Balancing Development and the Environment in a Changing World: Expressways, GDP, and Pollution in China

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Abstract

When productivity changes, how would an economy rebalance economic production and environmental preservation? We develop a conceptual framework to analyze the question, and predict that a productivity shock can have heterogeneous impacts on environmental quality and income. Exploiting a quasi-experiment provided by the dramatic expansion of China's national expressway system, we find empirical evidence that is consistent with the model's predictions: expressway access increases both pollution and GDP in initially poor counties, decreases pollution and GDP in initially rich counties, and decreases pollution while increasing GDP in counties with moderate levels of initial income. These findings cannot be fully explained by alternative theories such as the pollution haven hypothesis and home market effect.

Keywords: transport infrastructure; environmental Kuznets curve; pollution haven hypothesis; home market effect; trade integration

JEL: Q56; Q53; O13; H54; O18; R11

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I. Introduction

Understanding the interaction between the environment and development has been a central issue in economics (e.g., Arrow et al., 1995). How does a society maintain a balance between economic development and the environment in a changing world? How does an economy adapt, economically and environmentally, to changes in the conditions of economic production? To answer these questions, we propose a conceptual framework to illustrate how a representative agent makes the trade-off between preserving better environmental quality and producing more economic output, and we provide empirical evidence that is consistent with the theory.

In our conceptual framework, the decision maker, who cares about both environmental quality and pecuniary income, can exploit an endowment of environmental resources to generate income using emissions as the input, at the cost of worse environmental quality caused by the emissions. The optimal combination of environmental quality and income is then determined by properties of the income generation process and the decision maker's preference. We show that, facing a positive productivity shock that increases the pecuniary income produced by any level of emissions, the decision maker can have heterogeneous responses along the set of environment–development choices, and the heterogeneity depends on the initial income or pollution levels. Specifically, we predict that 1) if the initial income (or pollution) is sufficiently low, the shock will increase both income and pollution; 2) when the initial income (or pollution) is sufficiently high, the shock may reduce both income and pollution; and 3) at a moderate level of initial income (or pollution), the shock can increase income while decreasing pollution but will never reduce income while increasing pollution. The economic intuition behind the predictions is that, given different initial conditions, different economies can choose different development paths to take advantage of an opportunity to develop. Specifically, poor (and clean) regions prefer to grow in a more polluting way, while rich (and polluted) regions may be willing to sacrifice some income to improve environmental quality.

Motivated by this conceptual framework, we investigate its empirical relevance in the context of China's large-scale transport infrastructure improvement. From 2000 to 2012, the Chinese government made massive investments in constructing the national expressway network, which had the goal of connecting all the cities with urban population greater than 200,000. Although the expressways were designed to connect these metropolitan cities, they also connected some small counties simply because the counties were on the periphery of the large cities.[4] We interpret the expressway access as a positive productivity shock to the connected counties, because it increases the counties' ability to generate pecuniary income given pollution levels by reducing transportation costs, which helps them realize their various comparative advantages. We then estimate the impact of this positive productivity shock on the environmental and economic performances of Chinese counties using a difference-in-differences (DiD) approach, i.e., comparing the connected and the unconnected counties before and after expressway construction. The high degree of disparity in terms of the environment–development combinations across the counties allows us to explore how regions could respond differently to the same productivity shock across a wide range of initial income levels.[5]

To implement the estimation, we assemble a county-level panel dataset that includes detailed information on GDP, pollution, expressway expansion, and other socio-economic conditions for more than 1,600 Chinese counties from 2000 to 2012. To our knowledge, this is the most comprehensive dataset of this type for China. Using this dataset, we find

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[4] There are five *de facto* administrative levels of local government in China: the provincial, prefecture, county, township and village. Cities can be provincial, prefecture and county level, and are referred to as the urban centers or municipalities of their corresponding administrative divisions. Counties are the surrounding rural areas at the county level, supervised by the provincial or prefecture administrations. Intuitively, cities are urban areas and counties are rural areas in China.

[5] For example, per capita GDP in the richest 5% of Chinese counties was more than ten times higher than the poorest 5% counties in 2000.

that, compared with unconnected counties, the expressway access has indeed 1) increased both pollution (measured by pollutant emissions) and GDP in poor connected counties, 2) decreased both pollution and GDP in rich connected counties, and 3) increased GDP and decreased pollution in middle-income connected counties. These empirical findings are consistent with our theoretical predictions and, at the same time, challenge existing theories such as the pollution haven hypothesis and home market effect.

The paper unfolds as follows. The rest of this section discusses how this study is linked with previous literature. Section II presents the conceptual model and predictions. Section III describes the empirical setting and discusses how we estimate the impacts of expressway connection. Section IV introduces the dataset and provides descriptive statistics. Section V presents our main empirical results, checks their robustness, explores the channels at work, and investigates potential spill-over effects of expressway connection. Section VI discusses alternative explanations and their limitations. Section VII discusses policy implications and concludes with directions for future research.

Literature Connections

This study speaks to several strands of literature, including but not limited to, the environmental Kuznets curve and the economic and environmental consequences of transport infrastructure improvement.

In the environmental economics literature, much empirical research attempts to estimate a one-way causal link between income levels and environmental quality. In particular, following Grossman and Krueger (1995), a large number of studies have tested the environmental Kuznets curve, a popular hypothesis proposing an inverted U-shaped relationship between environmental degradation and income. However, no consensus has been reached on this pattern because empirical findings are mixed and those supporting the environmental Kuznets curve are often applicable only to specific contexts, time periods, and functional forms.[6] Arrow et al. (1995) and Stern (2004) object that the relationship between development and the environment cannot be characterized as one-way causality. The influential survey by Copeland and Taylor (2004) further argues that economic growth from different sources can have different implications for pollution, making the environmental Kuznets curve unstable in theory.

This study complements these contributions and offers additional insights. Our empirical pattern suggests that a more complicated relationship than the environmental Kuznets curve can emerge even from the same productivity shock, i.e., access to the expressway: the responding change in income and change in pollution are positively correlated when income is either high or low, while they are negatively correlated when income is moderate. Fundamentally, our conceptual framework emphasizes that the environment–development relationship results from an endogenous response to changes in underlying economic conditions. Describing and interpreting the relationship between the environment and development as simple causality is thus incorrect and has limited power in predicting environmental and economic consequences of focal policies or natural shocks.

This paper is also among the first efforts to estimate the economic and environmental consequences of transport infrastructure in an integrated framework. To date, one rich line of literature has focused on the economic impacts of transport infrastructure,[7] while another has emphasized its impacts on environmental resource conservation.[8] Both lines of literature have primarily debated the average effects of transport infrastructure. Our empirical analysis reveals, however, that there is significant heterogeneity in both the economic and environmental impacts of transport infrastructure.

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[6] See for example, Stern, 2010; Copeland and Taylor, 2004; Stern, 2004; Dinda, 2004; Yandle et al., 2004; Millimet et al., 2003; Dasgupta et al., 2002; Harbaugh et al., 2002.

[7] See, for example, Chandra and Thompon, 2000; Holl, 2004; Baum-Snow, 2007; Michaels, 2008; Banerjee et al., 2012; Datta, 2012; Duranton and Turner, 2012; Duranton et al., 2014; Rothenberg 2013; Zheng and Kahn, 2013; Faber, 2014; Baum-Snow, 2014; Baum-Snow et al., 2016a, 2016b; Donaldson and Hornbeck, 2016; Frye, 2016; Ghani et al., 2016; Qin, 2016; Jaworski and Kitchens, 2016; Alder 2017.

[8] See, for example, Chomitz and Gray, 1996; Nelson and Hellerstein, 1997; Pfaff, 1999; Cropper et al., 2001; Deng et al., 2011, Chakravorty et al., 2015; Kaczan, 2016.

The heterogeneities we find challenge existing explanations in the literature. In particular, neither the pollution haven hypothesis nor the home market effect can explain all of empirical findings. On the environmental side, the pollution haven hypothesis conjectures that better integration of markets result in a flow of polluting capital from rich regions to poorer regions that have lax environmental standards (e.g., early theoretical works by Pethig, 1976; Siebert, 1977, McGuire, 1982; survey by Copeland and Taylor, 2004).[9] On the economic side, with a focus on the scale of the economy, the home market effect proposes that transport infrastructure improvement can amplify the asymmetry between the peripheral and the core areas (e.g., Krugman, 1980, 1991; Helpman and Krugman, 1985; Faber, 2014). As discussed in more detail in Section VI, the pollution haven hypothesis has little to offer in explaining the heterogeneous impacts of expressway access on income, while the home market effect is inconsistent with further analysis of our data. Our theoretical framework, however, can reconcile the heterogeneity pattern in a concise way.

Several studies have explored the context of China and are thus closely related to our paper. Among them, Banerjee et al. (2012) investigated the economic impacts of railway construction in China during the late 19th and early 20th centuries and found that proximity to transportation networks had a moderately positive causal effect on per capita GDP levels across sectors but no effect on per capita GDP growth. Zheng and Kahn (2013) studied the economic impacts of high-speed rail and found that the expansion of the high-speed railway network increased housing prices in affected cities. Qin (2016) also examined the economic

[9] Empirical evidence on the pollution haven hypothesis is often obtained from aggregate country-level data (e.g., Eskeland and Harrison, 2003; Ederington et al., 2005; Frankel and Rose, 2005; Levinson and Taylor, 2008; Levinson, 2009; Managi et al., 2009). It is often difficult to draw credible causal inferences from such data, because institutional, cultural, and demographical settings are highly different across countries and openness to trade is seldom exogenous (Copeland and Taylor, 2004; Karp, 2011). The rapid expressway expansion in China provides us with a more credible setting to assess the impact of trade integration on the environment, because peripheral counties' access to expressways is arguably exogenous in our context and their institutional, cultural, and demographical difference can be controlled by fixed effects.

impacts of China's high-speed railway and found that affected counties on the upgraded railway lines experienced reductions in GDP and GDP per capita. In a recent study, Baum-Snow et al. (2016b) estimated the economic impacts of expressway expansions in Chinese cities using both structural and reduced-form approaches and found inconsistent results. Deng et al. (2011) show that roads have no impact on the levels of forests and on the rate of deforestation in Southern China. Chakravorty et al. (2015) show that road construction contributes to groundwater depletion in Northern China.

Notably, our empirical focus is similar to Faber (2014), which also excludes major cities and compares per capita GDP between connected and unconnected counties in China. We differ from Faber (2014), however, in several substantial ways. First, we assemble panel county-level data for a more recent, longer period, 2000–2012, while Faber (2014) uses data for 1997 and 2006. Second, we fully exploit the panel structure of our data and adopt a DiD identification strategy, while Faber (2014) relies on a cross-sectional instrumental variable (IV) approach, which is based on a hypothetical expressway network that would link all target cities with the least predicted cost of construction. The identifying assumption in the IV approach may be overly strong, as it requires the instrument to be uncorrelated with any confounding factors.[10] By contrast, the identifying assumption of our DiD approach likely holds because connected and unconnected counties indeed followed parallel trends before expressways construction. Third, in terms of empirical results, Faber (2014) finds that expressway connections significantly reduced economic growth in connected counties, while we find that the average impact of expressway connection on per capita GDP is indifferent from zero; Faber's theoretical model predicts a universal negative impact of expressway connection on peripheral counties' GDP, while we highlight the effect of heterogeneity and show that both positive and negative impacts exist.

[10] Faber (2014) acknowledges that his IV is not completely exogenous because it is correlated with some observables.

II. Theoretical Framework

Basic Setting

We conceptualize a small economy (a county) with some environmental endowment, E. The policymaker in this economy can exploit this endowment to generate pecuniary income, I, which, in our setting, can be measured by GDP or GDP per capita. The production process is defined by the production function, $I \equiv f(e,s)$, where e is polluting emissions, which are the input into this production, and s is a parameter of productivity, which can be affected by various economic conditions such as transaction costs, the extent of market integration, and the cleanness of the technology used in production. The emissions, however, reduce the environmental quality, $Q \equiv E - e$.

We assume that the social welfare in this economy is determined by pecuniary income I and environmental quality Q, and that the social welfare function is denoted as $u(I,Q)$. The policymaker then faces a resource allocation problem:

$$\max_{e} \quad u(I,Q) \equiv u(f(e,s), E - e) \quad \text{s.t.} \quad 0 \leq e \leq E, \tag{5}$$

where a trade-off has to be made between income generation and environmental preservation.

We make standard assumptions that the social welfare function is well-behaved: 1) $u_1 > 0$, $u_2 > 0$, 2) $u_{11} < 0$, $u_{22} < 0$, and 3) $0 < \frac{\partial\left(-\frac{u_1}{u_2}\right)}{\partial I} < \infty$, $0 < \frac{\partial\left(-\frac{u_2}{u_1}\right)}{\partial Q} < \infty$, $-\infty < \frac{\partial\left(-\frac{u_1}{u_2}\right)}{\partial Q} < 0$, and $-\infty < \frac{\partial\left(-\frac{u_2}{u_1}\right)}{\partial I} < 0$, guaranteeing that 1) pecuniary income and environmental quality are always good, 2) their marginal value is diminishing, and 3) the indifference curves are convex and the change rates of their slopes are finite.

We also assume that the production function $f(e,s)$ is continuously differentiable, increasing in input, i.e., $f_1(e,s) > 0$, and has non-increasing returns to scale, i.e.,

$f_{11}(e,s) \leq 0$. These assumptions guarantee that the environmental quality (*Q*)–pecuniary income (*I*) possibility frontier is decreasing and concave in both pecuniary income and environmental quality. It is also intuitive to assume that no income is generated if no resources are allocated, i.e., $f(0,s) = 0$, and that the economic shock has a non-zero impact on the marginal productivity, i.e., $f_{12}(e,s) \neq 0$.

In this model, the environmental endowment *E,* the productivity parameter *s,* and the shapes of the social welfare function $u(\cdot,\cdot)$ and the economic production function $f(\cdot,\cdot)$ are exogenous. Environmental quality Q, emissions e, and pecuniary income I are endogenous.

