Expressways, GDP, and Pollution: Evidence from China and an Explanatory Model

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Using Chinese county-level data from 2000 to 2012, we estimate the impact of expressway connection on local GDP in a difference-in-differences setting. We find that poor counties grow faster while rich counties grow slower after expressway connection, compared with their unconnected counterparts. This heterogeneity is driven neither by supply-side factors nor by the initial access to the nearby market, but by demand-side factors. To reconcile the empirical findings, we propose a trade model with hierarchical preference, which illustrates different trade-offs between environmental quality and GDP faced by decision makers with different initial levels of GDP. Consistent with additional predictions from the model, we further show empirically that rich counties pollute less and poor counties pollute more after expressway connection.

Keywords: transport infrastructure; environmental Kuznets curve; pollution haven hypothesis; home market effect; hierarchy of needs

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

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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 economy 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, statistically insignificant impact on connected counties' GDP or per capita GDP.

As this negligible 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 do find that expressway connection caused initially poor counties to grow faster than the unconnected counties. For the initially rich counties, however, the effect is the opposite: they tend to grow slower after being connected than the unconnected counties. 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 and those based on potential increasing return to scale, because the former would predict a universally positive income effect (e.g. the pollution haven hypothesis as in Copeland and Taylor, 1994; survey by Copeland and Taylor, 2004), while the latter would predict a more negative income effect on the poor counties than on the rich counties (e.g., the home market effect as in Krugman, 1980, 1991; Helpman and Krugman, 1985; Faber, 2014). A closer examination reveals that the heterogeneous impacts of expressway connection with respect to initial income cannot be explained by supply-side factors, such as the initial sectoral pattern in the local economy and endowments of land, population, and capital, or by factors related to the initial access the nearby market, measured by the distance between a focal county and its closest metropolitan city. We thus infer that the impact heterogeneity across initial incomes is driven by demand-side factors: poor people (or governments in poor regions) and rich people (or governments in rich regions) may have different preferences.

Given these analyses, we propose a trade model that spotlights how the preference of local government or consumers over the trade-off between environmental preservation and consumption of produced goods will shape the local economy's response to an economic opportunity that reduces trade cost. We show that our empirical result can be explained when the preference exhibits a hierarchy of needs in the flavor of Maslow (1943): consumption of produced goods is relevant primarily at a lower level of the hierarchy, while a taste for environmental quality dominates at a higher level of the hierarchy. With this preference specification, lower trade cost increases the ability of the local economy to transform polluting emissions into consumption, so it will help a poor economy enjoy higher total consumption (local GDP in empirics); for a rich economy, however, lower trade cost can present an opportunity to sacrifice more consumption for better environment, and the potential decrease in consumption must be accompanied by lower level of local polluting emissions.

We further test the additional prediction from the model on emissions using county-level panel data of local polluting emissions in China for the same period, 2000–2012. Our analysis confirms that, after expressway connection, rich counties become less polluted, while poor counties increase emissions. Expressway connection also makes poor counties host more polluting firms and adopt more pollution-intensive technology, while the opposite happens to rich counties. These results are consistent with our model.

This paper unfolds as follows. The rest of this section discusses how this study is linked and contribute 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 heterogeneity. In Section VI, we propose our model, and we provide additional evidence for our model in Section VII. Section VIII discusses policy implications and concludes with directions for future research.

Literature Connections

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

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., 2016a; Donaldson and

Hornbeck, 2016; Frye, 2016; Ghani et al., 2016; Jaworski and Kitchens, 2016; Alder 2017; Donaldson, forthcoming; also the survey by Redding and Turner, 2015). Notable examples that focus on China include Banerjee et al. (2012), Zheng and Kahn (2013), Faber (2014), Baum-Snow et al. (2016b), and Qin (2016).[1]

We improve on this line of research from several aspects. First, most studies investigating China's national expressways use aggregated prefecture- or city-level data. 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, because expressways are designed to connect these locations (as pointed out by, for example, Baum-Snow et al. 2016b). 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, and those often-proposed instrumental variables, which are based on geographical characteristics, generally lack variation over time. To achieve better identification, Faber (2014) is the first to focus on peripheral counties and leave out the city centers (targeted cities of the expressway system). In this study, we follow Faber (2014) and compare the economic performances between connected and unconnected *counties*. Second, compared with Faber (2014), which uses county-level data of two years (1997 and 2006), 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

[1] Banerjee et al. (2012) investigated the economic impacts of railway construction in China during the late 19th and early 20th centuries and found that proximity to transportation networks had a moderately positive causal effect on per capita GDP levels across sectors but no effect on per capita GDP growth. Zheng and Kahn (2013) 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. We will discuss our difference and improvement upon Faber (2014) in more detail below. Qin (2016) 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. Baum-Snow et al. (2016b) estimate the economic impacts of expressway expansion in Chinese cities using both structural and reduced-form approaches and find inconsistent results.

knowledge, our data set is the largest, longest, and most disaggregated one in this line of literature. Since China's national expressways have expanded by nearly 10 times during our sample period (from 11,650 kilometers in 2000 to 9,560,000 kilometers in 2012), our data and findings are also more relevant to today's policy. Third, having multiple periods of data allows us to use different empirical strategies. In particular, we can examine the outcome dynamics before and after expressway connection, and credibly test whether a DiD approach can be applied.[2] Finally, previous studies (especially the ones adopting a reduced-form approach) usually focus on the average treatment effect of expressway connection. In contrast, we emphasize the importance of heterogeneity and try to explain why it matters for the understanding of the impact of transport infrastructure improvement.

Our empirical results also speak to the literature on how trade affects pollution in China (e.g., Bombardini et al. 2016) and provide a mixed piece of evidence on the pollution haven hypothesis (PHH). 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. Empirical evidence on the hypothesis is often obtained from aggregate country-level data (e.g., Eskeland and Harrison, 2003; Ederington et al., 2005; Frankel and Rose, 2005; Levinson and Taylor, 2008; Levinson, 2009; Managi et al., 2009). It is often difficult to draw credible causal inferences from such data, because institutional, cultural, and demographical settings are different across countries and openness to trade is seldom exogenous (Copeland and Taylor, 2004; Karp, 2011). The rapid expressway expansion in China provides us with a more

[2] 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 has to rely 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.

credible setting to assess the impact of trade integration on the environment, because the access of peripheral counties to expressways is arguably exogenous in our context and their institutional, cultural, and demographical difference are small and can be controlled by fixed effects. Our heterogeneity result about the impact of expressway connections on local emissions is indeed consistent with the PHH; as mentioned above, however, the heterogeneity result about the impact on local GDP is inconsistent with the PHH. 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 variables (GDP in this case) that can indicate the theoretical mechanism underlying the hypothesis.

This study also contributes 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. However, no consensus has been reached on this pattern because empirical findings are mixed and those supporting the EKC are often applicable only to specific contexts, time periods, and functional forms.[3] Arrow et al. (1995) and Stern (2004) remark that the relationship between development and the environment cannot be characterized as one-way causality. Copeland and Taylor (2004) further argue that economic growth from different sources can have different implications for pollution, making the EKC 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 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. Our theory

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

further implies that, to better understand the relationship between income and emissions, because each economy is deciding its resource allocation between income generation and environmental preservation in one grand trade-off, we had better consider a third dimension about the factor that affects the trade-off, instead of a two-dimensional framework consider only income and emissions.

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.[4] Unconnected counties serve as the control group. The targeted cities are excluded from subsequent analysis because their expressway connections are endogenous.[5] In Figure 1, we present two maps of China, for 2000 and 2010, respectively, where the targeted cities (including all city 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:

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

where $y_{i,t}$ is 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. An unbiased estimate of β requires that the pre-treatment trends for both control and treatment groups be parallel.

[4] 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 are unable to properly include the lead- and lag- indicators of their connection in the parallel-trend tests.

[5] 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 further shows the target cities on the map and draws the expansion of China's national expressways from 1992 to 2010. A (prefectural) city typically includes a few urban districts and a dozen rural counties. If a (prefectural) city is targeted by the plan, we treat all of its urban districts as being targeted and exclude them from subsequent analysis.

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:

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

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

Identifying Assumptions

The routing of expressways is determined by the central and provincial governments. Although counties between major cities were not explicitly targeted by the *National Expressway Network Plan* (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.

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.[6] 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

[6] 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.

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 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. Our matching process is as follows: for each eventually-connected county in our data, we choose a non-connected county from the same province that has the most similar level of per capita GDP in 2000; 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 applying the DiD estimators brings about two merits. First, the test results for the parallel trends assumption, which we will introduce below, are improved using the matched sample as 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 mainly focus on the results using the matched sample and leave 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). The idea is that we generate a set of lead- and lag- 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 connected and unconnected counties follow similar trends before the connected counties become connected.

