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Article

Trapped in Tradition or Trailblazing Change? Unveiling the Dual Nature of Path Dependence in Manufacturing Pollution Control

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Abstract: This study employs panel data from 1884 listed manufacturing companies in China (2009–2021) to investigate the environmental effects of path dependence on atmospheric pollution emissions. Using dictionary-based textual analysis of annual reports, we measure three dimensions of path dependence—technological, institutional, and managerial—and examine their non-linear relationships with sulfur dioxide emissions through fixed-effects models. Our findings reveal consistent U-shaped patterns across all dependence types: moderate levels initially reduce emissions (the "honey phase") while excessive reliance leads to increased pollution (the "arsenic phase"). The analysis demonstrates that technological path dependence operates through sunk costs and learning effects, institutional dependence reflects regulatory inertia, and managerial dependence stems from organizational routines. Robustness tests using alternative pollution measures and instrumental variable approaches confirm these relationships. The study identifies significant heterogeneity in these effects. Non-state-owned enterprises exhibit stronger path dependence impacts due to greater flexibility, while high-maturity firms show amplified U-curves reflecting their accumulated experience. Conversely, capital-intensive enterprises display attenuated effects, suggesting diminishing returns to scale in pollution control. These findings highlight the dual nature of path dependence as both a stability mechanism and potential barrier to innovation. The policy implication is that manufacturing pollution control strategies should account for both dependence levels and firm-specific characteristics, maintaining path dependence within optimal ranges to harness stabilization benefits without impeding technological transitions. This research contributes to environmental governance literature by extending path dependence theory to pollution control and offering a multidimensional analytical framework for sustainable manufacturing transformation.

Keywords: Technological Dependence; Institutional Dependence; Management Dependence; Air Pollution; Manufacturing Industry

1. Introduction

The manufacturing industry is the cornerstone of the Chinese economy, carrying the crucial missions of technological innovation and industrial upgrading [1]. Manufacturing processes emit a significant amount of pollutants into the atmosphere, including sulphur dioxide, nitrogen oxides, and particulate matter—primary sources of air pollution that also contribute to climate chang. As climate governance becomes a global priority, air pollution control in manufacturing must be integrated into broader strategies for carbon neutrality and sustainable development. For instance, synergies between air pollution reduction and CO_2 mitigation can amplify the co-benefits of path-breaking innovations. As environmental regulations become more comprehensive and environmental technologies advance, mitigation efforts related to manufacturing have had significant results, resulting in a decrease in the growth rate of air pollution emissions [2]. However, total energy consumption continues to increase, with heavy polluting sectors such as petrochemicals and steel accounting for more than 50% of industrial air pollution emissions. This underscores the need to align path dependence research with climate-oriented industrial policies.

Although the challenges facing air pollution control in the manufacturing sector may appear to be caused by economic growth and inflexible energy consumption structures, the underlying mechanisms require further exploration. According to the theory of path dependence, once an institution, technological combination, or management approach is established, it persists for a period due to its self-reinforcing mechanism, regardless of whether it is beneficial for performance [3]. This can lead to a lock-in phenomenon, making it difficult, if not impossible, to adapt to changes in the environment [4]. This may result in two forms of lock-in, which are active and passive. Active lock-in refers to the initial selection of a certain technology (institutional or management) that generates increasing returns and attracts other technologies to adjust to it, further reinforcing the direction of technological change, and enabling both society and the economy to develop along a positive path. On the other hand, passive lock-in occurs when despite a particular technology (institutional or managerial) path being inefficient, the ongoing support provided by existing arrangements, as well as the concerted efforts of stakeholders to maintain it, lock entities into inefficient paths. Lacklustre implementation has long been one of the main reasons for the manufacturing sector's sluggish progress in air pollution control.

To address these challenges, it is necessary to deconstruct and transform the mechanisms that lead to inefficient pathways and leverage external forces to steer the subject towards a virtuous course. The current literature on path dependence primarily focuses on economic growth, structural change, industrial aggregation, and organizational behaviour, with limited analysis of the role of path dependence in pollution control. A few scholars have explored the concept of path dependence in the context of green growth [5], or analyzed the effects of the reduction in the path of global emissions [6]. Further, research that specifically focuses on the impact of path dependence on atmospheric pollution control is lacking. In the context of industrial air pollution control, does there exist a path dependence? If so, what type of path dependence is it? Should it be encouraged or discarded? Does the impact of path dependence on air pollution control vary among different enterprises? The answers to these questions will deepen research into pollution control and effectively facilitate the green transformation and high-quality development of the manufacturing industry.

The remainder of this paper is organized as follows: Section 2 describes the current state of research on path dependence on air pollution control. Section 3 elaborates the theoretical basics and research hypothesis. Section 4 is the methodology. Section 5 presents the empirical results. Section 6 compares the differences between this article and similar literature to highlight the marginal contribution of this research. Finally, Section 7 summarizes main conclusions and policy implications.

2. Literature Review

2.1. Essence and Measurement Methods of Path Dependence

The concept of path dependence can be traced back to palaeontology, with its theoretical evolution and interdisciplinary integration subsequently being introduced into fields such as sociology and economics [7]. In recent decades, it has become one of the core elements of evolutionary economic geography. In summary, path dependence refers to an event being the result of its own historical trajectory. The classic path dependence model is divided into four stages—an initial state (caused by historical contingency), self-reinforcement, path dependence (or lock-in), and path unlocking.

Path-dependent measurement methods and technologies can be broadly categorized into three types. First, a single indicator is used to measure the degree of path dependence. Second, a composite indicator is used to decompose and evaluate path dependence phenomena from multiple dimensions. Third, path dependence is described qualitatively through processes such as the generation of operational, search, and flexible conventions that reflect the organizational conventions of case firms or are measured through experimental methods, fuzzy set qualitative comparative analysis, and similar methods. The single-indicator method is simple but lacks comprehensiveness; the qualitative description method can encompass a wider range of dimensions but is subject to subjective interpretation; while the composite indicator method, although more comprehensive and objective, presents challenges in data acquisition. By comparison, dictionary-based approaches, which rely on predefined vocabularies or dictionaries to identify terms in texts and conduct quantitative analysis, are characterized by simplicity, clarity, speed, and efficiency, as well as ease of explanation [8]. However, there is currently a lack of methodology for evaluating path dependence in atmospheric pollution control.

2.2. Phenomenon of Path Dependence in Air Pollution Control

2.2.1. Technological Path Dependence in Air Pollution Control

Technological innovation research suggests that technological self-reinforcement, accumulation, and scale effects can lead to technological path lock-in to form technological path dependence [9]. In the context of climate-aware manufacturing, technological path dependence may hinder the adoption of low-carbon technologies, such as energy-efficient processes or carbon capture systems, due to entrenched investments in conventional pollution control methods. It may manifest in corporations persistently employing a particular technology or combination of technologies for air pollution control, despite historical factors, technological lock-ins, sunk investments, and so on, even when newer technologies or methods are more effective or cost-effective.

