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Economic Policy Uncertainty and Environmental Inequality: Effects and Mechanisms

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Abstract

This study examines how Economic Policy Uncertainty (EPU) shapes disparities in air pollution exposure across individuals with different levels of education. Using a shift–share instrumental variable based on world import demand to predict provincial EPU fluctuations, we construct an individual-level panel dataset linking personal exposure to EPU and SO_2 concentration across six survey waves from 2000 to 2015. The results indicate that a 1% increase in the EPU index leads to an average rise of approximately $1.15\mu g/m^3$ in SO_2 exposure among individuals without a high school degree, relative to those with one. Mechanism analyses suggest that this effect operates mainly through two channels: changes in government regulatory behavior and in firm-level emission decisions.

Keywords: Economic Policy Uncertainty; Environmental Inequality; Government Regulation; Firm Emission Decisions
JEL Codes: D63 D81 Q53

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1 Introduction

In response to mounting environmental challenges, many countries have introduced various measures to curb pollution. Despite these efforts, the unequal distribution of pollution persists, particularly among demographic groups differentiated byrace, income, and educational attainment. For example, in the U.S., Black individuals are disproportionately exposed to higher levels of air pollution compared with White individuals (Tessum et al., 2019). In China, urban workers holding rural household registration status tend to experience heightened exposure to environmental pollution (Schoolman and Ma, 2012). While these studies have advanced our understanding of environmental inequality, relatively little attention has been paid to frequent economic policy changes—a global phenomenon that may significantly influence disparities in pollution exposure.

Concerns about policy uncertainty have escalated since the global financial crisis of 2008, which triggered the frequent implementation of economic stimulus policies. Against this backdrop, the concept of Economic Policy Uncertainty (EPU) was developed to capture fluctuations in uncertainty regarding economic policy (Baker et al., 2016). Because uncertainty can shape expectations and decision environments, economic agents may respond differently to comparable levels of EPU depending on their adaptive capacity and institutional context. Moreover, heterogeneous responses arrise at the macroeconomic, firm, and individual levels, reflecting adjustments in performance, decision-making, and behavior (Karnizova and Li, 2014; Caggiano et al., 2017; Drobetz et al., 2018; Handley and Limão, 2015; Coibion et al., 2024). These behavioral patterns, in turn, represent key causal mechanisms identified in the environmental inequality literature (Banzhaf et al., 2019). Within this context, this study investigates how instability in economic policy contributes to environmental inequality, focusing on both the extent and the mechanisms through which EPU leads to unequal exposure to air pollution.

China provides an ideal setting for examining these research questions. Unlike in many developed countries, where lower-income or minority communities face greater exposure to pollution, in China air pollution is disproportionately concentrated in wealthier and more industrialized regions (Ma, 2010; Wolverton, 2009). This pattern reflects a trade-off between economic growth and environmental quality: industrial prosperity has come at the cost of air quality, while less developed areas experience lower exposure despite weaker economic conditions. Such dynamics suggest that China is undergoing a transitional stage in which the spatial and social distribution of pollution is still evolving, rather than reflecting entrenched disparities. Because this spatial configuration continues to shift with changes in economic activity and environmental governance, China offers a valuable context for exploring how economic policy uncertainty affects the emergence and transformation of environmental inequality.

Using China as a case study, we examine the effect of EPU on differential exposure to SO_2 concentration between individuals with and without a high school education. To this end, we compile a unique six-wave longitudinal dataset that links individual respondents' information with city-level SO_2 exposure and provincial measures of EPU from 2000 to 2015. This design enables a detailed examination of how macro-level uncertainty translates into disparities in micro-level environmental exposure. Furthermore, to uncover the pathways through which EPU affects environmental inequality, we explore several potential mechanisms suggested by prior research—specifically, changes in government regulatory behavior, firm emission reductions, and individual migration responses.

Two potential endogeneity issues may affect our analysis. The first involves bidirectional causality between EPU and personal environmental exposure. Specifically, rising inequality in pollution exposure may prompt governments to introduce compensatory or redistributive economic policies, which in turn could influence the level of EPU. The second concern relates to omitted variables. Over the past two decades, China has implemented numerous environmental and economic policies that vary spatially across regions (Wang and Yang, 2025). Because these policies are heterogeneous across space, they may simultaneously affect both regional EPU and pollution exposure. If such policy variation is not adequately controlled for, our estimates may conflate the independent effect of EPU with that of concurrent policy activities.

To address these challenges, we construct a province-level shift-share instrumental variable (IV) for EPU based on world import demand. Specifically, we compute global import demand by industry and weight it by each province's initial employment structure in 1990, capturing how differences in industrial composition determine each province's exposure to time-varying global import demand. When aggregating global import demand, we exclude trade flows involving China to prevent mechanical correlation with domestic activity. The identification assumption is that external variation in world import demand can serve as a predictor of similar trends in China's domestic economy, thereby correlating with domestic EPU, but remains orthogonal to regional disparities in pollution exposure—thus satisfying the exclusion restriction.

We find that increases in EPU widens the exposure gap to air pollution between individuals with and without a high school education. In particular, compared with those with a high school degree, a 1% rise in EPU index leads to an approximately $1.15ug/m^3$ relative increase in SO_2 exposure for individuals without a high school degree. We also conduct falsification tests to validate the exogeneity of industry-level global import demand (the shifter component) and perform additional robustness checks, including controlling for concurrent economic and environmental policies, to confirm the stability of our IV estimates. We then examine the mechanisms through which EPU affects environmental inequality, focusing on three channels: government regulation, firm emissions, and individual migration. The results indicate that higher EPU tends to weaken the stringency of environmental regulation. When cities face elevated levels of EPU, their SO_2 emissions per unit of output rise, as captured by the residual-based indicator of regulatory looseness that isolates the policy-driven component of environmental regulation after removing variation attributable to economic structure and technological capacity. Moreover, firms—particularly those located in counties with a higher concentration of individuals without a high school degree—are more likely to increase emissions under heightened uncertainty. In contrast, we find no statistically significant effect of EPU on individual migration, suggesting that population mobility does not serve as an active adjustment channel in this context.