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.*

Expressway Expansion Data

Historical GIS (geographic information systems) data on China's National Expressway Network were collected from the PR China Administrative Spatio-Temporal Expressway Database (STED) from the ACASIAN Data Center at 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.[7]

Pollution Data

Finally, we collect county-level emissions data from China's Environmental Survey and Reporting (ESR) database. Emissions data are used for the understanding of the channels of the GDP results.

The ESR database is maintained by the Ministry of Environmental Protection of China. It is used to monitor the polluting activities of all important polluting sources, including heavily polluting industrial firms, hospitals, residential pollutant discharging units, hazardous waste treatment plants, and urban sewage treatment plants. When we refer to the "polluting sector," we include all the sources, regardless of the type of the industry.

We use the ESR data from 2000 to 2012 in this study. During this period, the monitored polluting sources in total 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 unmonitored plants. The micro-level emissions data used in this study had been kept confidential for many years but recently became conditionally open to some researchers.[8]

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[7] 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 connected counties that were connected in the gap years, we have to interpolate the treatment status with various assumptions. 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.

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

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 oxygen required to oxidize soluble and particulate organic matter in water.[9] 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. COD is the primary measure of water pollution adopted in China.

Another reason why we focus on COD emissions 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.

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. Per capita COD emissions are calculated by dividing the total COD emissions by the population. We also check the robustness of our results using COD emissions only from key polluting plants and supplement our analysis by further discussing the results of other emissions measures, such as ammonia-nitrogen and SO_2.[10]

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[9] 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.

[10] 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 in Section VII 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 and per capita GDP in 2000 and 2012 separately for the matched and un-matched samples. From 2000 to 2012, per capita GDP of our sampled counties increased more than fivefold. We observe that, before matching, the eventually connected counties were generally richer from the unconnected counties in 2000. After matching, however, the connected and unconnected counties have very similar levels of initial GDP and per capita GDP.

Figure 2 further plots the distribution of per capita GDP separately before and after matching. It shows that connected counties share a common support with the unconnected matched counties.

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 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 similar to the findings in Faber (2014); but in our empirical setting, none of them is statistically significant. We further check the robustness of the estimates' accuracy by clustering the standard errors at different levels and arrive at the same conclusion.

We then test the parallel-trends assumption following Jacobson et al. (1993).[11] 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 had GDP trends similar to the unconnected counties'. The difference between the GDP levels of the connected and the unconnected counties remains unchanged in the first couple of years after the connection, and it becomes slightly negative in the long run. We thus conclude that the parallel trend assumption holds and expressway connection on average has a negligible negative impact on GDP and per capita GDP.

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 estimated heterogeneity based on estimates in Columns 1 and 4 of Table 3 and calculate the predicted impacts with their 95% confidence intervals at different initial income levels. A predicted impact of zero (highlighted by a red square) implies that expressway connection does not affect GDP or per capita GDP at a given initial income

[11] In Appendix Table S2 we summarize the regression results.

level. A positive value means that GDP increases, while a negative value means it decreases. In Figure 4, we observe that expressway connection positively affected GDP in the poor counties (statistically significant for the poorest 25%) and negatively affected GDP in the rich counties (statistically significant for the richest 60%).

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.

We probe the robustness of estimate accuracy by clustering the standard errors at three different levels: the county level, the province level, and the county and province-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 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.[12] This allows us to further 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.[13] These regressions again confirm that expressway connection has highly heterogeneous impacts on local economy.

Additionally, in the same spirit as Banerjee et al. (2012) and Faber (2014), we estimate the impacts of expressway connection on GDP using an instrumental variable approach. 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 one; otherwise, it is zero. 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 GDP or per capita GDP between 2000 and 2012. The IV approach may help to address concerns on potential compound treatments and selection issues based on expectation, in which the parallel trend test would help little in addressing. As reported in Appendix Table S3, we find the same pattern of a highly heterogeneous expressway impact as our matched DiD result.

Moreover, we estimate the expressway effect using the unmatched sample and find similar results. These findings are reported in Appendix Table S4. The parallel trends tests using the un-matched sample are also summarized in Appendix Table S5.

[12] The results from the linear specification suggest that the positive effects are statistically significant for the poorest 0–20%, 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.

[13] 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.

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 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. Second, although the expressway connection of one county would not affect other counties much on average, it 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 in 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 its interaction with the initial income reveal the potential spill-over effect and its heterogeneity. As reported in Appendix Table S6, the "neighboring connection" effect is positive for low-income unconnected counties, while it is negative for high-income unconnected counties. This finding shows that there exist some spill-overs, but the spillover effect works against the heterogeneity pattern in our main results, rather than contributing to it.[14] Were no such spillover, the heterogeneity we find in our main results should be even stronger.

To summarize, these robustness checks lend additional credibility of our main finding: counties with low initial income significantly increased their GDP after

[14] 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.

expressway connection, while counties with high initial income witnessed reductions in GDP.

V. Understanding the Heterogeneity

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

In a comparative advantage framework, reduction in trade costs will facilitate regions to specialize in producing products 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 value environmental quality less highly than high-income regions, which can have a comparative advantage in non-polluting industries. This hypothesis would however predict a positive income effect of trade cost reduction for both poor and rich regions (e.g., Copeland and Taylor, 1994), and thus cannot adequately explain 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 the overall impacts of expressway connection can be negative. As in Faber (2014), however, the home market effect also implies that the negative impact of expressway connection on the peripheral area's GDP is stronger if the core-periphery relationship is more asymmetric, i.e., if the focal county is poorer. This prediction contradicts our empirical observation that expressway access reduces income in richer counties while increasing income in poorer counties.

As each of the comparative advantage story and 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 dominates the home market effect, while in richer counties the home market effect dominates the comparative advantage mechanism.[15] Were this combined mechanism driving our empirical results, we should expect the heterogeneous impacts captured by initial per capita GDP to be diluted by heterogeneities across measures of comparative advantage and of factors related to the home market effect.

Given this consideration, we conduct diagnostic analyses, as reported in Table 5, where, conditional on income heterogeneity, we additionally interact the expressway connection dummy with a rich set of variables measured in 2000. In Column 1, 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. This is used to test whether home market effect is important, since the home market effect is supposed to be stronger when the initial trade cost is lower (e.g., Krugman, 1991; Faber, 2014), and can also shed some light on whether the initial access to nearby market is driving our income heterogeneity result. In Columns 2–8, we include a set of endowment and sectoral pattern measures, including population, land area, per capita land area, number of industrial firms, industrial output value, share of agriculture and share of manufacturing in GDP. The endowment variables are instrumental in determining the home market effect

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

in theory, and both the endowment and sectoral pattern variables proxy the local economy's comparative advantage.

Table 5 shows that, while there may exist some effect heterogeneity for some variables (such as population and land), none of them has a significant impact on our income heterogeneity results. More importantly, as shown in Column 9, if we include all these interactions in the regression, the coefficient of the income–treatment interaction becomes greater, which means the income heterogeneity becomes even more prominent. These findings remain the same if we use the income group dummy, instead initial GDP per capita, in the regressions, as reported in Appendix Table S7.

The results in Table 5 imply that factors related to the supply side and initial access to nearby markets do not drive our observed income heterogeneity result. Therefore, although we acknowledge the relevance of comparative advantage and home market effect in our context, we are prone to believe that demand-side factors, i.e. people (or local government) with different income levels having different preferences, are driving our main empirical findings.

VI. An Explanatory Model

The following questions naturally arise: first, is it true that poor people and rich people may have different preference? Second, what are the major differences in preferences between the poor and rich?

In the literature, 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; and Layard, 2005 for a review). Many cross-sectional empirical studies also 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, institutions, and notably environmental quality. The development and popularity of using the United Nations' Human Development Index and the Gross National Happiness Index (GNHI) Index as welfare measures, and the increasing awareness of climate change and pollution are illustrations of such changes in preferences.

In this study, we emphasize the importance of environmental considerations. The idea is motivated by the observation that developed countries tend to 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. We conceptualize this idea by modelling that poor and rich regions have different preferences on the GDP–environment trade-offs. Relatively speaking, poor regions may care more about their GDP, while rich regions may care primarily the environmental quality. Expressway connection brings about an opportunity for both regions to re-optimize in the bundle of the environment and GDP, helping rich counties clean up and poor counties earn higher income.

To illustrate this idea, below we build a trade model with a specific preference characterization and discuss the relevance of this preference characterization in the Chinese context. In the next section, we provide additional empirical evidence for the model's predictions.