2.2.2. Path Dependence in Air Pollution Control

Initial institutional arrangements often determine subsequent pathways. Institutional change may enter a virtuous cycle or become locked in an inefficient state along predefined pathways [10]. Sustainable policy frameworks, such as carbon pricing or green subsidies, may fail to achieve scalability if institutional path dependence favors short-term compliance over long-term climate resilience. It manifests as a reliance on government-provided institutional frameworks, policy support, and regulatory mechanisms, neglecting their own pivotal role and responsibilities in environmental governance.

2.2.3. Path Dependence in Air Pollution Control Management

After selecting a particular strategy or management practice organizations may continue to develop along this path due to factors such as historical reasons, corporate culture, and organizational inertia, even if new information or environmental changes offer better alternatives [11]. For example, management dependence on traditional performance metrics may overlook carbon footprint assessments, delaying the integration of climate goals into corporate strategy. It manifests as an over-reliance on existing management models, management experiences, or policy directives for tackling air pollution, with reluctance or inability to adapt promptly to new changes or requirements.

In practice, when path dependence overlap, double or even triple dependence can arise.

2.3. Path Dependence in Atmospheric Pollution Control

From a technological path dependence perspective, manufacturing enterprises often find themselves influenced by factors such as technology maturity and policy directives, gradually developing dependence on a particular technology in their selection process for air pollution control. As companies increasingly invest in technology, the phenomenon of technological lock-in becomes more pronounced. Enterprises may favour standardized technologies because of a lack of motivation among internal employees to learn new ones and a preference for technologies that are already proficiently mastered to reduce costs [12]. Over time, this can lead to the neglect or postponement of adopting more environmentally friendly but less mature technologies, inefficient management due to over-reliance on outdated techniques unable to meet new environmental requirements, or difficulty in transitioning to more effective pollution control technologies due to the sunk costs associated with existing technologies.

From the perspective of institutional path dependence, given the interplay between economics and politics, as well as the influence of cultural heritage, institutional change may be more complex than technological change. Thus, existing pollution control policies and regulations may resist the introduction of new policies (e.g., stakeholders may resist changes to an existing system), and the legitimacy of existing systems adds to the challenges in implementing institutional change. Thus, enterprises may find it difficult to respond promptly to environmental changes and new governance requirements due to rigid systems; the path-locking effect of existing frameworks will further increase the cost and difficulty of reform [13]; and the reliance on systems will exacerbate unfairness in environmental governance, with some enterprises potentially escaping their reduction responsibilities through loopholes in the system.

From the perspective of path dependence in management, business administrators, influenced by their own cognition, corporate culture, and other factors, gradually form a unique management model as they tackle atmospheric pollution. When an established management process and convention prevails in an organization, it persists with inertia; managers' cognitive frameworks may limit their perception and acceptance of new management methodologies; and corporate culture and values may solidify specific management approaches, resisting change [14]. An outdated management model may lead to inefficiencies, hindering the effective resolution of pollution issues. In addition, reliance on management may leave enterprises ill-equipped to adapt to new environmental requirements and market changes. The rigidity of the management model might impede the adoption of new management tools and methods by enterprises, thereby affecting the effectiveness of pollution control.

Moreover, in manufacturing air pollution control, there may be multi-path dependence [15]. The interplay between technological, institutional, and management path dependence could either accelerate or decelerate the green transition, depending on whether these dependencies align with low-carbon objectives. On the one hand, the path dependence of technology, institutions, and management may reinforce each other, resulting in delayed environmental governance and making it difficult to achieve sustainable governance. On the other hand, the interplay between different path dependence may lead to misallocation of governance resources and hinder the development and application of new technologies. Thus, while multi-pathway locking may contribute to pollution reduction to some extent, it ultimately necessitates path unlocking to propel atmospheric pollution control towards a more flexible, efficient, and sustainable direction. This is particularly critical for achieving climate-smart manufacturing systems.

3. Theoretical Basics and Research Hypothesis

Path dependence influences pollution control through distinct economic mechanisms. Technological path dependence operates via sunk costs (e.g., prior investments in pollution control equipment) and learning effects (e.g., efficiency gains from repeated use of established technologies). Institutional path dependence reflects regulatory inertia and policy continuity, where firms adhere to existing frameworks due to high adaptation costs and stakeholder resistance. Managerial path dependence arises from organizational routines and cognitive constraints, leading to persistent reliance on established management practices despite emerging alternatives. These mechanisms collectively underpin the non-linear effects of path dependence on pollution emissions.

To provide a more intuitive understanding of the mechanisms by which different types of path - dependence affect pollution emissions, the following **Figure 1** illustrates the specific theoretical frameworks of technological, institutional, and managerial path-dependence.

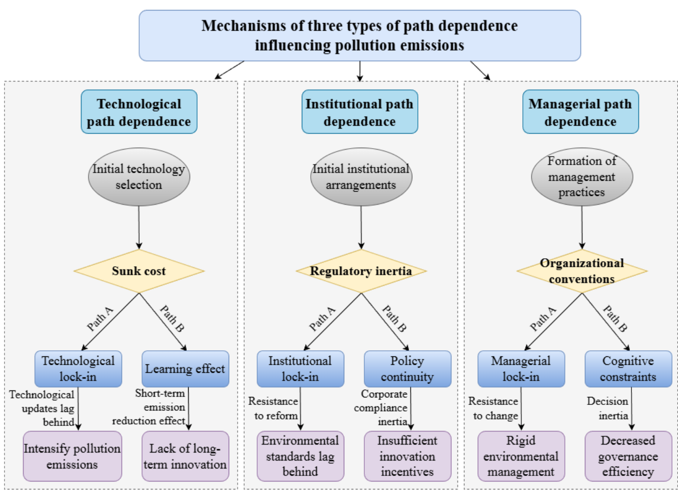

Figure 1. The theoretical framework.

Note: This figure depicts the mechanisms through which three distinct types of path-dependence, namely technological, institutional, and managerial, influence pollution emissions. It outlines the initial factors, intermediate effects, and ultimate consequences for each type, providing a comprehensive view of their complex inter-relationships.

3.1. Environmental Impacts of Technological Dependence

When adopting certain air pollution control technologies, manufacturing enterprises often require substantial financial investment for the procurement of equipment, as well as the modification of production lines. Once these investments are completed, they continue utilizing these technologies to amortize and recoup their investment costs. With time, enterprises gradually gain mastery over specific technologies, resulting in reduced operational costs and fault rates, thereby achieving commendable emission reduction effects. By employing a particular pollution-control technology on a long-term basis, enterprises can achieve economies of scale to reduce their unit costs. Given the cost considerations, companies may continue to rely on existing technologies. Although new technologies may emerge, uncertainty and risk abound, so enterprises may opt for continued use of existing technologies because of risk aversion. As technology advances and is applied, facilities, processes, and procedures must be developed in tandem. This can leave enterprises locked in their existing technological status, potentially decreasing rather than increasing emissions reduction efforts [16].