This paper contributes to the literature in two main ways. First, we extend prior research on the consequences of EPU. Although earlier studies document the positive association between EPU and pollutant emissions, they largely overlook the distributional implications of this relationship. We address this gap by examining how variations in provincial-level EPU in China affect disparities in pollution exposure based on educational attainment. Second, we contribute to the growing literature on the determinants of environmental inequality. Building on existing frameworks that emphasize firm siting decisions, household mobility, and discriminatory governance practices, we provide novel evidence that instability in economic policy can also serve as a significant driver of environmental inequality. Together, these contributions broaden our understanding of how macroeconomic uncertainty interacts with individual and regional heterogeneity to shape the unequal environmental outcomes.

The reminder of the paper is structured as follows. Section 2 reviews the related literature and presents the research hypotheses. Section 3 describes the data, empirical models, and descriptive patterns. Section 4 reports the baseline results, and Section 5 discusses the underlying mechanisms. Section 6 concludes.

2 Literature Review and Hypotheses

2.1 Literature Review

This paper relates to three strands of literature. First, a strand of research on EPU focuses on two aspects central to this study: how EPU is measured and how it affects environmental outcomes. EPU refers to uncertainty about future changes in key economic policies, including monetary, fiscal, and regulatory policies (Baker et al., 2016). To quantify EPU, Baker et al. (2016) develop a newspaper-based index that tracks the frequency of policy-related economic uncertainty in leading newspapers. This approach has since been applied to construct EPU indices for a wide range of countries. While effective at capturing national-level fluctuations, this approach does not account for potential regional variation in policy uncertainty within countries. Building on this method, Yu et al. (2021) construct a provincial-level EPU index for China using local newspaper data, allowing for analysis of the regional effects of EPU.

With consistent measures of EPU available across countries and regions, a growing body of research examines its environmental consequences. Empirical evidence consistently suggests that higher levels of EPU are associated with worse environmental outcomes. For example, Jun et al. (2023) find that higher EPU raises firm emissions in China. Similarly, Cui et al. (2023) show that EPU lowers green innovation, while Hailemariam et al. (2019a) find that it reduces investment in renewable energy. Together, these studies suggest that EPU might contribute to environmental degradation by hindering environmental progress and slowing the transition toward cleaner production. However, the literature on the environmental effects of EPU pays little attention to its distributional consequences—especially regarding who bears the environmental burden it amplifies. This omission is critical because an overall increase in pollutant emissions does not necessarily translate into uniform exposure across regions or population groups. Moreover, addressing this issue calls for insights from the broader literature on environmental inequality, which examines how pollution exposure varies across populations with different socioeconomic characteristics.

The second strand of literature relates to mechanisms of environmental inequality. Following extensive research showing that low-income and/or racial minorities are disproportionately exposed to pollutants (Hamilton, 1995a; Mohai et al., 2009), many scholars have focused on the possible mechanisms underlying these patterns: firm-level siting, household-level mobility, and government-level discriminatory governance. As the primary sources of pollution, firms may locate polluting activities based on local economic conditions that align with demographic patterns (Wolverton, 2009) or the stringency of environmental regulations (Chen et al., 2018). Meanwhile, individuals or households exposed to pollution may relocate according to their environmental preferences (Depro et al., 2015; Gao et al., 2023). Environmental policies also shape the distribution of pollution through regulation, monitoring, and enforcement (Hernandez-Cortes and Meng, 2023; Currie et al., 2023), as these efforts to control pollution prompt responses from firms and individuals. While prior studies emphasize firm siting, household migration, and regulatory enforcement as key mechanisms, few have explored how macroeconomic uncertainty might interact with these processes. This paper contributes to this literature by investigating whether higher levels of EPU intensify environmental inequality and through which channels this effect operates.

Third, although environmental inequality has been extensively studied in developed countries (Daniels and Friedman, 1999; Hamilton, 1995b; Mohai and Saha, 2006; Banzhaf et al., 2019), evidence from developing economies remains limited, despite their often more severe pollution levels. Moreover, the sources and patterns of environmental inequality in developing contexts may differ from those in advanced economies. For example, in China, the Han population constitutes about 91% of the total population,[1] making it less appropriate to analyze environmental inequality primarily through an ethnic or racial lens. Several studies explain the environmental inequality in China through the household registration system, migration, and geographical differences (Liu, 2005; Ma, 2010; Schoolman and Ma, 2012; Wu et al., 2017). These studies collectively underscore that environmental outcomes in China are deeply intertwined with institutional, spatial, and individual characteristics. Yet, the Chinese context also presents a distinct institutional and developmental setting where frequent economic policy adjustments and spatially uneven growth policies may interact with behavioral responses in distinctive ways. Examining China therefore provides an opportunity to understand how macroeconomic uncertainty may reshape environmental inequality.

Taken together, while previous studies have examined how EPU influences pollutant emissions and how pollution is unequally distributed, few have integrated these two strands of research. Little is known about whether and how EPU contributes to environmental inequality, especially in developing economies like China. This study addresses this gap by investigating the distributional consequences of EPU-induced pollution in the context of China.

[1] Data from the Seventh National Population Census of China, 2020.

2.2 Research Hypothesis

Drawing on prior studies, heightened EPU has been shown to increase aggregate pollution levels (Jun et al., 2023), yet the distributional consequences of such pollution surges remain underexplored. Previous research suggests that environmental inequality can arise through three key mechanisms: uneven reguratoly enforcement, firm siting decisions, and household mobility(Banzhaf et al., 2019). Building on these insights, we posit that elevated EPU disproportionately burdens individuals with lower educational attainment through three interconnected channels. First, local governments experiencing fiscal or economic stress during periods of heightened EPU may respond by relaxing environmental enforcement or assigning less stringent abatement targets (List and Sturm, 2006; Kahn and Mansur, 2013). Second, firms confronted with heightened uncertainty may expand polluting activities in areas where public opposition is weaker and regulatory oversight is less stringent—conditions often associated with counties that have lower income and education levels (Wolverton, 2009; Chen et al., 2018). Third, households with higher socioeconomic status possess greater mobility and resources to avoid deteriorating environmental conditions, while less-educated individuals are more likely to remain in highly polluted areas due to financial or informational constraints (Depro et al., 2015; Gao et al., 2023). Together, these mechanisms suggest that EPU exacerbates environmental inequality by concentrating pollution burdens on more vulnerable groups.

