Expressways, GDP, and the Environment: A Case of China*

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In a matched difference-in-differences setting, we show that China's expressway expansion helps poor rural counties grow faster in GDP while slowing the rich rural counties down. This heterogeneity is not driven by factors about initial market access, factor endowments, or sectoral patterns; however, it is consistent with the Chinese government's development strategy that relatively more developed regions prioritize environmental quality over economic growth, while poor regions pursue the opposite. We document that expressway connection indeed makes poor counties adopt dirtier technologies, host more polluting firms, and emit more pollutions, contrary to what happens to the rich connected counties. These results imply that recognizing the GDP–environment trade-off can help understand the full implications of infrastructure investment and other development initiatives.

Keywords: transport infrastructure; environmental Kuznets curve; pollution haven hypothesis; home market effect; political economy of the environment

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I. Introduction

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.

Using comprehensive data for more than 1,600 counties over the 13 years from 2000 to 2012, we estimate the impact of this large-scale transport network expansion on local economic development and explore the channels. To achieve better identification, we leave out the provincial capitals and metropolitan city centers, which the expressways were designed to connect, and focus on peripheral counties who gained access to expressways because they happened to be located on routes between metropolitan cities. We then compare the economic performances between connected and unconnected counties, and estimate the impacts of expressway connection in a matched difference-in-differences (DiD) setting. We find that expressway connection has a slightly negative impact on connected counties' real GDP or per capita GDP.[1]

As this negative average impact contrasts the long-held belief of the Chinese government that transport infrastructure can effectively promote economic growth of peripheral and poor regions (e.g., State Council of China, 2013, p. 3), we then explore potential heterogeneity within the impact of expressway connection across initial levels of per capita GDP. We find that this negligible average impact masks significant heterogeneity: expressway connection indeed causes initially poor counties to grow faster than the unconnected counties, while causing the initially rich counties to grow slower. This heterogeneity is robust to a variety of alternative specifications, such as controlling for different fixed effects, allowing the GDP trends of the counties to vary across different levels of initial income, using an instrumental variable approach, and a test addressing the issue of treatment spill-overs.

The heterogeneity finding challenges existing major explanations on the impacts of expressway connection or trade integration on the local economy, such as those based on the comparative advantage (e.g. the pollution haven hypothesis as in Copeland and Taylor, 1994;

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[1] We use real GDP and per capita GDP data in all the empirical analyses. All the findings still hold when nominal GDP measures are used.

survey by Copeland and Taylor, 2004) and those based on potential increasing return to scale (e.g., the home market effect as in Krugman, 1980, 1991; Helpman and Krugman, 1985; Faber, 2014): the former predict a universally positive effect on real income, but this prediction is inconsistent with the estimated negative impact for rich counties; the latter predict a significant role of initial access to the nearby core market in determining the impact of improving access, but further exploration of the data shows that the distance between a focal county and its closest metropolitan city is hardly influential in the impact of expressway connection. A closer examination also reveals that the heterogeneous impacts of expressway connection across initial income cannot be explained by a few factors related to comparative advantage or home market effect, such as the initial sectoral pattern in the local economy and endowments of land, population, and capital. We thus infer that the impact heterogeneity across different initial income levels is likely to be driven by factors that are largely overlooked in both lines of literature.

To reconcile our empirical findings, we emphasize one missing factor that is especially relevant: the environmental concern of local residents and governments. In many developing and developed countries, this concern is prominent: evidently, pollution is usually viewed as a necessary input in economic production (e.g., Pethig, 1976), and society needs to maintain a subtle balance between the environment and economic growth (e.g., Arrow et al., 1995). In our research context, the State Council of China (2005) explicitly required the rich regions to prioritize improving environmental quality, while directing the poor areas to promote industrialization and urbanization. It is thus possible that lower trade cost brought by expressways would help a poor economy enjoy higher GDP at the cost of the environment, while helping a rich economy to sacrifice more GDP for better environment quality.

We then examine this possibility by analyzing county-level panel data of local polluting emissions for the same period. We find that rich counties indeed become less polluted after expressway connection, while poor counties increase their emissions afterwards. Further investigation shows the channels: expressway connections make poor counties host more polluting firms, adopt more pollution-intensive technology, and accelerate industrialization, while the opposite happens to rich counties. These results are consistent with our argument that the poor and rich counties in China make use of expressway connection by pursuing different development objectives over the GDP–environment trade-off.

This paper unfolds as follows. The rest of this section discusses how this study is linked to previous literature. Section II describes the empirical setting and discusses our empirical strategy. Section III introduces the data and provides descriptive statistics. Section IV estimates the impacts of expressway connection on GDP and per capita GDP. Section V discusses potential explanations of the expressway impacts and explores the nature of the observed heterogeneity. In Section VI, we provide more evidence on the impact of expressway connection on local emissions, production cleanness, the distribution of polluting production, and local sectoral patterns, from which the explanation about the GDP–environment trade-off emerges. Section VII discusses policy implications and concludes with directions for future research.

Literature Connections

This paper builds on several strands of literature, including, but not limited to, those on development consequences of transport infrastructure improvement, the pollution haven hypothesis, the environmental Kuznets curve, and political economy of the environment.

In the past two decades, a large number of studies have examined the economic consequences of transport infrastructure improvement and provided important insights for development policies (e.g. Fernald, 1999; Chandra and Thompson, 2000; Holl, 2004; Baum-Snow, 2007; Michaels, 2008; Datta, 2012; Duranton and Turner, 2012; Duranton et al., 2014; Rothenberg 2013; Baum-Snow, 2014; Baum-Snow et al., 2014; Donaldson and Hornbeck, 2016; Frye, 2016; Ghani et al., 2016; Jaworski and Kitchens, 2016; Alder 2017; Asher and Novosad, 2018; Donaldson, forthcoming; also the survey by Redding and Turner, 2015). Notable examples that focus on China include, but are not limited to, Banerjee et al. (2012), Roberts et al. (2012), Zheng and Kahn (2013), Faber (2014), Bosker et al. (2015), Baum-Snow et al. (2017, 2018), Qin (2017), and Alder and Kondo (2018).[2]

[2] Banerjee et al. (2012) investigate 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) study the economic impacts of high-speed rail and find that the expansion of the high-speed railway network increased housing prices in affected cities. Faber (2014) explores a similar empirical setting to ours and finds that expressway connections significantly reduced economic growth in connected counties. Roberts et al. (2012) use prefecture-level data and a new economic geography approach to study the expressways and find that the expressways have no significant reduction in disparities across prefectures and no reduction in urban–rural disparities. Bosker et al. (2015) develops a structural new economic geography model to examine the impacts of expressways and Hukou system at the prefectural level and shows that the construction of the national expressway network reinforces existing

Given that most previous studies (especially the ones adopting a reduced-form approach) focus on the average treatment effect of expressway connection, we contribute to the literature primarily in two ways, and both of them lie in our emphasis on the heterogeneous impacts of expressway expansion.[3] First, our finding that expressway connection affects the poor and the rich counties in the opposite way has important policy implications: it confirms that transport infrastructure is crucial for poor economies to grow. In contrast, if one focuses on the (negative) average treatment effect of expressway connection on GDP, it can be tempting for policymakers to rush to a conclusion against investments in a transport infrastructure that could be quite growth-promoting at the early stage of development.

Second, as discussed earlier, focusing on the heterogeneity allows us to closely investigate the mechanism behind the impact of expressway expansion, and motivates us to introduce environmental considerations into the discussion. As environmental concerns play an important role in shaping a society's development strategies and economic activities, it is important to consider the trade-off between development and the environment when thinking about the impact of productivity-enhancing investment. Our analyses on industrial emissions, polluting firms, technology, and industry mix suggest that poor and rich counties can choose different development strategies. To the best of our knowledge, no previous studies in the literature have investigated all the economic and environmental outcomes in an integrated way like us.

Our data and empirical framework are closely related to Faber (2014). To achieve better identification, Faber (2014) is the first to leave out the city centers (targeted cities of the expressway system) and focus on peripheral counties. This is because the expressway connection to peripheral counties is less intentional than the connection to metropolitan cities.[4] We follow

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urbanization patterns. Baum-Snow et al. (2017) document the role of roads and highways in decentralizing Chinese cities, and Baum-Snow et al. (2018) estimate the economic impacts of market access brought by expressway expansion on Chinese cities. Qin (2017) examines the impacts of China's high-speed railway and finds that affected counties served by upgraded railway lines experienced reductions in GDP and GDP per capita. Alder and Kondo (2018) document systematic political distortion in the design of the Chinese highway network.

[3] A concurrent work by Baum-Snow et al. (2018) also investigates the heterogeneous impacts of expressways in China. They use an instrumental variable approach, study prefecture-level outcomes (which include core city districts and peripheral counties), and document that highways in China helped populous cities grow economically at the expense of hinterland cities. In contrast, we focus outcomes in peripheral counties over 2000–2012 and show that expressways benefit poor counties while hurting rich counties in GDP, and that the expressway impacts are not more positive for counties that are more populous or closer to their regional core cities.

[4] Most studies investigating China's national expressways use aggregate prefecture- or city-level data, except Faber (2014). The use of data of this level, either in a reduced-form approach, or in a structural approach based on a trade or economic geography model, may suffer from endogeneity problem. This is because the expressways were designed

Faber (2014) and compare the economic performances between connected and unconnected *counties*. We further improve on Faber (2014) in two aspects. First, Faber (2014) uses county-level data of two years (1997 and 2006), while we assemble a county-level panel data set for over 1,600 counties covering each year in the entire period of 2000–2012. To our knowledge, our data set is the largest, longest, and most disaggregated in this line of literature. Since total length of China's national expressways has expanded by nearly 10 times during our sample period (from 11,650 kilometers by the end of 1999 to 95,600 kilometers by the end of 2012), our data and findings are also more relevant to today's policy. Second, having multiple periods of data allows us to use different empirical strategies. We can examine the outcome dynamics before and after expressway connection, and we can more straightforwardly test whether a DiD approach can be applied.[5]

More broadly, our empirical results on the environmental outcomes also speak to the literature on how trade affects pollution in China (e.g., Bombardini and Li, 2016) and provide a mixed piece of evidence on the pollution haven hypothesis (PHH).[6] The PHH conjectures that increased integration of markets can shift polluting capitals from richer to poorer regions, where the laxer environmental regulations can create a comparative advantage in polluting industries (e.g., surveys by Copeland and Taylor, 2004; Karp, 2011). If we interpret expressway connection as an improvement in market integration, our heterogeneity result about its impact on local emissions is indeed consistent with the PHH: it reduces pollution in rich regions and increases pollution in poor regions. The heterogeneous impact on real GDP, however, is inconsistent with PHH, because the PHH would predict a universally positive impact on real GDP (Copeland and Taylor, 1994). More generally, this mixed piece of evidence highlights that, when testing a hypothesis that involves primarily one outcome variable (emissions in this case), it is helpful to examine additional outcome

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to connect certain prefectures and cities, and these connected places can be significantly different from the other unconnected prefectures and cities. An instrumental variable approach may address the concern to some extent, but a good instrument is often difficult to come by. In particular, the exclusion restriction is difficult to satisfy; those often-proposed instrumental variables, which are based on geographical characteristics, generally lack variation over time.

[5] Faber (2014) develops a creative instrumental variable, which is based on a hypothetical network that would link all targeted cities with the least cost, to further address the endogeneity concern. Faber (2014) finds a negative effect on average of expressway connection on local GDP growth. However, as acknowledged by the author (Faber, 2014, p. 1062), the exclusion restriction could be violated, and, limited by data availability, the test of parallel pre-trends relies on data of local government revenues, not the outcome variable GDP, of a single year (1990). Besides adopting the event-study approach to test whether our DiD setting is proper, we also confirm in Appendix Table S3 that our results are robust when an instrumental variable approach is used.

[6] Bombardini and Li (2016) investigate how China's expansion in exports affected air pollution and infant mortality across different prefectures in China between 1990 and 2010.

variables (real GDP in this case) that can indicate the theoretical mechanism underlying the hypothesis.

Our results are also related to the environmental Kuznets curve (EKC) literature. Following Grossman and Krueger (1995), many studies have tested the EKC, a popular hypothesis proposing an inverted U-shaped relationship between environmental degradation and income. Empirical evidence shows that the EKC is often applicable only to specific contexts, time periods, and functional forms.[7] Arrow et al. (1995), Stern (2004), and Copeland and Taylor (2004) all argue that the environment–income relationship depends on the mechanism behind economic growth so an EKC characterization is either too simplified or unstable in theory. Even though our focus is not to test the EKC, our empirical result implies that, first, the changes caused by expressway connection in income and emissions are always positively correlated for both the initially rich and poor counties, which is at most partially depicted by, if not inconsistent with, the EKC; second, the same kind of shock (expressway connection in this case) can cause the income and emissions to change together, but the direction of the change can differ across different levels of initial income. To better understand the relationship between income and emissions, because income generation and environmental preservation are simultaneously determined in one grand trade-off, we had better consider a third dimension about the factors that affect the trade-off, for example, an infrastructure investment, in addition to the two dimensions of income and emissions.