We consider new access to an expressway as a positive shock to the income-generation productivity of environmental resources, i.e., we assume an increase in s with $0 < f_2(e,s) < \infty$. The increase in the economy's ability to transform emissions into pecuniary income can be justified through two primary channels. First, the infrastructure improvement reduces trade and transportation costs, boosting the generated pecuniary income, even if the resource allocation plan within the income-generation process remains constant. Second, deeper market integration and increased opportunities for trade allow the connected counties to more effectively utilize their comparative advantages by re-optimizing their resource allocation within the income-generation process. As a result, any given environmental resources allocated to economic production will raise pecuniary income in the connected counties. We then conduct a comparative statics analysis with respect to this positive productivity shock. Alternative interpretations of the expressway access, such as the interpretation following the home market effect (e.g., Krugman, 1980, 1991), turn out to be inconsistent with the data, and we will discuss them in more detail in Section VI.

We make three additional remarks here. First, we assume that the policymaker alone can decide the environmental resource allocation. This situation is empirically relevant in the context of China, because local governments, which act as the policymakers in our model, hold strong control over the allocation of natural resources (notably land), capital flow, and even labor. For instance, since China's market reforms in the 1980s, local governments have been actively attracting and strategically choosing certain investors, industries, and talents in order to implement their development strategies, by offering the chosen companies tax rebates, infrastructure improvement, price discounts for land use, exemption from inefficient regulations, and other generous industrial policies (e.g., Qian and Roland, 1998; Bai et al., 2014). For labor, the Chinese government has historically used the *Hukou* system (household registration system) to control labor migration between rural and urban areas and within urban and rural areas. Even though migration restrictions have been relaxed in recent years, the costs of migration remain substantial because many social benefits (such as housing subsidies and medical insurances) are only available in one's birthplace *Hukou* area. For these reasons, we will interpret our empirical evidence as resulting from policy responses of the local government, rather than spontaneous reactions of capitalists or laborers to expressway access.

Second, as this model is static and the resource allocation problem does not involve an intertemporal trade-off, it has limited explanatory power when intertemporal trade-offs are important. Our model focuses on the trade-off between economic production and environmental preservation at a given period of time, which is reasonable given the short time horizon of many local officials in China. We are not alone in adopting a static approach; Greenstone and Jack (2015) build a static theoretical framework to understand why the marginal willingness to pay for environmental quality is low in developing countries.

Finally, we impose as few assumptions as possible about the pecuniary income generation process and social preferences. This minimalist approach helps us derive generic results that rely little on over-specified structures.

Analysis

We start our analysis graphically. In Figure 1, we show the solution of the model and analyze all possible outcomes after a positive productivity shock is introduced to the system. In Panel A, we first draw an environment–development diagram, in which the pecuniary income is on the horizontal axis and environmental quality on the vertical axis. The production function $f(e,s)$ determines a typical trade-off between producing economic output (more pecuniary income) and preserving the environment (fewer emissions). At one extreme, it allows the representative agent to choose a high level of pecuniary income but very little environmental protection. At the other extreme, the decision maker can choose a high level of environmental protection but very little economic output. All possible combinations of environmental quality and pecuniary income form the possibility frontier.

The social welfare function determines a set of social indifference curves, and the interior solution to the resource allocation problem $(f(e_0,s), E-e_0)$ occurs when the possibility frontier and the social indifference curve are tangent to each other, just as illustrated in Panel A of Figure 1. Mathematically, this first-order condition for an interior solution is

$$u_1(f(e,s),E-e)f_1(e,s) - u_2(f(e,s),E-e) = 0 \tag{6}$$

or simply

$$f_1(e,s) = \frac{u_2(f(e,s),E-e)}{u_1(f(e,s),E-e)}. \tag{7}$$

In other words, the productivity of environmental resources is equal to the ratio of the marginal utilities of environmental quality and pecuniary income, i.e., the relative prices of environmental quality and pecuniary income.

The inverse of the slope of the tangent line measures the marginal willingness to pay (WTP) for an improved environment. The steeper the tangent line, the less pecuniary income the society is willing to give up for an improvement in environmental quality.

We now analyze the impact of an increase in economic productivity, i.e., an increase in s, or equivalently, an expansion of the possibility frontier, on the optimal combination of emissions, environmental quality, and pecuniary income. Panels B, C and D illustrate the only three possible situations, respectively. The panels focus on the area near the initial and ending optimal choices, where, for clear exposition, the possibility frontiers are depicted approximately by locally linear lines. For example, as shown in Panel B, the possibility frontier expands outward from the bold, red, solid line to the bold, red, dashed line, because more pecuniary income can be generated from any given level of environmental resources allocated to production, i.e., better environmental quality can be achieved given any level of pecuniary income generation.

This expansion, however, can be decomposed into two steps. Firstly, it changes the marginal productivity of environmental resources in generating pecuniary income, i.e., the slope of the possibility frontier, *without changing the amount of pecuniary income that can be produced from the initial emissions.* This change is represented by the rotation from the bold, red, solid line to the bold, red, dotted line around the black dot, and the optimal combination is shifted from the black dot to the grey dot. We call this the "substitution" effect.

Secondly, the increase in economic productivity further increases the amount of pecuniary income that can be produced from any level of emissions *without changing the slope of the possibility frontier.* This change is represented by the rightward-upward shift from the bold, red, dotted line to the bold, red, dashed line, and the optimal combination moves from the grey dot to the white dot. We refer to this as the "expansion" effect.

The total effect of the productivity increase on the optimal combination of emissions, environmental quality, and pecuniary income is therefore the sum of the substitution effect and the expansion effect, i.e., the transition from the black dot to the white dot.

In Panel B, the substitution effect decreases pecuniary income (I) and emissions (e) and increases environmental quality (Q), while the expansion effect increases pecuniary income and environmental quality and decreases emissions. Eventually, the substitution effect dominates so that the positive shock in economic productivity decreases pecuniary income and emissions.

This situation, however, is not always true. In Panel C, the expansion effect still increases pecuniary income and decreases pollution. The substitution effect, however, increases pecuniary income and pollution. Eventually the substitution effect still dominates, but the positive productivity shock increases pecuniary income and pollution, in contrast to the case in Panel B.

The last possible situation is that the substitution effect is small – the shift of the possibility frontier does not change the slope of the frontier much – so that the expansion effect will dominate. Panel D illustrates this situation to the extreme by assuming the slope of the frontier does not change at all. The expansion effect then determines the overall effect, which is to increase pecuniary income and environmental quality and to decrease pollution.

In Appendix A, we deal with the three-phase heterogeneity more rigorously and generate three predictions:

Prediction 1. If the initial income (or pollution) is sufficiently low, a positive productivity shock increases both income and pollution, as in Panel C. This result comes from the fact that, when the initial income or emissions are low, 1) the slope of the possibility frontier will be unambiguously flattened and 2) the expansion effect will be small and dominated by the substitution effect;

Prediction 2. When the initial income (or pollution) is sufficiently high, a positive productivity shock can reduce both income and pollution, as in Panel B. This is a "possibility" result, and no more definite result about this case can be derived without imposing more structure about the process of generating pecuniary income;

Prediction 3. A positive productivity shock can increase income while decreasing pollution, as in Panel D, but can never reduce income while increasing pollution. This result comes from the monotonicity of the possibility frontier and the positive productivity shock.

III. Empirical Setting

Expansion of China's Expressway Network

With a vast territory and the world's largest population, China depends heavily on its inter-city expressways (controlled-access highways) to facilitate mass within-country trade. From its inception in the 1980s, China's national expressway network, officially known as the National Trunk Highway System, had expanded to more than 111,000 kilometers by 2015, making it the world's largest expressway system by length.

The expansion of China's national expressway network took place in several stages. The first expressway in China, constructed in 1984, connected two northern Chinese cities, Shenyang and Dalian. In 1992, the Chinese State Council approved the "5–7" (*Wu Zong Qi Heng*) expressway construction plan, which included five vertical (north-south) and seven horizontal (east-west) expressways with a total length of over 35,000 kilometers. The objective of the "5–7" network was to connect all provincial capitals and cities with an urban population of over 500,000 by 2020, and the network was completed in 2007, 13 years ahead of schedule.

In 2004, the State Council approved the construction of a larger expressway network called the "7–9–18" network, which comprises seven radial expressways connecting Beijing with other major cities, nine north–south vertical expressways and 18 east–west horizontal expressways. The "7–9–18" expressway network links all cities with an urban population of more than 200,000, major tourist cities, port cities, and expressways and railway hubs. The new target was achieved in 2011, nine years ahead of schedule.

Appendix Figure 1 illustrates the rapid expansion of China's national expressways from 1992 to 2010.

Many peripheral counties lying in between major cities were also connected during this expansion. Our empirical strategy exploits this feature and compares the economic and environmental outcomes between connected and unconnected counties before and after expressway construction. More specifically, the treatment group consists of counties that were not targeted by the "National Expressway Network Plan" (2004) but were connected because they were located on expressway routes between metropolitan cities. Unconnected counties serve as the control group. The targeted cities are excluded from subsequent analysis because their expressway connections are clearly endogenous.[11] In Figure 2, we present the targeted cities (including all city districts), connected counties, and unconnected counties, using different colors for 2000 and 2010. Because our county-level panel data cover 2000 to 2012, we exclude the 15% of counties that were already connected to national expressways before 2000, as they provide no variation in treatment status.

Econometric Model

We start our analysis by estimating the average treatment effect of expressway connection on environmental and economic outcomes using a generalized difference-in-differences (DiD) approach:

$$y_{i,t} = \alpha + \beta * Connect_{i,t} + \rho_t + \mu_i + \varepsilon_{i,t} \tag{1}$$

where $y_{i,t}$ is an outcome of interest for county i in year t; $Connect_{i,t}$ is a dummy indicator that equals 1 if county i is connected in year t and 0 otherwise; ρ_t is a time effect common to all counties in period t, μ_i is a time-invariant effect unique to county *i*; and $\varepsilon_{i,t}$ is an error term independent of μ_i and ρ_t.

[11] The targeted cities include cities with a population of over 200,000, tourist cities, port cities, and expressway and railway hubs. The "National Expressway Network Plan" (2004) referred to targeted cities as the "main controlling nodes". The list of targeted cities is reported in Appendix Table A. Appendix Figure 1 further shows the target cities on the map and draws the expansion of China's national expressways from 1992 to 2010.

We focus on four outcomes in each county: total and per capita emissions, and total and per capita GDP. We take the logarithms of the dependent variables so that the estimated coefficient represents the percentage change. An unbiased estimate of β requires that the pre-treatment trends for both control and treatment groups be parallel.

To estimate the heterogeneous impacts of expressway connection, we interact the treatment dummy with initial income (per capita GDP in 2000) and estimate the following equation:

$$y_{i,t} = \alpha + \beta * Connect_{i,t} + \gamma * (X_{i,2000} * Connect_{i,t}) + \rho_t + \mu_i + \varepsilon_{i,t} \qquad (2)$$

where $X_{i,2000}$ is the per capita GDP of county i in year 2000, and γ is the coefficient of the interaction.

Identifying Assumptions

The routing of expressways is determined by the central and provincial governments. Although counties between major cities were not explicitly targeted by the National Expressway Network Plan (2004), we cannot assume that routings were created randomly. Because the decision-making process is not entirely transparent, a reasonable concern is that the routing choices may not be orthogonal to unobservable factors that may affect the outcomes.

There are two hypotheses regarding the central government's routing decisions. The first is that the central government connects counties based on time-invariant characteristics such as the geographic features of a region, the cost of building expressways, and the regional economic and political importance of a county.[12] However, this type of endogeneity does not threaten our identification. In the DiD setting, county fixed effects control for all time-invariant factors that may affect the likelihood of a county being

[12] In our data, the connected counties are different from the control counties even before they were connected. Connected counties are in general richer, larger and emit more effluents than the non-connected counties (see Table 1). This pattern was also documented in Faber (2014), which investigated the early stage of China's expressway system.

connected. Year fixed effects further control for common shocks that affect all counties (such as national policies) in each year. Thus, as long as the treatment group and the control group follow parallel pre-treatment trends, β can still be identified.

The second hypothesis is that the central government of China connects counties in response to local economic or political shocks. For example, would the government intentionally reroute an expressway to connect a county because it experienced a negative income shock in the previous year? This would threaten our identifying assumption (parallel pre-treatment trends), but we believe that this hypothesis is highly unlikely to be true, because the National Expressway Network was planned years before any county was connected. Moreover, as the central government did not change the routings prior to construction, there is no evidence that counties could manipulate expressway connections in their favor to cope with temporary economic shocks. Finally, both the "5–7" network and the "7–9–18" network were completed years ahead of schedule. A reasonable assumption is that a peripheral county would not have *ex ante* information on the exact time when it would be connected. Allowing for all of these considerations, the expressway connection to a specific county in a specific year is likely to be exogenous, conditional on county and year fixed effects.

More formally, we can test the parallel-trend assumption using an event study approach, following Jacobson et al. (1993). The basic idea is that we can generate a set of leads and lags of the actual expressway access and test whether the leads of the treatments are statistically significantly different from zero. In Appendix B, we conduct this exercise and fail to reject that connected counties and unconnected counties follow similar trends.

IV. Data and Summary Statistics

Pollution Data

We collect county-level emissions data from China's Environmental Survey and Reporting (ESR) database. The ESR database is maintained by the Ministry of Environmental Protection of China. It is used to monitor the polluting activities of all important polluting sources, including heavily polluting industrial firms, hospitals, residential pollutant discharging units, hazardous waste treatment plants and urban sewage treatment plants. When we refer to the "polluting sector", we include all of these sources, regardless of the type of the industry.