Hypothesis 1 (Main Hypothesis): Higher levels of EPU are associated with greater increases in pollution exposure among individuals without a high school degree compared with those holding a high school degree.

Hypothesis 2 (Government Regulation Channel): Higher EPU weakens the stringency of environmental regulation, leading to greater regulatory slack in pollution control.

Hypothesis 3 (Firm Emission Channel): Higher EPU induces firms to increase emissions, with stronger effects in counties where low-education populations are more concentrated due to weaker public oversight and regulatory enforcement.

Hypothesis 4 (Individual Migration Channel): Higher EPU amplifies spatial disparities in pollution exposure by constraining the mobility of less-educated individuals and facilitating migration among more-educated populations.

3 Data and Methodology

3.1 Data

The data used in this study were obtained from three primary sources: (i) individual-level data from the China Health and Nutrition Survey (CHNS); (ii) the province-level EPU index for China, as constructed by Yu et al. (2021); and (iii) city-level SO_2 concentration data aggregated from National Aeronautics and Space Administration (NASA) satellite observations.

We use individual-level longitudinal data from the China Health and Nutrition Survey (CHNS), jointly conducted by the University of North Carolina at Chapel Hill and the Chinese Center for Disease Control and Prevention. The survey comprises ten waves collected between 1989 and 2015,[2] tracking households and individuals over time for longitudinal analysis. It employs a multistage, random cluster sampling method to select approximately 7,200 households, representing more than 30,000 individuals across 15 provinces with diverse geography, economic development, and public resources. The survey collects detailed individual-level information, including gender, age, and education attainment. Our analysis focuses on the period from 2000 to 2015 for two reasons. First, the provincial-level EPU is only available for this period. Second, from 2000 onward, the CHNS sample frame became more stable in terms of provincial coverage, with fewer changes compared to the earlier waves.[3] This stability enhances comparability across survey waves. We restrict the sample to individuals aged 18 to 60 and exclude observations with missing baseline education data.

The province-level EPU index for China is sourced from Yu et al. (2021). It is constructed using keyword searches related to economic policy and uncertainty in articles from local newspapers of each province.[4] A news article is classified as relevant if it contains at least one economic policy keyword and at least one uncertainty keyword. The annual total number of relevant articles is then divided by the total number of articles containing

[2]The ten survey waves were conducted in the 1989, 1991, 1993, 1997, 2000, 2004, 2006, 2009, 2011, and 2015.

[3]Liaoning province re-joined in 2000, and the sample composition largely remained consistent thereafter, except for the addition of three municipalities in 2011.

[4]Economic policy keywords include economy, promote/stimulate/expand consumption, adjust interest rates, expand/reduce investment, increase/reduce tax, tax policy, fiscal and tax reform, fiscal expenditure/system/stimulus, currency/monetary policy, export expansion, value-added/consumption/corporate income/personal income/property tax, tariff, transfer payments, local debt, pensions, policy pilots, strengthening supervision. Uncertainty keywords include uncertain, forcast, expected, pilot, trial, demonstration, maybe, possible, to be, hopeful.

economic policy keywords related for the same year, yielding the proportion of EPU-related articles. Finally, the proportion is standardized using the province-specific standard deviation, resulting in the EPU index. Compared to the original EPU index Baker et al. (2016), this index is constructed at the provincial level using Chinese-language newspapers, capturing regional heterogeneity in policy uncertainty across China.

SO_2 concentration data are derived from Satellite Aerosol Optical Depth (AOD) retrieval dataset provided by NASA (Van Donkelaar et al., 2010). The dataset provides monthly SO_2 concentrations at a spatial resolution of 0.5 degree $\times$ 0.625 degree (approximately 50 km $\times$ 60 km) from 1980 onward. We aggregate these data from the grid level to the city level. Compared with emissions data, SO_2 concentration data provides more accurate measure of pollution exposure, making it an appropriate metric for assessing environmental inequality.

We also include city- and community-level control variables in our analysis. City-level GDP data are obtained from the China Statistical Yearbook. For community-level characteristics, we use the CHNS community dataset, which provides validated indicators of local infrastructure and public services. We focus on four domains closely related to environmental exposure and living conditions: transportation, housing, sanitation, and social services. Summary statistics are Table 1.

Table 1: Summary Statistics

Variable	Obs	Mean	Std. dev.	Min	Max
Panel A: Core variables					
SO_2 concentration	30,498	24.800	14.629	3.151	61.094
EPU index	30,498	104.208	65.617	21.278	368.301
Below high school (=1)	30,498	0.755	0.430	0	1
Panel B: Individual-level control variables					
Age	30,498	43.322	10.588	18	60
Marital (=1)	30,498	0.886	0.318	0	1
Employment status (=1)	30,498	0.721	0.449	0	1
Panel C: City-level and Community-level control variables					
GDP	30,498	14885.620	13168.140	1029.900	71255.900
Transportation component score	30,498	5.586	2.356	0	10
Housing component score	30,498	7.146	2.304	0	10
Sanitation component score	30,498	6.606	2.933	0	10
Social services component score	30,498	3.362	2.910	0	10

3.2 Empirical Specification

We merge city-level SO_2 concentration and province-level EPU data with individual-level observations from the CHNS based on the city identifiers recorded in the survey. The resulting panel dataset allows us to examine whether the EPU index disproportionately affects individual-level SO_2 exposure between individuals with and without a high school degree. Our empirical analysis is based on the following baseline specification:

$$Exposure_{i,c,t} = \alpha_0 ln(EPU_{p,t}) + \alpha_1 Below\ HS_{i,2000} \times ln(EPU_{p,t}) + X\beta + \nu_i + \eta_t + \epsilon_{it} \quad (1)$$