The final connection between this study and previous ones is on how political incentives affect environmental policies and outcomes (e.g., List and Sturm, 2006; Burgess et al., 2012; Nagavarapu and Sekhri, 2014). In the Chinese context, Kahn et al. (2015) and Chen et al. (2018) provide evidence that career concerns pushed local officials to take greater effort to reduce local pollution; Jia (2017) documents the positive correlation between local pollutions and local officials' political connections, which is consistent with the hypothesis that political connections increase the political return of marginal pollutions. Adding to the literature, our paper suggests that recognizing the political incentives of local governments in China can help us understand the otherwise puzzling heterogeneity in both the economic and environmental performances of local economies after the significant improvement in transport infrastructure.

[7] 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), and Harbaugh et al. (2002).

II. Empirical Setting

Expansion of China's Expressway Network

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 State Council of China approved the "5–7" expressway construction plan, which included five north–south and seven 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 known as the "7–9–18" network, which comprises seven radial expressways connecting Beijing with other major cities, nine north–south expressways, and 18 east–west 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 expressway and railway hubs. The new target was achieved in 2011, nine years ahead of schedule.

Many peripheral counties lying between major cities were also connected during this expansion. Our empirical strategy exploits this feature and compares the economic 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 State Council of China (2004)'s *National Expressway Network Plan* but were connected between 2000 and 2012 simply because they were located on expressway routes between metropolitan cities.[8] Unconnected counties serve as the control group. All the urban districts in the targeted cities are excluded from subsequent analysis because their expressway connections are endogenous.[9] As a

[8] Our county-level panel data start from 2000, and about 15% of the counties were connected before 2000. These counties are not included in our empirical analysis for two reasons. First, they provide no variation in treatment status, so they do not help to identify the treatment effects. Second, since we do not know exactly when they were connected before 2000, we would not be able to properly include the lead- and lag- indicators of their connection in the parallel-trend tests, which we will discuss below.

[9] 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 S1. Appendix Figure 1 shows the targeted cities on the map and draws the expansion of China's national expressways from 1992 to 2010. A (prefectural) city typically

result, all our analyses are restricted to studying non-targeted peripheral and mostly rural Chinese regions. In Figure 1, we present two maps of China, for 2000 and 2010, respectively, where the targeted cities (all urban districts in a prefecture), connected counties, and unconnected counties are denoted by different colors.

Econometric Model

We estimate the average treatment effect of expressway connection using a generalized DiD approach:

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

where $y_{i,t}$ is real GDP or per capita GDP 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 if 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. We take the logarithms of the dependent variables so that the estimated coefficient represents the percentage change. The coefficient of interest is β.

To estimate the heterogeneous impacts of expressway connection, we introduce the interaction between the treatment dummy and initial income in the regression and estimate the following equation:

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

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

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* (State Council of China, 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.

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includes a few urban districts and a dozen rural counties. If a (prefectural) city is targeted by the plan, we treat all its urban districts as being targeted and exclude them from subsequent analysis.

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

The second hypothesis is that the central government 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? If so, this would threaten our identifying assumption and make pre-treatment trends not parallel, 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 would be that a peripheral county did not have *ex ante* information on the exact time when it would be connected. Appendix Table S2 also shows that the impact of expressway connection was mostly negligible on the year of connection, which suggests little evidence that the connected counties gamed around the timing of their connections. Allowing for all 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.

The endogeneity concern can be further addressed by combining the DiD estimator with matching: for each eventually-connected county in our data, we match it with a non-connected county that is in the same province and has the most similar level of real per capita GDP in 2000 within the province; then we apply the DiD estimators to the matched sample. While our main results are similar using both matched and unmatched sample, conducting a matching before

[10] In our unmatched sample, before the connected counties were connected, they were in general richer than unconnected counties (see Table 1). This pattern is also documented by Faber (2014), who investigates the early stages of China's expressway construction.

applying the DiD estimators brings two merits. First, the test results for the parallel trends assumption, which we will introduce below, are improved using the matched sample, since the standard errors are reduced. Second, it is more proper for us to interpret the income heterogeneity, because connected and unconnected counties in the matched sample are more comparable, sharing a common support in terms of initial income. As a result, in subsequent analysis, we focus on the results using the matched sample, leaving the results from the unmatched sample in appendices.

More formally, we can test the parallel-trend assumption using an event study approach, following Jacobson et al. (1993): we generate a set of lead- and lag-year indicators of the actual expressway access as independent variables in the regression and test whether the coefficients of the leads are statistically significantly different from zero. Details of the tests are discussed in Appendix I. As will be discussed in Section IV, we fail to reject the hypothesis that the connected and unconnected counties follow similar trends before the connected counties become connected.

The final threat to identification of the DiD approach is selection based on expectation. For example, despite that the connected and unconnected counties looked similar before expressways were constructed, it is not implausible to speculate that future growth potential or other considerations might determine expressway routing and thus selection into the treatment and control group. Were this type of selection significant, the parallel-trend test would help little in justifying our identification strategy. To address this type of potential selection, in one of the robustness checks, we estimate the impacts of expressway connection on GDP using an instrumental variable approach in the same spirit as Banerjee et al. (2012) and Faber (2014). We first construct straight lines that connect each pair of targeted cities, and then construct a variable for each county as follows: if the county is connected by one of the hypothetical straight lines, the variable is equal to 1; if otherwise, it is 0. We then use this variable as the instrumental variable of the actual expressway connection. The outcome variable in this instrumental variable regression is the change in real GDP or per capita GDP between 2000 and 2012.

III. Data and Summary Statistics

GDP and Socioeconomic Data

We collect county-level GDP and other socioeconomic data of 2000–2012 from the CEIC database and various statistical yearbooks in China, including provincial yearbooks, *China City Statistical*

Yearbooks, and *China County Statistical Yearbooks.* To get data for real GDP, we deflate nominal GDP by provincial CPI and cross-provincial CPI from the National Bureau of Statistics of China (Yu, 2006), taking Beijing-2000 as the base province-year. Our outcome variables are real GDP or GDP per capita at the county-year level.

Expressway Expansion Data

Historical geographic information systems (GIS) data on China's National Expressway Network were collected from the PR China Administrative Spatio-Temporal Expressway Database (STED) from the ACASIAN Data Center, Griffith University. The database contains data on China's expressway routes for 1992, 1993, 1998, 2000, 2002, 2003, 2005, 2007, and 2010. By combining the STED database with county-level GIS data, we can identify which counties were connected in which year.[11]

Pollution Data

To understand the channels of the GDP results, we also 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.

We use the ESR data from 2000 to 2012 in this study. During this period, the monitored polluting sources in total contributed 85% of total emissions of major pollutants in each county. Monitored polluting sources are required to report their environmental performance to county-level Environmental Protection Bureaus (EPBs) in each year. Local EPBs then verify the data and 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

[11] Because the STED data have gaps over years, we do not know exactly when a county was connected for 12% of the connected counties in the sample. For these counties, we have to interpolate the treatment status. Our empirical findings are not sensitive to the way we interpolate. Details on identifying the treatment status of each county-year are given in Appendix II.

unmonitored plants. The micro-level emissions data used in this study had been kept confidential for many years before it recently became conditionally open to some researchers.[12]

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 analysis, we focus on COD emissions. COD is a widely-used water quality indicator that assesses the effect of discharged wastewater on the water environment by measuring the amount of oxygen required to oxidize soluble and particulate organic matters in water. Higher COD levels mean a greater amount of oxidizable organic material in the sample, which reduces dissolved oxygen levels. A reduction in dissolved oxygen can lead to anaerobic conditions, which are deleterious to higher aquatic life forms.

One reason for our focus on COD emissions is that COD is the primary measure of water pollution adopted in China.[13] Another reason is that almost all key pollution sources and industries produce and report COD emissions (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 in certain areas of China, rather than by local governments at the county level. As we will introduce below, our explanation focuses on the general environment–GDP trade-off made by the county government, so we opt for the COD measures in empirics.

In practice, we focus on total COD emissions and per capita COD emissions. Total COD emissions are the sum of COD emitted by the key polluting plants and the estimated COD emitted by other polluting plants in each county. Per capita COD emissions are calculated by dividing the total COD emissions by the county's 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 emissions measures, such as ammonia nitrogen and SO_2.[14]

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[12] More details on the data are given in Lin (2013), Cai et al. (2016), and Wu et al. (2017).

[13] For example, COD abatement is used by the Chinese central government as a key performance indicator for assessing local government efforts at 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.

[14] It is known that environmental data can be manipulated in China (e.g., Ghanem and Zhang 2014). It is however unclear how potential manipulation incentives are distributed at the plant level. That said, as long as expressway access does not affect the incentives for data manipulation differentially across counties with different initial income levels, our empirical findings will still hold.

Descriptive Statistics

We match all the datasets at the county level from 2000 to 2012, during which the national expressway network expanded significantly. By 2012, more than 50% counties were connected.

In Table 1, we summarize the descriptive statistics of GDP measures in 2000 and 2012 separately for the matched and unmatched samples. From 2000 to 2012, real per capita GDP of our sampled counties increased nearly fivefold. We observe that, in the unmatched sample, the eventually connected counties were generally richer than the unconnected counties in 2000; in the matched sample, the connected and unconnected counties have more similar levels of initial GDP and per capita GDP. Figure 2 further plots the distribution of per capita GDP in the matched and unmatched sample, respectively. It shows that the connected counties and the matched, unconnected counties share a common support of initial income.

IV. Impacts of Expressway Connection on GDP

Average Treatment Effect of Expressway Connection

In Table 2, we report the average treatment effect of expressway connection on real GDP and per capita GDP. Our baseline results are presented in Columns 1 and 4, in which only county fixed effects and year fixed effects are included in the regressions. Then we test the robustness of these results by adding different controls. In Columns 2 and 5, we add provincial trends; and in Columns 3 and 6, instead of controlling for year fixed effects, we include province-year fixed effects.

We find that the estimated coefficients are negative and stable in all regressions. This negative effect is consistent with Faber (2014), even though the coefficients are not statistically significant in our empirical setting. We further check the robustness of the estimates' accuracy by clustering the standard errors at different levels, and we arrive at the same conclusion.

We then test the parallel-trends assumption following Jacobson et al. (1993). The estimated coefficients of the leads and lags of the treatment dummies are plotted on Figure 3. It shows that, before the connected counties were connected to the expressway system, they and the unconnected counties had similar GDP trends. This rule out the possibility that the timing of expressway connection is endogenous to county GDP, as the coefficients of the leads and lags are statistically insignificant in the first couple years before or after the year of connection. In the long run, however, we see that the lag term becomes negative and statistically significant.[15] This implies the negative impact of expressways on GDP takes time to materialize. This finding explains why there exists minor inconsistency between our findings and Faber's (2014): we use year-to-year variation between 2000 and 2012 to estimate the effect, while Faber (2014) compares the 10-year difference in the outcome variable between 1997 to 2006.[16] The estimated effects will become larger and more statistically significant if one uses long differences for comparison.

Heterogeneous Effects of Expressway Connection

In this section, we explore the heterogeneous effects of expressway expansion on GDP with respect to initial income. The baseline results are reported in Columns 1 and 4 of Table 3. The estimated coefficients of the expressway connection dummy are positive and statistically significant, while the coefficients of the interaction between the connection dummy and the initial income are negative and statistically significant at the 1% level. In other words, the impact of expressway access on GDP is more negative in initially richer counties than in initially poor counties.

Using information from the distribution of per capita GDP in 2000, we can further predict the impacts of expressway connection at different initial income levels. In Figure 4, we plot the predicted impacts with their 95% confidence intervals, based on estimates in Columns 1 and 4 of Table 3. In Figure 4, we observe that expressway connection positively affected real GDP in the poor counties (statistically significant for the poorest 25%) and negatively affected real GDP in the rich counties (statistically significant for the richest 40%).

We check the robustness of the findings in several different ways. First, we control for provincial time trends in the regressions (Columns 2 and 5 of Table 3) and find that the conclusions remain the same. Second, instead of including year fixed effects dummies, we include province-year fixed effects in the regressions in Columns 3 and 6. The province-year fixed effects account for annual shocks that are common to all counties in a province, for example, business cycles and differential trends and policies across provinces. The treatment effect is thus identified by comparing the outcomes of two counties in the same province in the same year. We find that even in this strictest case, expressway connection has strong heterogeneous impacts on GDP.

[15] In Appendix Table S2 we summarize the regression results.
[16] Note that our sample size and years of coverage are also different from Faber (2014), as described in Section III.

We further 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-year level (multi-way clustering suggested by Cameron et al., 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 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 3.

Besides, instead of interacting the expressway dummy with the continuous measure of initial per capita GDP, we construct an income group indicator that is equal to one if a county is in the high-income group in 2000.[17] This allows us to include income group-specific year fixed effects so that poor counties and rich counties can have different intrinsic dynamics of GDP growth, independent of expressway connection. The regression results are summarized in Table 4. In Columns 1 and 5, we include county fixed effects, year fixed effects and provincial trends. Columns 2 and 6 control for province-year fixed effects. Columns 3 and 7 allow poor counties and rich counties to grow with different trends; and finally, in Columns 4 and 8, we include year fixed effects separately for two income groups.[18] These regressions again confirm that expressway connection has highly heterogeneous impacts on local economy.

