records inspections conducted by China's environmental protection system and subsequent penalties for violations. Each penalty entry includes details such as issuance date, fine amount, and reason for penalty. Following the approach in accounting literature that uses SEC enforcement actions to proxy for audit quality (Ronen, 2010), I construct two city-month level measures: 1) the number of penalties attributed to low-quality EIA assessments, and 2) the total fine amount, which reflects violation severity. My analysis focuses on penalties imposed on firms established in 2018 or earlier, ensuring that any effects of EIA entry deregulation are not confounded by client heterogeneity between new entrants and incumbents.

3.2 Text-Based Quality Measures for Structural Analysis

While penalty data serve as valid indicators of extremely poor quality in reduced-form analysis, the structural model requires a continuous measure of EIA service quality. To construct such a measure, I employ natural language processing techniques applied to the full text of EIA reports. The approach is motivated by regulatory findings that plagiarism constitutes a major quality issue in EIA reporting. Specifically, I develop similarity metrics comparing each report against all existing market reports using Word2Vec embeddings and cosine similarity. The technical procedure involves three steps combining automated text collection, natural language processing, and similarity analysis:

[7] The website changed many times: initially http://114.251.10.205/#/pub-message, then http://114.251.10.92:8080/XYPT/, and now https://xypt.china-eia.com/XYPT/.

First, I compile EIA reports from three primary sources: 1) web searches via Google and Baidu using project and firm names during the 2013-2019 period; 2) pre-acceptance reports disclosed on specialized EIA forums; and 3) pre-approval reports published on provincial ecology and environment department websites. Using automated extraction programs, I convert .pdf and .doc files to plain text, extract project metadata via GPT-3.5 Turbo, and match reports to project characteristics. This process yields a final sample of approximately 40,000 reports with complete textual and project information.

Second, I implement a plagiarism detection system that operates at the paragraph level. After segmenting Chinese text into paragraphs using the `jieba` package in Python, I calculate pairwise similarity scores between all paragraphs. The similarity between paragraphs f and l is defined as the cosine distance between their feature vectors:

$$s(f, l) = \mathbf{v}^f \cdot \mathbf{v}^l. \tag{1}$$

To create paragraph-specific feature vectors, I use Word2Vec (Mikolov et al., 2013) with the pre-trained model from Li et al. (2018) as my benchmark. To enhance domain relevance, I fine-tune this model on my EIA corpus using the `gensim` package while maintaining the original hyperparameters. For robustness, I implement three alternative similarity measures: TF-IDF, pre-trained CoSENT, and CoSENT-Paraphrase models (Xu, 2022).

Third, I calculate the report-specific similarity score as the maximum report-to-report similarity index, identifying the most likely source of copied content. The report-to-report similarity index is averaged from the paragraph-to-paragraph similarity index. Additionally, I generate complementary quality metrics for cross-validation using readability (Fog index (Gross & Sadowski, 1985; Gunning, 1952)) and sentiment analysis (lexicon-based approach via Python package `cntext`) to capture different dimensions of report quality.

I select Word2Vec as the preferred model because it offers two key advantages for this application. First, it effectively detects paraphrased content—a critical capability given that simple text-matching approaches like TF-IDF underestimate plagiarism by missing semantically similar but differently worded passages. Word2Vec's continuous vector space captures conceptual similarity even when exact wording differs. To illustrate this capability, Figure A.2 presents a t-SNE visualization reducing Word2Vec embeddings to two dimensions for "assessment" and its twenty nearest neighbors. The clustering of semantically related terms like "evaluation" and "testing" demonstrates the model's ability to identify paraphrases that would escape detection by sparse vector methods. Second, Word2Vec provides superior stability and reproducibility compared to more complex deep learning architectures like CoSENT (Bacco, 2023). While newer models may capture more sophisticated paraphrasing

patterns, Word2Vec's consistency is paramount for structural estimation, where measurement reliability directly affects parameter identification. This methodological choice prioritizes estimation robustness over marginal gains in detection sophistication.

I do multiple exercises to validate text-based quality measures and demonstrate the advantages of the Word2Vec-based measure: First, I examine the distributions of similarity scores across different algorithms (Figure A.3). Panel A shows the benchmark Word2Vec-based quality measure. The mean similarity scores exceed 0.9 for all measures, reflecting the standardized structure of EIA reports. Both Word2Vec and TF-IDF (Panel B) yield left-skewed distributions with fat tails—a pattern consistent with plagiarism detection—while maintaining strong correlation. The systematically lower TF-IDF scores indicate that TF-IDF underestimates semantic similarity by ignoring paraphrasing. In contrast, two CoSENT architectures produce divergent distributions, particularly in the high-similarity range, suggesting greater sensitivity to architectural choices when identifying near-duplicate content.

Second, I leverage the entry deregulation reform as a natural experiment to validate the quality measures. Figure A.4 shows a significant upward shift in similarity distributions following reform implementation, consistent with anecdotal evidence of quality deterioration after market liberalization. This parallel movement across multiple similarity measures strengthens the validity of text-based metrics as indicators of service quality.

Third, I examine the relationship between text-based similarity scores and administrative penalty cases. Column (1) of Table A.9 reports OLS estimates regressing penalty incidence on Word2Vec similarity, showing positive and statistically significant coefficients. This pattern persists when using TF-IDF-based similarity scores (Column (2)) and after controlling for total sales (Columns (3) and (4)), confirming that text-based measures capture quality dimensions relevant for regulatory enforcement.

Fourth, I further investigate the functional form of the quality-penalty relationship using binscatter plots (Cattaneo et al., 2024), shown in Figure A.5. The relationship exhibits a threshold effect: the correlation between penalty probability and similarity scores is modest at low quality values but becomes sharply positive beyond a critical level. This pattern is consistent with regulatory enforcement targeting predominantly the most severe quality violations, and supports the use of similarity metrics as continuous measures of EIA report quality.

3.3 EIA Agency

I have gathered lists of EIA agencies, along with their respective entry and exit dates, from the MEE. The MEE operates an online management system that allows EIA agencies to register and submit EIA reports. Prior to the deregulation reform, the entry date of each EIA

agency was considered to be the date on which they obtained their EIA license. After the reform, an agency's entry is recognized as their registration date on the management system. The exit date is determined by when the EIA agency submits a withdrawal application, after which they are no longer able to submit any EIA reports.

3.4 EIA Case

I have also compiled all available EIA cases from the MEE. Due to the disposal of most historical records during the entry deregulation reform, I am limited to using EIA records from one month prior to the latest (since October 2019). Each EIA case provides information such as the submission date, name of the EIA agency, name of the project proposer or firm, project name, project address, and so forth. The project address is cross-referenced with the agency address obtained from the firm registration data, allowing me to examine interregional trade patterns of EIA before and after the implementation of the entry deregulation reform. I also complement the firm information including the industry type, firm size (measured by the registered capital) and entry date from Qichacha, an online platform that provides company information. To compare the EIA service price, I collected the procurement data from two sources. One is the government procurements, which include some procurement demand for EIA due to the construction of public facilities. Another source is an information platform listing firm procurement data, especially the procurement demanded from SOEs.

3.5 Summary Statistics

The reduced-form analysis employs a city-month panel spanning two years around the September 2019 deregulation reform, covering October 2018 through November 2020. This temporal window captures twelve months of pre-reform market conditions and fourteen months of post-reform outcomes, enabling identification of deregulation effects while minimizing contamination from other policy changes. The panel structure comprises 274 cities observed monthly, yielding approximately 6,850 city-month observations.

Table 1 presents summary statistics for key variables. Panel A reports province-level measures central to the identification strategy. Panel B presents city-level quality outcomes: low-quality EIA reports average 0.21 cases per city-month with associated fines of over 1.8 million CNY, while EIA evasion cases occur at similar frequencies (5.92 per city-month), suggesting quality problems manifest across multiple compliance dimensions.

4 Reduced-Form Evidence: The Power of Entry Deregulation and Reputation

4.1 Effect of Entry Deregulation on Service Quality

4.1.1 Empirical Strategies

This section presents the empirical strategies employed to examine how entry deregulation and the resulting intensification of competition affect service quality in the EIA sector.

A. OLS Estimator.—The baseline specification employs the following OLS regression to estimate the relationship between competition and service quality:

$$\ln y_{ct} = \beta \ln n_{pt} + \lambda_t + \delta_p + \varepsilon_{ct} \tag{2}$$

, in which y_{ct} denotes the service quality of EIA agencies in city c at year-month t, and n_{pt} represents the number of EIA agencies operating in province p at time t, serving as a proxy for local competition intensity.[8] The specification includes year-month fixed effects (λ_t) to control for temporal trends and province fixed effects (δ_p) to account for time-invariant provincial characteristics.[9] The error term is denoted by ε_{ct}.

However, OLS estimates are likely biased due to two endogeneity concerns. First, simultaneity bias arises because service quality and the number of EIA agencies are jointly determined in equilibrium following deregulation. This simultaneous determination could generate spurious correlations between competition and quality outcomes. Second, omitted variable bias may result from unobserved factors that influence both EIA service demand and firms' entry decisions. These factors include regional infrastructure development, environmental regulatory stringency, and local economic growth patterns. For instance, regions with local environmental regulation loosen may experience greater entry while facing lower quality penalties, biasing the estimated relationship downward. Given these countervailing forces, the direction of OLS bias remains theoretically ambiguous.

B. Instrumental Variable Strategy.—To address these endogeneity concerns, I implement an instrumental variable approach that exploits pre-reform variation in provincial market structure. The instrument must satisfy two conditions: relevance—it should predict the

[8]The logarithmic specification follows the theoretical literature, including Anderson and Peitz (2020) and Tan and Zhou (2021), which demonstrate that equilibrium quality levels exhibit concave relationships with the number of competing firms.

[9]The province-level competition measure reflects the institutional reality that environmental policies vary substantially across Chinese provinces (Chen et al., 2018; He et al., 2020), creating localized expertise requirements and effectively segmenting EIA markets at the provincial level. Empirical evidence supporting this geographic delineation is presented in Appendix C.

intensity of firm entry following deregulation, and exclusion—it should affect post-reform service quality only through its effect on competition levels.

I construct an instrument based on pre-deregulation net import dependence, a measure adapted from the trade literature (Balassa, 1965). For each province p, the net import dependence ratio is defined as:

$$\text{Dependence}_p \equiv \frac{\text{Import}_p - \text{Export}_p}{\text{Consumption}_p} \tag{3}$$

where Import_p represents the number of EIA projects located in province p that were assessed by agencies from other provinces, Export_p captures the number of projects outside province p that were assessed by agencies within province p, and Consumption_p denotes the total number of EIA assessments required for projects in province p.

This ratio captures the pre-reform market structure and inter-provincial dependencies. Positive values indicate net importing provinces that relied on external agencies for their EIA needs, while negative values identify net exporting provinces with excess capacity to serve other markets. The magnitude reflects the degree of market imbalance: provinces with more negative values possessed stronger comparative advantages in EIA services prior to deregulation. I discuss the relevance and exclusion assumptions as follows.

C. Instrument Relevance.—The relevance of pre-deregulation net import dependence as an instrument stems from the historical constraints on EIA market structure. Since the early 2000s, the number of EIA agencies remained essentially fixed due to extremely high regulatory licensing restrictions, while the EIA demand driven by the industrial development is divergent across provinces. This mismatch created distinct provincial patterns of market imbalance.

Agencies facing rising local demand were forced to expand their workforce to handle increased caseloads. However, such expansion beyond optimal scale generates organizational inefficiencies—communication and coordination problems that increase marginal service costs (Coase, 1960). Meanwhile, agencies in provinces with lower EIA demand maintained lower marginal costs and could profitably serve clients in high-demand provinces, despite bearing additional costs from learning different provincial environmental regulations. This cost differential created opportunities for interprovincial arbitrage and established the pre-deregulation trade patterns captured by our instrument.

Following deregulation, provinces with positive pre-reform import dependence (net importers) experienced stronger incentives for new firm entry, as local entrants could substitute for costly interprovincial trade. Therefore, the pre-reform import dependence is a potential predictor of the post-reform entry.

I provide two forms of evidence supporting the instrument's relevance. First, I docu-

ment substantial pre-deregulation trade imbalances using detailed provincial comparisons. Guangdong and Hunan provinces illustrate this pattern. When the EIA licensing system was initially established, the GDP difference between Guangdong and Hunan was negligible—only 15 million USD (430 versus 415 million USD in 2006). By 2019, this gap had expanded to 1.01 trillion USD (1.57 versus 0.66 trillion USD), generating a substantial divergence in EIA service demand over these thirteen years. Yet the number of agencies remained nearly constant throughout this period. Consequently, by 2019, Guangdong maintained only 1.5 times as many agencies as Hunan (68 versus 45) despite having 9.3 times more EIA projects.[10]

Figure A.6 visualizes trade flows using Sankey diagrams, where flow thickness represents the share of projects in destination provinces (right nodes) serviced by agencies from origin provinces (left nodes). Panel A reveals Guangdong's position as a major importer: only 74% of local projects are self-supplied, with 26% serviced by out-of-province agencies. Hunan agencies constitute the largest external provider, capturing 6% of Guangdong's total market. Panel B shows the complementary pattern for Hunan, whose agencies devote only 51% of capacity to local projects while exporting 49% to other provinces—including 16% specifically to Guangdong. These trade patterns generate pre-deregulation net import dependence values of 0.21 for Guangdong and -0.71 for Hunan.

Following deregulation, both provinces converged toward self-sufficiency. Panels C and D document this shift: Guangdong's import dependence declined to 0.03, while Hunan's export dependence moderated to -0.06. This convergence occurred nationwide—the variance of provincial dependence fell from 0.10 to 0.02—confirming that deregulation enabled market rebalancing through localized entry. The dramatic reduction in cross-provincial trade flows demonstrates how regulatory reform allowed previously constrained markets to adjust agency supply to match local demand.

Second, I demonstrate strong predictive power through statistical tests. The correlation between pre-deregulation net import dependence and post-deregulation entry equals 0.47, with a bivariate regression coefficient of 0.30 (see Figure A.7). This positive relationship confirms that provinces more dependent on imports experienced greater post-deregulation entry, validating the first-stage relationship.

D. Exclusion Restriction.—The exclusion restriction requires that pre-deregulation trade patterns affect post-reform quality only through their impact on the number of new entrants. This assumption is supported by two key facts: the deregulation timing was exogenously determined by political reform unrelated to the EIA industry, and the pre-reform trade patterns only reflect historical licensing decisions rather than contemporary market fundamentals.

To test whether pre-deregulation trade dependence is orthogonal to current market

[10]Data from National Bureau of Statistics of China (2020).

conditions, I regress it on 25 socioeconomic indicators in 2019 that plausibly affect EIA demand, including GDP, population, infrastructure (road network length), and environmental conditions (air quality indices). As reported in Table A.9, these variables show minimal explanatory power for pre-deregulation trade patterns: zero indicators achieve statistical significance at the 5% level, and only four reach 10% significance (Columns (1) and (2)). The F-statistics range from merely 0.1 to 4.0 (Column (5)).

In stark contrast, the same indicators strongly predict post-deregulation trade patterns: 16 achieve 5% significance and three more reach 1% significance (Columns (3) and (4)), with F-statistics ranging from 0.3 to 33.8—almost ten times larger (Column (6)). This sharp difference confirms that pre-deregulation trade patterns were indeed divorced from economic fundamentals, reflecting instead the arbitrary historical allocation of agency licenses. To reduce the potential concerns on the correlation between pre-deregulation trade flow and the economic indicators significant at 10% confidence level, I further include these covariates in robustness specifications.

E. Two-Stage Least Squares (TSLS) Estimator.—The first-stage equation exploits the differential impact of deregulation across provinces based on their pre-reform trade positions:

$$n_{pt} = \gamma \text{Dependence}_p \text{Post}_t + \lambda_{2,t} + \delta_{2,p} + \xi_{pt} \tag{4}$$

Here, $Post_t$ is an indicator for the post-deregulation period (after October 2019), and the interaction term $\text{Dependence}_p\text{Post}_t$ captures differential entry intensity based on pre-reform market imbalances. The specification includes year-month fixed effects ($\lambda_{2,t}$) and province fixed effects ($\delta_{2,p}$). ξ_{pt} denote error terms.

The corresponding second-stage equation is as follows:

$$y_{ct} = \beta_1 \widehat{n}_{pt} + \lambda_{1,t} + \delta_{1,p} + \varepsilon_{ct} \tag{5}$$

where $\widehat{n}_{pt}$ represents the predicted number of agencies from equation (4). Under the identifying assumptions, including relevance and exclusion restrictions, the parameter β_1 captures the elasticity of service quality with respect to the number of competing agencies—our primary coefficient of interest.

E. Reduced Form and Event Study Estimator.—The reduced form model is as follows:

$$y_{ct} = \beta_2 \text{Dependence}_p \text{Post}_t + \lambda_{3,t} + \delta_{3,p} + v_{ct} \tag{6}$$

, in which all variables and subscripts are defined as before.

Conceptually, the reduced form model utilizes the variation from exogenous entry deregula-

tion and predetermined factors correlating with the coincidence of firm entry. We can interpret β_2 as how much percentage change in quality is attributed to one-unit higher pre-deregulation dependence on EIA import.

My instrumental variable strategy is highly aligned with an approach called fuzzy DiD strategy discussed in literature, the main idea of which is to adopt a DiD interaction term as the instrument (de Chaisemartin & D'HaultfŒuille, 2018; Duflo, 2001; Kearney & Levine, 2015). The only difference is that the treatment status variable in my strategy, the net import dependence, is a continuous measure of the exposure to the shock (similar to **kearney˙media˙201**; Goldsmith-Pinkham et al. (2020) and Nunn and Qian (2014)). I emulate the standard fuzzy DiD strategy by splitting the continuous variable by median into a dummy and checking the robustness using techniques suggested by de Chaisemartin and D'HaultfŒuille (2018).