The dependent variable $Exposure_{i,c,t}$ is SO_2 concentration level in city c where individual i lives in year t. $EPU_{p,t}$ represents the level of Economic Policy Uncertainty in province p in year t, to which we apply a logarithmic transformation. $Below\ HS_{i,2000}$ is a dummy variable indicating whether individual i had completed a high school degree in the baseline year 2000. It takes the value 1 if the individual has not completed a high school degree and 0 otherwise. We use high school completion as the key educational threshold for two reasons. First, only 3.6% of population held a college degree in 2000, compared to 11.1% with a high school diploma. Thus, using college as a benchmark would yield a highly unbalanced distribution across groups. Second, high school completion was the most common educational milestone attainable during this period and served as a critical threshold for labor market participation and social mobility in China, distinguishing individuals with substantially different employment opportunities and migration prospects. To address potential endogeneity arising from contemporaneous demographic responses to policy uncertainty, we measure $Below\ HS_{i,2000}$ using individuals' educational status in the baseline year. For example, under high EPU conditions, individuals may be more likely to continue schooling rather than enter the labor market. X is a vector of control variables, including individual-, city-, and community-level characteristics. We also control for time trends in individual behavior using year fixed effects (η_t) and for time-invariant characteristics using individual fixed effects (ν_i). The parameter of interest, α_1, captures the relative change in individual-level SO_2 exposure between those with and without a high school degree, as driven by the EPU index.

There remains a potential issue of reverse causality between EPU and pollution exposure. Concerns about environmental inequality may motivate the government to adopt compensatory economic policies, which in turn influence EPU. To address this concern, we construct a shift-share instrumental variable (IV) for EPU using world import demand excluding China (Erten and Leight, 2021). The identification strategy assumes that the shift-share IV is strongly correlated with EPU while remaining uncorrelated with residual factors affecting pollution exposure. In particular, world import demand among foreign countries may exhibit a pattern correlated with China's domestic economic activity, yet, once China's trade flows are excluded, it is unlikely directly related to differential exposure to pollution within China.

We first use the UN Comtrade dataset to aggregate industry-level world import demand as:

$$Industry\ IM_{i,t} = \sum_{j \neq China} (Import_{j,i,t} - Import\ from\ China_{j,i,t}). \tag{2}$$

where $Import_{j,i,t}$ represents imports by country j of industry i from all countries in year t. $Import\ from\ China_{j,i,t}$ denotes country j's imports of industry i from China in the same year. We exclude imports from China to mitigate potential correlations of $Industry\ IM_{i,t}$ with domestic factors originating from China. Next, we use data from China's 1990 Census to calculate province-industry level employment share as:

$$Share_{p,i,1990} = Number\ of\ Employees_{p,i,1990}/Number\ of\ Employees_{p,1990}. \tag{3}$$

where $Share_{p,i,1990}$ represents the share of employment in industry i within province p. By holding the share at its 1990 level ensures that the identification strategy relies on pre-shock conditions. By holding this share constant in the initial year, we exploit regional variations in exposure to a common global demand shock (Goldsmith-Pinkham et al., 2020). Finally, we calculate province-level exposure to world import demand as:

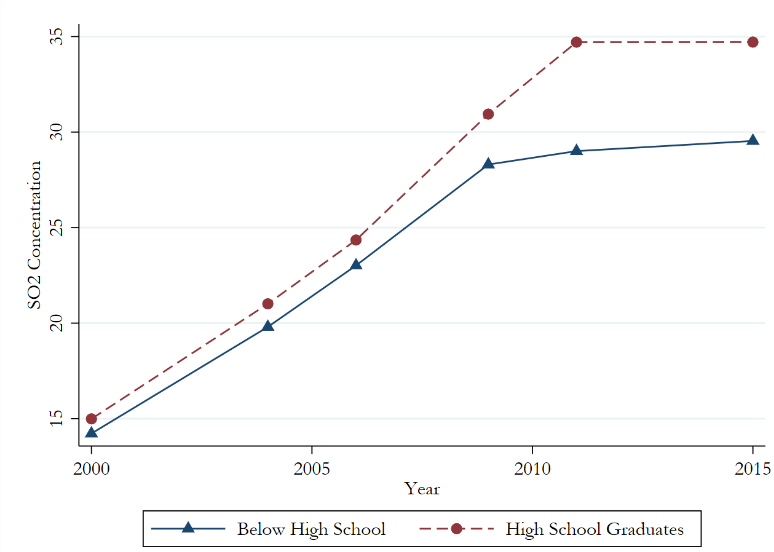
$$WID\ IV_{p,t} = Industry\ IM_{i,t} \times Share_{p,i,1990}. \tag{4}$$

4 Descriptive Patterns

Before turning to the empirical specification, we examine several descriptive patterns in our data to better understand the relationship between education and environmental exposure. These patterns not only highlight structural differences across demographic groups but also provide suggestive evidence on how macroeconomic uncertainty may affect pollution exposure.

Figure 1 presents the average SO_2 exposure for individuals with and without a high school degree between 2000 and 2015. Interestingly, individuals with higher education consistently exhibit greater exposure to SO_2 over time. At first glance, this pattern may appear counterintuitive. The environmental inequality literature typically regards education as a protective attribute, reflecting individuals' greater access to information and resources and their enhanced ability to mitigate or avoid environmental risks (Hsiang et al., 2019). Policy discourse similarly identifies less-educated groups as environmentally vulnerable, emphasizing their limited capacity to relocate, engage with regulators, or invest in protective measures. From this perspective, one might expect pollution burdens to fall more heavily on the less-educated. This finding also contrasts with evidene from many Western contexts, where environmental hazards such as industrial facilities are disproportionately located near low-income or minority neighborhoods and tend to avoid more affluent or better-educated communities (Banzhaf et al., 2019).