Additionally, we use straight lines as the instrument for actual expressways and report the results in Appendix Table S3. Again, we find the same pattern of a highly heterogeneous expressway impact as our matched DiD result. In Appendix Table S4, we estimate the expressway effect using the unmatched sample and find similar results (Appendix Table S4).[19] In Appendix Table S6, we check whether the results are driven by a few counties that have usually high or low initial income. We winsorize the sample by dropping the observations whose initial per capita

[17] The results from the linear specification suggest that the positive effects are statistically significant for the poorest 20% counties, so we divide the counties into two groups by the 20th percentile of their GDP per capita in 2000. Slightly perturbing the cut-off does not affect the conclusion.

[18] In Appendix Table S2, we also test the parallel trends assumption within each income group, and still find that the parallel trends assumption within each group holds.

[19] The parallel-trend tests using the unmatched sample are also summarized in Appendix Table S5.

GDP value is in the top or bottom 1% percentiles of all observations, and re-estimate Equations (1) and (2). This exercise, again, yield the same results.

Finally, we consider the concerns about two types of spillovers of the treatments that could confound our results. First, one might suspect that the expressway connection of one county could affect the average economic performance of other counties, either connected or unconnected, since all counties are economically connected to the national market after all. We believe that this type of spillover is less of a concern, because each county in our sample is small compared with the national market. Therefore, the impact of one county's expressway connection on all other counties would not be strong on average. That said, second, one county's expressway connection might still significantly affect their unconnected neighbors. To address this type of potential spillovers, we focus on 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 GDP of these never-connected counties. In practice, we apply Equation (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 of its interaction with the initial income reveal the potential spill-over effect and its heterogeneity. As reported in Appendix Table S7, the "neighboring connection" effect is positive for low-income unconnected counties, while it is negative for high-income unconnected counties. This finding shows that some spill-overs do exist, but their effect works against the heterogeneity pattern in our main results, rather than contributing to it.[20] Were no such spillover, the heterogeneity we find in our main results would be even stronger.

To summarize, these robustness checks lend additional credibility of our main finding: expressway connection significantly increased real GDP of the counties with low initial income, while reducing that of the counties with high initial income.

[20] Compared with the results in Table 3, we see that the coefficients of both the treatment indicator and the interaction term are substantially smaller. This is reasonable because the effect of having a neighboring county connected should be weaker than being directly connected on one's own.

V. Understanding the Heterogeneity

Our empirical setting and findings are closely related to two families of existing theories: first, those based on comparative advantage, for example, the pollution haven hypothesis; and second, those based on increasing return to scale, for example, the theory of the home market effect.

In a comparative advantage framework, reduction in trade cost will facilitate regions to specialize in productions in which they have a comparative advantage. Low-income regions and high-income regions may have different comparative advantages. For example, low-income regions can have a comparative advantage in polluting industries, because they may have less restrictive regulations on polluting industries than what the high-income regions have. Better realization of the comparative advantage can increase the real income of the poor region, explaining our positive estimate of the expressway connection impact on the poor counties' GDP. This hypothesis would however predict positive effects of trade cost reduction on real income also for the rich regions (e.g., Copeland and Taylor, 1994), contradicting the estimated negative income impact on 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 were formerly located in peripheral counties to move to core metropolitan areas to enjoy a larger home market. If core-periphery relations are sufficiently asymmetric, this trade integration can reduce economic output in peripheral counties. This is the argument provided in Faber (2014), which explains why his estimate of the average impact of expressway connection is negative, and it may explain why our estimate of the impact for the rich counties is negative. On the positive impact for the poor counties, however, the home market effect falls short.

As each of the comparative advantage mechanism and the home market effect can only partially explain our empirical findings, a combination of the two may be proposed: in poorer counties the comparative advantage mechanism could dominate the home market effect, while vice versa in richer counties.[21] Were this combined mechanism driving our empirical results, we should expect the heterogeneous impacts captured by initial per capita GDP to be diluted by

[21] For details on the argument, our analysis of a model of 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. (2017) incorporate both the pollution haven hypothesis and the home market effect in a different model, which focuses on the strategic tax setting and does not yield a closed-form solution.

heterogeneities across variables indicating comparative advantage and factors related to the home market effect.

Given this consideration, we conduct diagnostic analyses in Table 5, where, conditional on income heterogeneity, we introduce additional interaction variables between the expressway connection dummy and a rich set of variables measured in 2000, to explore whether the observed impact heterogeneity can be diluted by some of these interaction variables.

In Column 1 in Table 5, we interact the treatment variable with the distance between a focal county and its nearest targeted city, which proxies the initial trade cost and carries geographical information about the nearby market. The result shows that the expressway impact on local GDP is *negligibly more negative* for counties that are further away from their nearest target cities. This is inconsistent with the implication of the home market effect, since the home market effect is supposed to be weaker, i.e., the expressway impact on local GDP to be *less negative,* when the initial trade cost is higher (e.g., Krugman, 1991; Faber, 2014). Compared with Columns 1 and 4 in Table 3, Column 1 in Table 5 also suggests that the impact heterogeneity across initial GDP is robust when this additional interaction variable is introduced, so the impact heterogeneity across initial GDP is not driven by the difference, if any, between the poor and the rich counties in their initial accesses to nearby markets.

In Columns 2–8 in Table 5, we include a set of endowment and sectoral pattern measures, including population, land area, per capita land area, initial number of industrial firms, initial industrial output value, and initial shares of agriculture and of manufacturing in GDP. The endowment variables are instrumental in determining the home market effect in theory, and all the endowment and sectoral pattern variables proxy the local economy's comparative advantage. Compared with Columns 1 and 4 in Table 3, Columns 2–8 in Table 5 show that, while there may exist some effect heterogeneity across some variables (such as population and land), none of them can significantly dilute our income heterogeneity results.

Finally, as shown in Column 9 in Table 5, when we include all these interaction variables in the regression, not only does the coefficient of the expressway–income interaction remain statistically significantly negative, it also becomes even greater in its magnitude, suggesting the income heterogeneity would appear even more prominent if the other factors were considered.

These results imply that our observed income heterogeneity result is not driven by factors that are related to the comparative advantage mechanism, home market effect, and initial access to nearby markets, or by the combination of these factors. Therefore, although we acknowledge the relevance of the theories of comparative advantage and the home market effect in our context, we have to search for other factors to explain our main empirical finding.

VI. An Explanation about the GDP–Environment Trade-off

Discussion

One factor that has been missing in the analysis above is that residents or local government can have non-economic considerations when they respond to their connections to the expressways. In many developing and developed countries, a major non-economic consideration is about the environment.

The environmental concern is especially salient in the Chinese context during our sample period. Since the market reform in the 1980s, local officials had been evaluated primarily based on local economic performance, often measured by the GDP growth (e.g., Li and Zhou 2005; the survey by Xu, 2011). In the early 2000s, however, the Chinese government started seeking integrated sets of solutions to the intertwining economic, environmental, and social problems it faced, and explicitly put environmental considerations in policy decisions.[22] In particular, the central government directed the poor regions to aim at improving their economic performance, while emphasizing the environment for the rich regions (State Council of China, 2005):

> *Relatively developed regions should ... insist on prioritizing the environment, … optimize the industrial structure, … and take the lead in reaching the emission reduction target. … The regions of great development potential should … scientifically and reasonably utilize the carrying capacity of the environment to promote industrialization and urbanization. … Depending on the main ecological function of each region, different regions should formulate development strategies with different characteristics.*

The same directive also required local governments to follow this two-stage scheme of developmental objectives in evaluating officials, a practice later fully institutionalized by the Communist Party of China (Organization Department of the Party, 2013).[23]

[22] This transition was coined in 2003 as the "Scientific Outlook on Development" under the name of President Hu Jintao.

[23] The practical significance of these political incentives of Chinese local governments has been documented by a series of empirical studies. For example, Sun et al. (2014) and Zheng et al. (2014) provide consistent evidence that, in

This two-stage scheme of developmental objectives can have a real impact on the connected counties in our sample when they try to find a balance between GDP growth and the environmental concern. This is because local governments in China are influential in the local economy by imposing a strong control when allocating natural resources (notably land), capital flows, and even labor in their jurisdiction. Local governments have been actively choosing investors, industries, and talents to implement their development strategies by offering tax rebates, infrastructure improvements, price discounts for land use, exemptions from regulations, and other generous industrial policies (e.g., Qian and Roland, 1998; Bai et al., 2014).

We observe a few anecdotes that local governments responded to the two-stage developmental objectives by issuing policies that targeted certain industries and firms. For example, having the largest provincial economy in China, Guangdong required that manufacturing industries in rich regions relocate to less-developed regions starting from 2007, and its Party Secretary advocated that, without this mandate, the government "would in the long run not be able to create a beautiful living environment for the people" (Southern Daily, 2008). A nascent thread of empirical literature also documents that, in the 2000s, governments in the rich regions in China used higher pollution levies and stricter environmental mandates to push polluting industries away, while governments in the poor regions welcomed them (e.g., Lin and Sun, 2016; Wu et al., 2017).

Given all these considerations, we now examine whether the observed heterogeneous impacts of expressway connection on local GDP are associated with heterogeneous impacts on local polluting emissions, and how the heterogeneity is achieved by changes in production technologies, the distribution of polluting production, and local sectoral patterns. These explorations will shed some light on whether and how the rich and poor counties were pursuing different development strategies between GDP growth and environmental preservation in response to the expressway connection.

2004–2009, better environmental performance contributed to promotion of city mayors in China. Sun et al. (2014) further show that the impact was more prominent for mayors of larger cities. Kahn et al. (2015) document that local officials' effort in pollution reduction increased after the reform.

Effects on Emissions

In Table 6, we examine the impact of expressway on COD emissions and per capita COD emissions. We find that expressway on average slightly decreases emissions in the connected counties, and this effect is statistically insignificant. When we interact the expressway connection dummy with 2000 per capita GDP, a strong heterogeneity emerges: the expressway effect becomes more negative in richer counties. This finding is robust to including different controls and using different ways to cluster the standard errors. In Figure 5, we also predict the heterogeneous COD impacts at different initial income levels, and find that poor regions emit more COD and rich regions emit less COD after expressway connection.[24] This heterogeneity suggests that the higher GDP that expressway connection brings to the poor counties comes with an environmental cost; in the connected rich counties, GDP is however sacrificed for better environmental performance.

In Table 7, we examine several additional emission measures. In Columns 1 to 4, we use COD emissions from the key polluting plants as the outcome variable and find similar results. In Columns 5–8, we investigate the impact on ammonia nitrogen (NH_3-N) emissions.[25] Consistent with the result in Table 6, poor counties emit more ammonia nitrogen and rich counties emit less after expressway connection.

In Columns 9–12, we examine the impact on sulfur dioxide (SO_2) emissions, and the heterogeneity result disappears. We should however not interpret it as a piece of evidence against the hypothesis that local governments respond to expressway connection by different development strategies. This is because local county governments in our sample have little power to regulate SO_2 emissions. In China, 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 and metal industries. Most plants in these industries belong to large state-owned enterprises, not controlled by county governments. Therefore, the disappearance of the heterogeneity result for SO_2 emissions is not surprising.

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[24] In Appendix Table S8 we conduct parallel trends tests and find that pre-connection trends for COD and per capita COD are parallel. In Appendix Figure 2, we predict the expressway impact at different initial income level and show that the effect is positive in poorer counties and negative in richer counties.

[25] 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.

Production Cleanness, Polluting Firms, and Local Sectoral Patterns

To shed light on how the heterogeneous effects on both GDP and polluting emissions are achieved, we examine in Table 8 several other outcome variables, following the regression specified in Equation (2).

We report the results for COD emission intensity in Columns 1 and 2 in Table 8, which tell whether expressway connection makes the key polluting plants in each county use cleaner technology to reduce emissions per RMB-value of output. The strong heterogeneity suggests that the emission intensity increases in poor connected counties and decreases in rich connected counties. This pattern indicates that, after expressway connection, firms in poor counties adopt more pollution-intensive technology, while firms in rich counties adopt cleaner technology.

We then turn to the distribution of polluting production. The regression result in Column 3 in Table 8 shows that connected counties have a similar number of key polluting firms to non-connected counties on average; however, the strongly heterogeneous result in Column 4 suggests that the number of key polluting firms increases in poor connected counties but decreases in rich connected counties. Consistent results can also be found in total industrial output value. In Columns 5 and 6, the value of industrial output from heavily polluting firms increased in poor counties but decreased in rich counties.

Finally, in Columns 7 and 8 in Table 8, we show that the share of manufacturing increased in poor regions but decreased in rich counties. These results suggest that access to a larger market can help poor counties industrialize while helping rich counties de-industrialize.

Emerging Explanation

The empirical results in this section outline a consistent image reconciling our main result of the heterogeneous GDP impact across initial income levels. Expressway brings about an opportunity for local governments in both rich and poor counties to rebalance between GDP growth and their environmental concern. To the poor counties, it is an opportunity to develop at the cost of the environment – industrialization is promoted, and dirtier production is attracted there, while the rich counties respond by cleaning polluting production out, de-industrializing, and reducing emissions, but sacrificing the GDP. These different responses after being connected to the expressway system are consistent with the different developmental objectives that the State Council of China (2005) directed: the rich regions prioritize the environment, adjust their sectoral structure, and lead in emission reduction, while the poor promote industrialization to develop.

