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RESEARCH ARTICLE

Multilevel policy textual learning in Chinese local environmental policies

Wenna Chen[1], Li Liao[2] and Hongtao Yi[3]

[1]Center for Chinese Public Administration Research and School of Government, Sun Yat-sen University, Guangzhou, Guangdong, China, [2]School of Public Administration, Southwest Jiaotong University, Chengdu, Sichuan Province, China and [3]Askew School of Public Administration and Policy, Florida State University, Tallahassee, FL, USA
Corresponding author: Li Liao; Email: liliao.ppa@swjtu.edu.cn

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Abstract
While existing research on policy diffusion has provided substantial evidence regarding the drivers of policy adoption across jurisdictions, limited attention has been given to the dynamics of policy textual learning across different levels of government. We fill this gap by using regression analysis to examine the patterns of policy textual learning evident in the clause similarity of seven environmental statutory policies in China. Within China's decentralized and multilevel environmental governance, our findings reveal that horizontal policy textual learning is more prominent than vertical learning. Temporal distance negatively impacts policy textual learning, whereas spatial distance, contrary to traditional policy diffusion perspectives, does not universally explain multilevel policy textual learning. Additionally, subsequent versions of policy texts are not necessarily similar to earlier ones, challenging conventional assumptions about the adoption and adaptation of policies over time.

Keywords: environmental policy; local government; policy diffusion; policy learning; textual learning

Introduction

Policy learning is an intentional process that involves reflecting on past policies and adjusting their goals and methods (Hall 1993). It can occur through conceptual change and managerial updates (Dolowitz and Marsh 1996; Stone 1999). Policy learning is often perceived as a dichotomous measure of intentional policy change as part of the diffusion process, wherein one institution observes and emulates the actions of another to adopt a new policy. This notion is largely supported by the well-established body of research on state policy diffusion within the USA context (Berry and Berry 1990; Böhmelt et al. 2016). Empirical evidence indicates that policy diffusion commonly occurs horizontally among countries (Meckling and Jenner

2016; Zhou et al. 2019), states (Boehmke 2009; Nicholson-Crotty and Carley 2016), and cities (Feiock et al. 2012; Zhu and Zhao 2018). The concepts of top-down and bottom-up diffusion provide additional perspectives for understanding policy diffusion along the vertical dimension, where the former illustrates diffusion from higher to lower levels of government, while the latter describes diffusion from lower to higher levels (Fay et al. 2022; Shipan and Volden 2006; Zhu 2014). Collectively, these studies indicate that policy actors at different levels work together to influence policy adoption. However, there remains a gap in examining the policy textual learning across different levels of local governments.

Dolowitz and Marsh (1996) identify two fundamental questions inherent in policy diffusion: "learn from whom?" and "learn about what?" Concerning the first question, a wide range of mechanisms have been proposed to explicate the dynamics and mechanisms of policy diffusion. For instance, policy actors tend to embrace policies adopted by neighboring peers (Haider-Markel 2001) or those endorsed by co-partisans (Butler and Pereira 2018). Besides, policies with proven success in one area are more likely to gain recognition and spread to other areas (Volden 2006). Policy diffusion may also occur through social networks, such as those formed through career trajectories (Yi and Chen 2019) or cooperative interactions (Kammerer and Namhata 2018). However, concerning the second question of "learn about what?," existing literature predominantly focuses on whether a policy is adopted or not, rather than emphasizing the diffusion of policy content itself. This creates a crucial gap: how does policy content, particularly textual elements, diffuse across jurisdictions under multilayered governance settings? To what extent does horizontal textual learning differ from vertical learning in multilayered governance systems? Bridging these two questions—understanding "from whom" policies are learned and "what" aspects of policy content are learned—is essential for a more comprehensive understanding of policy diffusion.

We address these questions by examining the textual learning of environmental policy across provincial and city governments, both referring to local governments with jurisdiction to enact and implement policies in the Chinese context (Kostka and Nahm 2017). Provincial governments are assigned environmental protection goals by the central government, subsequently distributing these goals to city governments (Li 2019). The Chinese multilayered governance structure is considered a fragmented authoritarianism where both vertical and horizontal environmental bureaucratic management systems exist (Kostka and Zhang 2018; Schreurs 2017). In this context, horizontal coordination and competition alongside a vertical top-down chain of command may compel local governments to learn from specific policy actors, resulting in a certain pattern of policy textual change.

Theoretically, our research aims to contribute to the scholarship of environmental governance, policy transfer and diffusion, and policy learning as follows. First, we intend to interpret policy diffusion from the angle of policy textual learning, which extends the dichotomous measurement of the imitation of adoption behavior to a more nuanced form of policy diffusion. Second, we aspire to synthesize environmental decentralization to reveal the policy textual learning pattern horizontally and vertically in the multilevel environmental governance structure. Third, traditional diffusion mechanisms are incorporated to explain the existence of spatial and temporal features of policy textual learning among local governments (Berry and Berry 1990). The environmental policies initially adopted and amended are integrated as parts of the policy diffusion process to further disclose the policy textual learning dynamics in the environmental regulatory competition and imitation (Carley and Miller 2012; Carley et al. 2017; Konisky 2006). Methodologically, we resort to a computational text analysis method to construct similarity scores to capture the potential textual learning (Düpont and Rachuj 2022; Jansa et al. 2019).

The article is constructed as follows. First, we conduct a literature review of policy textual learning and environmental policy. Second, we propose four hypotheses to delineate the mechanisms that underpin the environmental policy textual learning across tiers of government, space, and time. Later, we illustrate the data source, variable construction, and model selection to ensure transparency of the data and appropriateness of the method. In the results section, we lay out the statistical results, examine the hypotheses, and discuss the statistical meaning of the variables. In the discussion part, we interpret the results in tandem with relevant literature to put forward the theoretical and methodological implications of the findings. In the end, we offer a conclusion of our main arguments, findings, and contributions.