Figure 1: SO_2 Exposure across Different Groups

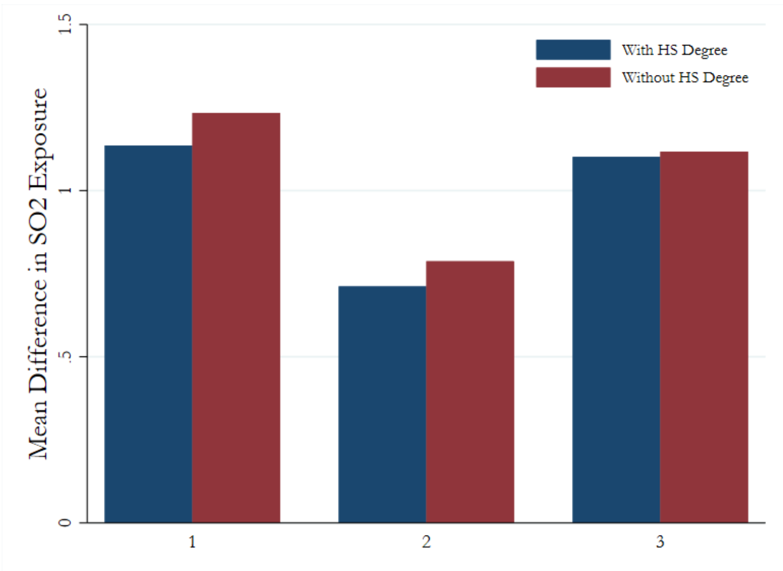


Note: Individual-level data from CHNS are merged with city-level SO_2 concentration data. We calculate the mean SO_2 exposure between 2001 and 2015 for individuals with and without a high school degree.

In contrast, the exposure gap observed in our data likely reflects context-specific dynamics in China. Highly educated individuals are more concentrated in economically dynamic and industrialized regions that offer better employment opportunities, public services, and urban amenities—but also experience higher pollution levels. While education confers longterm socioeconomic advantages, it does not necessarily protect against short-term residential or occupational exposure to environmental risks.

These persistent differences in baseline exposure provide a starting point for understanding environmental inequality. However, they do not reveal whether different groups are affected differentially by macroeconomic uncertainty. To explore this, we next examine how SO_2 exposure responds to changes in EPU across education groups.

Figure 2: EPU and SO_2 Exposure



Note: We use data from the 2010 and 2015 population censuses and merge individual-level observations with the corresponding province-level EPU index and city-level SO_2 concentration data. Provinces are divided into tertiles based on their changes in EPU levels. For each tertile, we calculate the mean change in SO_2 exposure between 2010 and 2015 for individuals with and without a high school degree within the same province. This descriptive exercise illustrates the correlation between changes in EPU and differences in pollution exposure across education groups.

Figure 2 illustrates how changes in EPU are associated with changes in SO_2 exposure by education group. Provinces are grouped into tertiles based on their EPU increase between 2010 and 2015, and for each tertile we compute the mean change in SO_2 exposure for individuals with and without a high school degree. While the overall level of SO_2 change does not follow a clear monotonic pattern across the tertiles, a consistent pattern emerges within each group: individuals without a high school degree experience a larger increase in pollution exposure than those with a high school degree. This descriptive pattern suggests that rising EPU may systematically widen the exposure gap between education groups. In the following section, we formally test this relationship using panel regression models that incorporate interaction terms between EPU and education level.

5 Results

5.1 Main results

We begin by estimating the baseline model described in equation 1. The main coefficient of interest is α_1, which captures the interaction effect between $ln(EPU_{p,t})$ and $Education_i$. Table 2 reports the estimation results. Column (1) presents estimates without control variables, showing that the coefficient of the interaction term is positive and statistically significant. In columns (2) and (3), we sequentially add individual-level and city/community-level control variables. The estimated coefficients remain similar in both magnitude and statistical significance across specifications. Our preferred specification in column (3) yields a coefficient of 0.612 on the interaction term, significant at the 1% level. This implies that, relative to individuals with a high school degree, a 1% increase in the EPU index leads to an additional 0.612 $\mu g/m^3$ increase in SO_2 exposure among individuals without a high school degree. The coefficient on $ln(EPU_{p,t})$ itelf is 1.008 and also statistically significant at the 1% level, indicating that higher EPU is associated with greater overall SO_2 concentrations. This finding aligns with Jun et al. (2023), who document a positive effect of EPU on firms' SO_2 emissions.

Table 2: Impact of EPU on Individual-level Exposure to Air Pollution

Dependent Variable: SO_2 Concentration	(1)	(2)	(3)
ln(EPU)	1.128***	1.132***	1.008***
	(0.126)	(0.126)	(0.127)
Below High-school # ln(EPU)	0.605***	0.605***	0.612***
	(0.137)	(0.137)	(0.138)
Observations	30,498	30,498	30,498
R-squared	0.979	0.979	0.979
Individual Control	NO	YES	YES
City/Community Control	NO	NO	YES
Individual FE	YES	YES	YES
Year FE	YES	YES	YES

Notes Standard errors clustered at the individual-level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3 reports the results of the two-stage least squares (2SLS) regressions, where the shift-share instrument (World Import Demand $\times$ Employment Share) is used to instrument for the EPU index. The first-stage estimation (column 1) shows that the shift-share IV is positively correlated with the EPU index, with the coefficient statistically significant at the 1% level. In the second stage (column 3), the 2SLS estimates indicate a positive and statistically significant coefficient on the interaction term. Specifically, relative to individuals with a high school degree, a 1% increase in EPU index leads to an approximately 1.148 ug/m^3 increase in SO_2 exposure among individuals without a high school degree.

Table 3: Result of 2SLS

	(1)	(2)	(3)
Dependent Variable:	ln(EPU)	Below high school # ln(EPU)	SO_2 Concentration
IV	0.00397***	0.00331***	
	(0.000301)	(0.000243)	
Below high school # IV	-0.000296**	-0.00154***	
	(0.000131)	(6.01e-05)	
ln(EPU)			1.788**
			(0.726)
Below high school # ln(EPU)			1.148*
			(0.588)
Observations	30,498	30,498	30,498
F-test of IV			89.13
Control Variables	YES	YES	YES
Individual FE	YES	YES	YES
Year FE	YES	YES	YES

Notes Column 1 and column 2 are the first stage of 2SLS. Column 3 is the second stage of 2SLS. Standard errors clustered at the individual-level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

This result suggests that the coefficient of the interaction term in Table 2 may be underestimated. We offer two explanations for why the 2SLS estimate is larger than the Two-Way Fixed Effects (TWFE) estimate. First, measurement errors in the EPU index can cause significant attenuation bias in the fixed-effects estimation. The EPU index is constructed from keyword searches in major provincial newspapers. However, due to space limitations and uneven coverage of policy-related news, the index may not fully capture underlying policy uncertainty, leading to a downward bias. Second, the 2SLS estimate represents a Local Average Treatment Effect (LATE), which may differ from the overall average treatemt effect. Because the shift-share instrument is more likely to affect provinces with high trade exposure and individuals whose employment depends directly or indirectly on trade-related sector, the estimated effect may be amplified. Given that extensive evidence links trade-intensive industries to higher pollution levels (Antweiler et al., 2001), the estimated EPU impact based on the IV specification may capture stronger effects than those observed in the full sample.