We illustrate this explanation in a trade model in Appendix III, which spotlights how the local government's preference between GDP and environmental quality can shape the local economy's response to an economic opportunity that reduces trade cost. We show a proposition to justify the possibility of the observed heterogeneous impacts of expressway connection on both local GDP and emissions.

VII. Concluding Remarks

Our findings have several implications. First, we confirm that transport infrastructure is important for early-stage development and can effectively promote economic growth of poor regions. In other words, China's efforts in improving infrastructure and expanding the expressway network can help to explain its great success in alleviating poverty in the past thirty years. This finding differs from Faber (2014), which emphasizes the negative impact of expressway connection on growth for Chinese counties.

Second, both Faber (2014)'s and Baum-Snow et al. (2018)'s results imply that expressway connection worsens the income inequality between the peripheral and core areas in China, while our findings suggest that the connection will reduce income inequality within the peripheral areas.

Third, while using the Chinese government's two-stage scheme of developmental objectives to reconcile the empirical findings seems highly China-specific, the insights behind this argument can be general. At various stages of economic development, the government often prioritizes certain objectives over others, and social preference can play an important role in shaping the economy. Since it is possible for these factors to drive first-order impacts on the economy, environment, and society, they deserve more attention in the literature. As an example, this study illustrates how recognizing the GDP–environment trade-off and the government's objectives can be important for the understanding of the otherwise puzzling impacts of infrastructure investment.

We conclude with some directions for further investigation. First, our reduced form estimates may fail to detect important general equilibrium effects. For example, the aggregate impact of many counties' connections on the national market could be non-negligible. Second, it is logically impossible to argue that our proposed explanation is the only explanation for the empirical results and alternatives may well exist. Further analysis on these issues are warranted.

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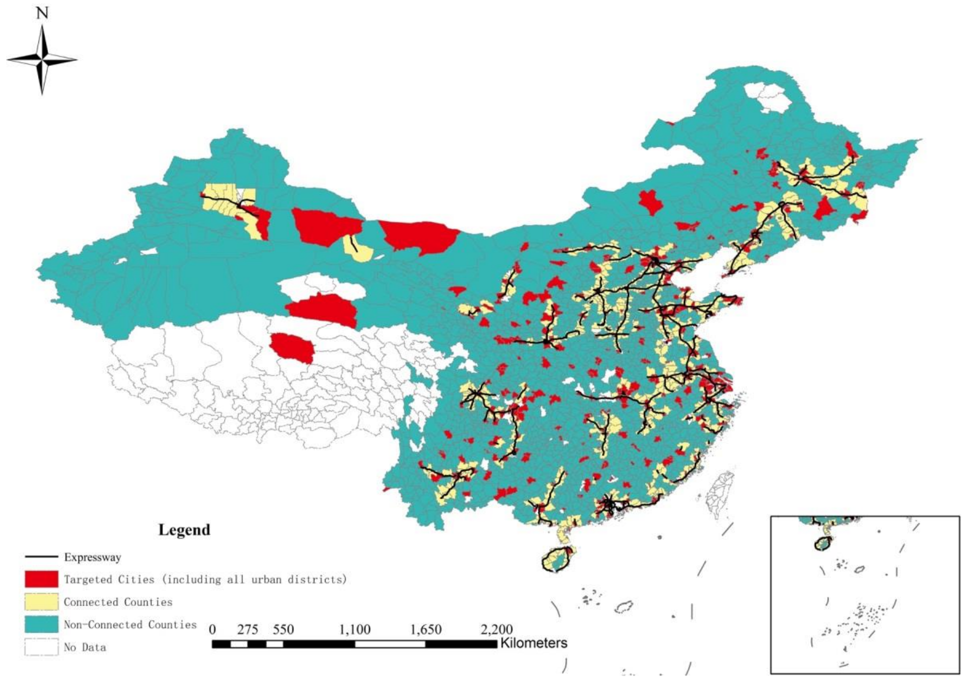
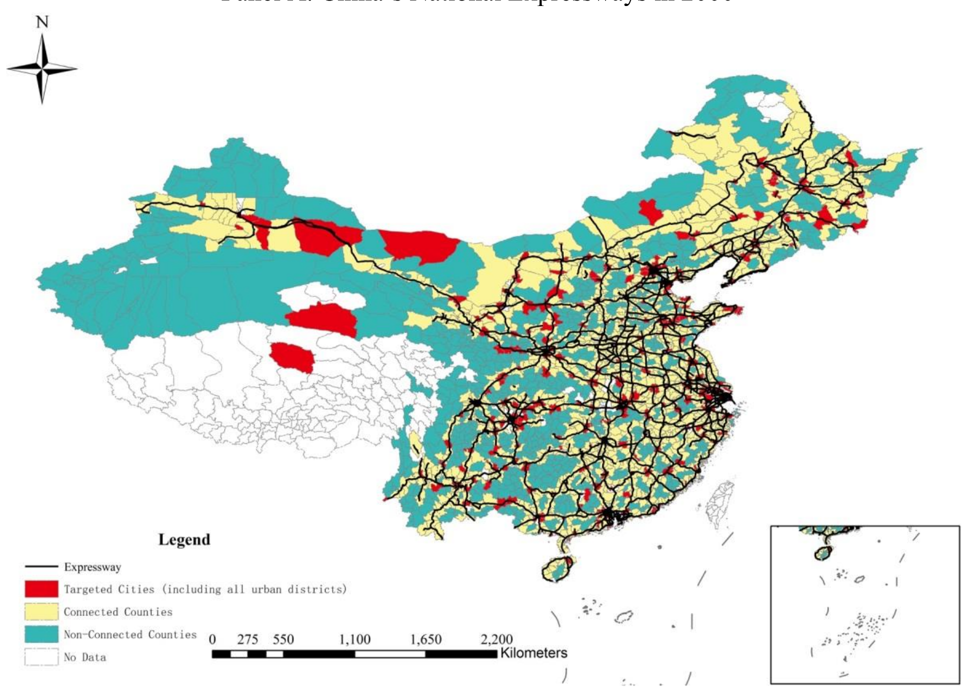
FIGURE 1. EXPANSION OF THE NATIONAL EXPRESSWAY SYSTEM IN CHINA

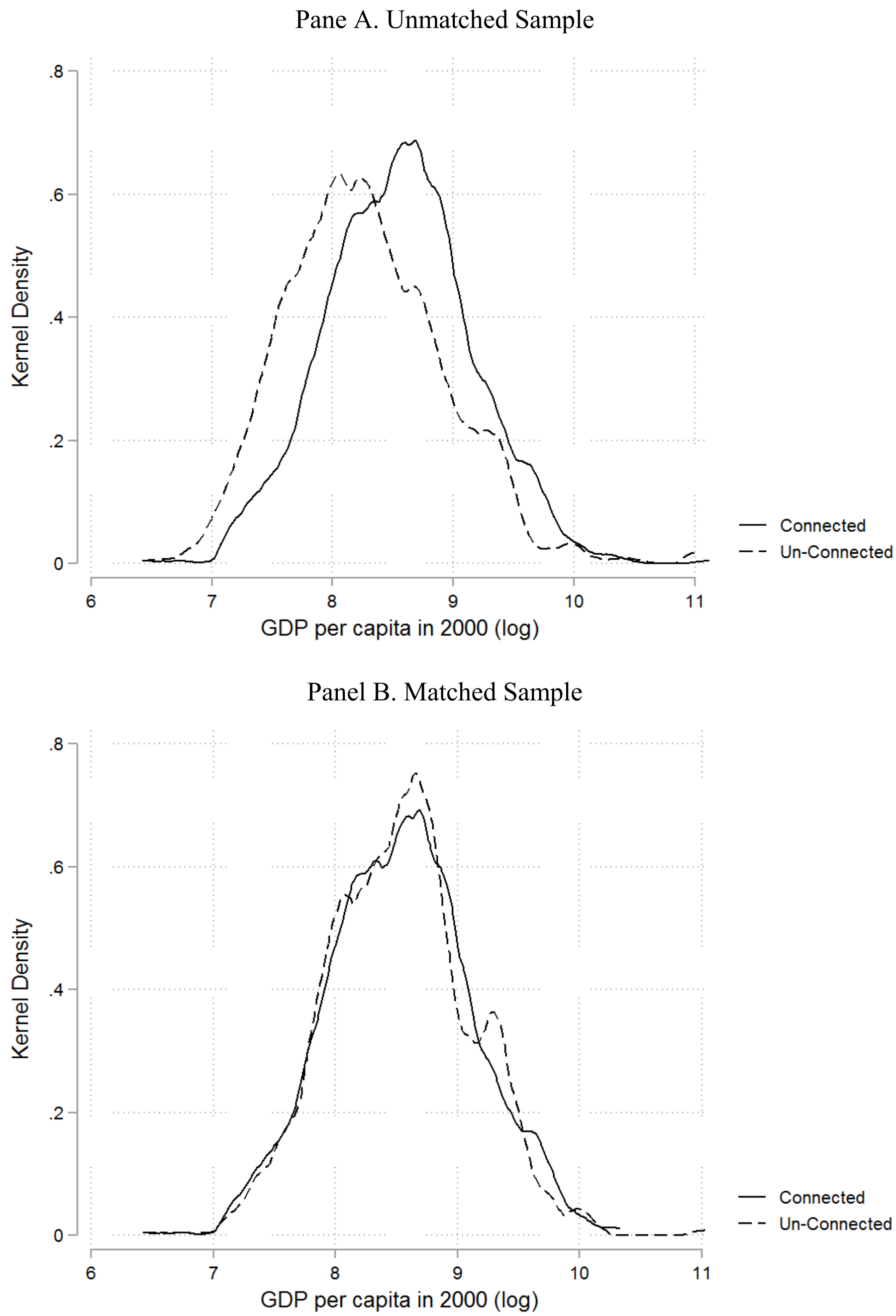


Panel A. China's National Expressways in 2000



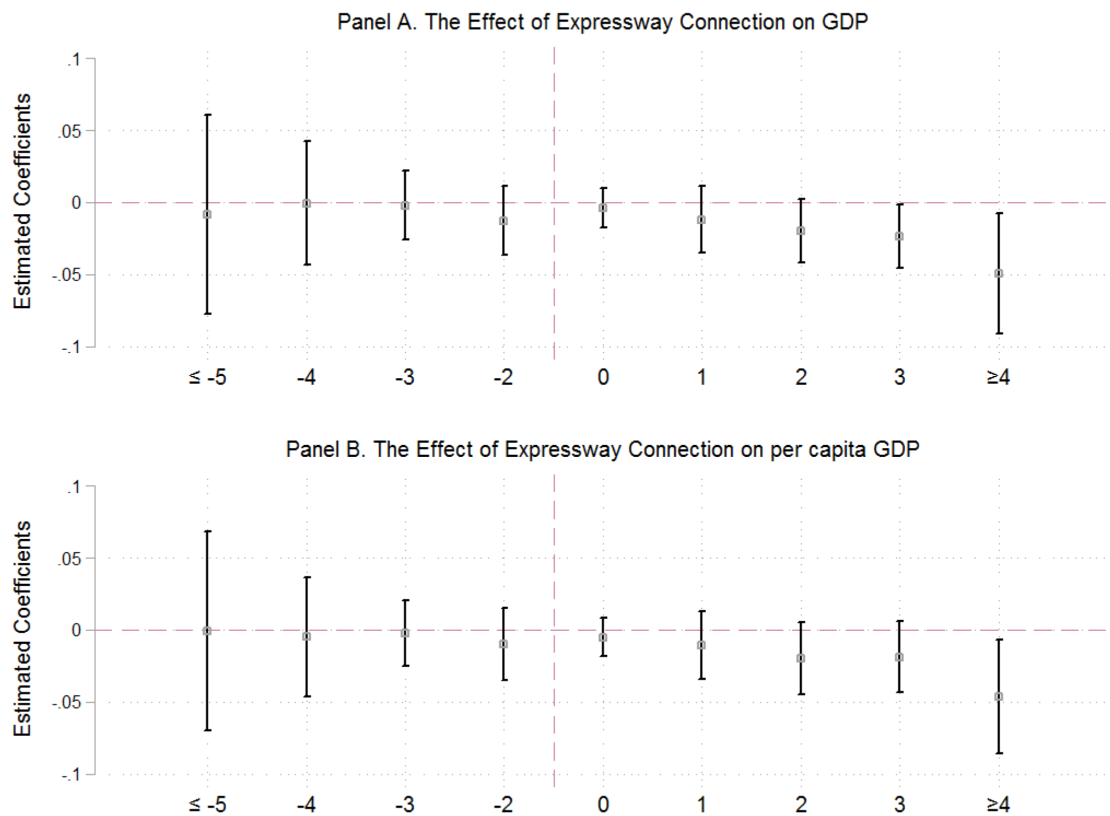
Panel B. China's National Expressways in 2012