We use the ESR data from 2000 to 2012 in this study. During this period, the monitored polluting sources in total contribute 85% of total emissions of major pollutants in each county. The monitored polluting sources are required to report their environmental performance to county-level Environmental Protection Bureaus (EPBs) each year. Local EPBs then verify the data and also estimate emissions of major pollutants from unmonitored plants based on their total industrial output. The overall emission measures for major pollutants in each county are constructed by summing emission levels reported by monitored plants and estimated emission levels from unmonitored plants. The micro-level emission data used in this study had been kept confidential for many years but recently became conditionally open to some researchers.[13]

Emissions degrade environmental quality. Major pollutants in the ESR database include chemical oxygen demand (COD), ammonia nitrogen (NH_3-N), sulfur dioxide (SO_2), and nitrogen oxides (NO_x). In our main analysis, we focus on COD emissions. COD is a widely-used water quality indicator that measures the oxygen required to oxidize soluble and particulate organic matter in water, in order to assess the effect of discharged

[13] More details of the data are described in Lin (2013), Cai et al. (2016), and Wu et al. (2017).

wastewater on the water environment.[14] Higher COD levels mean a greater amount of oxidizable organic material in the sample, which will reduce dissolved oxygen levels. A reduction in dissolved oxygen can lead to anaerobic conditions, which are deleterious to higher aquatic life forms.

Another reason why we focus on COD emissions is that almost all key pollution sources and industries produce and report COD emission levels (Lin, 2013; Sinkule and Ortolano, 1995), whereas other pollutants, such as SO_2, tend to be concentrated in a few industries that are tightly controlled by large state-owned enterprises (SOEs) in certain areas in China.

We use total COD emissions and per capita COD emissions in each county as our primary outcome variables on emissions. Total COD emissions are the sum of COD emitted by the key polluting plants and the estimated COD emitted by other polluting plants. Per capita COD emissions are calculated by dividing the total COD emissions by the population. We also check the robustness of our results using COD emissions only from key polluting plants and supplement our analysis by further discussing the results of other emission measures, such as ammonia-nitrogen and SO_2.

Expressway Expansion Data

Historical GIS (geographical information systems) data on China's National Expressway Network are collected from the PR China Administrative Spatio-Temporal Expressway Database (STED) from the ACASIAN Data Center at Griffith University. The database compiles information on China's expressway routes for 1992, 1993, 1998, 2000, 2002, 2003, 2005, 2007 and 2010. By combining the STED database with China's county-level GIS data, we are able to identify which counties were connected in which year.[15]

[14] For example, COD abatement is used by the Chinese central government as a key performance indicator for assessing local government efforts on environmental protection. In China's 11th Five-Year Plan (2006-2010), COD was used as a primary criterion (the other being ammonia-nitrogen) for setting national abatement targets and performance appraisals.

[15] Details on identifying the treatment status of each county-year are discussed in Appendix C.

Socioeconomic Data

Finally, we collected county-level socioeconomic data from CEIC database, various statistical yearbooks in China, including provincial yearbooks, China City Statistical Yearbooks, and China County Statistical Yearbooks. GDP and per capita GDP are the two main outcomes of interest.

Descriptive Statistics

We match all of the datasets at the county level from 2000 to 2012, during which the national expressway network expanded significantly. While only 11% counties had access to expressways in 2000, more than 50% counties were connected by 2012.

The summary statistics of the main variables are reported in Table 1. We report the mean and standard deviations for all counties, (eventually) connected counties and unconnected counties in 2000 and 2012. Average COD emissions decreased by 39% (from 1,800 tons to 1,100 metric tons) from 2000 to 2012, while per capita GDP increased more than fivefold, from 4,900 yuan to 31,000 yuan. Many counties managed to reduce emissions while sustaining strong economic growth.

The connected cities and non-connected cities were economically, geographically and environmentally different even before being connected. Connected counties are on average larger and more polluted than non-connected counties; in 2000, they were richer and more polluted. This observation suggests that county-level fixed effects must be controlled in an empirical approach.

V. Main Results

Average Treatment Effect of Expressway Connection on Emissions

In Table 2, we report the average treatment effect of expressway connection on COD emissions and GDP. Our baseline results are presented in Columns 1, 4, 7 and 10. County fixed effects and year fixed effects are included in these regressions. Column 1 shows that connected counties experienced an average reduction in total COD emissions of 18%. Column 4 shows that per capita COD emissions in connected counties decreased by 25%. Columns 7 and 10 summarize the results for GDP and per capita GDP. We observe that expressway connection does not have a statistically significant impact on GDP and per capita GDP.

We check the robustness of these findings in a variety of specifications. In Columns 2, 5, 8 and 11, for example, we control for provincial time trends and find similar results. In Columns 3, 6, 9 and 12, we include province-year fixed effects in the regressions. The effects of expressway connection on emission measures are robustly negative and statistically significant in all specifications. As shown in the table, we further check the robustness of estimates accuracy by clustering the standard errors at different levels, and we arrive at similar conclusions.

Heterogeneous Effects of Expressway Connection

In this section, we explore the heterogeneous effects of expressway expansion on GDP and pollution with respect to initial income. We interact the expressway connection dummy with per capita GDP in 2000 (yuan, log) and include both the treatment dummy and the interaction term in the regressions. We summarize the results in Table 3. The estimated coefficients of the treatment dummy are all positive and statistically significant at the 1% level, while the coefficients of the interaction terms are all negative and statistically significant. The results in Columns 1 to 4 show that the impact of expressway access on

COD emissions is more negative in initially richer counties than in initially poor counties. Similarly, Columns 5–8 suggest that connection to expressways has a more negative impact on GDP (or GDP per capita) for initially richer counties.

Table 3 shows that there are strong heterogeneous effects. However, we are unable to further infer the direction (or the sign) of these impacts without knowing the range of initial income levels. A more informative way is to predict the impacts at different initial income levels. In Figure 3, we plot the estimated heterogeneity based on Table 3 and calculate the predicted impacts (with their 95% confidence intervals) at different initial income levels. The upper panel shows the predicted impact on COD emissions, the central panel shows the predicted impact on GDP, and the bottom panel plots the distribution of the log of per capita GDP in 2000. A predicted impact of zero (highlighted by a red square) implies that expressway connection does not affect emissions or GDP at a given initial income level. A positive value means that emissions or GDP increases, while a negative value means it decreases. In Figure 3, we observe that expressway connection positively affected COD emissions for the poorest 25% counties and had a positive impact on GDP for the poorest 50%. Both COD emissions and GDP decreased after expressway connection for initially rich counties. Counties with moderate levels of initial income, i.e., from the 25^{th} to the 50^{th} percentile, saw a decrease in total emissions and an increase in total GDP after expressway connection. Table 4 summarizes the predicted impacts of expressway connection at different initial per capita GDP quantiles.

Note that we can also conduct a heterogeneity analysis with respect to initial COD emission levels. In our data, initial COD emissions and initial GDP are positively correlated across counties in 2000. Therefore, the heterogeneous impacts of expressway connection on emissions and GDP with respect to initial COD emission levels are analogous to the findings in Table 3; they are reported in the Appendix Table C.

Robustness Checks

We check the robustness of our findings in several different ways. First, one caveat of using Equation (2) to estimate the heterogeneous impacts is that it imposes a strong functional form on the heterogeneity, i.e., the heterogeneity is a linear function of initial income. In particular, the linear specification restricts the impacts of highway access on emissions and income to at most three, rather than four, different combinations. We therefore estimate the heterogeneity using a more flexible specification by including a set of dummy variables that indicate different initial income groups in the connected counties and interacting the income group dummies with the treatment status:

$$y_{i,t} = \alpha + \beta_k * (Income_k * Connect_{i,t}) + \rho_t + \mu_i + \varepsilon_{i,t}, \quad (3)$$

where $Income_k$ is a set of dummies indicating different initial income groups based on per capita GDP in 2000.

In light of the empirical findings in Table 4, we divide the (eventually) connected counties into five groups based on their per capita GDP levels in 2000: low income (0^{th}–10^{th} percentile), medium-low income (10^{th}–20^{th} percentile), medium income (20^{th}–40^{th} percentile), medium-high income (40^{th}–70^{th} percentile), and high income group (70^{th}–100^{th} percentile). The regression results are summarized in Table 5. All of the findings remain the same: counties in the low-income group significantly increased their emissions and income levels after expressway connection, while counties in higher income groups witnessed reductions in both emissions and income levels, and no group of counties saw a statistically significant increase in emissions and a decrease in income at the same time. These results suggest that the heterogeneity we have found does not depend on the functional form we imposed in Equation (2).[16]

Second, we probe the robustness of estimate accuracy by clustering the standard errors at three different levels: the county level, the province level and the county and province-

[16] We discuss the identifying assumption for the heterogeneous effects and related tests in Appendix D.

year level (multi-way clustering, suggested by Cameron, Gelbach, and Miller, 2011). The three clustering methods deal with three different potential correlations in the error term. Clustering the standard errors at the county level controls for arbitrary correlations across different years for the same county; clustering at the province level controls for arbitrary correlations within a province; clustering at both the county and province-year levels accounts for correlations across different years within the same county and correlations across all of the counties in the same province-year. We find that the significance levels are unaffected by different approaches to clustering standard errors, as reported in Table 6.

Third, we control for provincial time trends in the regressions (Column 2, 5, 8, 11 of Table 6) and find that the qualitative conclusions remain the same, although the estimated impacts become slightly smaller. Moreover, instead of including year fixed effects dummies, we include province-year fixed effects in the regressions in Columns 3, 6, 9 and 12. The province-year fixed effects account for annual shocks that are common to all counties in a province and thus provide a very general way to control for confounding factors such as business cycles and differential trends and policies across provinces. The treatment effect is identified by within-province comparisons of outcomes of interest. In other words, the effect of the expressway connection is estimated by comparing the outcomes of two counties in the same province in the same year. We find that, even in this strictest case, expressway connections have strong heterogeneous impacts on COD emissions and GDP.

Fourth, in Table 7, we provide the impacts of expressway expansion on several other emission measures. In Columns 1 to 4, we use COD emissions from the key polluting plants as the outcomes and find similar results. In Columns 5-8, we investigate ammonia-nitrogen (NH_3-N) emissions.[17] We consistently find that poor counties emit more ammonia-nitrogen and rich counties emit less after integration into a larger market. However, the data quality

[17] Ammonia-nitrogen is also an important measure of water pollution. It serves as a nutrient in water bodies and consumes large amounts of oxygen. As a result, rich ammonia-nitrogen is toxic to fish and other aquatic organisms and leads to eutrophication in the water.

for ammonia-nitrogen is relatively poor. For example, there are no data on ammonia-nitrogen in 2000, and a few hundred counties are missing readings from 2006 to 2010. As a result, only around 80% of the total number of observations are available for estimation.

Finally, we examine emissions of air pollutants such as nitrous oxides (NO_x) and sulfur dioxide (SO_2). We are unable to perform a comparable analysis on NO_x as data are only available for years after 2006. However, SO_2 emissions are available in all of the years in our study period, and thus we also provide the regression results for SO_2 in Columns 9–12 of Table 7.

Roughly 70% of SO_2 emissions were produced by the electricity and heating industries (mostly power plants), and the remaining 25–30% were emitted by the mineral products industry and the metal industry. Most plants in these industries belong to large state-owned enterprises (SOEs) and local county governments have little power to regulate them. Consequently, we expect the results for SO_2 to be less consistent. Consistent with the expectation, the estimates in Columns 5–8 of Table 7 show that, while SO_2 emissions decreased in connected counties on average, the heterogeneity results became statistically insignificant.

Assessing the Spill-over Effect

A general concern about the DiD approach is that, if the control group were somehow affected by the treatment through a spill-over, the estimate of the treatment effect could be biased and should be interpreted only as a relative effect. Accordingly, one may question whether our main results in Table 3 are driven by the spill-over effect of expressway connection on the unconnected counties. To understand how the potential spill-over effect could affect the interpretations of our findings, we focus on the counties that were never connected in the sample, and estimate the impacts of having at least one of the neighboring counties connected to the expressway system on emissions and GDP in these never-connected counties. In practice, we apply Equations (1) and (2) to the subsample of unconnected counties, substituting $Connect_{i,t}$ with a "neighbor connected" indicator that equals 1 if at least one of county i's neighboring counties are connected at year t, and 0 otherwise. The coefficients of this indicator and its interaction with the initial income would reveal the potential spill-over effect and its heterogeneity.

The results are reported in Table 8. Columns 1–4 show that the spill-over effect on emission measures is statistically insignificant on average, and so is its heterogeneity across initial incomes. Therefore, it is highly unlikely that the spill-over effect could be driving the heterogeneity in the expressway impact on emissions between connected and unconnected counties (Columns 2 and 4 in Table 3).

Columns 5–8 show positive average impacts on the GDP measures of unconnected counties when neighboring counties are connected to expressways; these effects are more negative or less positive if the focal unconnected county has higher initial income. This heterogeneity does suggest that an expressway connection can affect the GDP of some unconnected counties, but it also suggests that the spill-over effect works against the heterogeneity pattern in the income effect in our main results (Table 3, Columns 6 and 8), rather than contributing to it.

We can then conclude that our main results of heterogeneities across initial income levels in the emissions and income impacts of connection are not driven by the spill-over effect.

Channels

To understand how the connected counties realized their different development strategies after the expressway connection, we examine how expressway connection affects several other outcome variables, following the regression specified in Equation (3). Leaving more detailed results to Appendix Table E, we highlight here the results for only two outcomes: COD emission intensity and the share of manufacturing industry in the local GDP. The emission intensity is the average emissions from the key polluting sources from each dollar-value of output produced, measuring the cleanness of the polluting sector in each county. The share of manufacturing captures the industrial structure of each county.

In Figure 4, we plot the predicted impacts of expressway connection on the two additional outcome variables, as well as the predicted impacts on emissions and GDP, across different initial incomes of the counties. The lines showing the impacts on emissions and emission intensity cross the horizontal zero impact benchmark from above at almost the same income level (at the 25th percentile), and so do the lines showing the impacts on GDP and the share of manufacturing industry in GDP (at the 50th percentile). This observation suggests that the heterogeneity in the impacts on emissions and income across different initial incomes could have been caused by changes in the cleanness of the polluting sector and in the local industrial structure. For initially poor counties, expressway connection increases income and emissions, which is accompanied by a more emission-intensive polluting sector and expanded industrial manufacturing; for initially rich counties, connection decreases income and emissions, with the polluting sector becoming cleaner and the manufacturing industry shrinking; for the middle-income counties, after connection, the manufacturing industry grows, while the polluting sector becomes cleaner, generating an increase in local income and a decrease in emissions at the same time.