3.2. Environmental Impacts of Institutional Dependence

Air pollution control policies and regulations are often continuous and stable. Companies and their stakeholders will adapt their decisions accordingly, with these frameworks gradually evolving into a habituated reliance. When institutions are widely recognized through laws, regulations, and the like, corporations persistently adhere to existing systems, which promote pollution reduction within a certain period. As some corporations or groups derive specific benefits from existing systems, they may serve as powerful forces that resist any potential reforms that can harm their interests. Changing an existing institutional structure requires significant political and social costs, while the implementation of new institutions brings uncertainty and risks. Thus, the existing path is continuously relied upon. Although enterprises may already be experiencing diminishing marginal returns or even negative effects in pollution control, short-term efforts to change this situation are futile.

3.3. Environmental Impacts of Management Dependence

Over time, enterprises develop unique management processes and conventions that are effective means of enhancing efficiency and reducing costs, which may have led to more noticeable pollution control effects. Once managers become accustomed to a particular management paradigm, they may resist new management philosophies and methodologies. Corporate culture refers to the shared values, beliefs, and behavioral norms in an organization that shape its management style and decision-making processes. A culture that places a premium on stability and traditional values may stifle management innovation, despite changes in external conditions. Adopting a new management model also necessitates retraining employees—a time-consuming and costly endeavour that often prompts enterprises to cling to existing methodologies.

Moreover, when multiple pollution control measures are employed simultaneously, different policy instruments may interact, jointly influencing pollution emissions. When technology interacts with institutions, technology with management, institutions with management, or even when all three interact, multiple path dependence may arise in industrial air pollution control.

In summary, the following hypotheses are proposed:

Hypothesis 1. *In the context of manufacturing sector air pollution control, a non-linear technological dependence effect exists.*

Hypothesis 2. *In the context of manufacturing sector air pollution control, a non-linear institutional dependence effect exists.*

Hypothesis 3. *In the context of manufacturing sector air pollution control, a non-linear dependence effect exists.*

Hypothesis 4. *In the context of manufacturing sector air pollution control, non-linear multi-path dependence effects exist.*

4. Methodology

4.1. Sources of Data

This study employed a sample of 1884 listed companies in China's manufacturing sector, comprising 19,428 observations spanning from 2009 to 2021. The pollution data originate from China's industrial enterprises' pollution database (https://www.cnopendata.com/data/m/recent/gyqywrpf.html); the financial data are from the CSMAR (China Stock Market & Accounting Research, https://data.csmar.com/) and Wind databases (https://www.wind.com.cn/); the path-dependence data are obtained through keyword extraction methods for analyzing annual reports of listed companies (http://www.cninfo.com.cn/new/index). By matching the enterprise code in the pollution emission database with the securities code in the data of listed companies; merging the pollution data with financial and path-dependence data; and deleting ST, *ST, PT, and delisted enterprises as well as those with missing core variables, the final sample comprises 29 sub-industries of listed companies with manufacturing two-digit codes ranging from 13 to 42 (excluding sub-sector 16). Incomplete data were imputed with the mean method. To render the data sequence more stable and mitigate the effects of collinearity and heteroscedasticity, the explained and core explanatory variables were log-transformed.

4.2. Variable Settings

4.2.1. Explained Variable

The explained variable is sulphur dioxide emissions ($lnso_2$). To measure atmospheric pollution emissions levels, the logarithm of sulphur dioxide emissions was used as a proxy variable [17]. Moreover, nitrogen oxide emissions ($lnno_x$), particulate matter emissions ($lnsodu$), and air pollution equivalent logarithms ($lncape$) were selected as alternative explained variables for robustness tests. The data are sourced from the China Industrial Enterprises Pollution Database.

4.2.2. Explanatory Variables

The explanatory variable is path dependence, containing technological dependence ($lntech\_d$), institutional dependence ($lninst\_d$), and management dependence ($lnmana\_d$). The path-dependence variables are constructed based on the dictionary method [18], following two steps. First, keywords related to technology, institutions, and management were determined through a review of existing literature and official documents, forming a keyword dictionary. Second, keywords in the annual reports of listed companies were searched, and the Jieba word segmentation function of Python was utilized to segment the text into individual words and count the frequency of each word. Then, those with a frequency of five or more were filtered out (**Table 1**), and the frequency of technical keywords was summed up to obtain the technological dependence level for each year. The same method can be applied to calculate institution and management dependence. **Figure 2** describes the time-varying characteristics of path dependence. It can be observed that during the study period, the three levels of path dependence in air pollution control in the manufacturing industry all showed an increasing trend.

Table 1. Path dependence keyword extraction.

Variables	Keywords
Technological dependence	Technology, digitization, innovation, transformation, change, reform, advancement, breakthrough, impact, emerging, knowledge, information, high-tech, core, derivative, ecosystem, investment, upgrade, importation, cooperation, transfer, consultation, service, support, maintenance, promotion, advanced, automation, internet, optimization (a total of 30 words)
Institutional dependence	Regulation, norms, supervision, operation, competition, regulations, advantages, factors, execution, foundation, arrangements, construction, credit, incentives, protection, green, regulation, delegation, policy, laws, regulations, procedures, approval, internal, governance, disclosure, audit, criteria, culture (a total of 29 words)
Management dependence	Management, efficiency, systems, control, training, risk, standards, environment, market, systems, quality, restructuring, models, approaches, performance, participation, personnel, expectations, institutions, values, strategies, safety, costs, administration, subsidies, organizations, goals, resources, prevention, environmental protection (a total of 30 words)

We acknowledge that textual analysis of annual reports inherently captures managerial disclosure and strategic emphasis. Our measure of path dependence, therefore, primarily reflects the degree to which firms rhetorically commit to and emphasize their established technological, institutional, and managerial approaches in their official communications. This emphasis is a valid proxy for behavioral path dependence for two key reasons. First, sustained rhetorical commitment in formal documents signals organizational priority and resource allocation, which often translates into actual operational routines. Second, for the phenomenon of path dependence, the cognitive and discursive commitment to established paths is a fundamental component of the lock-in mechanism itself. While this measure may not directly observe operational behaviors, it effectively captures the discursive and strategic dimension of path dependence, which is a precursor to and a manifestation of behavioral lock-in.

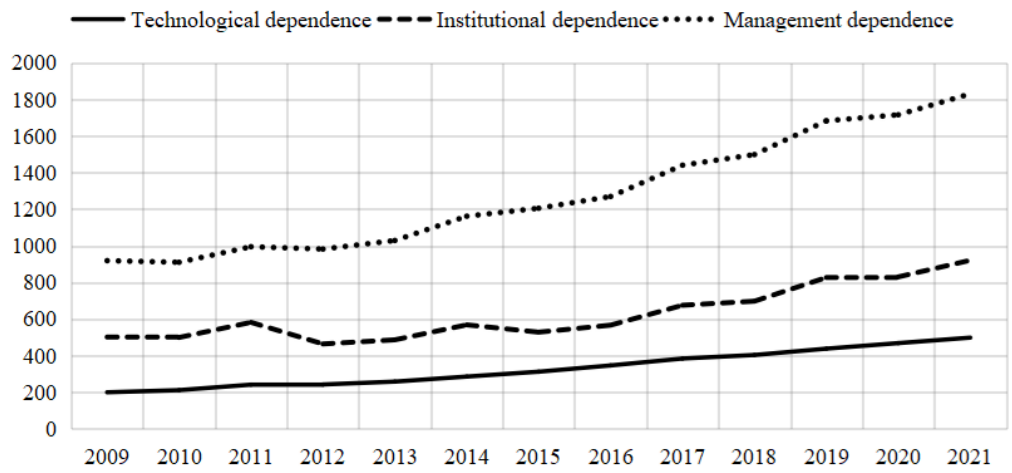

Figure 2. The evolution law of path dependence.