Our model has the following basic features: to make the part of trade as simple as possible, we adopt the classic comparative advantage setting, while assuming that increasing return to scale does not exist, so that the home market effect is ruled out; emissions are modeled as a byproduct of consumption good production, as in Pethig (1976); consumers have two potential sources of utility, i.e., the environmental quality and consumption of goods. 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 GDP an index of the consumption composite.

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 input other than the environment. We denote the input, output, 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. 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 $\bar{a} > 0$, and labor is assumed not be able to move across borders. 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 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 counties in 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–environment trade-off was heavily involved in the counties' responses to expressway connection. Therefore, in this model, we will assume away the dynamic aspect of the environmental quality, and will focus on the tradeoff between consumption and environmental preservation *at a given time.* Similar approaches have also been adopted in, for example, Pethig (1976) and Greenstone and Jack (2015). An environmental budget constraint must then hold:

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

Consumption. The representative consumer in the economy could derive utility from the environmental equality and consumption of the two goods. The utility function is assumed 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 of the scale of the consumption composite in equilibrium. For the time being, we allow for a general relationship between environmental quality and consumption in utility generation, $U(Q, C)$, 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 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.

Consumption–environment trade-off. Instead of assuming decentralized production and consumption decisions, we assume that a social planner maximizes the consumer's utility while acknowledging that consumption can affect the environmental quality through local production. Gaining simplicity, this approach allows us to model the consumption–environmental trade-off without specifying the decision of an environmental regulatory agency.[16] This approach is also empirically relevant in the context of China, because local governments, which act as the planner in our model, are given strong control over the allocation of natural resources (notably land), capital flows, and even labor in their jurisdiction. For instance, since China's market reforms in the 1980s, local governments have been strategically 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). For labor, the Chinese government has historically used the Hukou (household registration) 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. For these reasons, we will interpret our empirical evidence as resulting from the policy responses of local governments, rather than the spontaneous reactions of capitalists or laborers, to expressway access.

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,

[16] 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.

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

$$\tau\, p_2\,(x_2 - q_2) = p_1(q_1 - x_1), \qquad if\ x_1 < q_1\ and\ x_2 > q_2.$$ [17]

We can frame the program into two steps, which we now introduce backwardly. In the second step, given 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. In the first step, given the most emission-efficient way to generate the consumption composite, 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 consumption–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 $\beta = \frac{ck_1k_2}{ck_2+k_1}$.

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[17] 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 $p_i(q_i - x_i)$.

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 consumption–environment trade-off is equivalent to analyzing how a higher β would change the equilibrium in the model. We have now isolated the impact to depend only on the preference specification.

Preference. We propose that the planner's preference follows a hierarchy of needs, in the spirit of Maslow (1943): there exist a group of consumption–environment bundles, over which the planner's preference is well-behaved, while there also exist another group of bundles, over which the planner cares primarily about the environmental quality, but little about the consumption composite; any bundle in the second group is preferred by the planner over any bundle in the first group. In other words, the consumption composite is relevant primarily at a lower level of the hierarchy of needs, while the environmental quality dominates at the higher level.[18]

The defining features of our proposed preference specification suggest a utility function as follows:

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

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 $u(Q,C) < \bar{U}$; the boundary of the hierarchy of needs satisfies $\bar{U} > u(0,0)$, so that both

[18] One might expect a third, lowest level of the hierarchy at which the planner cares about the consumption composite but little about the environmental quality. Our later results will still hold with this extension.

levels of the hierarchy are relevant. The implied indifference curves are illustrated in Figure 5.

Not only can this characterization helps us illustrate the general preference difference between rich and poor regions, it also captures some salient features of the political incentives of local governments in China. Since China's economic reforms in the 1980s until early 2000s, the Chinese government had considered economic growth as its priority and paid little attention to environmental problems. Economic performances were used to evaluate and promote local officials during this period; and as a result, along with China's rapid economic growth, the country witnessed severe degradation of its ecological systems. As the country's environmental challenges mounted, however, the President then Hu Jintao proposed the "Scientific Outlook of Development" in 2003 and sought integrated sets of solutions to economic, environmental and social problems. [19] In 2005, the central government required considering environmental performance in evaluating local officials, and directed that "relatively developed regions should ... prioritize the environment," while "the regions of great potential to develop should … scientifically and reasonably utilize the carrying capacity of the environment to promote industrialization and urbanization" (State Council of China, 2005). In 2013, the current President Xi Jinping further institutionalized environmental performance in cadre evaluations and emphasized that the weight of environmental performance in the evaluations should depend on regional characteristics (Organization Department of the Communist Party of China, 2013). On the practical significance of the reform, for example, consistent with the change, Sun et al. (2014) and Zheng et al. (2014) provide evidence that, in 2004–2009, better environmental performance did contribute to promotion of city mayors, and Sun et al. (2014) further show that the impact was more prominent for mayors of larger cities.

[19] "Scientific Outlook of Development" sometimes is translated as the "Scientific Development Concept" or the "Scientific Development Perspective."

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 GDP is sufficiently low, then expressway connection will increase the GDP; if the initial GDP is sufficiently high, then expressway connection can decrease the GDP. Moreover, if the initial GDP is sufficiently high and expressway connection does decrease the GDP, then it must have also decreased emissions.*

Appendix III proves the proposition. 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 level of the hierarchy of needs. In this scenario, as illustrated by Panel A of Figure 6, 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 system is well-behaved.

When the initial consumption is sufficiently high, the initial equilibrium can fall in the higher level of the hierarchy of needs. In this scenario, as illustrated by Panel B of Figure 6, the planner cares primarily about the environmental quality, so she would like to sacrifice consumption as much as possible, as long as the economy still stays at the higher level of hierarchy of needs. An increase in the economy's ability to generate consumption presents an opportunity to the planner to sacrifice more of the consumption composite for better environmental quality without slipping into the lower level of hierarchy of needs, 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 level of the hierarchy of needs, 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 level of the hierarchy, our preference specification simplifies the exposition without losing much generality.

VII. Expressway and Pollution

Effects on COD Emissions

Our model also predicts that, in our dataset, for rich counties that saw negative income effect of expressway connection, the emission effect should be negative. 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 but 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. 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, consistent with the theoretical prediction.[20]

In Table 7, we examine several other emission measures. In Columns 1 to 4, we use COD emissions from the key polluting plants as the outcomes and find similar results. In

[20] 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 3, 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.

Columns 5–8, we investigate ammonia-nitrogen (NH_3-N) emissions.[21] Consistent with the result for COD, poor counties emit more ammonia-nitrogen and rich counties emit less after expressway connection.

In Columns 9–12, we examine sulfur dioxide (SO_2). We expect the results for SO_2 to be different because local county governments have little power to regulate them. 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, largely not controlled by county governments. As expected, we see that the heterogeneity results disappear for SO_2.[22]

Channels

To shed light on the channels through which expressway affects both GDP and pollution, we examine several other outcome variables, following the regression specified in Equation (2).

We report the results for COD emission intensity in Columns 1 and 2. The total emission measure tells us whether the overall environmental quality in a county has improved or deteriorated, while the intensity measure tells us whether the key polluting plants use cleaner technology to reduce emissions per dollar-value of output. The strong heterogeneity suggests that the emission intensity increased in poor connected counties and decreased in rich connected counties. This pattern indicates that firms in poor counties adopted more pollution-intensive technology, while firms in rich counties adopted cleaner technology.

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[21] 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.

[22] The data for nitrous oxides (NO_x) are not available before 2006 so we cannot perform similar exercises.

We then turn to the number of key polluting firms. The regression result in Column 3 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. This pattern is consistent with our model: some of the rich regions try to sacrifice more GDP for better environmental quality. 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, 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.

VIII. Conclusion

This paper investigates how expressway connection affects local GDP using county level data from China. We highlight the expressway impacts can be highly heterogeneous and the heterogeneity hinges on a county's initial income. After expressway connection, counties with lower initial GDP per capita will grow faster, while counties with initially higher GDP per capita will grow slower. The empirical findings challenge some popular explanations in the trade literature as both the comparative advantage and the home market effect cannot independently fully reconcile our findings. We further show that this heterogeneity cannot be explained by supply-side factors, or by initial access to nearby markets. Consequently, we infer that demand-side factors are behind this heterogeneity, and we build a trade model with hierarchical preference between consumption and environmental quality to explain our empirical results. We further test the model's prediction and show that, responding to expressway connection, initially poor counties grow in a more polluting way and host more polluting firms, while initially rich counties do the opposite, sacrificing some GDP for better environment.