Literature review

Policy textual learning

Walker (1969) posits that policy diffusion occurs through a direct copy, either verbatim or with minor modifications, across different jurisdictions. Under this traditional view, policy diffusion studies relying on the event history analysis approach typically identify instances of direct policy copying between jurisdictions. However, these studies fall short of revealing the extent to which policies have been copied versus revised. In contrast, the concept of policy textual learning, which refers to the evolution of policy content and ideas through the language and substance of policy documents, provides a deeper insight into the nuanced transformations that occur at the verbal or textual level (Garrett and Jansa 2015; Jansa et al. 2019). By employing computational methods, policy textual learning, generally operationalized as textual similarity, shifts the focus of policy diffusion from a binary mode of "adopted or not" to the understanding of language-based policy content adaptation.

Existing literature reveals two main categories of policy textual learning. The first form, boilerplate learning, typically occurs in contractual and regulatory policies (Bakos et al. 2014; Ciuriak and Ciuriak 2016). Scott et al. (2021) contend that boilerplate learning is driven by ossification pressure as a way to lower legal interpretation uncertainty, enhance consistency in agency communication, and signal the credibility of potential alternatives. The second form of textual learning is derived from nonformulaic language learning, which pertains to the inheritance of policy ideas and insights (Wilkerson et al. 2015). Linder et al. (2020) define the use of boilerplate language as procedural learning, different from the essential policy content learning inherent in policy idea evolution.

Textual learning can be captured by a variety of text analysis techniques, such as unigram bag-of-words (Grimmer and Stewart 2013), local alignment approach (Wilkerson et al. 2015), and transformer-based models (Kim et al. 2021). Existing literature in public administration and political science offers extensive insight into the underlying mechanisms of textual learning. For instance, Garrett and Jansa (2015) apply cosine similarity to quantify text similarity and assess policy diffusion, revealing that such textual diffusion is particularly driven by interest groups' model legislation. Building on this, Jansa et al. (2019) unearth the influence of legislative professionalism on policy language diffusion across states, again leveraging cosine similarity to track linguistic shifts. Collingwood et al. (2019) and DeMora et al. (2019), through plagiarism similarity, demonstrate the organizational influence imposed by the American Legislative Exchange Council in steering policy diffusion across state legislatures through template policy. Similarly, Linder et al. (2020) utilize a dyadic alignment score to explore how sponsors' ideology and policy diffusion networks significantly shape the degree of text reuse or similarity in state laws. Likewise, Hinkle (2015), relying on a dyadic approach, examines the role of Supreme Court rulings and circuit court rulings on the extent to which the text of policies overlap. Using the text reuse approach, Gava et al. (2021) corroborate the influence of direct democracy, parliamentary agendas, and media attention on the dissimilarity of bills adopted by the Swiss Parliament when shielding the influence from boilerplate. Notwithstanding these significant contributions to understanding policy textual learning across jurisdictions, the literature predominantly focuses on federal and state-level dynamics, leaving a notable gap in research regarding policy learning across different jurisdictions at the local level.

Environmental policy learning

A broad spectrum of internal and external factors influences local governments' decisions to adopt certain kinds of environmental policy. Rather than positioning these elements as rivaling factors, existing scholars have endeavored to synthesize both internal and external mechanisms to adequately capture the complexity of environmental policy adoption and diffusion patterns. Internal determinants encompass socioeconomic conditions, demographic characteristics, leadership qualities, entrepreneurship, focusing events, community attitude and interest, financial capacity, and political support. Horizontally, external actors impose substantive impacts on local environmental policymaking (Kalafatis 2018; Krause et al. 2019; Lubell et al. 2009). For instance, intergovernmental connections, such as geographic proximity and social networks, play an underpinning role in shaping city governments' sustainability and climate protection policies (Brody et al. 2008; Krause 2011; Yi et al. 2017; Yi and Chen 2019). Vertically, monitoring, subsidies, and persuasion from upper-level governments come into play in environmental governance in both federal and authoritarian systems (Feiock and West 1993; Liu et al. 2022). In addition to the aforementioned USA-based empirical research, other studies have also furnished compelling evidence regarding the mechanisms driving environmental policy adoption in European cities (Hakelberg 2014), German municipalities (Schulze 2024), and New Zealand (Bührs 2003).

Two primary arguments have been put forth to explain the environmental governance dynamics. On the one hand, in pursuit of continuous economic growth, governments may loosen the stringency of environmental regulations, thereby sacrificing ecological sustainability and leading to a "race to the bottom" in environmental regulation. Additionally, free-riding on the positive externality of environmental regulation impedes local governments from implementing stringent regulatory measures (Konisky and Woods 2010). On the other hand, "not in my backyard" environmentalism supports the "race to the top" contention, under which governments elevate environmental standards to phase out the outdated, high-polluting industries (Konisky 2006; Potoski 2001). While both arguments offer valuable insights, their explanatory power varies based on political, economic, and institutional contexts. The "race to the bottom" is more prevalent in contexts where local protectionism and fiscal decentralization thrive, whereas the "race to the top" is more likely to occur in jurisdictions with active citizen participation and under stringent national oversight (Engel 1996; Hong et al. 2019; Percival et al. 2021; Zhao and Percival 2017). Empirical evidence points to a mixed and intricate pattern shaped by these two competing forces. A race to the bottom has been corroborated to occur in the short term and under massive industrialization impetus, while a race to the top tends to dominate in the long term, particularly in cities under strong political influence (Rasli et al. 2018; Li and Wu 2017; Sadiqa et al. 2022).

Though scholars have dedicated themselves to uncovering the drivers of adopting environmental policy, few studies attempt to investigate the textual learning process in environmental policy. The textual learning of environmental policy is likely a cognizant and selective process, characterized by both verbatim and partial language copying from a model policy (Baka et al. 2020; Newmark 2002). To further advance environmental policy textual learning, it is essential to consider the multilevel nature of environmental governance. Our intention is to figure out how different levels of local government engage in policy textual learning, particularly in decentralized governance, where local governments take the initiative to draft and implement local environmental laws (Beyer 2006). Furthermore, investigating the flow of policy information both horizontally and vertically can enrich our understanding of the multilevel learning in environmental policies. Besides, we aim to understand whether traditional diffusion mechanisms continue to play a significant role in the multilevel policy diffusion.