5.2 Falsification Tests for WID IV

Borusyak et al. (2022) and Borusyak et al. (2025) emphasize that establishing the exogeneity of a shift-share instrument requires either the shift component or the share component to be exogenous. This study adopts a shift-based identification strategy, which relies on the principle that a share-weighted average of random shifts remains effectively random, even if shares themselves are econometrically endogenous. In other words, units with different exposure shares may systematically differ in unobserved characteristics, but the identifying variation arises from the exogenous shifts. Following Borusyak et al. (2025), we conduct balance tests on the shifts to confirm that the assumed exogenous variation is not correlated with proxies for potential confounders. Specifically, we perform two sets of tests. First, we regress potential province-level proxies for the unobserved residuals on the shift-share IV (regional balance test). Second, we regress potential industry-level confounders directly on the shift component (industry balance test).

Regional Balance Test We evaluate balance with respect to baseline economic and employment characteristics by examining whether our shift-share IV is correlated with province-level factors such as GDP, population, per capita GDP, industrial structure, employment shares, and average wages. Table 4 reports the results. The estimated coefficients are statistically insignificant across all specifications, indicating that the instrument is not systematically related to these regional characteristics. Overall, the results support the validity of our identification assumption and exogeneity of the shift-based variation.

Industry Balance Test We next examine whether the industry-level shifts used in constructing our instrument are correlated with potential cofounders that may jointly determine trade patters and pollution outcomes. Specifically, we asees the relationship between world import demand and several industry-level variables that may influence China's trade with the rest of the world, including NTR gaps, tariff rates, contract intensity, and other baseline industry attributes. Table 5 reports the results. For each year, we regress these potential confounders on the shift component. The estimated coefficients are statistically insignificant across all specifications, indicating that industry-level world import demand is orthogonal

Table 4: Regional Balance Test

Dependent Variable:	Coefficient	Observations
ln(GDP)	-4.945	464
	(3.461)	
ln(Population)	-2.541	464
	(2.846)	
ln(per capita GDP)	-2.404	464
	(1.489)	
Industrial structure (production ratio of secondary sectors)	27.00	464
	(23.89)	
Second Sector Employment Share	24.50	464
	(30.85)	
ln(Wage)	-0.929	464
	(3.022)	

Notes: This table shows the effects of baseline province attributes (in 2000) on city-level WID IV. Each row represents a separate regression. *** p<0.01, ** p<0.05, * p<0.1.

to these confounding factors. Overall, the findings support our identification assumption that the shifts are exogenous and not systematically related to indusrty characteristics.

Table 5: Industry Balance Test

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable:	NTR gap	U.S. NTR	China tariff	Contract intensity	Input	Output	Value added	Wage	Return on assets
WID 2000	-0.304	-124.3	-144.8	2.553	-757.8	-941.2	-236.4	-0.389	0.0918
	(1.320)	(123.9)	(156.0)	(1.937)	(2,836)	(3,595)	(972.6)	(0.576)	(0.177)
WID 2004	-0.630	-87.61	-110.5	0.712	-10.61	-11.25	3.648	-0.128	0.0139
	(0.909)	(86.03)	(108.0)	(1.386)	(1,974)	(2,503)	(676.9)	(0.404)	(0.124)
WID 2006	-0.704	-75.35	-105.6	0.303	254.1	308.4	75.57	-0.0343	-0.00202
	(0.737)	(70.19)	(87.65)	(1.138)	(1,614)	(2,046)	(553.5)	(0.331)	(0.101)
WID 2009	-0.670	-72.47	-106.4	0.322	151.6	177.6	40.75	-0.00332	-0.0495
	(0.726)	(69.12)	(86.10)	(1.120)	(1,590)	(2,015)	(545.1)	(0.326)	(0.0994)
WID 2011	-0.639	-52.51	-82.94	0.0252	331.3	396.9	88.92	0.0261	-0.0348
	(0.501)	(48.40)	(59.93)	(0.787)	(1,113)	(1,411)	(381.8)	(0.228)	(0.0697)
WID 2015	-0.667	-54.72	-80.64	0.212	59.09	48.77	-8.686	-0.0248	-0.0278
	(0.536)	(51.68)	(64.35)	(0.838)	(1,189)	(1,507)	(407.6)	(0.244)	(0.0745)
Observations	26	26	26	26	25	25	25	25	25

Notes: We regress baseline industry attributes (columns 1-3 for 1997 and columns 4-9 for 2000) on industry-level world import demand. Each row represents a separate regression. *** p<0.01, ** p<0.05, * p<0.1.

5.3 Robustness Checks

Another concern is that China implemented multiple environmental regulations over the study period to mitigate the adverse effects of rapid economic growth. These policies may simultaneously influence both EPU and environmental inequality, creating omitted-variable bias. To address this issue, we identify and control for the major air-related environmental regulations introduced during the same period.

Two Control Zones Policy In 1998, China launched a major environmental initiative designating certain regions as "acid rain control zones" or "SO_2 pollution control zones". These zones—primarily located in southern and central China—were selected based on their high SO_2 emissions. The central government set an ambitious target to cap SO_2 emissions within these areas at 2000 levels by 2010. To achieve this, local governments implemented stricter emission standards, invested in pollution control technologies, and promoted cleaner energy production. They were also responsible for monitoring compliance and coordinating with industries to meet emission targets. In our analysis, we identify the cities subject to this policy and the years of implementation. As shown in column (1) of Table 6, our main results remain robust when controlling for this policy, suggesting that the its implementation does not materially affect the empirical patterns observed in our study.