FIGURE 2. DISTRIBUTION OF PER CAPITA GDP OF THE CONNECTED AND UNCONNECTED COUNTIES IN 2000



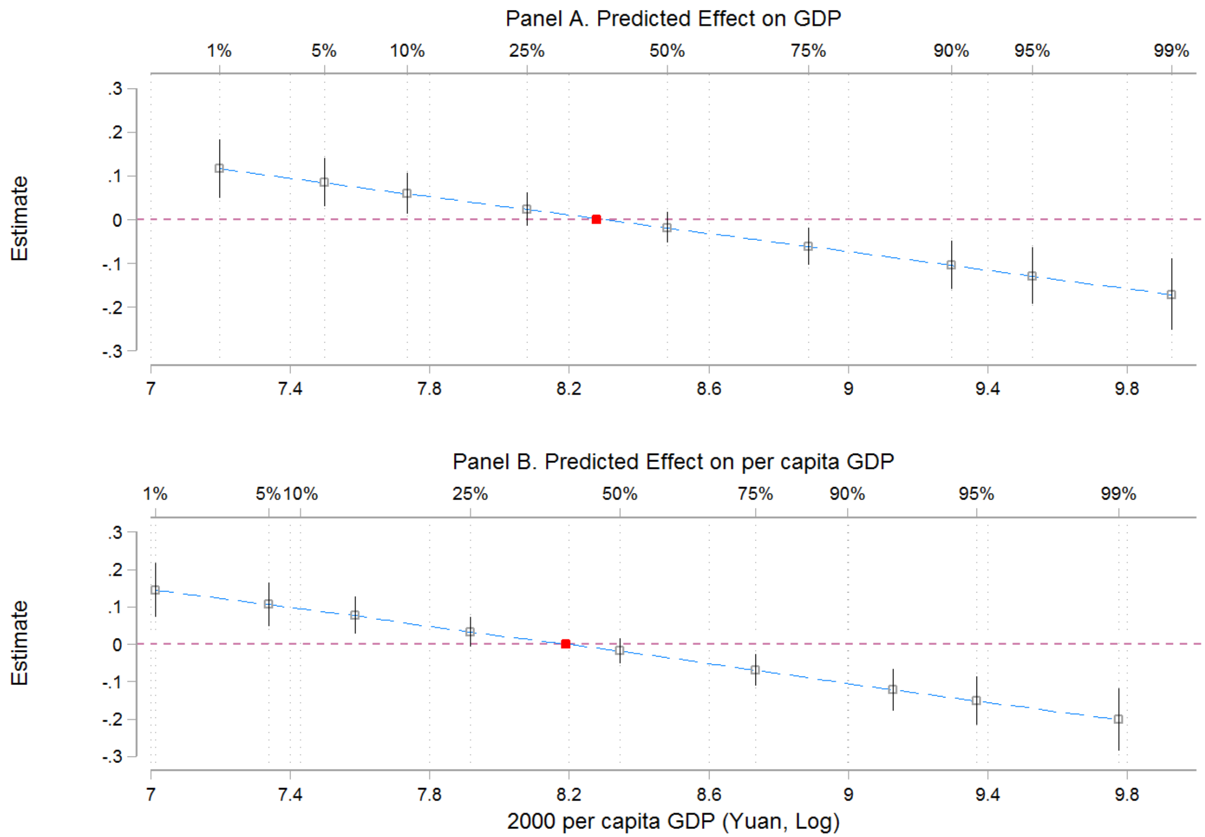
Notes: GDP data are deflated, where Beijing-2000 is the base province-year.

FIGURE 3. TESTS FOR PARALLEL TRENDS



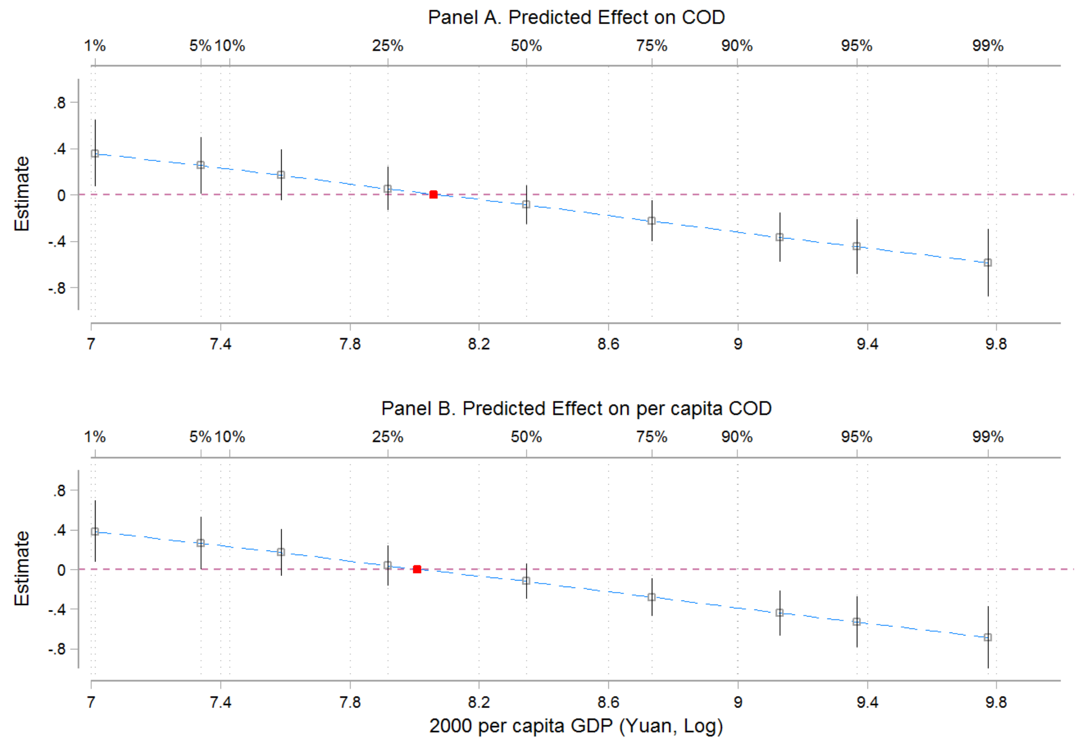
Notes: The figure plots the estimates and the 95% confidence intervals of the coefficients in the event study regressions following Jacobson et al. (1993). GDP data are deflated, where Beijing-2000 is the base province-year. The horizontal axes denote years before or after the expressway connection, where the year just before the connection year is the benchmark. See Appendix I for more details.

FIGURE 4. PREDICTED HETEROGENEOUS IMPACTS OF EXPRESSWAY CONNECTION



Notes: The figure shows the predicted effects of expressway connection at different initial income levels, and their 95% confidence intervals. GDP data are deflated, where Beijing-2000 is the base province-year. The impacts are positive for poorer regions and are negative for richer regions. The prediction is based on Table 3, Columns 1 and 4.

FIGURE 5. PREDICTED IMPACTS OF EXPRESSWAY CONNECTION ON EMISSIONS AT DIFFERENT INCOME LEVEL



Notes: The figure shows the predicted effects of expressway connection at different initial income levels, and their 95% confidence intervals. GDP data are deflated, where Beijing-2000 is the base province-year. The impacts are positive for poorer regions and are negative for richer regions. The prediction is based on Table 6, Columns 2 and 6.

Table 1. Summary Statistics of Sampled Counties

Variable	Un-Matched Sample			Matched Sample		
	Overall	Connected	Un-Connected	Overall	Connected	Un-Connected
GDP (million yuan, 2000)	2,978	3,416	2,455	3,067	3,265	2,868
	(6,910)	(3,241)	(9,588)	(4,616)	(2,942)	(5,827)
GDP (million yuan, 2012)	12,925	14,881	10,570	13,249	14,098	12,400
	(27,918)	(15,408)	(37,723)	(19,604)	(14,031)	(23,911)
GDP per capita (yuan, 2000)	5,710	6,231	5,081	6,084	6,087	6,082
	(5,114)	(4,567)	(5,646)	(4,287)	(3,946)	(4,608)
GDP per capita (yuan, 2012)	26,654	28,052	24,961	28,516	27,472	29,559
	(29,377)	(27,713)	(31,210)	(30,823)	(28,432)	(33,051)
# of Counties	1,646	897	749	1,614	807	807

Notes: County-level nominal GDP and population data are collected from provincial statistical yearbooks, China City Statistical Yearbooks, China County Statistical Yearbooks and China Economic Database from CEIC (www.ceicdata.com). GDP data are deflated overtime and across regions using provincial CPI and cross-provincial CPI from the National Bureau of Statistics of China (Yu, 2006), taking Beijing-2000 as the base province-year. Standard deviations are reported in the parentheses below the means.

Table 2. The Average Treatment Effects of Expressway Connection on GDP

	GDP (million yuan, log)			Per capita GDP (yuan, log)		
	(1)	(2)	(3)	(4)	(5)	(6)
Expressway	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
County FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	N	Y	Y	N
Provincial Trends	N	Y	N	N	Y	N
Province-Year FE	N	N	Y	N	N	Y
Obs.	13,440	13,440	13,440	13,347	13,347	13,347
R^2	0.87	0.90	0.91	0.86	0.89	0.90

Notes: This table estimates the impacts of expressway connection on GDP measures using a variety of specifications. GDP data are deflated, where Beijing-2000 is the base province-year. We probe the robustness of estimates accuracy by clustering the standard errors at three different levels: county level, province level and county and province-year level (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

	GDP (million yuan, log)			Per capita GDP (yuan, log)		
	(1)	(2)	(3)	(4)	(5)	(6)
Expressway	0.87***	0.75***	0.80***	1.06***	0.92***	0.98***
	(0.21)	(0.18)	(0.18)	(0.22)	(0.19)	(0.19)
	(0.41)	(0.29)	(0.29)	(0.44)	(0.29)	(0.29)
	(0.27)	(0.22)	(0.24)	(0.29)	(0.23)	(0.24)
Expressway*GDP pc	-0.11***	-0.09***	-0.10***	-0.13***	-0.11***	-0.12***
(yuan, log, Year 2000)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)
	(0.05)	(0.03)	(0.03)	(0.05)	(0.03)	(0.03)
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
County FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	N	Y	Y	N
Provincial Trends	N	Y	N	N	Y	N
Province-Year FE	N	N	Y	N	N	Y
Obs.	13,440	13,440	13,440	13,347	13,347	13,347
R^2	0.87	0.90	0.91	0.86	0.89	0.90

Notes: This table estimates the heterogeneous impacts of expressway connection on GDP measures using a variety of specifications. GDP data are deflated, where Beijing-2000 is the base province-year. We probe the robustness of estimates accuracy by clustering the standard errors at three different levels: county level, province level and county and province-year level (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 4. Heterogeneous Treatment Effect with respect to Different Initial Income Groups

	GDP (million yuan, log)				Per capita GDP (yuan, log)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Expressway	0.10***	0.11***	0.06**	0.06**	0.11***	0.12***	0.06**	0.07**
	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)
High Income*Expressway	-0.16***	-0.16***	-0.10***	-0.10***	-0.17***	-0.18***	-0.10***	-0.11***
	(0.02)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)
County FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Provincial Trends	Y	N	N	N	Y	N	N	N
Province-Year FE	N	Y	N	N	N	Y	N	N
Income Group Trends	N	N	Y	N	N	N	Y	N
Income Group * Year FE	N	N	N	Y	N	N	N	Y
Obs.	13,440	13,440	13,440	13,440	13,347	13,347	13,347	13,347
R^2	0.90	0.91	0.87	0.87	0.89	0.91	0.87	0.87

Notes: This table estimates the heterogeneous impacts of expressway connection on GDP. GDP data are deflated, where Beijing-2000 is the base province-year. 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 5. Explore Heterogeneity Patterns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A. GDP (million yuan, log)									
Expressway	0.87***	1.61***	0.44	0.71***	0.86***	0.89***	0.89***	0.91***	2.00***
	(0.21)	(0.24)	(0.31)	(0.22)	(0.25)	(0.21)	(0.29)	(0.21)	(0.34)
Expressway*GDP pc	-0.11***	-0.11***	-0.10***	-0.10***	-0.10***	-0.12***	-0.11***	-0.11***	-0.23***
(Year 2000)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)
Expressway*X	0.00	-0.11***	0.05**	0.07***	-0.00	0.01	-0.00	0.00*	/
(Year 2000)	(0.00)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.00)	(0.00)	/
Panel B. GDP per capita (yuan, log)									
Expressway	1.06***	1.76***	0.57*	0.84***	1.03***	1.07***	1.08***	1.10***	2.15***
	(0.22)	(0.25)	(0.33)	(0.24)	(0.26)	(0.22)	(0.31)	(0.22)	(0.35)
Expressway*GDP pc	-0.13***	-0.13***	-0.11***	-0.11***	-0.13***	-0.14***	-0.13***	-0.14***	-0.24***
(Year 2000)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)
Expressway*X	-0.00	-0.11***	0.05**	0.07***	0.00	0.01	-0.00	0.00**	/
(Year 2000)	(0.00)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.00)	(0.00)	/
X Indicator	Distance (km)	Population (log)	Land Area (log)	Land per capita (log)	# Industrial firms (log)	Output Value (log)	Agriculture (%)	Manufacturing (%)	All
County FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	13,347	12,245	12,236	12,236	12,210	13,264	13,347	13,347	12,144
R^2	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.87

Notes: This table estimates the heterogeneous impacts of expressway connection on GDP measures. GDP data are deflated, where Beijing-2000 is the base province-year. 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 6. The Effects of Expressway Connection on Emissions