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, in Faber (2014)'s core-peripheral setting, expressway connection worsens the income inequality between the peripheral and core areas, while our findings imply that, although the negligible average impact of expressway connection will not change the inequality between the peripheral and core areas much, the connection will reduce income inequality within the peripheral areas.

Third, economists have been well appreciating the importance of production-side factors, such as the capital, land, and labor endowments and production technology, in explaining the variations in economic and environmental performance. Our research suggests that demand-side factors can be equally important. Regions with different income levels may hold different preferences, and these differences should be considered in welfare evaluation and policy design.[23]

We conclude with some directions for further investigation. First, in our model, we assume that the environmental impacts of emissions are local, while pollution in one region in reality can affect neighboring regions. In such cases, a welfare-maximizing development path at the aggregate level would depend on the specific patterns of the externality. Second, as noted by Baum-Snow et al. (2016b), a fundamental problem of the reduced-form-based results is that "they do not provide a way to capture general equilibrium effects." For

[23] Along this line of thought, a recent study by Caron and Fally (2017) emphasizes the role of income-driven difference in consumption patterns in determining the cross-country difference in CO_2 emissions.

example, the aggregate impact of many counties' connections on the national market could be non-negligible. Future research on these issues is warranted.

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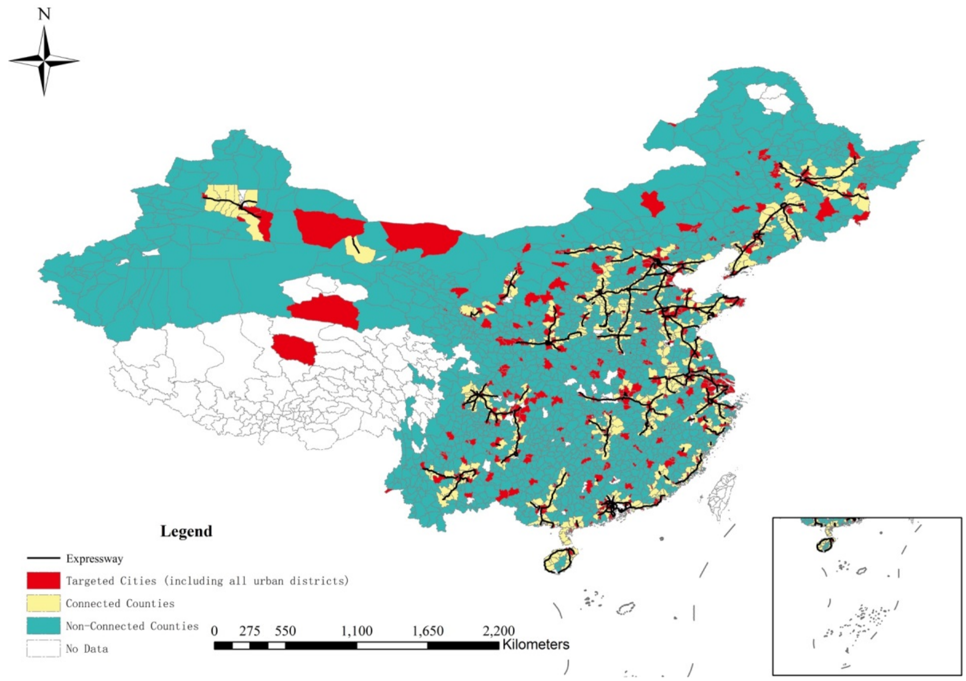
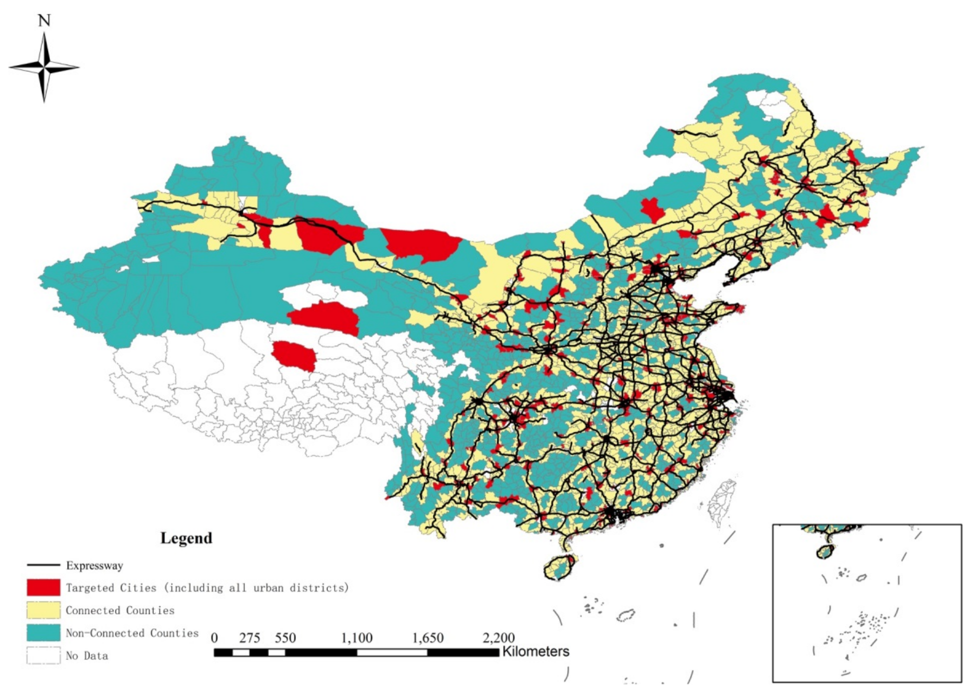
FIGURE 1. EXPANSION OF THE NATIONAL EXPRESSWAY SYSTEM IN CHINA



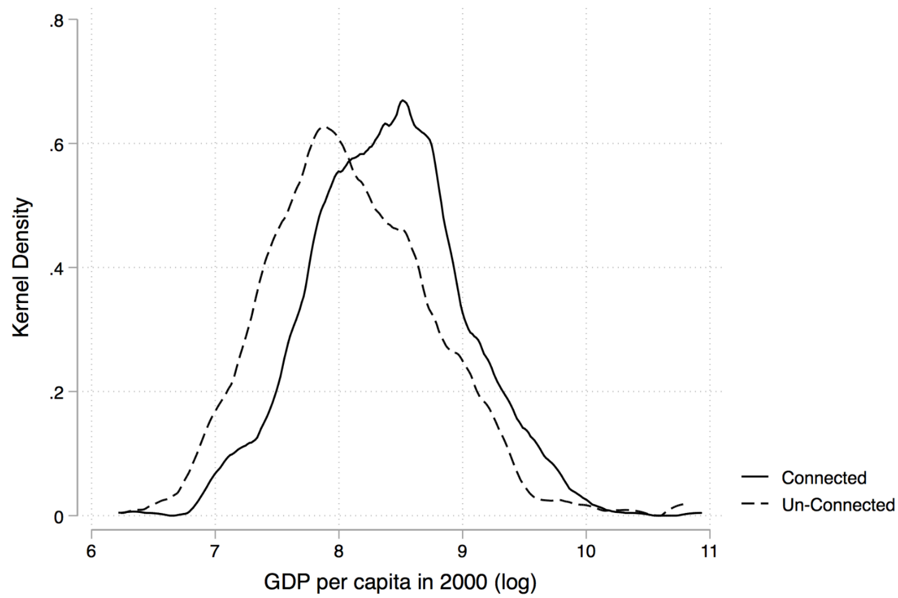
Panel A. China's National Expressways in 2000