Summary of Findings

To summarize, we find that the poorest 25% of counties achieve higher incomes at the cost of environmental degradation, which supports Prediction 1. Expressway connection has negative impacts on both GDP and emissions for the richer 50% of counties, consistent with Prediction 2. The expressway connection increases GDP while reducing emissions for counties in medium-low-income counties (25th–50th percentiles) but never reduces GDP while increasing emissions, consistent with Prediction 3. These changes are accompanied by changes in the cleanness of polluting industries and in the local industrial structure. Combining all three pieces of evidence, we can also infer that expressway connection expands rather than shrinks the possibility frontier, consistent with our interpretation of the expressway access as a positive productivity shock.

VI. Alternative Explanations

The empirical findings in this paper relate to two important theories in economic research: the pollution haven hypothesis and the home market effect. The pollution haven hypothesis proposes that market integration, which can be brought by transport infrastructure improvement, will cause polluting capital to flow from rich regions to poor regions. The economic rationale behind the hypothesis is realization of comparative advantage: low-income regions have comparative advantage in polluting industries because they do not value environmental quality highly, while high-income regions have comparative advantage in non-polluting industries. As trade cost is reduced, both regions can specialize in producing products in which they have comparative advantages. The hypothesis can then explain our observation that expressway access causes 1) richer counties to pollute less and poor counties to pollute more, 2) more polluting firms to emerge in poor counties than in rich counties, and 3) poor counties to start to industrialize while rich counties start to deindustrialize. The hypothesis, however, cannot adequately explain the negative impact of the expressway access on income levels in rich counties.

The home market effect conjectures that, because of economies of scale, market integration can cause mobile factors (e.g., capital, or even labor) that are formerly located in peripheral counties to move to core metropolitan areas to enjoy a larger home market. If the core-periphery relations are sufficiently asymmetric, this trade integration can reduce economic output in the peripheral counties (e.g., Faber, 2014). This argument can potentially explain the negative impacts of expressway connection on GDP and emissions in rich counties in our data, and could also provide an alternative to our interpretation of the expressway access as a positive productivity shock. As shown in Faber (2014), however, the home market effect implies that the negative impact of expressway connection on industrial output and GDP should be even stronger if the core-periphery relation is more asymmetric, i.e., if the focal county is poorer. This prediction contradicts our empirical observation that expressway access decreases income in the rich counties while increasing income in the poor and middle-income counties.

Another intuitive implication from the home market effect is that the impact of expressway connection depends on the distance between the peripheral county and the metropolitan area, i.e., the nearest target city in our context: the closer they are to each other, the stronger the potential negative income impact on the county will be (e.g., Faber, 2014). We therefore test whether there exists such heterogeneity conditional on the existing income heterogeneity shown in Table 9. The result shows, first, that the expressway connection's impact on the focal county's income does not have statistically significant heterogeneity across different distances to the nearest target city. Second, adding the connection–distance interaction term into the regressions has hardly any impact on the estimates of the coefficient of the connection–initial income interaction term in all the regressions, which implies that the observed heterogeneity across initial incomes is not driven by variation in the distances between connected counties and their nearest target cities. These findings do not support the home market effect.

As each of the theories can only partially explain our empirical findings and is inconsistent with part of the findings, one may propose a combination of them, i.e., the comparative advantage in polluting industry could be so strong in poor counties that the pollution haven hypothesis would dominate the home market effect, while this comparative advantage could be relatively weak in rich counties, so that the home market effect would dominate.[18] However, this combination still leaves two empirical findings unexplained:

[18] For details of the argument, our analysis of a model of the new economic geography with location-specific marginal cost of polluting industrial production, which derives a closed-form solution, is available upon request. Forslid et al. (Forthcoming) incorporate both the pollution haven hypothesis and the home market effect in a different model, which focuses on a strategic tax setting and does not yield a closed-form solution for the general case.

first, for moderate-income counties, expressway access increases income and decreases emissions; second, for any group of counties, expressway access never decreases income and increases emissions at the same time. Our theoretical framework with expressway access interpreted as a positive productivity shock, however, can reconcile these empirical findings without referring to the pollution haven hypothesis and home market effect.

Given these considerations, although we acknowledge the potential relevance of the pollution haven hypothesis and the home market effect in our context, we conclude that our model provides a concise, consistent, and more general explanation of our empirical findings.

VII. Conclusion

This paper analyzes how society would adapt to changes in economic production conditions through the trade-off between environmental preservation and economic development. Theoretically, we show that a positive productivity change can lead to an increase or a decrease in income and pollution levels, and that the heterogeneity depends on the initial income (or pollution) level. Empirically, we find heterogeneity in both environmental and economic consequences of expressway connection across different initial levels of income (and emissions), consistent with the theory.

Our findings have several policy implications. Firstly, the same type of productivity-enhancing policy or economic shock can cause different regions to choose different development strategies, and the optimal emission–income combination depends on a region's initial income or pollution levels. In the context of large income and environmental disparities, either within a large country such as China or India, or in a global platform consisting of developed and developing countries, a single unified economic or environmental policy can cause significant welfare losses. For example, tight environmental standards favored by rich regions can harm the poor regions that prefer more polluting development strategies.

Secondly, although a highly-diversified policy portfolio across different regions may be seen as optimal, this portfolio may nonetheless be susceptible to criticism from environmental organizations, which seek general improvement in environmental quality, or from parties that primarily focus on GDP growth and raising income. This could lead to political conflicts due to the variations in policy preferences regarding the trade-off between development and the environment across different income groups. As a result, redistributive policies can not only be a solution to the long-standing income inequality issue in China, but also can be useful for addressing the increasing challenges of political issues related to the environment.

Thirdly, the theoretical model also predicts that a positive economic productivity shock can degrade environmental quality in the initial stages of economic development. We may see a further deterioration of global environmental quality because many less-developed countries have not yet reached the middle-income level at which a win-win response in pecuniary income and environmental quality would emerge. One remedy for this challenge could be to introduce intense economic productivity shocks to less-developed countries to allow them to achieve the middle-income level within a short period of time. In practice, technology transfer from rich countries to poor countries or infrastructural improvements in poor countries are potentially effective solutions.

Recognizing the simplicity of our theoretical framework and its power to reconcile the empirical findings, we conclude by pointing out some directions for further investigation. In our model, we assume that the environmental impacts of emissions are local, while pollution in one region can in reality affect social welfare in neighboring regions as well. In such cases, a welfare-maximizing growth path at the aggregate level depends on the specific patterns of the externality. Besides, without a detailed micro-foundation of the possibility frontier, it is also difficult for the framework to specify the channels through which the negative impacts of expressway on income and emissions in richer counties are manifested. Therefore, more assumptions about the possibility frontier, e.g., considering the interaction between the inside and outside of the focal county could help to more clearly explain the mechanisms behind the empirical pattern we have observed.

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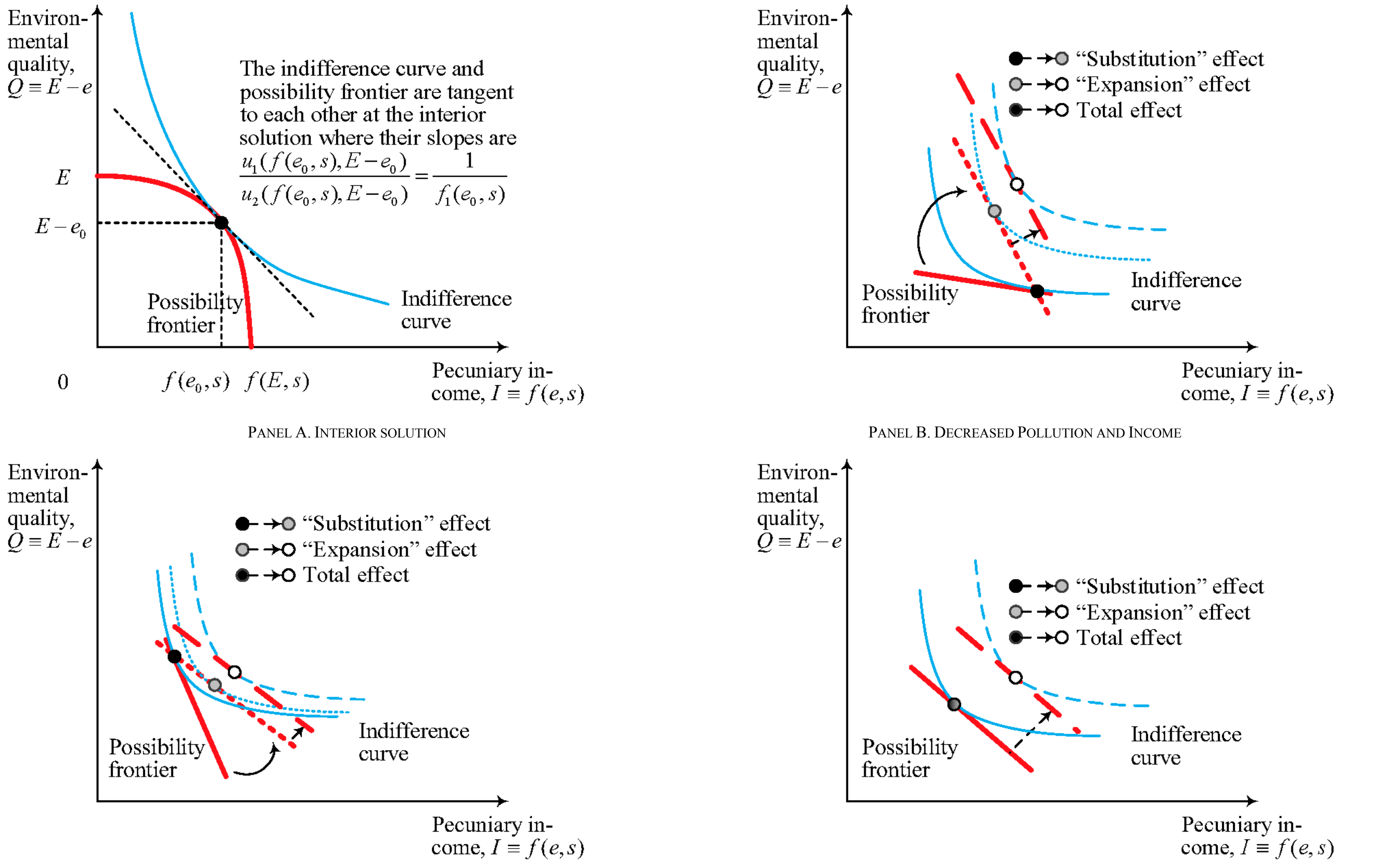