	COD Emissions (ton, log)				Per capita COD Emissions (kg, log)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Expressway	-0.09	2.84***	1.89**	2.45***	-0.12	3.21***	2.18**	2.79***
	(0.09)	(0.76)	(0.85)	(0.86)	(0.09)	(0.82)	(0.92)	(0.94)
	(0.05)	(0.81)	(0.75)	(0.67)	(0.06)	(0.88)	(0.86)	(0.78)
	(0.10)	(0.87)	(0.90)	(0.96)	(0.09)	(0.91)	(0.97)	(1.06)
Expressway*GDP pc		-0.34***	-0.23**	-0.30***		-0.39***	-0.27**	-0.34***
(yuan, log, Year 2000)		(0.09)	(0.10)	(0.10)		(0.10)	(0.11)	(0.11)
		(0.10)	(0.09)	(0.08)		(0.10)	(0.10)	(0.09)
		(0.10)	(0.11)	(0.11)		(0.11)	(0.11)	(0.12)
County FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	N	Y	Y	Y	N
Provincial Trends	N	N	Y	N	N	N	Y	N
Province-Year FE	N	N	N	Y	N	N	N	Y
Obs.	13,338	13,338	13,338	13,338	13,205	13,205	13,205	13,205
R^2	0.69	0.69	0.70	0.72	0.64	0.64	0.66	0.67

Notes: This table estimates the heterogeneous impacts of expressway connection on emission measures using a variety of specifications. GDP data are deflated, where Beijing-2000 is the base province-year. We probe the robustness of estimates accuracy by clustering the standard errors at three different levels: county level, province level and county and province-year level (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 Sites (ton, log)		Per capita COD Emissions from Key Polluting Sites (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	-0.05	3.55***	-0.09	4.03***	-0.08	3.64***	-0.13	4.31***	-0.07	-0.35	-0.08	-0.17
	(0.09)	(0.78)	(0.10)	(0.85)	(0.11)	(1.19)	(0.13)	(1.34)	(0.06)	(0.56)	(0.06)	(0.56)
Expressway*GDP pc		-0.43***		-0.49***		-0.44***		-0.52***		0.03		0.01
(yuan, log, Year 2000)		(0.09)		(0.10)		(0.14)		(0.16)		(0.07)		(0.07)
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.	14,551	14,551	14,408	14,408	11,380	11,380	11,249	11,249	13,548	13,548	13,413	13,413
R^2	0.07	0.08	0.07	0.07	0.14	0.14	0.16	0.16	0.13	0.13	0.12	0.12

Notes: This table estimates the heterogeneous impacts of expressway connection on other emission measures. GDP data are deflated, where Beijing-2000 is the base province-year. 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. Expressway Connection: Channels

	COD Emission Intensity (ton per RMB-value of output, log)		Number of Key Polluting Firms (log)		Output Value of Key Polluting Firms		Share of the Secondary Industry (%, log)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Expressway	-0.04	2.77***	-0.07	1.06**	0.04	1.17***	-0.00	0.63***
	(0.08)	(0.81)	(0.05)	(0.42)	(0.03)	(0.27)	(0.01)	(0.14)
Expressway*GDP pc		-0.33***		-0.13***		-0.13***		-0.07***
(yuan, log, Year 2000)		(0.09)		(0.05)		(0.03)		(0.02)
County FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	14,531	14,531	14,711	14,711	14,713	14,713	8,051	8,051
R^2	0.11	0.11	0.54	0.54	0.39	0.39	0.21	0.21

Notes: This table estimates the heterogeneous impacts of expressway connection environmental and economic outcomes. GDP data are deflated, where Beijing-2000 is the base province-year. 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.

Expressways, GDP, and the Environment: A Case of China

Online Appendices

Appendix I. Tests for Parallel Trends

Since different counties were connected to the expressways in different years, we can test 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 variable D_{it}^{k} is defined thus: 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 reported in Appendix Table S2. We find that the estimated coefficients of the placebo leads (we include five leads in the regressions) are not statistically different from zero, suggesting that there are no systematic differences in pre-treatment trends between the control and connected groups for both emissions and GDP measures. After two to four years of connection, expressway connection dummies become statistically significant. This is reasonable because it reflects the time taken for connected regions to adjust their production plans.

Using similar methodology, we can conduct the parallel trends test for the high and low income groups. In Columns 3 and 4, we find expressway connection increases GDP or per capita GDP for the poor income group. In Columns 5 and 6, we find the effect is negative for the rich group. For both groups, the placebo leads are statistically indifferent from zero.

Appendix II. 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, and 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 S9.

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; or (c) in 2010. However, these slight alterations to the treatment status of this small set of counties produce almost identical regressions results and are available upon request.

Appendix III: A Trade Model Formalizing the Explanation

Below we build a trade model with a specific preference characterization and derive a proposition explaining our empirical findings. When mapping from the model to the empirics, we interpret the expressway connection as a decrease in the trade cost between the focal economy and the rest of world, and real GDP an index of the consumption of a composite of goods.

The setting of the model is as follows. There are two sectors of consumption goods, $i = 1, 2$. Labor is the single input in their production, representing all inputs other than the environment quality, as in Pethig (1976). We denote the input, output, and emissions in each sector as a_i, q_i, and e_i, respectively.

Production. The production functions are assumed linear:

$$q_i = a_i, \qquad e_i = \frac{a_i}{k_i}, \qquad i = 1, 2,$$

where $k_i \equiv a_i / e_i$ is the exogenous sector-specific labor intensity that also determines the productivity of emissions in production of each good. The specification simplifies Pethig

(1976) and keeps the idea that the relative labor intensity between the two sectors will determine the economy's comparative advantage with respect to the rest of the world. To make the trade part in the model as simple as possible, this specification also assumes away increasing return to scale, so that the home market effect is ruled out. We assume $k_1 < k_2$, which means that sector 1 is environment intensive and 2 labor intensive.

Endowments. The economy's labor endowment is assumed as $\bar{a} > 0$. The endowment is assumed to be immobile across borders, representing the high barriers to mobility not only of labor but also other non-environmental inputs because of persistent migration restriction and prevalent local protectionism.[1] A labor budget constraint must then hold:

$$a_1 + a_2 \equiv a \leq \bar{a}.$$

The total emission is the sum of emissions from the two sectors, $e \equiv e_1 + e_2$, and we assume that the local environmental quality is $Q \equiv Q(e) \equiv \bar{e} - e$, where the ecological system would collapse if $e > \bar{e}$. In reality, the environmental quality has a dynamic aspect. As shown in Appendix Table S2, for each income group, however, the estimated impacts of expressway connection always have the same sign across all post-connection years. Consistent with the short-time horizon of many consumers and local officials in China, this empirical pattern suggests little evidence that an *intertemporal* development–preservation trade-off was heavily involved in the counties' responses to expressway connection. Therefore, in this model, we assume away the dynamic aspect of the environmental quality, and focus on the GDP–environment trade-off *at a given time.*

[1] For labor, the Chinese government has historically used the household registration system to control labor migration within rural and urban areas, respectively, and between them. Although migration restrictions have been relaxed in recent years, the costs of migration remain substantial because many social benefits, for example, housing subsidies and medical insurance, are available only in the area where a citizen is registered. Scholars have also considered barriers to firm mobility and local protectionism to be prominent in China. For example, see Wedeman (2003), Bai et al. (2004 and 2014), and Barwick et al. (2017).

Similar approaches have also been adopted in, for example, Pethig (1976) and Greenstone and Jack (2015). An environmental budget constraint must then hold:

$$e_1 + e_2 \equiv e \leq \bar{e}.$$

Planner. Instead of modelling decentralized production and consumption decisions, we assume that a social planner controls the production sectors and that he can derive utility from the environmental equality and consumption of the two goods. Not only stylizing the prominent role of Chinese local government in its jurisdiction, this approach gains simplicity for us by allowing us to model the GDP–environment trade-off without specifying the decision of an environmental regulatory agency.[2]

We assume the planner's utility function as $W \equiv U(Q, min\{x_1, cx_2\})$, where consumptions of the two goods are x_1 and x_2 and $c > 0$ is an exogenous parameter. To focus on the trade-off between the environmental quality and general consumption, for simplicity, we use the Leontief specification $min\{x_1, cx_2\}$ to assume away substitution between the consumption goods, as in Pethig (1976). Therefore, a fixed consumption composite,

$$x_1 = cx_2,$$

must hold in equilibrium, and we can then denote $C \equiv min\{x_1, cx_2\}$ as an index for the consumption composite in equilibrium, which maps to real GDP in empirics. For the time being, we allow for a general relationship between Q and C in $U(Q, C)$, and will specify it below.

Trade. We assume that the economy is linked to the rest of world where the two goods can be traded at some given prices, p_1 and p_2, respectively, while the local environmental quality is not tradable. We adopt this assumption of a small, open

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[2] Alternatively, in a decentralized setting, even if the consumers are assumed to own the production sectors (e.g., Pethig, 1976), for various reasons, for example, the agency problem in corporate management, it would still be difficult to justify that the consumer would be able to fully control production and not to take emissions as given. Therefore, to model the consumption–environment trade-off, modelling the decision making of an environmental regulatory agency would become necessary.

economy because each of the Chinese counties in our dataset that could be connected to the national expressway network is small with respect to the national market.

We assume trade across borders incurs an iceberg trade cost, $\tau > 1$, which means that only $1/\tau$ of purchases of the foreign good are available for consumption. Better transport infrastructure across borders, for example, connection to the expressway system in empirics, would be represented by a decrease in τ.

GDP–environment trade-off. We assume that the planner maximizes his utility by allocating labor, emissions, production, and consumption with the help of trade, while acknowledging that local production affects the local environmental quality. The planner's program is then

$$\max_{e_i, x_i, a_i, q_i} U(Q(e_1 + e_2), min\{x_1, cx_2\}),$$

subject to the production functions,

$$q_i = a_i, \qquad e_i = \frac{a_i}{k_i}, \qquad i = 1, 2,$$

endowment budget constraints,

$$e_1 + e_2 \equiv e \leq \bar{e}, \qquad a_1 + a_2 \equiv a \leq \bar{a},$$

and the balance of trade constraint,

$$\tau p_1 (x_1 - q_1) = p_2(q_2 - x_2), \qquad if\ x_1 \geq q_1\ and\ x_2 \leq q_2;$$

$$\tau p_2 (x_2 - q_2) = p_1(q_1 - x_1), \qquad if\ x_1 < q_1\ and\ x_2 > q_2.$$ [3]

We can frame the program into two stages, which we now introduce backwardly. At the second stage, given a certain amount of total emissions, the planner tries to maximize the consumption composite by finding the most efficient allocation of labor input and emissions into the two sectors, with the help of trade. At the first stage, given the most emission-efficient way to generate the consumption composite at the second

[3] The trade cost assumption implies that, if $x_i > q_i$, the home economy is paying $\tau p_i (x_i - q_i)$ for $\tau (x_i - q_i)$ units of good i, but only $x_i - q_i$ units of good i is arriving as import; if $x_i < q_i$, $q_i - x_i$ units is exported, and the revenue from the transaction is $p_i(q_i - x_i)$.

stage, and facing the endowment budget constraints, the planner decides the level of total emission that finds a balance between the environmental quality and consumption composite.

To avoid the GDP–environment trade-off from becoming trivial, we assume that the endowment budget constraints are not binding in equilibrium. In other words, the economy generates moderate emissions and the ecological system has not collapsed, and some unemployment always exists. Both descriptions are consistent with reality.

Along this logic, we can degenerate the program into a general form,

$$\max_{e \in (0,\bar{e})} U(\bar{e} - e, \beta e),$$

with three cases of β, which is the endogenous productivity of the economy in its emission–consumption transformation, depending on the trade cost and the economy's comparative advantage: (1) if $\frac{\tau p_2}{p_1} \leq \frac{k_1}{k_2}$, then the most emission-efficient way of consumption composite generation is to specialize in good 1 and import 2, and $\beta = \frac{ck_1}{c + \frac{\tau p_2}{p_1}}$; (2) if $\frac{p_2}{\tau p_1} \geq \frac{k_1}{k_2}$, then specializing in good 2 while importing 1 is the most efficient, and $\beta = \frac{\frac{p_2}{\tau p_1} ck_2}{c + \frac{p_2}{\tau p_1}}$; (3) if $\frac{p_2}{\tau p_1} < \frac{k_1}{k_2} < \frac{\tau p_2}{p_1}$, then trade is so costly that autarky becomes the most efficient, and $\beta = \frac{ck_1 k_2}{ck_2 + k_1}$.

Lower trade cost (τ) in the model, which maps to connection to the expressway system in empirics, will then increase β, because it allows the economy to take better advantage of their comparative advantage, either by adjusting their sectoral structure in production (transiting from the autarky case to either of the two specialization case), or by reducing the paid trade cost given their sectoral structure (within each of the two specialization cases). Therefore, analyzing how better transport infrastructure would change the GDP–environment trade-off is equivalent to analyzing how higher β would change the equilibrium in the model, and how the equilibrium will be changed depends on the specification of the planner's preference.