Research design and hypotheses

Multilevel environmental governance forms the backbone of sustainability policymaking in numerous countries, such as Germany, Mexico, India, and China, where governments across different layers of government engage in environmental governance (Abel 2021; Jörgensen et al. 2015; Kern 2019; Valenzuela 2014; Yi et al. 2019). Policy diffusion in these systems operates under the influence of both vertical and horizontal forces (Feiock and West 1993; Krause 2011). Horizontal diffusion reflects peer-to-peer learning within the same administrative layer, as governments emulate their counterparts to minimize costs, preserve competitive advantages, and achieve superior goals. Conversely, vertical pressures arise through top-down mechanisms, such as mandates or funding incentives and political support from higher-level governments, or through bottom-up influences, such as grassroots advocacy, snowball upscaling, and local experimentation (Shipan and Volden 2006; Zhang and Zhu 2019). This multilevel learning dynamic,

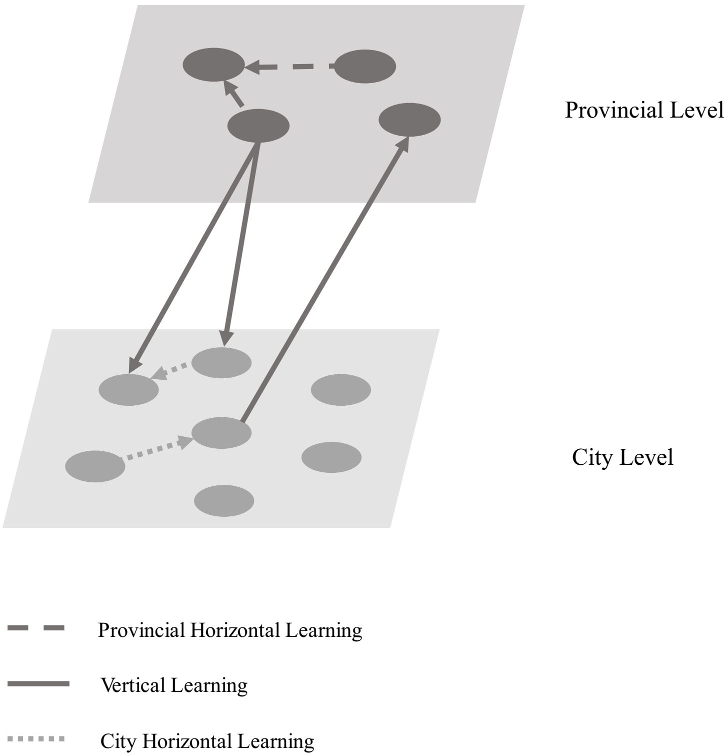

Figure 1. Multilevel policy learning.

illustrated in Figure 1, forms the basis for understanding environmental policy diffusion and learning in the Chinese context.

The Chinese environmental management system is more horizontally based than vertically based, where the local policy actors in environmental policymaking are loosely controlled by the upper-level governments (Kostka and Zhang 2018). Zhao and Percival (2017, p. 535) argue that "compared with the USA, China's system of environmental governance is far more decentralized," implying that Chinese local authorities have great discretion in determining and governing environmental issues, even though they are in theory under the supervision of the upper-level government. Local environmental protection bureaus (EPBs), "from provincial level down to the levels of cities, counties and townships," are the basic, decentralized organs responsible for monitoring emissions, allocating resources, recruiting personnel, and enforcing regulations. The local environmental system has long been castigated as patchy and flawed, failing to establish a robust foundation for regulatory enforcement (Li and Yao 2014). As substantiated, environmental decentralization exacerbates the negative effect of environmental regulation on energy efficiency (Wu et al. 2020).

Despite their theoretical subordination to central agencies like the Ministry of Environmental Protection, local EPBs often prioritize local objectives over national ones, protecting listed enterprises from stringent environmental regulation for the sake of economic growth (Beyer 2006). What is worse, the Chinese centralized political personnel system encourages local officials to engage in economic competition at the same level to triumph in the promotion tournaments, also aggravating local protectionism (Jiuli and Kunwang 2007). To ameliorate this, the Chinese central government expands its clout in fund allocation and inspection (Zhao and Percival 2017). Nevertheless, these top-down efforts rarely undermine local authority in regulating environmental issues (Luo et al. 2019).

Existing studies have substantiated the presence of policy textual learning horizontally in the USA (Hansen and Jansa 2021; Linder et al. 2020). In the decentralized context in China, we contend that this horizontal policy textual learning is likely to be more intense due to virtual rivalry among local governments and the lack of environmental control from above. The policy textual learning from horizontal actors is more pertinent and pivotal for prompt strategic adaptation and adjustment to safeguard local interests and excel in inter-regional contests. In contrast, local actors' motivation to conduct policy textual learning from vertical actors is not as compelling. Hence, we propose the first hypothesis as follows.

Horizontal Learning Hypothesis (H1): Multilevel environmental policy textual learning is more likely to happen horizontally than vertically.

Adjacency is a strong predictor in environmental policy diffusion among horizontal policy actors (Krause 2011; Carley et al. 2017; Yi and Chen 2019). Geographic proximity has been found to facilitate states' constitutional innovation and boilerplate textual learning in agencies' environmental impact statements (Engstrom et al. 2022; Scott et al. 2021). In line with the race-to-the-bottom and race-to-the-top theses, neighboring governments are more likely to prefer similar rather than dissimilar environmental regulation (Hecker et al. 2020; Verdolini and Galeotti 2011). When one government launches lax or strict environmental standards, neighboring governments will follow suit, aiming to mitigate the external negativity of pollution and to enhance competitiveness. This salience of geographic proximity is likely to persist in the multilevel governance context regardless of the administrative level (Fay et al. 2022). Because policy documents provided by neighboring actors are available heuristics to learn from (Berliner 2013; Tversky and Kahneman 1974). Rather than conducting distant policy learning, local actors are likely to learn from adjacent jurisdictions that share similar demographics, socioeconomic status, and resource endowment. Because the nearby policies are more learnable and transferable among jurisdictions where similar contextual factors exist, it lowers the cost to identify successful policy tools and the risk of policy migration. As a result, multilevel policy learning likely exhibits a spatial dependency pattern.