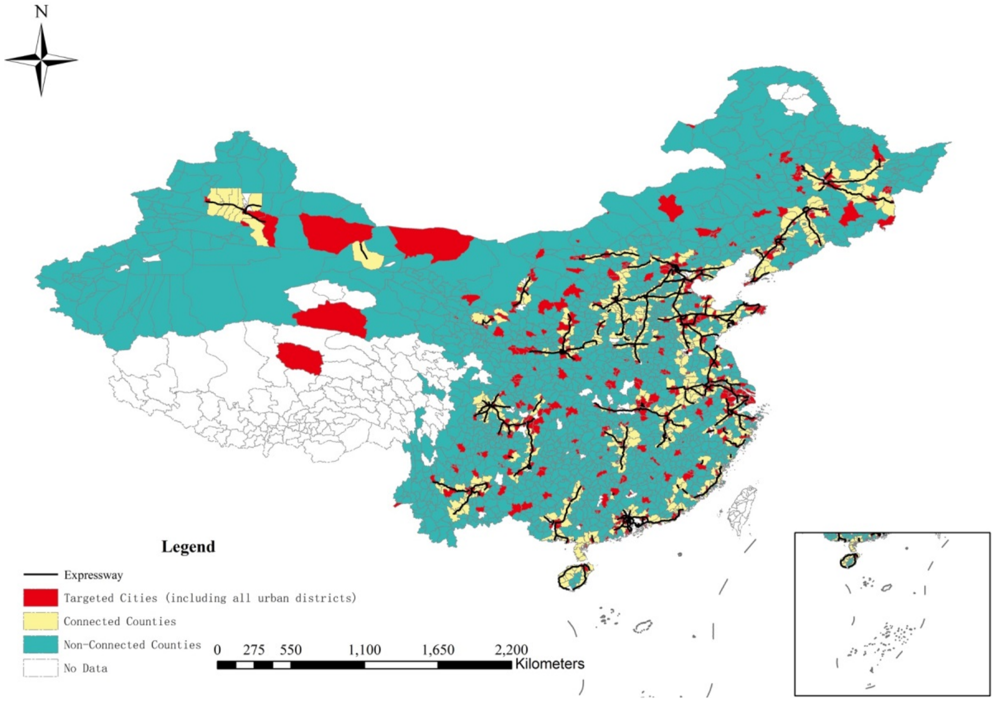
PANEL A. INTERIOR SOLUTION

PANEL B. DECREASED POLLUTION AND INCOME

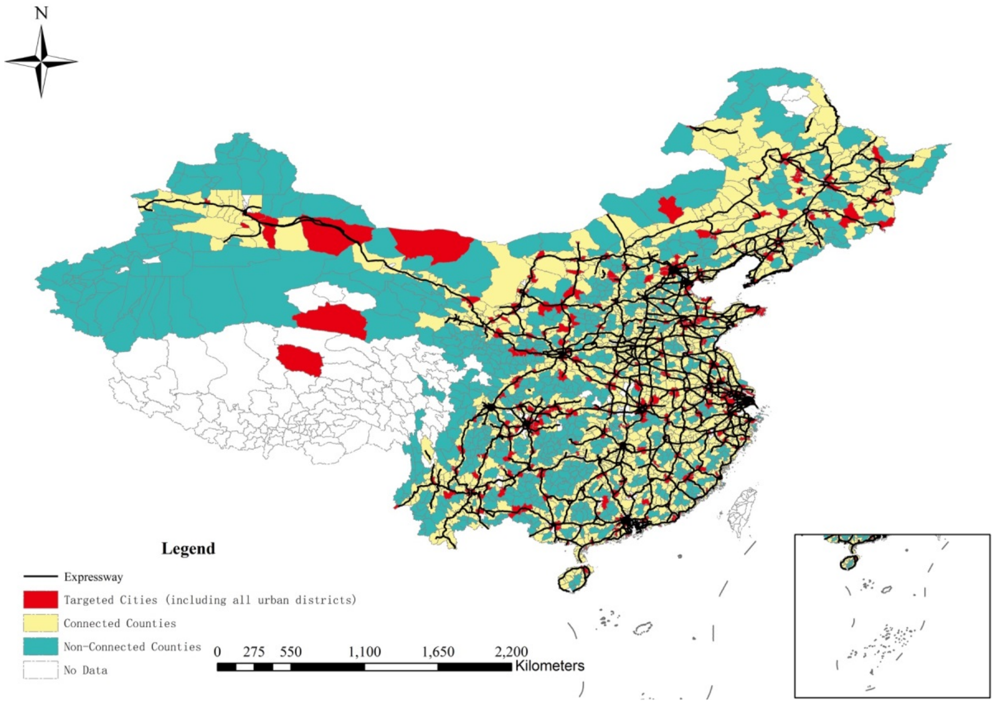
PANEL C. INCREASED POLLUTION AND INCOME

PANEL D. INCREASED INCOME AND DECREASED POLLUTION

FIGURE 1. THE EFFECT OF A POSITIVE PRODUCTIVITY SHOCK ON THE INCOME AND ENVIRONMENTAL QUALITY



PANEL A. CHINA'S NATIONAL EXPRESSWAYS IN 2000



PANEL B. CHINA'S NATIONAL EXPRESSWAYS IN 2012

FIGURE 2. EXPANSION OF THE NATIONAL EXPRESSWAY SYSTEM IN CHINA

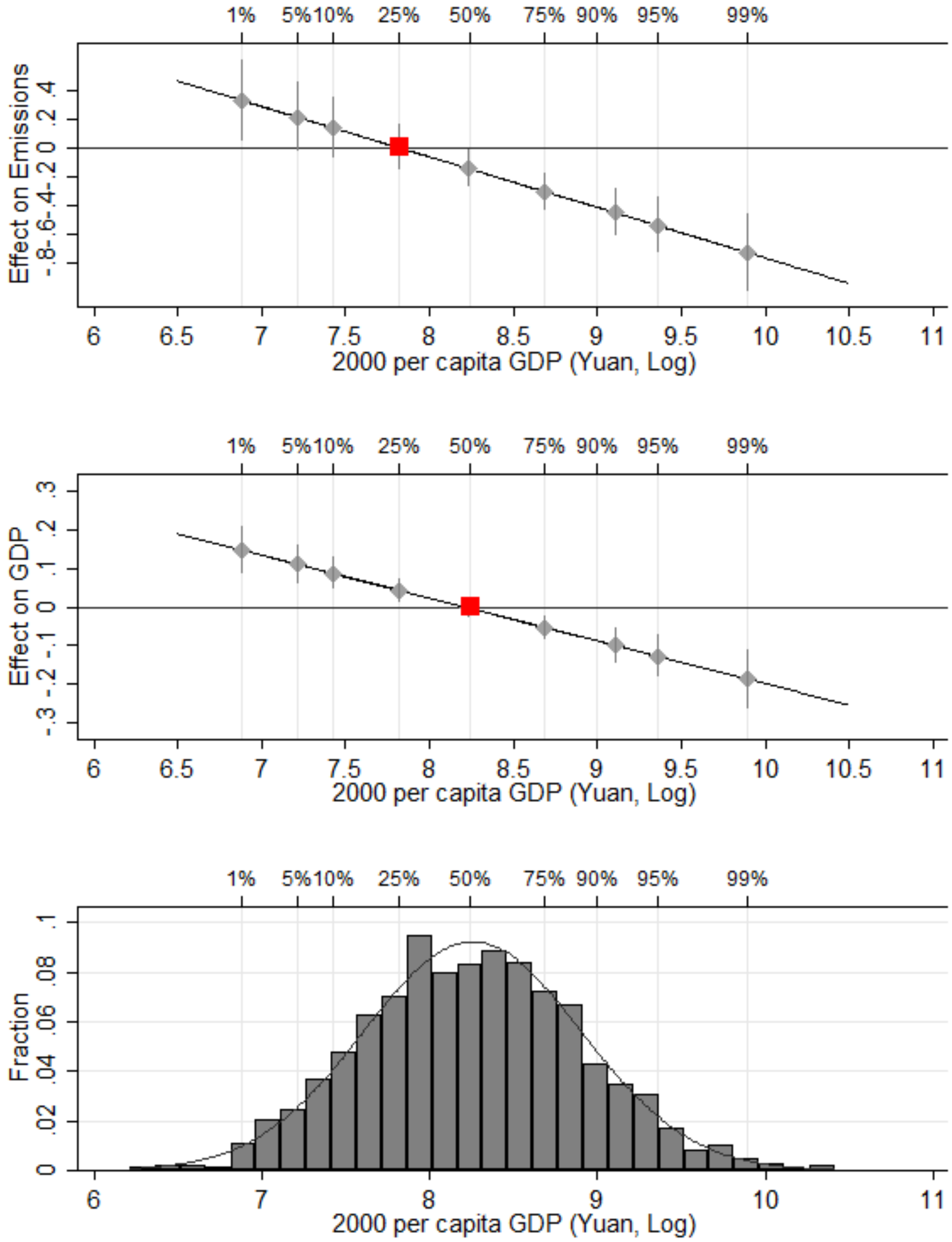


FIGURE 3. PREDICTED HETEROGENEOUS EFFECT OF EXPRESSWAY CONNECTION ON EMISSIONS AND GDP

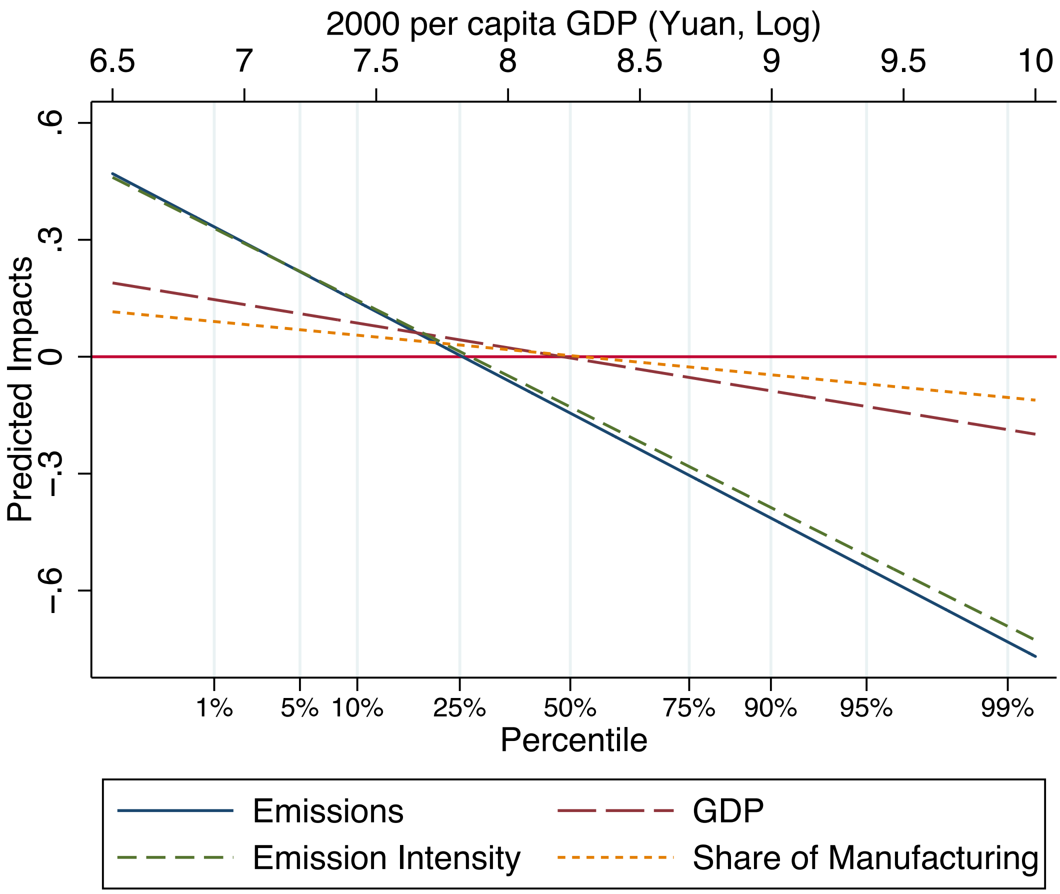


FIGURE 4. EXPLORE THE CHANNELS OF THE HETEROGENEOUS EFFECTS

Table 1. Summary statistics of sampled counties

Variable	Mean	Connected	Unconnected
COD emissions in 2000 (metric tons)	1,831	2,322	1,241
	(4,817)	(5,550)	(3,667)
COD emissions in 2012 (metric tons)	1,123	1,392	788
	(2,255)	(2,727)	(1,396)
GDP in 2000 (million yuan)	2,582	2,990	2,094
	(5,722)	(2,938)	(7,825)
GDP in 2012 (million yuan)	15,108	17,452	12,286
	(31,953)	(18,322)	(42,815)
GDP per capita in 2000 (yuan)	4,912	5,396	4,327
	(4,356)	(4,002)	(4,686)
GDP per capita in 2012 (yuan)	30,819	32,481	28,806
	(32,808)	(30,819)	(34,982)
Population in 2000 (thousand)	485	555	400
	(453)	(349)	(542)
Population in 2012 (thousand)	500	576	407
	(420)	(383)	(445)

Source: Standard deviations are reported in the parentheses below the means. COD emission data are collected from the Environmental Statistics Database (2000-2012) of the Ministry of Environmental Protection of China. County-level GDP and population data are collected from various sources including various provincial statistical yearbooks, China City Statistical Yearbooks, China County Statistical Yearbooks and the China Economic Data Database from CEIC (www.ceicdata.com).

Table 2. The average treatment effects of expressway connection on COD emissions and GDP

	COD emissions (tons, log)			Per capita COD emissions (kg, log)			GDP (million yuan, log)			Per capita GDP (yuan, log)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Expressway	-0.18***	-0.15***	-0.15**	-0.25***	-0.21***	-0.21***	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)	(0.07)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	(0.06)	(0.04)	(0.04)	(0.07)	(0.04)	(0.04)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	(0.07)	(0.07)	(0.07)	(0.08)	(0.07)	(0.08)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
County FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y	N
Provincial trends	N	Y	N	N	Y	N	N	Y	N	N	Y	N
Province-year FE	N	N	Y	N	N	Y	N	N	Y	N	N	Y
Obs.	18,810	18,810	18,810	18,378	18,378	18,378	19,835	19,835	19,835	19,472	19,472	19,472
R^2	0.08	0.12	0.16	0.08	0.13	0.17	0.91	0.92	0.93	0.90	0.92	0.93

Notes: This table estimates the impacts of expressway connection on COD emissions using a variety of specifications. We probe the robustness of estimate accuracy by clustering the standard errors at three different levels: the county, province and county and province-year levels (multi-way clustering suggested by Cameron, Gelbach, and Miller (2011)). These standard errors are respectively reported in the parentheses below the estimated coefficients. Our preferred specification clusters standard errors at the county level. *** p<0.01, ** p<0.05, * p<0.1.

Table 3. Heterogeneous treatment effect with respect to initial income

	COD emission (tons, log)		Per capita COD emission (kg, log)		GDP (million yuan, log)		Per capita GDP (yuan, log)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Expressway	-0.18***	2.77***	-0.25***	3.27***	-0.01	0.91***	-0.01	1.16***
	(0.06)	(0.72)	(0.07)	(0.78)	(0.01)	(0.18)	(0.01)	(0.19)
Expressway*GDP pc		-0.35***		-0.42***		-0.11***		-0.14***
(yuan, log, in 2000)		(0.08)		(0.09)		(0.02)		(0.02)
County FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	18,810	18,179	18,378	18,007	19,835	19,213	19,472	19,091
R^2	0.08	0.08	0.08	0.08	0.91	0.91	0.90	0.90

Notes: This table estimates the heterogeneous impacts of expressway connection on COD emissions and GDP. Standard errors are clustered at the county level and reported in the parentheses below the estimated coefficients. *** p<0.01, ** p<0.05, * p<0.1.

Table 4. Predicted effect of expressway connection at different initial income levels

Per capita GDP percentile in 2000	Effect on COD emissions	Effect on per capita COD emissions	Effect on GDP	Effect on per capita GDP
	(1)	(2)	(3)	(4)
1% (log = 6.886)	0.33**	0.36**	0.15***	0.19***
	(0.15)	(0.16)	(0.03)	(0.03)
5% (log = 7.211)	0.22*	0.23*	0.11***	0.15***
	(0.12)	(0.13)	(0.03)	(0.03)
10% (log = 7.428)	0.14	0.15	0.09***	0.12***
	(0.11)	(0.12)	(0.03)	(0.03)
25% (log = 7.817)	0.00	0.03	0.04**	0.06***
	(0.08)	(0.09)	(0.03)	(0.03)
50% (log = 8.236)	-0.14**	-0.21***	0.00	0.00
	(0.07)	(0.07)	(0.01)	(0.01)
75% (log = 8.687)	-0.3***	-0.40***	-0.05***	-0.06***
	(0.07)	(0.07)	(0.02)	(0.02)
90% (log = 9.106)	-0.45***	-0.57***	-0.10***	-0.12***
	(0.08)	(0.09)	(0.02)	(0.02)
95% (log = 9.360)	-0.54***	-0.56***	-0.13***	-0.16***
	(0.10)	(0.11)	(0.03)	(0.03)
99% (log=9.895)	-0.73***	-0.91***	-0.19***	-0.23***
	(0.14)	(0.15)	(0.04)	(0.04)

Notes: This table summarizes the predicted impacts of expressway connection on COD emissions and GDP at different initial per capita GDP levels using regression results in Table 3. Standard errors are clustered at the county level and reported in the parentheses below the estimated coefficients. *** p<0.01, ** p<0.05, * p<0.1.