The reduced form motivates an event study model to estimate the dynamic effects as well as examine the pre-trends. Specifically, the regression equation is as follows:

$$y_{cpt} = \gamma_{-6} \text{ Dependence } {}_pT_t^{\leq -6} + \sum_{k=-5,\neq -1}^{5} \gamma_k \text{ Dependence } {}_pT_t^k + \gamma_6 \text{ Dependence } {}_pT_t^{\geq 6} + X_{pt}\beta + \lambda_{2,t} + \delta_{2,p} + \varepsilon_{cpt}$$

, in which T_t^k equals one if month t is the k-th month relative to the deregulation shock. $T_t^{\leq -6}$ equals one if month t is six months before the deregulation; the same logic for $T_t^{\geq 6}$. I set period -1, the last month before the deregulation shock, as the reference period. X_{pt} denotes the covariates we establish in the baseline regressions. γ_k for $k \geq 0$ captures the dynamic effect of competition on outcomes of our interest.

4.1.2 Results

A. Baseline OLS Estimates.—Panel A of Table 2 presents OLS estimates from Equation (2). Column (1) reports the baseline specification, where the coefficient of 0.071 indicates that a one percent increase in agency count is associated with a 0.07% increase in low-quality reports (calculated as $1.01^{0.071}$–1). This positive relationship suggests that greater competition correlates with deteriorating service quality.

To examine whether competition affects not only the frequency but also the severity of quality violations, Column (2) employs fine amounts as an alternative quality measure. The coefficient increases nearly 3-fold to 0.611, indicating that conditional on producing low-quality reports, agencies in more competitive markets produce substantially more harmful violations. This pattern extends to EIA evasion cases—instances where assessments fail to include required facilities—with positive coefficients in both count (Column 3) and fine

amount (Column 4) specifications. These consistent patterns across different quality measures suggest a robust correlation between competition and service degradation, motivating our instrumental variable analysis to establish causality.

B. First Stage.—Panel B of Table 2 reports first-stage estimates demonstrating that pre-deregulation trade dependence strongly predicts post-reform entry patterns. The coefficient of 0.625 indicates that a one-unit increase in import dependence following deregulation is associated with a 62.5% increase in agency count. The instrument satisfies standard relevance criteria. The Olea-Pflueger (2013) robust F-statistic of 27.89 exceeds conventional thresholds for weak instruments. The positive and statistically significant first-stage coefficient provides additional confidence in instrument strength (Angrist & Kolesár, 2023). These diagnostics confirm that pre-reform trade imbalances generate sufficient variation in post-deregulation entry to identify causal effects.

C. TSLS Estimates.—Column (1) of Panel C presents the TSLS estimates of competition's causal effect on service quality. The coefficient of 0.249 implies that a one percent increase in agency count causally increases low-quality reports by 0.25% (calculated as $1.01^{0.249} - 1$). This effect is economically substantial: the 321% increase in agencies induced by deregulation translates to a 43% increase in low-quality reports (calculated as $4.21^{0.249}$–1), or approximately 0.09 additional low-quality reports per city-month relative to a baseline of 0.21. The intensity-based measure in Column (2) reveals even larger effects, with a coefficient of 0.906—approximately four times the count-based estimate. Similar patterns emerge for EIA evasion measures (Columns (3)–(4)), confirming that competition-induced quality degradation manifests across multiple dimensions of service provision.

The IV estimates substantially exceed their OLS counterparts, suggesting that unobserved factors generate positive selection into entry. These could include strengthening environmental regulations that simultaneously increase quality standards and induce entry of high-quality agencies (Cui & Moschini, 2020; Duflo et al., 2013), or positive demand shocks from specifically environmentally responsible firms that attract high-quality entrants. The IV strategy isolates variation from trade rebalancing, removing these confounding influences to reveal competition's adverse effect on quality.

D. Reduced Form and Event Study Estimates.—Table 3 presents reduced-form estimates confirming the direct relationship between the instrument and outcomes. A one-standard-deviation increase in pre-deregulation trade dependence is associated with a 5% increase in low-quality reports (calculated as 0.33×0.163, Column (1)) and a 20% increase in fine amounts (0.33×0.593, Column (2)), providing model-free evidence of the instrument's impact.

Figure 3 presents event-study estimates testing for pre-trends and examining dynamic treatment effects. The results reveal four key empirical patterns. First, Panels A–E show

statistically insignificant and economically small coefficients across all pre-deregulation periods for both agency counts and the four quality measures, ruling out pre-trends that could threaten identification. Second, Panel A demonstrates that post-deregulation, provinces with higher import dependence experience greater increases in EIA agencies relative to less import-dependent provinces. This pattern aligns with the descriptive analysis in A.7, confirming the strong correlation between pre-deregulation import patterns and post-deregulation agency entry. Third, the post-deregulation quality dynamics in Panels B–E reveal rapid and persistent effects. Fine amounts for low-quality reports increase in period 3, while evasion cases (Panels D and E) rise earlier in period 2. This timing corresponds to the average one-month duration for EIA report writing and approval, followed by 1–2 months of construction before inspections occur. Fourth, all quality measures peak in period 4 before declining, though remaining positive. This dynamic pattern suggests the market adjusts gradually to entry deregulation, with initial negative quality effects moderating over time, potentially due to reputation formation among new agencies and demand concentration towards high-performing agencies.

4.2 Effect of Reputation Shocks on Agency Market Share

4.2.1 Empirical Strategies

This section outlines the empirical approach to examining how reputation affects market dynamics in the EIA industry. The analysis exploits the government's disclosure of penalties imposed on EIA agencies as a quasi-experimental shock to agency reputation. The generalized DiD strategy estimates the causal effect of negative reputation shocks on agency market shares by comparing the before-after difference in outcomes between penalized and non-penalized agencies across disclosure periods.

A. DiD Estimators.—The baseline specification employs a two-way fixed effect (TWFE) OLS model:

$$s_{jt} = \alpha \text{PenaltyDisclosure}_{jt} + \delta_j + \omega_t + \varepsilon_{jt} \tag{7}$$

, in which s_{jt} denotes the market share of agency j during year-quarter t. The treatment indicator $\text{PenaltyDisclosure}_{jt} = 1$ if a penalty on agency j is disclosed in year-quarter h, with $h \leq t$. δ_j and ω_t capture disclosure-cohort fixed effects and year-quarter fixed effects. The regression sample includes all agencies penalized at most once during 2020–2023. One potential concern is that market share changes among penalized agencies may create spillover effects on competitors' market shares, potentially biasing the reputation effect upward. To address this spillover concern, the analysis excludes agencies that operate in the same market as penalized agencies for one year before and after the penalty announcement.

This specification relies on two key identifying assumptions. First, the parallel trends

assumption requires that, absent the penalty disclosure, market shares of penalized and non-penalized agencies would have evolved along parallel trajectories. Second, the homogeneous treatment effect assumption implies that the average treatment effect remains constant across different disclosure cohorts and time periods. Under these assumptions, the coefficient α identifies the average treatment effect on the treated (ATT), the causal impact of reputation damage on market share.

Recent econometric literature has demonstrated that TWFE estimators can produce biased estimates in staggered treatment settings when treatment effects are heterogeneous across units or time. To address these concerns, I implement the heterogeneity-robust estimators developed by Dube et al. (2025) and Callaway and Sant'Anna (2021), both of which relax the homogeneity assumption and provide consistent estimates even when treatment effects vary across cohorts and periods. These alternative estimators decompose the overall treatment effect into properly weighted averages of group-time specific effects, avoiding the negative weighting problem that can arise with traditional TWFE approaches in staggered adoption designs.

B. Event-Study Estimators.—In order to test for pretrends and examine the dynamics of treatment effects, I estimate an event-study version of the TWFE model. Specifically, I estimate the following specification:

$$s_{jt} = \sum_{k=-3, k\neq -1}^{9} \alpha_k \text{PenaltyDisclosure}_{jt}^{k} + \delta_j + \omega_t + \varepsilon_{jt} \tag{8}$$

where $\text{PenaltyDisclosure}_{jt}^{k}$ is the set of indicators that equals one if agency j in period t is k quarters relative to its penalty disclosure date. I omit the coefficient at $k = -1$ to zero, making period -1 as reference. The pre-disclosure coefficients ($k < 0$) test for differential pre-trends, while post-disclosure coefficients ($k \geq 0$) trace out the dynamic treatment effects over time.

To ensure robustness to treatment effect heterogeneity, I complement my TWFE event study with three alternative estimators that explicitly account for heterogeneous treatment effects in staggered designs: local projections estimator (Dube et al., 2025), Callaway-Sant'Anna (2021) estimator, and Sun-Abraham (2021) estimator. These heterogeneity-robust approaches provide consistent estimates of dynamic treatment effects even when treatment effects evolve heterogeneously across treated units.

4.2.2 Results

A. DiD Estimates.—Table 4 presents estimates of α from Equation (7). Column (1) shows that negative reputation shocks reduce agency market shares by 17.6 percentage point, a statistically significant effect. However, this TWFE OLS estimate may be biased if treatment effects are heterogeneous across groups or time periods.

To investigate treatment effect heterogeneity, I partition the sample by market size at the mean and run a regression in Equation (7) using each subsample. The results reveal substantial differences: agencies in small markets experience a 25.2 percentage point decline (Column (2)), more than double the 12.2 percentage point decline in large markets (Column (3)). When expressed as absolute market share losses relative to pre-treatment levels, the disparity becomes even more pronounced—small markets lose 8.49% compared to 1.49% in large markets. This five-fold difference suggests that penalty information disseminates more effectively in smaller markets.

I next examine heterogeneity by firm size, a dimension particularly relevant in markets with repeat clients where larger firms' reputations are typically more established and closely monitored. Dividing the sample at the median of real capital value (from firm registration data), I find that large agencies experience modestly larger market share losses than small agencies (Columns (4)–(5)). The difference of 1.66% (4.27% vs. 2.61%) is substantially smaller than the market-size heterogeneity of 7.01%. This limited firm-size heterogeneity likely reflects the fact that EIA clients are predominantly first-time market participants with minimal prior information to differentiate agencies beyond publicly disclosed penalties.

Given evidence of substantial heterogeneity, particularly across market sizes, the homogeneous treatment effect assumption underlying TWFE may be violated. To address this concern, Columns (6) and (7) report results using heterogeneity-robust estimators: the local projections estimator (Dube et al., 2025) and Callaway-Sant'Anna (2021) estimator. These methods yield remarkably consistent estimates of 8.9 and 7.8 percentage points, respectively, both statistically significant. These estimates imply reputation-induced market share declines of 1.10–1.18%, less than half the magnitude suggested by TWFE. This comparison indicates that violating the homogeneity assumption generates substantial upward bias in conventional DiD estimates.

B. Event-Study Estimates.—Figure 4 presents the event-study coefficients using four different estimators to assess pre-trends and examine treatment effect dynamics. Pre-disclosure coefficients cluster near zero for most estimators, supporting no pre-trends assumption, a weaker version of the parallel trends assumption. The Callaway-Sant'Anna estimates display some evidence of pre-trends, potentially reflecting information leakage through private channels before official penalty disclosure.

Post-disclosure dynamics reveal two key patterns. First, TWFE estimates consistently exceed heterogeneity-robust alternatives across all post-treatment periods, corroborating the upward bias identified in the DiD analysis. Second, while TWFE suggests declining treatment effects over time, heterogeneity-robust estimators indicate remarkably stable effects persisting at least three years post-disclosure.

These persistent effects demonstrate that reputation responds sharply to new quality information and remains durably affected. This pattern confirms that agency quality is largely unobservable to clients ex ante, forcing them to rely heavily on public signals when making contracting decisions. The stability of effects over time suggests that reputation, once damaged, is difficult to rebuild in this market.

5 Illustrative Model

This section provides a stylized model to examine how entry (de)regulation affects product/service quality, and the role of reputation concerns in mitigating the entry deregulation effect. The model captures the key institutional features of emerging markets: unobservable quality, reputation mechanisms, and regulatory policy only applied to entry regulation.

5.1 Setup

A. Overview and Timing.—Consider a market with a finite number of potential entrants. Each entrant, denoted by $j \in \{1, 2, \ldots, J_N\}$, is heterogeneous with respect to their productivity $\gamma \in \{\gamma_L, \gamma_H\}$ with $\gamma_L, \gamma_H \in \mathcal{R}^+$. The market operates in two stages: entry and operation. In the entry stage, each potential entrant observes its privately known productivity γ and the publicly observable entry cost c_e, influenced by administrative barriers to entry, to decide whether to enter. Firms enter if expected profits exceed the entry cost.

Successful entrants become incumbents choose quality level and then engage in a two-period competition. In each period, incumbents simultaneously set service price to maximize the present value of profits, after which customers select providers. Service quality is uniform across a firm's customers, reflecting descriptive evidence of greater between-firm than within-firm quality variation over time (see Appendix D).

I assume that firms directly set quality levels rather than adjusting them through investment or depreciation, departing from quality ladder models (Pakes & McGuire, 1994) for both empirical and methodological reasons. Empirically, field work reveals that service firms can adjust quality without investing in capital or technology and tolerating quality shocks. Managers of EIA agencies consciously decide whether reports rely on rigorous testing or

fabricated results, directing their subordinates accordingly. When reports are rejected by authorities—though this occurs rarely (approximately 0.1%)—agencies routinely resubmit improved reports without changing personnel. These observations indicate that quality is not a capital stock affected by investment decisions and stochastic shocks, but rather a flexible choice variable. Methodologically, this quality choice framework enables closed-form solutions in the theoretical model and simplifies the empirical analysis by focusing on customer beliefs about quality rather than modeling quality evolution (discussed further in Section 6).

Quality is unobservable to customers, capturing the lemon market problem. Productivity and cost structures, which could potentially signal quality, are similarly unobservable to customers. Firms compete *à la* Bertrand with uniform pricing, eliminating price as a quality signal. The sole mechanism for quality inference is regulatory penalties, disclosed by the regulator at each period's end. These penalties inform customers about firm quality, shaping their subsequent purchasing decisions.

In summary, the timing of the game is as follows:

1. Each entrant j chooses whether to enter.
2. Each firm j simultaneously sets service quality q_j and price p_{j1} [period 1].
3. Customers select service providers. Market demand is realized.
4. Regulatory enforcement occurs, imposing penalties on firms based on their quality choices.
5. Each firm j simultaneously sets price p_{j2} [period 2].
6. Customers observe current prices and historical penalties, then select service providers. Market demand is realized.
7. Regulatory enforcement occurs and payoffs are realized.

B. Linear Demand System.—Suppose that J firms enter successfully, indexed by $j \in \{1, 2, \ldots, J\}$, each offering services with demand characterized by a linear system (Spence, 1976). Firm j's sales depends on the vector of service prices $\mathbf{p}$ $(= (p_1, p_2, \ldots, p_J))$ and the vector of expected penalty probability $\widehat{\mathbf{P}}_t$. The demand function is given by

$$s_{jt} = s(\mathbf{p}_t, \hat{\mathbf{P}}_t) = a - b(p_{jt} + h\hat{P}_{jt}) + \sigma \sum_{k \neq j} (p_{kt} + h\hat{P}_{kt}). \tag{9}$$

where b governs own-price elasticity and σ governs cross-price elasticity, both common across firms. The parameter h denotes the fine amount, making $h\widehat{P}_{jt}$ the expected fine. Penalties fall

entirely on customers, reflecting the industrial reality that litigation costs are legally borne by clients and that reputation damage often exceeds direct litigation costs (Minutti-Meza, 2014).

The linear demand system offers two advantages. First, it enables closed-form solutions, facilitating theoretical comparative statics without numerical methods. Second, it implicitly captures customer heterogeneity, aligning with real markets. This system can be micro-founded through a Hotelling model where customers value services differentially (Choné & Linnemer, 2020), reflecting the EIA industry's project-level variation in environmental risk assessment needs.

C. Law Enforcement Process.—The regulator inspects service quality and decides penalties after demand realization. The probability that a project of quality q incur penalties, denoted as function $P(\cdot)$, evolves deterministically according to quality choice: $P(q) = \alpha_0 - \alpha_1 q + \eta$, where $\alpha_1 > 0$ implies higher quality reduces penalty probability. ν is the idiosyncratic shock following a normal distribution, reflecting randomness in enforcement activities: $\eta \sim N(0, \sigma_\eta^2)$. While I employ a linear specification for tractability, a logit form ($P(q) = \frac{1}{1+\exp(-\alpha_0+\alpha_1 q+\eta)}$) yields qualitatively similar results.

Reputation dynamics operate through customer belief updating about penalty probabilities. Assuming customers correctly perceive the enforcement process, they infer firm j's penalty probability $\widehat{P}_{jt}$ based on observed penalties and prior quality beliefs. The corresponding expectation of quality $\tilde{q}_{jt}$ is $\frac{\alpha_0 - \widehat{P}_{jt}}{\alpha_1}$. In period 1, lacking firm-specific penalty data, customers rely on common prior beliefs: $\tilde{q}_{j1} = \bar{q}, \widehat{P}_{j1} = \alpha_0 - \alpha_1 \bar{q}$ for all j, where $\bar{q}$ represents the expected quality level. Assume that the prior belief has a idiosyncratic shock normally distributed with zero mean and variance σ_q^2. In period 2, customers update beliefs about quality and penalty probability using observed period-1 penalties: $\tilde{q}_{j2} = \frac{\sigma_\eta^2 \bar{q}_j + \sigma_q^2(\alpha_0 - P_j)/\alpha_1}{\sigma_\eta^2 + \sigma_q^2}, \widehat{P}_{j2} = P(\tilde{q}_j)$.