Spatial Isomorphism Hypothesis (H2): Environmental policies are less likely to textually learn from policies introduced by geographically distant governments.

In tandem with the spatial learning hypothesis, the temporal aspect is crucial in multilevel policy textual learning. Policymaking is a historically dependent process, and neglecting time constraints is considered utopian idealism (Friedmann 1967; Simon 1955). Rather than behaving in a random, stochastic, and ahistorical manner, policymaking tend to comply with certain historical antecedents (Howlett and Rayner 2006). Extant theories offer varying understandings of historical change. Path dependency implies the inertial nature of policy change, with strong reliance on what happened in the past. Historical narratives presume the irreversible course of action or causal trajectory along the historical timeline. Howlett and Goetz (2014) argue that time should be recognized as a source of institutions and resources. Subject to tenure limitation, policymakers tend to imitate more recent policies while disregarding the older ones to minimize information-seeking costs.

Historical Continuity Hypothesis (H3): Environmental policy is more likely to textually learn from recent policies than from older policies.

Not solely focusing on the initial proposal of a policy, the focus on environmental policies' postadoption is also crucial (Rai 2020; Rice and Rogers 1980). Environmental policies are amended from time to time to modify measures and regulations in environmental issues (Beyer 2006). The strength of content learning can differ between the initial adoption phase and the post-adoption phase of environmental policy. To accommodate the shift in the social and political environment, the policy amendment takes place as a necessary means to buttress ongoing policy reinvention that does not end with the stage of initial adoption (Glick and Hays 1991; Yu et al. 2020). The initial policy adoption and subsequent policy amendment could be distinguished in the following ways. As revealed by Carley et al. (2017), initial adoption of environmental policy is more amenable to the external environment, while the amendment is heavily influenced by internal factors. The initially crafted policies have a stronger tendency to mimic and borrow from others' policy paradigms rather than building new policies from scratch due to strong normative pressure. In contrast, in the amendment stage, policymakers could contemplate the internal needs and compensate for the defects of the initial adoptions by integrating local circumstances originally neglected.

Initial Learning Hypothesis (H4): Compared to amended versions of policies, the initial versions of environmental policies have a higher tendency to be a result of horizontal learning.

Data and method

To test the hypotheses, we focus on local environmental regulations that deal with urgent environmental problems related to air, water, and resources. All policy data are collected from PKULaw.com, which covers the most comprehensive statutes and regulations by Chinese local legislative organs. Both provincial and municipal people's congresses and the standing committees are authorized to promulgate local environmental regulations as long as they do not violate superior legislation (Ferris and Zhang 2003). The administrative organs, like the Environmental Protection Agency and the Development and Reform Commission, also have the authority to launch environmental regulations. But we did not include them in the analysis because they are considered unofficial legislation. We web-scraped PKULaw in October 2021 and extracted the environmental documents, ending up with policy documents in the forms of measures (*Banfa*), regulations (*Tiaoli, Fagui*), provisions (*Guiding*), and decisions (*Jueding*), which epitomize Chinese environmental regulations (Palmer 1998). For instance, the air pollution prevention and control statutes in Guangzhou, Guizhou, and Guiyang cities use rubrics of *Guiding, Banfa,* and *Tiaoli*. The environmental topics in our dataset cover air pollution protection and control, urban greening, noise pollution prevention and control, water resource management, water resource protection, water saving, wetland protection, and water pollution prevention and control.[1] The focus on different types of policies enables us to test the hypotheses in a broader scope to ensure their generalization.

We resort to a bill pair approach to construct a similarity score as the dependent variable (Kim et al. 2021; Linder et al. 2020; Wilkerson et al. 2015). All the environmental documents are paired in a way that the latter policy is assumed to learn from the old policies released in the preceding years. For instance, a water-saving regulation launched in 2000 could be paired with all other water-saving regulations published in 1999 or before, where the contemporary learning between policies published in the same year is not included to address endogeneity (Desmarais et al. 2015).

In the model shown below, *Similarity Score* of policy documents A and B is the dependent variable, where policy A was adopted by government i in year T, which was later than policy B adopted by government j in year t. Policy document A does have the potential to learn from policy B adopted in the preceding years (t < T). Policy A is the focal policy to learn, and Policy B is the source policy to be learned from.

$$Similarity\ Score_{Doc_{AiT},Doc_{Bjt}} = \alpha_0 + X_{A,B} + C_{A,B} + \varepsilon_{A,B}$$

Similarity Score is constructed by calculating the percentage of clauses in Policy A deemed similar to Policy B. For instance, if 7 out of 10 clauses in Policy A are deemed similar to the clauses in Policy B, then the *Similarity Score* is 0.7. We rely on the bag-of-words approach to calculate the clause pair similarity.[2] As shown in Table A10 in the appendix, the bag-of-words approach's performance related to accuracy and computation time supersedes the text reuse and word vectors. Interested readers can refer to Figure A2 and the appendix for technical details. Figure A3 in the appendix exhibits the histogram of *Similarity Score* across environmental policies, where on average, the *Similarity Score* is 29.15%, as

[1]Following the National Bureau of Statistics' environmental protection classification, we identified policies within each category. Documents were then screened based on sample size. Regulations on drainage management, mountain protection, environmental impact assessment, dust pollution prevention and control, and soil pollution were excluded due to low diffusion rate with insufficient number of documents ($n < 30$ for each category). Waste management was also excluded due to its heterogeneous focuses on domestic, rural, and construction wastes.