Table 5. Heterogeneous treatment effect with respect to different initial income groups

	COD emissions (tons, log)	Per capita COD emissions (kg, log)	GDP (million yuan, log)	Per capita GDP (yuan, log)
	(1)	(2)	(3)	(4)
Low*Expressway	0.34**	0.37*	0.21***	0.25***
	(0.17)	(0.19)	(0.04)	(0.04)
Med Low*Expressway	0.07	-0.01	0.05*	0.06**
	(0.15)	(0.16)	(0.03)	(0.03)
Med*Expressway	-0.20	-0.27*	-0.04**	-0.04**
	(0.14)	(0.16)	(0.02)	(0.02)
Med High*Expressway	-0.19*	-0.26**	-0.08***	-0.07***
	(0.10)	(0.11)	(0.02)	(0.02)
High*Expressway	-0.44***	-0.56***	-0.05	-0.07***
(yuan, log, in 2000)	(0.10)	(0.11)	(0.03)	(0.03)
County FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Obs.	18,810	18,378	19,835	19,472
R^2	0.08	0.08	0.91	0.90

Notes: This table estimates the heterogeneous impacts of expressway connection on COD emissions and GDP. Standard errors are clustered at the county level and reported in the parentheses below the estimated coefficients. *** p<0.01, ** p<0.05, * p<0.1.

Table 6. Robustness checks: heterogeneous treatment effect with respect to initial income

	COD emissions (ton, log)			Per capita COD emissions (kg, log)			GDP (million yuan, log)			Per capita GDP (yuan, log)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Expressway	2.77***	1.58**	1.88**	3.27***	1.73**	2.06**	0.91***	0.56***	0.55***	1.16***	0.80***	0.80***
	(0.72)	(0.74)	(0.74)	(0.78)	(0.81)	(0.82)	(0.18)	(0.16)	(0.16)	(0.19)	(0.16)	(0.16)
	(0.87)	(0.70)	(0.69)	(0.96)	(0.79)	(0.77)	(0.32)	(0.27)	(0.27)	(0.34)	(0.25)	(0.25)
	(0.79)	(0.76)	(0.83)	(0.86)	(0.84)	(0.91)	(0.23)	(0.19)	(0.20)	(0.24)	(0.19)	(0.20)
Expressway*GDP per capita	-0.35***	-0.21**	-0.25***	-0.42***	-0.23**	-0.27***	-0.11***	-0.07***	-0.07***	-0.14***	-0.10***	-0.10***
(yuan, log, in 2000)	(0.08)	(0.09)	(0.09)	(0.09)	(0.10)	(0.10)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
	(0.10)	(0.08)	(0.08)	(0.11)	(0.10)	(0.09)	(0.04)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)
	(0.09)	(0.09)	(0.10)	(0.10)	(0.10)	(0.11)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)
County FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y	N
Provincial trends	N	Y	N	N	Y	N	N	Y	N	N	Y	N
Province-year FE	N	N	Y	N	N	Y	N	N	Y	N	N	Y
Obs.	18,179	18,179	18,179	18,007	18,007	18,007	19,213	19,213	19,213	19,091	19,091	19,091
R^2	0.08	0.12	0.16	0.08	0.13	0.17	0.91	0.92	0.93	0.90	0.92	0.93

Notes: This table estimates the heterogeneous impacts of expressway connection on COD emissions and GDP using a variety of specifications. We probe the robustness of estimate accuracy by clustering the standard errors at three different levels: the county, province and county and province-year levels (multi-way clustering suggested by Cameron, Gelbach, and Miller (2011)). These standard errors are respectively reported in the parentheses below the estimated coefficients. Our preferred specification clusters standard errors at the county level. *** p<0.01, ** p<0.05, * p<0.1.

Table 7. The effects of expressway connection on other emission measures

	COD Emissions from Key Polluting Firms (ton, log)		Per capita COD Emissions from Key Polluting Firms (kg, log)		NH3-N Emissions (ton, log)		Per capita NH3-N Emissions (kg, log)		SO2 Emissions (ton, log)		Per capita SO2 Emissions (kg, log)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Expressway	-0.12*	3.39***	-0.19***	3.93***	0.03	4.30***	-0.01	5.28***	-0.11**	-0.19	-0.13***	-0.01
	(0.06)	(0.75)	(0.07)	(0.81)	(0.08)	(1.02)	(0.09)	(1.16)	(0.04)	(0.53)	(0.05)	(0.54)
Expressway*GDP pc		-0.42***		-0.49***		-0.51***		-0.63***		0.01		-0.01
(yuan, log, in 2000)		(0.09)		(0.10)		(0.12)		(0.14)		(0.06)		(0.06)
County FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	18,810	18,179	18,378	18,007	15,962	15,425	15,595	15,257	18,726	18,096	18,295	17,924
R2	0.09	0.09	0.09	0.09	0.12	0.12	0.15	0.15	0.14	0.14	0.13	0.12

Notes: This table estimates the heterogeneous impacts of expressway connection on other emission measures. Standard errors are clustered at county level and reported in the parentheses below the estimated coefficients. *** p<0.01, ** p<0.05, * p<0.1.

Table 8. Assessing Potential Spill-overs

	COD Emissions (ton, log)		Per capita COD Emissions (kg, log)		GDP (million yuan, log)		Per capita GDP (yuan, log)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Neighbor-connected	-0.04	0.35	-0.09	0.91	0.06***	0.68**	0.07***	0.93***
	(0.10)	(1.11)	(0.12)	(1.27)	(0.02)	(0.28)	(0.02)	(0.28)
Neighbor-connected*GDP pc		-0.05		-0.13		-0.08**		-0.11***
(yuan, log, Year 2000)		(0.14)		(0.16)		(0.04)		(0.03)
County FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	7,894	7,683	7,711	7,632	8,974	8,732	8,773	8,688
R^2	0.09	0.10	0.10	0.10	0.90	0.90	0.89	0.90

Notes: This table estimates the potential spillover effects of expressway connection. We keep only the unconnected counties and create a “neighbor connected” indicator that equals to 1 if at least one of an unconnected county's neighboring counties is connected by the expressways. We include the interaction term to explore potential spillover heterogeneity with respect to initial income levels. Standard errors are clustered at county level and reported in the parentheses below the estimated coefficients. *** p<0.01, ** p<0.05, * p<0.1.

Table 9. Heterogeneity with respect to distance to target cities

	COD Emissions (ton, log)		Per capita COD Emissions (kg, log)		GDP (million yuan, log)		Per capita GDP (yuan, log)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Expressway	2.77***	2.52***	3.27***	2.99***	0.97***	0.93***	1.14***	1.09***
	(0.72)	(0.74)	(0.78)	(0.80)	(0.18)	(0.19)	(0.19)	(0.20)
Expressway*GDP pc	-0.35***	-0.35***	-0.42***	-0.42***	-0.12***	-0.11***	-0.14***	-0.13***
(yuan, log, Year 2000)	(0.08)	(0.09)	(0.09)	(0.09)	(0.02)	(0.02)	(0.02)	(0.02)
Expressway*Distance		0.04*		0.04*		0.00		0.00
(10km)		(0.02)		(0.02)		(0.00)		(0.00)
County FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	18,179	17,987	18,007	17,818	16,564	16,394	16,462	16,292
R^2	0.08	0.08	0.08	0.08	0.91	0.91	0.91	0.91

Notes: Standard errors are clustered at county level and reported in the parentheses below the estimated coefficients. *** p<0.01, ** p<0.05, * p<0.1.

Online Appendices to “Balancing Development and the Environment in a Changing World: Expressways, GDP, and Pollution in China”

A. Proofs of Predictions

Mathematically, the impact of a productivity change on the choice of emissions can be derived by totally differentiating the first-order condition:

$$\frac{de}{ds} = \frac{u_{11}f_1f_2 + u_1f_{12} - u_{12}f_2}{-A} = \frac{\left(\frac{u_{11}}{u_1}f_1 - \frac{u_{12}}{u_1}\right)f_2 + f_{12}}{-\frac{A}{u_1}},$$

where

$$A \equiv u_{11}f_1^2 - 2u_{12}f_1 + u_1f_{11} + u_{22} < 0 \tag{8}$$

is the second-order condition for interior solutions. Thus the total effect on emissions is positive, if and only if

$$\left(\frac{u_{11}}{u_1}f_1 - \frac{u_{12}}{u_1}\right)f_2 + f_{12} > 0.$$

We first observe that any solution to this model occurs along the possibility frontier, determined by the economic production function, $I \equiv f(e,s)$. This identity derives the following proposition:

Proposition 1. A positive productivity shock increases pecuniary income unless its impact on emissions is sufficiently negative, i.e., $\frac{dI}{ds} < 0$ if and only if $\frac{de}{ds} < -\frac{f_2}{f_1} < 0$. It is then impossible for a positive productivity shock to simultaneously increase emissions and reduce pecuniary income.

Proof: The identity gives $\frac{dI}{ds} \equiv \frac{df(e,s)}{ds} = f_1\frac{de}{ds} + f_2 < 0$ if and only if $\frac{de}{ds} < -\frac{f_2}{f_1}$.
Note $f_1 > 0$ and $f_2 > 0$. The result follows. □

We then characterize the impacts of a positive productivity shock on emissions and pecuniary income when the initial pecuniary income or emissions are sufficiently low:

Proposition 2. If the initial pecuniary income or emissions are sufficiently low, then a positive productivity shock increases emissions, i.e., $\bar{I}$ and $\bar{e}$ are thresholds such that, if $I \leq \bar{I}$ and $e \leq \bar{e}$, then $\frac{de}{ds} > 0$ and $\frac{dI}{ds} > 0$, where $\bar{I} = f(\bar{e}, s)$.

Proof. First observe that $f_{12}(0, s) > 0$. Suppose $f_{12}(0, s') \leq 0$ for some s'. Since $f_{12}(0, s') \neq 0$, $f_{12}(0, s') < 0$. Since $f(e, s)$ is continuously differentiable, there are e' and s'' such that $f_{12}(e, s) < 0$ for any $0 \leq e \leq e'$ and $s' \leq s \leq s''$. Thus for any $0 < e \leq e'$, $f_1(e, s'') \equiv f_1(e, s') + \int_{s'}^{s''} f_{12}(e, s) ds < f_1(e, s')$. Therefore, $f(e, s'') = \int_0^e f_1(x, s'') dx < \int_0^e f_1(x, s') dx = f(e, s')$, contrasting $f_2(e, s) > 0$, as $s' \leq s''$.Hence $f_{12}(0, s) > 0$.

Also note that $\left(\frac{u_{11}}{u_1} f_1 - \frac{u_{12}}{u_1}\right)$ is finite. To illustrate this, $\frac{u_{11}}{u_1} f_1 - \frac{u_{12}}{u_1} = \frac{u_{11}}{u_1}\frac{u_2}{u_1} - \frac{u_{12}}{u_1} = \frac{u_{11}u_2 - u_{12}u_1}{u_1^2} = \frac{\partial\left(-\frac{u_2}{u_1}\right)}{\partial I}$, which is finite. Therefore, as e → 0, i.e., as $I \equiv f(e, s) \equiv \int_0^e f_1(x, s) dx \to 0$,

$$\left(\frac{u_{11}}{u_1} f_1 - \frac{u_{12}}{u_1}\right) f_2 + f_{12} \equiv \left(\frac{u_{11}}{u_1} f_1 - \frac{u_{12}}{u_1}\right) \int_0^e f_{12}(x, s) dx + f_{12} \to f_{12}(0, s) > 0 \qquad (4)$$

Hence as $e \to 0$, i.e., as $I \to 0$, $\frac{de}{ds} > 0$. By Proposition 1, $\frac{dI}{ds} > 0$. □

The intuition of this proposition can be illustrated by an extreme case in which the initial income is exactly zero, as shown in Appendix Figure 2. Firstly, a positive productivity shock does not substantially shift the possibility frontier around the initial solution when the initial income is low. In an extreme case in which the initial income is zero, as represented by the black dot in Appendix Figure 2, this shift does not make a difference, as shown by the equivalence of the grey and white dots. In other words, the expansion effect in the impact of a positive productivity shock is limited, meaning the substitution effect determines the direction of this impact.

Secondly, consider the substitution effect. An outward shift of the possibility frontier suggests that the frontier must be flattened when the initial allocation of environmental resources to economic production is low, i.e., when the initial income is low. The marginal productivity of environmental resources in generating pecuniary income then increases. The decision-maker then chooses a combination of higher emissions, lower environmental quality, and higher pecuniary income in response to this increase.

Proposition 2 also implies that the adoption of cleaner technology in economic production, which shifts the possibility frontier outward, can also increase total emissions if the initial income and emissions are sufficiently low.

Proposition 2 raises another question: could the impacts of economic shocks on pecuniary income and emissions ever be negative? The decision-maker's problem, equation (1), is equivalent to

$$\max_{I} \quad u(I,Q) \equiv u\big(I, E-g(I,s)\big) \quad \text{s.t.} \quad 0 \leq I \leq f(E,s) \tag{5}$$

where $g(.,.)$ satisfies that $g(f(e,s),s)=e$. Note that $g_1 = 1/f_1 > 0$; $g_2(0,s)=0$; $g_2(I,s)<0$ for any $I>0$; $g_{12} = \frac{f_2 f_{11} - f_{12} f_1}{f_1^3} > 0$ if and only if f_{12} is sufficiently negative.

Assuming interior solutions, the first-order condition of the problem above is

$$u_1\big(I, E-g(I,s)\big) - u_2\big(I, E-g(I,s)\big) g_1(I,s) = 0. \tag{6}$$

The second-order condition is

$$B \equiv u_{11} - 2u_{12}g_1 + u_{22}g_1^2 - u_2 g_{11} < 0 \tag{7}$$

which must hold given interior solutions. Totally differentiating the first-order condition, we have

$$\frac{dI}{ds} = \frac{-u_{12}g_2 + u_{22}g_1g_2 - u_2g_{12}}{-B} = \frac{-\frac{u_{12}}{u_2}g_2 + \frac{u_{22}}{u_2}g_1g_2 - g_{12}}{-\frac{B}{u_2}}$$

$$< 0 \text{ if and only if } g_{12} > \left(-\frac{u_{12}}{u_2} + \frac{u_{22}}{u_2}g_1\right)g_2 > 0. \tag{8}$$

This result presents the possibility that a positive productivity shock reduces emissions and pecuniary income.