Notes: Using dictionary method to calculate the frequency of technological dependence, institutional dependence, and management dependence of all manufacturing enterprises respectively, and taking the arithmetic mean of each frequency of all enterprise over 2009–2021.

4.2.3. Control Variables

To exclude the interference of other factors, we focus on the influence of core explanatory variables and try to minimize the possibility of missing variables. Referring to the study [19], the following variables are controlled in the model: (1) Tobin's Q value ($tobin$), estimated by enterprise value/asset replacement cost; (2) book-to-market ratio ($mbratio$), reflected by book value/market value; (3) whether to disclose the internal control evaluation report (equal to 1 if disclosed and 0 otherwise) ($isdis\_Eva$); (4) whether to disclose the internal audit report (equal to 1 if disclosed and 0 otherwise) ($isdis\_Audit$); (5) number of directors with overseas background ($overseas$); and (6) degree of separation of two rights ($seperation$) (%), measured by ownership/control.

4.3. Empirical Models

To investigate the impact of path dependence on air pollution control, based on the micro data of listed manufacturing companies, the panel fixed effect model is constructed as follows:

$$lnso_{2it} = \alpha_1 + \beta_{11} lndep_{it} + \beta_{12} lndep_{it}^2 + \sum_{i=1}^{n} \gamma_{it} X_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (1)$$

where the explained variable ($lnso_{2it}$) represents air pollution emission, which is measured by the logarithm of sulphur dioxide emission of listed manufacturing companies. The core explanatory variable ($lndep_{it}$) represents path dependence, including three forms—technological dependence ($lntech\_d$), institutional dependence ($lninst\_d$), and management dependence ($lnmana\_d$). As the impact of path dependence on air pollution emissions may be non-linear, the model also includes the square term of the explanatory variable ($lndep_{it}^2$), and the coefficients β_{11} and β_{12} represent the impacts of path dependence and its square term on air pollution emissions, respectively. α_1 is the constant term. The control variables (X_{it}) include Tobin's Q value ($tobin$), book-to-market ratio ($mbratio$), whether to disclose the internal control evaluation report ($isdis\_Eva$), whether to disclose the internal audit report ($isdis\_Audit$), the number of directors with overseas background ($overseas$), and the separation of two rights ($seperation$). The coefficients (γ_{it}) are the regression coefficients of the control variable to the explained variable; μ_i and δ_t represent the fixed effect of the enterprise and year, respectively; and ε_{it} is the random error term.

As mentioned earlier, path dependence may intersect with one another, jointly influencing atmospheric pollution emissions to create a phenomenon of multiple path dependence. To this end, a panel regression model was constructed to examine whether there exist multiple path dependence in air pollution control.

$$lnso_{2it} = \alpha_2 + \beta_{21} interac_{it} + \beta_{22} interac_{it}^2 + \sum_{i=1}^{n} \omega_{it} X_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (2)$$

where cross-products ($interac_{it}$) denote path-dependence variables that may exhibit either double dependence, such as the interaction between technological dependence and institutional dependence ($techinst_{it}$), technological dependence and management dependence ($techmana_{it}$), institutional dependence and management dependence ($instmana_{it}$), or even triple dependence (tim_{it}), in which technological, institutional, and managerial factors interact simultaneously. $interac_{it}^2$ account for the square terms corresponding to the aforementioned multi-path dependence variables. ω_{it} represents the coefficients of the control variables in Model (2). The remaining connotations are consistent with Model (1).

5. Empirical Results

5.1. Descriptive Statistics

Table 2 presents the descriptive statistics of the variables.

Table 2. Descriptive statistics of the variables.

Variables	N	Minimum	Maximum	Mean	Standard Deviation
$lnso_2$	19,428	6.563	7.432	7.050	0.251
$lnno_x$	19,428	6.698	7.911	7.432	0.262
lnsodu	19,428	7.139	8.343	7.868	0.261
lncape	19,428	0.137	0.160	0.151	0.005
lntech_d	19,428	0.000	7.624	5.708	0.729
lninst_d	19,428	0.000	7.688	6.377	0.707
lnmana_d	19,428	0.000	8.351	7.101	0.759
tobin	19,428	0.000	126.952	2.261	2.921
mbratio	19,428	0.000	1.463	0.566	0.256
isdis_Eva	19,428	0.000	1.000	0.929	0.257
isdis_Audit	19,428	0.000	1.000	0.678	0.467
overseas	19,428	0.000	9.000	0.746	1.097
separation	19,428	0.000	60.323	5.236	7.870

5.2. Model Validation

Before performing regression analysis, it is necessary to examine for multicollinearity in the explanatory variables. The variance inflation factor (VIF) analysis revealed that the VIF values for all variables were less than 5, indicating the absence of severe multicollinearity. Furthermore, given the results of both the F-test and the Hausman test, a fixed effect model should be used for regression analysis.

5.3. Benchmark Regression

To investigate the impact of path dependence on the atmospheric pollution emissions of manufacturing listed companies, this study employed technology dependence, institutional dependence, and management dependence as central explanatory variables and utilized Equation (1) for regression analysis. The results are presented in **Table 3**. It is important to emphasize that the primary objective of this analysis is to identify the existence and shape of a non-linear relationship, rather than to pinpoint precise, universal turning points. As presented in the table (Column 1), the negative coefficient of technological dependence has a significant dependence effect on air pollution control in the manufacturing sector. Moreover, the squared term for technological dependence exhibits a significant positive impact, indicative of a U-shaped curve in its influence on sulphur dioxide emissions, which is currently on the left half of the curve. Therefore, short-term technological dependence can facilitate atmospheric pollution reduction. However, if excessive reliance occurs, in where technological dependence crosses the inflection point beneath the U-shaped curve's bottom, an increase in technological emissions may occur. This validates Hypothesis 1. Based on Columns (2) and (3), all the regression coefficients for path dependence and their squared terms passed the significance test at the 1% level, with the linear and quadratic coefficients having opposite signs. This indicates a similar non-linear impact of institutional and managerial dependence on corporate pollution emissions. Hypotheses 2 and 3 are validated.

Table 3. Summary of the benchmark regression results.