Panel B. China's National Expressways in 2012

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

Pane A. Unmatched Sample



Panel B. Matched Sample

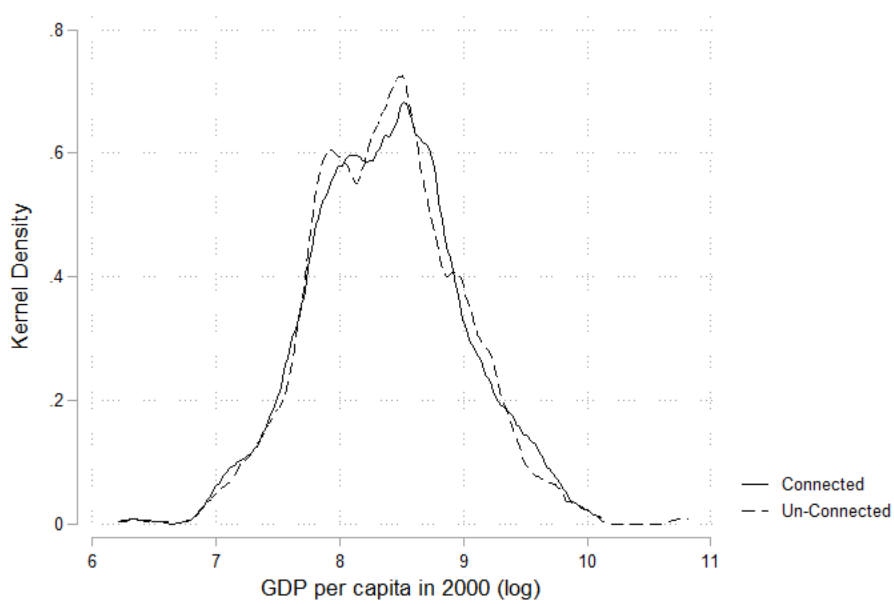
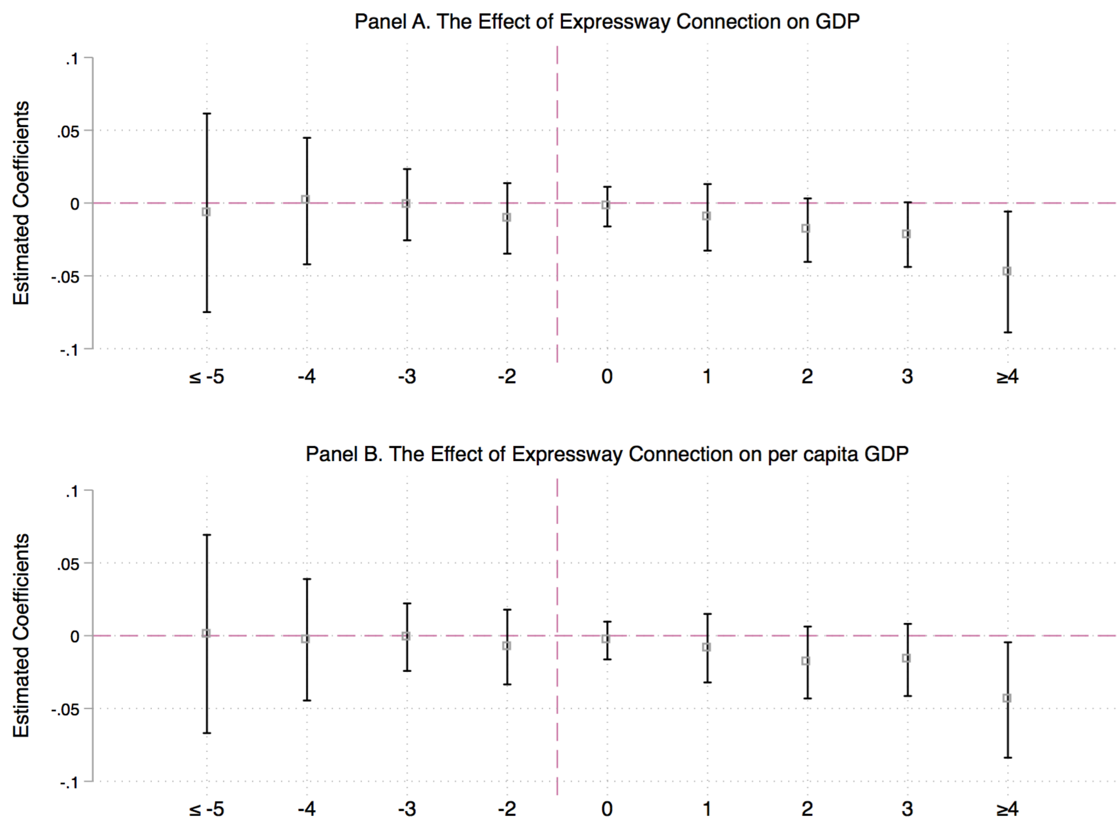
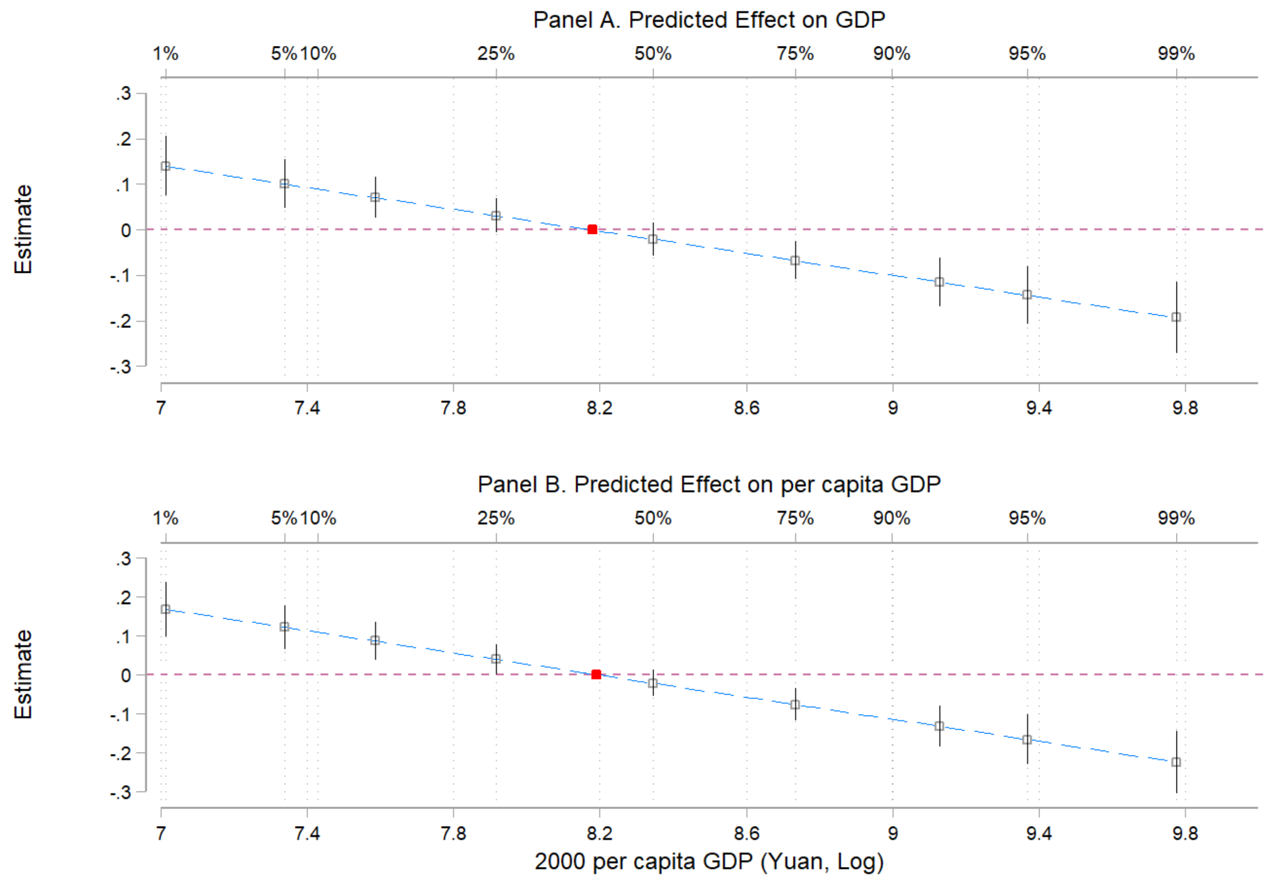