Political incentives and planner's preference. Given all the discussion in the main text, we assume in our model that the planner's preference exhibits the two-stage scheme of developmental objectives: at the lower stage, the planner's preference is well-behaved between the consumption composite and environmental quality, as directed by the State Council of China (2005) about the less developed regions. After the consumption–environment combination derives a certain level of satisfaction, the planner steps into the higher stage in which the planner cares primarily about the environment.[4]

This preference specification suggests a utility function as follows:

$$U(Q,C) = \begin{cases} u(Q,C), & if\ u(Q,C) < \overline{U}; \\ \overline{U} + v(Q), & if\ u(Q,C) \geq \overline{U}, \end{cases}$$

where $v(Q)$ is nonnegative and increasing; $u(Q,C)$ is well-behaved, which means it exhibits positive and diminishing marginal utilities, diminishing marginal rates of substitution, and no Giffen property in the "demand" of consumption composite given $u(Q,C) < \overline{U}$; the boundary between the two stages of developmental objectives satisfies $\overline{U} > u(0,0)$, so that both stages are relevant in the model. The implied indifference curves are illustrated in Appendix Figure 2.[5]

[4] More generally, one might expect a third, lowest stage of development objectives where the planner cares only about the consumption composite. Our later results will still hold with this extension.

[5] Our preference specification may also reflect more general differences between the preferences of rich and poor people. For example, many empirical studies have shown that the relationship between pecuniary income and happiness is curvilinear, and after a certain level of income the relationship becomes weak or creases to exist (e.g., Frey and Stutzer, 2002; Easterlin, 2003; Kahneman and Deaton 2010; the review by Layard, 2005). Many cross-sectional empirical studies indicate that more developed countries do not report higher happiness levels once GDP per capita exceeds certain level (e.g., Helliwell, 2003). Instead, people start to care about other nonpecuniary things such as health, political rights and institutions, and importantly the environmental quality. For example, a general observation exists that some rich economies spend large amounts of money and resources to restore environmental quality, while fast-growing developing countries, such as China and India, often face severe pollution problems. Such differences in preferences seem to be consistent Maslow's (1943) theory of hierarchy of needs: after basic level of needs are met individuals will desire higher level of needs.

With this preference specification, we can derive the following proposition, which reconciles our empirical findings:

Proposition. *Given* $\bar{e}$ *and* $U(Q,C)$*, there exists a critical level of the consumption composite,* $\bar{C}$*, such that, if* $C < \bar{C}$ *in equilibrium, then* $\frac{dC}{d\beta} > 0$*; if* $C > \bar{C}$ *in equilibrium, then* $\frac{dC}{d\beta} < 0$ *is possible, where* $\bar{C}$ *is defined by* $u(\bar{e}, \bar{C}) = \bar{U}$*. Moreover, if* $C > \bar{C}$ *in equilibrium and* $\frac{dC}{d\beta} < 0$*, then* $\frac{de}{d\beta} < 0$*. In empirics, if the initial real GDP is sufficiently low, then expressway connection will increase the real GDP; if the initial real GDP is sufficiently high, then expressway connection can decrease the real GDP. Moreover, if the initial real GDP is sufficiently high and expressway connection does decrease the real GDP, then it must have also decreased emissions.*

Proof. Given $\bar{e}$ and $U(Q,C)$, the initial β determines the initial (C,Q) bundle in equilibrium. When the initial β is small, the initial (C,Q) bundle falls in the lower stage, and it is the interior solution of $\max_e \; u(\bar{e}-e, \beta e)$, which solves the first-order condition, where the second-order condition is guaranteed by the diminishing marginal rates of substitution. Note that a change in β mimics a change in the price of the consumption composite in a standard two-good consumption choice problem. Because $u(Q,C)$ exhibits no Giffen property, $\frac{dC}{d\beta} > 0$.

When the initial β is sufficiently large, the initial (C,Q) bundle falls in the higher stage, and they come from the corner solution of $\max_e \bar{U} + v(Q)$ subject to $u(\bar{e} - e, \beta e) \geq \bar{U}$. The solution then satisfies $u(Q,C) = \bar{U}$, $C = \beta e$, and $Q = \bar{e} - \frac{C}{\beta}$. Note that $u(Q,C) = \bar{U}$ is the path generated by an increasing β within the higher stage. Since $u(Q,C)$ exhibits positive marginal utilities, C and Q are negatively correlated along this path. Therefore, $\frac{dC}{d\beta} < 0$, $\frac{dQ}{d\beta} > 0$, and $\frac{de}{d\beta} < 0$.

Note that $u(\bar{e}, \bar{C}) = \bar{U}$ defines the lower limit of the consumption composite that can be achieved in the higher stage, as β approaches infinity. Therefore, when $C < \bar{C}$ in the initial equilibrium, the initial (C, Q) bundle must fall in the lower stage; when $C > \bar{C}$ in the initial equilibrium, the initial bundle can fall in the lower or higher stage. The results then follow. ■

The intuition is as follows: when the initial level of the consumption composite is sufficiently low, the initial equilibrium must have fallen in the lower stage of developmental objectives. In this scenario, as illustrated by Panel A of Appendix Figure 3, the planner cares about both the consumption composite and environmental quality, and an increase in the economy's ability to generate consumption will increase the consumption composite, given the preference is well-behaved.

When the initial consumption is sufficiently high, the initial equilibrium can fall in the higher stage of developmental objectives. In this scenario, as illustrated by Panel B of Appendix Figure 3, the planner cares primarily about the environmental quality, so he would like to sacrifice consumption as much as possible, as long as the economy still stays at the higher stage. An increase in the economy's ability to generate consumption presents an opportunity to sacrifice more of the consumption composite for better environmental quality without slipping into the lower stage of development objectives, resulting in a lower level of the consumption composite, a better environment, and lower emissions.

Note that in a more general model, the consumption composite can be included in the utility function at the higher stage of developmental objectives, which means to consider $v(Q, C)$ instead of $v(Q)$. As long as the consumers and the planner value the environmental quality on the margin sufficiently more highly than the consumption composite ($v_C/v_Q < 1/\beta$), the proposition will still hold. Excluding the consumption composite from the utility function at the higher stage, our preference specification simplifies the exposition without losing much generality.

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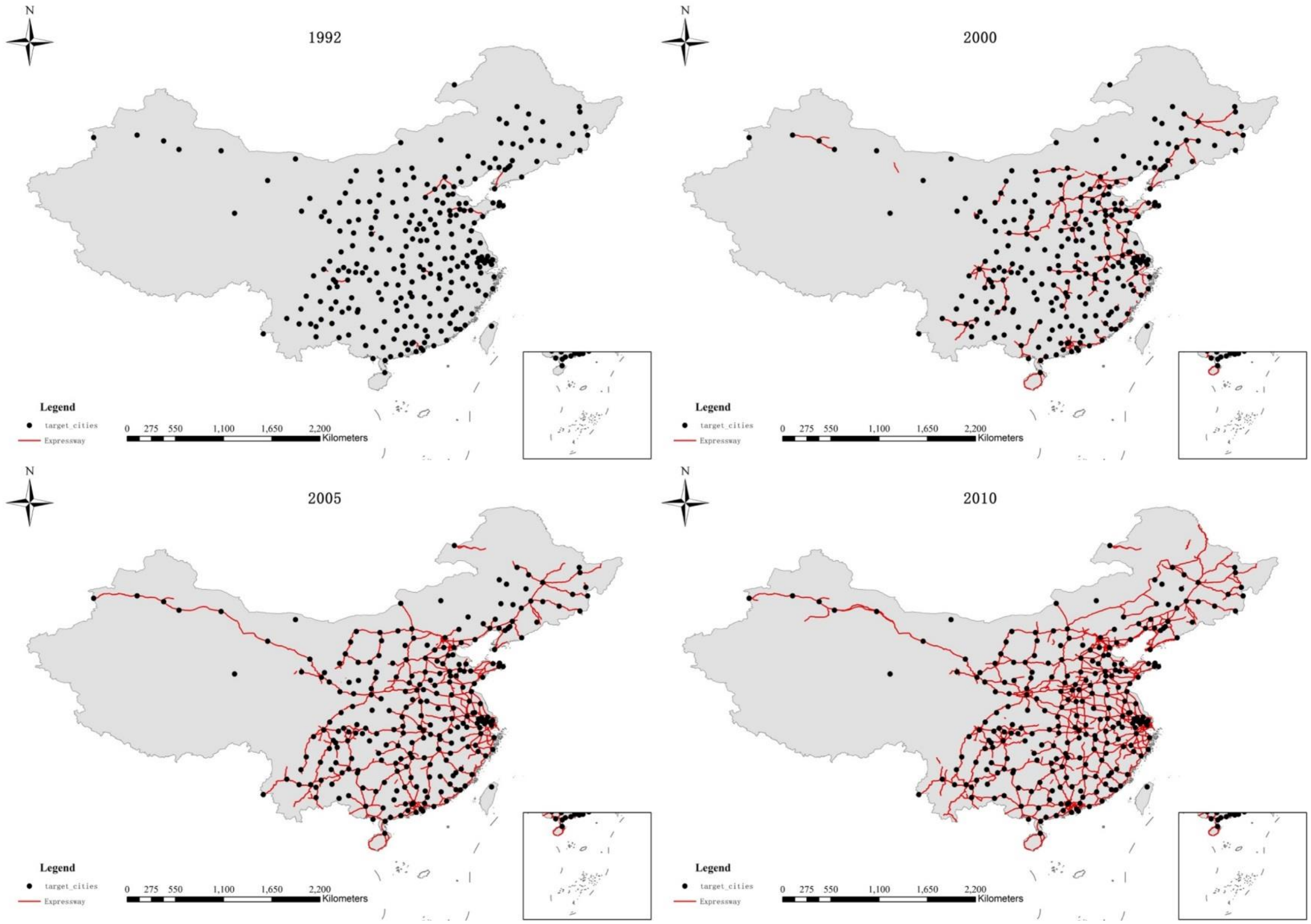
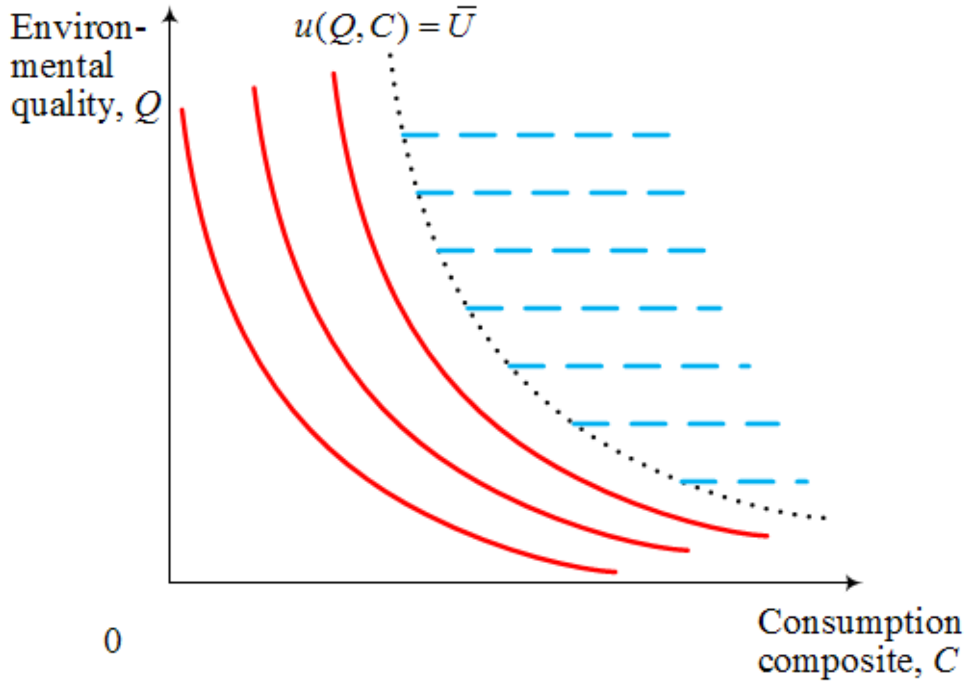
APPENDIX FIGURE 1. EXPANSION OF THE NATIONAL EXPRESSWAY SYSTEM IN CHINA



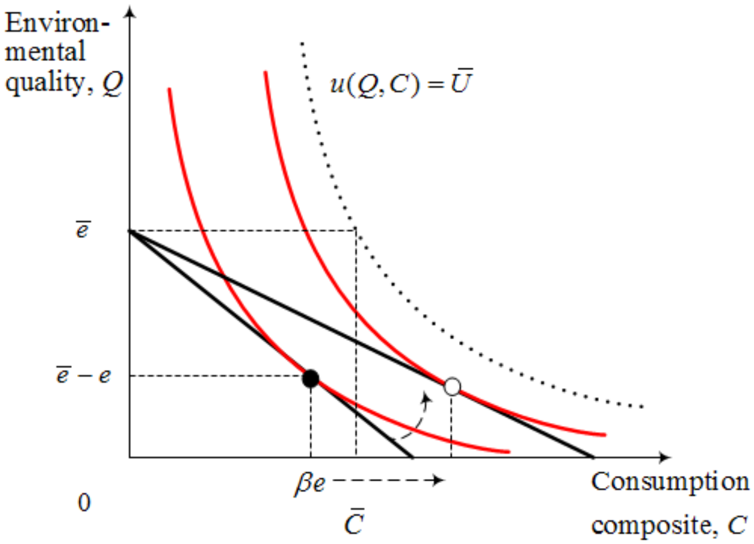
APPENDIX FIGURE 2. INDIFFERENCE CURVES IMPLIED BY THE PREFERENCE EXHIBITING TWO STAGES OF DEVELOPMENT OBJECTIVES