Variables	(1)	(2)	(3)
lntech_d	−0.5159*** (0.0207)		
lntech_d²	0.0857*** (0.0021)		
lninst_d		−0.5835*** (0.0190)	
lninst_d²		0.0853*** (0.0017)	
lnmana_d			−0.6989*** (0.0172)
lnmana_d²			0.0940*** (0.0016)
tobin	0.0008 (0.0007)	0.0003 (0.0008)	0.0001 (0.0006)
mbratio	−0.0066 (0.0099)	−0.0050 (0.0107)	−0.0195** (0.0090)
isdis_Eva	0.1350*** (0.0076)	0.1835*** (0.0084)	0.1135*** (0.0073)
isdis_Audit	0.0486*** (0.0042)	0.0621*** (0.0049)	0.0380*** (0.0038)
overseas	0.0063* (0.0034)	0.0134*** (0.0038)	0.0052 (0.0030)
separation	−0.0012** (0.0005)	−0.0013*** (0.0005)	−0.0011*** (0.0004)

Note: The figures in parentheses represent robust standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

With respect to the control variables, all impacts on the explained variable were statistically significant except for Tobin's Q ($tobin$) and the book-to-market ratio ($mbratio$). Specifically, the regression coefficients for the variables of whether internal control evaluation reports and internal audit reports were disclosed, as well as the number of directors with overseas experience, were all positive. This may suggest that despite the choice to disclose such reports or to have a greater number of directors with overseas experience, these companies might not have placed a strong emphasis on environmental performance or environmental responsibility, resulting in higher pollution emissions. Furthermore, the regression coefficient for the degree of separation between ownership and management was negative, indicating that when there is a higher degree of separation between ownership and management within a firm, the level of atmospheric pollution emissions tends to decrease. This could be because the separation of ownership and management introduces additional monitoring and accountability mechanisms, thereby promoting environmentally friendly behaviors.

Furthermore, Model (2) was employed to examine whether there exist multiple path dependence in air pollution control for manufacturing industries, and the regression results are presented in **Table 4**. As presented in Column (1), the dual dependence on technology and institution has a significant non-linear effect on pollution emissions, characterized by a U-shaped curve, that is, as the degree of dual dependence increases, atmospheric pollution emissions initially decrease before increasing. This implies that, in its initial phase, as technological and institutional dual dependence intensifies, atmospheric pollution emissions will initially decrease, exhibiting the effects of pollution control. However, when this interdependence surpasses a certain threshold, its square effect begins to manifest, leading to an increase in atmospheric pollution emissions. This implies that excessive interdependence may exacerbate pollution. **Table 4** presents the regression results for the other dual dependence on technology and management and on institution and management (Columns (2) and (3)), where the signs and significance levels of the coefficients are similar. This reveals potential path dependence in the implementation of air pollution control measures by listed manufacturing companies. Thus, enterprises may become overly reliant on certain methods or strategies in terms of technology, institution, or management, which initially reduce pollution. However, excessive reliance can limit their ability to adopt more effective or innovative pollution control measures, leading to an increase in emissions. Hypothesis 4 is validated. Regarding the triple dependence in Column (4), while the regression coefficients remain significant at the 1% level, their impacts on atmospheric pollution emissions are much smaller compared with dual dependence. This implies that the interaction among the three path dependence is not simply a linear addition but may exhibit an offsetting effect, resulting in a smaller marginal effect of additional path dependence. Furthermore, the interplay between a three-way dependence is more complex than that of a two-way dependence, thereby further increasing the uncertainty and dynamism of path dependence effects.

Table 4. Summary of multi-path dependence regression results.

Variables	(1)	(2)	(3)	(4)
techinst	−0.0442*** (0.0028)			
techinst^2	0.0012*** (0.0000)			
techmana		−0.0437*** (0.0026)		
techmana^2		0.0011*** (0.0000)		
instmana			−0.0515*** (0.0023)	
instmana^2			0.0010*** (0.0000)	
tim				−0.0031*** (0.0004)
tim^2				0.0001*** (0.0000)
Control variables	Yes	Yes	Yes	Yes
N	19428	19428	19428	19428
R^2	0.3535	0.3796	0.4123	0.3776
F-statistic	894.62	927.72	1350.49	837.59

Note: The figures in parentheses represent robust standard errors. *** denotes significance at the 1% level.

5.4. Robustness Test

5.4.1. Replace the Explained Variable

As mentioned previously, the level of industrial atmospheric pollution emissions was measured in terms of sulphur dioxide emissions. To examine the robustness of the conclusion, we use nitrogen oxide emissions ($lnno_x$), particulate matter emissions ($lnsodu$), and air pollution equivalent logarithms ($lncape$) as alternative variables for the explained variable in Model (1) (refer to **Appendix A Tables A1–A3**).

5.4.2. Sub-Sample Analysis Based on Information Transparency

To examine the robustness of our findings to potential measurement errors in the path dependence variables, we conduct a sub-sample analysis. This test addresses the concern that keyword frequencies may capture managerial rhetoric rather than actual behavioral lock-in (the core construct of path dependence). The underlying logic is that if the textual measures primarily reflect empty discourse, the estimated relationship with pollution emissions should be weaker or non-existent among firms with low-quality information disclosure, where the gap between rhetoric and reality is likely largest. Conversely, a stable relationship across different transparency levels would lend credibility to the measures.

We employ the effectiveness of internal controls (*isvalid*) as a proxy for information transparency and split the sample into high- and low-transparency subgroups. The results, presented in **Appendix A Table A4**, demonstrate that the U-shaped relationships for all three types of path dependence remain statistically significant and stable in both sub-samples. Notably, the regression coefficients (absolute values) of path dependence variables on pollution emissions are larger in the high-transparency group. This pattern supports the validity of our measurement approach: the amplified effects in the high-transparency subgroup suggest keyword frequencies reflect substantive corporate behaviors rather than rhetorical claims. Thus, consistent findings across subgroups rule out the possibility that our results are driven solely by managerial rhetoric (refer to **Appendix A Table A4**).

5.4.3. Abnormal Values in Truncated Data Sets

Given the potential for outliers or extreme values to induce bias in estimates, winsorization—a technique that substitutes extreme values with less stringent thresholds (such as 5% and 95%)—was employed to assess sensitivity to extreme values. This was followed by a fixed effects regression with Model (1) again (refer to **Appendix A Table A5**).

5.4.4. Grouped Regression across Sub-Sectors

Differences in atmospheric pollution emissions across sub-sectors may lead to enhanced or mitigated total path dependence effects. Further testing is required. Based on the sample enterprises' sulfur dioxide emissions (logarithmic values), all enterprises were divided into three groups: the high-emission group, consisting of the top 10 sub-sectors such as black metal, non-metallic mineral, and other metal industries; the medium-emission group, including food manufacturing, beverage, chemical fiber, rubber and plastic, printing and recording, wood processing, textiles and clothing, general equipment, and other manufacturing industries as well as leather, fur, feathers and their products, and footwear industry; and the low-emission group, comprising the remaining nine sub-sectors. Employ model (1) for grouped regression (refer to **Appendix A Table A6**).