D. Firms' Problem.—Incumbent firms compete *à la* Bertrand and make quality and price decisions each period. Firm j's per-period profit is set to be the product of sales and markups:

$$\pi_{jt} = s_{jt}(p_{jt} - c_j q_j) \tag{10}$$

Improving quality incurs a marginal cost c_j, proportional to the inverse of firm's productivity: $c_j \propto 1/\gamma_j$.

Firms are forward-looking, maximizing the present value of profits. Firm j's value function in period 1 is:

$$\begin{aligned} V_{j1} &= \pi_{j1} + \beta \pi_{j2} \\ &= s(\mathbf{p}_1, \hat{\mathbf{P}}_1)(p_{j1} - c_j q_j) + \beta s(\mathbf{p}_2, \hat{\mathbf{P}}_2)(p_{j2} - c_j q_j). \end{aligned} \tag{11}$$

where β denotes the discount factor.

Between entry and operation period 1, firms receive no new information. Therefore, firms

make entry decisions by comparing the future value in period 1 V_{j1} with the entry sunk cost c_e. I define an index function $\phi(\gamma)$ indicating whether a firm with productivity γ enters. Firms with productivity above a threshold γ^* will enter. Obviously, the threshold is a function of entry sunk costs: $\gamma^*(c_e)$. $\phi(\gamma) = 1$ is equivalent to $\gamma > \gamma^*$.

5.2 Effect of Entry Deregulation and the Role of Reputation

This section shows the analytical results on the effect of entry regulation on firm productivity and service quality, and the role of reputation in enhancing the effect of entry regulation. Entry deregulation is defined as a reduction in the entry sunk cost c_e. The results are presented in three propositions:

Proposition 1 *There exists a threshold $\tilde{c}_e$ in the set of feasible entry costs such that: (i) for all $c_e > \tilde{c}_e$, only high-productivity firms (γ_H) enter; (ii) for all $c_e < \tilde{c}_e$, all firm types enter. Average service quality $\bar{q}$ is higher when $c_e > \tilde{c}_e$ than when $c_e < \tilde{c}_e$.*

The proof appears in Appendix E. Intuitively, entry costs below the threshold enable low-productivity firms to enter, intensifying competition and reducing period-2 markups. Consequently, firms have weaker incentives to invest in quality for reputation building, preferring to exploit their market niche, resulting in a lemon market equilibrium.

One might argue that this model overlooks pro-competitive effects of deregulation on quality, as documented by Mussa and Rosen (1978). This omission stems from the simplifying assumption that customers cannot differentiate firms in period 1. Relaxing this assumption—allowing customers to receive noisy quality signals and categorize firms into quality groups—would enable quality competition that could improve quality in more competitive environments. The empirical model incorporates both quality and price competition.

Next, I examine how reputation affects the relationship between entry regulation and quality.

Proposition 2 *Average quality $\bar{q}$ increases with: (i) reputation updating speed δ, (ii) signal informativeness (higher α_1 and lower σ_η). The quality differential between regulated (above-threshold) and deregulated (below-threshold) entry costs decreases in these parameters.*

This proposition yields three insights. First, reputation mechanisms unambiguously increase average quality: high-productivity firms in deregulated markets invest in reputation to attract customers from low-productivity competitors in period 2. Second, reputation attenuates the benefits of entry regulation: the incentive to build reputation for market share gains diminishes in regulated markets where only high-productivity firms operate. Third, strengthening reputation formation via law enforcement and penalty disclosure—through higher

penalties, better quality detection, or more precise enforcement—amplifies the reputation mechanism, partially substituting for entry regulation in maintaining quality standards.

6 Empirical Model

Motivated by the findings in the previous section, I extend the theoretical model to an empirical model. The model builds on the dynamic oligopoly framework developed by Ericson and Pakes (1995).

6.1 Model Environment

A. Timing of Game.—Time is discrete with an infinite horizon, denoted by $t \in \{0, 1, 2, \dots\}$. In each period, N_e potential entrants appear in the market, indexed by $1, 2, \dots, N_e$. These entrants disappear in the following period if they choose not to enter. Incumbents in period t are indexed by $j \in \{1, 2, \dots, J_t\} \equiv \mathcal{J}_t \subset \mathbb{N}^+$.

The timing is as follows:

1. Incumbent firms observe their current state (reputation) and scrap value shocks ϕ and make exit decisions ρ. They then observe private quality fixed costs ξ and decide on quality q. Potential entrants observe their private entry costs c_e and decide whether to enter (λ), choosing quality conditional on entry.

2. All active firms set their prices.

3. Customers select service providers and sales are realized.

4. Firms' reputations are updated based on quality realizations.

B. Equilibrium Concept.—I set the equilibrium as the MME. Three reasons justify this choice: First, MME ensures computational tractability relative to Markov Perfect Equilibrium (MPE). Given that EIA markets average 700 agencies, any equilibrium strategy depending on the full set of individual states would induce insurmountable curse of dimensionality problems. MME dramatically reduces computational burden by assuming firms track low-dimensional moments of fringe firms rather than all individual states. Second, MME aligns with observed firm behavior from field work. Interviews reveal that EIA managers monitor the quality and reputation of leading firms while maintaining general awareness of industry-wide reputation dynamics. This evidence supports the assumption that firms base decisions on summary statistics of fringe firms and the states of dominant firms. Third, MME provides a natural framework for distinguishing between strategic dominant firms and non-strategic fringe firms, consistent with observed market structure.

6.2 Demand and Customer Beliefs of Quality

I use a logit demand system instead of the linear demand system used in the theoretical model to explicitly characterize customer heterogeneity, which facilitates counterfactual analysis based on customers' characteristics. Assume that there are n_t customers with projects pending for construction in market t. Customer i's utility from seeking service from firm j in period t is given by

$$v_{ijt} = b(\Pi_t - p_{jt}) + \tilde{q}_{jt} + \varepsilon_{ijt} \tag{12}$$

in which Π_t represents the customer's net operating revenue in market t, calibrated from statistical indicators. p_{jt} denotes the contract price averaged at the firm level. $\tilde{q}$ represents firm's reputation. ε_{ijt} captures idiosyncratic preference shocks and is assumed to follow the type I extreme value distribution.

I model reputation evolution through a linear index specification. Specifically, reputation in period t evolves according to:

$$\tilde{q}' = \tilde{q}_i + \nu_i - \eta \tag{13}$$

where ν_i represents a private reputation shock taking values $\{0, 1\}$. The probability of positive shock depends on quality choice: $\Pr(\nu_i = 1 \mid q_i) = \frac{\alpha q_i}{1+\alpha q_i}$ and $\Pr(\nu_i = 0 \mid q_i) = \frac{1}{1+\alpha q_i}$. Thus, reputation increases with probability proportional to quality investment. The term η captures exogenous reputation decay, equaling 1 with probability δ and 0 otherwise.

This reputation specification balances theoretical foundation with empirical tractability. Theoretically, it corresponds to Board and Meyer-ter-Vehn (2013) with binary quality choices and Bayesian updating. Empirically, it follows Pakes and McGuire (1994)'s classical framework, ensuring computational feasibility.

6.3 Firms, States, Strategies and Transitional Kernels

Define the sets of incumbent firms and dominant firms in period t as $F_t \subset \mathcal{J}_t$ and $D_t \subset \mathcal{J}_t$, respectively. Each period, twenty firms can potentially enter, matching the maximum observed entry in our data. Let $\tilde{\mathcal{Q}}$ denote the set of possible reputation states, comprising fifteen discrete levels. Each element represents a reputation level $\tilde{q}$, interpreted as customers' quality beliefs. Dominant firms occupy the top five reputation states, denoted $\tilde{\mathcal{Q}}_d$, while fringe firms occupy the remaining states $\tilde{\mathcal{Q}}_f$. I restrict the maximum number of dominant firms to $\bar{D} = 4$, exceeding the maximum of two observed empirically.

The set of all possible dominant firms' states $\mathcal{S}_d$ equals $\left\{ d \in \tilde{\mathcal{Q}}_d^{\bar{D}} \mid d(1) \geq d(2), \ldots, \geq d(\bar{D}) \right\}$ by assuming anonymity. Let the fringe firm state f_t be a count measure specifying, for each potential state $x \in \tilde{\mathcal{Q}}_f$, the number of fringe firms at that state. The fringe state space is

$\mathcal{S}_f = \{f \in \mathbb{N}^{|\tilde{\mathcal{Q}}_f|} \mid \sum_{x \in \tilde{\mathcal{Q}}_f} f(x) \leq J\}$. The full industry state space is $\mathcal{S} = \mathcal{S}_f \times \mathcal{S}_d$, where $s = (f, d) \in \mathcal{S}$.

I define the moment-based industry state to reduce dimensionality. Let Θ denote the set of possible fringe moments θ, where the fringe moment is the first moment of fringe firm states: $\theta \equiv \sum_{x \in \tilde{\mathcal{Q}}_f} x \cdot f(x)$. The moment-based industry state is $\hat{s} \equiv (\theta, d)$ with state space $\hat{\mathcal{S}} \equiv \Theta \times \mathcal{S}_d$.

Firms employ moment-based strategies as defined by Ifrach and Weintraub (2017). An incumbent's moment-based strategy $\mu \in \hat{\mathcal{M}}$ maps from its own state $\tilde{q}$ and industry state $\hat{s}$ to quality and exit actions: $\mu : (\tilde{\mathcal{Q}}, \hat{\mathcal{S}}) \to \mathcal{A}$, where $\mathcal{A}$ denotes the action space. Entrants' moment-based strategy $\lambda \in \hat{\Lambda}$ maps from industry state $\hat{s}$ to entry decisions.

The perceived transition kernel $\hat{\mathbf{P}}_{\mu',\mu,\lambda}[\tilde{q}', \hat{s}' \mid \tilde{q}, \hat{s}]$ represents the probability of transitioning from state $(\tilde{q}, \hat{s})$ to $(\tilde{q}', \hat{s}')$ when the targeted incumbent plays strategy μ' while others play (μ, λ). This kernel decomposes into three components: fringe moment transitions $\hat{\mathbf{P}}_{\mu,\lambda}[\theta' \mid \hat{s}]$, fringe-to-dominant transitions $\mathbf{P}_{\mu',\mu,\lambda}[(f \to d) \mid \hat{s}]$, and dominant firm transitions

$$\mathbf{P}_{\mu',\mu,\lambda}[\tilde{q}', d' \mid \tilde{q}, \hat{s}]$$

.

The transition kernel over moments follows the long-run average approach of Fershtman and Pakes (2012). For example, for any moment-based state $\hat{s}$ in the recurrent class $\mathcal{R}_{\mu,\lambda}$, the fringe moment transition kernel is:

$$\hat{\mathbf{P}}_{\mu,\lambda}[\theta' \mid \hat{s}] = \lim_{T \to \infty} \frac{\sum_{t=1}^{T} \mathbf{1}\{\hat{s}_t = \hat{s}, \theta_{t+1} = \theta'\}}{\sum_{t=1}^{T} \mathbf{1}\{\hat{s}_t = \hat{s}\}} \tag{14}$$

I restrict at most one firm to transition from fringe to dominant status per period, consistent with empirical patterns.

6.4 Firms' Problem and Equilibrium

Firms' optimization comprises two components: per-period profit maximization and forward-looking value maximization. The static component follows the theoretical model, with firms competing à la Bertrand in prices.

For dynamic decisions, incumbent firm j chooses $\nu' = (q', \rho')$ to maximize the perceived discounted present value of future profits given other firms' strategies (μ, λ):

$$\hat{V}(\tilde{q}_{jt}, \hat{s}_t \mid \mu', \mu, \lambda) = \hat{\pi}(\tilde{q}_{jt}, \hat{s}_t) + \rho'\phi + (1 - \rho') \left[\xi q' + \beta \mathbb{E}_{\mu',\mu,\lambda}[V(\tilde{q}'_{jt}, \hat{s}'_t) \mid \tilde{q}_{jt}, \hat{s}_t]\right] \tag{15}$$

where $\rho' = 1$ indicates exit with scrap value ϕ. The scrap value for all firms are drawn from a normal distribution ($\phi \sim N(\mu_\phi, \sigma_\phi)$) and is known to continuing firms making exit decisions, ξ represents the fixed cost of improving one unit of quality. The quality fixed cost includes software licenses, staff incentives, and managerial efforts. The expectation is taken with respect to the perceived transition kernel $\hat{\mathbf{P}}_{\mu',\mu,\lambda}(\tilde{q}', \hat{\boldsymbol{s}}' \mid \tilde{q}, \hat{\boldsymbol{s}})$.

Potential entrants live for one period only if they choose not to enter. Entrant j in period t chooses λ' to maximize:

$$\max_{\lambda'} \left\{ 0, \beta \mathbb{E}_{\lambda',\mu,\lambda}[\hat{V}(\tilde{q}^e, \hat{s}' \mid \mu, \lambda) \mid \hat{s}] - c_e \right\} \tag{16}$$

where c_e represents the sunk entry cost, which is composed of both upfront investment, such as searching for employees and establishing relationships with software providers, and administrative entry cost.

The MME is formally defined as:

Definition 1 *The Moment-based Markov Equilibrium consists of a recurrent subset of states $\hat{\tilde{\mathcal{S}}}$, quality and exit strategies $\mu = (q, \rho) \in \hat{\mathcal{M}}$, entry strategy $\lambda \in \hat{\Lambda}$, and perceived transition kernel $\hat{\mathbf{P}}_{\mu',\mu,\lambda}[\cdot \mid \cdot]$ such that:*

1. *Incumbent optimality: $\mu = \arg\max_{\mu' \in \hat{\mathcal{M}}} \hat{V}(\tilde{q}, \hat{s} \mid \mu', \mu, \lambda)$ for all $(\tilde{q}, \hat{s}) \in \tilde{\mathcal{Q}} \times \hat{\tilde{\mathcal{S}}}$*
2. *Entry optimality: $\lambda(\hat{s}) = \max\{0, \beta \mathbb{E}_{\mu,\lambda}[\hat{V}(\tilde{q}^e, \hat{s}' \mid \mu, \lambda) \mid \hat{s}] - c_e\}$ for all $\hat{s} \in \hat{\tilde{\mathcal{S}}}$*
3. *The optimal behavior given the perceived transition kernel generates EDVs that are consistent with the kernel in the recurrent subset of states.*

The existence of the MME is guaranteed when the best response strategy function exhibits continuity properties, as established by **doraszelski˙computable˙2010<empty citation>**. However, maintaining this continuity requirement can be challenging in computational implementations. To address potential violations of continuity, Ifrach and Weintraub (2017) introduce an additional sufficient condition: the perceived transition kernel must be both irreducible and aperiodic within the recurrent class. My empirical approach ensures equilibrium existence and continuity of the best response strategy through two complementary mechanisms. First, during parameter estimation, I employ kernel smoothing techniques that inherently preserve continuity in the policy functions. Second, in my counterfactual analyses, I implement verification procedures that explicitly test for irreducibility and aperiodicity of the transition kernels in the simulation algorithm.

7 Estimation and Results

This section details the model estimation and results. The parameters of interest fall into four categories: demand parameters θ_b, cost parameters c, transition parameters θ_t, and dynamic parameters θ_d. The estimation proceeds in three steps. Firstly, I estimate the demand and cost parameters using the price and quantity data. Next, I estimate the reputation transition process using quality measures of EIA reports and the reputation recovering from the demand estimation. Then, I estiamte the conditional choice probabilities of firms using kernel functions. Finally, I estimate the dynamic parameters using the moment inequalities estimator.

7.1 Demand and Cost Parameters

The demand system follows a discrete choice framework where clients choose among competing EIA providers. Under the Type I extreme value distribution assumption for idiosyncratic utility shocks, the market share equation becomes:

$$\ln(s_{jt}/s_{0t}) = b(\Pi_t - p_{jt}) + \zeta_{jt} \tag{17}$$

where s_{jt} denotes firm j's market share in province-year-quarter t, and s_{0t} represents the outside option share. Following interview evidence from regulatory officials, I set the outside share at 1% of the observed market size, corresponding to the estimated evasion rate of mandatory EIA procedures. Robustness checks using alternative outside share definitions—including the combined share of firms below 0.01% market share and detection-rate-adjusted evasion estimates—yield qualitatively similar results.

To address the endogeneity of price, I instrument for it using the quality characteristics of rival firms. The underlying assumption is that rivalry quality is correlated with the firm's own quality and price via competition, but does not affect the firm's price directly. I employ a TSLS estimator for the above demand equation. From this regression, I estimate the sensitivity of client's profit to price b. Then I recover firm j's reputation $\tilde{q}_{jt}$, as the residual component of the demand curve: $\tilde{q}_{jt} = \ln(s_{jt}/s_{0t}) - bp_{jt}$, a practice used by Khandelwal (2010).

The demand estimation results are reported in Table 5. By assuming that the outside good market share as 1% and using OLS regression, the estimated profit sensitivity parameter is 0.058, though statistically insignificant (Column (1)). By treating the rivalry quality as IV and using TSLS estimator, the first-stage estimate implies a positive association between rivalry quality and price, aligned with the fact that rivalry quality is positively associated with the firm's own quality, production cost, and price. The second-stage estimate implies a

price sensitivity parameter as 2.86 (Column (3)), over five-folds of the OLS estimate. The downward bias of the OLS estimate could be attributed to the correlation between demand shocks and price. The model in Column (3) is used as the preferred specification. I check the baseline robustness by defining outside goods as the benchmark firms with market share less than 0.1% and report all results in Columns (4)–(6). The price sensitivity parameter estimated using the IV strategy (2.675) is similar in terms of magnitude to the baseline one (2.860).