FIGURE 3. TESTS FOR PARALLEL TRENDS



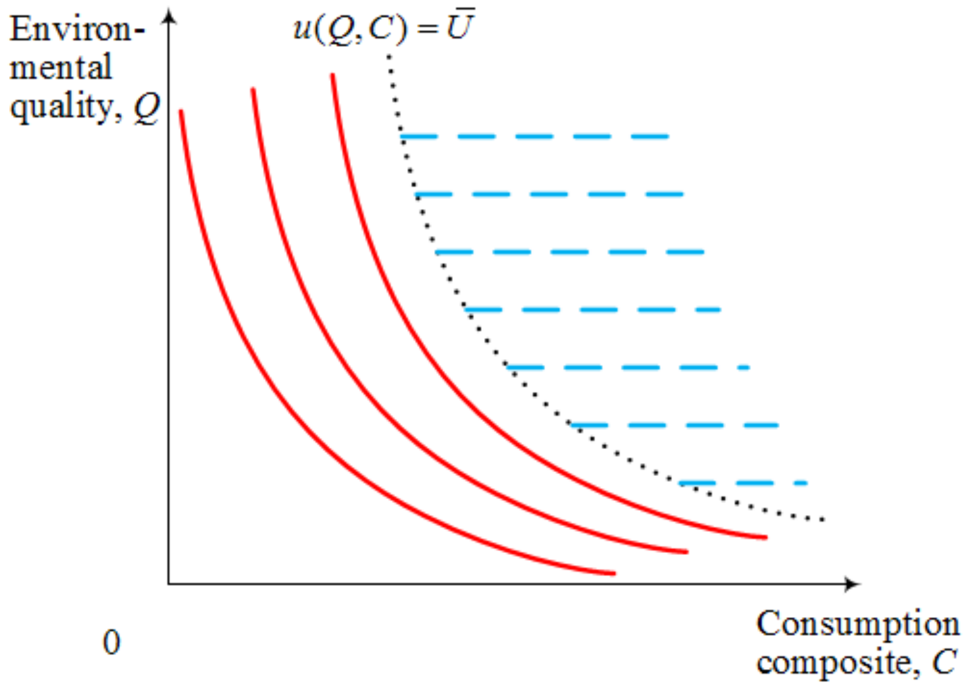
Notes: The figure plots the estimates and the 95% confidence intervals of the coefficients in the event study regressions following Jacobson et al. (1993). The horizontal axes denote years before or after the expressway connection, where the year just before the connection year is the benchmark. See 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. The impacts are positive for poorer regions and are negative for richer regions. The prediction is based on Table 3, Columns 1 and 4.

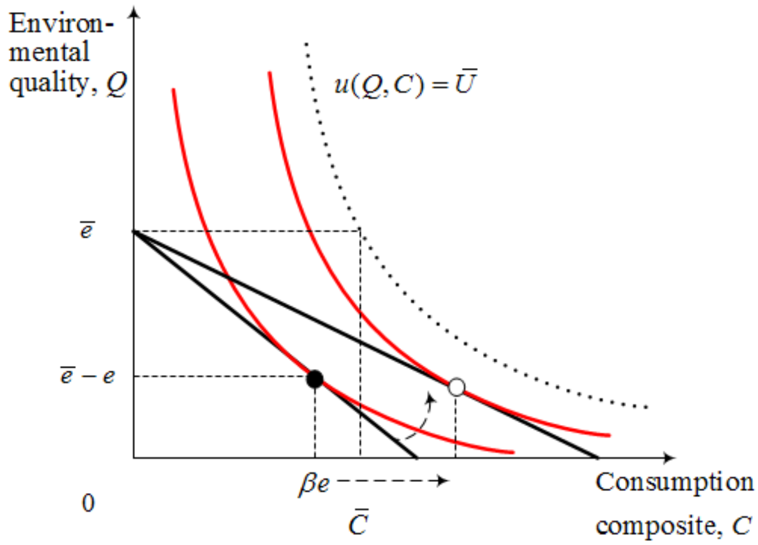
FIGURE 5. INDIFFERENCE CURVES IMPLIED BY THE PREFERENCE EXHIBITING A HIERARCHY OF NEEDS



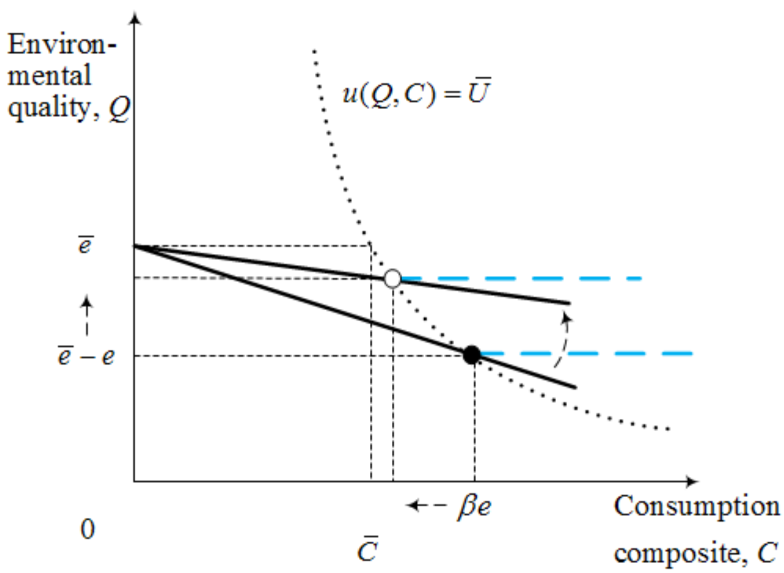
Notes: The solid, red curves are examples of the indifference curves at the lower level of the hierarchy. The dashed, blue lines are examples of the indifference curves at the higher level of the hierarchy. The dotted, black curve is defined by $u(Q,C) = \overline{U}$, which is the asymptotic curve of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

FIGURE 6. IMPACT OF LOWER TRADE COST

Panel A. Initial equilibrium at the lower level of the hierarchy of needs



Panel B. Initial equilibrium at the higher level of the hierarchy of needs



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 the higher level of the hierarchy, 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 1. Summary Statistics of Sampled Counties

Variable	Un-Matched Sample			Matched Sample		
	Overall	Connected	Un-Connected	Overall	Connected	Un-Connected
GDP (2000)	2,582	2,990	2,094	2,666	2,848	2,484
	(5,722)	(2,938)	(7,825)	(3,894)	(2,668)	(4,816)
GDP (2012)	15,108	17,452	12,286	15,430	16,426	14,433
	(31,953)	(18,322)	(42,815)	(22,530)	(16,364)	(27,336)
GDP per capita (yuan, 2000)	4,912	5,396	4,327	5,253	5,258	5,249
	(4,356)	(4,002)	(4,686)	(3,698)	(3,457)	(3,930)
GDP per capita (yuan, 2012)	30,819	32,481	28,806	32,808	31,685	33,932
	(32,808)	(30,819)	(34,982)	(34,000)	(31,428)	(36,402)
# of Counties	1,646	897	749	1,614	807	807

Notes: Standard deviations are reported in the parentheses below the means. County-level 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).

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)	(0.01)	(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	0.91	0.93	0.93	0.90	0.92	0.93

Notes: This table estimates the impacts of expressway connection on GDP measures using a variety of specifications. 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	0.98***	0.67***	0.70***	1.17***	0.83***	0.88***
	(0.19)	(0.17)	(0.17)	(0.21)	(0.18)	(0.18)
	(0.36)	(0.29)	(0.29)	(0.40)	(0.29)	(0.29)
	(0.25)	(0.22)	(0.23)	(0.27)	(0.22)	(0.24)
Expressway*GDP pc	-0.12***	-0.08***	-0.09***	-0.14***	-0.10***	-0.11***
(yuan, log, Year 2000)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
	(0.04)	(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	0.91	0.93	0.93	0.90	0.92	0.93

Notes: This table estimates the heterogeneous impacts of expressway connection on GDP measures using a variety of specifications. 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	0.09***	0.10***	0.06**	0.06**	0.10***	0.11***	0.07**	0.06**
	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)
High Income*Expressway	-0.15***	-0.15***	-0.11***	-0.10***	-0.16***	-0.16***	-0.12***	-0.11***
	(0.02)	(0.02)	(0.04)	(0.03)	(0.02)	(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	0.93	0.93	0.91	0.91	0.92	0.93	0.90	0.90

Notes: This table estimates the heterogeneous impacts of expressway connection on GDP. 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	0.98***	1.71***	0.59**	0.82***	1.00***	1.00***	1.01***	1.03***	2.21***
	(0.19)	(0.23)	(0.30)	(0.21)	(0.23)	(0.19)	(0.27)	(0.19)	(0.33)
Expressway*GDP pc	-0.12***	-0.13***	-0.11***	-0.11***	-0.12***	-0.15***	-0.12***	-0.13***	-0.26***
(Year 2000)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)
Expressway*X	0.00	-0.11***	0.04**	0.07***	0.00	0.02**	-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	1.17***	1.85***	0.71**	0.95***	1.17***	1.18***	1.20***	1.21***	2.37***
	(0.21)	(0.24)	(0.31)	(0.22)	(0.25)	(0.21)	(0.29)	(0.21)	(0.34)
Expressway*GDP pc	-0.14***	-0.14***	-0.13***	-0.13***	-0.15***	-0.16***	-0.15***	-0.15***	-0.28***
(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***	0.01	0.02*	-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