5.4.5. Consider Endogeneity Issues

Endogeneity concerns—including sample selection bias, omitted variables, and bidirectional causality—are carefully addressed through multiple empirical strategies to ensure the robustness of our findings. To mitigate sample selection bias, our analysis utilizes a comprehensive sample of 1884 listed manufacturing firms across 29 two-digit sectors, providing broad coverage that minimizes selection-related distortions. For omitted variable bias, we incorporate a comprehensive set of time-varying firm-level controls in all regression specifications, including Tobin's Q (*tobin*) as a measure of investment opportunities, book-to-market ratio (*mbratio*) indicating financial performance, and internal governance variables (*isdis_Eva* and *isdis_Audit*) capturing the quality of internal control and audit disclosures. The stability of our core results across different model specifications, as presented in **Table 3**, suggests that omitted variable bias is unlikely to drive our findings.

Most importantly, we address potential reverse causality through two distinct instrumental variable (IV) approaches. First, we employ a dynamic panel approach using lagged values of the core explanatory variables as instruments, leveraging the temporal precedence of path dependence measures relative to current pollution outcomes. Second, we construct a more robust instrument based on peer effects within industries, utilizing the average level of technological path dependence among other firms in the same two-digit industry and year (excluding the focal firm) as an instrument for the focal firm's own path dependence. This instrument satisfies the relevance condition because firms within the same industry face similar technological environments and tend to converge toward industry norms, while plausibly satisfying the exclusion restriction since peer firms' path dependence should not directly affect the focal firm's emissions except through shaping its own strategic technological choices.

The IV regression results, presented in **Appendix A Tables A7** and **A8**, provide strong evidence supporting our main findings. The first-stage F-statistics exceed conventional thresholds (e.g., F = 128.03 for the peer-effects instrument in **Table A8**), decisively rejecting weak instrument concerns. Both identification strategies yield statistically significant coefficients for the U-shaped relationship between path dependence and pollution emissions, with the peer-effects instrument showing particularly strong explanatory power. The consistency of results across these complementary approaches reinforces the conclusion that our findings are not driven by endogeneity bias, providing robust evidence that the identified U-shaped relationship reflects a causal effect of path dependence on manufacturing pollution.

The above robustness test results are consistent with those of the benchmark regression, thereby confirming the robustness of the preceding conclusions.

5.5. Heterogeneity Analysis

To examine the heterogeneous effects of path dependence across different firm characteristics, we conduct subgroup analyses based on ownership types, firm maturity, and investment scale. The complete regression results are presented in **Appendix A Tables A9–A11**, while key findings are summarized below.

5.5.1. Ownership Types (State-Owned vs. Non-State-Owned)

The analysis reveals systematic differences in path dependence effects between state-owned and non-state-owned enterprises (see **Appendix A Table A9**), with both groups exhibiting the characteristic U-shaped relationship where initial technological, institutional, and managerial dependence reduces emissions but excessive reliance leads to rebound effects. Non-state-owned enterprises demonstrate stronger path dependence effects, evidenced by consistently larger coefficient magnitudes across all three dependence dimensions, attributable to their greater innovation motivation and organizational flexibility enabling rapid adoption of new pollution control technologies, superior resource allocation efficiency for effective emission reduction tool utilization, and heightened sensitivity to cost-revenue dynamics making them more responsive to environmental regulations [20]. In contrast, state-owned enterprises exhibit a more attenuated U-shaped relationship, likely reflecting institutional constraints and different innovation incentives, underscoring the need for ownership-specific policy approaches to optimize path dependence effects in pollution control.

5.5.2. Firm Maturity Levels

The analysis reveals distinct path dependence effects across firm maturity levels (see **Appendix A Table A10**), with high-maturity enterprises demonstrating significantly stronger U-shaped relationships across all three dependence dimensions compared to their low-maturity counterparts. This enhanced sensitivity manifests in larger coefficient magnitudes for technological, institutional, and managerial path dependence among established firms, attributable to their superior technological and managerial efficiency derived from accumulated experience and resource advantages, scale economies that amplify the emission impacts of marginal changes in dependence levels, and enhanced innovation capacity enabling more rapid adaptation to new regulatory requirements and technological opportunities [21]. The steeper U-curve for mature firms indicates that while they achieve greater emission reductions at optimal dependence levels, they also face heightened rebound risks when dependence exceeds critical thresholds, underscoring the particular importance of dynamic capability maintenance for long-established enterprises in pollution control.

5.5.3. Investment Scale Differences

The analysis reveals a distinctive pattern in path dependence effects across investment scale levels (see **Appendix A Table A11**), with high-investment enterprises exhibiting attenuated but still significant U-shaped relationships compared to their low-investment counterparts. Contrary to conventional expectations, the smaller coefficient magnitudes for technological, institutional, and managerial path dependence among capital-intensive firms suggest diminishing marginal returns to scale in pollution control, potentially reflecting investment efficiency constraints where excessive capital allocation without corresponding managerial innovations leads to resource underutilization, scale economy paradoxes where large production volumes dilute the emission reduction effectiveness of incremental technological improvements, and regulatory compliance burdens that create formalistic environmental responses rather than substantive innovation-driven solutions. This attenuated U-curve pattern indicates that while high-investment firms achieve moderate emission reductions through resource-intensive approaches, they face structural limitations in leveraging path dependence for transformative environmental performance improvements, highlighting the critical need for complementary organizational innovations alongside capital investments in manufacturing pollution control [22].

6. Discussion

This study examines the dual role of path dependence in manufacturing pollution control, revealing a consistent U-shaped relationship across technological, institutional, and managerial dimensions. The findings demonstrate that while moderate path dependence initially reduces emissions (the "honey phase"), excessive reliance risks increasing pollution (the "arsenic phase")—a pattern particularly pronounced in non-state-owned, high-maturity, and low-investment-scale enterprises.

Our research extends path dependence theory to environmental governance by identifying three concurrent dependence mechanisms. The dictionary-based measurement approach, while capturing discursive commitments in corporate disclosures, primarily reflects strategic emphasis rather than operational behaviors. This methodological choice aligns with the cognitive dimensions of organizational lock-in but acknowledges limitations in directly observing behavioral routines. Future studies could strengthen this approach by integrating textual analysis with behavioral metrics such as patent filings for technological lock-in or compliance records for institutional dependence.

The nonlinear relationship necessitates differentiated policy approaches. For enterprises with low-to-moderate dependence, policies can carefully leverage existing paths' stabilization benefits. However, for firms exhibiting high dependence, the priority shifts to preventing lock-in through knowledge transfer, pilot subsidies, and innovation-friendly regulations. The heightened effects in non-state-owned and mature enterprises highlight opportunities for targeted interventions, such as phased carbon pricing that rewards path-breaking innovation over path-following compliance.

While establishing the U-shaped pattern, this study does not identify precise inflection points or fully explore multi-path dependence interactions. Future research should investigate how path dependence interacts with climate-specific variables like carbon disclosure or renewable adoption, particularly under rapid policy shifts like carbon neutrality mandates. Additionally, interactions with unexamined factors such as CSR initiatives or leadership styles may further nuance the observed relationships.

Unlike macro-level studies of path dependence in economic growth or industrial aggregation [23–25], our firm-level analysis reveals how micro-foundations of technological, institutional, and managerial lock-in collectively shape environmental performance. This granular perspective complements national and industry-level analyses by elucidating the organizational mechanisms through which path dependence influences pollution outcomes.