Given the demand parameter estimates and the first-order condition from the firm's profit-maximization problem, I recover the marginal cost:

$$\hat{c} = \frac{1}{N^J} \sum_{jt} p_{jt} + \frac{1}{\hat{b}_\theta (1 - s_{jt})} \tag{18}$$

in which N^J equals the number of observations. The estimated marginal cost equals 723 CNY. All of the estimated static parameters are summarized in Table 7

The marginal cost is assumed to be homogeneous across firms and invariant to the quality choice. To test these assumptions, I first estimate costs separately for sub-samples of firms grouped by age and size. The estimates from these groups are not statistically different from one another, lending support to the homogeneity assumption. Second, I add the quality measure into the marginal cost and find that the quality parameter is statistically insignificant (p-value equals 97%). By changing the quality from lowest to highest, the price only changes for 28.33 CNY, implying a small magnitude of economic significance.

7.2 Reputation Transition Parameters

I discretize the reputation state into 20 levels and estimate the transition parameters using two alternative strategies. First, I assume that the transition process follows an AR(1) specification and estimate the sensitivity to past reputation and current quality. The results are shown in Column (1) of Table 6. The impact of past reputation decays at a rate of 0.94 (0.984^4) per annum, implying relatively persistent reputation dynamics. Discretizing quality yields stable results, though the quality sensitivity is somewhat larger (Column (2)). Second, I adopt the baseline reputation transition process in Equation (**??**) and estimate it using the ML estimator. The estimated sensitivity to past reputation, α (Column (3)), is similar to that from the AR(1) process. Increasing quality from the lowest to the highest level in the sample generates a reputation adjustment of 0.95 ($1 - \frac{1}{1+1.522\times 13}$). The estimated probability of an outside shock is 0.453, indicating substantial risk of reputation loss when firms choose low quality.

7.3 Policy Functions and Transition Probabilities

I estimate the entry, exit, quality policy functions using regression combined with discretization rather than explicitly assuming functional forms for policy functions to reduce the small sample errors. Specifically, I estimate spline regressions where policy decisions depend on a firm's own state, the industry fringe moment, and the states of other dominant firms. The results are shown in Appendix Table A.9.

I estimate the fringe moment and fringe-dominance transition probabilities using OLS regression, then discretize the results into the state space. I adopt OLS rather than frequency-based estimators because the transitions are sparse in my data and frequency methods would yield imprecise estimates, often assigning zero probability to low-frequency but feasible transitions. Specifically, I estimate the fringe moment transition function by regressing the current fringe moment on its lagged value. For fringe-dominance transitions, I estimate the probability of occurrence using a linear probability model. I then discretize the predicted values across the firm state space to construct the transition matrix. The results are shown in Appendix Table A.9.

7.4 Dynamic Parameters

The dynamic parameters include the discount factor β, distribution of quality marginal cost $G_\xi(\cdot)$, the scrap value $G_\phi(\cdot)$, and entry cost $G_e(\cdot)$. The annual discount factor is calibrated to 0.974, which implies a quarterly discount factor of $\beta = 0.9^{\frac{1}{4}}$.

I estimate the distribution of marginal cost ξ and scrap value ϕ, using a moment inequalities estimator. The identifying assumption is that a firm's observed policy, σ_i, yields a higher present value than any alternative policy, σ'_{ik}. This implies a set of moment inequalities that the true parameter vector must satisfy. The estimator finds the parameter values that minimize the violation of these optimality conditions. Specifically, I solve the following minimization problem:

$$\hat{\theta}'_d = \arg \min_{\theta'_d \equiv (G_\xi(\cdot), G_\phi(\cdot))} \sum_{k=1}^{n_k} \left(\min\{0, \hat{V}_{jt}(\hat{\boldsymbol{s}}_k; \sigma_i, \boldsymbol{\sigma}_{-i}; \theta'_d) - \hat{V}_{jt}(\hat{\boldsymbol{s}}_k; \sigma'_{ik}, \boldsymbol{\sigma}_{-i}; \theta'_d)\} \right)^2 \tag{19}$$

in which n_s is the number of simulations. To implement the estimator, I draw $n_k = 500$ alternative policies to generate a set of inequalities. For each alternative policy simulation k, I draw a firm i and state $\hat{\boldsymbol{s}}_k$ and construct an alternative policy σ'_{ik} by perturbing the firm's observed policy: $\sigma'_{ik}(\hat{\boldsymbol{s}}_k) = \sigma_{ik}(\hat{\boldsymbol{s}}_k) + \varepsilon_k$. ε_k are drawn uniformly from the width of ± 0.1 standard deviation. The value function, $\hat{V}_{jt}(\cdot)$, is approximated via forward simulation.

However, it is burdensome to compute the value function given the set of parameters in

each round of computation. To reduce this burden, I exploit the fact that the value function is linear in the dynamic parameters, which substantially reduces the computational burden:

$$\begin{aligned} V_i(\mathbf{s};\boldsymbol{\sigma}) =& W^1(\mathbf{s};\boldsymbol{\sigma}) + W^2(\mathbf{s};\boldsymbol{\sigma})\cdot\xi + W^3(\mathbf{s};\boldsymbol{\sigma})\cdot\phi \\ =& \mathbb{E}\left[\sum_{t=0}^{\infty}\beta^t\hat{\pi}_i\left(\boldsymbol{s}_t\right) \mid \boldsymbol{s}_0=\mathbf{s}\right] - \mathbb{E}\left[\sum_{t=0}^{\infty}\beta^t\hat{\rho}_i\left(\boldsymbol{s}_t\right) \mid \boldsymbol{s}_0=\boldsymbol{s}\right]\cdot\xi \\ &+ \mathbb{E}\left[\sum_{t=0}^{\infty}\beta^t\hat{\imath}_i\left(\boldsymbol{s}_t\right) \mid \boldsymbol{s}_0=\boldsymbol{s}\right]\cdot\phi \end{aligned} \tag{20}$$

This linearity means the value function does not need to be recomputed in each step of the numerical optimization. Particularly, I simulate 2,000 paths of 100 quarters to estimate W^i for each initial firm state $\boldsymbol{s}$. The policy functions, transition kernels used in the simulation are estimated before.

I use the Laplace-based MCMC estimator (**victor˙mcmc˙2003**) to search for $\hat{\theta}_d$ in Equation (19) for two reasons. First, the MCMC estimator is able to recover the distribution of parameters, in contrast to direct optimization that searches for a single parameter. Second, the Laplace-based estimator assumes that the Bayesian prior distribution of the parameters follows the Laplace distribution. By doing so, the estimator accommodates the pattern that many posterior modes occur precisely at zero rather than near it, thereby inducing sparsity and accelerating optimization.

The final step of estimation is to recover the entry cost distribution, $G_e(\cdot)$. A firm enters if its value of entry exceeds its privately drawn entry cost. This implies the observed entry probability is equal to the cumulative distribution function of entry costs evaluated at the value of entry:

$$\Pr\left(\chi_e\left(\hat{s}\right)=1\right) = G_e\left(\beta\mathbb{E}\left[V\left(\tilde{q}^e,\hat{s}' \mid \mu,\lambda\right) \mid \hat{s},\chi_e=1\right]\right). \tag{21}$$

I invert this relationship to non-parametrically estimate $G_e(\cdot)$, using kernel regression to interpolate for unobserved states.

The estimated parameters are shown in Panel B of Table 7. The mean of the quality fixed cost is 549 kCNY with a standard deviation of 412 kCNY, implying substantial heterogeneity across agencies in quality investment. The distribution of exit values has a mean of 33.03 mCNY and a standard deviation of 24.85 mCNY. These exit values, while modest compared with most manufacturing firms, are consistent with the EIA industry's low asset intensity.

The non-parametrically estimated CDF of the entry cost distribution is shown in Appendix Figure A.9. I select a parametric distribution to approximate the estimated CDF. Comparing the fits of uniform and normal distributions, I find that the normal distribution exhibits substantially heavier tails than the local linear estimates, whereas the uniform distribution

closely matches both the upper and lower bounds of the non-parametric estimates. I therefore adopt a uniform distribution with support [16.44, 29.70] mCNY as the benchmark specification for entry costs. Entry costs are low for two reasons: first, upfront physical capital investment is minimal for service firms; second, the entry deregulation reform substantially reduced administrative barriers to entry.

8 Counterfactual Analysis

This section documents three sets of counterfactual. First, I quantify how information structure affect the optimal stringency of entry regulation by simulating three scenarios: full information, asymmetric information, and asymmetric information with reputation. Second, I show how the timing of entry regulation and deregulation affects the market outcomes by simulating four scenarios: constant regulation, delayed regulation, and delayed deregulation, and laissez faire. Third, I show the relationship between traditional entry barrier-based regulatory policies and reputation-enhancing policies by simulating combinations of different levels of both policies.

8.1 Information Asymmetry, Reputation, and Optimal Intensity of Entry Regulation

The results are summarized in Figure 5 and Table 8. I set the number of potential entrants as five as the benchmark. In Panel A of Table 8, Four findings emerge: First, moral hazard degrades service quality and customer surplus while boosting firms' profits. When customers lack firm-specific quality information and form no reputations (Column (2)), entrant numbers rise, and average service quality halves compared to the full-information case (Column (1)). This quality decline, coupled with penalty costs, reduces customer surplus from -12.9 to -37.1. Although firms' profits increase, social welfare, accounting for externalities, falls, assuming quality degradation imposes a \$1 million or \$5 million external cost.

Second, entry regulation prompts low-productivity firms to exit, enhancing customer welfare. With a \$2 billion entry cost (Column (2)), raising it to \$3 billion (Column (3)) reduces entrants and restores service quality to full-information levels (Column (1)). At a \$4 billion entry cost (Column (4)), only one firm enters, raising service prices but doubling customer surplus by mitigating moral hazard.

Third, reputation concerns alleviate moral hazard and complement entry regulation. Assuming customers update quality beliefs via adaptive learning from regulator-provided information (Columns (5)–(7)), service quality improves from 0.185 to 0.397 (Column (5)

versus Column (2)) at a $2 billion entry cost, assuming higher values denote better quality. Tighter regulation amplifies these benefits (Column (6) versus Column (3) and Column (7) versus Column (4)).

Fourth, entry regulation yields positive welfare effects. Raising the entry cost from $2 billion to $3 billion increases customer surplus by over 60%, from -37.1 to -14.3, while firms' profits decline by less than 50%, implying a positive net welfare effect. Including externalities, regulation's benefits grow larger.

9 Conclusion

This paper examines how reputation mechanisms fundamentally alter the optimal design of entry regulation in markets characterized by information asymmetry. Motivated by the pervasive quality problems in professional service markets and the coexistence of entry regulation and reputation mechanisms, I investigate their separate and interactive effects using China's environmental impact assessment industry as an empirical setting. I first document causal evidence showing that entry regulation and reputation both play important roles in the EIA market. Building on these reduced-form findings, I develop an illustrative model to show that while entry regulation improves welfare under asymmetric information, this benefit is substantially attenuated when reputation mechanisms are present. I estimate a rich dynamic oligopoly model that incorporates endogenous reputation formation and entry/exit decisions. The counterfactual analysis shows that ignoring reputation dynamics leads to over-regulation, with optimal entry barriers being when reputation is properly accounted for, resulting in potential welfare gains.

These findings have immediate policy implications for regulatory design across professional service markets, particularly in emerging and developing economies: while sophisticated regulatory tools such as continuous quality monitoring, product testing, and ex-post enforcement require substantial administrative capacity and resources often lacking in these contexts, entry regulation provides a simple, implementable tool that can be enforced at a single point in time with minimal ongoing oversight. Rather than attempting to build costly monitoring systems or relying on weak judicial enforcement of quality standards, policymakers can achieve significant quality improvements through appropriately calibrated entry barriers that screen out low-quality providers ex-ante. This framework provides developing country policymakers with a practical approach: start with moderate entry barriers to ensure minimum quality standards, then gradually liberalize as information transmission improves and reputation mechanisms mature, rather than maintaining permanently high barriers that impede market development.

This study opens several avenues for future research. First, while I focus on reputation for quality, firms may build reputation along multiple dimensions—such as reliability, innovation, and customer service—that interact in complex ways and jointly influence regulatory effectiveness. Second, governments could optimize entry regulation and information disclosure policies jointly rather than treating the information environment as given; understanding these complementarities could lead to more efficient policy packages. Third, the welfare implications of regulation may differ substantially across consumer segments with varying abilities to process quality signals and learn from market outcomes, suggesting that targeted regulatory approaches might outperform uniform standards. Finally, extending this framework to incorporate strategic information disclosure by firms, industry associations' role in reputation transmission, and cross-border regulatory harmonization would further enrich our understanding of how information, reputation, and regulation interact to shape market outcomes in an increasingly interconnected global economy.

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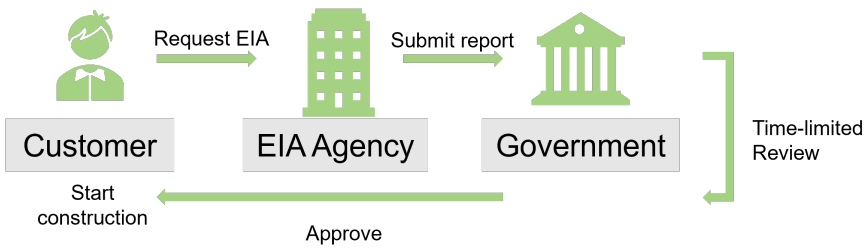
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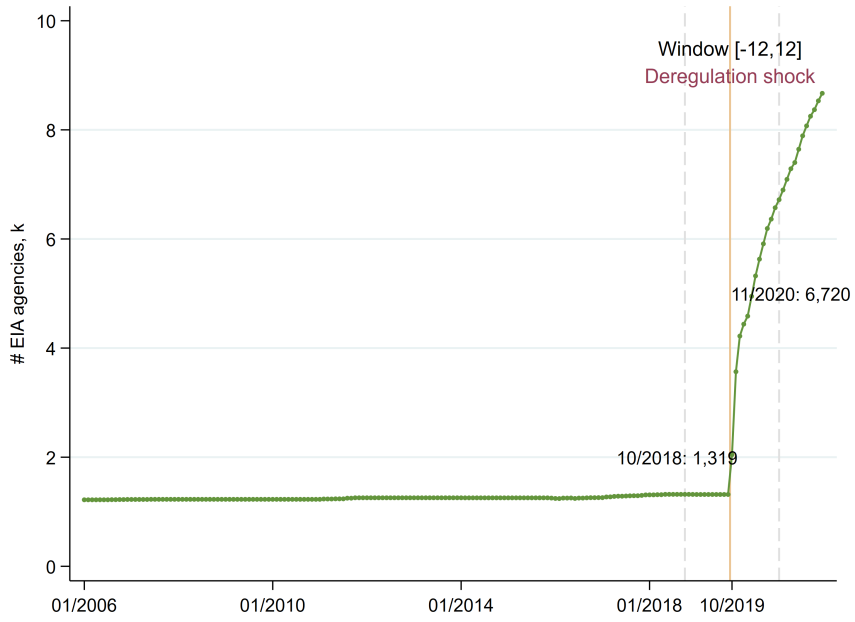
Figures and Tables

Figure 1: General EIA Procedure



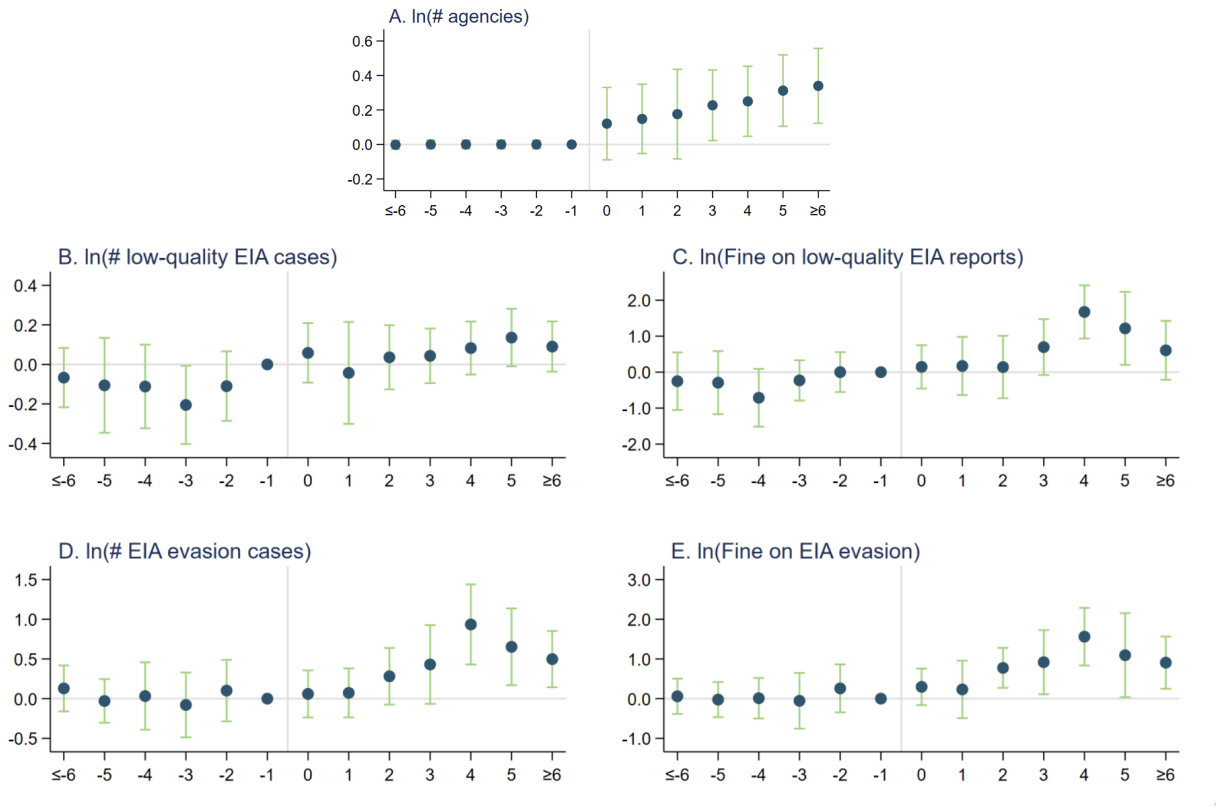
Notes: This figure plots the general procedure of EIA, which is integrated from the authoritative EIA training manual (Programme, 2002) and the EIA law in China (FAO, 2003).