[2]Clause pairs with similarity above 0.5 are deemed similar, while below 0.5 is deem dissimilar. We chose this threshold based on practical observations, as it effectively distinguished between similarity and dissimilarity and aligned with intuition. As we provide true examples for clause comparison in Figures A1–1 and A1–2 in the appendix, showing that the similarity threshold set with a .5 threshold is intuitive. To avoid arbitrariness, we also include another dependent variable by averaging the clause pair similarity between two policy documents without using a cutoff point. The results are presented in Table A5 in the appendix, showing no significant discrepancies compared to the findings in Table 1.

indicated in Table A2 in the appendix. For different environmental issues, the distribution of *Similarity Score* displays differentiated tendencies toward textual learning across seven kinds of environmental policies, where the mean of *Similarity Score* is lower in air pollution and water pollution, but is highest in wetland.

In the model specification, variable vector $\mathcal{X}_{A,B}$ denotes variables that test the hypotheses. To test the 1st hypothesis, *Horizontal Learning* is constructed as a binary variable, which is coded as 1 when policy A and policy B are adopted at the same level, that is, both adopted by cities or by provinces; it is coded as 0, if policy A and policy B are not adopted in the same level. Turning to the 2nd hypothesis, *Spatial Distance* is coded as the geographic distance (in 1,000 km) between the governments issuing policy A and policy B. To test the 3rd hypothesis, *Temporal Distance* is coded as the publication year difference between policy A and policy B by deducting the year of publication of policy B from policy A's. In relation to the 4th hypothesis, *Initial Learning* is measured as a binary variable to capture whether policy A and policy B are the first-ever adopted environmental policies in their jurisdictions. If neither policy A nor policy B is the initially adopted policy, then *Initial Learning* is coded as 0.

In terms of control variables, we include a batch of covariates to account for the confounders at the policy levels and location levels. To capture the bureaucratic professionalism, *Similar Judiciary System* is included, coded as 1 if policy B's and policy A's issuing governments have a similar judiciary system, either with or without specialized collegial panels for environmental protection trials. *City Learner* is coded as 1 whenever policy A is adopted at the city level, otherwise 0. As a reflection of self-perpetuation and self-reinforcement (Howlett and Cashore 2007), we include *Self-Learning* as a control variable, coded as 1 if policy A and policy B are adopted by the same government, otherwise 0. Because environmental protection has long given way to economic development in Chinese local governments, which are propelled by promotion tournaments and yardstick competitions. We include *Foreign Investment* to capture the absolute difference in foreign investment in governments issuing policy A and policy B. To exclude potential socioeconomic confounding factors, we also include variables of *Population Difference, Birthrate Difference,* and *Secondary Industry Difference* to account for the disparity between policy A's and policy B's local socioeconomic factors, which might affect the similarity of environmental policies.

Besides, the model also includes location dummies to account for the time-invariant factors in government i. For instance, governments' legislative tradition could potentially be stable and influence policy formulation. By the same token, the sourced policies' governments could also enjoy some characteristics that make them more popular to be learned, such as prestige for environmental protection. Hence, we include location dummies of government j to exclude the confounding factors. We also include year dummies of policy A to remove the possibility that learning capacity would be different across time. We estimate the coefficients with Ordinary Least Squares (OLS) and multilevel modeling, which have been applied in the text similarity literature (Düpont and Rachuj 2022; Engstrom et al. 2022). All variables' sources, descriptive statistics, and correlation are provided in the appendix Tables A1–A3.

Results

Tables 1 and 2, respectively, present the results of OLS linear regression and multilevel linear regression.[3] The coefficients estimated are quite close across OLS and multilevel regressions, where the level of significance is more conservative in the multilevel linear estimates. For the first hypothesis, *Horizontal Learning* is found to be a significant and positive predictor across different environmental policies, with the only exception being the noise pollution policy, with an insignificant coefficient. On average, the environmental policies' similarity score at the same level would increase by 2.134 percentage points, as shown in Model 1 in Table 1. Considering *Horizontal Learning*'s consistent and substantive impact on six out of seven environmental policies, the first hypothesis is corroborated.

Moving on to the second hypothesis, the negative coefficient of *Spatial Distance* is observed in some environmental policies, including air pollution, greening, noise pollution, and water pollution, as shown in Table 1. However, its coefficient is not significant in water resource, water saving, and wetland policies. After including a random intercept at the dyad level in the multilevel models in Table 2, the *Spatial Distance* does not make a difference for the remaining dyadic variances, making the coefficients less significant. The possible explanation is that geographic imitation is more common at the horizontal level, as argued by the policy diffusion literature (Berry 1994). We test whether the spatial distance is more important at the horizontal level in Appendix Table A6, but we fail to find the contingent effect of horizontal learning on the impact of spatial distance. Nearly half of environmental policies do not rely on geographic connections to conduct policy learning. The empirical results only partially support the second hypothesis that spatially proximate policies are more similar.

Turning to the third hypothesis, we could find that *Temporal Distance* has negative and significant coefficients across all environmental policies, with no significant impact on noise pollution policy. It substantiates the third hypothesis that more temporally distant policies have less textual commonality. Turning to the fourth hypothesis, the influence of *Initial Learning*, the positive coefficients of *Initial Learning* are detected in three out of seven environmental policies, including air pollution, greening, and wetland. It indicates that these three policies have higher similarity scores with the policies that were initially adopted locally. However, the effect of *Initial Learning* is unexpectedly negative in water resource policy.

Overall, we contend that the first and the third hypotheses are supported, and the second and the fourth hypotheses are partially supported, as summarized in Table 3. The results might partially be explained by the distinctive characteristics pertinent to the environmental domains. For instance, the noise pollution showcases a different policy learning mode, which might be attributed to the nature of the noise pollution that generally emerges and resolves internally with less reliance on external resources or measures to settle.