7. Conclusions

This study is based on the annual data of 1884 listed manufacturing enterprises in China from 2009 to 2021. A fixed effects model was constructed to examine the path-dependent effect on air pollution and the heterogeneities. The major findings include the following: (i) Significant technological dependence, institutional dependence, and management dependence exist in the process of air pollution control in manufacturing industries. Furthermore, the U-shaped characteristics of the impacts of these three types of path dependence and their interactions on atmospheric emissions indicate that as the degree of path dependence and their interactions increases, atmospheric emissions initially decrease before increasing. (ii) In non-state-owned enterprises, high-maturity enterprises, and low-capitalization enterprises, the path-dependent emission reduction effects are more pronounced.

Based on the empirical findings of this study, the following policy implications arise: Firstly, due to the non-linear impact of path dependence on atmospheric pollution emissions, efforts should be made to keep path dependence at a low level (the left part of the U-shaped curve) to harness the emission reduction effect (known as the honey phase) and avoid exacerbating pollution emissions due to excessive reliance (known as the arsenic phase). Thus, path dependence is a double-edged sword that requires policymakers to use it judiciously. Secondly, given the heterogeneity in pollution emissions resulting from path dependence across different sample groups, differentiated emission reduction plans should be proposed, integrating the effectiveness of pollution control for enterprises in various sub-industries. Such plans should enhance the emission reduction effects of non-state-owned enterprises, high-maturity enterprises, and enterprises with low investment scales, ensuring fairness and efficiency in pollution reduction efforts. In summary, while advancing pollution mitigation efforts, it is crucial to avoid over-reliance on single or combined remediation pathways. Encouragement should be given to diversified and innovative solutions, with regular assessments and adjustments to treatment strategies made to ensure sustained and effective control of atmospheric pollution over the long term.

In conclusion, effectively managing path dependence is not only crucial for controlling atmospheric pollution but also a key determinant in facilitating the manufacturing sector's transition to a green and low-carbon future, ultimately contributing to the broader climate goals.

This study measures the path dependence level of air pollution control in listed manufacturing companies from multiple dimensions using dictionary-based methods. It also reveals the non-linear emission reduction effect and environmental heterogeneity of path dependence. However, certain limitations remain. For example, the study does not explore the inflection point of the U-shaped curve associated with path dependence effects, nor does it examine the influencing factors of multi-path dependence, which require further systematic research in the future.

Author Contributions

Conceptualization: S.W. (Sufeng Wang), S.W. (Shuyan Wang) and Y.S.; Methodology: S.W. (Sufeng Wang); Software: S.W. (Shuyan Wang); Validation: S.W. (Shuyan Wang); Formal analysis: S.W. (Sufeng Wang) and S.W. (Shuyan Wang); Investigation: S.W. (Shuyan Wang) and Y.S.; Resources: S.W. (Sufeng Wang); Data curation: S.W. (Shuyan Wang); Writing—original draft preparation: S.W. (Sufeng Wang), S.W. (Shuyan Wang) and Y.S.; Writing—review

and editing: S.W. (Sufeng Wang); Visualization: Y.S.; Supervision: S.W. (Sufeng Wang); Project administration: S.W. (Sufeng Wang); Funding acquisition: S.W. (Sufeng Wang). All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

Data are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare no conflict of interest.

Appendix A

Table A1. Summary of regression results for replacing the explained variable ($lnno_x$).

Variables	$lnno_x$		
$lntech\_d$	−0.5442*** (0.0234)		
$lntech\_d^2$	0.0902*** (0.0023)		
$lninst\_d$		−0.6144*** (0.0215)	
$lninst\_d^2$		0.0895*** (0.0019)	
$lnmana\_d$			−0.7367*** (0.0193)
$lnmana\_d^2$			0.0988*** (0.0017)
Control variables	Yes	Yes	Yes
N	0.3274	0.3496	0.4703
R^2	19,428	19,428	19,428
F-statistic	895.57	1095.08	1031.11

Note: The figures enclosed in parentheses represent robust standard errors. *** denotes significance at 1%.

Table A2. Summary of regression results for replacing the explained variable ($lnsodu$).

Variables	$lnsodu$		
$lntech\_d$	−0.5476*** (0.0235)		
$lntech\_d^2$	0.0906*** (0.0023)		
$lninst\_d$		−0.6145*** (0.0214)	
$lninst\_d^2$		0.0894*** (0.0019)	
$lnmana\_d$			−0.7370*** (0.0192)
$lnmana\_d^2$			0.0987*** (0.0017)
Control variables	Yes	Yes	Yes
N	0.3293	0.3497	0.4735
R^2	19,428	19,428	19,428
F-statistic	847.06	1117.00	1047.48

Note: The figures enclosed in parentheses represent robust standard errors. *** denotes significance at 1%.

Table A3. Summary of regression results for replacing the explained variable ($lncape$).

Variables	*lncape*		
lntech_d	−0.0109*** (0.0005)		
lntech_d^2	0.0018*** (0.0000)		
lninst_d		−0.0123*** (0.0004)	
lninst_d^2		0.0018*** (0.0000)	
lnmana_d			−0.0147*** (0.0004)
lnmana_d^2			0.0020*** (0.0000)
Control variables	Yes	Yes	Yes
N	0.3624	0.3853	0.5205
R^2	19,428	19,428	19,428
F-statistic	928.53	1225.20	1124.80

Note: The figures enclosed in parentheses represent robust standard errors. *** denotes significance at 1%.

Table A4. Summary of sub-sample analysis based on information transparency.

Variables	(1)		(2)		(3)	
	High	**Low**	**High**	**Low**	**High**	**Low**
lntech_d	−0.4306*** (0.0267)	−0.3773*** (0.0319)				
lntech_d^2	0.0792*** (0.0025)	0.0536*** (0.0051)				
lninst_d			−0.5418*** (0.0253)	−0.2535*** (0.0299)		
lninst_d^2			0.0840*** (0.0021)	0.0278*** (0.0042)		
lnmana_d					−0.6645*** (0.0263)	−0.4782*** (0.0325)
lnmana_d^2					0.0926*** (0.0020)	0.0594*** (0.0046)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
N	17,878	1550	17,878	1550	17,878	1550
R^2	0.2633	0.5572	0.2964	0.5478	0.4197	0.5871
F-statistic	633.86	142.72	786.53	137.48	731.02	168.26

Note: Sub-sample analysis is conducted by dividing the full sample into high and low information transparency groups, based on firm information transparency (measured by the variable $isvalid$, where "0" indicates ineffective internal control and "1" indicates effective internal control). The data for the *isvalid* are sourced from the CSMAR (China Stock Market & Accounting Research, https://data.csmar.com/). The sub-sample sizes are 17,878 for the high-information-transparency group and 1550 for the low-information-transparency group, respectively.
The figures enclosed in parentheses represent robust standard errors. *** denotes significance at 1%.

Table A5. Summary of winsorize processing outliers regression results.