Figure 2: Time Trend of EIA Agency Number



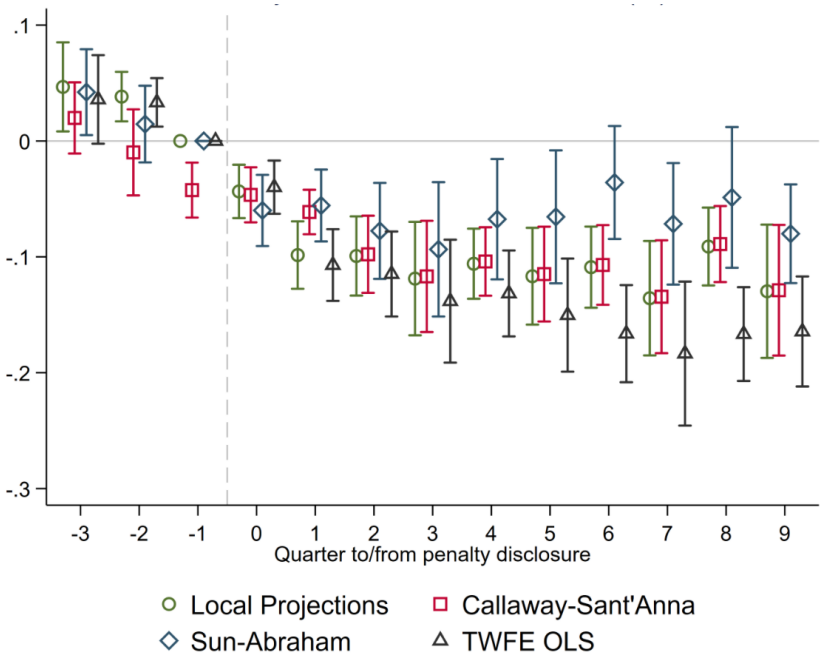
Notes: This figure plots the number of EIA agencies in China from February 2016 to September 2021. The solid vertical line represents the timing of allowing the entry of new EIA agencies and one year before and after that month is the sample period. The solid line shows the total number of EIA agencies at the monthly level, which is nearly constant before October 2019 and sharply increased after. The growth rate of agencies sharply reaches the summit (over 80%) in November 2019 and then goes down to a level fair to the pre-deregulation period.

Figure 3: Estimating Effect of Entry Deregulation-Induced Entry on Service Quality: Event Study



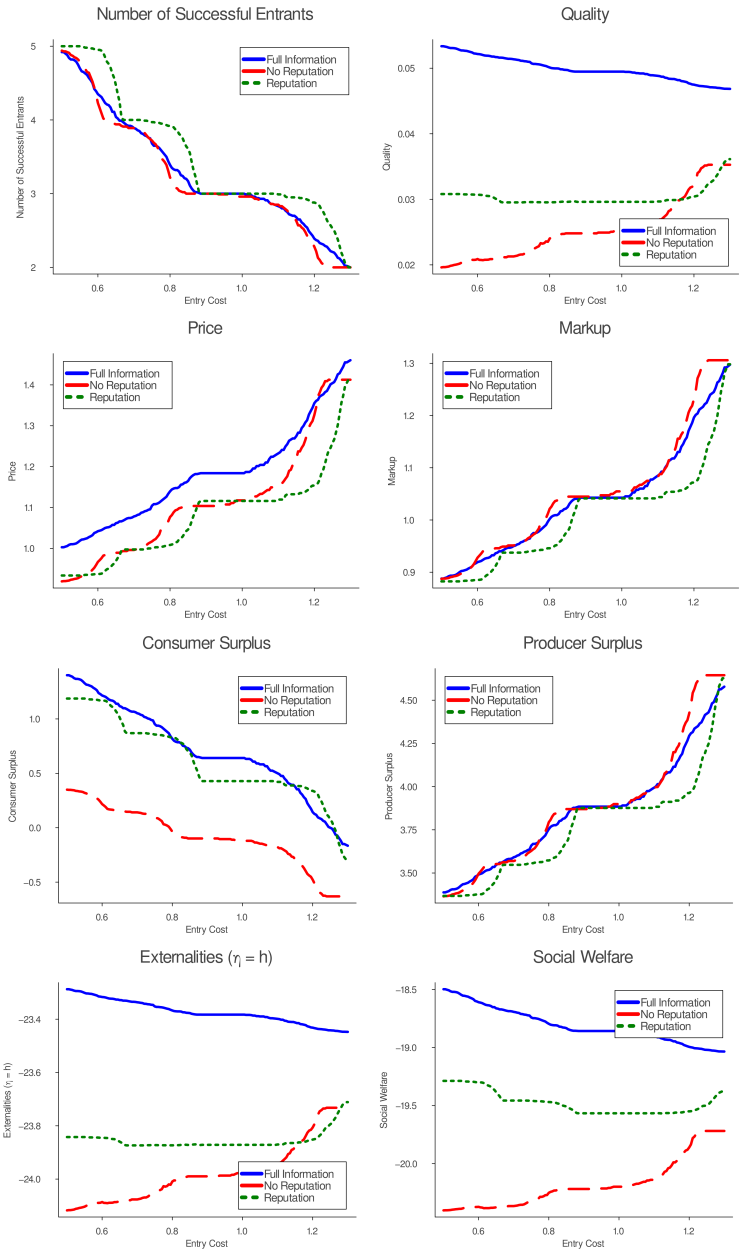
Notes: This figure shows the estimated dynamic effects of our interest. The point estimates are plotted with the 95% confidence interval based on the doubly clustered standard errors on province and year-month levels. Panel A shows the dynamic effect of entry deregulation on agency count, corresponding to the reduced form in equation (6)). Panel B to E shows the dynamic effects of entry deregulation on four indicators of information provision.

Figure 4: Estimating Effects of Negative Reputation Shock on Market Share: Event Study Estimates



Notes: This figure plots the event-study estimates of the effect of negative reputation shock on market share. These estimates are based on four estimators: local projections estimator (Dube et al., 2025) (in green with circle markers), Callaway-Sant'Anna (2021) estimator (in red with rectangle markers), Sun-Abraham (2021) estimator (in blue with diamond markers), and TWFE OLS estimator (in black with triangular markers). The markers represent the point estimates of the dynamic prestige premium, while the bounded lines represent the corresponding 95% confidence intervals, with standard errors clustered at the province level. The outcome variable is market share in percentage points.

Figure 5: Counterfactual Analysis I: Intensity of Entry Regulation



Notes: This figure plots the simulation results of the impact of intensity of entry regulation on market outcomes in three cases: full information (solid blue line), asymmetric information (dashed red line), and reputation (dotted green line). I simulate 100 sample path of 1,000 periods and show the mean outcomes on the figure. Panel A–H plot the number of successful entrants, service quality, price, markup, consumer surplus, profit, externalities, and social welfare respectively.

Table 1: Summary Statistics of Key Variables

	Obs	Mean	SD	Min	Max	Median
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Province Characteristics						
# EIA Agencies	650	93.94	96.03	3.00	561.00	55.00
Net import dependence	26	-0.02	0.33	-1.07	0.59	0.05
Panel B. City Characteristics						
# low-quality EIA cases	6,850	0.21	0.90	0.00	25.00	0.00
Fine on low-quality EIA (10kCNY)	6,850	189.44	583.42	0.00	23,139.90	50.50
# EIA evasion cases	6,850	5.92	11.45	0.00	205.00	2.00
Fine on EIA evasion (10kCNY)	6,850	51.36	382.43	0.00	19,785.01	4.85

Notes: This table summarizes the statistics of key variables in the regression sample period.

Table 2: Estimating Effect of New Entries on Service Quality

Dependent variable (IHS-transformed)	(1) # low-quality EIA cases	(2) Penalty on low-quality EIA (kCNY)	(3) # EIA evasion cases	(4) Penalty on EIA evasion (kCNY)
Panel A. OLS estimates				
# agencies	0.071**	0.611*	0.391***	0.674***
	(0.025)	(0.329)	(0.093)	(0.207)
Mean dep. var.	0.13	4.16	1.52	2.38
Adjusted R^2	0.246	0.661	0.702	0.559
Panel B. First stage estimates				
Dependence × Post	0.655***	0.655***	0.655***	0.655***
	(0.210)	(0.210)	(0.210)	(0.210)
Mean dep. var.	4.16	4.16	4.16	4.16
Olea-Pflueger F-stat	27.89	27.89	27.89	27.89
Panel C. TSLS estimates				
# agencies	0.249**	0.906*	0.563***	0.672**
	(0.102)	(0.478)	(0.182)	(0.265)
1% increase in # agencies	0.00393	0.0198	0.00925	0.0186
100% increase in # agencies	0.314	2.930	0.899	2.605
Observations	6,850	6,850	6,850	6,850

Notes: This table summarizes the estimated effects of entry-deregulation-induced competition on service quality. Observations are at the year-month-city level. The sample includes 274 cities from October 2018 to November 2020. Each regression includes year-month and province fixed effects. Panel A reports OLS estimates of quality measures on log agency count. Panel B presents first-stage results from equation (4) with the Olea-Pflueger F-statistic for the weak instrument test. Panel C reports TSLS estimates from equation (5). Standard errors reported in parentheses are doubly clustered at the province and year-month levels. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 3: Estimating Estimating Effect of New Entries on Service Quality: Reduced Form

Dependent variable	(1) ln(# low-quality EIA cases)	(2) ln(Fine on low-quality EIA)	(3) ln(# EIA evasion cases)	(4) ln(Fine on EIA evasion)
ln(EIA)	0.163***	0.593*	0.369***	0.440**
	(0.052)	(0.317)	(0.122)	(0.196)
Adjusted R^2	0.344	0.661	0.673	0.532
Year-month FE	Y	Y	Y	Y
City FE	Y	Y	Y	Y
Observations	6,850	6,850	6,850	6,850

Notes: This table summarizes the reduced form estimates of net import dependence on service quality outcomes. Unit of observation is city-year-month. All specifications include year-month and province fixed effects. Standard errors in parentheses doubly clustered at the province and year-month levels. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 4: Effect of Negative Reputation Shock on Market Share

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Model	TWFE OLS Estimates					Local projections DiD Estimates	Callaway-Sant'Anna Estimates
	Whole sample	Market size		Market share		Whole sample	
Sample		Large	Small	Large	Small		
Penalty Disclosure	-0.176***	-0.122***	-0.252***	-0.321***	-0.229***	-0.089***	-0.078***
	(0.038)	(0.029)	(0.063)	(0.067)	(0.033)	(0.021)	(0.012)
Adjusted R2	0.051	0.041	0.144	0.056	0.109		
Dep. Var. Mean	0.132	0.121	0.339	0.133	0.114	0.124	0.151
Observations	278,562	264,741	13,821	259,964	18,598	104,901	200,268

Notes: This table reports the estimated effects of negative reputation shocks on agency market share. The unit of observation is agency-year-quarter, covering 2020–2023. All specifications include year-quarter and disclosure-cohort fixed effects. Standard errors, clustered at the province level, are reported in parentheses. Columns (1)–(5) present TWFE estimates from Equation (7): Column (1) uses the full sample, while Columns (2)–(3) stratify by market size (large/small) and Columns (4)–(5) stratify by firm size. Column (6) reports local projections DiD estimates (Dube et al., 2025), and Column (7) reports Callaway-Sant'Anna (2021) estimates. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 5: Demand Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	Market share of outside good = 1%			Outside good = benchmark firms		
	OLS	First stage	TSLS	OLS	First stage	TSLS
ln(net income - price)	0.058		2.860***	0.094***		2.675***
	(0.057)		(0.605)	(0.027)		(0.427)
Rivalry quality		0.880***			0.664***	
		(0.126)			(0.079)	
Olea-Pflueger F-stat			48.95			71.47
Observations	2,979	2,979	2,979	7,645	7,645	7,645

Notes: This table presents demand estimation results at the market-agency level. Two specifications of the outside good are employed: Columns (1)–(3) define the outside good market share as 1% in each market, while Columns (4)–(6) define it as services provided by benchmark firms with market shares below 0.1%. For each specification, we report OLS estimates (Columns (1) and (4)), first-stage estimates from the instrument (Columns (2) and (5)), and TSLS estimates (Columns (3) and (6)). Heteroskedasticity-robust standard errors are reported in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 6: Estimating Reputation Transition Process

	(1)	(2)	(3)
	AR(1) process		Linear index model
	Original quality	Discretized quality	Discretized quality
Quality_{t-1}	0.079***	0.087***	
	(0.013)	(0.013)	
Reputation_{t-1}	0.984***	0.977***	
	(0.003)	(0.003)	
δ			0.453***
			(0.114)
α			1.522***
			(0.036)
Mean Dep Var	7.394	7.394	7.394
Adjusted R^2	0.993	0.993	
Observations	3,747	3,747	3,747

Notes: This table shows the estimation results for the reputation transition process. Column (1) shows the results by specifying the transition process as AR(1) and using the original quality score. Column (2) uses the discretized quality. Column (3) changes the model specification to the linear index model used in the structural model. The standard errors reported in parentheses are estimated via block bootstrapping over markets. Specifically, I draw 100 subsamples of complete market histories and estimate all parameters to account for the serial correlation within each market. The standard errors are clustered at the market level.

Table 7: Model Parameters

	(1)	(2)
Parameter	Estimate	SE
Panel A. Static Parameters		
Sensitivity to price (b)	2.675	(0.427)
Marginal cost (c, mCNY)	0.723	
Probability of outside shock (δ)	0.453	(0.114)
Reputation's Sensitivity to quality (α)	1.522	(0.036)
Panel B. Dynamic Parameters (mCNY)		
Quality fixed cost		
Mean (μ_ξ)	-0.549	(0.094)
Standard deviation (σ_ξ)	0.412	(0.065)
Exit value		
Mean (μ_ϕ)	33.029	(6.491)
Standard deviation (σ_ϕ)	24.849	(4.869)
Sunk entry cost		
Lower bound (c_{el})	16.440	(2.166)
Upper bound (c_{eh})	29.698	(8.082)

Notes: This table presents the estimated parameters for the empirical model. Panel A displays the static parameters and Panel B displays the dynamic parameters. The standard errors for dynamic parameters are estimated via block bootstraping over markets. Specifically, I draw 100 subsamples of 15 whole market histories and estimate all parameters to account for the serial correlation within each market.

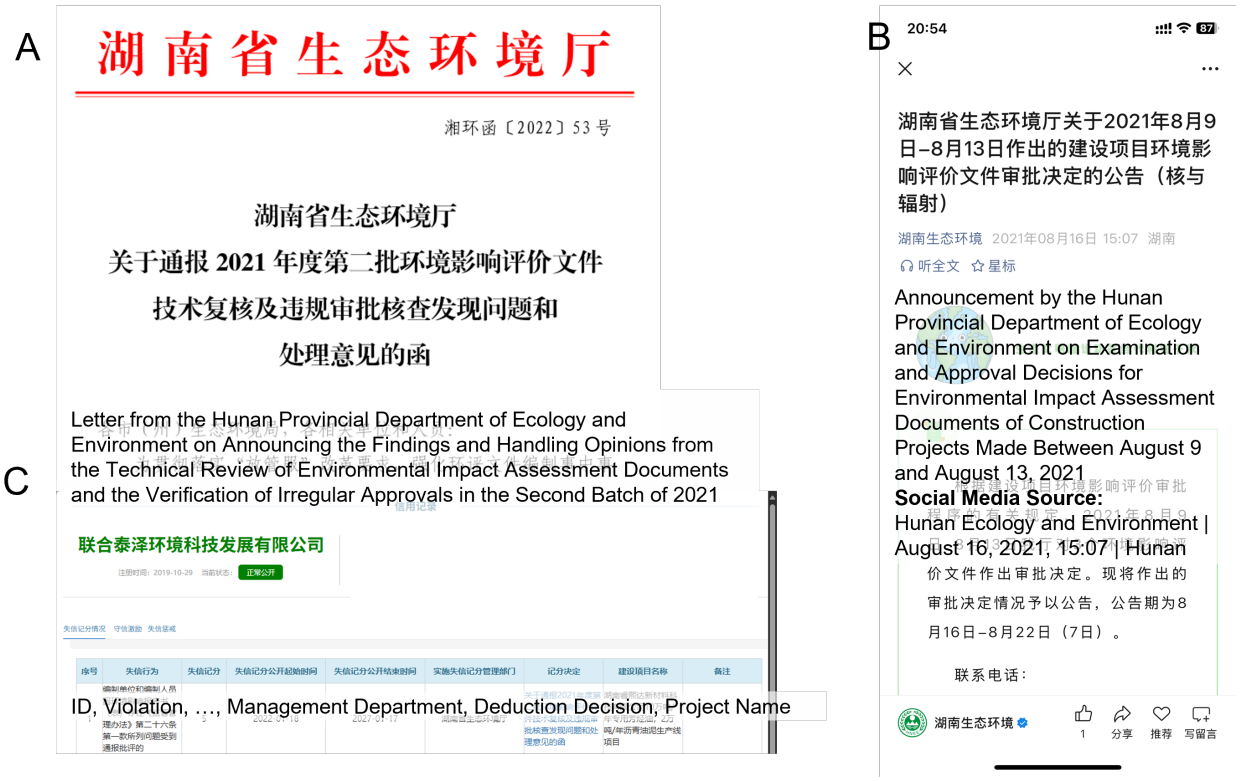
Table 8: Numerical Examples of the Illustrative Model