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

Table 6. 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	2.74***	1.67**	2.25***	-0.12	3.13***	1.89**	2.53***
	(0.09)	(0.73)	(0.82)	(0.83)	(0.09)	(0.79)	(0.90)	(0.91)
	(0.05)	(0.77)	(0.70)	(0.62)	(0.06)	(0.84)	(0.81)	(0.72)
	(0.10)	(0.84)	(0.88)	(0.93)	(0.09)	(0.88)	(0.94)	(1.03)
Expressway*GDP pc		-0.34***	-0.21**	-0.28***		-0.39***	-0.24**	-0.32***
(yuan, log, Year 2000)		(0.09)	(0.10)	(0.10)		(0.09)	(0.11)	(0.11)
		(0.09)	(0.09)	(0.08)		(0.10)	(0.10)	(0.09)
		(0.10)	(0.10)	(0.11)		(0.10)	(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. 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	3.45***	-0.09	3.95***	-0.08	3.84***	-0.13	4.53***	-0.07	-0.33	-0.08	-0.17
	(0.09)	(0.75)	(0.10)	(0.82)	(0.11)	(1.12)	(0.13)	(1.27)	(0.06)	(0.54)	(0.06)	(0.55)
Expressway*GDP pc		-0.42***		-0.49***		-0.47***		-0.56***		0.03		0.01
(yuan, log, Year 2000)		(0.09)		(0.10)		(0.13)		(0.15)		(0.06)		(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. 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, log)		Output Value of Key Polluting Firms		Number of Key Polluting Firms (log)		Share of the Secondary Industry (%, log)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Expressway	-0.04	2.85***	-0.07	0.88**	0.04	0.90***	-0.00	0.61***
	(0.08)	(0.78)	(0.05)	(0.40)	(0.03)	(0.27)	(0.01)	(0.14)
Expressway*GDP pc		-0.35***		-0.11**		-0.10***		-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. Standard errors are clustered at county level and reported in the parentheses below the estimated coefficients. *** p<0.01, ** p<0.05, * p<0.1.

Online Appendices to “Expressways, GDP, and Pollution: Evidence from China and an Explanatory Model”

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.[1] After three 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.

[1] The coefficient of the placebo lead (>=5 years) is statistically significant at the 10% level for per capita COD emissions. This suggests that the connected counties and unconnected counties had slightly different per capita COD emissions five or more years previously. We believe this is consistent with our identification strategy because the rest of the coefficients of the placebo leads, which are closer to the actual connection time, are all statistically insignificant.

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, we also find that these slight alterations to the treatment status of this small set of counties does not affect our main regression results.

Appendix III: Proof of the Proposition

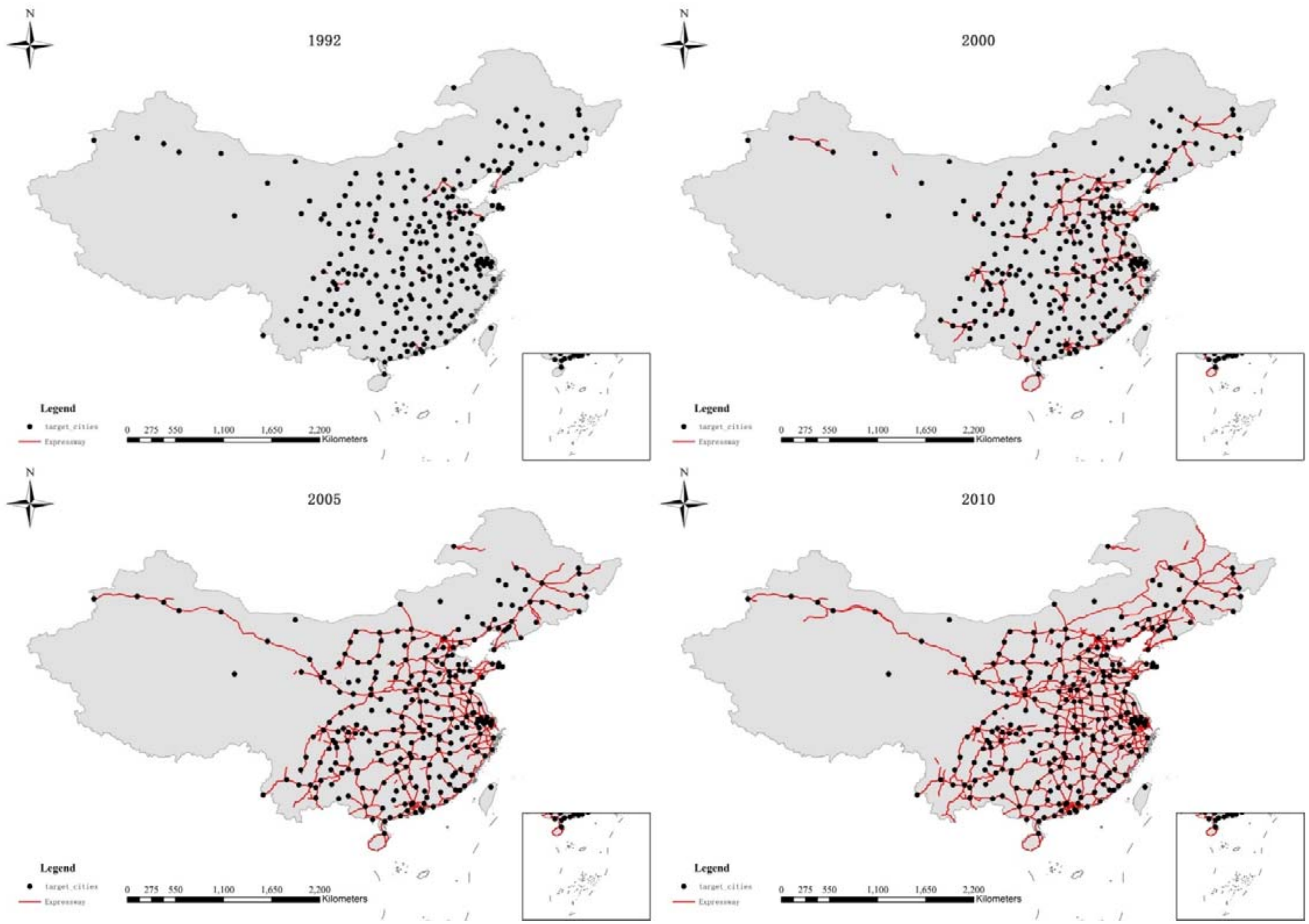
Proposition. *Given $\bar{e}$ and $U(Q,C)$, there exists a critical level of the consumption composite, $\bar{C}$, such that, if $C < \bar{C}$ in equilibrium, then $\frac{dC}{d\beta} > 0$; if $C > \bar{C}$ in equilibrium, then $\frac{dC}{d\beta} < 0$ is possible, where $\bar{C}$ is defined by $u(\bar{e},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

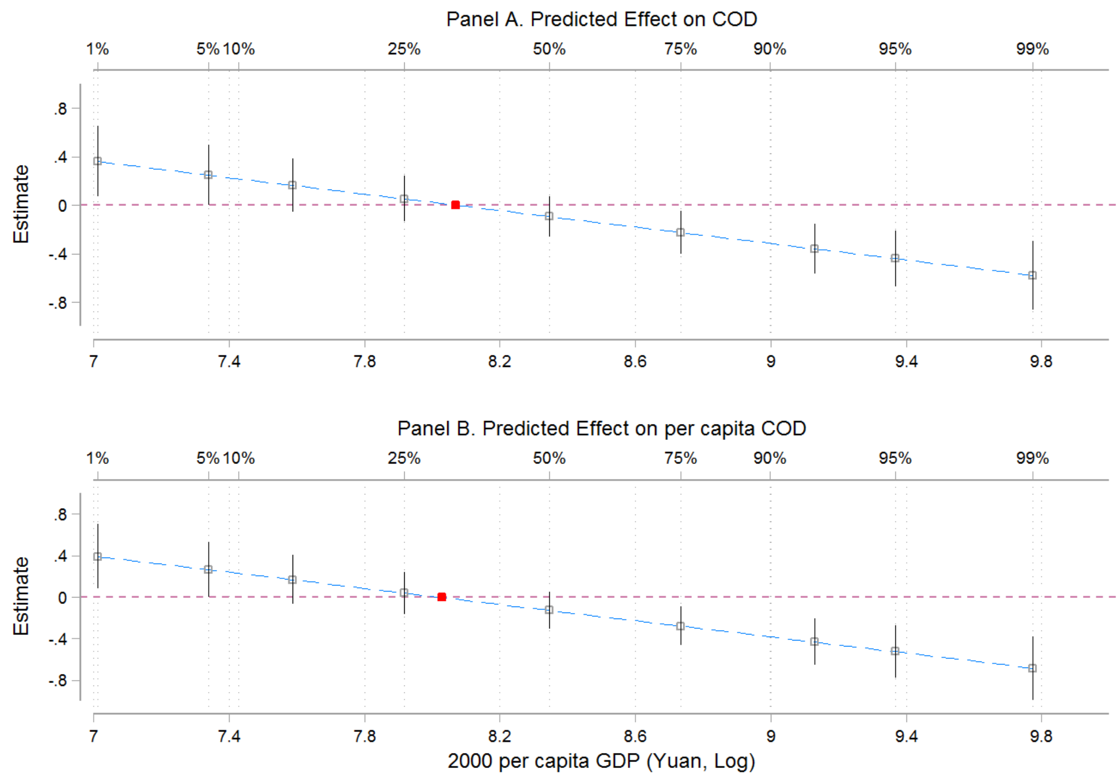
When the initial β is sufficiently large, the initial (C,Q) bundle falls in the higher level of hierarchy, and they come from the corner solution of $\max_{e} \bar{U} + v(Q)$ subject to $u(\bar{e} - e, \beta e) \geq \bar{U}$. The solution then satisfies $u(Q,C) = \bar{U}$, $C = \beta e$, and $Q = \bar{e} - \frac{C}{\beta}$. Note that $u(Q,C) = \bar{U}$ is the path generated by an increasing β within the higher level of the hierarchy of needs. 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 hierarchy of needs, as β approaches infinity. Therefore, when $C < \bar{C}$ in the initial equilibrium, the initial (C, Q) bundle must fall in the lower level of the hierarchy of needs; when $C > \bar{C}$ in the initial equilibrium, the initial bundle can fall in the lower or higher level of the hierarchy. The results then follow.■