In terms of the control variables, *Self-Learning* exerts the largest impact on environmental policy similarity. Consistent with our hypothesis, self-learning has

[3]We place all the variables into the models to keep the results more succinct across different environmental policies. The models testing the bivariate effect of a single predictor are presented in appendix Tables A4–1–A4–4, with no alarming difference from the multivariate models.

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Table 1. OLS linear regression of policy learning

	Dependent variable: Similarity Score							
	Overall	Air pollution	Green space	Noise pollution	Water resource	Water saving	Wetland	Water pollution
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Horizontal learning	2.214***	1.441***	4.486***	−1.053	2.271***	3.113***	1.878***	1.930***
	(0.167)	(0.298)	(0.461)	(1.017)	(0.394)	(0.456)	(0.377)	(0.485)
Spatial distance	−1.064***	−0.532**	−1.926***	−1.145**	−0.205	−0.375	−0.399	−0.981***
	(0.119)	(0.251)	(0.178)	(0.545)	(0.292)	(0.273)	(0.256)	(0.300)
Temporal distance	−0.970***	−0.889***	−0.703***	−0.021	−0.311***	−0.837***	−1.002***	−1.189***
	(0.014)	(0.033)	(0.025)	(0.119)	(0.062)	(0.072)	(0.119)	(0.043)
Initial learning	1.800***	1.693***	2.444***	−0.266	−2.365***	1.163*	3.915***	−0.318
	(0.195)	(0.374)	(0.316)	(1.387)	(0.747)	(0.655)	(0.777)	(0.623)
Similar judiciary system	0.021	0.185	0.599***	−0.481	−0.083	−0.154	−0.072	0.017
	(0.161)	(0.241)	(0.218)	(1.024)	(0.619)	(0.531)	(0.402)	(0.386)
City learner	7.182***	−4.414**	−9.457***	15.915***	31.781***	8.803***	−4.435	−5.516**
	(1.821)	(1.744)	(1.975)	(3.295)	(3.099)	(2.079)	(7.305)	(2.808)
Self-learning	36.004***	34.576***	37.472***	55.481***	35.771***	48.887***	24.957***	24.133***
	(0.538)	(1.157)	(0.839)	(2.010)	(1.300)	(1.421)	(1.645)	(0.952)
Foreign investment difference	0.088***	−0.539***	0.257***	0.566	−0.168	−0.059	−0.132	−0.195***
	(0.029)	(0.111)	(0.063)	(0.421)	(0.122)	(0.121)	(0.112)	(0.049)
Population difference	−0.067	2.920***	0.824***	1.938***	0.703***	−1.961***	2.277	−0.378
	(0.078)	(0.371)	(0.313)	(0.597)	(0.095)	(0.494)	(3.336)	(0.399)
Birthrate difference	−0.052**	−0.521***	0.010	0.620***	−0.106	−0.096	−0.174	−0.033
	(0.021)	(0.059)	(0.033)	(0.230)	(0.085)	(0.118)	(0.209)	(0.062)
Secondary industry difference	−0.070***	−0.258***	0.005	0.165	−0.101***	−0.101***	0.200***	−0.080***
	(0.010)	(0.026)	(0.014)	(0.102)	(0.035)	(0.034)	(0.066)	(0.029)
Constant	31.509***	43.106***	57.981***	32.006**	−9.892	14.786***	80.923***	28.806***
	(3.942)	(6.688)	(5.148)	(12.829)	(6.110)	(5.689)	(7.646)	(3.650)
Learner location dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Learner year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Source location dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Policy fixed effects	Yes	N/A	N/A	N/A	N/A	N/A	N/A	N/A

(*Continued*)

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Table 1. (*Continued*)

	Dependent variable: Similarity Score							
	Overall	Air pollution	Green space	Noise pollution	Water resource	Water saving	Wetland	Water pollution
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Observations	30,715	6,179	11,797	710	2,894	3,438	1,832	3,865
R2	0.642	0.659	0.590	0.751	0.708	0.654	0.835	0.601
Adjusted R2	0.638	0.649	0.583	0.728	0.697	0.641	0.825	0.591
Residual std. error	11.107	8.426	9.166	9.328	9.532	10.201	6.813	9.310
F Statistic	163.599***	67.752***	88.303***	33.142***	66.375***	52.651***	81.493***	58.003***

Note: *p $<$ 0.1; **p $<$ 0.05; ***p $<$ 0.01.
Standard Error in the parentheses.

Table 2. Multilevel linear regression of policy learning

	Dependent variable: Similarity Score							
	Overall	Air pollution	Greening	Noise pollution	Water resource	Water saving	Wetland	Water pollution
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Horizontal learning	2.257***	1.474***	3.704***	−2.520**	2.732***	3.745***	1.983***	1.964***
	(0.167)	(0.305)	(0.469)	(0.902)	(0.443)	(0.455)	(0.376)	(0.480)
Spatial distance	−0.914***	−0.279	−1.474***	−0.408	−0.361	−0.782	−0.430	−0.773*
	(0.191)	(0.304)	(0.287)	(0.833)	(0.439)	(0.428)	(0.303)	(0.369)
Temporal distance	−0.960***	−1.032***	−0.723***	−0.225**	−0.321***	−0.746***	−1.074***	−1.171***
	(0.013)	(0.026)	(0.020)	(0.087)	(0.057)	(0.050)	(0.076)	(0.035)
Initial learning	1.751***	1.465***	2.437***	−0.748	−2.289**	0.976	3.808***	−0.112
	(0.191)	(0.353)	(0.298)	(1.152)	(0.704)	(0.597)	(0.709)	(0.602)
Similar judiciary	−0.022	0.248	0.415	0.153	−0.194	−0.096	−0.177	0.232
System	(0.166)	(0.258)	(0.218)	(1.039)	(0.653)	(0.531)	(0.399)	(0.423)
City learner	0.431	−0.400	−7.776**	4.923	4.389	4.858	−8.148*	3.825**

(*Continued*)