	(1) Full Information	(2)	(3) No Information	(4)	(5)	(6) Adaptively Updated Reputation	(7)
	$c_e = 2$	$c_e = 2$	$c_e = 3$	$c_e = 4$	$c_e = 2$	$c_e = 3$	$c_e = 4$
Panel A. Numerical Case: Five Potential Entrants							
# of successful entrants	2	4	2	1	2	1	1
Service quality	0.425	0.185	0.441	0.522	0.397	0.781	0.781
Service price	1.576	1.480	1.591	1.799	1.558	1.949	1.949
Customers' surplus	-12.906	-37.071	-14.281	-7.612	-12.654	-6.976	-6.976
Firms' profit	6.518	15.501	7.896	5.465	6.732	4.854	4.854
Social welfare ($\eta_1 = 1$)	-8.999	-22.550	-7.746	-3.087	-7.167	-3.408	-3.408
Social welfare ($\eta_1 = 5$)	-19.444	-26.469	-13.186	-6.844	-12.142	-8.552	-8.552
Panel B. Numerical Case: Three Potential Entrants							
# of successful entrants	2	2	2	1	1	1	1
Service quality	0.410	0.438	0.438	0.519	0.765	0.765	0.765
Service price	1.516	1.541	1.541	2.421	2.565	2.565	2.565
Customers' surplus	-14.460	-22.623	-22.623	-47.146	-42.080	-42.080	-42.080
Firms' profit	10.068	13.076	13.076	22.707	20.911	20.911	20.911
Social welfare ($\eta_1 = 1$)	-8.798	-11.946	-11.946	-27.220	-25.052	-25.052	-25.052
Social welfare ($\eta_1 = 5$)	-26.420	-21.538	-21.538	-38.347	-40.583	-40.583	-40.583

Appendices

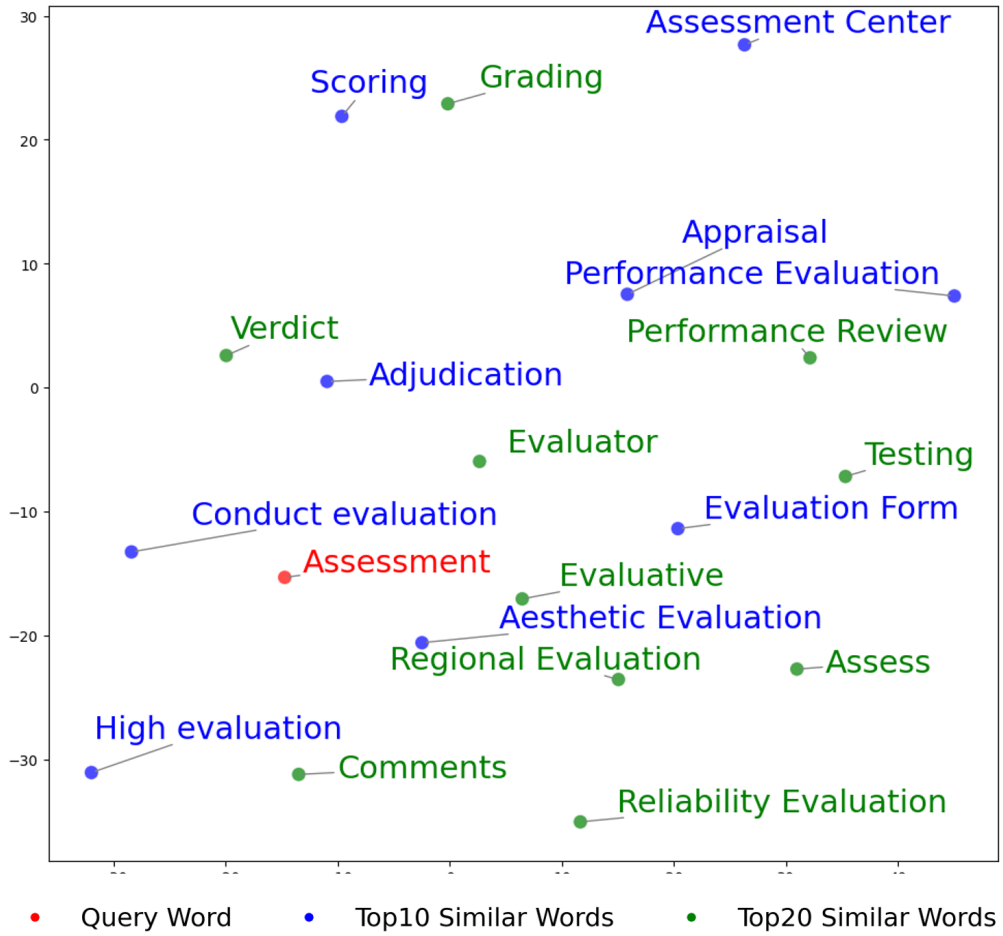
Appendix A Figures and Tables

Figure A.1: Penalty Disclosure Channels



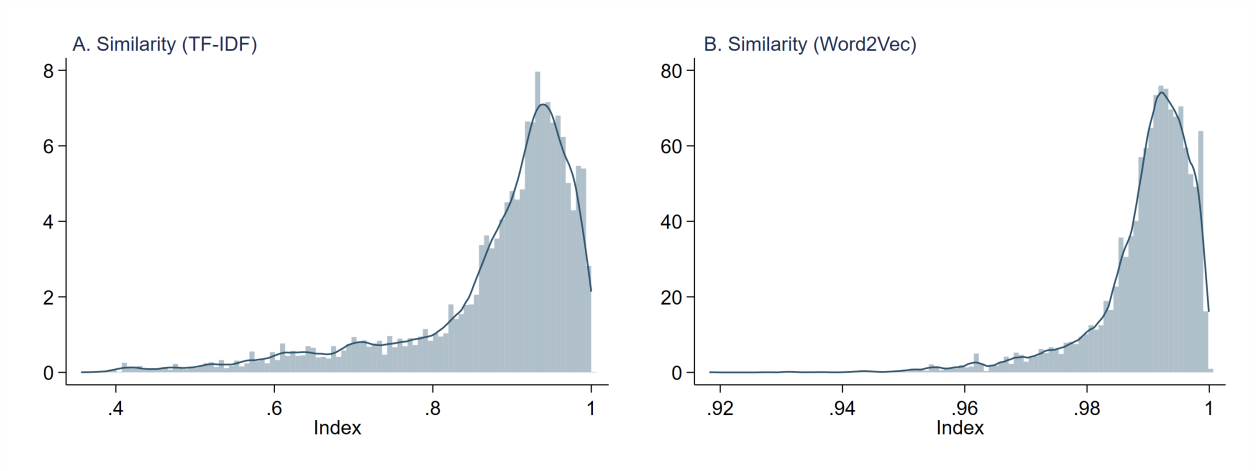
Notes: This figure plots three methods of disclosure for EIA penalties. Panel A shows official decision letters posted on regulatory authority websites. Panel B shows the disclosure through the social media, WeChat official accounts. Penal C shows the records published on the centralized EIA platform.

Figure A.2: Detecting Semantic Similarity using Word2Vec Model



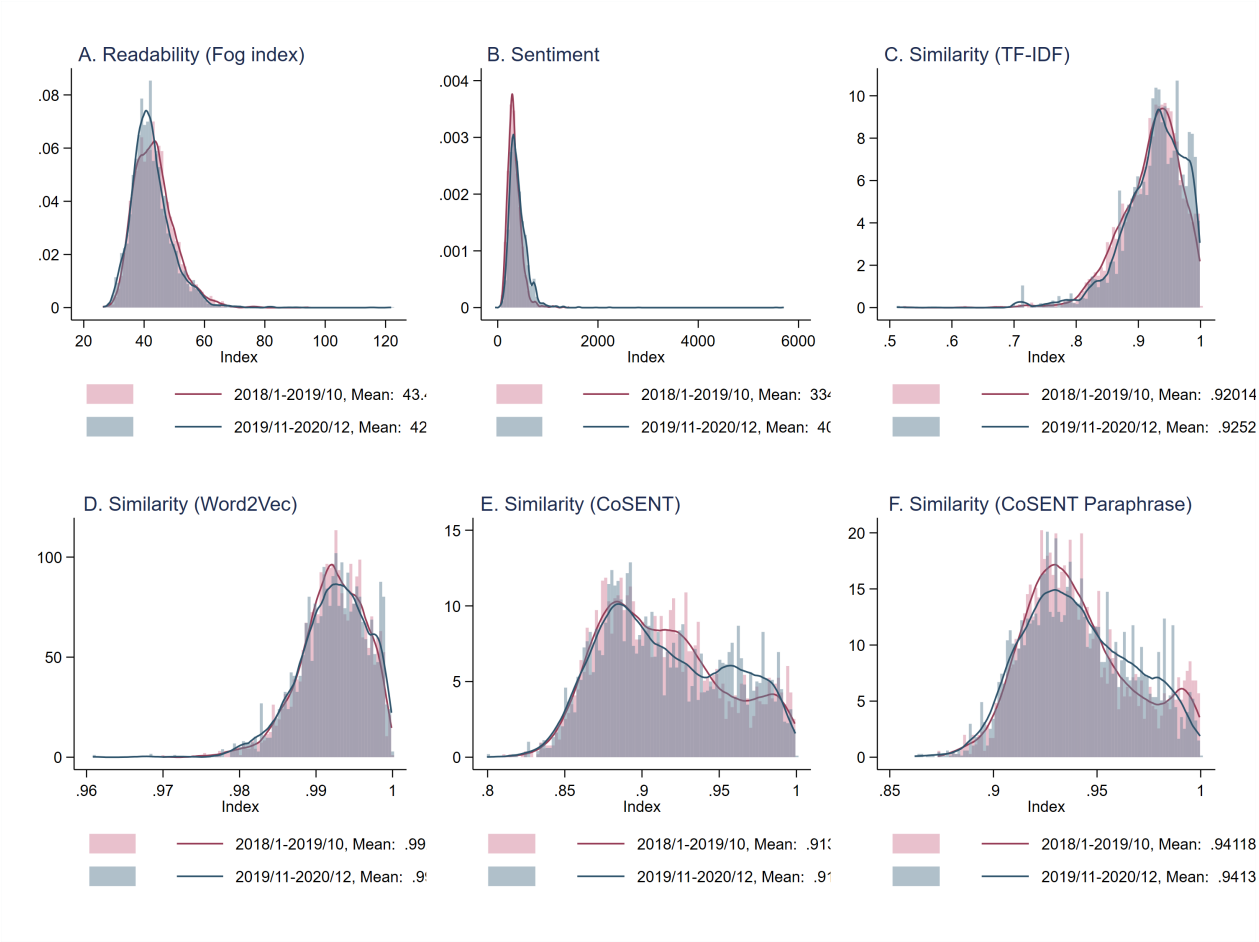
Notes: This figure plots the twenty most similar words to "assessment" based on the Word2Vec model and cosine similarity. The word vectors of all words are projected into two dimensions (x and y axes) using the t-SNE technique. The query word "assessment" is plotted as a red point. The top ten most similar words are plotted as blue points, and words ranked 11–20 in similarity are plotted in green.

Figure A.3: Distribution of Text-Based Quality Metrics



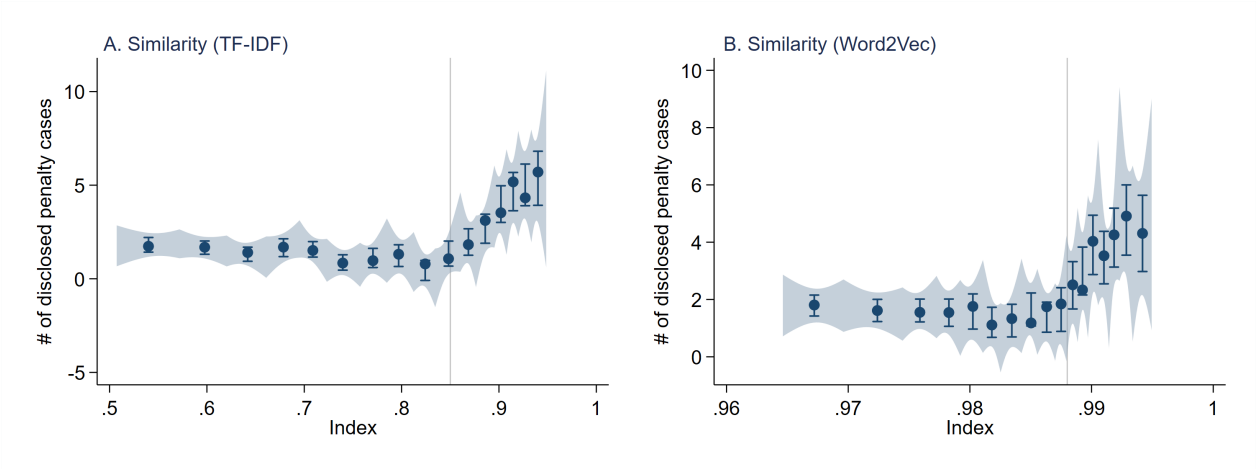
Notes: This figure plots the histogram and the kernel density estimate of quality scores derived from textual analysis of EIA reports.

Figure A.4: Distribution of Text-Based Quality Metrics Before/After Entry Deregulation



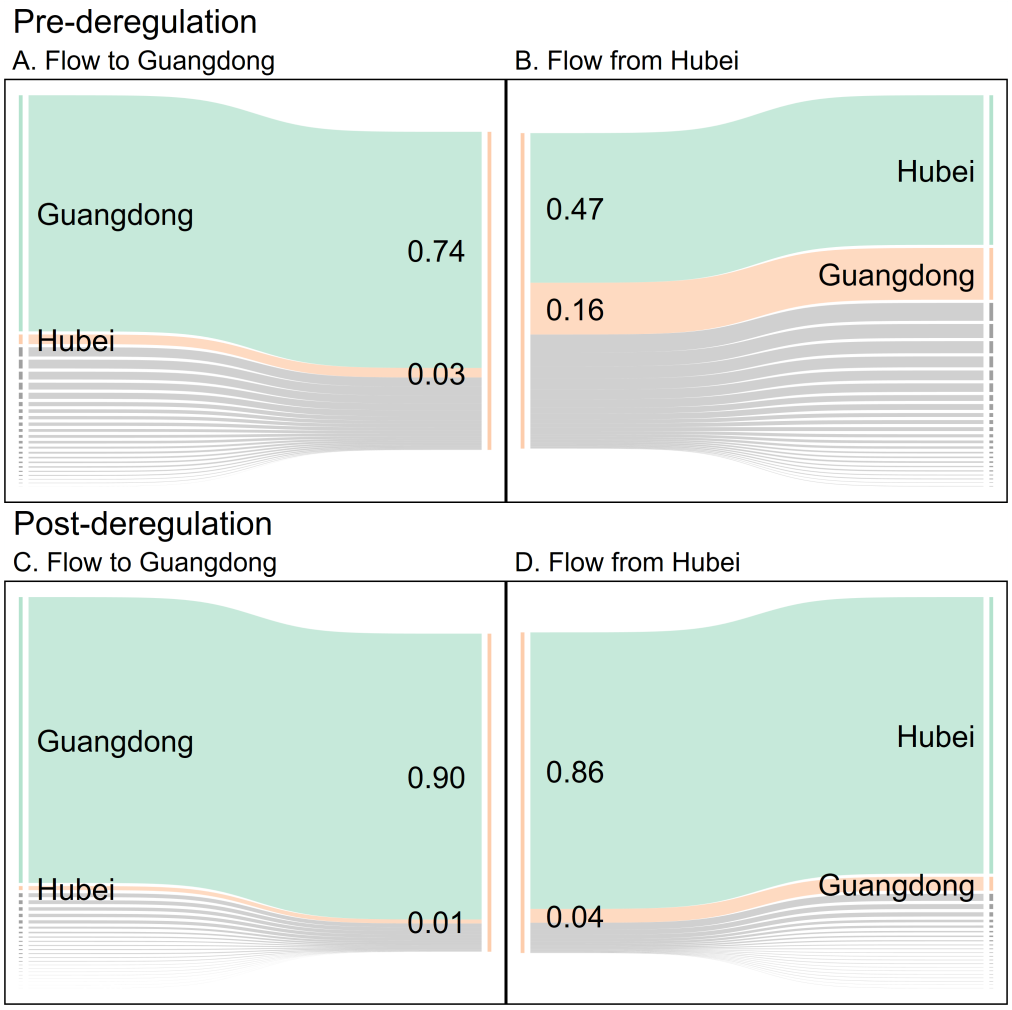
Notes: This figure plots the histogram and the kernel density estimate of text-based quality metrics before and after the entry deregulation in red and blue colors, respectively.