Environmental Constrained Target To further address potential omitted-variable bias from local environmental regulations, we collect annual city-level government work report over the study period. These reports, publicly available through official channels, document the policy actions undertaken by local governments, including environmental targets. We construct a dummy variable indicating whether a city's government set explicit environmental constraint targets in a given year. These targets typically specify goals for pollution reduction, energy efficiency improvement, or investment in environmental infrastructure and are often aligned with national or provincial policy frameworks. Including this variable controls for variation in local regulatory intensity. As shown in column (2) of Table 6, the inclusion of this variable does not significantly alter our results, indicating that local environmental policy variation does not drive our main findings.

Air Pollution Information Disclosure In 2013, China introduced a nationwide real-time air quality monitoring and disclosure program to enhance public access to air quality information. The program was implemented in three phases and, by 2015, had expanded to over 1,400 monitoring stations across 337 cities. This system provides real-time data on key air pollutants—including PM2.5, SO_2, NO_2, and ozone—allowing citizens and policymakers to monitor local air quality conditions. The program has substantially increased public awareness and triggered behavioral responses to mitigate exposure (Barwick et al., 2024).

To account for its potential confounding effect, we identify the implementation year for each city and include a corresponding dummy variable. As reported in column (3) of Table 6, the inclusion of this control does not alter our main conclusions: EPU continues to have a significant impact on environmental inequality even after adjusting for the information disclosure program.

Table 6: Control for Other Environmental Regulations

Dependent Variable: SO_2 Concentration	(1)	(2)	(3)
Control for:	Two Control Zones Policy	Environmental Constrained Target	Air Pollution Informatin Open
ln(EPU)	2.017***	1.818***	2.550***
	(0.723)	(0.676)	(0.726)
Below high school # ln(EPU)	1.291***	1.142***	1.016***
	(0.590)	(0.584)	(0.580)
Observations	30,498	30,498	30,498
F-Test of IV	92.87	103.8	89.02
Control Variables	YES	YES	YES
Individual FE	YES	YES	YES
Year FE	YES	YES	YES

Notes Standard errors clustered at the individual-level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

6 Mechanisms

In this section, we investigate three potential mechanisms that may explain the effects of EPU documented in Section 5. Since pollution exposure is jointly determined by emission levels and the spatial ditribution of pollution sources, the ways in which local governments regulate, firms operate, and individuals respond to uncertainty constitute the channels through which EPU affects exposure outcomes. Specifically, we focus on how EPU influences (1) government regulatory behavior, (2) firm emission behavior, and (3) individual migration behavior. These mechanisms may interact with one another; rather than fully decompose their effects, our aim is to assess whether each factor plays a significant role.

6.1 Government Regulatory Behavior

Governments may strategically relax environmental regulations in response to rising EPU. When uncertainty increases, local officials may face stronger pressure to retain investment maintain growth, leading them to loosen environmental enforcement in order to attract or protect firms (Javorcik and Wei, 2003). While much of the existing literature documents such dynamics across countries, we test whether city-level environmental regulatory intensity in China responds to EPU.

We construct a difference-based indicator to proxy for the looseness of environmental regulation at the city level, following Javorcik and Wei (2003):

$$Regulation\ Slack_{c,t} = \frac{\Delta SO_2Emission_{c,t}/SO_2Emission_{c,t-1}}{\Delta Output_{c,t}/Output_{c,t-1}} \tag{5}$$

where the numerator reflects the percentage change in industrial SO_2 emissions and the denominator captures the percentage change in industrial output. A larger value of this ratio implies that emissions are rising faster than output, indicating weaker effective regulation.

Because this raw indicator may also reflect structural or technological factors unrelated to policy, we first regress it on a set of city-level covariates—including the share of foreign-invested firms, share of secondary industry, GDP per capita, patent grants, industrial electricity use, and fixed asset investment—and take the residuals as a purified indicator of regulatory looseness. This residual captures variation more closely associated with policy enforcement rather than with underlying economic structure.

We then estimate the following specification:

$$Residual\ Regulation\ Slack_{c,t} = \beta_0 + \beta_1 \ln(EPU_{p,t}) + \mu_p + \lambda_t + \varepsilon_{c,t} \tag{6}$$

where μ_p and λ_t denote province and year fixed effects. Standard errors are clustered at the province level.

Table 7: EPU and Environmental Regulation Strength

Dep. Var.: Residual Regulation Slack	(1)	(2)
ln(EPU)	8.071**	8.071*
	(4.061)	(5.415)
Observations	2,973	2,973
R-squared	0.099	0.099
Province FE	YES	YES
Year FE	YES	YES
SE Type	Robust	Wild Bootstrap

Notes: The dependent variable is the residual from a first-stage regression removing structural and technological determinants of environmental regulation intensity. Column (1) reports heteroskedasticity-robust standard errors; Column (2) reports wild cluster bootstrap-t standard errors clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1.

Table 7 reports the results. Across specifications, the coefficient on $\ln(EPU)$ is positive, indicating that policy uncertainty is associated with greater regulatory slack. Since higher value of the indicator reflect emissions growing faster than output, this suggests that local governments relax environmental regulation when EPU rises. The coefficient is significant at the 5% level with robust standard errors and at the 10% level with wild bootstrap-t inference, which accounts for the limited number of province-level clusters. Although the R-squared is relatively low (0.099), this is expected because the dependent variable is a residual-based measure that isolates the policy-driven component. Overall, the results support the hypothesis that local governments strategically ease regulatory enforcement in times of hightened uncertainty, consistent with the pollution haven logic.