Proposition 3. If the impact of a positive productivity shock on marginal productivity is sufficiently negative, i.e., if $f_{12} < \frac{f_2 f_{11}}{f_1} - \left(-\frac{u_{12}}{u_2} + \frac{u_{22}}{u_2} g_1\right) g_2 f_1^2 < 0$, then it reduces both emissions and pecuniary income.

Proof. Note $g_1 = \frac{1}{f_1} = \frac{u_1}{u_2}$. Under the condition of the proposition, $\frac{dI}{ds} < 0$. By Proposition 1, $\frac{de}{ds} < 0$. □

This intuition of Proposition 3 is as follows: As the "expansion" effect always pushes the optimal income rightwards, the only source of a potential reduction in income is the "substitution" effect. When the marginal productivity is sufficiently low, i.e., when the slope of the possibility frontier is sufficiently steep, the "substitution" effect results in an optimal outcome with a lower income. A reduction in income can thus happen only when the positive productivity shock sufficiently reduces marginal productivity. Given the positive productivity shock, a lower pecuniary income also suggests that emissions must have decreased.

A direct implication of Proposition 3 given the result from Proposition 2 is that reductions in both emissions and income can happen only when the initial income is sufficiently high.

B. Tests for Parallel Trends

Since different counties were connected to the expressways in different years, we can test the the parallel-trend assumption using an event study approach, following Jacobson et al. (1993). Specifically, we estimate the following equation:

$$y_{it} = \sum_{k\geq -5, k\neq -1}^{k=5} D_{it}^{k} \cdot \delta_k + \rho_t + \mu_i + \varepsilon_{it}$$

where y_{it} represents the outcomes of interests in county i in year t. The dummy variables D_{it}^{k} is defined in the following way: for county i, which was never or always connected by an expressway within the sample period, $D_{it}^{k} = 0$ for any k and t. For county i, which was connected by an expressway within the sample period, we first define s_i as the year in which this county was first connected to the expressway network, and we then define $D_{it}^{-5} = 1$ if $t - s_i \leq -5$, and 0 otherwise; $D_{it}^{k} = 1$ if $t - s_i = k$, and 0 otherwise, where $k = -4, -3, -2, 0, 1, 2, 3, 4$; and $D_{it}^{3} = 1$ if $t - s_i \geq 5$, and 0 otherwise. The county fixed effect is μ_i; the year fixed effect is ρ_t.

Note that the dummy for $k = -1$ is omitted in the equation, and the post-treatment effects are therefore relative to the year immediately prior to expressway connection. The parameter of interest δ_k dynamically estimates the effect of expressway connection k years after it first gains an expressway connection. We include leads of first expressway connection in the equation, testing whether this treatment has an impact on outcomes up to five years prior to actual connection. A test of the parallel-trend assumption is that the "placebo" leads of the treatments have no impact on the outcomes, i.e. $\delta_k = 0$ for all $k \leq -2$.

The regression results are represented in Appendix Table B. We find that the estimated coefficients of the placebo leads (we include 5 leads in the regressions) are not statistically different from zero, suggesting that there are no systematic differences in the pre-treatment trends between the control and connected groups for both emission and

GDP measures.[1] After three to four years of connection, expressway connection dummies become statistically significant. This is reasonable because it takes time for connected regions to adjust their production plans.

[1] The coefficient of the placebo lead (>=5 years) is statistically significant at 10% level for per capita COD emission. That suggests five or more year ago, the connected counties and unconnected counties were slightly different in terms of per capita COD emission. We think this is not threatening our identification strategy, because the rest of coefficients of the placebo leads, which were closer to the actual connection time, are all statistically insignificant.

C. Identifying Treatment Status for Each County

One caveat of this dataset is that expressway connection information is not available for all years. While the study period ranges from 2000 to 2012, we lack expressway data for 2001, 2004, 2006, 2008 and 2009.We interpolated data for these years by considering three different scenarios to create a balanced panel dataset.

We will use 2001 as an example. First, if a county was connected before 2001 (1992-2000), then it must be connected in 2001 as well. Second, if a county was not connected in 2000 or 2002, we can infer that it was not connected in 2001. Third, for a small set of counties, the data show that they had expressway connections in 2002 but not in 2000, so there are two possibilities: (a) these counties were connected in 2002, or (b) in 2001.

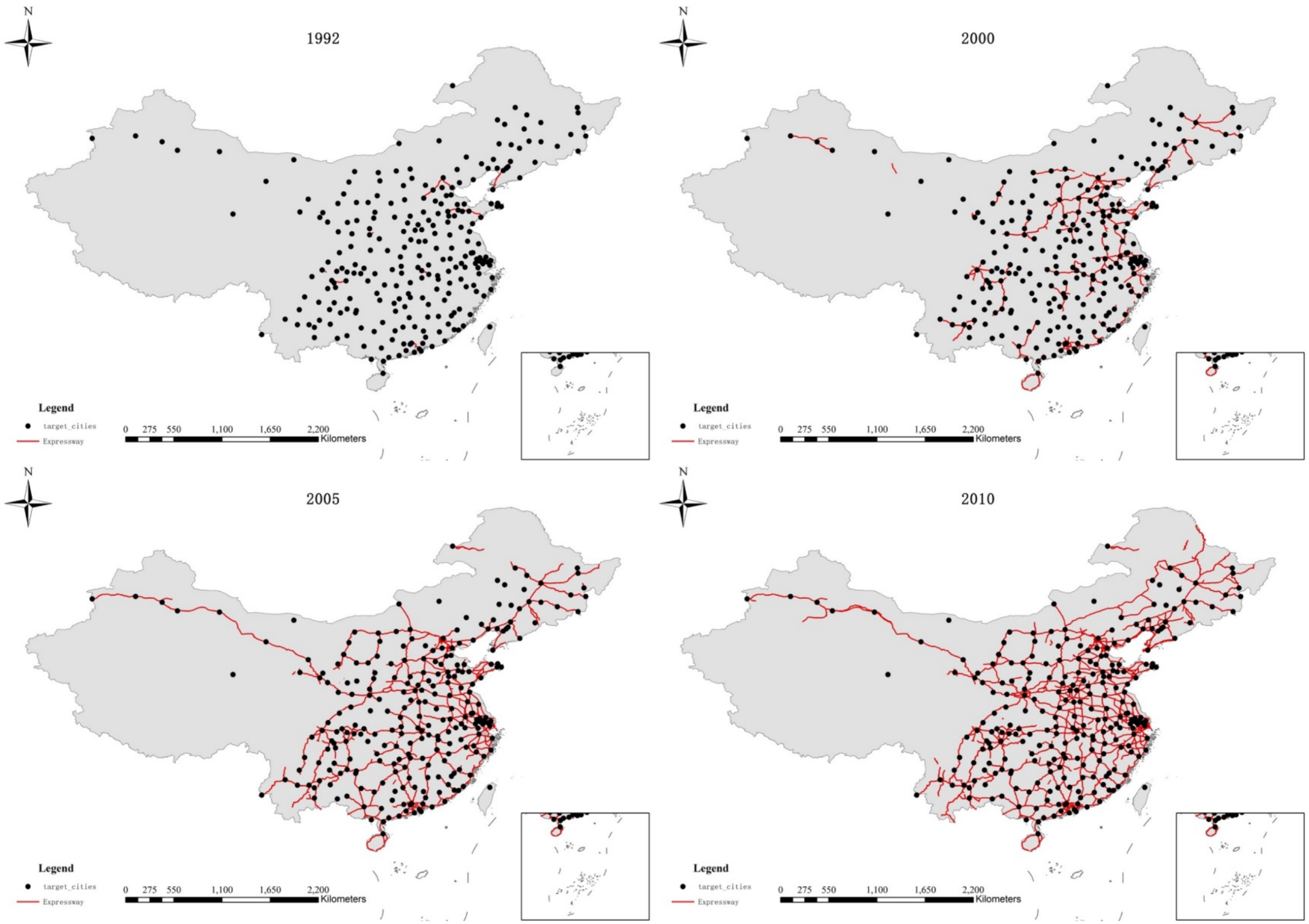
Theoretically, this uncertainty creates a measurement error in the treatment status on the first year when a county was connected. However, only a small portion of the connected counties (12%) in the data fall into the third category. In our main analysis, we assume that a county was connected in the latter year for which the data are available, using possibility (a) to determine the treatment status. We then check the robustness of our findings using the alternative possibility (b) and find that it has a negligible impact on our estimations. The results using (b) are reported in Appendix Table D.

We do not have expressway data for two consecutive years in 2008 and 2009, requiring slight changes to the method of interpolation. Firstly, we interpolated counties in both 2008 and 2009 as having an expressway connection if the counties had expressway connections in 2007. Secondly, counties without an expressway connection in both 2007 and 2010 were interpolated as also not having an expressway connection in 2008 and 2009. Finally, a few counties that had expressway connections in 2007 but not in 2010 were again further categorized into three scenarios: (a) the expressway connection was created in 2008; (b) in 2009; and (c) in 2010. However, we also find that these slight alterations to the treatment status of this small set of counties does not affect our main regression results.

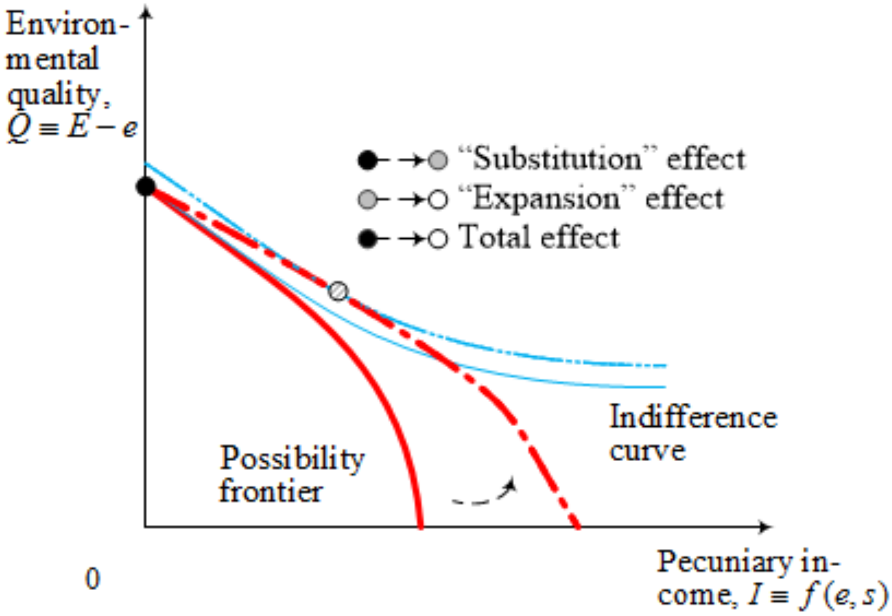
D. Test for Parallel Trends for Sub-groups

One concern relates to the identifying assumption for the heterogeneous effects. Although the non-connected counties can serve as a suitable control group for the connected counties as a whole, as suggested in Appendix Table C, this does not necessarily imply that they are suitable control groups for each sub-group in the connected counties. In other words, we need to test whether there is a trend break for all of the sub-groups in the connected counties and show that the expressway effects are zero before connection. To do so, we conduct separate event-studies for each outcome variable in Table 3 and for each income group, as discussed above. Then, in each regression, we include five placebo leads and five lags of the treatment dummy using equation (4) and test whether the leads and lags of the treatment dummy are statistically significantly different from zero.

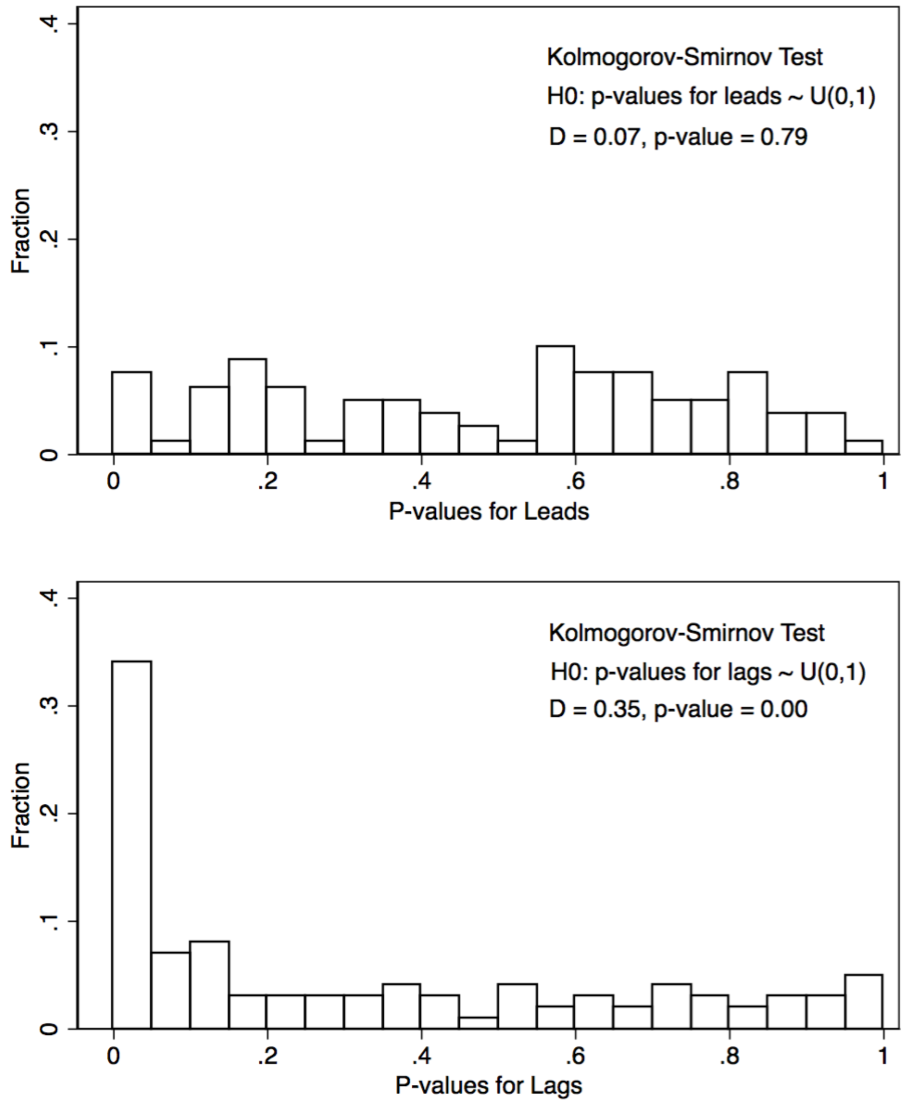
This process gives us 80 coefficients of the leads of the treatment (as lead = 1 is dropped from the regression) and 100 coefficients of the lags of the treatment in total. A classic result in statistics is that, under null hypothesis, the p-values based on a continuous test statistic are uniformly distributed from 0 to 1 (e.g., Hung et al., 1997). Therefore, if the p-values of the 80 coefficients of the leads of the treatment is uniformly distributed from 0 to 1, we can be more confident that the sub-group parallel trend assumption holds. This is exactly what we observe in the data: as shown in the upper panel of Appendix Figure 3, the p-values of the estimated coefficients for the leads are evenly distributed from 0 to 1. In sharp contrast, the distribution of the p-values of the 100 coefficients for the lags, as shown in the bottom panel of Appendix Figure 3, is skewed to the left, with a large portion falling between 0 and 0.1. This pattern confirms that the treatment effect for each sub-group is mostly statistically significant. We also conduct a formal Kolmogorov–Smirnov test with the null hypothesis being that the p-values are uniformly distributed from 0 to 1 for both cases, and we cannot reject that null hypothesis for leads but reject the null for lags.