Figure A.5: Binscatter of Text-Based Quality Metrics and Penalty Probability



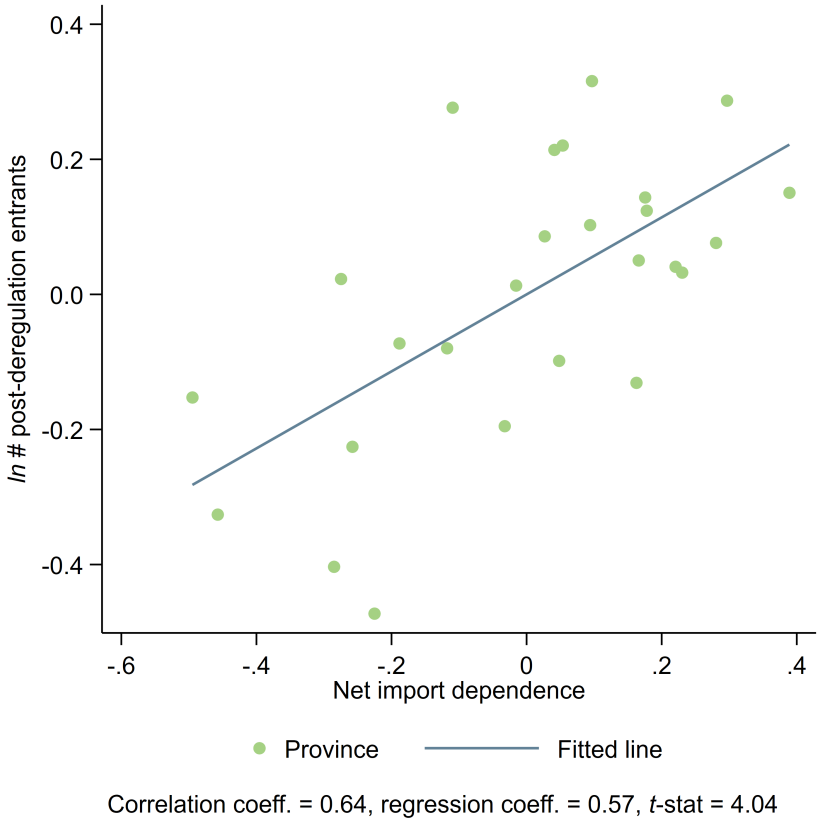
Notes: This figure plots the association between text-based quality metrics and penalty probability across the quality distribution. Each point represents the average penalty rate within quality score quantiles.

Figure A.6: Representative Case Flows Before and After the Deregulation



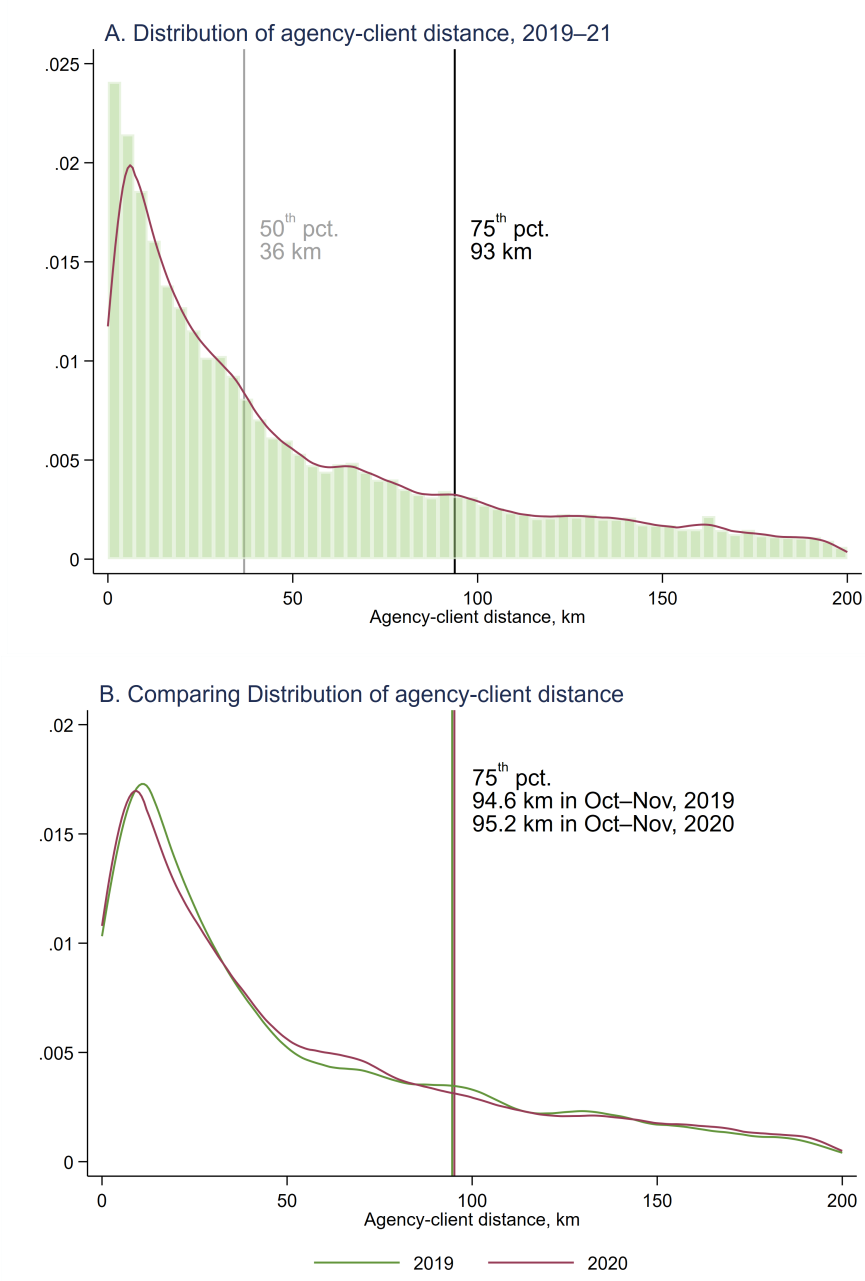
Notes: This figure shows inter-provincial EIA service flows. Left nodes represent provinces where agencies are located and right nodes represent provinces where client projects are located. Flow thickness indicates the share of projects in destination provinces (right) serviced by agencies from origin provinces (left). Annotations show each province's import/export share and net import dependence.

Figure A.7: Bivariate Relationship between Pre-deregulation Net Import Dependence and Post-deregulation Agency Entry



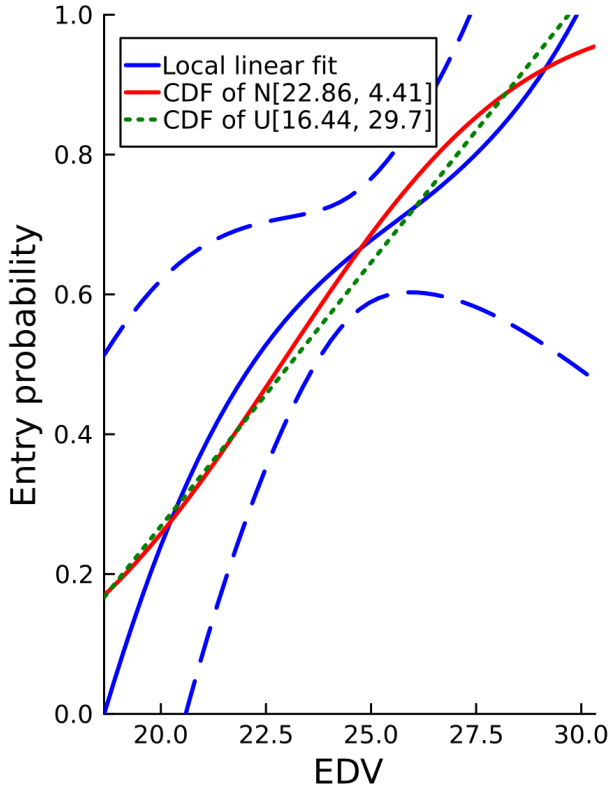
Notes: This figure shows scatter plots of pre-deregulation net import dependence versus number of new entrants one year post-deregulation. To reduce potential spurious correlation, agency counts are residualized using covariates that show significance at the 10% level in Section 4.1.1.D.

Figure A.8: EIA Catchment Area



Notes: This figure depicts the distribution of distances between the EIA agencies and client facilities. Panel A shows the histogram and kernel density estimate for all projects from October 2019 to November 2020. Panel B compares the distance distributions before (2019, solid line) and after (2020, dash line) deregulation.

Figure A.9: Estimating Entry Cost Distribution



Notes: This figure shows the estimated CDFs of entry cost distributions. The blue solid line represents the local linear regression fit using a kernel function. The blue dashed lines are 95% confidence intervals estimated via block bootstrapping. The red solid line fits the entry cost using the CDF of a normal distribution with the mean and standard deviation estimated via maximum likelihood. The green dotted line fits the entry cost using OLS regression, representing the CDF of a uniform distribution.

Table A.9: Association between Text-Based Quality Metrics and Penalty Probability

	(1)	(2)	(3)	(4)
Outcome variable	# Penalty cases			
Service quality (TF-IDF-based)	5.783***		6.095***	
	(0.680)		(0.685)	
Service quality (Word2Vec-based)		52.988***		54.133***
		(9.636)		(9.753)
Agency age (in 2020)	0.018***	0.018***	-0.028***	-0.027***
	(0.001)	(0.001)	(0.007)	(0.007)
Total sales (# projects)			0.019***	0.019***
			(0.001)	(0.001)
Constant	-4.810***	-52.485***	-4.835***	-53.414***
	(0.484)	(9.429)	(0.485)	(9.545)
Dep. Var. Mean	2.421	2.421	2.421	2.421
Adjusted R^2	0.370	0.361	0.364	0.361
Observations	1,972	1,972	1,972	1,972

Notes: This table presents the association between text-based quality metrics and penalty probability in each quantile. Each column shows a separate regression. The regression equation is as follows:

$$\bar{e}_j = \alpha q_j + X_j\beta + \varepsilon_j \tag{A.2}$$

, in which $\bar{e}_j$ denotes the number of penalties throughout 2020–2023, q_j denotes the quality measure, and X_j represents firm characteristics including age and total sales.

Table A.9: Relationship between Socioeconomic Characteristics and Net Import Dependence

2[3]*Independent variable (natural-log-transformed)	(1)	(2)	(3)	(4)	(5)	(6)
	Univariate regression coefficient (SE)				F-statistic	
	Before deregulation		After deregulation		Before	After
Investment in industrial pollution abatement	-0.015	(0.067)	-0.076***	(0.023)	0.0521	11.01
GDP	-0.086	(0.067)	-0.084***	(0.022)	1.653	14.88
GDP per capita	-0.219	(0.133)	-0.123**	(0.051)	2.733	5.841
Industry, value added	-0.087	(0.057)	-0.079***	(0.020)	2.319	16.22
Manufacturing, value added	-0.081*	(0.045)	-0.072***	(0.012)	3.204	33.76
Population	-0.074	(0.081)	-0.090***	(0.030)	0.850	9.100
Urban population	-0.089	(0.071)	-0.094***	(0.021)	1.588	20.72
Rural population	-0.039	(0.066)	-0.052	(0.037)	0.356	2.006
Transport services, value added	-0.086	(0.063)	-0.089***	(0.019)	1.844	21.02
Rail network length	0.129	(0.455)	-0.209	(0.241)	0.0807	0.750
Road network length	-0.040	(0.064)	-0.022	(0.038)	0.405	0.341
Passenger traffic volume	-0.112*	(0.058)	-0.072***	(0.020)	3.703	13.08
Freight traffic volume	-0.088	(0.052)	-0.085***	(0.016)	2.852	28.42
Road freight mileage	-0.048	(0.057)	-0.068***	(0.018)	0.707	15.31
Amount of passenger vehicles	-0.052	(0.077)	-0.095***	(0.025)	0.463	14.62
Number of employees in urban	-0.066	(0.080)	-0.092***	(0.026)	0.664	12.57
Unemployment rate	-0.482	(0.403)	-0.272	(0.234)	1.431	1.349
Labor force in urban	-0.068	(0.081)	-0.093***	(0.026)	0.705	13.04
Air quality index	-0.206	(0.150)	-0.184*	(0.106)	1.871	2.995
CO	-0.464	(0.430)	-0.474*	(0.248)	1.165	3.653
NO_2	-0.346	(0.203)	-0.298***	(0.061)	2.912	24.08
O_3	1.237*	(0.673)	0.198	(0.218)	3.386	0.830
PM10	-0.109	(0.128)	-0.110	(0.096)	0.728	1.320
PM2.5	-0.297*	(0.149)	-0.219***	(0.078)	3.989	7.909
SO_2	-0.030	(0.119)	-0.114*	(0.058)	0.0635	3.821

Notes: This table summarizes the univariate regressions of net import dependence on socioeconomic variables. Columns (1)-(2) report coefficients and standard errors for pre-deregulation dependence (October-November 2019); columns (3)-(4) report post-deregulation results (October-November 2020). F-statistics in columns (5)-(6) test joint significance. The standard errors in parentheses are heteroskedasticity-robust. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table A.9: Timeline of EIA in China

Date (mdy)	Event
9/13/1979	The China Environmental Protection Law (1979) contained broad elements requiring the EIA
10/28/2002	A new Law on Environmental Impact Assessment was approved by the National People's Congress
3/23/2015	SEPA sold all equity shares of EIA agencies to other entities, which is called the political disconnection reform.
12/29/2018	The Standing Committee of the National People's Congress adopted the new EIA law, announcing an entry deregulation reform.
9/20/2019	The MEE published the Supervision and Management Measures for the Preparation of Environmental Impact Reports (Tables) for Construction Projects, announcing the free entry.

Notes: This table reports the timeline of major EIA regulatory reforms in China, including establishment of the EIA system, agency licensing requirements, and the 2019 deregulation reform that eliminated administrative entry barriers.

Table A.9: Quality Variance Decomposition

Quality Index	(1) Between-agency-quarter Variance	(2) Within-agency-quarter Variance	(3) Total Variance
Benchmark			
Similarity (Word2Vec)	0.0015	0.0007	0.0020
Robustness			
Similarity (TF-IDF)	0.0058	0.0039	0.0088
Similarity (CoSENT)	0.0007	0.0003	0.0010
Similarity (CoSENT paraphrase)	0.00012	0.00004	0.00015
Readability (avg. length of sentences)	201.928	107.749	286.496
Readability (# of prep./conj.)	0.037	0.018	0.051
Readability (Fog)	51.244	27.312	72.679
Sentiment	29181.695	12219.688	38013.801

Notes: This table summarizes the quality variance decomposition results. The total variance of each quality measures (in Column (3)) are decompsed into between-agency-quarter (Column (1)) and within-agency-quarter part (Column (2)).

Table A.9: Policy Functions Estimation

	(1)	(2)	(3)	(4)	(5)
	Quality policy		Entry policy	Exit policy	
	Dominant firm	Fringe firm		Dominant firm	Fringe firm
Own reputation b-spline 1	2.329	2.439		9.982	9.811
	(2.280)	(2.288)		(1.567)	(1.572)
Own reputation b-spline 2	7.573	7.684		11.073	10.901
	(2.284)	(2.292)		(1.569)	(1.575)
Own reputation b-spline 3	-10.048	-9.938		8.018	7.849
	(2.295)	(2.303)		(1.577)	(1.582)
Own reputation b-spline 4	29.449	29.561		13.296	13.121
	(2.323)	(2.330)		(1.596)	(1.602)
log(fringe moment) b-spline 5	-0.875	-0.875	1.256	0.048	0.048
	(0.049)	(0.049)	(0.191)	(0.034)	(0.034)
Dominant firm 1's reputation b-spline 1	-11.903	-11.903	-2.514	-7.519	-7.519
	(2.961)	(2.961)	(9.609)	(2.059)	(2.059)
Dominant firm 1's reputation b-spline 3	-17.161	-17.161	-4.512	-10.263	-10.263
	(4.435)	(4.435)	(14.556)	(3.089)	(3.089)
Dominant firm 1's reputation b-spline 4	-10.157	-10.158	-1.146	-6.895	-6.894
	(2.428)	(2.428)	(7.675)	(1.684)	(1.684)
Dominant firm 2's reputation b-spline 1	9.633	9.460	2.945	-2.305	-2.054
	(1.343)	(1.374)	(9.611)	(0.919)	(0.940)
Dominant firm 2's reputation b-spline 3	11.371	11.181	0.070	-2.828	-2.552
	(1.920)	(1.946)	(15.690)	(1.323)	(1.341)
Dominant firm 2's reputation b-spline 4	10.717	10.506	8.597	-2.965	-2.658
	(1.252)	(1.302)	(6.203)	(0.846)	(0.880)
Dominant firm 2's reputation b-spline 5	0.000	0.000	-20.098	0.000	0.000
	(.)	(.)	(13.548)	(.)	(.)
Dominant firm 3's reputation b-spline 1		0.063	-0.094		-0.081
		(0.106)	(0.216)		(0.064)
Adjusted R^2	0.218	0.218	0.798	0.187	0.187

Notes: This table presents estimation results for the dominant and fringe firms' quality policy functions (Columns (1) and (2)), entry policy function (Column (3)), and dominant and fringe firms' exit policy functions (Columns (4) and (5)). The estimation is based on spline regression with up to five orders of B-splines. The explanatory variables for estimating the dominant firm's quality and exit policy functions include the firm's own reputation, the logarithm of the fringe moment, and the other two dominant firms' reputations. The fringe firms' quality function estimation includes the firm's own reputation, the logarithm of the fringe moment, and the other two dominant firms' reputations as explanatory variables. The entry policy estimation uses the logarithm of the fringe moment and the other two dominant firms' reputations as explanatory variables.

Table A.9: Estimating Fringe Moment Transition and Fringe-Dominance Transition Processes

	(1) Fringe moment transition	(2) Fringe-dominance transition
Fringe moment	0.961***	-0.169***
	(0.014)	(0.044)
Constant	0.083***	0.439***
	(0.034)	(0.108)
σ	0.107	0.233
Adjusted R^2	0.947	0.101
Observations	279	310

Notes:This table shows the estimation results for the fringe moment transition (Column (1)) and fringe-dominance transition processes (Column (2)). Standard errors in parentheses are Newey-West robust in Column (1) to account for serial correlation and heteroskedasticity. In Column (2), standard errors are heteroskedasticity-robust.

Appendix B History of Environmental Impact Assessment in China

This section recalls the timeline of EIA in China. Table A.9 shows a chronicle of EIA policy changes.

B.1 High Administrative Barriers to Entry

When the State Environmental Protection Administration (SEPA) established the EIA agencies according to the EIA Law in 2002, some regulations succeeded from the planned economy: only SOEs, of which the share held by government departments and universities, had the authority to do this business. Though the industry was open to private firms later, SEPA and the rare agencies tightly connected to the government were still incentivized to limit entrants and seek rents from EIA approval. In fact, SEPA insisted on such a strict entry standard until 2019, the year that witnessed the entry deregulation.