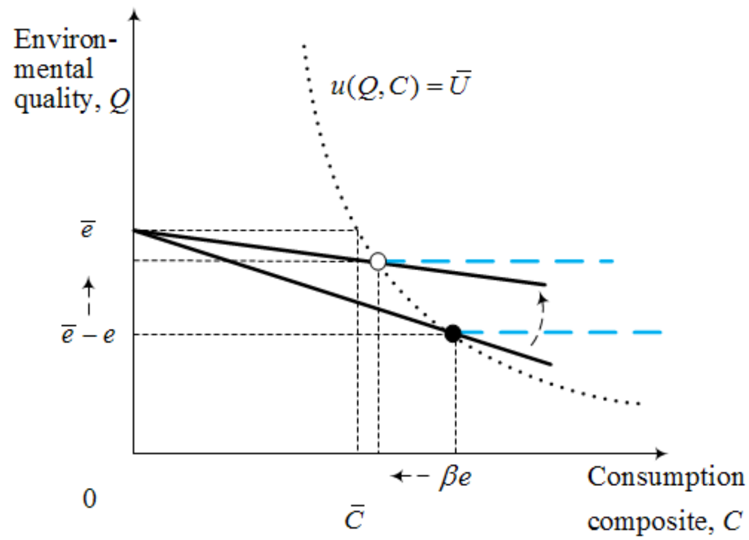
Notes: The solid, red curves are examples of the indifference curves at the lower stage of development objectives. The dashed, blue lines are examples of the indifference curves at the higher stage. The dotted, black curve is defined by $u(Q,C)=\bar{U}$, which is the asymptotic curve of the indifference curves at the lower stage when the utility level approaches $\bar{U}$ from below.

APPENDIX FIGURE 3. IMPACT OF LOWER TRADE COST

Panel A. Initial equilibrium at the lower stage of developmental objectives



Panel B. Initial equilibrium at the higher stage of developmental objectives



Notes: The solid, black lines represent the endogenous frontier of the economy to transform emissions into the consumption composite with the help of trade. The solid, red curves and the dashed, blue lines are indifference curves at the lower and higher stages of developmental objectives, respectively. A lower trade cost expands the frontier, so the equilibrium moves from the black dot to the white dot. As the result, in Panel A, the consumption composite increases; in Panel B, the consumption composite decreases, while the environmental quality increases and emissions decrease.

Table S1. 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.

Table S1 (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.

Table S2. Parallel Trends Tests Separately for Different Income Groups

	Overall		Low Income Group		High Income Group	
	GDP (log)	Per capita GDP (log)	GDP (log)	Per capita GDP (log)	GDP (log)	Per capita GDP (log)
	(1)	(2)	(3)	(4)	(5)	(6)
>= 5Years Before	-0.01	-0.00	-0.09	-0.08	0.01	0.01
	(0.04)	(0.04)	(0.08)	(0.08)	(0.03)	(0.03)
4 Years Before	-0.00	-0.00	-0.06	-0.06	0.01	0.01
	(0.02)	(0.02)	(0.04)	(0.04)	(0.02)	(0.02)
3 Years Before	-0.00	-0.00	-0.01	-0.00	-0.00	-0.00
	(0.01)	(0.01)	(0.03)	(0.02)	(0.01)	(0.01)
2 Years Before	-0.01	-0.01	-0.01	0.00	-0.01	-0.01
	(0.01)	(0.01)	(0.02)	(0.03)	(0.01)	(0.01)
Year of Connection	-0.00	-0.01	0.02	0.03*	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
1 Year Later	-0.01	-0.01	0.02	0.04	-0.02	-0.02
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
2 Years Later	-0.02*	-0.02	0.03	0.05*	-0.03***	-0.03***
	(0.01)	(0.01)	(0.02)	(0.03)	(0.01)	(0.01)
3 Years Later	-0.02**	-0.02	0.03	0.05*	-0.04***	-0.04**
	(0.01)	(0.01)	(0.02)	(0.03)	(0.01)	(0.01)
>=4 Years Later	-0.05**	-0.05**	0.02	0.03	-0.06***	-0.06***
	(0.02)	(0.02)	(0.04)	(0.03)	(0.02)	(0.02)
County FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Obs.	13,440	13,347	2,976	2,951	10,464	10,396
R^2	0.87	0.86	0.91	0.90	0.87	0.86

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. GDP data are deflated, where Beijing-2000 is the base province-year. Standard errors are clustered at the county level and reported in the parentheses. ** p<0.01, ** p<0.05, * p<0.1.

Table S3. Estimates Using Straight-Line IV

	1st Stage: Expressway	2SLS: Δ log (GDP) between 2000 and 2012		2SLS:Δ log (per capita GDP) between 2000 and 2012	
	(1)	(2)	(3)	(4)	(5)
Straight-Line IV	0.34***				
	(0.03)				
Expressway		-0.05	1.79***	0.03	2.19***
		(0.06)	(0.56)	(0.08)	(0.52)
Expressway*GDP pc			-0.22***		-0.26***
(yuan, log, Year 2000)			(0.06)		(0.06)
Specification	1st Stage	2SLS	2SLS	2SLS	2SLS
Province FE	Y	Y	Y	Y	Y
Observations	1,684	1,586	1,564	1,547	1,547
R^2	0.23	0.25	0.27	0.29	0.32

Notes: Each column in the table represents a separate regression. The instrumental variable (IV) is constructed using straight lines that connect pairs of target cities. If a county is located on the straight line between two target cities, the IV equals to 1, and otherwise 0. For columns 3 and 5, the straight-line IV interacted with per capita GDP in 2000 is used to instrument the expressway connection interacted with per capita GDP in 2000. GDP data are deflated, where Beijing-2000 is the base province-year. Standard errors are clustered at the province level. * significant at 10% ** significant at 5% *** significant at 1%.

Table S4. The Effects of Expressway Connection on GDP: Results from Un-matched Sample

	GDP (million yuan, log)				Per capita GDP (yuan, log)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Expressway	-0.01	2.80***	1.74**	2.03***	-0.01	3.27***	1.94**	2.25***
	(0.01)	(0.74)	(0.77)	(0.77)	(0.01)	(0.80)	(0.84)	(0.85)
	(0.02)	(0.87)	(0.72)	(0.70)	(0.02)	(0.97)	(0.83)	(0.80)
	(0.01)	(0.81)	(0.79)	(0.86)	(0.01)	(0.89)	(0.87)	(0.94)
Expressway*GDP pc		-0.35***	-0.22**	-0.26***		-0.41***	-0.25***	-0.29***
(yuan, log, Year 2000)		(0.09)	(0.09)	(0.09)		(0.09)	(0.10)	(0.10)
		(0.10)	(0.09)	(0.08)		(0.11)	(0.10)	(0.09)
		(0.09)	(0.09)	(0.10)		(0.10)	(0.10)	(0.11)
County FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	N	Y	Y	Y	N
Provincial Trends	N	N	Y	N	N	N	Y	N
Province-Year FE	N	N	N	Y	N	N	N	Y
Obs.	19,835	18,179	18,179	18,179	19,472	18,007	18,007	18,007
R^2	0.87	0.08	0.12	0.16	0.86	0.08	0.13	0.17

Notes: This table estimates the impacts of expressway connection on GDP measures using the sample before matching. GDP data are deflated, where Beijing-2000 is the base province-year. We probe the robustness of estimates accuracy by clustering the standard errors at three different levels: county level, province level and county and province-year level (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 S5. Parallel Trends Tests Using the Un-Matched Sample

	GDP (million yuan, log)	Per capita GDP (yuan, log)
	(1)	(2)
>= 5Years Before	-0.02	-0.02
	(0.04)	(0.04)
4 Years Before	0.00	-0.01
	(0.02)	(0.02)
3 Years Before	-0.00	-0.01
	(0.01)	(0.01)
2 Years Before	-0.01	-0.01
	(0.01)	(0.01)
Year of Connection	0.00	-0.00
	(0.01)	(0.01)
1 Year Later	-0.01	-0.01
	(0.01)	(0.01)
2 Years Later	-0.01	-0.01
	(0.01)	(0.01)
3 Years Later	-0.02*	-0.02
	(0.01)	(0.01)
>=4 Years Later	-0.04**	-0.04**
	(0.02)	(0.02)
County FE	Y	Y
Year FE	Y	Y
Obs.	19,835	19,472
R^2	0.87	0.86

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. GDP data are deflated, where Beijing-2000 is the base province-year. Standard errors are clustered at the county level and reported in the parentheses. ** p<0.01, ** p<0.05, * p<0.1.

Table S6. The Effects of Expressway Connection on GDP: Outliers Dropped

	GDP (million yuan, log)			Per capita GDP (yuan, log)		
	(1)	(2)	(3)	(4)	(5)	(6)
Expressway	0.76***	0.70***	0.74***	0.88***	0.83***	0.88***
	(0.21)	(0.19)	(0.19)	(0.21)	(0.19)	(0.19)
	(0.40)	(0.31)	(0.31)	(0.41)	(0.31)	(0.31)
	(0.29)	(0.23)	(0.24)	(0.28)	(0.23)	(0.24)
Expressway*GDP pc	-0.09***	-0.09***	-0.09***	-0.11***	-0.10***	-0.11***
(yuan, log, Year 2000)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)
	(0.05)	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
County FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	N	Y	Y	N
Provincial Trends	N	Y	N	N	Y	N
Province-Year FE	N	N	Y	N	N	Y
Obs.	13,116	13,116	13,116	13,023	13,023	13,023
R^2	0.87	0.90	0.91	0.87	0.89	0.91

Notes: This table estimates the heterogeneous impacts of expressway connection on GDP measures using a variety of specifications. Counties with very high (top 1%) and very low (bottom 1%) initial per capita GDP are dropped. GDP data are deflated, where Beijing-2000 is the base province-year. We probe the robustness of estimates accuracy by clustering the standard errors at three different levels: county level, province level and county and province-year level (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 S7. Heterogeneous Effect of Neighbor County Expressway Connection

	GDP (million yuan, log)			Per capita GDP (yuan, log)		
	(1)	(2)	(3)	(4)	(5)	(6)
Neighbor Expressway	0.52*	0.55**	0.50**	0.78***	0.65***	0.63**
	(0.29)	(0.22)	(0.25)	(0.29)	(0.22)	(0.25)
N-Expressway*GDP pc	-0.06	-0.06**	-0.06*	-0.09**	-0.07***	-0.07**
(yuan, log, Year 2000)	(0.04)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)
County FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	N	Y	Y	N
Provincial Trends	N	Y	N	N	Y	N
Province-Year FE	N	N	Y	N	N	Y
Obs.	8,732	8,732	8,732	8,688	8,688	8,688
R^2	0.87	0.89	0.89	0.86	0.88	0.89

Notes: This table estimates the heterogeneous impacts of expressway connection on GDP measures using a variety of specifications. GDP data are deflated, where Beijing-2000 is the base province-year. Standard errors clustered at the county level are reported in the parentheses below the estimated coefficients. *** p<0.01, ** p<0.05, * p<0.1.

Table S8. Parallel Trends Tests for Emissions

	COD Emissions (ton, log)	Per capita COD Emissions (kg, log)
	(1)	(2)
>= 5Years Before	0.05	0.11
	(0.11)	(0.12)
4 Years Before	0.02	0.06
	(0.09)	(0.09)
3 Years Before	0.06	0.07
	(0.04)	(0.05)
2 Years Before	0.02	0.05
	(0.06)	(0.07)
Year of Connection	-0.04	-0.03
	(0.05)	(0.05)
1 Year Later	-0.01	-0.01
	(0.06)	(0.06)
2 Years Later	-0.10	-0.12
	(0.08)	(0.08)
3 Years Later	-0.08	-0.09
	(0.07)	(0.08)
>=4 Years Later	-0.08	-0.11
	(0.08)	(0.09)
County FE	Y	Y
Year FE	Y	Y
Obs.	13,338	13,205
R^2	0.06	0.06

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.

Table S9. The Effects of Expressway Using Alternative Treatment Indicator

	GDP (million yuan, log)		GDP per capita (yuan, log)		COD Emissions (ton, log)		Per capita COD Emissions (kg, log)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Expressway	-0.03	0.88***	-0.02	1.11***	-0.10	2.88***	-0.13	3.29***
	(0.02)	(0.19)	(0.02)	(0.21)	(0.09)	(0.78)	(0.09)	(0.84)
Expressway*GDP pc		-0.11***		-0.13***		-0.35***		-0.40***
(yuan, log, Year 2000)		(0.02)		(0.02)		(0.09)		(0.10)
County FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	13,440	13,440	13,347	13,347	13,338	13,338	13,205	13,205
R2	0.87	0.87	0.86	0.86	0.06	0.06	0.06	0.06

Notes: This table estimates the heterogeneous impacts of expressway connection environmental and economic outcomes. GDP data are deflated, where Beijing-2000 is the base province-year. 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.