6.2 Firm Emission Behavior

EPU may also influence firms' emission decisions. Prior studies suggest several channels: First, firms may postpone or scale back investments in energy conservation and emission control under uncertainty, as EPU exacerbates information asymmetry and increases financing constraints (Nagar et al., 2019). Second, looser regulatory enforcement may weaken firms' compliance incentives (Benlemlih and Yavaş, 2024). Third, heightened uncertainty can depress revenues, promoting governments to raise taxes and firms to shift focus away from emission reduction (Dang et al., 2019; Hailemariam et al., 2019b). Overall, the literature generally finds a positive link between EPU and firm-level emissions.

We explore how firms respond to EPU in counties with differing educational by estimating the following model:

$$\begin{aligned} Emission\ Outcome_{f,c,t} &= \alpha_0 + \alpha_1 \ln(EPU_{p,t}) + \alpha_2 Below\ HS_{c,baseline} \\ &+ \alpha_3 ln(EPU_{p,t}) \times Below\ HS_{c,baseline} + \delta_f + \eta_t + \lambda_{p\times t} + \epsilon_{f,c,t} \end{aligned} \tag{7}$$

where $Emission\ Outcome_{f,c,t}$ denotes one of three outcomes: (1) SO_2 emissions per unit of output, (2) SO_2 emissions per unit of output among firms with non-zero emissions (intensive margin), and (3) a dummy variable indicating whether the firm reports positive SO_2 emissions (extensive margin). $Below\ HS_{c,baseline}$ equals one if the share of adults without a high school diploma in county c exceededs the national median in the baseline year 2000. The interaction term tests whether EPU has stronger effects in counties with lower educational attainment. The model includes firm fixed effects (δ_f), year fixed effects (η_t), and province-by-year fixed effects ($\lambda_{p\times t}$). Standard errors are clustered at the firm level.

We use firm-level data from the Environmental Survey and Reporting (ESR) database of the Ministry of Environmental Protection, covering 2000–2014. The ESR provides detailed SO_2 emission and output data for key pollution-intensive firms across China. We restrict the sample to firms with valid city identifiers and exclude those with no temporal variation in emissions.

Table 8: EPU and Firm SO_2 Emission Behavior

	(1)	(2)	(3)
Sample:	All	Intensive Margin	Extensive Margin
Dep. Var.:	Emission per Output		Dummy
ln(EPU) # Below HS	141.6**	145.4**	0.002
	(58.61)	(59.73)	(0.002)
Observations	713,761	687,448	713,761
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Province-by-Year FE	YES	YES	YES

Notes: The dependent variables are firm-level SO_2 emissions per unit of output (columns 1 and 2) and an indicator for positive emissions (column 3). Column (2) restricts the sample to firms with positive emissions, while column (3) uses a dummy equal to one if SO_2 emission > 0. All regressions include firm, year, and province-by-year fixed effects. Standard errors, clustered at the firm level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 8 reports the results. Column 1 shows that in counties with higher shares of low-educated individuals, a one log-point increase in EPU leads to a statistically significant rise in firm-level SO_2 emissions per unit of output. Column 2, which restricts the sample to firms with positive emissions, similarly indicates that emission intensity increases by 145.4 units under higher EPU in disadvantaged counties. Column 3 shows no significant effect of EPU on the extensive margin. Taken together, these results suggest that in counties with more vulnerable populations, firms respond to EPU shocks by increasing pollution intensity rather than by changing their participation in emission activities. This pattern is consistent with the interpretation that firms in less advantaged areas may have weaker incentives or lower capacity to invest in emission-reduction during periods of heightened uncertainty.

6.3 Individual Migration Behavior

Beyond local governments and firms, individuals may consider both environmental quality and economic policy uncertainty when making migration decisions. Building on evidence that pollution and employment shape migration patterns (Gao et al., 2023; Wilson, 2021;

Fields, 1976), we examine how EPU affects individuals' relocation choices.

We estimate the following specification:

$$\begin{aligned} Migration_{i,p,t} = \alpha_0 + \alpha_1 \triangle(EPU_{i,t} - EPU_{i,t-1}) + \alpha_2 Education_i \\ + \alpha_3 \triangle(EPU_{i,t} - EPU_{i,t-1}) \times Education_i + \epsilon_{it} \end{aligned} \tag{8}$$

where $Migration_{i,p,t}$ is a dummy variable equal to 1 if individual i changes province of residence in year t relative to $t-1$, and 0 otherwise. $\triangle(EPU_{i,t} - EPU_{i,t-1})$ is the change in EPU faced by individual i, and $Education_i$ is a dummy for education attainment.

Migration data are drawn from China Labor Dynamics Survey (CLDS), which targets working-age individuals (15-64) and tracks education, employment, and occupational mobility. We construct a 16-year panel from 2000-2015 using respondents' retrospective migration histories in the 2015 survey. Changes in province of residence between consecutive years define the dependent variable.

Table 9 presents the results. The interaction term between EPU and education is negative (-0.004) but statistically insignificant. This suggests that fluctuations in EPU do not systematically influence individuals' migration decisions, indicating that population mobility is unlikely to serve as a mechanism through which EPU affects environmental inequality.

Table 9: EPU Fluctuations and Individuals' Migration Decision

Dependent Variable: Whether migration occurred (=1)	(1)
ΔEPU	0.00102
	(0.00115)
Above College	-0.00270
	(0.00259)
Above College# ΔEPU	-0.00357
	(0.00268)
Observations	11,262
Control Variables	YES
Year FE	YES
Origin Province FE	YES
Destination Province FE	YES

Notes Standard errors clustered at the individual-level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

7 Conclusion

Understanding the environmental consequences of Economic Policy Uncertainty (EPU) is crucial for designing sustainable development strategies in an increasingly uncertain global economy. Using a unique dataset linking province-level EPU indices, city-level SO_2 concentrations, and individual-level exposure, we show that higher EPU significantly widens the air pollution exposure gap between individuals with and without a high school education. This inequality arises primarily through institutional and behavioral responses—changes in government regulation and firm emissions—while individual migration appears unaffected.

These findings have important policy implications. Maintaining stable economic policies can help reduce environmental inequality, particularly by preventing regulatory relaxation during periods of econoimic stress. An integrated approach that aligns economic and environmental objectives can promote both economic stability and environmental justice, ensuring that vulnerable populations are not disproportionately exposed to pollution during periods of macroeconomic uncertainty.

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