Variables	(1)	(2)	(3)
lntech_d	−0.5159*** (0.0207)		
lntech_d^2	0.0857*** (0.0021)		
lninst_d		−0.5835*** (0.0190)	
lninst_d^2		0.0853*** (0.0017)	
lnmana_d			−0.6989*** (0.0172)
lnmana_d^2			0.0940*** (0.0016)
Control variables	Yes	Yes	Yes
N	19,428	19,428	19,428
R^2	0.3146	0.3383	0.4576
F-statistic	841.42	1041.40	993.64

Note: The figures enclosed in parentheses represent robust standard errors. *** denotes significance at 1%.

Table A6. Summary of grouped regression results based on SO_2 emissions.

Variables	(1)			(2)			(3)		
	High	**Medium**	**Low**	**High**	**Medium**	**Low**	**High**	**Medium**	**Low**
lntech_d	−0.5343*** (0.0327)	−0.5802*** (0.0319)	−0.4727*** (0.0333)						

Table A6. *Cont.*

Variables	(1)			(2)			(3)		
	High	Medium	Low	High	Medium	Low	High	Medium	Low
lntech_d²	0.0882*** (0.0031)	0.0931*** (0.0040)	0.0830*** (0.0033)						
lninst_d				−0.5978*** (0.0331)	−0.6570*** (0.0234)	−0.5391*** (0.0278)			
lninst_d²				0.0860*** (0.0029)	0.0919*** (0.0028)	0.0815*** (0.0026)			
lnmana_d							−0.6895*** (0.0284)	−0.7765*** (0.0268)	−0.6761*** (0.0269)
lnmana_d²							0.0921*** (0.0025)	0.1009*** (0.0030)	0.0927*** (0.0025)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	7718	3521	8189	7718	3521	8189	7718	3521	8189
R^2	0.3645	0.3384	0.2786	0.3528	0.3581	0.3165	0.4693	0.4656	0.4441
F-statistic	466.53	157.12	287.19	441.89	225.60	396.70	438.98	210.80	377.82

Note: The figures enclosed in parentheses represent robust standard errors. *** denotes significance at 1%.

Table A7. IV-2SLS estimation with lagged path dependence instruments.

Variables	(1)		(2)		(3)	
	lntech_d	$lnso_2$	*lninst_d*	$lnso_2$	*lnmana_d*	$lnso_2$
L.lntech_d	−0.1184*** (0.0236)					
lntech_d		−1.2358*** (0.1521)				
L.lninst_d			−0.0844*** (0.0230)			
lninst_d				−1.2823*** (0.2049)		
L.lnmana_d					−0.1151*** (0.0254)	
lnmana_d						−1.2110*** (0.1282)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
N	17,544	17,544	17,544	17,544	17,544	17,544
F-statistic (first stage)	25.11		13.53		20.49	

Note: *L.lntech_d*, *L.lninst_d*, and *L.lnmana_d* denote the one-period lagged values of the corresponding explanatory variables, used as instruments in the IV estimation. The figures enclosed in parentheses represent robust standard errors. *** denotes significance at 1%.

Table A8. IV-2SLS estimation with peer firms' path dependence instruments.

Variables	(1)		(2)		(3)	
	lntech_d	$lnso_2$	*lninst_d*	$lnso_2$	*lnmana_d*	$lnso_2$
indavg.lntech_d	−0.3424*** (0.0303)					
lntech_d		−2.0934*** (0.1785)				
indavg.lninst_d			−0.4919*** (0.0324)			
lninst_d				−1.5242*** (0.0944)		
indavg.lnmana_d					−0.5820*** (0.0323)	
lnmana_d						−1.4027*** (0.0686)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
N	19,425	19,425	19,425	19,425	19,425	19,425
F-statistic (first stage)	128.03		229.91		324.41	

Note: *indavg.lntech_d*, *indavg.lninst_d*, and *indavg.lnmana_d* represent industry-year averages of path dependence levels excluding the focal firm, employed as instrumental variables.
The figures enclosed in parentheses represent robust standard errors. *** denotes significance at 1%.

Table A9. Heterogeneity test of enterprise ownership.

Variables	(1)		(2)		(3)	
	State-Owned	Non-State-Owned	State-Owned	Non-State-Owned	State-Owned	Non-State-Owned
lntech_d	−0.4709*** (0.0308)	−0.5286*** (0.0234)				

Table A9. *Cont.*

Variables	(1)		(2)		(3)	
	State-Owned	Non-State-Owned	State-Owned	Non-State-Owned	State-Owned	Non-State-Owned
lntech_d^2	0.0813*** (0.0032)	0.0856*** (0.0024)				
lninst_d			−0.5100*** (0.0267)	−0.6005*** (0.0214)		
lninst_d^2			0.0772*** (0.0028)	0.0857*** (0.0019)		
lnmana_d					−0.6330*** (0.0270)	−0.7161*** (0.0195)
lnmana_d^2					0.0872*** (0.0028)	0.0948*** (0.0018)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
N	6761	12,667	6761	12,667	6761	12,667
R^2	0.3729	0.2775	0.4094	0.2937	0.4896	0.4397
F-statistic	478.84	447.23	450.90	654.29	444.13	627.57

Table A10. Heterogeneity test of enterprise maturity.

Variables	(1)		(2)		(3)	
	High	Low	High	Low	High	Low
lntech_d	−0.4686*** (0.0233)	−0.3768*** (0.0333)				
lntech_d^2	0.0771*** (0.0025)	0.0658*** (0.0031)				
lninst_d			−0.5461*** (0.0218)	−0.3384*** (0.0289)		
lninst_d^2			0.0794*** (0.0022)	0.0521*** (0.0028)		
lnmana_d					−0.6430*** (0.0208)	−0.5420*** (0.0325)
lnmana_d^2					0.0861*** (0.0022)	0.0745*** (0.0029)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
N	10,331	9097	10,331	9097	10,331	9097
R^2	0.3935	0.2413	0.4491	0.2160	0.5036	0.3945
F-statistic	540.23	254.46	661.80	143.44	630.62	180.63

Note: The figures enclosed in parentheses represent robust standard errors. *** denotes significance at 1%.

Table A11. Heterogeneity test of investment scale.

Variables	(1)		(2)		(3)	
	High	Low	High	Low	High	Low
lntech_d	−0.4330*** (0.0286)	−0.5436*** (0.0236)				
lntech_d^2	0.0795*** (0.0030)	0.0872*** (0.0024)				
lninst_d			−0.4846*** (0.0248)	−0.5989*** (0.0218)		
lninst_d^2			0.0751*** (0.0024)	0.0862*** (0.0021)		
lnmana_d					−0.6169*** (0.0248)	−0.7222*** (0.0198)
lnmana_d^2					0.0867*** (0.0023)	0.0958*** (0.0020)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
N	8262	11,166	8262	11,166	8262	11,166
R^2	0.3812	0.2645	0.3567	0.3163	0.4743	0.4357
F-statistic	352.65	426.58	358.66	502.46	380.84	506.97

Note: The figures enclosed in parentheses represent robust standard errors. *** denotes significance at 1%.

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