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Table 2. (*Continued*)

	Dependent variable: Similarity Score							
	Overall	Air pollution	Greening	Noise pollution	Water resource	Water saving	Wetland	Water pollution
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	(1.505)	(1.432)	(2.376)	(3.173)	(4.514)	(3.357)	(3.503)	(1.253)
Self-learning	32.249***	32.868***	32.187***	60.664***	35.801***	46.557***	25.258***	26.121***
	(0.604)	(1.188)	(0.873)	(2.185)	(1.507)	(1.679)	(1.774)	(1.108)
Foreign investment	0.101***	−0.349**	0.272***	−0.235	−0.308**	0.101	−0.117	−0.166***
Difference	(0.029)	(0.110)	(0.060)	(0.376)	(0.116)	(0.112)	(0.107)	(0.046)
Population difference	−0.023	0.262	0.429**	1.321***	0.640***	−0.857***	−0.330	0.077
	(0.064)	(0.150)	(0.151)	(0.345)	(0.083)	(0.236)	(0.298)	(0.091)
Birthrate difference	−0.049*	−0.366***	0.014	0.357*	−0.083	−0.211**	0.074	−0.014
	(0.020)	(0.051)	(0.030)	(0.156)	(0.077)	(0.081)	(0.105)	(0.052)
Secondary industry difference	−0.067***	−0.140***	0.002	0.035	−0.093**	−0.074**	0.134**	−0.061*
	(0.009)	(0.022)	(0.013)	(0.070)	(0.031)	(0.029)	(0.049)	(0.025)
Intercept	25.191***	32.597***	47.070***	28.713***	27.995***	25.562***	57.531***	33.328***
	(2.609)	(6.182)	(3.611)	(6.571)	(5.135)	(5.684)	(12.237)	(3.690)
AIC	235663.555	44342.749	85636.886	5121.015	21405.020	25756.022	12523.648	28367.567
Observations	30,715	6179	11,797	710	2894	3438	1832	3865
N – Dyad ID	889	608	560	165	452	530	616	512
N – Learner location	152	76	81	19	36	44	47	34
N – Source location	143	67	78	18	37	43	41	33
$\sigma^2_{\text{Dyad ID}}$	7.738	5.091	11.968	43.384	16.815	27.390	8.029	6.384
$\sigma^2_{\text{Learner Location}}$	52.751	23.629	31.479	21.655	130.156	89.866	131.669	9.153
$\sigma^2_{\text{Source Location}}$	36.952	49.366	41.676	55.780	81.967	26.487	58.866	45.801
$\sigma^2_{\text{Residual}}$	118.029	67.976	74.971	55.568	77.516	83.967	38.875	81.271

Note: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.
Standard Error in the Parentheses.

Table 3. Summary of hypothesis testing outcomes

Hypothesis	Supported environmental domains	Hypothesis testing
Horizontal learning (H1)	Air pollution, green space, water resource, water saving, wetland, water pollution	Supported
Spatial distance (H2)	Air pollution, green space, noise pollution, water pollution	Partially supported
Temporal distance (H3)	Air pollution, green space, water resource, water saving, wetland, water pollution	Supported
Initial learning (H4)	Air pollution, green space, water resource, wetland	Partially supported

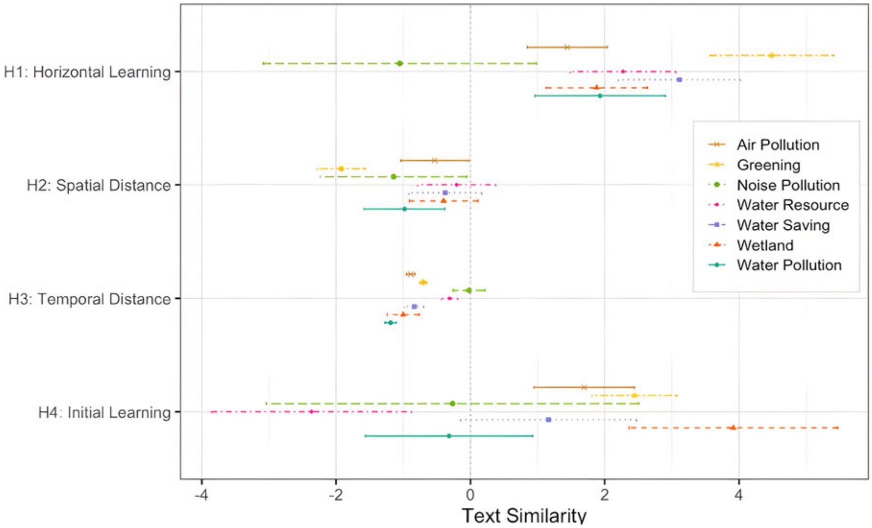

Figure 2. Estimates overview of textual learning hypotheses.

substantial explanatory power over the textual learning of environmental policies, which are historically dependent and self-bounded without noticeable deviation from the past (Cashore and Howlett 2007). Regarding the demographic factors, *Population Difference* has a significant and positive coefficient in some environmental domains, indicating that the local governments are more likely to learn from populous governments. The model results from Table 1 are visualized in Figure 2 for a clear overview of the estimates of four hypotheses across seven environmental policies.

Discussion

Text analysis offers a new avenue for examining the textual learning of environmental policies issued by governments across different layers. We put forward four tentative hypotheses to test the strength of textual learning in environmental statutory policies. In this section, we seek to converse with the

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literature on textual similarity, policy diffusion, and environmental policy to further discuss the results, illuminate the theoretical and empirical contributions, and point out the limitations and directions for future studies.

Traditional policy diffusion studies have provided fruitful evidence of policy diffusion across jurisdictions horizontally, which could be driven by a wide range of well-recognized forces like normative factors and institutional pressures (Berry and Berry 1990; Volden 2006). In a wide range of environmental domains, we further substantiate that policy textual learning is stronger horizontally than vertically. It implies that local governments are more likely to learn from their peers than from upper-level or lower-level governments. Given that the Chinese multilevel environmental system is rather decentralized, this finding might be generalizable to contexts featuring environmental decentralization, where local governments at the same level might have stronger motivation to vie against one another to compete in economic growth (Luo et al. 2019).