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



APPENDIX FIGURE 2. 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. The impacts are positive for poorer regions and are negative for richer regions. The prediction is based on Table 6, Columns 1 and 4.

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 (cont'd). 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)
>= 5 Years Before	-0.01	0.00	-0.09	-0.08	0.02	0.03
	(0.03)	(0.03)	(0.07)	(0.07)	(0.03)	(0.03)
4 Years Before	0.00	-0.00	-0.05	-0.05	0.02	0.02
	(0.02)	(0.02)	(0.04)	(0.03)	(0.02)	(0.02)
3 Years Before	-0.00	-0.00	-0.02	-0.01	0.00	0.00
	(0.01)	(0.01)	(0.03)	(0.02)	(0.02)	(0.02)
2 Years Before	-0.01	-0.01	-0.02	-0.00	-0.00	-0.00
	(0.01)	(0.01)	(0.02)	(0.03)	(0.01)	(0.01)
Year of Connection	-0.00	-0.00	0.02	0.02	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
1 Year Later	-0.01	-0.01	0.03*	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	0.04*	-0.03***	-0.03***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
3 Years Later	-0.02*	-0.02	0.04*	0.05**	-0.04***	-0.04**
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
>=4 Years Later	-0.05**	-0.04**	0.01	0.02	-0.06***	-0.06***
	(0.02)	(0.02)	(0.03)	(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	3,012	2,982	10,428	10,365
R^2	0.91	0.90	0.94	0.93	0.91	0.90

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

Table S3. Estimates Using Straight-Line IV

	Expressway	Δ log (GDP) between 2000 and 2012		Δ log (per capita GDP) between 2000 and 2012	
	(1)	(2)	(3)	(4)	(5)
Straight-Line IV	0.34***				
	(0.03)				
Expressway		-0.05	1.69***	0.03	2.07***
		(0.06)	(0.55)	(0.08)	(0.51)
Expressway*GDP pc			-0.21***		-0.25***
(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	0.26	0.29	0.30	0.34

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. 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 Unmatched Sample

	GDP (million yuan, log)				Per capita GDP (yuan, log)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Expressway	-0.01	2.77***	1.58**	1.88**	-0.01	3.27***	1.73**	2.06**
	(0.01)	(0.72)	(0.74)	(0.74)	(0.01)	(0.78)	(0.81)	(0.82)
	(0.02)	(0.87)	(0.70)	(0.69)	(0.01)	(0.96)	(0.79)	(0.77)
	(0.01)	(0.79)	(0.76)	(0.83)	(0.01)	(0.86)	(0.84)	(0.91)
Expressway*GDP pc		-0.35***	-0.21**	-0.25***		-0.42***	-0.23**	-0.27***
(yuan, log, Year 2000)		(0.08)	(0.09)	(0.09)		(0.09)	(0.10)	(0.10)
		(0.10)	(0.08)	(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	0.91	0.08	0.12	0.16	0.90	0.08	0.13	0.17

Notes: This table estimates the impacts of expressway connection on GDP measures using the sample before matching. 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 Unmatched Sample

	GDP (million yuan, log)	Per capita GDP (yuan, log)
	(1)	(2)
>= 5Years Before	-0.01	-0.02
	(0.04)	(0.04)
4 Years Before	0.01	-0.00
	(0.02)	(0.02)
3 Years Before	-0.00	-0.00
	(0.01)	(0.01)
2 Years Before	-0.00	-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	-0.05***	-0.04**
	(0.02)	(0.02)
County FE	Y	Y
Year FE	Y	Y
Obs.	19,835	19,472
R^2	0.91	0.90

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

Table S6. Heterogeneous Effect of Neighboring County Expressway Connection

	GDP (million yuan, log)			Per capita GDP (yuan, log)		
	(1)	(2)	(3)	(4)	(5)	(6)
Neighbor Expressway	0.68**	0.53**	0.48**	0.93***	0.63***	0.61***
	(0.28)	(0.21)	(0.23)	(0.28)	(0.21)	(0.23)
N-Expressway*GDP pc	-0.08**	-0.06**	-0.05*	-0.11***	-0.07***	-0.07**
(yuan, log, Year 2000)	(0.04)	(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.	8,732	8,732	8,732	8,688	8,688	8,688
R^2	0.90	0.92	0.92	0.90	0.92	0.92

Notes: This table estimates the heterogeneous impacts of expressway connection on GDP measures using a variety of specifications. 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 S7. Alternative Specifications for Heterogeneity Patterns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. GDP (million yuan, log)								
Expressway	0.06**	0.05*	0.69***	-0.31**	-0.05	0.05	0.03	0.23
	(0.03)	(0.03)	(0.12)	(0.14)	(0.04)	(0.04)	(0.04)	(0.17)
Expressway*High Income	-0.11***	-0.11***	-0.10***	-0.09**	-0.09**	-0.10***	-0.12***	-0.11***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Expressway*X		0.00	-0.10***	0.05***	0.07***	0.00	0.00*	/
(Year 2000)		(0.00)	(0.02)	(0.02)	(0.01)	(0.00)	(0.00)	/
Panel B. GDP per capita (yuan, log)								
Expressway	0.07**	0.07**	0.71***	-0.32**	-0.05	0.05	0.04	0.22
	(0.03)	(0.03)	(0.12)	(0.15)	(0.04)	(0.05)	(0.04)	(0.18)
Expressway*High Income	-0.12***	-0.12***	-0.12***	-0.11***	-0.11***	-0.11***	-0.13***	-0.12***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Expressway*X		-0.00	-0.11***	0.05***	0.07***	0.00	0.00**	/
(Year 2000)		(0.00)	(0.02)	(0.02)	(0.01)	(0.00)	(0.00)	/
X Indicator	None	Distance (km)	Population (log)	Land Area (log)	Land per capita (log)	Share of Agriculture (%)	Share of Manufacturing (%)	All
County FE	Y	Y	Y	Y	Y	Y	Y	Y
Income Group * Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	13,440	13,440	12,338	12,329	12,329	13,440	13,440	12,329

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

Table S8. Parallel Trends Tests for Emissions

	GDP (million yuan, log)	Per capita GDP (yuan, log)
	(1)	(2)
>= 5Years Before	-0.01	-0.02
	(0.04)	(0.04)
4 Years Before	0.01	-0.00
	(0.02)	(0.02)
3 Years Before	-0.00	-0.00
	(0.01)	(0.01)
2 Years Before	-0.00	-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	-0.05***	-0.04**
	(0.02)	(0.02)
County FE	Y	Y
Year FE	Y	Y
Obs.	19,835	19,472
R^2	0.91	0.90

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

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	-0.02	1.00***	-0.02	1.22***	-0.10	2.75***	-0.13	3.18***
	(0.02)	(0.18)	(0.02)	(0.20)	(0.09)	(0.76)	(0.09)	(0.81)
Expressway*GDP pc		-0.12***		-0.15***		-0.34***		-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	0.91	0.91	0.90	0.90	0.06	0.06	0.06	0.06

Notes: This table estimates the heterogeneous impacts of expressway connection environmental and economic outcomes. 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.