B.2 Privatization

Some may find an alternative channel through which the entry deregulation affects market outcomes: the rents captured by the bureaucrats dissipated after the entry deregulation, and the bureaucrats were incentivized to penalize more to maintain their income. I argue it is unrealistic because the political connection has already been eliminated far before the entry deregulation.

The Ministry of Environment and Ecology (MEE) decided to decouple the EIA agencies and EBC in terms of ownership in 2015. Before 2017, the MEE sold all equity shares of EIA agencies to other entities and cannot claim residuals from them. The MEE also enhanced the in-dependence of agencies by hiring third-party experts to review EIA reports and setting a strict double-blind review procedure. As the spokesperson of the MEE said, "conditions for opening access for EIA agencies are ripe now." (Ministry of Ecology and Environment 2019) The potential factors perceivably inducing adverse effects of free entry have been reduced to a minimal level from the view of the MEE.

Appendix C Scope of Competition

I measure the local level of EIA competition by counting the number of EIA agencies within a province. The primary reason for exploring the province-level competition is the variation in environmental policies across provinces in China (Chen et al., 2018; He et al., 2020), which

leads to localized expertise of EIA agencies and province-level segmented EIA markets. This measurement method also aligns with common practices in the literature (Bloom et al., 2015; Propper et al., 2007). Panel A of Figure A.8 presents a histogram of the distance between the EIA agency and the client's plant. Half of the services are rendered to clients within a distance of 36 km; 75% within 93 km. Consequently, any agency located with-in a 186 km (93×2) radius of another agency overlaps in potential clients, thereby becoming a potential competitor. Notably, this radius of 186 km closely approximates the average radius of the shortest axis of the minimum enclosing ellipse of a province in China (216 km). Given that most provinces have their capital as well as economic center located close to the geographical centroid, this circle has already captured most of the competition for an agency in one province. The above logic is graphically shown in Panel B of Figure A.8. Taken two reasons together, we aggregate the number of EIA agencies at the province level to capture local competition intensity.

Appendix D Decomposition of Within-Quarter-Agency and Across-Quarter-Agency Quality Variation

This appendix provides empirical evidence supporting a key modeling assumption: that agencies strategically choose quality levels for their services each quarter, rather than maintaining fixed quality characteristics over time or tailor the quality level for each client. To validate the quality choice assumption, I decompose the total variance in service quality into between-agency-quarter and within-agency-quarter components. If agencies maintain relatively constant quality levels over time, we would expect minimal between-quarter variation for a given agency. Conversely, if agencies actively adjust quality in response to market conditions, reputation concerns, and competitive pressures, we should observe substantial between-agency-quarter variation. Additionally, if agencies tailor quality levels for different customers, we would expect large within-quarter variation relative to across-quarter variation and vice versa.

The variance decomposition follows:

$$\operatorname{var}(q_{i,jt}) = \underbrace{\operatorname{var}_j(\bar{q}_{jt})}_{\text{Between-agency-quarter dispersion}} + \underbrace{\sum_{jt} \omega_{jt} \times \operatorname{var}_i(q_{i,jt} \mid i \in jt)}_{\text{Within-agency-quarter dispersion}} \tag{D.1}$$

where $q_{i,jt}$ denotes the quality of report i produced by agency j in year-quarter t, $\bar{q}_{jt}$ represents the average quality of agency j in quarter t, and ω_{jt} is the report share of agency-quarter jt

in the total corpus.

Table A.9 presents the variance decomposition results across multiple quality metrics, including text similarity measures (TF-IDF, Word2Vec, CoSENT), readability indices, and sentiment scores. The results reveal a consistent pattern: between-agency-quarter variance substantially dominates within-agency-quarter variance across all quality dimensions.

For the benchmark Word2Vec similarity measure, between-agency-quarter variance accounts for approximately 75% of total quality variance (0.0015 out of 0.0020). This pattern is also pronounced for TF-IDF similarity, where between-agency-quarter variance represents 66% of total variance. Similar dominance appears across readability metrics and sentiment measures, with between-agency-quarter variance consistently accounting for 60–75% of total quality dispersion, providing strong empirical support for modeling quality as a quarter-level dynamic choice variable.

Appendix E Illustrative Model: Deriving Proposition 1

To obtain the results of the comparative static analysis, I first define the Subgame Perfect Nash Equilibrium (SPNE).

Definition 2 *Assume that all firms play symmetrically, a SPNE is defined as a combination of firms' and customers' strategies: For firms,*

1. *the price set by firm j in period 1 maximizes the period profit for all $j \in J$: $p_{j1}^* = \arg\max_p V_{j1}(p, \mathbf{p}_{1,-j}^*, \mathbf{p}_2^*, \mathbf{q}_1^*, \mathbf{q}_2^*)$.*

2. *the quality set by firm j in period 1 maximizes the period profit for all $j \in J$: $q_{j1}^* = \arg\max_p V_{j1}(\mathbf{p}_1^*, \mathbf{p}_2^*, q, \mathbf{q}_{1,-j}^*, \mathbf{q}_2^*)$.*

3. *the price set by firm j in period 2 maximizes the period profit for all $j \in J$: $p_{j2}^* = \arg\max_p V_{j2}(p, \mathbf{p}_{2,-j}^*, \mathbf{q}_2^*)$.*

4. *the quality set by firm j in period 2 maximizes the period profit for all $j \in J$: $q_{j2}^* = \arg\max_p V_{j2}(\mathbf{p}_2^*, q, \mathbf{q}_{2,-j}^*)$.*

For customers, the probability of choosing firm j in period 1 equals

$$s_{j1}(\mathbf{p}_1) = a + \sigma \sum_{k \neq j} p_{k1} - b p_{j1} + ((J-1)\sigma - b)(\alpha_0 \bar{P} - \alpha_1 \bar{q})$$

; in period 2 the probability equals

$$s_{j2}(\mathbf{p}_2, \mathbf{q}_1) = a + \sigma \sum_{k \neq j} (p_{k2} - \alpha_0 \alpha_1 q_{k1}) - b(p_{j2} - \alpha_0 \alpha_1 q_{j1}) + ((J-1)\sigma - b)\alpha_0 \bar{P}.$$

.

By Kuhn's Theorem, such a SPNE exists.

Secondly, I explicitly solve the equilibrium by backward induction. Firms have no incentive to improve the quality in period 2, implying $q_{j2} = 0, \forall j \in J$. The first-order conditions of the purchase probabilities give two equalities: $\frac{\partial s_{j1}}{\partial p_{j1}} = -b$ and $\frac{\partial s_{j2}}{\partial q_{j1}} = b\alpha_0\alpha_1$. Together with the first-order conditions of firms optimization problems, I have:

$$\frac{\partial V_{j1}}{\partial p_{j1}} = 0 \Rightarrow s_{j1} = b(p_{j1} - c_j q_{j1}) \tag{E.1}$$

$$\frac{\partial V_{j1}}{\partial q_{j1}} = 0 \Rightarrow c_j s_{j1} = \beta b \alpha_0 \alpha_1 p_{j2} \tag{E.2}$$

$$\frac{\partial V_{j1}}{\partial p_{j2}} = 0 \Rightarrow s_{j2} = b p_{j2} \tag{E.3}$$

Denote $((J-1)\sigma - b)(\alpha_0 \bar{P} - \alpha_1 \bar{q}) \equiv H$ and $2b - \sigma(J-1) \equiv K$. Summing up Equation (E.1) for all j implies $\sigma(J-1)Jp_{j1} + J(a+H) = 2bJp_{j1} - b\sum_k c_k q_{k1}$ given that $p_{j1} = p_{k1}, \forall j \neq k$. Reorganize the equation gives:

$$p_{j1} = \frac{a + H + b\sum_k c_k q_k}{K} \tag{E.4}$$

Replace p_{j1} in Equation (E.1) gives an expression of s_{j1}:

$$s_{j1} = \frac{b(a+H) + b^2 \sum_{k \neq j} c_k q_{k1} + b(\sigma(J-1) - b)c_j q_{j1}}{K}. \tag{E.5}$$

Extending s_{j2} and summing up by j in Equation (E.3) give

$$K \sum_j p_{j2} = Ja + JK\alpha_0 \bar{P} - \alpha_0 \alpha_1 (K - b) \sum_j q_{j1}. \tag{E.6}$$

By $p_{j1} = p_{k1}, \forall j \neq k$, p_{j2} can be represented as a function of $\mathbf{q_1}$:

$$p_{j2} = \frac{a}{K} + (\frac{b}{K} - 1)\alpha_0 \bar{P} - \frac{\alpha_0 \alpha_1}{J}(1 - \frac{b}{K}) \sum_j q_{j1} \tag{E.7}$$

This equilibrium is unique given that it is the inner solution.

Thirdly, before the comparative static analysis, I prepare one assumption and definition of the aggregate outcomes of our interest: average productivity and average quality. First, I provide a realistic assumption:

Assumption 1 *For any firm j in the entrant set J, $\sqrt{J}c_j > \alpha_0\alpha_1$.*

This assumption aligns with the reality. α_0 and α_1 are 0.5 and 0.24 by the estimation of the law enforcement process using the whole sample. The smallest recorded number of entrants is above 500. The marginal cost of quality investment must be over one to permit positive profit in the case that the quality is defined within $[0, 1]$ and the lowest service price is over ten thousand.

Then, I formally define the average productivity and the average quality. The average productivity is defined to be the simple sum of productivity of all incumbent firms unconditional on the market share: $\bar{\gamma} \equiv \frac{1}{||J||}\sum_{j\in J}\phi(\gamma_j)\gamma_j$. The market-level average quality is defined to be sales-based. Specifically, it is the quality of incumbents weighted by the market share: $\bar{q} = \sum_{j\in J} q(\gamma_j, \bar{\gamma})s_j(\gamma_j, \bar{\gamma})\phi(\gamma_j)$.

Fourthly, I want to show the relationship between the equilibrium choices and the inherent productivity, assuming that the firm chooses entry. Express $\mathbf{s}_1, \mathbf{p}_2$ in the Equation (E.2) as functions of $\mathbf{q}_1$ using Equations (E.5) and (E.7) and show the full derivative of q_{j1} wrt c_j. After reorganizing the equation and eliminating j, I get

$$\frac{\partial q_1}{\partial c} = -\frac{c}{c^2 - \beta\alpha_0^2\alpha_1^2/J}. \tag{E.8}$$

By Assumption 1,

Lemma 1 $\frac{dq_1}{dc} < 0$ *for all incumbents.*

Then calculate the derivative of s_1 wrt c from Equation (E.5) and obtain:

$$\frac{\partial s_1}{\partial c} = (\frac{b^2}{2b - \sigma(J-1)} - b)(c\frac{\partial q_1}{\partial c} + q). \tag{E.9}$$

Obviously, the first term is positive and the second term $c\frac{\partial q_1}{\partial c} + q_1$ is negative. Therefore,

Lemma 2 $\frac{\partial s_1}{\partial c} < 0$ *for all incumbents.*

Fifthly, I prove that the average productivity decreases in the marginal firm's marginal cost of quality.

With a large enough number of entrants, the margianl cost of the marginal firm c^* makes the EDV approximates entry cost c_e: $c_e \approx s_1^*(p_1^* - c^*q_1^*) + \beta b p_2^*$ by defining x^* as

the variable value of the marginal firm. Taking first derivative wrt c^* for the RHS gives: $\frac{ds_1^*}{dc^*}(p_1^* - c^* q_1^*) + s_1^*(\frac{dp_1^*}{dc^*} - q_1^* - c^* \frac{dq_1^*}{dc^*}) + \beta b 2 p_2^* \frac{dp_2^*}{dc^*}$.

The first term has a negative sign given the positive markup, $\frac{\partial J}{\partial c^*} < 0$, and Lemma 1. By replacing $\frac{dp_1^*}{dc^*}$ using the derivative based on Equation (E.4), the second term is also negative. The third term is negative by $\frac{\partial J}{\partial c^*} < 0$ and Lemma 2. By $c_e > 0$, $\frac{dc^*}{dc_e} < 0$. By replacing c^* with the corresponding γ^*, We are done.

Appendix F Empirical Model: Computational Details

This section introduces the computational details, particularly the equilibrium solving algorithm and forward simulation used in the counterfactual analysis. The algorithm is based on policy function iteration.

Algorithm 1: Equilibrium Solving Algorithm using Policy Function Iteration

Initialize: Policy functions (ρ, ι, λ)
Set $n := 1, \Delta := \varepsilon + 1$
while $n < n^{\max}$ *and* $\Delta > \varepsilon$ **do**
  Let $\lambda'(\hat{s}) := \beta \mathbb{E}_{\mu,\lambda}\left[\hat{V}\left(x^e, \hat{s}_{t+1} \mid \mu', \mu, \lambda\right) \mid \hat{s}_t = \hat{s}\right]$ for all $\hat{s} \in \hat{\mathcal{S}}$
  Compute the transition process for $F\left(\theta' \mid \theta\right)$ using forward simulation with Tauchen's discretization for normal AR(1) processes
  Solve for $\rho' := \arg\max_{\tilde{\rho}} \hat{V}(x, \hat{s} \mid \tilde{\rho}, \rho, \iota, \lambda)$, for all $(x, \hat{s}) \in \tilde{\mathcal{Q}} \times \hat{\mathcal{S}}$
  Solve for $\iota' := \begin{cases} 1 & \text{if } \hat{V}(x, \hat{s} \mid \rho, \iota, \lambda) > \delta \\ 0 & \text{otherwise} \end{cases}$
  $\Delta := \max\left\{||\rho' - \rho||, ||\iota' - \iota||\right\}$
  Update $\rho := \rho + \frac{\rho' - \rho}{1 + n^\sigma}$ and $\lambda := \lambda'$
  Increment $n := n + 1$
end

Remarks:

1. To accelerate convergence, I initialize policy functions using additional information rather than setting them to some arbitrary values. Specifically, I start by solving the equilibrium for a single dominant firm. Then, I use the equilibrium value and policy functions $f(\cdot \mid \theta, d_1)$ as the initial functions $f(\cdot \mid \theta, d_1, d_2), \forall d_2$ for the case with two dominant firms. This process is repeated until the number of dominant firms reaches the preset value.

2. The parameter σ is chosen to speed up convergence by smoothing the updates of

strategies between iterations. I use $\sigma = 2/3$ as suggested by Ifrach and Weintraub (2017).

3. The upper bound of the state space is set to be unreachable in counterfactual simulations, even in the case of a single monopolistic firm. The lower bound is set to the minimum observed in the sample. The state space is divided into ten evenly spaced grids to balance the efficiency and accuracy of the estimation.

The forward simulation procedure used in both the equilibrium solving algorithm and estimation algorithm is as below:

Algorithm 2: Forward Simulation Procedure

Initialize: Policy functions (ρ, ι, λ)
for $n_s = 1 : n_s^{\max}$ **do**
  Start with state $s_0 = (f_0, d_0)$, and $\hat{s}_0 = (\theta_0, d_0)$ where $\theta_0 = \theta(f_0)$
  for $t = 1, \ldots, T$ **do**
    Determine exit: $s' := s_t \cdot \iota(\hat{s}_t)$
    Draw entry probabilities pr_λ^D and enter if $\lambda(\hat{s}) > \text{pr}_\lambda^D$
    Draw state rising probabilities pr_r^D and outside shock probability pr_o^D
    Determine state transition: $s' := s' \cdot (\nu(q(s', \hat{s}_t)) > \text{pr}_r^D) - (\delta > \text{pr}_o^D)$
    Transit fringe to dominance if $i >$ fringe-dominance threshold, for some $i \in f$
    Update: $s_{t+1} := s', \theta_{t+1} := \theta(f_{t+1}), \hat{s}_{t+1} := (\theta_{t+1}, d_{t+1})$
  end
end
This results in a dataset (θ_{it}, d_{it}) for $t = 1, \ldots, T$ and $i = 1, \ldots, N$
Compute $g(\hat{s})$ using OLS, and use Tauchen's algorithm to obtain $P(\theta'|\hat{s})$
Compute $\hat{\pi}(\cdot)$ based on the average profit $\pi(\hat{s}_{it})$.

The estimation and counterfactual simulation processes are performed on the HPC2021 System at the University of Hong Kong. The whole estimation process takes 14 hours by splitting bootstrap tasks into 35 parts. The counterfactual simulation process takes 43 hours by parallelizing 80 tasks in 160 CPUs distributed in two computation nodes.

Appendix G Parameters in the Numerical Example

In the numerical example revealing the effect of entry regulation, I calibrate parameters for demand, law enforcement process, and cost. Demand parameters include b (sales multiplied by own-price elasticity), σ (sales multiplied by cross-price elasticity), and a (intercept term). Elasticities are derived from Gerakos and Syverson, 2015, which examines the US financial audit sector-a comparable service industry. The average own-price elasticity is -2.82, and

cross-price elasticity is 0.74. Each of the top four auditors holds a 25% market share in a total size of approximately two thousand clients. Combining these values, b equals 1.41 and σ0.37. The intercept term a equaling 1.1 ensures feasible sales, calculated as 0.5 thousand clients $+1.41 \times 2$ million - 3 competing firms $\times 0.37 \times 2$ million. These parameters are used in the case with five potential entrants to align the audit industry. For two-entrant scenarios, the market size adjusts to one thousand clients. Law enforcement parameters-effect of lag penalty α_1, effect of service quality α_2, and fine amount h-are estimated from China's EIA industry. Fine h scales proportionally to service price: $h_{\text{auditors}} = h_{\text{EIA}} \times \frac{\text{Average audit price}}{\text{Average EDA price}} = 8.2$.