APPENDIX FIGURE 1. EXPANSION OF THE NATIONAL EXPRESSWAY SYSTEM IN CHINA



APPENDIX FIGURE 2. AN EXTREME EXAMPLE WITH ZERO INITIAL INCOME



APPENDIX FIGURE 3. DISTRIBUTIONS OF P-VALUES FOR LEADS AND LAGS OF THE TREATMENT

Appendix Table A. China's Expressways and Main Controlling Nodes (Cities)

#	Main controlling nodes	Length (km)
M1	Beijing, Tianjin, Cangzhou, Dezhou, Ji'nan, Tai'an, Linyi, Huai'an, Jiangdu, Jiangyin, Wuxi, Suzhou, Shanghai	1245
M2	Beijing, Tianjin, Cangzhou, Dezhou, Ji'nan, Tai'an, Qufu, Xuzhou, Bengbu, Hefei, Tongling, Huangshan, Quzhou, Nanping, Fuzhou	2030
M3	Beijing, Baoding, Shijiazhuang, Handan, Xinxiang, Zhengzhou, Luohe, Xinyang, Wuhan, Xianning, Yueyang, Changsha, Zhuzhou, Hengyang, Chenzhou, Shaoguan, Guangzhou, Shenzhen, Hong Kong (Port), Macao (Port)	2285
M4	Beijing, Baoding, Shijiazhuang, Taiyuan, Linfen, Xi'an, Hanzhong, Guangyuan, Mianyang, Chengdu, Ya'an, Xichang, Panzhihua, Kunming	2865
M5	Beijing, Zhangjiakou, Ji'ning, Hohhot, Baotou, Linhe, Wuhai, Yinchuan, Zhongning, Baiyin, Lanzhou, Xi'ning, Geermu, Lhasa	3710
M6	Beijing, Zhangjiakou, Ji'ning, Hohhot, Baotou, Linhe, Ejina Qi, Hami, Turpan, Urumqi	2540
M7	Beijing, Tangshan, Qinhuangdao, Jinzhou, Shenyang, Siping, Changchun, Harbin	1280
M11	Hegang, Jiamusi, Jixi, Mudanjiang, Dunhua, Tonghua, Dandong, Dalian	1390
M15	Shenyang, Liaoyang, Anshan, Haicheng, Dalian, Yantai, Qingdao, Rizhao, Lianyungang, Yancheng, Nantong, Changshu, Taicang, Shanghai, Ningbo, Taizhou, Wenzhou, Fuzhou, Xiamen, Shantou, Shanwei, Shenzhen, Guangzhou, Foshan, Kaiping, Yangjiang, Maoming, Zhanjiang, Haikou	3710
M21	Changchun, Shuangliao, Fuxin, Chaoyang, Chengde, Tangshan, Tianjin, Huanghua, Binzhou, Qingzhou, Laiwu, Linyi, Lianyungang, Huai'an, Nanjing, Yixing, Huzhou, Hangzhou, Jinhua, Lishui, Nanping, Sanming, Longyan, Meizhou, Heyuan, Huizhou, Shenzhen	3580
M25	Ji'nan, Heze, Shangqiu, Fuyang, Lu'an, Anqing, Jingdezhen, Yingtan, Nancheng, Ruijin, Heyuan, Guangzhou	2110
M31	Daqing, Songyuan, Shuangliao, Tongliao, Chifeng, Chengde, Beijing, Bazhou, Hengshui, Puyang, Kaifeng, Zhoukou, Macheng, Huangshi, Ji'an, Ganzhou, Lianping, Guangzhou	3550
M35	Erenhot, Ji'ning, Datong, Taiyuan, Changzhi, Jincheng, Luoyang, Pingdingshan, Nanyang, Xiangfan, Jingzhou, Changde, Loudi, Shaoyang, Yongzhou, Lianzhou, Guangzhou	2685
M41	Baotou, Ordos, Yulin, Yan'an, Tongchuan, Xi'an, Ankang, Dazhou, Chongqin, Qianjiang, Jishou, Huaihua, Guilin, Wuzhou, Maoming	3130
M45	Lanzhou, Guangyuan, Nanchong, Chongqing, Zunyi, Guiyang, Majiang, Duyun, Hechi, Nanning, Beihai, Zhanjiang, Haikou	2570
M51	Chongqing, Neijiang, Yibin, Zhaotong, Kunming	838

Source: The National Expressway Network Plan, Ministry of Transport Planning Academe of China, 2004.

Appendix Table A (continued). China's Expressways and Main Controlling Nodes (Cities)

#	Main controlling nodes	Length (km)
M10	Suifenhe (Port), Mudanjiang, Harbin, Daqing, Qiqihar, Manzhouli (Port)	1520
M16	Hunchun (Port), Dunhua, Jilin, Changchun, Songyuan, Baicheng, Ulanhot	885
M20	Dandong, Haicheng, Panjin, Jinzhou, Chaoyang, Chifeng, Xilinhot	960
M26	Rongcheng, Wendeng, Weihai, Yantai, Dongying, Huanghua, Tianjin, Bazhou, Laiyuan, Shuozhou, Ordos, Wuhai	1820
M30	Qingdao, Weifang, Zibo, Ji'nan, Shijiazhuang, Taiyuan, Lishi, Jingbian, Dingbian, Yinchuan	1600
M36	Qingdao, Laiwu, Tai'an, Liaocheng, Handan, Changzhi, Linfen, Fuxian, Qingyang, Pingliang, Dingxi, Lanzhou	1795
M40	Lianyungang, Xuzhou, Shangqiu, Kaifeng, Zhengzhou, Luoyang, Xi'an, Baoji, Tianshui, Lanzhou, Wuwei, Jiayuguan, Hami, Turpan, Urumqi, Kuytun, Khorgas (Port)	4280
M46	Nanjing, Bengbu, Fuyang, Zhoukou, Luohe, Pingdingshan, Luoyang	712
M48	Shanghai, Chongming, Nantong, Yangzhou, Nanjing, Hefei, Lu'an, Xinyang, Nanyang, Shangzhou, Xi'an	1490
M50	Shanghai, Suzhou, Wuxi, Changzhou, Nanjing, Hefei, Lu'an, Macheng, Wuhan, Xiaogan, Jingmen, Yichang, Wanzhou, Dianjiang, Guang'an, Nanchong, Suining, Chengdu	1960
M52	Shanghai, Huzhou, Xuancheng, Wuhu, Tongling, Anqing, Huangmei, Huangshi, Wuhan, Jingzhou, Yichang, Enshi, Zhongxian, Dianjiang, Chongqing	1900
M56	Hangzhou, Huangshan, Jingdezhen, Jiujiang, Xianning, Yueyang, Changde, Jishou, Zunyi, Bijie, Liupanshui, Qujing, Kunming, Chuxiong, Dali, Ruili (Port)	3405
M60	Shanghai, Hangzhou, Jinhua, Quzhou, Yingtan, Nanchang, Yichun, Changsha, Shaoyang, Huaihua, Guiyang, Anshun, Qujing, Kunming	2370
M66	Fuzhou, Nanping, Nancheng, Nanchang, Jiujiang, Huangmei, Huangshi, Wuhan, Xiaogan, Xiangfan, Shiyan, Shangzhou, Xi'an, Pingliang, Zhongning, Yinchuan	2485
M68	Quanzhou, Yong'an, Ji'an, Hengyang, Yongzhou, Guilin, Liuzhou, Nanning	1635
M70	Xiamen, Zhangzhou, Longyan, Ruijin, Ganzhou, Chenzhou, Guilin, Majiang, Guiyang, Bijie, Luzhou, Longchang, Neijiang, Chengdu	2295
M72	Shantou, Meizhou, Shaoguan, Hezhou, Liuzhou, Hechi, Xingyi, Shilin, Kunming	1710
M76	Guangzhou, Zhaoqin, Wuzhou, Yulin, Nanning, Baise, Funing, Kaiyuan, Shilin, Kunming	1610

Source: The National Expressway Network Plan, Ministry of Transport Planning Academe of China, 2004.

Appendix Table B. Event Study: Effects of Expressway Connection

	COD emissions (tons, log)	Per capita COD emissions (kg, log)	GDP (million yuan, log)	Per capita GDP (yuan, log)
	(1)	(2)	(3)	(4)
>= 5 Years before	0.18	0.29*	-0.01	-0.02
	(0.12)	(0.15)	(0.04)	(0.04)
4 Years before	0.10	0.16	0.01	-0.00
	(0.09)	(0.10)	(0.02)	(0.02)
3 Years before	0.04	0.10	-0.00	-0.00
	(0.05)	(0.07)	(0.01)	(0.01)
2 Years before	0.02	0.04	-0.00	-0.01
	(0.06)	(0.06)	(0.01)	(0.01)
Year of connection	-0.08*	-0.08*	0.00	-0.00
	(0.04)	(0.04)	(0.01)	(0.01)
1 Year later	-0.04	-0.04	-0.01	-0.01
	(0.07)	(0.09)	(0.01)	(0.01)
2 Years later	-0.15**	-0.20**	-0.01	-0.01
	(0.07)	(0.08)	(0.01)	(0.01)
3 Years later	-0.17**	-0.21**	-0.02**	-0.02
	(0.08)	(0.08)	(0.01)	(0.01)
4 Years later	-0.27***	-0.37***	-0.05***	-0.04**
	(0.09)	(0.11)	(0.02)	(0.02)
County FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Obs.	18,810	18,378	19,835	19,472
R^2	0.08	0.08	0.91	0.90

Notes: We conduct an event study by including leads and lags of the first expressway connection dummy in the regressions. The dummy indicating one-year-prior treatment status is omitted from the regression. Standard errors are clustered at the county level and reported in the parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table C. Heterogeneous Treatment Effect across Initial Emissions

	COD emissions (tons, log)		Per capita COD emissions (kg, log)		GDP (yuan, log)		Per capita GDP (yuan, log)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Expressway	-0.18***	2.02***	-0.25***	2.12***	-0.01	0.07**	-0.01	0.07*
	(0.06)	(0.18)	(0.07)	(0.21)	(0.01)	(0.03)	(0.01)	(0.04)
Expressway*initial emissions		-0.35***		-0.37***		-0.01**		-0.01**
(ton, log, year 2000)		(0.02)		(0.03)		(0.01)		(0.01)
County FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	18,810	16,579	18,378	16,246	19,835	16,820	19,472	16,558
R^2	0.08	0.10	0.08	0.09	0.91	0.91	0.90	0.90

Notes: This table estimates the heterogeneous impacts of expressway connection on COD emissions and GDP. Standard errors are clustered at the county level and reported in the parentheses below the estimated coefficients. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table D. Treatment Effect Using an Alternative Expressway Connection Dummy

	COD emission (tons, log)		Per capita COD emissions (kg, log)		GDP (yuan, log)		Per capita GDP (yuan, log)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Expressway	-0.18***	3.13***	-0.25***	3.73***	-0.03**	0.90***	-0.02	1.18***
	(0.06)	(0.75)	(0.07)	(0.82)	(0.01)	(0.17)	(0.01)	(0.18)
Expressway*GDP pc		-0.40***		-0.48***		-0.11***		-0.14***
(yuan, log, year 2000)		(0.09)		(0.10)		(0.02)		(0.02)
County FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	18,810	18,179	18,378	18,007	19,835	19,213	19,472	19,091
R^2	0.08	0.08	0.08	0.08	0.91	0.91	0.90	0.90

Notes: This table estimates the heterogeneous impacts of expressway connection on COD emissions and GDP using a different expressway connection dummy. Standard errors are clustered at the county level and reported in the parentheses below the estimated coefficients. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table E. Explore the Channels: Heterogeneous Effects of Expressway Connection

	COD Emission Intensity (ton, log)		Share of the Secondary Industry (%, log)		Number of Key Polluting Firms (log)		Output Value of Key Polluting Firms	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Expressway	-0.16***	2.67***	0.00	0.54***	0.02	0.96***	-0.07**	0.72*
	(0.06)	(0.75)	(0.01)	(0.13)	(0.02)	(0.27)	(0.04)	(0.40)
Expressway*GDP pc		-0.34***		-0.06***		-0.11***		-0.09**
(yuan, log, Year 2000)		(0.09)		(0.02)		(0.03)		(0.05)
County FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	18,768	18,139	10,202	9,914	18,810	18,179	18,809	18,178
R^2	0.09	0.09	0.19	0.19	0.41	0.42	0.57	0.58

Notes: Standard errors are clustered at county level and reported in the parentheses below the estimated coefficients. *** p<0.01, ** p<0.05, * p<0.1.