Also, as a direct examination of the traditional diffusion mechanisms, our second hypothesis tests the influence of geographic distance on textual learning strength. Unexpectedly, the geographic hypothesis only stands in specific environmental policies like greening and water pollution, with no positive influence on textual learning over other environmental policies. The following findings potentially speak to the idiosyncrasy of the geographic hypothesis. Environmental policy diffusion studies have found that the inter-governmental relationship goes beyond the geographic boundary, shaped by the forces of interest groups, social media, and formal and informal networking (Baka et al. 2020; Carley and Nicholson-Crotty 2018; Yi et al. 2019). The interaction between *Horizontal Learning* and *Spatial Distance*, shown in Table A6 in the appendix, does not offer extra explanations for the insignificance of the geographic proximity in some environmental spheres. As such, this interaction signifies that the invalidity of the geographic factor is not contingent upon horizontal or vertical diffusion channels. It parallels the findings in a systematic review of policy diffusion that regulatory policy diffusion does not strongly depend on neighbors' adoption of policies (Mallinson 2020). In this regard, future studies are suggested to explore how networking that goes beyond the local geographic constraint connects governments in the multilayered governance structure that affects policy textual learning.

Echoing other research, the negative effect of temporal distance has also been substantiated in other circumstances, such as the textual learning in state constitutions across the American states (Engstrom et al. 2022) and boilerplate language reuse (Peacock et al. 2019; Scott et al. 2021). It implies that future policy textual learning studies should integrate the effect of temporal distance, considering its significance across various kinds of circumstances. Resonating with the adoption and reinvention literature (Carley et al. 2017), our study does confirm the difference between the initial adopted policy and the later adopted policy in policy textual learning, where the former has a higher tendency for learning than the latter, as shown in Table 1.

The tendency to learn among initial adopters might be moderated by the temporality. According to the negative sign of the interaction effect in Table A7 in the appendix, the initially adopted environmental policies have less tendency to learn from one another if they were issued by geographically distant jurisdictions.

However, the impact of *Initial Learning* is not moderated by the *Spatial Distance*, with no significant interaction of these two terms as indicated in Table A8 in the appendix. Suspecting the effect of *Spatial Distance* might be moderated by the bureaucratic professionalism, we interact it with *Similar Judiciary System* in Table A9. However, no significant interaction effect is found. It again alludes to the insignificance of the geographic distance, a fundamental factor in the policy diffusion theory. This finding is in line with observations from some environmental policy diffusion studies that geographic proximity is not able to account for the full range of relationships between governments (Baka et al. 2020; Carley and Nicholson-Crotty 2018). Future studies could explore how formal and informal networking, beyond the geographic boundary, influences policy textual learning across jurisdictions.

By employing the method of textual analysis, we rely on policy clauses as the basic unit to construct the similarity score between policy documents. Granted that the textual analysis provides a new angle to examine the policy diffusion and transfer process, we should continue to test its validity in other types of policy documents (Hinkle 2015; Linder et al. 2020), such as local action initiatives that might contain more localized and idiosyncratic content.

Conclusion

Based on our analysis of Chinese environmental policies, we find that horizontal textual learning is more prominent than vertical learning across various environmental domains, which may be attributed to the decentralized nature of China's environmental governance system. While geographic proximity, a traditional driver of policy diffusion, only shows significance in specific areas like greening and water pollution policies, temporal distance consistently demonstrates a negative effect on textual learning. These findings suggest that environmental policy learning is more complex than what conventional diffusion theories might suggest, particularly in contexts characterized by decentralized environmental management and inter-jurisdictional competition. The applicability of these results may extend to governance systems that share similar institutional characteristics, especially in areas where local governments operate with considerable autonomy in environmental governance.

It is important to note that different institutional contexts may yield varying patterns of textual learning. Different from the decentralization in the Chinese environmental management system, a centralized regulatory system might take other forms of policy textual learning. An active civil society might give rise to other types of textual learning, such as the bottom-up or top-down policy transfers. Moreover, future studies are needed to test whether textual learning holds in other policy domains, like food safety and social regulation, to reveal additional features of textual learning.

Despite these insights, a limitation of existing policy diffusion literature, including our own, lies in the lack of a strict distinction between policy document types. Potentially, different document types may possess varying degrees of legal binding power and enforcement consequences, which could significantly impact policy learning. Hence, future studies could dive into this stream of research to further enrich the understanding of policy textual learning.

Textual similarity approach enables a more fine-grained approach to capturing policy learning across policy documents. It expands the analytical boundary of policy diffusion studies from focusing on institutions to revealing the policy document changes in language, style, and content in a more nuanced manner. Taking advantage of the current boom in natural language processing, policy diffusion research might prosper with research tools helping detect real-time policy change with higher efficiency and more accuracy. We still have many intriguing research questions that remain unanswered in this domain, providing great opportunities for future studies.

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Data availability statement. Replication materials are available in the Journal of Public Policy Dataverse at https://doi.org/10.7910/DVN/W8OP2J.

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Wenna Chen is an assistant professor at the Department of Public Administration, School of Government, Sun Yat-Sen University. Her research focuses on public sector innovation, policy diffusion, leadership turnover and mobility, integrated studies, collaborative governance, and citizen satisfaction.

Li Liao is a research fellow at the School of Public Administration, Southwest Jiaotong University. His research focuses on bureaucratic control and the application of natural language processing techniques to the study of the policy process.

Hongtao Yi is a Professor and Reubin O'D. Askew Eminent Scholar Chair at the Askew School of Public Administration and Policy, Florida State University. His work focuses on the intersection of public administration, public policy, and energy and environment, with a research agenda on the role of networks as a governance mechanism and an empirical approach. He currently serves as Editor of *Public Administration Review*.

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